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INFORMATION TRANSMISSION AROUND BLOCK TRADES ON THE SPANISH STOCK MARKET [1]

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Abstract _____

Current financial research is placing increasing attention on the effects of large transactions, or Block Trades (BT), on the financial markets. In order to analyze whether BT transmit information, we assume that information can be better reflected by changes in asset true value, proxied by the midpoint of bid-ask best quotes, instead of transactions prices or returns. Moreover, following market microstructure literature, we also look at changes in relative spread and in their adverse selection component. The Madrid Stock Exchange offers us a particularly appropriate testing ground for examining these issues, since this topic has not been facilitated as in other markets till 1998.

We analyze 195 BT, classified according with trading volume, the side of the market initiating the BT (buyer, seller or indeterminate initiated), its type (inside the spread, sweeping or not classified) and if they change or not the asset true value.

The main result of the paper is that it seems that there is BT information transmission when we look at adverse selection spread component in the different subsample classification, but there is no significant permanent effect in returns. We also observe changes in liquidity around BTs but the effect is related with temporary spread component. _____

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1. Introduction.

Information transmission through order flow is one important issue in financial research. The general markets efficiency assumption is based on that point. From the theoretical financial literature on information, the value of private information depreciates quickly (see, for example, Foster and Viswanathan (1990)). Thus, informed investors prefer large transactions (Block Trades) in order to get into a valuable position as soon as possible. On the other hand, it is also known that informed investors, in order to conceal their superior private information, are interested in camouflaging their desired trades into small or medium size trades (Kyle (1985)). However, given the important increase in institutional trading and the internationalization of investors in recent years, Block Trades (BT) are observed all over the world.

From the empirical point of view, is not clear whether these BTs may be understood as strategic trading motivated by information or whether they may be viewed only as a consequence of institutional investors balancing their portfolios.[1] Most of the empirical research about BTs focuses on information transmission by looking at permanent and temporary effects of BTs on asset prices or returns. The permanent part is interpreted as being information motivated, whereas the temporary one is associated with price pressure or liquidity costs. Scholes (1972), Kraus and Stoll (1972), Holthausen, Leftwich and Mayers (1987, 1990) and Chan and Lakonishok (1993, 1995) are interesting examples for this issue on the NYSE. Both effects (permanent and temporary) seem to be present and the sign depends on the type of BT. However, the results depend on the sample and the methodology used in the study.

Similar analyses for order driven markets can be found in Ball and Finn (1989), for the Sidney Stock Exchange, and Riva (1996), for the Paris Bourse. Gemmill (1996), for the London Stock Exchange, has recently analyzed the liquidity effects of BTs under different publication rules. In related literature, Seppi (1992) and Daley,

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[1] Formal models of information disclosure through BTs can be found in Easley and O'Hara (1987) and Seppi (1990). Easley and O'Hara show how BTs significantly increase the probability market participants attach to the existence of private information. Seppi (1990) develops a model where, under not very restricted circumstances, information-based BTs are traded in a partial-pooling equilibrium.

Hughes and Rayburn (1995) among others, investigate the extent to which block price changes around quarterly earnings announcements.

This paper investigates the impact of BTs in Madrid Stock Exchange (MSE). In order to analyze whether these transactions transmit information, we propose a new approach. In sharp contrast with previous BT research, we assume that information can be better reflected by changes in true asset value, proxied by the midpoint of bid-ask best quotes. Looking at these intrinsic value changes instead of price changes, we avoid the effects of liquidity (noninformative) trades. These kinds of transactions modify asset prices without affecting their true value (the so-called bid-ask bounce).[2] At the same time, it allows us to consider very informative bid-ask changes which are not the consequence of a new transaction (and, therefore, no new price is established), but which reflect worthy changes in the investor's preferences for assets. Therefore, we will look at changing true asset value orders instead of trades.

Related with information effects, market microstructure literature analyzes how prices absorb information, measured by changes in the adverse selection spread component.[3] Adverse selection can be understood as a measure of information asymmetries. Thus, if we observe a decrease in adverse selection component around BTs, we could conclude that BTs transmit information diminishing information asymmetries between agents. This adverse selection must be differenciated of liquidity in general. Therefore, given the previous evidence of BT studies, we will analyze the behavior of relative spreads around BTs to detect changes in liquidity not related with information transmission.

The MSE offers us a particularly appropriate testing ground for examining these issues. In MSE, this topic has not been facilitated as in other markets till 1998.[4] Thus, BTs were dealt like small trades. This market microstructure characteristic can lead investors to avoid this type of trades because of the effort of crossing a BT and evident risk of interference. For this reason, we expect transacted BTs to be very informative.

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[2] Seppi (1992) also points out that the conclusions obtained by looking at price changes may be affected by the potential presence of a variety of price pressure effects.

[3] A good reference is O'Hara (1995).

[4] Examples of these special BT devices are the upstairs market in the NYSE (Hasbrouck, Sofianos and Sosebee (1993)) and the broader bid-ask spread in the Paris Bourse (Riva (1996)).

This argument, together with the new approach that we propose, makes this study innovative in current literature on information transmission around BTs.

The main result of the paper is that it seems that there is BT information transmission when we look at adverse selection spread component in the different subsample classification, but there is no significant permanent effect in returns. We also observe changes in liquidity around BTs but the effect is related with temporary spread component.

The remainder of the article is organized as follows. Section II reviews briefly the MSE microstructure and, particularly, the block trading process. The dataset and sampling rules are presented in section III. Section IV discusses the methodology used and results obtained in the analysis. Finally, section V offers some concluding remarks.

2. Institutional Settings of the Spanish Stock Market.

The electronic continuous market for equities in MSE is a purely order driven market. Through this system, 142 companies are traded. The main characteristic is a single order book for every stock. We find three main periods in the daily market:

a) Preopening period (from 9:00h to 10:00h): In this period, introduction, modifications and cancellations of limit orders are allowed. Depending on demand and supply, the system calculates a preopening price in real time. At 10:00h the system assigns shares to orders at prices better than or equal to the opening price.

b) Open market period (from 10:00h to 17:00h): During this period limit and market orders are introduced. If a counterpart is found they are automatically executed. If not, the order remains on the book until an incoming order fits it, or the order is canceled. In this period prices change in real time depending on the flow of buy and sell orders.

c) Special operations period (from 17:00h to 20:00h): In this period it is possible to report pre-agreed trades with an effective volume bigger than 20% of the daily turnover. So, this period is specifically designed for BT transactions.

In addition to this possibility, traders can use the preopening period to trade BT. Introduction of pre-agreed large trades in this period consists in buying at the

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maximum possible price of the day (15% more than the closing price of the previous day) and selling the same quantity of shares with a 15% reduction on the closing price. With this behavior you can be sure to trade at the opening price.

We will not use these closed market BTs in this study. The reason is that we want to identify clear information signals. We could hardly identify BTs information effects because of the overnight problem in the opening prices. In order to observe the information effects of BTs, we will focus on the open market period. In this way, we avoid other news that could affect the opening asset price during the closed periods.

Investors willing to trade BTs in the open market suffer two handicaps. First, traders must introduce a limit order to execute a BT. So, it is impossible to cross a transaction outside the limit order book. Second, it is not possible to trade outside the spread of best buy and sell prices. As a consequence, is very difficult to trade large blocks of shares in this period. In this context, a BTs trader can face two different market situations: (i) When there is a level of prices available between best buy and best sell (spread bigger than tick size), traders quickly introduce pre-agreed sell and buy limit orders for the same amount of shares at the price available inside the spread. (ii) When there is no such available price and traders do not want to wait, they sweep the necessary orders to open the spread and get a price available inside it. This sweeping activity is particularly necessary for stocks that are so liquid that it is very difficult to find an available price. Obviously, it imposes an additional cost.

Crossing both types of BT, when one side order has been introduced, there is always the possibility that another limit order may arrive and the pre-agreed BT cannot be completely crossed.[5] We call this issue "interference risk".

3. Data.

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[5] Since November 6th 1998, a new device to report and trade BTs in the open market period has been operative. This feature allows market members, as other European markets already do, to trade BTs outside the best bid-ask spread of the book. In any case, this possibility is set according to certain relationship with market prices. Specifically, there are two current ways to trade a block: (i) For the stocks belonging to the IBEX-35 Index (the 35 most liquid stocks in MSE), members can report arranged blocks to the Exchange. As a consecuence, interference risk has been eliminated. Minimum required amount of shares for trade is 5% of the daily turnover in the last quarter of the year. In this context, the spread is the on line weighted average price of the six best levels of bid and ask. (ii) For all the stocks on the MSE, market members can introduce orders bigger than 10% of the daily

Data on all orders on the MSE in the open market, during the one-year period from May 1996 to April 1997, were collected from MSE files. As we indicated, we only select orders which change true asset value. From now on, these orders will be termed *orders*. In spite of the posible existence of other orders between any two of them, they will be considered in our analysis as consecutive. So, the kth order changing the true asset value and the following one will be referred as the k and $k+1$ orders, respectively. The available information for each of these orders includes: time it occurs (stamped to the nearest second), date, bid, ask, transaction price and number of shares transacted since the previous order.[6] The value of the MSE Index (IBEX-35) for each second was also obtained from MSE files.

As a description of MSE, table 1 presents some summary statistics about the size distribution of all trades crossed in MSE during the period considered. As can be observed, the mean trading volume is 3.4 million pesetas. Whereas the number of trades with 1 million or less represents more than 60% of all trades, these trades only represent 5.9% of effective trading volume. Throughout this paper, we define BTs as any trade whose value is over 50 million pesetas and, at the same time, is greater than 20% of the average effective trading daily volume for the respective asset.[7] According to this definition, there were 2,381 BTs during this period. They represent 9.1% of trading volume, but only 0.06% of the total number of trades.

3.1. Sampling rules.

In order to select our sample of BTs, some filters were applied to the available firms and BTs. Firstly, we only consider BTs corresponding to the 50 most liquid firms. This restriction allows us to use a highly continuous trading sample. In this way, disturbing nontrading effects are eliminated. We exclude a BTs if there is a payment or stock split (or any payment in the firm) in the 13 calendar-days window for each one (6

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turnover in the last quarter with a deviation of 15% from last closing price. Here there is no time and price priority rule and members can select any order.

[6] For orders which do not produce transactions, we consider the price of the corresponding previous transaction. For the first order of the day we use the accumulated volume of shares transacted in the preopening period.

[7] This cut-off was chosen because it is the institutional requirement for "specially communicated trades" in MSE.

calendar-days before and 6 calendar-days after it).[8] These BTs are likely to be noninformationally motivated, as Choe and Masoulis (1992) point out. BTs for which additional blocks occurred in the stock during the same 13 calendar-days window are also excluded. In this way, selected BTs are not affected by the close presence of another BT. For reasons of data availability (motivated by the estimation period chosen) we also exclude BTs occurring less than 14 calendar-days after the beginning of the period analyzed and 14 calendar-days before the end. Finally, we only analyze blocks occurring between 11:00h and 16:00h. The first and the last hour of the trading day are excluded because of the disturbing effects of opening and closing trades. Many large transactions at the opening can not be considered as BTs. They are only a large number of individual transactions crossed together and printed as one transaction. On the other hand, transactions during the last hour may incorporate end-of-the-day effects (see Amihud and Mendelson (1986) and Harris (1986)).

It must be said that some of the BTs selected according to these criteria did not appear in the original sample of orders changing the asset true value proxy. However, we decided to include them because their information effects could operate with some periods of delay or advance.[9]

After all these sampling rules, the number of BTs we finally consider is reduced to 195, corresponding to 41 firms. They represent 1.3% of the trading volume during all the period analyzed. BTs trading volume ranges from 51 to 27,668 million pesetas and the mean value is about 947 million pesetas.

The analyses will be performed individually for each BT. The estimation period we consider is a 29 calendar-days window for each BTs (14 calendar-days before and 14 calendar-days after BT).[10] It is clear, considering the differences between assets, that the number of orders in this fixed period is very different from one asset to

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[8] There is nothing special in this figure. The only interest is to separate BT effects as far as possible from others.

[9] We will observe this possibility when traders choose to introduce the BT order not in the first level of book prices. If there is enough time another order can arrive and when BT is crossed we will not observe a change in true asset value.

[10] The estimation period must be long enough to provide precise estimates of parameters and short enough to keep the number of trades manageable. We consider this period as one which appropriately meets both requirements.

another. The range goes from 235 orders for the least liquid asset to 4,460 for the most liquid, with 1,487 being the average number for all BTs in the sample.

3.2. Descriptive statistics

Unfortunately, our dataset does not identify the party initiating the large transaction. However, as is clear from empirical literature on BTs, the signs of the expected effects differ for buyer and seller-initiated transactions. A buyer-initiated BT is expected to produce a permanent increase in the asset price, whereas the inverse effect is expected for a seller-initiated BT. In order to sort BTs as buyer or seller-initiated, we calculate the difference between the BT price and the true value proxy at the previous trade. If this difference is positive, we classify BTs as *buyer-initiated*, whereas if it is negative we classify it as *seller-initiated*. BTs whose price equals the previous asset true value are classified as *indeterminate-initiated*.[11]

The dataset identifies most BTs according to an *inside the spread* or *sweeping* classification. BTs not included in either of these types are considered as *not classified*.[12] Intuitively, we expect stronger effects in sweeping BTs because of the additional cost they impose. BTs were also sorted by whether or not they change the asset true value. As above, we expect greater effects in BTs that change the asset true value. Additionally, BTs are classified in four groups according to their trading volume. Each group has about the same number of BTs, with *BB* being the group with the biggest BTs, *SS* the group with the smallest, and *BS* and *SB* the medium size group. We expect a direct relationship between information transmission and BTs size.

Tables 2 and 3 illustrate some of the distinguishing features of the BTs in the sample. Table 2 shows the sample composition regarding the side initiating the BT, type and changes or not in asset true value. As can be observed in panel A, the sample distribution is very similar regarding the side initiating the BT, especially in the volume transacted. The number of indeterminate-initiated BTs seems to be greater than the

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[11] This criterion has been used previously by Blume, Mackinlay and Terker (1989) and Hausman, Lo and Mackinlay (1992), among others. The "tick test" algorithm (which classifies a transaction by looking at the previous transaction's price) proposed in Lee and Ready (1991), is a less information-consuming method. Hausman, Lo and Mackinlay (1992) consider the true value rule considerably more accurate.

[12] These are BTs whose limit orders were introduced in the book but not at its first level of prices, and they wait to execution.

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other types for small and medium BTs. Panel B shows that the largest BTs by volume transacted are traded inside the spread, whereas the not classified BTs seem to be the small ones. However, the number of BTs in each group is very similar. Panel C shows that the biggest BTs change the asset true value. But this relationship is inverse for the other size BTs.

Table 3 describes the day-of-the-week and hour-of-the-day distribution of the BTs sample. The first value in each cell is the percentage of the number of BTs and the second is the corresponding trading volume. We find a clear seasonal pattern in our sample. First, from MSE microstructure, it is clear that investors tend to use the less competitive hours of the day to cross large transactions. We see in table 3 that the 13:00-14:00h period is the time of the trading day where the biggest BTs are crossed. We also observe differences in day of the week. Surprisingly, on Friday (the day of the week when futures contracts expire) we do not observe special derivatives effect, whereas we see a large volume activity during the first part of the week.

4. Methodology and Results.

There are certain features that characterize our dataset. First, orders are sampled at irregularly spaced random intervals (whenever changes in true value occur). So, observations are unlikely to be identically distributed, since some of them are very closely spaced in time while others may be separated by hours. Second, asset prices are always quoted in discrete units or ticks (discreteness). Among the existing models of stock price discreteness, ordered probit is the only specification that can easily capture the impact of explanatory variables on prices changes while also accounting for price discreteness and irregular transaction intervals. [13] However, the use of ordered probit specification comes up against a major problem with illiquid stocks. We must limit tick movements because of the necessary degrees of freedom in the estimation procedure. So, this method is not useful for our sample.

Therefore, in order to diminish the discreteness problem, we will use returns instead of prices. On the other hand, to solve the irregular random intervals problem, we will use two alternative specifications: the use of differences in time between

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[13] A description of this estimation procedure can be found in Hausman, Lo and Mackinlay (1992).

consecutive orders as an explanatory variable and the use of a time adjustment for our exogenous and endogenous variables.

As mentioned in the introduction, one of the variables we focus on is changes in asset true value. The true value idea is taken from market microstructure literature. Glosten and Milgrom (1985) advocate the use of the midpoint of bid-ask quotes as a proxy for the true value. For asset j, the true value after the kth order is denoted by m_{jk}, and is obtained as:

$$m_{jk} = \frac{A_{jk} + B_{jk}}{2} \tag{1}$$

where A_{jk} and B_{jk} are the ask and bid prices of asset j on the kth order, respectively. The point here is that if large trades convey valuable information, agents revise their estimation of the true price and their subsequent orders will modify the book quotes. These modifications are considered informative (whether or not there is a new transaction), because they represent changes in the amount investors are willing to pay or to receive for assets. We use continuously compounded returns of relative change in the true value proxy as the information variable. This variable will be denoted by R_{jk}.

BTs imply an important change in Normal Market Size. In addition to information transmission, BTs can involve temporary changes in liquidity. The idea is that BTs can affect investors optimal portfolio or related variables and impose an inventory cost. These liquidity effects of BTs are analyzed with regard to changes in relative spread. Many market microstructure articles focus on relative spread to study liquidity effects around dividend or earning announcements.[14] The relative spread for asset j, after the kth order is denoted by S_{jk}, and is defined by:

$$S_{jk} = \frac{A_{jk} - B_{jk}}{(A_{jk} + B_{jk})/2} \tag{2}$$

Additionally, we consider that BTs can affect some variables such as accumulated volume and differences in time between orders. One conclusion of market microstructure literature is that market activity can be measured by trading volume.

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[14] Lee, Mucklow and Ready (1993) and Rubio and Tapia (1996) are some representative examples of this literature.

Some papers have shown that it is important to control for some activity variables when we want to measure the information flow.[15] As Seppi (1992) indicates, when we look at BTs we may consider a proxy of activity. In this way, volume appears as one appropriate variable reflecting information arrival. We denote VOL_{jk} the square root of accumulated number of shares traded on asset j between orders $k-1$ and k.[16] On the other hand, we denoted as $Dift_{jk}$ the square root of time elapsed in seconds between orders $k-1$ and k on asset j.[17] Engel and Lange (1997) show that this variable can signal changes in order flow regime. So, we also look at these variables looking for changes in regime around BTs.

Preliminary evidence of BTs effects on previous variables is shown in table 4. In this table, we show percentage changes in relative spread, differences in time and accumulated volume dividing each observation by its average calculating the following statistic:

$$K_{jk} = \left(\frac{C_{jk}}{\overline{C}_j} - 1 \right) 100 \tag{3}$$

where C is S, $Dift$ y VOL. For returns we use the statistic:

$$K_{jk} = R_{jk} - \overline{R}_j \tag{4}$$

The average of these statistics across all BTs is calculated for ten orders just before and after them. The cross-sectional distribution of each average is used to study the significant level of the event. We can observe different evidence in table 4. First, relative spreads seem to decrease before and after the BT. This indicates an increase in liquidity. This effect is specially important just after BTs. From market microstructure theory, this reduction can be caused by the reduction in information asymmetries or trading cost. Regarding returns we cannot observe any significant variation around BTs. On the other hand, volume is large before and after BTs. Before BTs, there is a decrease in volume, this could indicate that agents are waiting for BT arrival. We observe nothing relevant after BTs. The only abnormal volume is the next BT order.

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[15] Previous research (Lee, Mucklow and Ready (1993) for the NYSE, and Rubio and Tapia (1996) for the MSE) has found clear effects of trade volume on relative spread. Therefore, we will consider volume as a control variable.

[16] We use the square root to avoid the outlier problem.

This could be a sign of agents updating their demands and portfolios. The positive and significant numbers we find in time differences show that time between orders increases just before and after a BT. Again, this could be an indication of investors waiting for trading and updating their expectations. However, this evidence is contrary to insider trading behavior, as is shown in Engel and Lange (1997) and theoretical papers that indicate that insiders would use noisy trading intervals to camouflage their trades. So, the preliminary evidence around BTs shows different behavior of relevant variables as spreads, volume and differences in time.

However, the observed effects on our variables may be due to variables affecting them other than BTs information transmission. In order to isolate the BTs effect, we need to control the endogenous variables considered for alternative influential variables around BTs. The control variables we use are well known in financial literature.

As we have pointed out, volume appears to be one appropriate control variable for information arrival. Therefore, we use *VOL* as an independent variable in the regression analysis. Three lags of this variable are considered in order to allow some delay in its effects. In order to avoid the disturbing overnight effect, we also consider an end-of-the-day dummy variable.[18] This variable, denoted by *Dend*, equals 1 if kth order on asset j is the first order of the day and 0 otherwise. We also take into account market return as an exogeneuos variable. We take the IBEX-35 Index as our market index. We take the nearest in seconds value for each order in the sample period. Its return is denoted by R_{IBEX}. We also use three lags of this variable in order to allow some delay in its effects. The aforementioned *Dift* is also considered as a control variable.

Finally, to pick up effects around BTs, we consider 21 dummy variables (a window of 10 orders before and after each BT) denoted DBT_τ. Each dummy equals 1 for order ocurring τ orders after the BT, and 0 otherwise. The order corresponding to the BT itself is considered as the reference order, $\tau = 0$. So, after controlling by the mentioned variables, their coefficients show us the effect of BTs on our endogenous variables before and after they occur.

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[17] When a change of day occurs, we use the time from the market opening.

As has been pointed out in the introduction, we consider three different endogenous variables: true asset value returns, relative spreads and adverse selection spread component. They will capture price, liquidity and information transmission effects respectively. Because no two firms have an identical timing of orders, we cannot estimate our regressions as a multivariate system across all BTs. So, we run one time-series regression for each BT. The coefficients are therefore averaged over all of them and over the different subsamples considered. If BTs are relevant for these variables, we will observe significant coefficients for the appropriate BTs dummy variables. These are the relevant variables in our analysis. The remaining variables are included only to control for external effects.

4.1. Returns Evidence.

Next, we show the regression for each BT used to analyze the BTs effects on true asset value returns. The time-series regression for each BTs j is:

$$R_k = \alpha + \sum_{\tau=-1}^{\tau=-3} \phi_\tau R_\tau + \sum_{\tau=0}^{\tau=-3} \lambda_\tau R_{IBEX\tau} + \sum_{\tau=0}^{\tau=-3} \beta_\tau VOL_\tau \\ + \gamma Dift + \varphi Dend + \sum_{\tau=-5}^{\tau=5} \delta_\tau DBT_\tau + \omega_k \tag{5}$$

where we use three lags of the endogeneous variable and DBT stands for the dummy variable employed to pick up effects around BTs.[19]

The first column of table 5 shows the results of the above regression. We only report the results for the total sample of BTs. First, we observe mean reversion in returns. This expected result is consistent with other results in literature. Secondly, clock time measured by $Dift$ is also significant. Other control variables seem relevant and coefficient signs are as expected (R_{IBEX}, VOL, $Dend$). So, the use of these variables to control seems to be justified.

Next, we show BT dummy coefficients. In general, they are not statistically significant. The contemporary coefficient is negative and significant. The most striking

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[18] It has been well-documented that overnight returns differ substantially from intraday returns (Amihud and Mendelson (1987) and Stoll and Whaley (1990)).

[19] The range of observations for each regression goes from 235 to 4,460. We run 195 regressions.

result is that in the different subsample classifications this coefficient does not change its sign or is not statistically relevant[20]. This is especially important in the buyer and seller classification. This is not consistent with previous BT studies and with our intuition. This negative effect of the contemporaneous BT dummy is offset by the effect of two orders later. In the end, there is no significant permanent effect in returns. The reason for this result could be the specific analyzed problems that traders face in MSE in crossing a BT. These problems could cause that BTs price would not be the real one. The idea is that investors willing to buy (sell) a BT would pay (renounce) an additional fee that is not observed by market participants. In this enviroment, BTs prices are not informative and there is no impact in returns.

Alternatively in order to control for irregular interval problem, we calculate equally time returns according with the expresion:

$$TAR_k = \left[(1 + R_k)^{1/Dift_k}\right] - 1 \qquad (6)$$

The analogous regression we now run is:

$$TAR_k = \alpha + \sum_{\tau=-1}^{\tau=-3} \phi_\tau TAR_\tau + \sum_{\tau=0}^{\tau=-3} \lambda_\tau TAR_{IBEX\tau} +$$
$$\sum_{\tau=0}^{\tau=-3} \beta_\tau TAVOL_\tau + \varphi Dend + \sum_{\tau=-5}^{\tau=5} \delta_\tau DBT_\tau + \omega_k \qquad (7)$$

where TAR_{IBEX} is calculated in the same way as TAR, whereas $TAVOL$ is VOL divided by $Dift$.

With this specification, the results are slightly different. In general, the control variables are not relevant or their coefficients are lower than before and BT dummies are not significant. Although we cannot construct a statistical test to evaluate the appropriateness of time adjustment, by looking at adjusted R squared we can conclude that, in general, adjustment with $Dift$ as an exogeneous variable is better than TAR adjustment. This is why we do not include these results.

4.2. Information Transmission Evidence.

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[20] The subsample results can be obtained from the authors by request.

To test the information transmission hypothesis, we look at the spread adverse selection component. The way in which we estimate this component is taken from Foster and Viswanathan (1993). These authors measure adverse selection as the returns response to unexpected volume. Given their evidence we estimate the following regression:

$$VOL_k = \alpha + \sum_{\tau=-1}^{\tau=-3} \phi_\tau R_\tau + \sum_{\tau=-1}^{\tau=-3} \beta_\tau VOL_\tau + \gamma Dift + \varphi Dend + \omega_k \qquad (8)$$

$$R_k = \alpha + \lambda \omega_{jt} + \sum_{\tau=-5}^{\tau=5} \delta_\tau \omega_{jt} DBT_\tau + u_{jt} \qquad (9)$$

*   The first equation estimates the unexpected volume for each change in true return through residuals. The second equation measures the reaction of returns including as explanatory variables these residuals and BT dummies. In this context, coefficient λ measures mean adverse selection and coefficients δ measure abnormal adverse selection around BTs. Results are included in second colmun of table 5. We can observe that the adverse selection component, measured as the coefficient of residuals, is not important. The only significant coefficient is the one associated with four orders after BT. These results are consistent with Admati and Pfleiderer model where liquidity traders pool their trades. So insiders only act in these periods and not in the mid-day where they would be detected. So, BT do are not as informative as expected. When we look at different subsample classifications, the results are slightly different.[21] The contemporary BT dummy is significantly positive for buyer and seller BTs but not for indeterminated BTs. This is consistent with the sign of the initiator party. The same dummy is also significant and positive in sweeping BTs. This result is also consistent because of the aditional cost this type of BTs impose. Both results are indicative of infortmation transmission. There exist an increase of adverse selection for these subsample classification and the signs are consistent.

As a last test of information transmission, we consider volume as an endogenous variable. Volume will measure abnormal activity around BTs. In this case, this would

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[21] The subsample results can be obtained from the authors by request.

be a signal of insiders around BTs and information flow in the market.[22]. The regression is:

$$VOL_t = \alpha + \sum_{\tau=-1}^{\tau=-3} \beta_\tau VOL_\tau + \varphi Dend + \sum_{\tau=-5}^{\tau=5} \delta_\tau DBT_\tau + \omega_k \qquad (10)$$

Results are in thrid column of table 5. Before the BT we see an unclear pattern, with a negative coefficient just before the BT but a positive one two orders before. However, after BTs there is a significant decrease in market activity that could be explained by the information transmitted by BT.

4.3. Liquidity Evidence.

For relative spread, S_k, the time-series regression run for each BTs is shown by the following expression:

$$S_t = \alpha + \sum_{\tau=-1}^{\tau=-3} \phi_\tau S_\tau + \sum_{\tau=0}^{\tau=-3} \beta_\tau VOL_\tau + \gamma Dift + \varphi Dend + \sum_{\tau=-5}^{\tau=5} \delta_\tau DBT_\tau + \omega_k \qquad (11)$$

We show the results in the last column of table 5. Regarding effects on relative spread, the lagged variables are positive and significant. As expected, we observe an autorregresive process in this variable. Another important variable is volume. We observe a negative contemporaneous coefficient and positive lagged ones. Negative relationship has been documented in other research in MSE (Rubio and Tapia (1996)). This evidence is also consistent with Admati and Pfleiderer (1988) model and, at the same time, is contrary to the results of Lee, Mucklow and Ready (1993) for the US market. The positive lagged ones could be related to updating expectations and consequently to adverse selection literature in the same way as in American markets.

The most important result related to liquidity is the negative and significant BT dummy coefficients just before and contemporary with BT arrival. This is related with an increase in liquidity. After BTs there is a decrease of liquidity so part of the effect is temporal. This result is related with a decreas in temporary spread components as inventory cost or operative cost. This is relevant because these coefficients have been obtained taking into account volume as a control variable. Looking at MSE, this is a

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[22] See Admati and Pfeiderer (1988).

stronger result because previous research did not find any effect on relative spread after controlling for volume.[23]

6. Concluding Remarks.

This study analyzes the role of BTs in MSE. The contribution is the use of orders that change true asset value. Moreover, we apply this methodology to a market where BTs are not provided. Thus, BTs are dealt on the MSE like small ones. This market microstructure characteristic gives us a special testing ground.

We study three different effects around BTs: price, liquidity and information transmission. To capture the effects on this variables, we consider three different endogenous variables: true asset value returns, relative spreads and adverse selection spread component. With this approach, we do not find clear effects of BTs. It seems that there is information transmission when we look at adverse selection spread component in the different subsample classification, but there is no significant permanent effect in returns.

We also observe changes in liquidity around BTs. In related papers, other authors have obtained clear effects of BTs on prices depending on BT type but they do not study changes in relative spread. We obtained a temporal increase in liquidity related with temporary spreads components.

As we have already pointed out, we suspect that the reasons for these differences could be related to methodology and MSE market microstructure. To discover whether these different results are due to methodology or BTs facilities requires that this methodology be applied to other markets with block trading facilities.

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[23] Rubio and Tapia (1996) show that relative spreads do not change in MSE around dividend announcements when they control for activity variables as volume or number of transactions.

References

[1] Admati, A. and P. Pfleiderer: "A Theory of Intraday Patterns: Volume and Price Variability", *The Review of Financial Studies*, 1, 1988, pp. 3-40.

[2] Amihud, Y. and H. Mendelson: "Asset Pricing and the Bid-Ask Spread." *Journal of Financial Economics*, 17, 2, 1986, pp. 223-249.

[3] Amihud, Y. and H. Mendelson: "Trading Mechanisms and Stock Returns: An Empirical Investigation." *Journal of Finance*, 42, 1987, pp. 533-553.

[4] Ball, R. and F. Finn: "The Effect of Block Transactions on Share Prices. Australian evidence." *Journal of Banking and Finance* , 13, 1989, pp. 397-419.

[5] Blume, M., C. Mackinlay and B. Terker: "Order Imbalances and Stock Price Movements on October 19 and 20, 1987." *Journal of Finance*, 44, 1989, pp. 827-848.

[6] Chan, L. and J. Lakonishok: "Institutional Trades and Intraday Stock Price Behavior." *Journal of Financial Economics*, 33, 1993, pp. 173-199.

[7] Chan, L. and J. Lakonishok: "The Behavior of Stock Prices around Institutional Trades." *Journal of Finance*, 50, 1995, pp. 1147-1174.

[8] Choe, H. and R. Masoulis: "Measuring the Impact of Dividend Capture Trading: A Market Microstructure Analysis." Working paper, Vanderbilt University, 1992.

[9] Daley, L., J. Hughes and J. Raiburn: "The Impacts of Earnings Announcements on the Permanent Price Effects of Block Trades." *Journal of Accounting Research*, 33, 2, 1995, pp. 317-334.

[10] Easley, D. and M. O'Hara: "Prices, Trade Size and Information in Security Markets." *Journal of Financial Economics*, 19, 1987, pp. 69-90.

[11] Engel and Lange (1997)

[12] Foster, F. and S. Viswanathan: "A Theory of Interday Variations in Volumes, Variances and Trading Costs in Securities Markets" *The Review of Financial Studies*, 3, 1990, pp. 593-624.

[13] Foster, F. and S. Viswanathan: "Variations in Trading Volume, Return Volatility, and Trading Cost: Evidence on Recent Price Formation Models" *Journal of Finance*, 48, 1993, pp. 187-211.

[14] Gemmill, G.: "Transparency and Liquidity: A Study of Block Trades on the London Stock Exchange under Different Publication Rules." *Journal of Finance*, 5, 1996, pp. 1765-1790.

[15] Glosten, L. and P. Milgrom: "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders." *Journal of Financial Economics*, 14, 1985, pp. 71-100.

[16] Harris, L.: "A Transaction Data Study of Weekly and Intradaily Patterns in Stock Returns." *Journal of Financial Economics*, 16, 1, 1986, pp. 99-117.

[17] Hasbrouck, J., G. Sofianos and D. Sosebee: "NYSE Systems and Trading Procedure", *NYSE Working Paper*. 93-01, 1993.

[18] Hausman, J., A. Lo and C. Mackinlay: "An Ordered Probit Analysis of Transaction Stock Prices." *Journal of Financial Economics*, 31, 1992, pp. 319-379.

[19] Holthausen, R., R. Leftwich and D. Mayers: "The Effect of Large Block Transactions on Security Prices." *Journal of Financial Economics*, 19, 1987, pp. 237-267.

[20] Holthausen, R., R. Leftwich and D. Mayers: "Large Block Transactions, the Speed of response, and Temporary and Permanent Stock-Price Effects." *Journal of Financial Economics*, 26, 1990, pp. 71-95.

[21] Kraus, A. and H. Stoll: "Price Impacts of Block Trading on the New York Stock Exchange." *The Journal of Finance* 27, 1972, pp. 569-588.

[22] Kyle, A.: "Continuous Auction and Insider trading." *Econometrica*, 53, 1985, pp. 1315-1335.

[23] Lee, C., B. Mucklow and M. Ready: "Spreads, Depths and the Impact of Earnings Information: An Intraday Analysis." *Review of Financial Studies*, 6, 1993, pp. 345-374.

[24] Lee, C. and M. Ready: "Inferring Trade Direction from Intraday Data." *The Journal of Finance*, 46, 2, 1991, pp. 733-747.

[25] O'Hara, M.: Market Microstructure Theory. Blackwell Publisher, Massachusetts, 1995)

[26] Riva, F.: "Block Trading on the Paris Bourse Central Market: An Empirical Study.", Proceedings of Organization and Quality of Equity Markets, Paris (1996).

[27] Rubio, G. and M. Tapia: "Adverse Selection, Volume and Transactions around Dividend Announcements in a Continuous Auction Markets." *European Financial Management*, 2, 1, 1996, pp. 39-67.

[28] Scholes, M.: "The Markets for Securities: Substitution versus Price Pressure and the Effects of Information on Share Prices." *Journal of Business*, 45, 1972, pp. 179-211.

[29] Seppi, D.: "Equilibrium Block Trading and Asymmetric Information." *The Journal of Finance*, 45, 1, 1990, pp. 73-94.

[30] Seppi, D.: "Block Trading and Information Revelation around Quarterly Earnings Announcements." *The Review of Financial Studies*, 5, 2, 1992, pp. 281-305.

[31] Stoll, H. and R. Whaley.: "Stock Market and Volatility." *Review of Financial Studies*, 3, 1990, pp. 37-71

[32] White, H.: "A Heteroscedasticity-Consistent Covariance Estimator and a Direct Test for Heteroscedasticity." *Econometrica*, 48, 1980, pp. 817-839.

Table 1

Number and effective trading volume (in millions of pesetas) of all trades crossed in open MSE during the period May 1996-April 1997, sorted by trading volume. Those with trading volume greater than 50 million are additionally sorted by their percentage of the average trading daily volume. The percentage of the total is in parentheses.

	number of trades (%)	trading volume (%)
< 1 mil.	2,413,137 (60.28)	810,396 (5.9)
> 1 mil. and < 10 mil.	1,335,059 (33.35)	4,348,807 (31.6)
> 10 mil. and < 50 mil.	226,666 (5.66)	4,435,662 (32.2)
> 50 mil.	28,420 (0.71)	4,174,179 (30.3)
< 5%	22,048 (0.55)	2,048,370 (14.9)
> 5% and < 10%	2,002 (0.05)	421,378 (3.1)
> 10% and < 20%	1,989 (0.05)	442,291 (3.2)
> 20% and < 40%	1,099 (0.03)	350,160 (2.5)
> 40%	1,282 (0.03)	911,980 (6.6)
All trades	4,003,282	13,769,044

Table 2

Size distribution of our sample in number of BTs and trading volume (in percentage terms). Regarding trading volume, BTs are classified in four groups, including the biggest in *BB* and the smallest in *SS*. In panel A, BTs are classified according to the side of the market initiating the BTs (buyer, seller or indeterminate initiated), in panel B they are classified according to type (inside the spread, sweeping or not classified) and in panel C according to whether they change the asset true value or not.

	BB		BS		SB		SS	
	N. of BT (%)	Vol. (%)	N. of BT (%)	Vol. (%)	N. of BT (%)	Vol. (%)	N. of BT (%)	Vol. (%)
PANEL A								
Buyer-init.	0.35	0.32	0.26	0.32	0.21	0.34	0.22	0.33
Seller-init.	0.39	0.45	0.25	0.33	0.29	0.39	0.16	0.34
Indeterminate-init.	0.26	0.23	0.49	0.35	0.50	0.30	0.61	0.33
PANEL B								
Inside the spread	0.47	0.76	0.34	0.49	0.35	0.48	0.30	0.39
Sweeping	0.31	0.20	0.33	0.43	0.32	0.40	0.31	0.53
Not classified	0.22	0.04	0.33	0.08	0.33	0.13	0.39	0.08
PANEL C								
Change in true asset value	0.67	0.65	0.47	0.35	0.51	0.35	0.52	0.37
No change in true asset value	0.33	0.35	0.53	0.65	0.49	0.65	0.48	0.63

Table 3

Day-of-the-week and hour-of-the-day distributions (in percentages terms) of the BTs sample. The first value is the percentage of the number of blocks and the second one is the corresponding trading volume.

	MON. (%)	TUE. (%)	WED. (%)	THU. (%)	FRI. (%)	All days (%)
11:00 - 12:00	5.64	5.64	3.59	2.05	1.03	17.95
	6.81	3.17	1.96	0.86	0.18	12.96
12:00 - 13:00	6.15	8.72	4.10	3.59	6.15	28.72
	5.45	7.63	2.11	3.94	2.45	21.58
13:00 - 14:00	4.62	4.10	5.64	1.54	6.15	22.05
	7.79	7.98	17.84	1.20	3.89	38.71
14:00 - 15:00	2.05	6.67	2.05	1.54	6.15	18.46
	0.51	12.10	1.43	0.43	1.29	15.75
15:00 - 16:00	2.56	3.59	2.05	2.56	2.05	12.82
	1.43	4.25	2.56	2.40	0.36	10.99
All periods	21.03	28.72	17.44	11.28	21.54	
	21.99	35.13	25.91	8.82	8.16	

Table 4

For the characteristics of relative spread, accumulated volume, and differences in time, we show the percentage changes, averaged across all BTs, according with the following statistic:

$$K_{jk} = \left(\frac{S_{jk}}{\bar{S}_j} - 1 \right) 100$$

where $\bar{S}_j$ is the average of each characteristic. For returns we use the statistic: $K_{jk} = R_{jk} - \bar{R}_j$. The asterisk indicates significance at 5% and double asterisk at 10%.

	S_{jk}	$Dift_{jk}$	VOL_{jk}	$R_{jk} - \bar{R}_j$
-10	2.77	16.69	-25.43*	0.41E-05
-9	5.55	-10.11	-2.45	-1.33E-05
-8	1.56	3.74	-24.02*	-6.93E-05
-7	-1.93	8.00	-26.50**	-2.53E-05
-6	0.63	9.03	-22.09*	2.90E-05
-5	-7.28	58.39*	8.67	-4.65E-05
-4	-4.31	28.65*	-2.13	0.76E-05
-3	-13.44*	101.36*	4.41	-3.78E-05
-2	-5.11	74.35*	42.44**	-0.67E-05
-1	-25.45*	118.87*	35.92	-4.13E-05
0	-5.18	44.52*	5793.02*	-3.66E-05
1	2.13	75.39*	316.71*	1.62E-05
2	-6.98	54.37*	20.57	-3.72E-05
3	-6.33	53.76*	-14.70	1.17E-05
4	-5.88	58.32*	-0.27	-4.51E-05
5	-9.77*	56.42*	4.92	0.04E-05
6	-10.71*	56.35*	-12.53	-6.79E-05
7	-13.75*	28.21**	-16.45	-3.28E-05
8	-11.41*	51.11*	3.71	-3.25E-05
9	-11.26*	53.99*	42.33**	-6.29E-05
10	-6.82	22.16	16.56	2.12E-05

Table 5

For each BTs in the sample, three time series regressions are run with three different specifications. In particular the regressions are:

$$R_k = \alpha + \sum_{\tau=-1}^{\tau=-3} \phi_\tau R_\tau + \sum_{\tau=0}^{\tau=-3} \lambda_\tau R_{IBEX\tau} + \sum_{\tau=0}^{\tau=-3} \beta_\tau VOL_\tau + \gamma Dift + \varphi Dend + \sum_{\tau=-10}^{\tau=10} \delta_\tau DBT_\tau + \omega_{jt}$$

$$S_t = \alpha + \sum_{\tau=-1}^{\tau=-3} \phi_\tau S_\tau + \sum_{\tau=0}^{\tau=-3} \beta_\tau VOL_\tau + \gamma Dift + \varphi Dend + \sum_{\tau=-10}^{\tau=10} \delta_\tau DBT_\tau + \omega_t$$

$$VOL_t = \alpha + \sum_{\tau=-1}^{\tau=-3} \beta_\tau VOL_\tau + \varphi Dend + \sum_{\tau=-10}^{\tau=10} \delta_\tau DBT_\tau + \omega_t$$

where R_{IBEX} is the return of IBEX-35, VOL is the square root of accumulated volume between orders changing asset true value, Dift is the square root of time elapsed between orders, Dend is a dummy variable for end-of-the-day effects, DBT stands for the dummy variable employed to pick up effects around BTs. Two time series regressions are run with two different specifications. In particular the regressions are:

$$VOL_k = \alpha + \sum_{\tau=-1}^{\tau=-3} \phi_\tau R_\tau + \sum_{\tau=-1}^{\tau=-3} \beta_\tau VOL_\tau + \gamma Dift + \varphi Dend + \omega_{jt}$$

$$R_k = \alpha + \lambda \omega_{jt} + \sum_{\tau=-5}^{\tau=5} \delta_\tau \omega_{jt} DBT_\tau + u_{jt}$$

The coefficients are cross sectional averaged across all of them. White (1980) standard errors are used.

	R	Adverse Selection	VOL	S
CONS	1.5588E-05	0.622E-05	13.49*	0.00121*
$R_{(-1)}$	-0.32*	---	---	---
$R_{(-2)}$	-0.07*	---	---	---
$R_{(-3)}$	-0.04*	---	---	---
R_{IBEX}	0.40*	---	---	---
$R_{IBEX(-1)}$	0.16*	---	---	---
$R_{IBEX(-2)}$	0.10*	---	---	---
$R_{IBEX(-3)}$	0.05*	---	---	---
VOL	0.132E-05*	---	---	-2.41E-05*
$VOL_{(-1)}$	0.00298E-05	---	0.02*	1.59E-05*
$VOL_{(-2)}$	-0.0166E-05	---	0.06*	0.421E-05*
$VOL_{(-3)}$	-0.0194E-05	---	0.04*	0.0720E-05*
$S_{(-1)}$	---	---	---	0.40441*
$S_{(-2)}$	---	---	---	0.21956*
$S_{(-3)}$	---	---	---	0.05397*
Dift	-0.470E-05*	---	1.36*	-0.169E-05*
Dend	52.493E-05*	---	64.22*	0.00224*
λ	---	0.000290E-05	---	---
-5	1.5507E-05	-0.0131E-05	-2.93	-4.41E-05
-4	8.8251E-05	0.384E-05	2.86	8.45E-05
-3	-7.297E-05	-0.0381E-05	-1.99	-24.0E-05
-2	-17.42E-05	-0.0255E-05	9.79*	26.2E-05
-1	3.8204E-05	0.509E-05	-8.01*	-55.5E-05*
0	-72.46* E-05	-0.0783E-05	348.24*	-0.00311*
1	-11.36 E-05	0.0112E-05	4.38	-29.8E-05
2	58.358* E-05	5.64E-05	-26.57*	-12.2E-05
3	-8.642E-05	0.753E-05	-19.45*	31.1E-05**
4	19.328 E-05	0.0724E-05**	-5.95*	18.7E-05
5	-13.33 E-05	-0.0206E-05	-2.43*	-4.79E-05