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Liquidity and market makers: a pseudo-experimental analysis with ultrahigh frequency data

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An analysis is given of the effect of market makers on liquidity using a transaction-level database. For this purpose, the focus is on a financial market where a change in regulations created explicitly the category of market maker in 1997 and that date is used to construct a pseudo-experiment. In contrast with other studies that use ultrahigh frequency data, the days to be analysed are selected using a statistical procedure to match observations before and after the change in regulation. The propensity score is used to perform the matching. After choosing the days, an estimate of an ordered probit model is made to explain the intraday behaviour of price changes. The coefficient estimates from the ordered probit model are used to calculate a measure of liquidity based on the steepness of the response function of price changes to volume. The results show that liquidity, measured in this way, has not been affected by the introduction of the market makers.

Keywords: market makers, change in regulations, ordered probit model, liquidity

1. INTRODUCTION

The success of securities markets is related basically with the level of liquidity they are able to accomplish. The importance of liquidity in financial markets has generated a large body of literature. Most of the research has concentrated on the trading behaviour of specialists and market makers and their effect on liquidity. In general specialists are supposed to promote a 'fair and orderly market'[1] by posting bid and ask quotes. In compensation they receive some benefits in terms of informational advantages and/or cash compensations. Their 'forced' market presence helps to maintain price continuation and stabilize security markets.

However, many security markets are concerned about market makers not fulfilling their obligations. Board *et al.* (2000), in their analysis of the London Stock Exchange, show that only a few firms of market makers meet the criteria for fair weather market making as identified by a set of indicators. Some other authors have raised doubts about the actual competition between market makers in multiple dealers markets like the NASDAQ (Christie and Schultz, 1994).

[1] NYSE regulations.

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The objective of this article is to propose a new method to evaluate the effect of the introduction of market makers on the liquidity of securities markets. For this purpose we use data on a particular financial asset, the Spanish Government Bond Future traded at MEFF (Spanish Futures Market Exchange). The basic idea is to compare liquidity, measured by the econometric procedure proposed by Hausman *et al.* (1992), before and after the introduction of market makers using transaction-level data. The case of MEFF is specially interesting because it provides a pseudo-experimental situation given that at the beginning of 1997 MEFF created explicitly the category of 'market maker'. Most of the research on market makers' activity uses transaction-level data because it offers the most appropriate empirical set-up to analyse the trading behaviour of market makers. Two decades ago researchers were satisfied if they could work with monthly data; after that economists were able to work with weekly, daily and hourly data. Recently, there are more and more studies based on transaction-by-transaction data or what Engle (2000) calls ultra-high frequency data (UHFD).[2]

The paper is organized as follows. Section 2 contains a summary of recent findings on the trading behaviour of market makers. Section 3 describes the selection procedure. Section 4 contains the description of the econometric technique used to measure liquidity, based on the ordered probit model proposed by Hausman *et al.* (1992). Section 5 discusses the effect of market makers on liquidity using the results of the estimation performed in Section 4. Finally, Section 6 contains the conclusions.

2. MARKET MAKERS AND LIQUIDITY

The basic objective of market makers is to guarantee liquidity in securities markets by posting bid and ask quotes even when other traders are not present in the market. Market makers are supposed to maintain market presence and assure price continuity. It is their 'forced' market presence that distinguishes them from other traders. There are many liquidity providers in a financial market but the presence of a market maker should increase liquidity by reducing the cost of transactions and the bid–ask spread. Therefore, even though market makers are not the only liquidity providers of securities markets, that is their main job and it is reasonable to search for procedures to evaluate their performance. The effect of market makers on liquidity can be measured through alternative indicators, one of the most popular being the quoted spread.

The issue of liquidity in financial markets under alternative configuration of market makers competition is controversial. Dennert (1993) shows that, under certain assumptions, liquidity traders would prefer a monopolistic market maker instead of several competing market makers. In markets like the NYSE there is only one specialist for each security. In other securities markets, like NASDAQ, there are multiple market makers and, therefore, competition among them is important in order to produce narrow bid–ask spreads and improve liquidity.[3] However,

[2] Goodhart and O'Hara (1997) provide a useful survey.

[3] On exchanges like NYSE the specialist faces competition from other liquidity providers as public limit orders or floor traders.

Christie and Schultz (1994) find that odd-eighths quotes are very rare in most of the actively traded NASDAQ securities. They attribute the lack of odd-eighths quotes to the implicit collusion of market makers, which guarantees that the spread is at least \$0.25. In fact Christie *et al.* (1994) show that after the release in the newspapers of the findings by Christie and Schultz (1994) many market makers increased their use of odd-eighths quotes reducing the effective spread by nearly 50%.

However, the dynamics of price changes and the spread is not only related with the level of competition among a fixed number of market makers but also with their entry and exit behaviour. Wahal (1997) analyses the entry and exit of market makers in NASDAQ using daily data on transaction prices, volume, number of transactions and number of market makers per security. The number of market makers in each security is specified as a function of trading intensity, volatility and the bid-ask spread. Wahal (1997) estimates a Poisson regression and concludes that the end-of-day volatility and spread are related with the number of market makers dealing in each security: spreads changes are larger in magnitude for issues with few market makers.[4]

Therefore one of the basic tasks of market makers is to provide additional liquidity to securities markets. One of the functions of market makers in order to maintain a 'fair and orderly market' and provide liquidity is price stabilization: the specialist should ensure that trading moves smoothly, with small price fluctuations. For this reason a reasonable measure for liquidity is the effect of market makers on the price impact of trades. Probably the most appropriate methodology to estimate this impact is the ordered probit model proposed by Hausman *et al.* (1992). In addition this specification is adequate to deal with the discreteness of prices changes and the irregularly spaced nature of transactions. In this paper we use the estimation of the ordered probit to construct a measures of liquidity based on the price impact of trades. To our knowledge this is the first time that the direct effect of market makers on liquidity has been measured using a pseudo-experiment that compares the steepness of the price reaction function under two alternative situations: with and without market makers.

3. MATCHING DAYS BEFORE AND AFTER MARKET MAKERS: THE USE OF THE PROPENSITY SCORE

Most of the papers on the microstructure of financial markets use rich datasets where all the transactions are recorded. The fact that many financial markets are fully computerized allows researchers to find such data. However, the massive amount of information generated makes it difficult to obtain a long time series because market managers do not keep all the information on all the sessions and, moreover, the quantity of information is so large that it would be very difficult to extract any conclusion without concentrating on a few days or weeks. For instance, Goodhart *et al.* (1994) work with seven hours of trading in the electronic system of Reuters, D2000-2, for one day of June of 1993. Lyons (1995) analyses data

[4] Wahal (1997) studies also the possibility of simultaneity bias without finding any empirical support for it.

that cover one week of August 1992. For different reasons Christie and Schultz (1998) choose 15 November 1991.

In this paper we use data on the Spanish Government Bond Futures Market traded at the Barcelona Financial Futures and Options Exchange (MEFF). The contracts call for the delivery of a 10 millions pesetas (60 101 Euros)[5] face value National Government Bond with a 6.5% annual coupon. This 10-year Government Bond Future contract was presented in March of 1992, the first delivery date being June of 1992. At the beginning of 1997 MEFF created the category of the 'market maker' with an explicit objective: to 'guarantee liquidity in the market by simultaneously quoting buy and sell prices for determined contracts and maintaining such quotes throughout the trading period'. Before the creation of the category of 'market maker' there were three kinds of member: clearing members, non-clearing members and custodian clearing members. This complementary category of 'market maker' implied a change in the Regulations of the market that imposes many conditions on the members that had to play the role of market makers.

3.1 The Introduction of Market Makers as a Pseudo-Experiment

The basic objective of this paper is to evaluate the effect of the market makers on the liquidity using the Spanish Government Bond Futures market. For this reason we want to analyse the impact of market makers on the transaction-level price dynamics, separating the period before the introduction of market makers from the period afterwards. Given the difficulty and cost of getting a long time series for this kind of data,[6] we had to choose a few trading days before the end of 1996 (contract December 1996) and after the beginning of 1997 (contract March 1997).[7] We can consider this situation as a pseudo-experiment. Therefore, the days of 1996 play the role of the control group. The exposed group includes the days after the beginning of 1997.

The procedure to choose these days is not a trivial one. We could simply choose six days randomly but this approach would be problematic because many of the unexposed days (control group) may not be good controls, given that they may be very different from the exposed days with respect to the background variables (volatility, volume, etc.) for reasons unrelated with the presence of market makers. The fact that we can choose only a few days leads to a high probability of a 'bad' random selection because of the small sample size. The smaller the final sample size the higher the probability of obtaining very different days, in terms of their background variables, using random selection.

For this reason we looked for a method to select days from both subsamples that make them 'comparable' in a sense that will be discussed later. Rosembaum and Rubin (1985) argue that multivariate matching sampling is known to be one of the most robust methods for reducing bias due to imbalances in observed

[5] Exchange rate: 1 Euro = 166.386 pesetas.

[6] The managers of the market do not keep all the trading information for each day. The session has to be reproduced in order to obtain transaction-level data, which implies the use of most of the computer resources of the market to perform this task.

[7] We originally considered six days.

covariances. The idea is based on a matching procedure that produces a control group that is similar to the exposed group with respect to the explanatory variables. Therefore we adopt the methodology based on the propensity score as proposed by Rosembaum and Rubin (1985) and Rubin and Thomas (1992). For this purpose we combine information obtained at daily frequency, which allows us to obtain the matched sample, with transaction-level data for the chosen days, which we use to estimate the price impact of trades.

Although the procedure is different to the one used in Christie *et al.* (1994) the problem we want to solve is similar to theirs. Christie *et al.* (1994) argue that, after the publication in the newspapers on 26 May 1994 of the finding in Christie and Schultz (1994), there was a large reduction in the effective spread on many securities due to the end of the implicit collusion of market makers. In order to show this fact they compare the evolution of the spread and the proportion of odd-eighths quotes using transaction-level data for a few days before and after that date. However, they had to make sure that the change in the spread was not due to other factors that could explain a decline in trading cost, such as changes in volatility, prices or trading volume. In order to check if the cost of making markets decreased after 26 May they regress, using daily data, the time series of inside spreads on volatility, volume and prices together with a dummy variable that represented the days after 26 May. They find that the dummy variable is negative and statistically significant, which supports their hypothesis that the end of the implicit collusion among market makers was the reason behind the reduction in the bid/ask spread. Therefore they use a few days of transaction-level data to check the basic hypothesis of their paper and daily data to make sure that what they observe at that frequency (smaller spreads and higher odd-eighths proportion than before 26 May) is not due to other economic factors, besides market makers competition, that could also affect those variables.

We also proceed in two stages. First of all, we want to make sure that what happened with liquidity after the end of 1996 was caused by the presence of market makers and not by changes in other economic variables that could also affect liquidity. For this reason we select three days before and three days after the end of 1996 using the matching procedure proposed by Rubin and Rosembaum (1985). In the second stage we use transaction-level data to measure the steepness of the reaction function of prices to transactions using the procedure propose by Hausman *et al.* (1992).

3.2 Matching using the Estimated Propensity Score

Christie *et al.* (1994) use a regression to control for other economic factors that could have an effect on liquidity besides the 26 May dummy. However, this is not the only alternative to control for the impact of those economic factors in the evaluation of market maker trading behaviour. In this paper we use the estimated propensity score to make days 'comparable' and avoid the effect of other economic variables besides the presence or absence of market makers. This technique works as follows. Let Y denote the matrix of explanatory variables for a particular day and let z indicate whether the day belongs to the control group ($z = 0$) or the exposed group ($z = 1$). The days before the end of 1996 belong to the control group and the days after that day belong to the group exposed to the action of the market makers. The matching procedure is based on the propensity score which is the conditional probability of exposure given the explanatory variables, $e(Y) = Pr(z = 1|Y)$. The days in the exposed and control group selected to have the same $e(Y)$ will have the same distribution of Y. The logit model is a reasonable choice for the conditional distribution

$$q(Y) = \log\left(\frac{1 - e(Y)}{e(Y)}\right) = \delta_0 + \delta_1 Y$$

where δ_0 and δ_1 are the coefficients to be estimated, $q(Y)$ is the log odds against exposure and the Ys are the explanatory variables. In our application the explanatory variables are those economic factors that can affect the measure of liquidity besides the effect of market makers. As in Christie *et al.* (1994) we include volume and volatility.[8] The sample covers the trading three months before the end of 1996 and three months after that date.[9]

The procedure for constructing the matched sample is based on the nearest available matching on the estimated propensity score. In essence with this procedure we make sure that the probability of belonging to the first part of the sample is similar for one day before and after the end of 1996. Therefore matching in terms of $q(Y)$ balances the observed covariates Y. The nearest available matching on the estimated propensity scores works as follows. First of all the exposed and control days are ordered in function of the estimated $q(Y)$. Second a day is chosen randomly from the exposed group and is matched with the control day having the nearest estimated $q(Y)$. Both days are removed from the sample and the procedure is repeated until we get three days of each group.[10]

Using this procedure we selected the following days:

(a) for the control group: 11/11/96, 15/11/96 and 19/11/96.
(b) for the exposed group: 22/1/97, 24/1/97 and 27/2/97.

3.3 Descriptive Statistics of Transaction-Level Data

In this subsection we describe the basic characteristics of the transaction-level data for the chosen days. A database is produced that contains the price and volume of transactions coded as regular trades (market or 'M') and quotes that are best bid or ask, with their respective volume. The system records every change (an improvement of the best bid or ask price, a change in volume of the best bid or ask or a transaction) as an observation. From the original database an operative dataset is constructed where each transaction was matched with the best bid and ask quoted immediately before it. There is no problem in doing this matching because trading is centralized in one location and operations are

[8] We also consider internal return and open interest.
[9] In financial markets learning takes place very quickly and, therefore, three months after the institutional change should be enough to identify the effect of market makers. In fact Christie *et al.* (1994) use data for one month after their pseudo-experimental change.
[10] See Rosenbaum and Rubin (1985) for additional details.

recorded by strict order of arrival.[11] The difference between the best ask and best bid is checked to be positive in all cases.

Table 1 presents the descriptive statistics for the selected days. It is broken into two parts. The first part contains the unweighted averages of the variables while the second part presents the weighted averages. The weights are constructed using the time that the members of the market have the prices/quotes on their screens and, therefore, are the seconds since last change. The variables that appear in the table are the spread, the prices (bid, ask and transactions), the volume (bid, ask and transactions), the average time between changes and the average time between trades, both measured in seconds. In addition the rows ask ini and bid ini contain the proportion of transactions that took place at the ask price and at the bid price respectively.

Table 1 shows that the average weighted spread in the days of 1997 is smaller than the average weighted spread in the days of 1996. However, the difference of means test cannot reject the null hypothesis that both means are equal (*t*-statistic

Table 1. Descriptive statistics

Means	11/11/96	15/11/96	19/11/96	22/01/97	24/01/97	27/02/97
Spread	2.21	1.874	1.867	1.841	1.94	1.618
Ask price	6547.46	6633.78	6665.99	6886.58	6828.21	6825.85
Ask volume	35.16	53.81	60.2	71.85	63.5	75.14
Bid price	6546.13	6632.65	6664.86	6885.47	6827.05	6824.88
Bid volume	37.17	60.76	60.07	76.62	66.79	73.14
Transaction price	6546.53	6633.17	6665.64	6885.79	6827.38	6825.42
Transaction volume	12.36	13.54	14.44	15.96	15.43	15.08
Ask ini	51.2%	50.7%	54.3%	51.2%	54.4%	53.8%
Bid ini	48.7%	49.2%	45.7%	48.7%	45.5%	46.1%
Time between changes	6.71	2.46	2.40	1.97	1.57	2.72
Time between transactions	16.01	5.63	5.27	4.73	3.60	5.94
Weighted means						
Spread	2.111	1.676	1.666	1.675	1.804	1.467
Ask price	6548.21	6633.13	6664.45	6887.96	6829.81	6825.58
Ask volume	29.37	45.56	56.51	57.89	57.88	65.56
Bid price	6546.94	6632.12	6663.45	6886.95	6828.34	6824.70
Bid volume	30.29	50.66	48.22	67.91	55.02	61.8

The spread is measured in ticks (1 thick = 6.01 euros). Prices are measured in euros 10. Volume is measured in number of contracts Time is measured in seconds.

[11] In other datasets this task is more complicated. For instance in the official ISSM tapes the price of trades that generate quote revisions are sometimes reported with a lag and, therefore, the order of price and quote revision is reversed which implies that observations have to be matched with caution.

equal to 0.88).[12] It is also interesting to notice that the buyer-initiated transactions represent in all days a proportion of trades higher than the seller-initiated transactions. In fact the average proportion of buyer-initiated transactions is 52.6% versus 47.4% of seller initiated-transactions.

Figures 1–6 represent the relationship between time since the beginning of the session, measured in seconds after 9 a.m., and the cumulative number of transactions, measured on the X-axis. These figures are specially relevant because they contain all the information on the frequency of transactions per unit of time. In fact, these figures show the time deformation phenomenon. The higher the slope the lower the frequency of transactions. For instance, it is interesting to point out the low frequency of transactions between 2 p.m. (18 000) and 3 p.m. (21 600), typical lunch time in Spain.

4. PRICE DYNAMICS, MARKET MAKERS AND LIQUIDITY

The evolution of prices in financial markets is essential for many reasons. From the microstructure perspective the dynamics of price changes is a determinant to set margin requirements, analyse the degree of competition and the behaviour of market makers, etc.

However, many theoretical financial models characterize the dynamic evolution of prices, without any reference to market microstructure, using processes like random walks or Brownian motions. These processes do not take into account several important microstructure properties of the prices of financial assets, mainly two:

(1) Price changes are quoted in integer increments of a minimum amount called ticks. For instance, in the Spanish Government Bonds Futures Market the tick is equal to 1000 pesetas (6.01 Euros). This property, especially when we deal with intraday data, cannot be represented by a continuous time process.
(2) Transactions are irregularly spaced and their timing is random. Therefore, transaction prices will have the same properties. In time series econometrics observations are usually spaced regularly in time (years, months or days). The aggregation of transactions over regularly spaced intervals implies the loss of important information like, for instance, the time between trades (Engel and Russell, 1998).

To solve the estimation problems created by the discrete nature of price changes several procedures have been proposed. Harris (1990) and Ball (1988) consider rounding processes and Cho and Frees (1988) propose a barrier model. In essence these models assume that the true unobserved price process is continuous while the observed price process is discrete. Both procedures capture the discrete nature of price changes and generate consistent estimates. However, they have important limitations. Essentially, the difference between true and observed price is misleading because the observed price is, in fact, the true price. In addition, the

[12] The same is true for the test of means differences for the weighted spread ($t = 0.67$).

class of unobservable processes that leads to a tractable model is very restrictive.[13] Therefore, it is not possible to include other economic variables that could influence prices changes apart from its own past evolution.

Hausman *et al.* (1992) argue that the ordered probit model is appropriate for modelling an endogenous variable that is discrete and takes on values that are ordered. There is no need to make any assumption about the true generating process and, in addition, the ordered probit can explain price changes using variables that are not constrained to be lags of price changes. The specification is a generalization of the linear probability model where the relationship between the endogenous and the explanatory variables is nonlinear. One of the few applications of this technique to transaction-level data can be found in Hausman *et al.* (1992) where they analyse the determinants of price changes using a sample of the ISSM (Institute for the Study of Security Markets) dataset.

4.1 The Ordered Probit Model

The ordered probit model is an econometric technique that can deal with discrete and ordered data, like prices in some securities markets, where changes are multiples of an integer (tick) and irregularly spaced.

Let $P(t_0), P(t_1), \ldots, P(t_n)$ be the price of transactions observed at time $t_0, t_1, \ldots, t_n$. Let $\mathrm{d}P$ be the price change between two transactions

$$\mathrm{d}P_k \equiv P(t_k) - P(t_{k-1})$$

where this difference is an integer multiple of a tick. The index k refers to the time of transactions while the index t_k refers to real time. In figures 1 to 6, k is the number of transactions represented in the X-axis and t_k is presented in the Y-axis.

Let $\mathrm{d}P_k^*$ be a continuous and unobservable random variable that follows the process

$$\mathrm{d}P_k^* = X_k'\beta + u_k \quad E(u_k|X_k) = 0 \quad u_k \sim N(0, \sigma_k^2)$$

where X is a set of explanatory variables and the us are random variables which are independent but not identically distributed.

The basic element of the ordered probit model is the relationship between the continuous unobservable variable, $\mathrm{d}P^*$, and the observed discrete variable $\mathrm{d}P$. The intuition behind this relationship is simple: $\mathrm{d}P^*$ moves around with changes in X and u but only when the process hits or crosses over a threshold $\mathrm{d}P$ will jump to the next discrete value.

Therefore, the relationship between $\mathrm{d}P$ and $\mathrm{d}P^*$ can be written as

$$\mathrm{d}P = \begin{cases} s_1 & \text{if} \quad \mathrm{d}P_k^* \in (-\infty, \alpha_1] \\ s_2 & \text{if} \quad \mathrm{d}P_k^* \in (\alpha_1, \alpha_2] \\ & \quad \ldots \quad \ldots \quad \ldots \\ s_m & \text{if} \quad \mathrm{d}P_k^* \in (\alpha_{m-1}, \infty) \end{cases}$$

[13] In essence analytical results are obtained only if the unobserved process is a Geometric Brownian Motion.

where the α represent the partition boundaries and s_i is the number of ticks, which is function of the value of dP^* and increases as a function of i.

Before beginning the estimation it is necessary to define the level of price resolution or the number of partitions of dP^*. There is a trade off in this choice. On the one hand we get a fine tuning of all price changes if we have a high degree of resolution. On the other hand, if the resolution is too fine there may be problems of identification when the number of observations in a particular state is too small. Theoretically, the increase in price resolution will have no effect on the asymptotic properties of the parameters even though the performance in finite sample properties could be affected. It is also possible to specify the conditional variance, $\sigma(W_k)$, as a function of a set of economic variables.

Therefore, the distribution of the observed price changes, d*P*, conditional on the variables that explain the mean, *X*, and the variance, *W*, is determined by the limits of the partitions and the distribution of u

$$P(dP_k = s_i|X_k, W_k) = \left\langle \begin{array}{rll} P(X_k'\beta + u_k \leq \alpha_1|X_k, W_k) & \text{if} & i = 1 \\ P(\alpha_{i-1} \leq X_k'\beta + u_k \leq \alpha_i|X_k, W_k) & \text{if} & 1 < i < m \\ P(\alpha_{m-1} \leq X_k'\beta + u_k|X_k, W_k) & \text{if} & i = m \end{array} \right.$$

where $P(.|.)$ indicates conditional probability.

If we assume that the distribution of u is normal then the conditional distribution $P(dP|X, W)$ can be written as

$$= \left\langle \begin{array}{ll} \Phi\left(\dfrac{\alpha_1 - X_{k'}\beta}{\sigma(W_k)}\right) & \text{if} \quad i = 1 \\ \Phi\left(\dfrac{\alpha_i - X_{k'}\beta}{\sigma(W_k)}\right) - \Phi\left(\dfrac{\alpha_{i-1} - X_{k'}\beta}{\sigma(W_k)}\right) & \text{if} \quad 1 < i < m \\ 1 - \Phi\left(\dfrac{\alpha_{m-l} - X_k'\beta}{\sigma(W_k)}\right) & \text{if} \quad i = m \end{array} \right.$$

where Φ is a standard normal cumulative distribution. Hausman *et al.* (1992) argue that the distributional assumption is not important when estimating the probability of the states. The logistic distribution could have been used instead of the normal distribution. However, conditional heteroscedasticity is more difficult to be captured in an ordered logit and, for this reason, they choose the ordered probit specification. The likelihood function of the ordered probit can be written as

$$\begin{aligned} L(dP|X, W) = \sum_{k=1}^{n} \Bigg[& I_{1k} \log \Phi\left(\frac{\alpha_1 - X_k'\beta}{\sigma(w_k)}\right) \\ & + \sum_{i=2}^{m-1} I_{ik} \log\left[\Phi\left(\frac{\alpha_i - X_k'\beta}{\sigma(W_k)}\right) - \Phi\left(\frac{\alpha_{i-1} - X_k'\beta}{\sigma(W_k)}\right)\right] \\ & + I_{mk} \log\left[1 - \Phi\left(\frac{\alpha_{m-1} - X_k'\beta}{\sigma(W_k)}\right)\right]\Bigg] \end{aligned}$$

where I_{ik} is an indicator variable that takes on the value 1 if the kth price change, $\mathrm{d}P_k$, is in the state i, s_i.

4.2 The Econometric Specification of the Conditional Mean and Variance

We have discussed previously the problem associated with choosing a very high degree of price resolution. As the identification question implied by a very high resolution is an empirical matter, it is important to examine our data in order to find the right degree of resolution. Figures 7 to 12 show the histograms of price changes for the selected days. These empirical distributions are symmetric, centred at 0 and have very thin tails. It is interesting to notice how similar these histograms are to the ones in Hausman *et al.* (1992) in spite of being related to completely different assets. Figures 7 to 12 also show that the frequency of price changes above 4 ticks or below −4 ticks is very low. Therefore, the values that define the states are −4 or less, −3, −2, −1, 0, 1, 2, 3 and 4 or more.

Once the probabilistic structure of the model is specified we need to decide on the set of X and W variables that define the conditional mean and the conditional variance. A very simple specification for these equations is the Brownian motion process in which the mean and the variance would be

$$X_k'\beta = \mu \Delta T_k$$
$$\sigma(W_k)^2 = \gamma^2 \Delta T_k$$

where ΔT is the time difference between two consecutive transactions.

However, from a microstructure point of view, there are many other variables that can explain the conditional mean and the conditional variance. The chosen set of explanatory variables is closely related to the one suggested by Hausman *et al.* (1992) and includes the time between transactions, the bid/ask spread, the bid/ask indicator, volume and lags of price changes.

To allow for clock time effects we include the time between two consecutive transactions (ΔT). Engle and Russell (1998) emphasize the importance of this variable by modelling explicitly its behaviour as an autoregressive conditional process. We have already stressed the importance of the difference between 'clock' time and transaction time. In order to have dependence between the conditional mean (variance) and the 'clock' time it is necessary to include the time between transactions as an explanatory variable. Moreover, this variable can help to decide if price changes are stable in 'clock' time or in transaction time. The unit of measurement of this variable is seconds.

The bid/ask spread (*SP*), measured in number of ticks, controls for the effect of the bid/ask 'bounce' among others phenomena. The buyer-initiated or seller-initiated indicator (BAI bid/ask indicator) takes value 1 if the transaction price is equal to the ask price and −1 if the transaction price is equal to the ask price. This is not the only possible measure for this variable. Blume *et al.* (1988) and Hausman *et al.* (1992) define this indicator as 1 if the transaction price is greater than the average of the quoted bid and ask prices and −1 if the transaction price is less than the average of the bid and the ask prices. If the transaction price is equal to the average of the bid and ask prices the indicator is equal to 0. Other studies use the so-called tick test that classifies as a buy, a sell or indeterminate if the price is greater, smaller or equal to the previous transaction price.

Another important variable in the specification of the conditional mean is volume, V. Given that the final objective is to measure the effect of a transaction of a particular size on the conditional distribution of price changes, the specification must include volume as an explanatory variable. Many papers on empirical finance have analysed this relationship.[14] Karpoff (1987) points out two basic stylized facts that summarize the relationship between volume and price changes: first, the correlation between trade volume and price changes is positive in securities markets. Second, the correlation between volume and the absolute value of price changes is positive in stock and futures markets. In our specification the possibility of asymmetric effects in the relationship between volume[15] and price changes is captured by the product of the bid/ask indicator and volume. The objective of this indicator is to represent the possibility that buyer initiated transactions push price up and seller initiated transactions drive prices down.

Finally the specification of the conditional mean includes also lags of prices changes (dP). With this dynamic specification we can check if there is mean reversion in prices.

With respect to the conditional variance we have considered as explanatory variables the time between transactions and the lagged spread. There is evidence (Hasbrouck, 1991; Huang and Stoll, 1997) that the bid/ask spread is related to the informational content of prices and its volatility.

The final specification for the conditional mean and the conditional variance is, therefore

$$\begin{aligned} X_k'\beta &= \beta_1\Delta T + \beta_2 BAI_{k-1} + \beta_3 BAI_{k-2} + \beta_4 BAI_{k-3} + \beta_5 V_{k-1}BAI_{k-1} \\ &\quad + \beta_6 V_{k-2}BAI_{k-2} + \beta_7 V_{k-3}BAI_{k-3} + \beta_8 \mathrm{d}P_{k-1} + \beta_9 \mathrm{d}P_{k-2} + \beta_{10}\mathrm{d}P_{k-3} \\ \sigma(W_k)^2 &= 1 + \delta_1^2 SP_{k-1} + \delta_2^2 \Delta T_k \end{aligned}$$

4.3 Estimation results

Table 2 shows the results of the maximum likelihood estimation of the ordered probit model for the selected days. The estimation was performed using the algorithm ML to maximize likelihood functions in the econometric package TSP. The results were checked using the algorithm MAXLIK of GAUSS. The outcomes were the same and stable with respect to changes in the initial conditions. Columns Z1 and Z2 present two tests that are asymptotically normal under the null hypothesis that the coefficient is 0. The covariance matrix is calculated using the analytic second derivatives, in Z1, and the product of the analytical gradients, in Z2.

There are several facts of interest in Table 2. First, the estimation of the threshold parameters that define the partitions is very precise for all the days. Second, the spread and the time between transactions are very significant in the explanation

[14] Karpoff (1987) presents a summary of the literature on the relationship between return and volume in financial markets.

[15] The log transformation was also used for volume. See Montalvo (1998).

Table 2. Estimation results

	11/11/96			15/11/96			19/11/96		
	param	Z1	Z2	param	Z1	Z2	param	Z1	Z2
variance									
SP	0.195	4.176	3.780	0.900	6.881	6.218	1.184	6.770	5.939
dT	0.016	5.754	5.566	0.108	7.131	6.303	0.103	6.553	5.613
cond. mean									
dT	0.001	0.358	0.405	−0.011	−1.417	−1.672	−0.004	−0.462	−0.558
BAI(k−1)	0.094	1.447	1.307	0.042	0.571	0.516	0.089	1.128	1.082
BAI(k−2)	−0.028	−0.403	−0.391	0.042	0.543	0.502	−0.066	−0.784	−0.772
BAI(k−3)	0.057	0.889	0.810	−0.079	−1.114	−1.088	0.097	1.253	1.220
V(k−1)BAI(k−1)	−0.000	−0.093	−0.075	−0.003	−1.005	−0.952	0.002	0.774	0.725
V(k−2)BAI(k−2)	0.003	1.106	1.264	0.007	2.666	2.576	0.007	2.825	2.814
V(k−3)BAI(k−3)	−0.002	−0.707	−0.512	0.004	1.507	1.514	0.001	0.269	0.275
dP(k−1)	−0.254	−4.207	−3.982	−0.610	−7.166	−6.560	−0.994	−8.183	−7.210
dP(k−2)	−0.038	−0.653	−0.651	−0.516	−6.311	−5.729	−0.495	−5.625	−4.918
dP(k−3)	−0.026	−0.488	−0.421	−0.078	−1.238	−1.207	−0.198	−2.782	−2.277
A1	−5.972	−8.340	−7.270	−12.096	−8.861	−8.047	−13.017	−8.446	−7.073
A2	−3.912	−11.907	−11.269	−9.141	−9.795	−8.951	−9.757	−9.200	−7.846
A3	−2.706	−13.392	−13.043	−5.597	−10.871	−9.841	−6.407	−9.876	−8.610
A4	−1.546	−13.525	−13.156	−2.766	−11.429	−10.420	−3.178	−10.382	−9.155
A5	1.477	13.602	13.420	2.707	11.402	10.474	3.218	10.233	8.937
A6	2.824	13.344	13.229	5.556	10.797	9.841	6.398	9.817	8.416
A7	4.139	11.677	11.256	8.618	9.925	8.738	9.574	9.264	7.740
A8	6.287	7.172	6.797	12.005	8.694	8.002	13.425	8.297	7.256
logl	−1816.77			−4974.14			−5048.28		

(*continued*)

Table 2. Continued

	22/01/97			24/01/97			27/02/97		
	param	Z1	Z2	param	Z1	Z2	param	Z1	Z2
variance									
SP	1.166	7.213	6.405	0.952	8.913	7.693	1.635	5.007	4.348
dT	0.112	6.939	6.160	0.152	8.967	8.371	0.111	5.191	4.387
cond. mean									
dT	0.001	0.107	0.130	−0.020	−2.057	−2.354	0.009	0.914	1.111
BAI(k−1)	−0.185	−2.307	−2.121	−0.157	−2.412	−2.175	−0.186	−1.582	−1.406
BAI(k−2)	−0.083	−1.043	−0.970	−0.093	−1.435	−1.425	0.116	0.978	0.957
BAI(k−3)	−0.005	−0.071	−0.070	0.072	1.185	1.186	−0.042	−0.393	−0.386
V(k−1)BAI(k−1)	0.008	3.382	3.165	0.006	3.049	3.058	0.008	2.076	2.095
V(k−2)BAI(k−2)	0.007	2.782	2.444	0.003	1.503	1.513	0.003	0.759	0.822
V(k−3)BAI(k−3)	0.002	0.841	0.859	0.004	2.174	2.089	0.003	0.746	0.707
dP(k−1)	−1.005	−8.796	−7.840	−0.743	−10.273	−9.215	−1.596	−6.303	−5.591
dP(k−2)	−0.561	−6.262	−5.963	−0.322	−5.519	−5.154	−0.937	−5.353	−4.903
dP(k−3)	−0.169	−2.466	−2.432	−0.180	−3.568	−3.481	−0.309	−2.746	−2.407
A1	−13.988	−8.639	−7.708	−11.915	−11.725	−9.084	−19.287	−5.519	−4.737
A2	−9.670	−9.915	−8.403	−8.579	−12.761	−10.968	−12.715	−6.624	−5.136
A3	−6.308	−10.562	−9.336	−5.571	−13.690	−12.056	−8.228	−6.910	−5.854
A4	−3.164	−11.055	−9.835	2.873	−14.308	−12.600	−4.048	−7.204	−6.207
A5	3.250	11.153	10.031	2.781	14.207	12.663	4.109	7.211	6.280
A6	6.495	10.563	9.473	5.410	13.656	12.060	7.959	6.928	5.981
A7	9.727	9.944	8.521	8.364	12.764	10.797	13.218	6.469	5.410
A8	13.451	8.998	7.465	11.697	11.382	9.649	18.219	5.774	5.056
logl	−5751.75			−8009.95			−4312.53		

Z1 is the ratio parameter estimate/standard deviation calculated using the standard deviation obtained from the second derivative (Newton).
Z2 is the ratio parameter estimate/standard deviation calculated using the standard deviation obtained from the product of the first derivatives (BHHH).

of the conditional variance and, in all the cases, both coefficients are positive.[16] This implies that the longer the time between two consecutive transaction or the spread the higher is the conditional variance. Third, the coefficient of the time between trades is not significantly different from 0 in the explanation of the conditional mean with the exception of one day. Fourth, the first lag of the bid/ask indicator is significantly different from 0 for the days in 1997 but not for the days prior to 1997. In addition, the first lag of the product of the bid/ask indicator by the volume is significant for the selected days of 1997, while the same variable, but the second lag, is significant in the case of the days of 1996. Finally, the lagged price changes are very significant and negative showing which is indication of mean reversion.

4.4 Specification Testing

In general diagnostic testing in least squares regression is based on the properties of the residuals. In the case of the ordered probit it is not possible to calculate directly the residuals because the endogenous variable is latent and, therefore, unobservable. However it is possible to construct generalized residuals following the proposal contained in Gourieroux *et al.* (1985) and Hausman *et al.* (1992). These residuals can be obtained as

$$\hat{u}_k \equiv E(u_k/\mathrm{d}P_k, X_k, W_k; \hat{\theta})$$

where the estimated θ contains all the parameters of the model. Based on these residuals Gourieroux *et al.* (1985) derive the test for serial correlation from the lagged endogenous variables. Given that the model is estimated by maximum likelihood we can use the score to test the null hypothesis of no serial correlation. Consider the following model for the unobservable $\mathrm{d}P^*$

$$\mathrm{d}P_k^* = \rho \mathrm{d}P_{k-j}^* + X_k'\beta + u_t \quad |\rho| < 1$$

The score statistic is obtained as

$$\hat{c}_j = \frac{(\sum \mathrm{d}\hat{P}_{k-j}\hat{u}_k)^2}{\sum \mathrm{d}\hat{P}_{k-j}^2 \hat{u}_k^2}$$

where the latent variable is estimated conditional on the same variable as the generalized residual.

$$\mathrm{d}\hat{P}_k \equiv E(\mathrm{d}P_k^*/\mathrm{d}P_k, X_k, W_k; \hat{\theta}) = X_k'\hat{\beta} + \hat{u}_k$$

Under the null hypothesis that $\rho = 0$ then the score statistic is asymptotically a $\varkappa_1^2$. Table 3 reports the score statistic for $j = 1, \ldots, 8$. Only very few statistics are statistically significant at the 5% level which indicates that the lag structure in the specification is enough to capture the serial dependence in the data because there is little autocorrelation not accounted for in the specification.

[16] Hausman *et al.* (1992) find exactly the same result.

Table 3. Score test statistics

	11/11/96	15/11/96	19/11/96	22/01/97	24/01/97	27/02/97
c1	0.85	1.23	1.34	2.34	0.38	0.87
	(0.36)	(0.27)	(0.25)	(0.13)	(0.54)	(0.35)
c2	0.09	0.93	0.98	1.87	0.24	0.03
	(0.76)	(0.33)	(0.32)	(0.17)	(0.62)	(0.86)
c3	0.95	2.04	1.54	2.58	0.76	0.65
	(0.33)	(0.15)	(0.21)	(0.11)	(0.38)	(0.42)
c4	1.76	2.95	2.35	3.87	1.34	1.04
	(0.18)	(0.09)	(0.13)	(0.05)	(0.25)	(0.31)
c5	0.87	4.03	0.98	17.32	0.24	1.89
	(0.35)	(0.04)	(0.32)	(0.00)	(0.62)	(0.17)
c6	0.67	8.95	1.53	56.72	0.12	1.07
	(0.41)	(0.00)	(0.22)	(0.00)	(0.73)	(0.30)
c7	1.82	42.3	3.06	6.81	2.37	2.97
	(0.18)	(0.00)	(0.08)	(0.01)	(0.12)	(0.08)
c8	1.12	14.43	2.31	5.39	2.89	3.42
	(0.29)	(0.00)	(0.13)	(0.02)	(0.09)	(0.06)

p-values are included between parenthesis.

Table 4. Cross-autocorrelation coefficients

Order	11/11/96	15/11/96	19/11/96	22/01/97	24/01/97	27/02/97
1	−0.003	0.002	−0.012	0.006	−0.010	−0.004
2	0.002	−0.001	0.003	0.009	0.002	0.009
3	0.001	0.005	− 0.005	0.013	−0.008	−0.011
4	− 0.021	−0.053	−0.042	−0.096	0.026	−0.057
5	0.001	−0.012	0.008	−0.017	−0.003	0.016
6	0.000	−0.010	0.006	−0.016	−0.008	−0.008
7	0.006	0.005	−0.012	0.019	0.006	0.007
8	0.005	−0.008	−0.003	−0.008	−0.011	0.003

This table shows the cross-autocorrelation of generalized residuals with the fitted price changes.

Hausman *et al.* (1992) propose also an informal specification test for the ordered probit model. They argue that if the model is correctly specified the sample correlation between the generalized residual and the lagged generalized fitted values should be close to 0. Table 4 presents these correlations up to the eighth lag and shows that all of them are smaller than 0.1 in absolute value which is another indication that the model seems to be properly specified.

5. THE PRICE IMPACT OF TRANSACTIONS

There are several indicators that could be used in order to measure liquidity. In general a market is more liquid than another if a transaction of the same size generates a smaller price change. Therefore, if a market has a high degree of liquidity then the response function of prices to traded volume should be flat. Given that one of the basic functions of a market maker is to ensure that trading moves smoothly with small price fluctuations we could use the steepness of the response function in order to measure their impact on liquidity.

Using the parameters estimated from the ordered probit we can obtain such a function. However, the parameter estimates cannot be used directly to measure the impact of volume on prices for two reasons: first the estimated parameters represent the marginal effect of volume on an unobservable variable, dP^* and not on dP. Second, the random variables u are not identically distributed because they can have different variances.

In order to make a comparison between the response function of days before and after 1 January 1997, we have to calculate the impact of the conditional mean on the conditional distribution of dP and not on dP^*. To perform this calculation it is necessary to substitute the parameter estimates in the distribution function of the ordered probit model and choose particular values for the X variables, computing explicitly the probabilities. The values for the X variables are the average time between two transactions (ΔT), the mean spread (SP) and the mean volume times the bid/ask indicator lagged two and three periods ($V(-2)$BAI(-2) and $V(-3)$ BAI(-3)). The BAI indicator and its lags are fixed at 1 which means that the last three transactions took place at the ask price. Finally, we consider two alternative sequences of prices changes: first that the sequence of the last three price changes were 1/1/1, which is to say that the price has increase in 3 ticks during the last three transactions. Second, we consider the sequence 0/0/0 which implies that there was no price change during the last three transactions.[17]

Table 5 shows the results of the calculation described above. In the first row the table shows the effect on the expected price change of a 10-contracts transaction.[18] In principle it could be surprising to see that the expected price change is negative. However, the situation is such that, after three buys at the ask price the probability of next transaction being a sell is high which implies that the price change could be negative because of a bid/ask bounce. The solution to this problem implies including the contemporaneous bid/ask indicator in the specification of the conditional mean. However, this simple solution has an important drawback because the simultaneity of price changes and the bid/ask indicator will lead to bias in the coefficient estimates.

An alternative solution considers changes in the conditional mean due to transactions larger than 10 contracts. The second row of Table 5 presents the expected change in prices, measured in ticks, for an increase of the size of the transaction in 40 contracts (from 10 to 50), 90 contracts and 190 contracts. As can be seen in Table 5 the increase from 10 to 50 contracts implies a price change between 0.048 and 0.069 ticks when the previous sequence of transactions had price changes of 1/1/1. When the transaction size increases from 10 to 100 contracts the estimated value of the price change goes from 0.108 to 0.154.

[17] We can consider these two situations as extreme cases.
[18] In the case of the selected days from 1996, and given that the coefficient on the first lag of volume is not significantly different from 0, we consider that those 10 contracts were referred to the second lag.

Table 5. Price impact of trades

Price sequence	dP	Volume	11/11/96	15/11/96	19/11/96	22/01/97	24/01/97	27/02/97	t
1/1/1	E(dP)	10	−0.056	−0.238	−0.309	−0.353	−0.293	−0.448	1.319
	dE(dP)	50	0.048	0.063	0.056	0.070	0.060	0.049	−0.379
	dE(dP)	100	0.109	0.140	0.125	0.155	0.134	0.109	−0.348
	dE(dP)	200	0.230	0.294	0.260	0.320	0.279	0.225	−0.279
0/0/0	E(dP)	10	0.057	0.034	0.028	−0.008	−0.004	−0.016	2.711
	dE(dP)	50	0.048	0.062	0.054	0.065	0.058	0.043	−0.088
	dE(dP)	100	0.109	0.139	0.122	0.147	0.131	0.098	−0.082
	dE(dP)	200	0.233	0.299	0.260	0.316	0.279	0.208	−0.075

Volume is measured in number of contracts.

In the case of the sequence without price change it is interesting to notice that, during the selected days of 1996, the conditional expectation of the price change when the last transaction volume is 10 contracts, is positive. Therefore, after three buys at the ask price without price change, if the last transaction had a volume of 10 contracts, the price is pushed up by an amount between 0.056 and 0.028 ticks. However, for the days of 1997 and a volume of 10 contracts, the bid/ask bounce leads to a negative price change.[19]

Figures 13 to 18 show the distribution of the probability of price changes, measured in number of ticks, for the two sequences 1/1/1 and 0/0/0. Obviously, the probability distribution in the first case is switched to the left with respect to the second one. This fact is common to every day, which is a sign of robustness of the method.

Is the market more liquid after the introduction of market makers? The final column in Table 5 presents the contrast of means differences for the days before and after the introduction of the market makers for different sequences of trades and alternative size volume. None of them is significantly different from 0, which implies that we cannot reject the null hypothesis that the mean price change is the same before and after the introduction of market maker for the sequences and the transaction sizes analysed.

6. CONCLUSIONS

Market makers are required to maintain price continuity and to ensure that 'trading moves smoothly with minimal price fluctuations' in order to provide liquidity to securities markets. For this reason it is always important to know if market makers fulfil their obligations. Recent studies find that, in some cases, market makers collude when fixing quotes, abandon the market when volatility is very high or keep an unfair weather. This behaviour is at odds with their basic obligation. In this paper we analyse the effect of the introduction of market makers on the liquidity of the Spanish Government Bonds Futures Market. We focus on this market because at the beginning of 1997 a change of regulation created explicitly the institution of the market maker and, therefore, we can use this case as a pseudo-experimental situation.

In order to separate the effect of market makers on liquidity from the effect of other economic conditions we choose the days before and after the beginning of the experiment using a matching procedure on daily data. The estimated propensity score is used to perform the matching. After choosing the days we estimate, using transaction-level data, an ordered probit model to explain the intraday behaviour of price changes. This estimation procedure is adequate for variables like price changes that are discrete and irregularly spaced when using transaction data. The specification of the conditional mean include as explanatory variables the time between transactions, lags of price changes, lags of the bid/ask indicator and lags of the volume. In addition the specification of the conditional variance depends on the spread and the time between transactions.

[19] Hausman *et al.* (1992) also show that for small volume of trade the price changes are negative no matter what sequence of prices changes is used.

The coefficient estimates from the ordered probit model are used to calculate a measure of liquidity based on the steepness of the price change as a function of volume. The results show that liquidity, defined as the effect of a trade of a given size on prices, has not been affected by the introduction of the market makers. Although this definition of liquidity is consistent with the price continuity and 'minimal price fluctuation' requirements, there are alternative definitions of liquidity that have been used in the literature. In addition, as Hasbrouck and Sofianos (1993) point out 'in consideration of the market maintenance obligation, the specialist may be forced to participate in relatively high proportion of difficult, high impact trades'. This is the reason why they find that 'trades in which specialists participate are associated with large quote revisions'.

We have also shown that the average bid/ask spread has not changed with the introduction of market makers. However, the relative importance of the components of the spread (asymmetric information, inventory and transaction costs) may have been affected. In future research we will examine the components of the spread before and after the introduction of the market makers to determine if the proportion of each component in the spread has changed.

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