Estimating the Probability of Informed Trading: Further Evidence from an Order-driven Market¹

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Abstract

Nyholm (2002, 2003) [J. of Financial Research, 25, pp. 485; J. of Applied Econometrics, 18, pp. 457] has proposed a new procedure to infer the probability of informed negotiation on a trade-to-trade basis through a regime-switching model. We provide further empirical evidence about the performance of this model by using trade-related information, such as the degree of aggressiveness and the trade size, from a pure order-driven market. It is evidenced that the switching scheme of the basic model is closely related to the arrival of different types of orders and not necessarily to information. This feature also applies when controlling for market variables other than order aggressiveness –as trade size. The updating process in the non-linear setting proves so complex that it is necessary to account for different microstructure effects to provide probabilities related to information arrivals.

1 Introduction

One of the most important topics in financial literature is concerned with market informational asymmetries and their implications for asset prices. Investors holding private information lead to permanent changes in prices as they trade optimally to profit from their advantage. Uninformed traders, on the contrary, mostly negotiate for consumption or liquidity reasons, and do not affect permanently equilibrium prices. The advantageous behaviour of the informed investors is masked by the noisy activity of uninformed traders, and as a consequence it is not possible to identify their particular nature but in terms of probability. This uncertainty implies a risk for liquidity suppliers, who have to face an adverse selection problem.

Measuring the degree of asymmetry deserves attention for its economic implications on the transaction costs and on the price formation process. It is a well-known feature that bid-ask spreads include a component tied to the adverse selection risk, as liquidity suppliers try to compensate in this way the higher expected loss derived from dealing with informed agents (Bagehot, 1972); consistent with this hypothesis, thinly-traded and lowest-priced stocks, which are less widely followed and hence subject to a greater degree of informational asymmetry, tend to show a larger adverse selection component in their spreads. The degree of informational asymmetry can thus be inferred through the size of the adverse selection cost. Alternatively, it is also possible to appraise the probability of informed negotiation (PIN henceforth) as a telling measure of asymmetry in the price formation process, which rises, for instance, the average relative frequency in which new private information is incorporated into prices.

Recent microstructure literature has suggested some empirical procedures to address this issue. The seminar work in the area is due to Easley *et al.* (1996), who developed a method based on a mixture of three Poisson processes to model arrivals of (relevant) information. More recently, Nyholm (2002, 2003) has suggested a method based on a regime switching model. The most appealing feature of this procedure is that the behaviour of the informed investors is regarded as a latent variable whose dynamics can be estimated endogenously from trade-to-trade data. The core of this method is a non-linear generalization of the well-known trade-indicator regression of Glosten and Harris (1988). The trade-indicator model states basically the predictability of the quote midpoint change on the basis of observable variables such as the direction (either purchase or sell) of the last transaction. The Nyholms's approach generalizes this idea upon the assumption of two states underlying different midquote revisions. When the dynamics of the process is in 'excited' state, the changes in the midpoint prove more sensitive to spreads and it is heuristically assumed that the trade at that time is initiated by an informed investor. Private information arrivals are to a great extent identified through large midquote changes in relation to the average half-spread. This feature is, however, potentially troublesome, since it is not clear that the immediate update process corresponds one-toone with information arrivals and, moreover, what is regarded as a 'large' change potentially due to private information is clearly conditioned by the mean specification. The estimates resultant from an oversimplified modelling could lead to misleading conclusions.

The main aim of this paper is to provide further insight on the empirical performance of this new procedure. To extent the evidence presented by Nyholm on a quote-driven dealer market (the New York Stock Exchange, NYSE), we exploit the information conveyed by trade-related variables which are publicly observable in order-driven markets. Such an extension does not offer any theoretical inconvenience, because the aggregate behaviour of the limit-order book is similar to that of a market maker and, in fact, it has been evidenced the role of limit-order traders as liquidity suppliers.¹ Moreover, there exists a growing interest for this type of market as new trading systems and recently restructured exchanges apply a limit-order book design. The information from those markets, which is publicly disclosed, is likely useful to address the occurrence of private trades. The conclusions resultant from a deeper analysis can shed light on the performance of the regime-switching model.

Specifically, we use the aggressiveness of the traded orders as a key variable to enhance estimates. This magnitude underlies the trader's decision and is related to impatience and willingness to trade facing less and less competitive prices. Despite of its potential relevance, it has been paid relatively little attention in this framework. There are a number of reasons for which order aggressiveness seems worthwhile. First, it is tied to the informed process in which prices are updated. It is accepted in the wide literature related to the topic of order submission strategies that the more aggressive is the order, the more information is conveyed. Second, it subsumes to some

¹The possibility of applying this model on both specialist- and order-driven markets is remarked in Nyholm (2002).

extent the information related to the market environment and the asset dynamics. Trade-related variables such as the thickness of the book, the price volatility, the size of the book, among others, are determinants of the degree of aggressiveness. This fact allows us for a fairly parsimonious analysis in the non-linear context of the regime switching model, as a small number of variables are linked to a large set of useful information. Third, aggressiveness is a magnitude observable for market suppliers and, in the case of an order-driven market, it can easily be computed from the publicly visible information which is disseminated by the limit-order book. Investors can use this information at any time to improve their knowledge and define optimal strategies. Therefore, it seems legitimate to incorporate this information to refine the results of the original model.

We apply the baseline and several extensions on data from the Spanish Stock Exchange. This is a pure, electronic order-driven market without market makers that operates with a fully centralized computerized system similar to the Toronto's Computer Assisted Trading System (CATS) popular around the world. We form three groups of assets attending on the different levels of traded volume and proceed to infer the PIN dynamics on each asset. The importance of the degree of aggressiveness is supported by an overwhelming statistical evidence. It is seen that the switching scheme of the basic formulation, which does not acknowledges the order design explicitly, is in reality closely related to the arrivals of a particular type of aggressive order –those that impose, on average, the highest immediate revision of the midquote revision. The effect due to order design is far more important than that related to any other variable on the trader's decision, such as the size or the direction of the trade. Therefore, any attempt to enhance the specification by adding market variables still neglecting aggressiveness – as done in Nyholm (2003) - does not prevent the model to switch according to the above pattern. The revision process is sensitive to so many different microstructure factors that just controlling for order typology is not sufficient to isolate private information in the latent variable. The specification must be further generalized including additional microstructure effects, as trade size, in order to obtain probabilities measures coherent with information arrivals patterns. Extensions accounting for further effects could yield better results, yet on the cost of putting considerable strain on an already heavily-parameterized model, which seems unfeasible in practice.

This paper contributes to the previous microstructure literature in several ways. First, we provide an extensive discussion of an available procedure intended to approach the probability of informed trading on a trade-to-trade basis. We show that the information conveyed in some market-related variables observable by traders in real time must necessarily be exploited to improve the basic formulation and get estimates which are related to some extent with the probability of private information arrivals. These measures might be suitable of being used as proxies of information for further empirical applications in the continuous-trade framework. Second, despite of the simplicity assumed in some empirical models, the analysis applied here underlines the great complexity of the immediate updating process. The price revision displays a non-linear behaviour that is sensitive to several microstructure effects related to the market environment. This evidence is relevant to improve the knowledge about liquidity dynamics and traders' behavior. We have also assessed the role played by some of those variables in the price updating process, among which the degree of aggressiveness is remarkably important. Despite its intuitive relevance, aggressiveness has received less comparative attention than other trade-related variables such as the trade size, no doubt because of the limitations of the databases used in earlier works. The increasing availability of detailed information about trades and orders from exchanges over the world, as well as the overall evidence about the important role of aggressiveness in the price revision process, make this variable worthy of attention in further research.

The balance of the paper is organized as follows. Section two briefly describes the general theoretical background of the model. Section three states the basic setup of the Nyholm's model and discusses further generalizations. Section four introduces the dataset and presents the usual descriptive analysis. Section five discusses the main findings and the implications from the estimation of several models. Finally, section six summarizes and concludes.

2 Theoretical background

Informational asymmetries were early studied by Bagehot (1971) and Jaffe and Winkler (1976), who suggested the distinction between informed and noise traders. Since then, a great deal of literature has focused on the consequences of market asymmetries. Of these issues, two are of special interest for market microstructure purposes.

One is to identify the different components (adverse selection, inventorycarrying and order-processing costs) that characterize the bid-ask spreads. The theoretical and empirical work in this area is extensive, so a concise revision of the literature is beyond the aim of the paper. Earlier statistical models used the simple time-series properties of the transaction prices (Roll, 1984; Choi, Salandro and Shastri, 1988; Stoll, 1989) while another category of models focus on structural models based on the trade-indicator regression model and its extensions: among others, Glosten and Harris (1988), George, Kaul and Nimalendran (1991), Lin, Sanger and Booth (1995), Madhavan and Cheng (1997) and Huang and Stoll (1997). Hasbrouck (1988, 1991a, 1991b) uses an alternative framework based on the vector autoregression.

The second issue is related to estimate the probability of informed transactions as an alternative measure of asymmetric information. The few number of empirical procedures to address this topic so far contrasts to the wide framework related to identify the adverse selection component. The original contribution is due to Easley *et al.* (1996) who developed a sequential model based on a mixture of three Poisson processes. The most attractive feature of this methodology is its simplicity: an averaged PIN measure over a given period can be inferred on the basis of the daily number of buyer- and seller-initiated trades. Applying this model to the U.S. market, the authors found significant lower PIN measure for more liquid stocks. This procedure is widely accepted and has subsequently been used and extended to address a wide range of empirical issues in market microstructure.

Nyholm proposed a different approach to estimate the probability of informed trading. This model belongs to the framework of the trade-indicator model and hence inherits the advantages related to this formulation, but also most of its disadvantages. The most appealing feature is that a conditional PIN measure could be estimated for each trade, thus providing an interesting basis for further empirical applications. Nyholm applies the model on stocks from the NYSE and evidences a higher average PIN measure for the less liquid assets. We discuss in greater extent the main features of the tradeindicator model and its extension towards the regime switching model in the following section.

Finally, there exists an extensive body of literature related to aggressiveness, mainly focusing on the order submission strategies and their determinants. Cohen *et al.* (1981) early analyzed order submission. Biais, Hillion and Spatt (1995) outlined the relation between the order flow and the state of the limit order book in the Paris Bourse, finding evidence on strategies based on order placement: traders tend to place limit orders when the spread is large and the order book is thin, and the opposite is true for market orders. Harris and Hasbrouck (1996) also provide evidence about the performance of order submission strategies on the NYSE. Recent papers analyze the determinants underlying the trader's decision to submit more aggressive orders. The trade-off between execution probability and adverse selection risk *versus* payment for immediacy plays a key role in this decision; as such, it is seen that trade- and market-related variables (like spread, order size, thickness and transient volatility) condition the trader's decision as to which type of order to submit (Ranaldo, 2004). Griffiths *et al.* (2000) evidenced that buy (sell) aggressive orders are more likely with small-firm stocks and when the limit-order book has a wide bid-ask spread and high (low) depth on the same (opposite) side as the order.

3 The basic Markov regime-switching model

Traders who hold private information can make a profit while fundamental prices do not reflect full information. They trade advantageously and force prices to change to correct unbalance. In addition, stock prices change as public information is released. The trade-indicator model combines both sources and assumes that quotes are adjusted to reflect the private information revealed by both the previous trade and the current random arrivals of public information,

$$\Delta M_t = \alpha \frac{S_{t-1}}{2} Q_{t-1} + \varepsilon_t; \quad \varepsilon_t \sim \left(0, \sigma^2\right); \ t = 1, ..., T \tag{1}$$

where ΔM_t denotes the variation of the midpoint of the bid-ask spread, S_t is the size of the quoted spread and Q_t is the trade-indicator variable signalling whether transactions are at the ask $(Q_{t-1} = 1)$ or at the bid side $(Q_{t-1} = -1)$. The arrival of public information is regarded as a white noise process, ε_t . The coefficient α measures the size of the adjustment on the half-spread and includes the effect attributable to both adverse selection and inventory holding costs. We shall denote $X_{t-1} = (S_{t-1}Q_{t-1})/2$ to avoid overloading unnecessarily the subsequent equations.

The Nyholm's approach extends the central idea of the trade-indicator model in (1) by allowing for non-linear dynamics. The midquote revision is conditioned to two latent states that are assumed to represent the particular nature of the trader. The model is thus defined on a stochastic process, say I_t , which takes a binary range of values depending on whether the trade at time t is initiated by an informed agent $(I_t = 1)$ or by a noise investor $(I_t = 0)$,

$$\Delta M_t = \alpha_0 X_{t-1} + \varepsilon_t, \quad \text{if } I_{t-1} = 0; \quad \varepsilon_t \sim (0, \sigma^2) \quad (2)$$

$$\Delta M_t = (\alpha_0 + \alpha_1) X_{t-1} + \varepsilon_t, \quad \text{if } I_{t-1} = 1; \quad \varepsilon_t \sim (0, \sigma^2)$$

where α_0 gauges midquotes response to non-informational trades (i.e., liquidity trades) and α_1 reflects the additional effect when trades are initiated by informed investors. Private information arrivals lead to higher revisions on midquotes, so α_1 is expected to be significantly different from zero.

The latent variable I_t is assumed to follow a first-order Markov regime switching process, so the probability of being in a particular state at t only depends on the state prevailing in period t - 1, t = 1, ..., T. The dynamics of the process is characterized by a 2×2 transition matrix, here denoted as \mathbb{P} , which governs the whole process and determines the probability of being at each state at any time. The on-diagonal elements p_{ii} of this matrix are assumed to be unknown, constant parameters such that,

$$p_{ii} = \Pr\left(I_t = i | I_{t-1} = i\right); \ 0 < p_{ii} < 1, i = \{0, 1\}$$
(3)

and,

$$\mathbb{P} = \begin{pmatrix} p_{00} & 1 - p_{11} \\ 1 - p_{00} & p_{11} \end{pmatrix}$$
(4)

The model specification must be completed by assuming a particular distribution for the error term in (2). While the trade-indicator regression equation can usually be estimated through GMM without making this assumption, the regime-switching modelling requires of maximum likelihood or Bayesian methods. It is assumed that the disturbance term is driven by independent, identically distributed Gaussian innovations with variance σ^2 regardless of the particular value of the underlying latent variable.² The set of parameters $\theta = (\alpha_0, \alpha_1, \sigma, p_{00}, p_{11})'$ is then estimated by quasi-maximum likelihood (QML), since the assumption of normality cannot be regardless as realistic. In general, it provides consistent –though inefficient– estimates provided correct specification and moderate departures from the assumption of normality.

 $^{^{2}}$ The error term is aimed to capture public information shocks. Note that it is implicitly assumed independence between public and private information.

The QML estimates are then used to infer the dynamics of the hidden Markov chain that characterizes the arrival of private information. The conditional PIN estimate at any time t is inferred as the smoothed probability $\Pr(I_t = 1 | \Psi_T; \hat{\theta})$, where Ψ_T denotes the set of available information up to time T. Nyholm (2002) suggests a measure representative of the unconditional PIN over the entire period in the spirit of Easley *et al.* (1996), determined as the mean value of the smoothed probabilities. Note that under the implicit assumption of ergodicity in the Markov chain, this measure is representative of the unconditional probability of the process being at excited regime, $\Pr(I_t = 1)$, so it can readily be estimated as $\tilde{p}_{00}/(\tilde{p}_{00} + \tilde{p}_{11})$, with $\tilde{p}_{ii} = 1 - \hat{p}_{ii}$. Other alternatives might be possible as well, but we shall focus on this estimate because it is directly implied by the regime-switching dynamics and therefore seems the most natural measure.³

3.1 Extending the model: a discussion

An implicit consequence of the model involved is that the midquote revision drives to transitory changes in prices when $I_t = 0$, and permanent changes in prices when $I_t = 1$. Both the transitory and the permanent updating of prices are consequently characterized through the estimates of α_0 and $(\alpha_0 + \alpha_1)$, so average transitory price updates are typically regarded as smaller than permanent ones. However, since the model does not involve an inter-temporal dimension beyond one period (one trade), it is not easy to figure out how a change that lasts long in time can truly be identified.⁴ It seems clear that these states are related to large and small *immediate* revisions in prices, but not necessarily to permanent and transitory changes.

Actually, this argument constitutes the main criticize for structural models based on the trade-indicator setup and, in fact, there are some concerns about the ability of these models to identify precisely the adverse selection component (van Ness, van Ness and Warr, 2001). Hasbrouck (1991) advocates to use the vector autoregression method for appraising the long-run price impacts of trading. Nevertheless, the trade-indicator models have been

 $^{^{3}}$ Nyholm (2003) measures the inconditional probability of information arrivals after classificating each trade. This implies to make an exogenous decision about the threshold level of probability which determines the values whether each observation is classificated as informed.

⁴The model assumes that all price effects are incorporated in the first transaction price, as predicted by the semi-strong form market efficiency (Glosten and Milgrom, 1985).

applied intensively in recent literature, finding a qualitative evidence largely consistent with the hypothesis conjectured a-priori. Similarly, the evidenced reported by Nyholm on the empirical application of the regime-switching model on the NYSE is roughly consistent with the main patterns related to asymmetric information. Some caution should be exercised, as these estimates are based on estimates which are likely to be subject to measurement errors.

In estimating the Nyholm's model, the regime-switching scheme identifies each state through the prediction errors of the mean equation. If errors are relatively large, the underlying observations are much likely classified as excited so that a larger revision can reduce the error size. It is therefore remarkably important to define the mean equation as precise as possible in this framework. Yet the basic model assumes that a narrow set of information (the observed bid-ask spread and the trade-indicator variable) is enough to characterize the hidden dynamics underlying the arrivals of private information. This makes the estimation of the model fairly feasible, but it could turn out to be too simplistic.

Note that there is a great deal of observable information which could be relevant to the better comprehension of information arrivals in the quote-toquote framework. Hasbrouck (1991), Huang and Stoll (1997), Dufuor and Engle (2000) and recently Pascual, Escribano and Tapia (2004), among others, have evidenced the empirical relevance of several variables related to market environment in the price revision process. An appealing feature of the trade-indicator setup is that the basic formulation can readily be extended to incorporate different microstructure effects, such as those related to trade-related variables. Such a generalization could easily be performed by introducing indicator variables that are 1 under a specific condition and 0 otherwise. The whole idea is, in summary, that the basic relation between the midpoint updating ΔM_t and the signed half-spread X_{t-1} stated in (1) and (2) could be much enhanced by using extra information related to market conditions.

>From an econometric viewpoint, estimating the *linear* trade-indicator regression or an extended model adding categories results only in different interpretations of the parameter estimates coupled with a potential gain in statistical efficiency. However, the picture can radically be different in the context of the regime-switching model, because the ultimate aim here is to characterize the dynamics of the hidden Markov chain. Any unexpected large shock in the midquote is likely regarded as an information arrival. An oversimplified mean equation that neglects relevant microstructure effects could imply model misspecification, and eventually lead to unreliable estimates of the regime switching dynamics, which is the whole point of the procedure.

Nyholm (2003) includes the effects of trade size in a further extension of the basic model. He finds that the volume of trades affects quote reactions subsequent to normal-information, but no volume-effect seems to apply to private-information initiated trades. This point is, nevertheless, really unappealing, since a number of papers have reported the heterogenous response of the price updating process on trade size (among others, Huang and Stoll, 1997; and Ahn et al., 2002). Furthermore, it is believed that large trades tend to convey more information because informed investors would be willing to trade large amounts at any given price (Easley and O'Hara, 1987) and because of the potential role of volume as a signal of the precision of beliefs (Blume et al., 1994). The trade size is an important variable because underlies the investor's decision, though it could be not as much important as other variables in the current context or should not be regarded solely. We propose to use another variable related to the investor's decision –degree of aggressiveness– as starting point to enhance the basic formulation, and then assess the robustness of the results from the basic model when these effects are ignored.

3.1.1 Order aggressiveness

Investors trade through very different types of orders, thus generating a complex link between the dynamics of prices and the order submission process. As orders are placed following trading strategies, they contain information which could be processed to infer the PIN more accurately. Traders can submit three basic types of (official) orders in the Spanish Stock Exchange: *limit orders, market to limit orders* and *market orders*. This nomenclature is slightly different from that used in other exchanges. *Limit orders* specify common conditions such as the quantity and the direction (either purchase or sell), but also the price and the date when the order will be withdrawn. The price plays a key role in this type of order. In fact, If the price submitted do not find counterpart in the limit order book, the order is added to the book improving the liquidity of the system (by either widening the depth of an existing quote or posting new quotes). On the contrary, if there is counterpart available, the order behaves as *market to limit* or *market order* depending on the price (when this occurs we speak in terms of *marketable limit orders*). On the other hand, any market or market to limit order consume liquidity. Market to limit orders only specifies the quantity and direction of the trade, so they are executed immediately at the prevailing quote. They are not allowed to walk up the book, hence, if the quantity available at the best price is not sufficient to fulfill the total volume required, the non-executed part keeps waiting for balancing entries in the other side of the book at the limit price. Finally, market orders are intended to achieve a full execution by allowing the order to walk up the book till completion. They provide the fastest execution, but imply higher costs than more passive orders.

An appealing analysis consists of ranking orders according to their degree of aggressiveness. Most aggressive orders trade at any given price, so they likely convey more information that less aggressive orders –in other words, they are more likely submitted by informed investors. We initially classify market orders (those which imply immediate execution) in the same spirit than Bias et al (1995). We consider three categories (we initially do not distinguish between purchase and sell orders):

- A1 The most aggressive orders, namely A1, demand a quantity larger than that available at the prevailing quote (either ask or bid). They are executed by walking up the book to complete the volume required or find a less competitive price. They imply a high degree of impatience because show the willingness to trade at any given price. The immediate effect is to widen the spread and change the midquote.
- A2 The second level, namely A2, includes orders submitted by investors that are willing to trade at the current bid or ask quote a quantity larger than that available, so they do not allow to walk up the book. The depth at the current quote is then fully consumed to partially fill the order and the remaining part is transformed into a limit order at the transaction price. The immediate effect is to change the midpoint but, alike A1 orders, the effect on the spread depends on the size of the pre-trade spread size and the quotes.
- A3 Finally, category A3 includes orders trading for a quantity lower or equal than that available at the current bid or ask quote. The immediate effect is a full execution and either a reduction or the full consumption of the available depth at the best quote.

All trades composing the database fall into one of these three categories.⁵ So let $\mathbf{A} = \{A1, A2, A3\}$ be a set of subscripts and $D_{\mathbf{j},t}, \ j \in \mathbf{A}$, an indicator taking value equal to one if the particular trade at time t is qualified as in its subscript, and zero otherwise. We incorporate this potential valuable information into (2) to control for systematic changes in the midquote given the order typology and a two-stated latent variable,

$$\Delta M_t = \sum_{j \in \mathbf{A}} \alpha_{0,\mathbf{j}} X_{t-1} D_{\mathbf{j},t-1} + \varepsilon_t, \quad \text{if } I_{t-1} = 0; \quad (5)$$

$$\Delta M_t = \sum_{j \in \mathbf{A}} (\alpha_{0,\mathbf{j}} + \alpha_{1,\mathbf{j}}) X_{t-1} D_{\mathbf{j},t-1} + \varepsilon_t, \quad \text{if } I_{t-1} = 1;$$

where $\varepsilon_t \sim (0, \sigma^2)$. In this formulation, the latent variable is driven by the unexpected shocks given the particular type of order. Note that imposing the linear restrictions $\alpha_{0,j} = \alpha_0$ and $\alpha_{1,j} = \alpha_1$ leads to the basic formulation, so the suitability of this extension over the benchmark model can readily be tested with a standard likelihood ratio test.

The former model allows the three classes of order to exist regardless the state of nature. Informed agents could submit conservative market limit orders to avoid be early detected as a part of their strategies, and uninformed agents could submit aggressive orders due to imperative liquidity reasons.⁶ The factors determining order placement depend partially on unobservable variables, such as the investor's information set and their personal preferences towards risk and portfolio allocation, and observable variables, such as spread, book thickness, previous order placement, price volatility, etc. (see Griffiths 2000; and Ranaldo 2004). Despite of the endogenous nature of the order placement, aggressiveness is regarded here as an exogenous variable. In the context of the trade-indicator model, in which the trade flow –and even the trade size– is also treated as exogenous, this assumption is admissible.

⁵Trades are necessarilly initiated by some type of market order or marketable limit orders, so limit orders that not imply an inmediate execution are necesserally excluded. Keim and Madhaven (1995) show that liquidity traders are likely to use market orders, but that informed traders whose information value decays slowly tend to use limit orders. Nevertheless, Griffiths et al. evidence that small limit orders or orders that not generate an inmediate execution has in general a small or unsignificant price impact. Easley et al. show that there is a gradual decrease in information asymmetry between transactions.

⁶Griffiths et al. (2000) report that aggressive sells are morel likely motivated by liquidity than aggressive purchases.

4 Data description

The Spanish Stock Exchange (SSE hereafter) is a computerized limit order market. It uses a centralized electronic system known as SIBE (*Sistema de Interconexión Bursátil Español*) similar to that in Brussels (NTS), Paris (CAC), Stockholm (SAX) or Toronto (CATS). The exchange opens at 8.30 with a call auction after which stocks are traded on a continuous basis from 9.00 through 17.30. There are no market makers or floor traders, so liquidity is strictly supplied by a limit-order book which collects all the buy and sell proposals submitted by traders.

The dataset was facilitated by the Sociedad de Bolsas S.A and contains information about every event that takes place in the first level of the limit order book. Both introductions and cancellations of limit orders as well as new transactions generate new records of trades and quotes. The sample period covers from September 1st to December 29th, 2000. For each stock, the quote-by-quote data set reports the transaction data (time stamp, price, volume in number of shares) and the order flow (time stamp, prevailing quotes, accumulated traded volume and depth in shares). Thus, the data set provides information on market orders and the best buy and sell prices (limit orders at and within the previous quotes), but does not provide data outside the prevailing spread. The information of the state of the book is publicly visible and it is disseminated continuously during the trading session. It provides information in real time on the better quotes (pre-trade transparency) and transactions (post-trade transparency).

We processed the dataset to obtain the relevant variables for the analysis. We only use transactions on the SSE, which are easily identified through the change in the accumulated volume at any time. Each transaction is exactly classified as either a buyer- or a seller-initiated trade by the location flags available from the dataset, without need of a classification algorithm. Also, the size of the spread immediate prior to the trade is readily collected. Finally, the order flow is processed by an algorithm that determines the degree of aggressiveness as a function of the traded size, the prevailing depth and the quotes.

We applied some filters to rule out potential anomalies. Stocks that not fulfill minimum daily activity requirements are excluded. We then apply a similar procedure than that in Easley *et al.* (1996) in order to make meaningful comparisons attending on the degree of trade activity. We rank stocks on traded volume in year 2000 and build seven groups. We then focus on stocks included in the second, fourth and sixth volume categories, namely Groups 1, 2 and 3, roughly representative of high, medium and low trading activity, respectively, and proceed to infer the PIN measure on each asset.

Table 1 presents some basic summary statistics over the sampled period for the 39 assets included in the sample. The variables refer to the liquidity levels, the traded volume, the price and the volatility of the assets involved. All these statistics underline the huge differences in terms of trading activity. The average traded volume in million of \bigoplus ranges from 6.25 (Group 3, low liquidity) to 321.61 (Group 1, high liquidity). Overall, it can be seen than assets in Group 3 are on average more illiquid, more volatile and less priced than assets in Group 2 and 3. This feature also applies when comparing assets from Group 2 to those in Group 1. It should be expected, therefore, that the PIN measure decrease monotonically over the three groups, as there are clear differences between the liquidity levels of the assets.

[Please Insert Table 1 about here: Sample Descriptive Statistics]

5 Empirical evidence

5.1 Basic model

We turn to analyzing the results from estimating (2). The mean, median, maximum and minimum of the parameter estimates as well as their mean asymptotic standard errors are reported in Table 1. The mean value of the estimates for α_0 ranks between 0.06 for the group of frequently-traded assets and 0.080 for the other two groups. Overall these estimates represent a half of those reported in Nyholm (2002). The estimates are much closer to those in Nyholm (2003), which correspond with twenty of the most actively traded assets from the NYSE. The estimates for α_1 in Table 1 are within 1.37 (Group 1, high volume) and 1.31 (Group 3, low volume). Though is tempting to make a direct comparison of these coefficients across volume categories, some care should apply in doing so. The higher estimate of α_1 seems to suggest that a greater adjustment is made for liquid assets, but these coefficient would apply on the average spread, which is smaller for liquid assets. A higher scale on a smaller margin could not lead necessarily to a higher price revision.

[Please Insert Table 2 about here: Baseline Model]

The estimations for the probabilities of informed trading over the analyzed period would be comprised between a 12.7% for the group of most liquid assets and a 16.7% for the group of thinly-traded stocks. These probabilities are higher than those reported in Nyholm –especially in the low volume category– essentially because the excited state is found here to be more persistent in all the volume groups. Setting apart the quantitative differences between the estimates from both different markets, the qualitative conclusions are similar and a smaller probability of asymmetric information for frequently-traded assets would be evidenced.

5.2 Order aggressiveness

The arguments for the inclusion of order aggressiveness as a compelling variable in this framework find an overwhelming statistical support. The loglikelihood function value is largely increased for all stocks (see Appendix A), and the likelihood-ratio tests for equality of estimated coefficients is always strongly rejected. There is indeed a great deal of valuable information conveyed in the order categories. While an acceptation would have implied that the price revision is independent of the architecture of the orders, it is evidenced that this issue is indeed relevant to set forth immediate changes in prices. For induction, variables other than aggressiveness could affect the immediate price revision as well. This evidence is in contrast to the basic model setup, which regards the price revision exclusively as a matter of information.

[Please Insert Table 3 about here: Order I Model]

The results from the estimation of the extended model are presented in Table 3. The A2 orders, which do not allow to walk up the book, generate the largest revision in the midquote across the three volume portfolios. Most aggressive orders of the A1 type also induce important revisions, although not as large as A2. Finally A3 orders imply the lowest price impact, much more moderate than the other categories. The most relevant feature is that the highest revision is not related to the most aggressive orders that, nevertheless, are more likely to convey information. This feature could be explained as that the immediate revision in prices is sensitive to both information and order design, and A2-type orders favor larger price revisions over A1 because of their design.⁷ Immediate revisions include a possible effect due to the private

⁷A similar feature is evidenced in Degrise et al. (2003) by using time windows around

information, but also a transitory effect due to microstructure effects, such as the order architecture. As this framework is based on immediate effects, it turns out that A2-type orders can on average exhibit higher revisions.⁸

Including the systematic effect due to the different types of orders has a severe impact on the inferred dynamics of the hidden Markov chain. The probabilities of transition show a very persistent non-excited state, specially in the group of active assets, and a fugacious excited state. The overall effect on the PIN estimates is a dramatic reduction across the three volume groups –the inferred PIN measures are on average halved and now range between 5.5% for frequently-traded assets and 7% for more illiquid assets. It is shown that the PIN dynamics are extremely sensitive to the specification of the mean equation.

There are several meaningful implications that arise from this analysis. The most important one is related to the consequences of the misspecification implied on the basic model. While it is not clear that the two states fully correspond to liquidity- and informed-initiated trades, it is evident on the other hand that order design is a key variable for the immediate price revision. The characteristic response proves quite heterogenous depending on the type of order, yet this feature is explicitly neglected in the basic specification. Since information is identified through larger revisions, and the systematic chances due to the different degrees of aggressiveness are not acknowledged, what does it prevent the model to switch simply as a function of the arrival of different types of orders? Thus, the latent variable of the model would implicitly account for the heterogenous response in the updating process

⁸Note that the inmediate relative price updating measured through the midquote change on the signed half-spread should not be misunderstood with the *price impact* as measured in Griffiths et al. The price impact is a more sophisticated measure given by the ratio of the realized price (the weighted average of the prices filling the order) to the pre-trade prevailing quote. Griffiths et al. evidence that the price impact increases monotically with order aggressiveness.

the aggressive order. To see this feature, consider this simple example. Let the pre-trade bid and ask quotes be b'_0 and a'_0 respectively. Assume for simplicity that the ask side includes only another quote, a''_0 , and that a trader is willing to buy a quantity exceeding the depth available at a'_0 and that would be partially filled with the depth at a''_0 . This trader could submit either an A1 or an A2 order. The immediate midquote change from the A1 order would be $(a''_0 - a'_0)/2$, while the change from the A2 order be $(a''_0 - b'_0)/2$. The latter exceeds the former in $(a'_0 - b'_0)/2$, the pre-trade half-spread. Therefore, A1 orders must walk up the book up to a far out quote in order to provoke a higher ceteris-paribus inmediate revision than A2 orders.

attributable to the degrees of aggressiveness.

The basis of the econometric formulation is so little restrictive that this hypothesis cannot be rejected at first sight –aggressiveness is able to generate differentiated enough responses in terms of 'small' and 'large' midquote changes. But, more important, the inferred probability measures would be related to same of the microstructure patterns commonly associated to information because so is aggressiveness. For instance, the basic model could find a smaller PIN measure for liquid assets because so is the frequency of aggressive orders arrivals, as observed in Griffiths *et al.*⁹ Also, the inferred probability could exhibit meaningful intraday patterns, as reported in the studies of Nyholm, because the likelihood of observing different types of order also tends to exhibit intraday patterns (see, for instance, Chung, Van Ness, and Van Ness, 1999).

If this conjecture is true, the unconditional PIN measure from the basic model should be closely related to the probability of observing aggressive orders that impose larger revisions, as the contrast between the two states is then more evident. It turns out illuminating to compare the cross-sectional PIN estimates from the basic model to the sample probability of A2 orders. The latter probability, say Pr(A2), is just computed as the average value of the indicator variable $D_{A2,t}$. Both measures are depicted in Figure 1. The linear correlation between both series is very high, over 83%, with the PIN estimates nearly matching the path followed by Pr(A2). Roughly speaking, the PIN measures seem to account for the probability of A2 occurrence plus a random term; this added component is no doubt related to the probability for which orders belonging to other groups, more likely A1, generate a similar response to that of A2 orders.

[Please Insert Figure 1 about here: PIN and Pr(A2) Comparison]

The conclusion is that the probability measure implied from the Nyholm's model basically tells how frequently A2 orders (and orders that generate similar effects) arrive at the market rather than how private information is disclosed. This measure can only be seen as a rough and unreliable estimation of the targeted probability. The relevant questions refer then to the consequences implied when including variables other than aggressiveness, and to

 $^{^9 \}rm Recall$ that average PIN for small, medium and high volume portfolios reported are 12.8%, 16.5% and 17.8%. The average probability of occurrence of A2 orders for those categories is 11.3%, 14.3% and 15.90%

what extent a model that (at least) includes aggressiveness would be able to measure properly information arrivals. We provide further results on both questions below.

5.3 Further results

A. Trade size

We analyze the effects of including variables other than aggressiveness in the regime-switching framework. Following Nyholm (2003), we consider three categories of trade size –small, medium and large– depending on a set of threshold points. As the sample includes stocks with quite different trading activities, rather than taking fixed points (e.g., 1000 shares) for all the assets we consider threshold values given by the empirical distribution of trade size of each asset. Thus, we define three indicator variables, $D_{\mathbf{j},t}$, with subscripts belonging to $S = \{l, m, s\}$ and taking values 1/0 to indicate whether the order at time t traded a volume greater than the fourth quintile (j = l), within the first and fourth quintile (j = m), and less than the first quintile (j = s). The baseline model is then extended by incorporating these categories,

$$\Delta M_t = \sum_{j \in \mathbf{S}} \alpha_{0,\mathbf{j}} X_{t-1} D_{\mathbf{j},t-1} + \varepsilon_t, \quad \text{if } I_{t-1} = 0; \quad (6)$$

$$\Delta M_t = \sum_{j \in \mathbf{S}} (\alpha_{0,\mathbf{j}} + \alpha_{1,\mathbf{j}}) X_{t-1} D_{\mathbf{j},t-1} + \varepsilon_t, \quad \text{if } I_{t-1} = 1;$$

As in the former case, imposing the set of linear restrictions $\alpha_{0,j} = \alpha_0$ and $\alpha_{1,j} = \alpha_1$ leads to the baseline formulation.

[Please Insert Table 4 about here: Size-extended Model]

The outcomes from this model are reported in Table 4. The log-likelihood function increases (see Appendix A) yet not as much as when accounting for order aggressiveness.¹⁰ The results are qualitatively similar to those reported in Nyholm (2003). First and most important, the regime-switching dynamics

 $^{^{10}}$ Furthermore, the joint hypothesis of overall equality of coefficients among the indicator categories cannot be rejected at the 1% confident in some assets belonging to the medium and low volume groups.

of the size-extended model do not differ from those of the baseline model, and therefore the resultant PIN estimates are basically the same.¹¹ A glance at Figure 2, where the cross-sectional PIN estimates from both the baseline and the volume-extended models are exhibited, confirms this feature. Clearly, the resultant probability estimates are still biased by the unconditional likelihood of A2 orders.

[Please Insert Figure 2: Baseline and Size-extended Comparison]

Second, the same unappealing pattern related to the coefficients of the size categories is evidenced: while the adjustment seems to be sensitive to size-effects in the normal state, the differences across coefficients are not so conclusive in the excited state. We applied *t*-tests as in Nyholm (2003) to analyze whether those differences are statistically significant. The results show that the difference between the coefficients related to small and large sizes in the normal state, $(\hat{\alpha}_{0,s} - \hat{\alpha}_{0,l})$, is not significant at the 5% confident in only four cases (medium (3) and small (1)) but, on the contrary, the test on the difference $(\hat{\alpha}_{1,s} - \hat{\alpha}_{1,l})$ in the excited state cannot be rejected in 29 cases.¹²

The conclusions on the relation between private information and trade size based on the evidence from this model are necessarily misleading, because the latent variable is still related to the order typology, not to information arrivals. All the categories related to trade size include aggressive and non-aggressive orders, and consequently the pattern attributable to the different degree of aggressiveness is still present across categories, thus driving ultimately the switching process. It seems clear that this effect will likely apply when accounting for other microstructural effects (e.g., hourly effects) through 1/0 categories still neglecting aggressiveness. The basic conclusion is therefore that any specification of the mean equation in this context should control, at least, for the systematic effect due to the order design, so that the regime-switching scheme can depend on unexpected shocks given this variable. Whether this is sufficient or not, is analyzed in the next section.

¹¹Note that Nyholm (2003, tables 2, 3) reports averaged estimates for p_{00} and p_{11} of 0.907 and 0.096 in the basic model. The respective averaged estimates for the size-extended model are 0.908 and 0.093.

¹²We avoid presenting these statistics for saving space, but they are available upon request.

B. Extending the mean equation

The general conclusion from the previous analysis is that it is crucial to filter the systematic effects in the mean equation as much as possible so that the latent variable can correspond to information arrivals. This aim suggests a potential conflict between tractability and the need of a precise specification, which could even be unattainable from a practical viewpoint –there are a large number of variables related to market and stock conditions that could be relevant in this analysis.

We analyze several extensions in increasing complexity. To assess to what extent the inferred probabilities are related to information, we consider three basic properties in the spirit of Easley et al. (1996). First, the PIN measures should decrease with the trading activity. Our groups of assets show sizeable differences on the degree of liquidity, so the averaged estimated PIN should exhibit a similar pattern. Second, the cross-sectional estimates should be correlated positively with the spread. Spread is partially driven by informational asymmetries, and therefore the inferred PIN should have some predictive power on this variable. We apply a similar procedure than Easley et al. (1996) and compute the correlation between the relative average-spread of the assets and the cross-sectional unconditional PIN estimates implied by the different regime-switching models estimated.¹³ Third, the PIN estimates should ideally be correlated with other measures approaching the probability of information. There are not alternative procedures to infer the PIN in the trade-to-trade frequency, but the method of Easley et al. (1996) provides unconditional estimates for each asset over the period analyzed (PIN_{EKOP}) henceforth), so the cross-sectional unconditional probabilities between both procedures could be compared to. These procedures are not expected to yield the same point estimates (they are based on very different methodologies and assumptions), but the PIN dynamics inferred from both methods should be correlated positively as they are supposed to approach the same phenomenon.

The simplest formulation corresponds to (5), which is denoted as Order I to distinguish from further generalizations. We consider a slightly more general classification that splits A3 orders into two subcategories: A3(D) is formed by orders that trade a quantity for the depth at the prevailing

¹³The average spread is calculated for any asset as the mean value of the relative spread over the sample period (see Table 1 for descriptive statistics). Bootstrap tests easily reject the hypothesis that the different groups have the same mean average-spread.

quote, and A3(L) include orders that trade a quantity lower than the depth. The reason is that it could be a different systematic effect for orders that consume the available depth over orders that just trade a lower volume, as it is later observed. The A3(L) orders are the least aggressive in the sample and typically provoke only changes of minor importance.¹⁴ The set of categories related to aggressiveness is now indexed as $\mathbf{A}^* = \{A1, A2, A3(D), A3(L)\}$. We denote the resultant model as Order II.

We further generalize this model and account for other systematic effects, namely those that rely on the trader's decision. On the one hand, we consider order direction. Previous literature has evidenced the possibility of asymmetric responses in buy and sells. The resultant model, namely Order III, combines aggressiveness and direction (denote $\mathbf{D} = \{b, s\}$ the set of subindexes denoting whether the trade is a buy or a sell) and includes eight different cross-categories and 19 parameters to be estimated. The specification of this model is as follows,

$$\Delta M_{t} = \sum_{i \in \mathbf{A}^{*}} \sum_{j \in \mathbf{D}} \alpha_{0, \mathbf{ij}} X_{t-1} D_{\mathbf{ij}, t-1} + \varepsilon_{t}, \quad \text{if } I_{t-1} = 0; \quad (7)$$

$$\Delta M_{t} = \sum_{i \in \mathbf{A}^{*}} \sum_{j \in \mathbf{D}} \left(\alpha_{0, \mathbf{ij}} + \alpha_{1, \mathbf{ij}} \right) X_{t-1} D_{\mathbf{ij}, t-1} + \varepsilon_{t}, \quad \text{if } I_{t-1} = 1;$$

where the double-indexed indicator variables $D_{\mathbf{ij},t}$ signals whether the transaction verifies the double condition or not.

On the other hand, we combine trade size and aggressiveness. The role of trade size has been discussed earlier. This model would include twelve cross-categories and require to estimate 27 parameters. Naturally, it would be of great interest the general specification accounting for all these effects simultaneously, but a total of 56 parameters to be estimated in a highly nonlinear system simply makes it impracticable. In fact, the model extending for aggressiveness and order size is already troublesome, particularly for the group of less-frequently traded assets. We consider a slightly restricted model instead, namely Order IV, in which the size categories do not apply for A3(L) orders. Regardless the trade size, only minor effects are expected for these

¹⁴Market orders trading below the depth cannot generate an instantaneous change in the midquote. The change of midquotes is measured here between consecutive trades. Thus, it is possible to observe a change related to a trade initiated by such an order if quotes were posted after the last trade and prior to the order.

orders in any case.¹⁵ This model requires of estimating 23 parameters. The specification of the model is as follows,

$$\Delta M_t = \sum_{i \in \mathbf{A}^*} \sum_{j \in \mathbf{S}} \alpha_{0,\mathbf{ij}} X_{t-1} D_{\mathbf{ij},t-1} + \varepsilon_t, \quad \text{if } I_{t-1} = 0; \quad (8)$$

$$\Delta M_t = \sum_{i \in \mathbf{A}^*} \sum_{j \in \mathbf{S}} \left(\alpha_{0,\mathbf{ij}} + \alpha_{1,\mathbf{ij}} \right) X_{t-1} D_{\mathbf{ij},t-1} + \varepsilon_t, \quad \text{if } I_{t-1} = 1;$$

where the restriction $\alpha_{0,\mathbf{A3}(\mathbf{L})\mathbf{j}} = \alpha_{0,\mathbf{A3}(\mathbf{L})}$ and $\alpha_{1,\mathbf{A3}(\mathbf{L})\mathbf{j}} = \alpha_{1,\mathbf{A3}(\mathbf{L})}$ is added in the estimation procedure.

Table 5 shows provides some descriptive statistics about the relative frequency in which aggressiveness, order size and order direction are jointly observed. It can be seen that there is a slight predominance of sell orders as the period was characterized by negative returns (see Table 1 above). The least aggressive orders predominate on the sample and it can be seen that aggressiveness increases as assets are less frequently traded.

[Please Insert Table 5: Sample frequencies]

The outcomes from estimating models Order II, Order III and Order IV are presented in Tables 6, 7 and 8. Table 9 summarizes the results from applying the three criteria commented above to compare the performance of the different models. It shows the average unconditional PIN estimates for each model –including the baseline and the size-extended model earlier estimated, the boostrapped tests and p-values for the *t*-test of equality of means among the observations of the different groups, and the level of correlation between the PIN estimates and both the relative spread or the PIN_{EKOP} measure across the three volume groups.

[Please Insert Table 6,7,8: Order II, Order III, Order IV Models]

[Please Insert Table 9: Model Performance Analysis]

¹⁵We considered a grid of 50 pre-estimated starting values to minimize the posibility of convergence to local extrema, but it seems virtually impossible to guarantee the convergence to the global optimum in such a heavily parameterized system.

The estimation of different models yields very different outcomes, underlining once again the extreme sensitiveness of the regime-switching process to the specification of the mean equation. The huge increase in the log-likelihood function as the model tries to reflect new effects show the complexity of the revision process in the regime-switching setting, and the naiveness of the basic formulation. The largest relative increases are shown when splitting the A3 category into two sub-categories and when adding the effect of tradesize (see Appendix A). The effects of considering direction, though relevant, seems of second order.

We firstly comment the basic results evidenced for applying the procedure of Easley *et al.* (1996). The PIN_{EKOP} estimates show a decreasing pattern across the liquidity measures and the estimates are correlated positively with the mean spread (42%) as expected.¹⁶ These estimates are comparable in magnitude with those reported in Easley et al. (1996). The unsuitability of the baseline model is clearly seen through this analysis, as the inferred probabilities are negatively correlated with the PIN_{EKOP} estimates. Intuitively, both measures are approaching different things. Models Order I and Order II, which only include degrees of aggressiveness, also exhibit inconsistent features with the hypothesis of a latent variable related to information arrivals. The PIN measures from Model Order I are strongly correlated negatively with the average spread, and those from Model Order II do not differ significantly across the volume groups. It is remarkable the strong effect that splitting the A3 aggressiveness category into two subcategories has on the dynamics of the regime-switching process. The extension adding trade direction to order aggressiveness in Model Order III provides gains in likelihood, and it is seen that there are indeed different revisions depending on the direction of the order, but again the PIN estimates do not differ significantly across volume categories. The latent variable cannot be regarded as information arrivals in any case.

The extension towards acknowledging effects related to aggressiveness and trade size yields some optimistic outcomes. We firstly focus on the results when considering only the high- and medium-volume groups. It is seen that

¹⁶We do not present the estimation of the relevant parameters to save space. These results are available upon request. The tests for the equality of mean values across volume groups are always rejected at the 90% confident level, but cannot be rejected in some case for higher levels. As the number of observations are small, the standard error of the test is still seizable. Demanding large confident levels in this context could imply large losses of power.

the higher the trade size is, the higher the revision is for any of category of aggressiveness and for any value of the latent variable. The averaged values of the parameter estimates indicate that the major revisions are due to the A1 orders that trade for large volumes, but the differences seems of minor importance when comparing the median. The A2 orders still impose higher revision in the non-excited state and when the order trade small or medium sizes. The A3(L) orders show a negative, (significant in most cases) adjustment in the normal state, and a relatively small, positive revision in excited state.¹⁷ The PIN estimates are on average much lower for assets in Group 1 and the bootstrap test rejects easily the hypothesis of an equal mean value. Furthermore, the inferred probabilities are highly correlated with the spread (64%), and show some significant degree of correlation with the PIN_{EKOP} estimates (30%). This suggests that including more structure in the mean equation begins to isolate successfully the information arrivals from the microstructure effects.

Now, observe the evidence for the assets in the less-frequently traded group. First, while the volume-effect still applies and the larger the size is the larger the revision, the more passive orders seem to gain power over the most aggressive ones when trading large volumes in excited state. The average values (both mean and median) in the revision for A3(D) orders are higher than those of A1 orders. This feature seems to make little sense. Also, the revision for A2 orders in excited state is (significantly) negative in two cases. Finally, the mean value of the PIN estimates is (not significantly) higher than that from the medium-volume group. The overall effect in relation to the spread and the PIN_{EKOP} consists of a large reduction which halves the correlations with these variables.

This feature shows a worse performance of the estimation procedure on the group of more illiquid assets. Note that there are far less observations available for those assets and that their dynamics are more likely to exhibit irregular patterns and anomalities such as outliers.¹⁸ As the econometric

¹⁷The negative value mean that some bid (ask) quotes were posted beyond the midquote value existing at the time of the last trade and prior to the buy (sell) order that later initiated the observed trade. Note that negative values can also be observed in model OrderII (Table 6), though corresponding to the revision in excited state. The latent variable, which determines which observations belong to each state, cannot measure the same thing over the two models.

 $^{^{18}}$ Note in Table 5 that the small proportion of A1 orders trading for a large volume over the total (less than 1%) implies a small number of observations to infer the parameters.

specification involves a large number of parameters in a complex setting, the applicability of the model is not as straightforward as in the baseline case. Also, like in the case of adding trade size on the basic model, the strange results evidenced across the size categories could indicate that some relevant microstructure effects are still neglected in the mean equation and the latent variable does not correspond fully with information. Nevertheless, it seems unfeasible to overload more than that an already heavily-parameterized model.

6 Concluding remarks

The main aim of this paper has been to provide insight on the performance of the procedure put forward by Nyholm (2002, 2003) for estimating the probability of informed trades on the basis of quote-to-quote information. The basic model assumes a very simple specification that allows for a feasible estimation, but which nevertheless proves to be an over-simplification. Conclusions based on that formulation are necessarily misleading.

The main problem is that the procedure infers information arrivals through large immediate revisions in the midquotes and, simultaneously, neglects the heterogenous response of the immediate midquote revision to microstructure variables. The immediate midquote updating is sensitive to information arrivals (permanent component), but also show transient effects, among which aggressiveness plays a major role in the two-staged conception of the model. The inferred measure from the misspecificated model are related to the probability of arrival of a type of orders, namely orders that trade volumes larger than the depth and which are not allowed to walk up the book. The reason is that these orders impose on average a far more pronounced immediate revision, and so the model implicitly regards this fact as a latent factor. As liquid (informed) agents do submit aggressive (non-aggressive) market orders, this is not a valid measure of informed trading.

The relevant question is then whether a further extended model based on the regime-switching modelling could yield a reasonable approach of the PIN dynamics. The systematic responses due to microstructure effects must be filtered, which suggests add 1/0 categories in an extension of the basic model. However, the price updating process proves very complex in the

For instance, the mean sample size for Group3 is 1200 observations, meaning that only 12 observations are available on average for that category.

regime-switching framework and is not sufficient with controlling solely for order aggressiveness to ensure estimates related to private information. The model should ideally account, among other potentially relevant effects, for important factors such as the endogenous variables in the trader's decision. However, the model becomes overparameterized very quickly and it seems impracticable to include further effects properly in addition to those related to aggressiveness and trade size, which prove be key variables in this context.

Therefore, applying the regime-switching model imply a collection of technical limitations. First, the model inherits some drawbacks of the tradeindicator model. Second, the PIN estimates prove to be extremely sensitive to the model specification. Third, the model cannot be extended beyond some point to capture some potential relevant effects, as commented before. Furthermore, the extended model including aggressiveness and trade size implies a large number of parameters to be estimated through maximum likelihood in the regime-switching framework. The procedure loses tractability and could turn out inapplicable when there are relatively few observations or if the data are not well-behaved, as it is often the case of less-frequently traded assets. While it is clear what happens when neglecting the effects related to trade size and aggressiveness, the results evidenced for the extended regime switching model are not completely conclusive. The model successfully assigns less probability of information arrivals to the more liquid assets, and shows certain ability to yield estimates that are correlated with the spread and the PIN estimates from the model by Easley et al. (1996), regarded here as proxies of information. However, the PIN estimates do not differ across the medium- and low-volume categories, whereas the indicators of liquidity for those groups are clearly different. The poor results evidenced for the illiquid assets could be due to model misspecification. Though the estimates from an extended model might optimistically be used as a potential proxies of information in the continuous trading framework, some natural caution should be exercised. So far, the approach based on the regime-switching model is the only procedure intended to estimate private information arrivals on a tradeto-trade basis, a topic with relevant empirical applications and of interest for both traders and academics. Further research on this issue is deserved.

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Appendix: Mean Log-likelihood function

	Group 1: High-volume assets												
Asset	ACE	ACR	ACS	AGS	ALB	ANA	AUM	DRC	MAP	NHH	REE	SOL	VAL
Sample Size	23091	27832	19137	19714	14641	22745	6190	35401	8234	18319	21349	21512	19716
Baseline	3.332	3.294	2.183	2.694	1.694	1.884	2.325	3.103	1.855	2.635	2.987	2.882	3.385
Size-ext.	3.336	3.301	2.198	2.698	1.702	1.890	2.336	3.108	1.862	2.646	2.993	2.893	3.393
Order I	3.591	3.514	2.312	2.863	1.819	2.051	2.454	3.300	1.983	2.805	3.162	3.060	3.593
Order II	3.648	3.593	2.351	2.902	1.849	2.085	2.485	3.351	2.023	2.858	3.232	3.128	3.660
Order III	3.651	3.595	2.354	2.911	1.851	2.089	2.502	3.356	2.028	2.868	3.233	3.131	3.662
Order IV	3.674	3.649	2.433	2.993	1.923	2.139	2.571	3.392	2.058	2.901	3.279	3.169	3.698
					Group	2: Me	dium-v	olume	assets				
Asset	AEA	AZC	AZK	CPF	CRI	ENC	PAS	PQR	SOS	TAZ	VDR	VIS	ZOT
Sample Size	3243	5115	4112	3129	2662	4606	1332	4368	2591	3243	1264	9709	5200
Baseline	1.639	2.245	2.431	2.095	1.095	1.649	1.256	2.806	2.301	2.264	1.176	2.936	2.822
Size-ext.	1.652	2.256	2.433	2.098	1.114	1.651	1.260	2.819	2.306	2.274	1.192	2.833	2.827
Order I	1.825	2.439	2.592	2.260	1.288	1.786	1.383	3.094	2.498	2.438	1.299	3.196	3.033
Order II	1.860	2.495	2.617	2.338	1.321	1.816	1.470	3.160	2.541	2.478	1.328	3.283	3.086
Order III	1.863	2.506	2.635	2.349	1.331	1.820	1.492	3.170	2.578	2.499	1.341	3.285	3.089
Order IV	1.946	2.544	2.674	2.383	1.403	1.902	1.552	3.187	2.571	2.517	1.385	3.336	3.149
					Grou	ıp 3: L	ow-vol	ume as	sets				
Asset	ASA	BAM	CAF	DGI	ENA	IBG	МСМ	NEA	PAC	RIO	UBS	VWG	ZNC
Sample Size	1070	1739	673	2228	2525	804	789	923	1122	728	938	835	893
Baseline	2.936	3.183	0.941	2.088	1.922	1.425	0.531	2.489	3.305	1.646	3.856	-0.570	2.733
Size-ext.	2.950	3.194	0.946	2.103	1.925	1.443	0.556	2.496	3.308	1.587	3.891	-0.552	2.735
Order I	3.113	3.459	1.091	2.280	2.123	1.589	0.612	2.740	3.581	1.715	4.203	-0.490	2.897
Order II	3.235	3.506	1.151	2.326	2.147	1.525	0.649	2.756	3.661	1.740	4.274	-0.430	2.945
Order III	3.248	3.521	1.195	2.334	2.165	1.694	0.678	2.847	3.680	1.826	4.276	-0.418	2.965
Order IV	3.304	3.592	1.204	2.416	2.250	1.713	0.815	2.947	3.732	1.988	4.353	-0.395	3.054

The table shows the mean value of the log-likelihood function of the estimated models. *Baseline* is the basic model in (2); *Size-ex* is the size-extended model in (6); *Order1 to Order4* are the models with i) three aggressiveness categories, ii) four aggressiveness categories, iii) four aggressiveness categories and order direction, iv) four aggressiveness categories and trade size.

Tables

Grow J: Hig-b-vulwe sexts ACE Accenal SA 22901 0001 2.83 15745 1071 3.34 9.02 00011 ACS Construcción y Servicios, S.A. 1917 0.0031 3.13 3.44 9.02 0.0011 AGS Aguas de Barcelona, S.A. 1917 0.0031 1.32 21637 18112 346.38 9.16 2.62 1.424 1.0013 ALB ALB, S.A. 14946 0.0031 1.004 1.445 1.890 4.808 9.46 7.43 3.799 0.012 AUM Aurea Conc. Infraestructuras, S.A. 1390 0.0040 1.37 1.9464 1.942 1.428 1.448 1.929 0.0022 MAP Mapfre, S.A. 1819 0.0044 4.32 1.5101 1.815 1.930 0.838 4.84 1.929 0.0012 NLH MH Huckes, S.A. 1819 0.0044 4.32 1.5101 1.815 1.817 1.848 1.928 1.316 0.1015 0.0115 SOL SOL Melia, S.A. 1.214 0.0044	Ticker	Company Name	Sample Size	Relative Spread	Spread in ticks	Bid Depth €	Ask Depth €	Volume Mill €	% Price Change	Mid- point	Price Volat.
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		Grou	р 1: Н	igh-vol	ume as	sets					
ACR Aceralia SA 2782 0004 3.13 1423 1202 1813 3.41 9.24 0017 ACS Construccion y Scrucios, S.A. 19714 00037 5.20 13752 11420 24816 -26.2 1424 00013 ALB Alba, S.A. 22765 00031 1261 1811 20807 46.08 4.31 7799 00012 AUM Acceiona, S.A. 2276 00031 1261 1811 20807 46.08 4.34 1799 00012 AUM Aurea Cone. Infraestructuras, S.A. 1940 00049 8.37 19461 19414 4228 2279 10.35 10.05 00022 NIH NH Hill 0 00466 12.77 1676 15826 26.93 14.48 19.29 00012 VAL Valleermoso, S.A. 2194 00404 2.98 12061 1183 20162 -14.06 1002 00101 VAL Valleermoso, S.A. 2191 0.0041 7.20 15992 1303 31.0 0.014 1.31 <td>ACE</td> <td>Acesa S.A.</td> <td>23091</td> <td>0.0031</td> <td>2.83</td> <td>15745</td> <td>16717</td> <td>333.84</td> <td>7.45</td> <td>9.02</td> <td>0.0014</td>	ACE	Acesa S.A.	23091	0.0031	2.83	15745	16717	333.84	7.45	9.02	0.0014
ACS Construction y Servicions, S.A. 1913 0.009 10.22 2167 1412 34.83 -9.16 26.3 0.001 ACS Aguas de Barcelona, S.A. 1444 0.0057 5.00 13753 11900 348.16 -2.63 1434 0.0017 ANA Acciona, S.A. 2174 0.0033 12.61 18111 20670 466.06 4.34 3790 0.0017 ANA Acciona, S.A. 2174 0.0033 12.61 18111 20670 466.06 4.34 3790 0.0012 MAP Magfre, S.A. 3240 0.0046 3.87 19463 19344 72.22 7.38 10.55 0.0017 REE Rod Elcirica de España, S.A. 2136 0.0043 4.52 1231 8.525 131.7 -310 0.0058 0.0017 VAL Vallehermoso, S.A. 11976 0.0044 2.98 12.61 11.876 21.61 0.16 4.06 0.0018 AZC Asturian del Z	ACR	Aceralia SA	27832	0.0034	3.13	14325	12092	189.13	-3.41	9.24	0.0017
AGS Aguas de Barcelona, S.A. 19714 0.007 5.20 1372 1102 24.16 -3.62 14.44 0.0011 ALB Alba, S.A. 10005 1600 14645 15800 38198 -9.86 2774 0.0012 AUM Aucea Conc. Infraestructuras, S.A. 5600 0.0035 357 19461 1944 742.28 2739 10.012 MAP Maprice, S.A. 5800 0.0017 6.26 15010 18105 4522 5.33 10.35 0.0017 SOL Sol Melin, S.A. 21340 0.0047 6.26 15010 18105 4522 5.33 13.29 0.0017 SOL Sol Melin, S.A. 21340 0.0047 6.26 15010 18105 4.86 1.662 1.823 1.61.6 1.6.49 0.0017 SOL Sol Melin, S.A. 2134 0.0042 2.87 1.533 1.035 0.0016 Cross-sectional averaged value 1993 0.0042 1.597 1.5103 3.11.6 0.11.6 1.6.49 0.0017 AZC	ACS	Construcción y Servicios, S.A.	19137	0.0039	10.32	21657	18412	346.38	-9.16	26.59	0.0014
ALB A.Ma A.Ma A.Ma A.Caciona, S.A. 14641 0.003 16.00 14645 15800 34.08 2.87.8 2.77.4 0.0012 ANA Acciona, S.A. 22745 0.0033 12.61 18211 2.0670 446.08 4.44 13.79 0.0012 DRC Dragados, S.A. 1349 0.0046 3.87 19403 19341 4.228 2.789 10.57 0.0012 MAP Mapfre, S.A. 1819 0.0047 6.26 15010 18183 428.27 5.39 13.29 0.0016 REE Red Eléctrica de España, S.A. 21140 0.0043 4.52 12513 8.525 13.10 6.00 0.0019 VAL Vallehermoso, S.A. 1976 0.0044 2.88 12161 11876 21.06 0.66 0.0016 AZC Asturiana del Zinc, S.A. 3145 0.0076 7.40 10503 358 48.71 -1.171 9.90 0.0031 AZK Azkoyen S.A. 1112 0.0076 7.40 10503 3589 48.71 <	AGS	Aguas de Barcelona, S.A.	19714	0.0037	5.20	13752	11920	248.16	-2.62	14.24	0.0013
ANA Acciona, S.A. 2245 0.003 1.2 (1) 18211 2070 4.46.08 4.34 3799 0.0019 MAP Marea Conc. Infraestructuras, S.A. 549 0.0049 8.37 20969 15162 166.08 7.43 1721 0.0019 MAP Mapfre, S.A. 8191 0.0046 12.77 16776 15826 26.03 14.48 19.29 0.0015 NHH NH Hoteles, S.A. 1219 0.0044 4.52 1213 8525 133.17 5.39 13.29 0.0017 SOL Sol Melia, S.A. 1216 0.0044 4.52 12181 5.16.12 1.016 1.064 0.0019 VAL Vallehermoso, S.A. 1216 0.0045 7.20 1.992 1.513 2.21.1 8.03 1.51 0.0014 AZC Azucarca Ebro Agricola, S.A. 5115 0.0076 7.40 10503 8308 4.81 -11.71 9.09 0.0039 CFF Campofrio Alimentacion, S.A.	ALB	Alba, S.A.	14641	0.0058	16.00	14645	15860	383.98	-9.86	27.74	0.0017
AUM Aurea Conc. Infraestructuras, S.A. 619 00049 8.37 20969 15162 180.00 7.33 172.1 00015 DRC Dragados, S.A. 3340 00065 3.87 19463 19344 742.8 27.89 10.57 0.0015 NHH NIH Hotels, S.A. 1819 00047 6.26 15100 18105 24.82.7 5.39 10.55 0.0015 SOL Sol Melia, S.A. 1212 00044 2.98 12161 11876 21.01 16.6 16.79 0.0019 VAL Vallehermoso, S.A. 1917 0.004 2.98 12.161 11876 21.13 8.01 15.51 0.0016 Cross-sectional averaged value 1933 0.0076 7.40 1503 8308 44.71 17.17 9.09 0.0031 AZC Asturiana del Zinc, S.A. 5115 0.0076 7.40 1503 8308 45.71 17.71 0.008 CPF Campofrio Alimentación, S.A. 512 <td>ANA</td> <td>Acciona, S.A.</td> <td>22745</td> <td>0.0033</td> <td>12.61</td> <td>18211</td> <td>20670</td> <td>466.08</td> <td>4.34</td> <td>37.99</td> <td>0.0012</td>	ANA	Acciona, S.A.	22745	0.0033	12.61	18211	20670	466.08	4.34	37.99	0.0012
DRC Dragados, S.A. 14401 0006 3.87 19443 19443 19444 19242 27.87 10.57 00015 MAP Mapfre, S.A. 1839 00066 12.77 16776 16826 26693 14.48 1929 00022 REE Red Electrica de España, S.A. 2139 00043 4.52 1513 8525 133.17 5.53 10.55 00017 SOL Sol Melia, S.A. 1916 0.0044 2.98 12161 11876 213.05 -910 6.79 00018 VAL Vallehermoso, S.A. 19837 0.0043 7.20 15903 321.61 0.16 1.6.40 0.0016 Azucarera Ebro Agricola, S.A. 2343 0.0096 12.87 9295 8493 2.103 321.1 -0.03 1.51 0.0076 AZC Asturiana del Zine, S.A. 115 0.0076 7.40 10313 2.009 6.35 64440 6400 22.11 -22.52 6.91 0.0039	AUM	Aurea Conc. Infraestructuras, S.A.	6190	0.0049	8.37	20969	15162	168.06	7.43	17.21	0.0019
MAP Mapfre, S.A. 8234 0.0066 12.77 16776 15826 266.93 14.48 19.29 0.0002 NHH NH Hoteles, S.A. 18319 0.0047 6.26 15010 18105 428.27 5.39 13.29 00016 SOL Sol Melin, S.A. 12161 0.0043 4.52 12131 13.05 201.6 1.406 1062 0.0018 VAL Vallehermoso, S.A. 12161 0.0043 7.20 15902 13103 321.61 0.167 0.0018 Cross-sectional averaged value 19716 0.0043 7.20 15902 15103 321.61 0.0031 AZK Azucarera Ebro Agricola, S.A. 115 0.0076 7.40 10503 8308 48.71 -11.71 9.90 0.0031 AZK Azucarera Ebro Agricola, S.A. 115 0.0076 7.32 1159 11312 7.72 26.09 6.24 12.25 0.0022 CPF Campofrio Alimentación, S.A. 212 <t< td=""><td>DRC</td><td>Dragados, S.A.</td><td>35401</td><td>0.0036</td><td>3.87</td><td>19463</td><td>19344</td><td>742.28</td><td>27.89</td><td>10.57</td><td>0.0015</td></t<>	DRC	Dragados, S.A.	35401	0.0036	3.87	19463	19344	742.28	27.89	10.57	0.0015
NHH NH Hoteles, S.A. 1819 0.0047 6.26 15010 18105 4.252 1.513 8.25 1.31.71 5.93 1.529 00016 VAL Vallehermoso, S.A. 12149 0.0043 4.52 12113 8.52 113.17 5.93 10.55 0.0017 VAL Vallehermoso, S.A. 19716 0.0044 2.98 12161 11876 21.02 4.106 10.62 0.0018 Cross-sectional averaged value 7837 0.0043 7.20 15992 1510 31.61 0.016 1.6.0 0.0016 AEA Azucarera Ebro Agricola, S.A. 1243 0.0096 12.87 9295 8499 32.13 -8.03 1.51 0.0076 AZC Asturiana del Zinc, S.A. 115 0.0076 7.40 1506 32.16 6.24 12.25 0.0021 AZK Azkoyen S.A. 1312 0.0083 6.54 14.93 1.017 9.0031 CRI Cristaleria Española, S.A. 1264 </td <td>MAP</td> <td>Mapfre, S.A.</td> <td>8234</td> <td>0.0066</td> <td>12.77</td> <td>16776</td> <td>15826</td> <td>266.93</td> <td>14.48</td> <td>19.29</td> <td>0.0022</td>	MAP	Mapfre, S.A.	8234	0.0066	12.77	16776	15826	266.93	14.48	19.29	0.0022
REE Red Eléctrica de España, S.A. 2139 0.003 4.52 1231 8.53 113.17 5.93 10.55 0.0017 SOL Sol Melia, S.A. 21512 0.0045 4.68 1262 11823 201.62 14.06 1062 0.0019 VAL Vallehermoso, S.A. 1716 0.0044 2.98 12616 11876 21305 9.10 6.79 0.0018 Cross-sectional averaged value 19837 0.004 2.8 15105 0.016 1.40 0.0031 AZC Aztucarera Ebro Agricola, S.A. 321 0.0056 1.287 9295 \$499 32.13 -8.03 13.51 0.0034 AZC Asturiana del Zinc, S.A. 5115 0.0076 7.40 10033 8308 48.71 -11.71 9.90 0.0031 CFF Campofrio Alimentación, S.A. 3129 0.0080 9.84 11425 7475 26.09 6.24 12.25 0.0026 CRI Cristaleria Española, S.A. 2602 0.0075 23.72 11159 11317 57.2 1.79	NHH	NH Hoteles, S.A.	18319	0.0047	6.26	15010	18105	428.27	-5.39	13.29	00016
SOL Sol Melia, S.A. 21512 0.0045 4.68 12620 11823 261.62 -14.06 1062 0.0019 VAL Vallehermoso, S.A. 1983 0.0043 2.20 15103 321.61 0.16 1.60 0.0018 Cross-sectional averaged value 1983 0.0043 7.20 15992 15103 321.61 0.16 1.640 0.0014 AEA Azucarera Ebro Agricola, S.A. 513 0.0076 7.40 10033 8308 4.871 -11.71 9.90 0.0031 AZC Asturiana del Zinc, S.A. 5115 0.0076 7.40 10033 8308 4.871 -11.71 9.90 0.0031 AZK Azkoyen S.A. 4112 0.0036 5.35 64440 6400 2.71 2.252 6.91 0.0022 Cristaleria Española, S.A. 3129 0.0087 3.23 9.059 6638 30.59 -1.618 0.0024 PAS Banco Pastor, S.A. 2.91 0.00	REE	Red Eléctrica de España, S.A.	21349	0.0043	4.52	12513	8525	133.17	-5.93	10.55	0.0017
VAL Vallehermoso, S.A. 19716 0.0044 2.98 12161 11876 213.05 -9.10 6.79 0.0018 Cross-sectional averaged value 19837 0.0043 7.20 1592 151.03 321.61 0.16 16.40 0.0016 AEA Azucarera Ebro Agrícola, S.A. 323 0.0056 7.40 10503 8108 4871 11.171 9.00 0.0031 AZC Asturiana de Zinc, S.A. 5115 0.0056 7.40 10503 8108 4871 11.171 9.00 0.0031 AZC Astrona de Zinc, S.A. 1115 0.0056 7.40 1105 1312 2.0005 2.12 2.252 6.91 0.0032 CRI Cristaleria Española, S.A. 2662 0.0076 1.322 838 9608 56.68 -15.73 17.84 0.0032 PAS Banco Pastor, S.A. 1332 0.0048 2.204 2.369 61.64 0.011 45.97 0.00024 SOS Sos Aran	SOL	Sol Melia, S.A.	21512	0.0045	4.68	12662	11823	261.62	-14.06	1062	0.0019
Cross-sectional averaged value 19837 0.043 7.20 15902 15103 321.61 0.16 16.40 0.0016 Group 2: Medium-volume assets AEA Azucarera Ebro Agrícola, S.A. 3243 0.0066 12.87 9295 8499 32.13 -8.03 13.51 0.0034 AZK Asturiana del Zinc, S.A. 5115 0.0076 7.40 10030 8308 48.71 -11.71 9.90 0.0031 AZK Azkoyen S.A. 4112 0.0093 6.35 64440 6400 22.71 -22.52 6.91 0.0039 CFR Cristaleria Española, S.A. 2662 0.0076 13.52 8389 9.088 8.64 17.37 17.84 0.0032 PAS Banco Pastor, S.A. 1322 0.0093 4.59 5059 6638 30.59 -16.18 9.06 0.0026 TAZ Transportes Azkar, S.A. 1264 0.017 26.59 9601 8222 24.55 -7.04 21.00	VAL	Vallehermoso, S.A.	19716	0.0044	2.98	12161	11876	213.05	-9.10	6.79	0.0018
Group 2: Medium-volume assets AEA Azucarera Ebro Agrícola, S.A. 3243 0.0096 12.87 9295 8499 32.13 -8.03 13.51 0.0034 AZC Asturiana del Zine, S.A. 5115 0.0076 7.40 10503 8308 48.71 -11.71 9.90 0.0031 AZK Azkoyen S.A. 4112 0.0096 7.40 10503 8308 48.71 -11.71 9.90 0.0031 CRI Cristaleria Española, S.A. 2662 0.0075 23.72 11159 11312 37.22 -17.91 31.97 0.0026 PAS Banco Pastor, S.A. 1332 0.0047 13.52 8338 9608 56.68 -15.73 17.84 0.0032 SOS Sos Arana, S.A. 1332 0.0048 22.04 23699 232.68 16.41 0.11 45.97 0.0007 SOS Sos Arana, S.A. 1324 0.017 9.69 8023 8519 17.86 -16.18 9.06 <		Cross-sectional averaged value	19837	0.0043	7.20	15992	15103	321.61	0.16	16.40	0.0016
AEA Azucarera Ebro Agrícola, S.A. 3243 0.0096 12.87 9295 8499 32.13 -8.03 13.51 0.0034 AZC Asturiana del Zinc, S.A. 5115 0.0076 7.40 10503 8308 48.71 -11.71 9.90 0.0031 AZK Azkoyen S.A. 1112 0.0093 6.35 64440 6400 22.71 -22.52 6.91 0.0031 CPF Campofrio Alimentación, S.A. 2662 0.0075 23.72 11159 11312 37.22 -17.91 31.97 0.0028 PAS Banco Pastor, S.A. 2662 0.0075 23.72 11159 11312 37.22 -17.91 31.97 0.0028 Sos Arana, S.A. 2591 0.0017 9.69 8023 8519 17.86 -16.18 9.00 0.0024 VDR Portland Valderrivas, S.A. 2591 0.0107 9.69 8023 8519 17.86 -16.18 9.00 0.0024 ZOT Zardoya Otis, S.A.<		Group	2: Mee	lium-vo	olume a	issets					
AZC Asturiana del Zinc, S.A. 5115 0.0076 7.40 10503 8308 48.71 -11.71 9.90 0.0031 AZK Azkoyen S.A. 4112 0.0093 6.35 64440 6400 22.71 22.52 6.91 0.0039 CPF Campofrio Alimentación, S.A. 2662 0.0075 23.72 11159 11122 37.22 -17.91 31.97 0.0028 ENC Grupo Empresarial Ence, S.A. 4606 0.0076 13.52 8538 9608 56.68 -15.73 17.84 0.0032 PAS Banco Pastor, S.A. 1322 0.0048 22.04 23699 232.68 16.41 0.11 45.97 0.0067 SOS Sos Arana, S.A. 2591 0.0107 96.9 8023 8519 17.86 -16.18 9.060 0.0026 TAZ Transportes Azkar, S.A. 1264 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0024 VDR Portland Valderrivas, S.A. 1264 0.0127 26.59 9601 8222 24.5	AEA	Azucarera Ebro Agrícola, S.A.	3243	0.0096	12.87	9295	8499	32.13	-8.03	13.51	0.0034
AZK Azkoyen S.A. 4112 0.0093 6.35 6440 6400 22.71 -22.52 6.91 0.0039 CPF Campofrio Alimentación, S.A. 3129 0.0080 9.84 11425 7475 26.09 6.24 1225 0.0026 CRI Cristaleria Española, S.A. 2662 0.0075 23.72 11159 11312 37.22 -1791 31.97 0.0028 PAS Banco Pastor, S.A. 1332 0.0048 22.04 23699 23268 16.41 0.11 45.97 0.0007 PAS Banco Pastor, S.A. 2591 0.0017 9.69 8023 8519 17.86 -16.18 9.06 0.0027 TAZ Transportes Azkar, S.A. 1264 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0024 VDR Portland Valderrivas, S.A. 1264 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0024 VIS Viscofan, S.A. 5200 0.0051 4.67 10840 13100 6.08 <t< td=""><td>AZC</td><td>Asturiana del Zinc, S.A.</td><td>5115</td><td>0.0076</td><td>7.40</td><td>10503</td><td>8308</td><td>48.71</td><td>-11.71</td><td>9.90</td><td>0.0031</td></t<>	AZC	Asturiana del Zinc, S.A.	5115	0.0076	7.40	10503	8308	48.71	-11.71	9.90	0.0031
CPF Campofrio Alimentación, S.A. 3129 0.0080 9.84 11425 7475 26.09 6.24 12.25 0.0026 CRI Cristaleria Española, S.A. 2662 0.0075 23.72 11159 11312 37.22 -17.91 31.97 0.0028 ENC Grupo Empresarial Ence, S.A. 1332 0.0048 22.04 23699 92268 16.41 0.11 4.93 0.0006 PAS Banco Pastor, S.A. 4368 0.0093 4.59 5059 6638 30.59 -12.04 4.93 0.0007 SOS Sos Arana, S.A. 2591 0.0107 9.69 8023 8519 17.86 -16.18 9.06 0.0024 VDR Portland Valderrivas, S.A. 1264 0.0127 26.59 9601 8222 24.55 7.04 21.00 0.0024 VIS Viscofan, S.A. 500 0.0051 4.67 10840 13100 60.68 0.88 9.07 0.0021 Zordoya Otis, S.A. 500 0.0051 4.67 10840 13100 60.68 0.88	AZK	Azkoyen S.A.	4112	0.0093	6.35	64440	6400	22.71	-22.52	6.91	0.0039
CRI Cristaleria Española, S.A. 2662 0.0075 23.72 11159 11312 37.22 -17.91 31.97 0.0028 ENC Grupo Empresarial Ence, S.A. 4666 0.0076 13.52 8538 9608 56.68 -15.73 17.84 0.0032 PAS Banco Pastor, S.A. 1332 0.0048 22.04 23699 9268 16.41 0.11 45.97 0.0005 SOS Sos Arana, S.A. 2591 0.0107 9.69 8023 8519 17.86 -16.18 9.06 0.0026 TAZ Transportes Azkar, S.A. 2591 0.017 26.59 9601 8222 24.55 -7.04 21.00 0.0024 VDR Portland Valderrivas, S.A. 9709 0.0085 3.56 7535 6224 86.65 -34.51 6.42 0.0021 Zord oya Otis, S.A. 500 0.0051 4.67 10840 13100 60.68 0.88 9.07 0.0021 Cross-sectional averaged value	CPF	Campofrío Alimentación, S.A.	3129	0.0080	9.84	11425	7475	26.09	6.24	12.25	0.0026
ENC Grupo Empresarial Ence, S.A. 4606 0.076 13.52 8338 9608 56.68 -15.73 17.84 0.0021 PAS Banco Pastor, S.A. 1332 0.0048 22.04 23699 23268 16.41 0.11 45.97 0.0006 PQR Parques Reunidos, S.A. 2591 0.0107 9.69 8023 8519 17.86 -16.18 9.06 0.0027 SOS Sos Arana, S.A. 2591 0.0107 9.69 8023 8519 17.86 -16.18 9.06 0.0026 TAZ Transportes Azkar, S.A. 2543 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0021 VDR Portland Valderrivas, S.A. 1264 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0021 Zordoya Otis, S.A. 2500 0.0051 4.67 10840 13100 60.68 0.88 9.07 0.0021 Zordoya Otis, S.A. 500 0.0051 4.67 10840 13100 60.68 0.88 9.07	CRI	Cristaleria Española, S.A.	2662	0.0075	23.72	11159	11312	37.22	-17.91	31.97	0.0028
PAS Banco Pastor, S.A. 1332 0.0048 22.04 23699 23268 16.41 0.11 45.97 0.0006 PQR Parques Reunidos, S.A. 2591 0.0107 9.69 8023 8519 17.86 -16.18 9.06 0.0026 TAZ Transportes Azkar, S.A. 2591 0.0107 9.69 8023 8519 17.86 -16.18 9.06 0.0026 TAZ Transportes Azkar, S.A. 2241 0.0127 26.59 9601 8222 24.55 7.04 21.00 0.0024 VDR Portland Valderrivas, S.A. 1264 0.0121 8.28 4561 57811 38.02 -33.89 7.18 0.0024 ZOT Zardoya Otis, S.A. 1264 0.0058 3.56 7535 6224 58.65 -34.51 6.42 0.0028 ZOT Zardoya Otis, S.A. 1300 0.0058 1.178 9745 9491 36.18 -13.26 15.08 0.0021 Corss-sectional averaged value 3890 0.0051 3.79 4633 5017 4.34 -24.80<	ENC	Grupo Empresarial Ence, S.A.	4606	0.0076	13.52	8538	9608	56.68	-15.73	17.84	0.0032
PQR Parques Reunidos, S.A. 4368 0.0093 4.59 5059 6638 30.59 -12.04 4.93 0.0037 SOS Sos Arana, S.A. 2591 0.0107 9.69 8023 8519 17.86 -16.18 9.06 0.0026 TAZ Transportes Azkar, S.A. 2243 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0024 VDR Portland Valderrivas, S.A. 1264 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0021 Zord Zardoya Otis, S.A. 5200 0.0051 4.67 1080 13100 60.68 0.88 9.07 0.0021 Corss-sectional averaged value 3800 0.0085 11.78 9745 9491 36.18 -13.26 0.0035 0.0024 BAM Bami S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 DGI Dogi International Fabrics, S.A. 1739 0.0173 37.81 8755 6339 4.80 1.106 21.9	PAS	Banco Pastor, S.A.	1332	0.0048	22.04	23699	23268	16.41	0.11	45.97	0.0006
SOS Sos Arana, S.A. 2591 0.0107 9.69 8023 8519 17.86 -16.18 9.06 0.0026 TAZ Transportes Azkar, S.A. 3243 0.0121 8.28 4561 57811 38.02 -33.89 7.18 0.0007 VDR Portland Valderrivas, S.A. 1264 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0024 VIS Viscofan, S.A. 9709 0.0058 3.56 7535 6254 58.65 -34.51 6.42 0.0021 ZOT Zardoya Otis, S.A. 500 0.0051 4.67 10840 13100 60.68 0.88 9.07 0.0021 Cross-sectional averaged value 3890 0.005 11.78 9745 9491 36.18 -13.26 15.08 0.0021 ASA Tavex Algodonera, S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 BAM Bami S.A. 1739 0.0173 37.81 8755 6339 4.80 -11.06 0.199 <td>PQR</td> <td>Parques Reunidos, S.A.</td> <td>4368</td> <td>0.0093</td> <td>4.59</td> <td>5059</td> <td>6638</td> <td>30.59</td> <td>-12.04</td> <td>4.93</td> <td>0.0037</td>	PQR	Parques Reunidos, S.A.	4368	0.0093	4.59	5059	6638	30.59	-12.04	4.93	0.0037
TAZ VDR Transportes Azkar, S.A. 3243 0.0121 8.28 4561 57811 38.02 -33.89 7.18 0.0047 VDR Portland Valderrivas, S.A. 1264 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0024 VIS Viscofan, S.A. 9709 0.0058 3.56 7535 6254 58.65 -34.51 6.42 0.0021 Zort Zardoya Otis, S.A. 5200 0.0051 4.67 10840 13100 60.68 0.88 9.07 0.0021 Cross-sectional averaged value 3890 0.0085 11.78 9745 9491 36.18 -13.26 15.08 0.0029 Cross-sectional averaged value 3890 0.0085 11.78 9745 9491 36.18 -13.26 15.08 0.0029 Group 31 Envevolume assets ASA Tavex Algodonera, S.A. 1070 0.017 3.20 9499 6958 8.61 0.99 3.02 0.0031 CAF Cons.y Aux. de Ferrocarriles, S.A. 1739 0.0	SOS	Sos Arana, S.A.	2591	0.0107	9.69	8023	8519	17.86	-16.18	9.06	0.0026
VDR Portland Valderrivas, S.A. 1264 0.0127 26.59 9601 8222 24.55 -7.04 21.00 0.0024 VIS Viscofan, S.A. 9709 0.0058 3.56 7535 6254 58.65 -34.51 6.42 0.0028 ZOT Zardoya Otis, S.A. 5200 0.0051 4.67 10840 13100 60.68 0.88 9.07 0.0021 Cross-sectional averaged value 3890 0.0085 11.78 9745 9491 36.18 -13.26 15.08 0.0029 Stow-volume asset ASA Tavex Algodonera, S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 BAM Bami S.A. 1739 0.0173 3.781 8755 6339 4.80 -11.06 21.99 0.0024 DGI Dogi International Fabrics, S.A. 673 0.0173 37.81 8755 6339 4.80 -11.06 21.99 0.0024 DGI Dogi International Fabrics, S.A. 673 0.0172 <	TAZ	Transportes Azkar, S.A.	3243	0.0121	8.28	4561	57811	38.02	-33.89	7.18	0.0047
VIS ZOT Viscofan, S.A. 9709 0.0058 3.56 7535 6254 58.65 -34.51 6.42 0.0028 ZOT Zardoya Otis, S.A. 5200 0.0051 4.67 10840 13100 60.68 0.88 9.07 0.0021 Cross-sectional averaged value 3890 0.0085 11.78 9745 9491 36.18 -13.26 15.08 0.0029 Group 3: Low-volume assets ASA Tavex Algodonera, S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 BAM Bami S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 DGI Dogi International Fabrics, S.A. 1070 0.0173 37.81 8755 6339 4.80 -11.06 21.99 0.0024 DGI Dogi International Fabrics, S.A. 2525 0.0216 10.92 3289 4724 13.60 27.98 5.11 0.0056 IBG Iberpapel Gestión, S.A. 80 0.0172	VDR	Portland Valderrivas, S.A.	1264	0.0127	26.59	9601	8222	24.55	-7.04	21.00	0.0024
ZOT Zardoya Otis, S.A. Cross-sectional averaged value 5200 0.0051 4.67 10840 13100 60.68 0.88 9.07 0.0021 Cross-sectional averaged value 3890 0.0085 11.78 9745 9491 36.18 -13.26 15.08 0.0029 Group 3: Low-volume assets ASA Tavex Algodonera, S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 BAM Bami S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 DGI Dogi International Fabrics, S.A. 1070 0.0173 37.81 8755 6339 4.80 -11.06 21.99 0.0024 DGI Dogi International Fabrics, S.A. 2228 0.017 8.18 5035 3827 7.65 44.44 6.72 0.0044 ENA Enaco, S.A. 804 0.0195 20.09 4063 5455 2.48 -10.36 <th< td=""><td>VIS</td><td>Viscofan, S.A.</td><td>9709</td><td>0.0058</td><td>3.56</td><td>7535</td><td>6254</td><td>58.65</td><td>-34.51</td><td>6.42</td><td>0.0028</td></th<>	VIS	Viscofan, S.A.	9709	0.0058	3.56	7535	6254	58.65	-34.51	6.42	0.0028
Cross-sectional averaged value 3890 0.0085 11.78 9745 9491 36.18 -13.26 15.08 0.0029 Group 3: Low-volume assets ASA Tavex Algodonera, S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 BAM Bami S.A. 1739 0.0107 3.20 9499 6958 8.61 0.99 3.02 0.0031 CAF Cons.y Aux. de Ferrocarriles, S.A. 1739 0.0173 37.81 8755 6339 4.80 -11.06 21.99 0.0024 DGI Dogi International Fabrics, S.A. 2228 0.0127 8.18 5035 3827 7.65 -44.44 6.72 0.0044 ENA Enaco, S.A. 2525 0.0216 10.92 3289 4724 13.60 27.98 5.11 0.0056 IBG Iberpapel Gestión, S.A. 789 0.0228 54.29 12438 6440 7.52 11.36 23.62 0.0025	ZOT	Zardoya Otis, S.A.	5200	0.0051	4.67	10840	13100	60.68	0.88	9.07	0.0021
Group 3: Low-volume assets ASA Tavex Algodonera, S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 BAM Bami S.A. Cons.y Aux. de Ferrocarriles, S.A. 1739 0.0173 3.20 9499 6958 8.61 0.99 3.02 0.0031 CAF Cons.y Aux. de Ferrocarriles, S.A. 673 0.0173 37.81 8755 6339 4.80 -11.06 21.99 0.0024 DGI Dogi International Fabrics, S.A. 2228 0.0127 8.18 5035 3827 7.65 44.44 6.72 0.0044 ENA Enaco, S.A. 2525 0.0216 10.92 3289 4724 13.60 27.98 5.11 0.0056 IBG Iberpapel Gestión, S.A. 789 0.0228 54.29 12438 6440 7.52 11.36 23.62 0.0025 NEA Nicolás Correa, S.A. 923 0.0172 5.18 8104 3469 2.09 -		Cross-sectional averaged value	3890	0.0085	11.78	9745	9491	36.18	-13.26	15.08	0.0029
ASA Tavex Algodonera, S.A. 1070 0.0161 3.79 4633 5017 4.34 -24.80 2.37 0.0035 BAM Bami S.A. 1739 0.0107 3.20 9499 6958 8.61 0.99 3.02 0.0031 CAF Cons.y Aux. de Ferrocarriles, S.A. 673 0.0173 37.81 8755 6339 4.80 -11.06 21.99 0.0024 DGI Dogi International Fabrics, S.A. 2228 0.0127 8.18 5035 3827 7.65 -44.44 6.72 0.0044 ENA Enaco, S.A. 2525 0.0216 10.92 3289 4724 13.60 27.98 5.11 0.0056 IBG Iberpapel Gestión, S.A. 804 0.0195 20.09 4063 5455 2.48 -10.36 10.37 0.0034 MCM Miquel y Costas & Miquel, S.A. 789 0.0228 54.29 12438 6440 7.52 11.36 23.62 0.0025 NEA Nicol		Grou	p 3: L	ow-volu	ime ass	sets					
BAM Bami S.A. 1739 0.0107 3.20 9499 6958 8.61 0.99 3.02 0.0031 CAF Cons.y Aux. de Ferrocarriles, S.A. 673 0.0173 37.81 8755 6339 4.80 -11.06 21.99 0.0024 DGI Dogi International Fabrics, S.A. 2228 0.0127 8.18 5035 3827 7.65 -44.44 6.72 0.0044 ENA Enaco, S.A. 2525 0.0216 10.92 3289 4724 13.60 27.98 5.11 0.0056 IBG Iberpapel Gestión, S.A. 804 0.0195 20.09 4063 5455 2.48 -10.36 10.37 0.0034 MCM Miquel y Costas & Miquel, S.A. 789 0.0228 54.29 12438 6440 7.52 11.36 23.62 0.0025 NEA Nicolás Correa, S.A. 923 0.0172 5.18 8104 3469 2.09 -35.14 3.08 0.0032 RIO Bodegas Riojanas, S.A. 1122 0.0164 2.50 6184 5137 6.18	ASA	Tavex Algodonera, S.A.	1070	0.0161	3.79	4633	5017	4.34	-24.80	2.37	0.0035
CAF Cons.y Aux. de Ferrocarriles, S.A. 673 0.0173 37.81 8755 6339 4.80 -11.06 21.99 0.0024 DGI Dogi International Fabrics, S.A. 2228 0.0127 8.18 5035 3827 7.65 -44.44 6.72 0.0044 ENA Enaco, S.A. 2525 0.0216 10.92 3289 4724 13.60 27.98 5.11 0.0056 IBG Iberpapel Gestión, S.A. 804 0.0195 20.09 4063 5455 2.48 -10.36 10.37 0.0034 MCM Miquel y Costas & Miquel, S.A. 789 0.0228 54.29 12438 6440 7.52 11.36 23.62 0.0025 NEA Nicolás Correa, S.A. 923 0.0172 5.18 8104 3469 2.09 -35.14 3.08 0.0032 PAC Papeles y Cartones de Europa, S.A. 1122 0.0164 2.50 6184 5137 6.18 -36.71 1.60 0.0032 UBS Urbanizaciones y Transportes, S.A. 728 0.0196 17.35 6227 <	BAM	Bami S.A.	1739	0.0107	3.20	9499	6958	8.61	0.99	3.02	0.0031
DGI Dogi International Fabrics, S.A. 2228 0.0127 8.18 5035 3827 7.65 -44.44 6.72 0.0044 ENA Enaco, S.A. 2525 0.0216 10.92 3289 4724 13.60 27.98 5.11 0.0056 IBG Iberpapel Gestión, S.A. 804 0.0195 20.09 4063 5455 2.48 -10.36 10.37 0.0034 MCM Miquel y Costas & Miquel, S.A. 789 0.0228 54.29 12438 6440 7.52 11.36 23.62 0.0025 NEA Nicolás Correa, S.A. 923 0.0172 5.18 8104 3469 2.09 -35.14 3.08 0.0032 PAC Papeles y Cartones de Europa, S.A. 1122 0.0164 2.50 6184 5137 6.18 -36.71 1.60 0.0032 RIO Bodegas Riojanas, S.A. 728 0.0196 17.35 6227 3652 6.85 -2.60 8.94 0.0025 UBS Urbanizaciones y Transportes, S.A. 938 0.0219 1.63 8342 6229	CAF	Cons.y Aux. de Ferrocarriles, S.A.	673	0.0173	37.81	8755	6339	4.80	-11.06	21.99	0.0024
ENA Enaco, S.A. 2525 0.0216 10.92 3289 4724 13.60 27.98 5.11 0.0056 IBG Iberpapel Gestión, S.A. 804 0.0195 20.09 4063 5455 2.48 -10.36 10.37 0.0034 MCM Miquel y Costas & Miquel, S.A. 789 0.0228 54.29 12438 6440 7.52 11.36 23.62 0.0025 NEA Nicolás Correa, S.A. 923 0.0172 5.18 8104 3469 2.09 -35.14 3.08 0.0032 PAC Papeles y Cartones de Europa, S.A. 1122 0.0164 2.50 6184 5137 6.18 -36.71 1.60 0.0032 RIO Bodegas Riojanas, S.A. 728 0.0196 17.35 6227 3652 6.85 -2.60 8.94 0.0025 UBS Urbanizaciones y Transportes, S.A. 938 0.0219 1.63 8342 6229 2.44 -26.14 0.76 0.0033 VWG Volkswagen Aktiengesellchft, S.A. 835 0.0244 46.55 8742 6869	DGI	Dogi International Fabrics, S.A.	2228	0.0127	8.18	5035	3827	7.65	-44.44	6.72	0.0044
IBG Iberpapel Gestión, S.A. 804 0.0195 20.09 4063 5455 2.48 -10.36 10.37 0.0034 MCM Miquel y Costas & Miquel, S.A. 789 0.0228 54.29 12438 6440 7.52 11.36 23.62 0.0025 NEA Nicolás Correa, S.A. 923 0.0172 5.18 8104 3469 2.09 -35.14 3.08 0.0032 PAC Papeles y Cartones de Europa, S.A. 1122 0.0164 2.50 6184 5137 6.18 -36.71 1.60 0.0032 RIO Bodegas Riojanas, S.A. 728 0.0196 17.35 6227 3652 6.85 -2.60 8.94 0.0025 UBS Urbanizaciones y Transportes, S.A. 938 0.0219 1.63 8342 6229 2.44 -26.14 0.76 0.0033 VWG Volkswagen Aktiengesellchft, S.A. 835 0.0244 46.55 8742 6869 10.63 11.58 54.14 0.0046 ZNC Española del Zinc, S.A. 893 0.0211 5.55 5132	ENA	Enaco, S.A.	2525	0.0216	10.92	3289	4724	13.60	27.98	5.11	0.0056
MCM Miquel y Costas & Miquel, S.A. 789 0.0228 54.29 12438 6440 7.52 11.36 23.62 0.0025 NEA Nicolás Correa, S.A. 923 0.0172 5.18 8104 3469 2.09 -35.14 3.08 0.0035 PAC Papeles y Cartones de Europa, S.A. 1122 0.0164 2.50 6184 5137 6.18 -36.71 1.60 0.0032 RIO Bodegas Riojanas, S.A. 728 0.0196 17.35 6227 3652 6.85 -2.60 8.94 0.0025 UBS Urbanizaciones y Transportes, S.A. 938 0.0219 1.63 8342 6229 2.44 -26.14 0.76 0.0033 VWG Volkswagen Aktiengesellchft, S.A. 835 0.0244 46.55 8742 6869 10.63 11.58 54.14 0.0046 ZNC Española del Zinc, S.A. 893 0.0211 5.55 5132 4579 4.06 -73.23 2.92 0.0040	IBG	Iberpapel Gestión, S.A.	804	0.0195	20.09	4063	5455	2.48	-10.36	10.37	0.0034
NEA Nicolás Correa, S.A. 923 0.0172 5.18 8104 3469 2.09 -35.14 3.08 0.0035 PAC Papeles y Cartones de Europa, S.A. 1122 0.0164 2.50 6184 5137 6.18 -36.71 1.60 0.0032 RIO Bodegas Riojanas, S.A. 728 0.0196 17.35 6227 3652 6.85 -2.60 8.94 0.0025 UBS Urbanizaciones y Transportes, S.A. 938 0.0219 1.63 8342 6229 2.44 -26.14 0.76 0.0033 VWG Volkswagen Aktiengesellchft, S.A. 835 0.0211 5.55 5132 4579 4.06 -73.23 2.92 0.0040 ZNC Española del Zinc, S.A. 1174 0.0186 16.70 6957 5284 6.25 -16.35 11.13 0.0035	MCM	Miguel v Costas & Miguel, S.A.	789	0.0228	54.29	12438	6440	7.52	11.36	23.62	0.0025
PAC Papeles y Cartones de Europa, S.A. 1122 0.0164 2.50 6184 5137 6.18 -36.71 1.60 0.0032 RIO Bodegas Riojanas, S.A. 728 0.0196 17.35 6227 3652 6.85 -2.60 8.94 0.0025 UBS Urbanizaciones y Transportes, S.A. 938 0.0219 1.63 8342 6229 2.44 -26.14 0.76 0.0033 VWG Volkswagen Aktiengesellchft, S.A. 835 0.0214 46.55 8742 6869 10.63 11.58 54.14 0.0046 ZNC Española del Zinc, S.A. 893 0.0211 5.55 5132 4579 4.06 -73.23 2.92 0.0040	NEA	Nicolás Correa, S.A.	923	0.0172	5.18	8104	3469	2.09	-35.14	3.08	0.0035
RIO Bodegas Riojanas, S.A. 728 0.0196 17.35 6227 3652 6.85 -2.60 8.94 0.0025 UBS Urbanizaciones y Transportes, S.A. 938 0.0219 1.63 8342 6229 2.44 -26.14 0.76 0.0033 VWG Volkswagen Aktiengesellchft, S.A. 835 0.0214 46.55 8742 6869 10.63 11.58 54.14 0.0046 ZNC Española del Zinc, S.A. 893 0.0211 5.55 5132 4579 4.06 -73.23 2.92 0.0040 Cross-sectional averaged value 1174 0.0186 16.70 6957 5284 6.25 -16.35 11.13 0.0035	PAC	Papeles y Cartones de Europa, S.A.	1122	0.0164	2.50	6184	5137	6.18	-36.71	1.60	0.0032
UBS Urbanizaciones y Transportes, S.A. 938 0.0219 1.63 8342 6229 2.44 -26.14 0.76 0.0033 VWG Volkswagen Aktiengesellchft, S.A. 835 0.0214 46.55 8742 6869 10.63 11.58 54.14 0.0046 ZNC Española del Zinc, S.A. 893 0.0211 5.55 5132 4579 4.06 -73.23 2.92 0.0040 Cross-sectional averaged value 1174 0.0186 16.70 6957 5284 6.25 -16.35 11.13 0.0035	RIO	Bodegas Riojanas, S.A.	728	0.0196	17.35	6227	3652	6.85	-2.60	8.94	0.0025
VWG Volkswagen Aktiengesellchft, S.A. 835 0.0244 46.55 8742 6869 10.63 11.58 54.14 0.0046 ZNC Española del Zinc, S.A. 893 0.0211 5.55 5132 4579 4.06 -73.23 2.92 0.0040 Cross-sectional averaged value 1174 0.0186 16.70 6957 5284 6.25 -16.35 11.13 0.0035	UBS	Urbanizaciones y Transportes, S A	938	0.0219	1.63	8342	6229	2.44	-26.14	0.76	0.0033
ZNC Española del Zinc, S.A. 893 0.0211 5.55 5132 4579 4.06 -73.23 2.92 0.0040 Cross-sectional averaged value 1174 0.0186 16.70 6957 5284 6.25 -16.35 11.13 0.0035	VWG	Volkswagen Aktiengesellchft S A	835	0.0244	46.55	8742	6869	10.63	11.58	54.14	0.0046
Cross-sectional averaged value 1174 0.0186 16.70 6957 5284 6.25 -16.35 11.13 0.0035	ZNC	Española del Zinc. S A	893	0.0211	5.55	5132	4579	4.06	-73.23	2.92	0.0040
a and sectorist when show the sector	20	Cross-sectional averaged value	1174	0.0186	16.70	6957	5284	6.25	-16.35	11.13	0.0035

Table 1Sample Descriptive Statistics

The table shows the name and ticker of all the companies included in the sample. The number of observations and the mean values related to the spread, depth, volume, price and volatility are also provided. *Relative Spread*, *Spread in ticks*, *Bid Depth* ϵ , *Ask Depth* ϵ and *Midqoute* are time-weighted means over the eighty day period. *Volume Mill* ϵ is the total volume traded in ϵ during this period of time. % *Price Change* shows the return calculated from the first transaction price in day 1 to the last transaction price in day 80. Finally, *Price Volatility* is measured as the standard deviation of transaction prices for the period. Means of these variables are also show for each of the three activity portfolio formed.

Parameter	Mean	Median	Minimum	Maximum	Mean St. Error.
		Group 1:	High-volume ass	ets	
α	0.066	0.066	0.046	0.077	0.005
α ₁	1.372	1.384	1.278	1.464	0.032
σ	0.017	0.014	0.007	0.039	0.001
p ₀₀	0.905	0.902	0.880	0.923	0.005
p ₁₁	0.342	0.336	0.266	0.409	0.020
PIN	0.127	0.128	0.096	0.168	0.001
		Group 2: N	Iedium-volume as	ssets	
α	0.081	0.081	0.048	0.109	0.017
α1	1.344	1.317	1.198	1.600	0.061
σ	0.031	0.021	0.010	0.070	0.002
P 00	0.878	0.890	0.834	0.916	0.012
p ₁₁	0.380	0.387	0.291	0.470	0.040
PIN	0.165	0.153	0.122	0.221	0.002
		Group 3:	Low-volume asso	ets	
α	0.081	0.085	0.015	0.132	0.018
α1	1.306	1.259	1.051	1.634	0.079
σ	0.059	0.026	0.004	0.368	0.004
P 00	0.887	0.879	0.861	0.932	0.019
p ₁₁	0.427	0.428	0.323	0.499	0.068
PIN	0.166	0.173	0.096	0.215	0.005

Table 2Baseline Model

The table summarizes the parameter estimates (average value, median, maximum, minimum and average asymptotic standard error) from estimating the baseline model (see equation (2) and description in the main text) and the inferred probabilities of informed negotiation (PIN). The subindexex 0 and 1 refers to the normal and excited state respectively.

Parameter	Mean	Median	Minimum	Maximum	Mean St. Eror.
		Group 1:	High-volume as	sets	
$\alpha_{0,A1}$	0.328	0.312	0.238	0.414	0.025
α _{1,A1}	2.180	1.995	1.475	4.058	0.211
$\alpha_{0,A2}$	1.223	1.240	1.062	1.327	0.029
$\alpha_{1,A2}$	4.127	4.294	2.369	5.702	0.511
a _{0,A3}	0.020	0.019	0.003	0.043	0.005
$\alpha_{1,A3}$	1.096	0.906	0.562	2.366	0.188
σ	0.016	0.013	0.006	0.037	0.001
P 00	0.946	0.951	0.878	0.978	0.008
p ₁₁	0.138	0.133	0.054	0.244	0.025
PIN	0.060	0.055	0.023	0.129	0.001
		Group 2: M	ledium-volume a	issets	
$\alpha_{0,A1}$	0.397	0.360	0.272	0.774	0.058
α _{1,A1}	2.443	2.356	1.631	3.827	0.367
α _{0,A2}	1.193	1.195	0.944	1.398	0.049
$\alpha_{1,A2}$	5.447	3.964	1.665	20.021	0.835
$\alpha_{0,A3}$	0.019	0.023	0.001	0.042	0.010
$\alpha_{1,A3}$	0.823	0.801	0.459	1.443	0.196
σ	0.029	0.019	0.009	0.062	0.001
P00	0.937	0.933	0.918	0.959	0.016
p ₁₁	0.159	0.143	0.082	0.240	0.058
PIN	0.070	0.071	0.049	0.095	0.003
		Group 3:	Low-volume ass	sets	
$\alpha_{0,A1}$	0.419	0.427	0.236	0.627	0.112
$\alpha_{1,A1}$	3.300	3.067	1.381	5.641	3.190
α _{0,A2}	1.123	1.120	0.766	1.419	0.162
α _{1,A2}	4.719	3.971	0.395	13.440	2.206
α _{0,A3}	0.027	0.029	-0.010	0.058	0.022
$\alpha_{1,A3}$	0.644	0.828	0.007	1.570	0.270
σ	0.056	0.023	0.003	0.351	0.006
P 00	0.921	0.939	0.794	0.967	0.095
p ₁₁	0.142	0.140	0.000	0.348	0.110
PIN	0.083	0.070	0.038	0.185	0.004

Table 3Order I Model

The table summarizes the parameter estimates (average value, median, maximum, minimum and average asymptotic standard error) from estimating the size-extended model (see equation (5) and description in the main text) and the inferred probabilities of informed negotiation (PIN). The subindex 0 and 1 refers to the normal and excited state respectively, and the subindeces A1, A2 and A3 refer to the degree of aggressiveness.

Parameter	Mean	Median	Minimum	Maximum	Mean St. Error.
		Group 1:	High-volume ass	ets	
$\alpha_{0,L}$	0.174	0.174	0.146	0.205	0.017
$\alpha_{1,L}$	1.503	1.449	1.394	1.634	0.080
$\alpha_{0,M}$	0.033	0.035	0.007	0.053	0.008
$\alpha_{1,M}$	1.297	1.270	1.203	1.462	0.045
$\alpha_{0,S}$	0.057	0.057	0.039	0.077	0.007
$\alpha_{1,S}$	1.338	1.306	1.182	1.537	0.059
σ	0.017	0.014	0.001	0.007	0.039
P00	0.906	0.904	0.882	0.924	0.005
P ₁₁	0.344	0.343	0.272	0.410	0.020
PIN	0.125	0.126	0.095	0.167	0.001
		Group 2: M	ledium-volume as	ssets	
$\alpha_{0,L}$	0.166	0.151	0.106	0.278	0.046
$\alpha_{1,L}$	1.593	1.571	1.252	2.346	0.265
$\alpha_{0,M}$	0.073	0.070	0.051	0.115	0.016
$\alpha_{1,M}$	1.263	1.244	1.027	1.499	0.069
$\alpha_{0,S}$	0.040	0.035	-0.008	0.091	0.020
$a_{1,S}$	1.380	1.411	1.119	1.662	0.114
σ	0.031	0.021	0.010	0.068	0.002
P00	0.881	0.890	0.839	0.915	0.015
P ₁₁	0.381	0.393	0.282	0.463	0.042
PIN	0.161	0.152	0.121	0.219	0.004
		Group 3:	Low-volume asso	ets	
$\alpha_{0,L}$	0.205	0.153	0.095	0.362	0.049
$\alpha_{1,L}$	1.858	1.501	1.187	6.291	0.368
$\alpha_{0,M}$	0.076	0.080	0.010	0.126	0.022
$\alpha_{1,M}$	1.243	1.230	0.947	1.555	0.094
$\alpha_{0,S}$	0.035	0.026	-0.011	0.100	0.031
$\alpha_{1,S}$	1.406	1.347	0.134	2.624	0.177
σ	0.059	0.025	0.004	0.362	0.004
P 00	0.888	0.885	0.859	0.957	0.021
p ₁₁	0.420	0.438	0.313	0.492	0.072
PIN	0.161	0.173	0.065	0.201	0.006

Table 4Size-extended Model

The table summarizes the parameter estimates (average value, median, maximum, minimum and average asymptotic standard error) from estimating the size-extended model (see equation (6) and description in the main text) and the inferred probabilities of informed negotiation (PIN). The subindex 0 and 1 refers to the normal and excited state respectively, and the subindeces L, M and S refer to the large, medium and small trade size categories.

	A1	A1	A2	A2	A3(D)	A3(D)	A3(L)	A3(L)
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
			Grou	ıp 1: High-	volume ass	ets		
Small	1.48%	1.77%	1.12%	1.33%	0.71%	0.61%	5.15%	7.83%
Medim	2.13%	2.30%	3.32%	3.23%	2.78%	2.47%	18.45%	25.31%
Large	0.45%	0.43%	1.29%	1.10%	1.24%	1.14%	6.75%	7.60%
Total	4.06%	4.50%	5.73%	5.66%	4.73%	4.22%	30.35%	40.75%
			Grou	ıp 2: High-	volume ass	ets		
Small	1.65%	1.95%	1.53%	1.94%	0.83%	0.77%	4.68%	6.66%
Medim	2.69%	3.02%	3.84%	4.47%	2.86%	2.43%	16.24%	24.42%
Large	0.57%	0.57%	1.26%	1.29%	1.23%	1.20%	5.48%	8.42%
Total _	4.91%	5.54%	6.63%	7.69%	4.92%	4.40%	26.40%	39.51%
			Grou	ıp 3: High-	volume ass	ets		
Small	1.59%	2.12%	1.33%	2.61%	1.63%	0.69%	4.02%	6.05%
Medim	3.17%	3.52%	3.31%	4.72%	4.48%	2.25%	12.91%	25.58%
Large	0.64%	0.60%	1.22%	1.23%	2.40%	0.94%	4.26%	8.73%
Total	5.40%	6.24%	5.86%	8.55%	8.51%	3.89%	21.19%	40.36%

Table 5Sample Frequencies

The table summarizes the relative frequencies of jointly observing the degree of aggressiveness (A1, A2, A3(D), A3(L)), the direction of the order (buy or sell) and the size of the trade (small, medium, large).

Parameter	Mean	Median	Minimum	Maximum	Mean St. Error.
		Group	1: High-volume	assets	
$\alpha_{0,A1}$	0.289	0.289	0.166	0.397	0.025
$\alpha_{1,A1}$	1.876	1.782	1.461	2.521	0.151
$\alpha_{0,A2}$	1.190	1.194	1.025	1.280	0.029
$\alpha_{1,A2}$	2.998	2.808	1.857	5.123	0.492
α _{0,A3(D)}	0.351	0.357	0.136	0.539	0.033
α _{1,A3(D)}	2.363	2.368	1.442	3.770	0.275
$\alpha_{0,A3(L)}$	0.041	0.039	0.028	0.061	0.006
$\alpha_{1,A3(L)}$	-0.111	-0.101	-0.187	-0.071	0.027
σ	0.015	0.012	0.006	0.036	0.000
P 00	0.805	0.812	0.732	0.859	0.022
p ₁₁	0.157	0.140	0.097	0.288	0.027
PIN	0.188	0.182	0.149	0.254	0.001
		Group 2	: Medium-volum	e assets	
α _{0,A1}	0.370	0.326	0.210	0.770	0.051
$\alpha_{1,A1}$	2.318	2.103	1.583	3.748	0.283
$a_{0,A2}$	1.158	1.137	0.932	1.364	0.053
$a_{1,A2}$	2.938	3.134	1.055	4.886	0.681
α _{0,A3(D)}	0.316	0.315	0.123	0.516	0.056
α _{1,A3(D)}	3.102	2.794	1.153	8.807	0.495
α _{0,A3(L)}	0.035	0.033	-0.015	0.067	0.013
a _{1,A3(L)}	-0.082	-0.089	-0.503	0.456	0.091
σ	0.027	0.019	0.008	0.059	0.001
P 00	0.811	0.814	0.710	0.930	0.035
p ₁₁	0.144	0.123	0.063	0.274	0.060
PIN	0.179	0.168	0.078	0.274	0.003
		Group	3: Low-volume	assets	
$\alpha_{0,A1}$	0.370	0.389	0.204	0.519	0.069
$a_{1,A1}$	2.743	2.611	1.390	5.478	0.461
$a_{0,A2}$	1.099	1.097	0.738	1.327	0.084
$\alpha_{1,A2}$	4.332	2.401	0.930	13.280	0.642
a _{0,A3(D)}	0.190	0.203	-0.066	0.392	0.067
α _{1,A3(D)}	2.902	2.256	1.025	6.737	0.531
$\alpha_{0,A3(L)}$	0.033	0.016	0.000	0.141	0.025
a _{1,A3(L)}	-0.081	-0.016	-0.461	0.011	0.074
σ	0.053	0.023	0.003	0.329	0.003
P 00	0.809	0.829	0.653	0.920	0.057
p ₁₁	0.177	0.149	0.000	0.379	0.093
PIN	0.184	0.176	0.096	0.335	0.006

Ta	bl	e 6
Order	II	Model

The table summarizes the parameter estimates (average value, median, maximum, minimum and average asymptotic standard error) from estimating the model with four categories of aggressiveness (see description in the main text) and the inferred probabilities of informed negotiation (PIN). The subindex 0 and 1 refers to the normal and excited state respectively, and the subindeces A1, A2 and A3(D) and A3(L) refer to the degree of aggressiveness.

							Ulu		Juci							
		(Group1					Grou	ıp2			Group3				
	Mean	Med.	Min.	Max.	S.E.	Mean	Med.	Min.	Max.	S.E.	Mean	Med.	Min.	Max.	S.E.	
$\alpha_{0,A1-B}$	0.298	0.311	0.166	0.405	0.037	0.381	0.347	0.240	0.699	0.071	0.406	0.361	0.215	0.785	0.108	
$\alpha_{0,A1-S}$	0.270	0.287	0.196	0.377	0.034	0.370	0.354	0.184	0.806	0.064	0.341	0.320	0.146	0.625	0.091	
$\alpha_{1,A1-B}$	1.827	1.800	1.412	2.530	0.190	2.577	2.392	1.377	4.133	0.390	3.409	2.887	1.127	10.039	0.501	
$\alpha_{1,A1-S}$	2.077	1.966	1.398	3.665	0.278	2.452	2.198	1.323	3.809	0.352	2.357	2.210	1.171	4.466	0.513	
$\alpha_{0,A2-B}$	1.176	1.209	0.925	1.271	0.043	1.130	1.123	0.891	1.355	0.083	1.069	1.020	0.485	1.457	0.141	
$\alpha_{0,A2-S}$	1.204	1.213	0.985	1.341	0.033	1.155	1.180	0.951	1.372	0.077	1.094	1.101	0.801	1.270	0.129	
$\alpha_{1,A2-B}$	3.513	2.954	1.276	6.966	0.860	2.998	2.533	0.893	6.923	0.759	3.655	2.891	0.415	15.328	0.902	
$\alpha_{1,A2-S}$	2.835	2.633	0.745	4.429	0.401	3.883	2.637	0.503	20.796	0.818	5.019	3.480	0.547	18.179	1.209	
α _{0,A3(D)-B}	0.357	0.341	0.162	0.555	0.040	0.319	0.326	0.163	0.437	0.074	0.200	0.201	-0.004	0.503	0.076	
α _{0,A3(D)-S}	0.350	0.379	-0.005	0.527	0.072	0.324	0.319	0.047	0.502	0.082	0.241	0.276	-0.159	0.592	0.120	
α _{1,A3(D)-B}	2.227	2.318	1.462	3.773	0.266	2.770	2.386	1.418	5.055	0.532	3.364	2.557	0.991	8.366	0.744	
a _{1,A3(D)-S}	2.315	2.137	1.228	3.840	0.386	3.122	2.399	0.890	8.054	0.780	2.336	2.173	0.442	5.442	0.546	
α _{0,A3(L)-B}	-0.010	-0.007	-0.036	0.000	0.006	0.010	0.006	-0.066	0.145	0.024	0.004	0.003	-0.024	0.046	0.025	
$\alpha_{0,A3(L)-S}$	0.040	0.035	0.025	0.067	0.008	0.035	0.042	-0.013	0.146	0.018	0.023	0.023	-0.007	0.075	0.023	
α _{1,A3(L)-B}	0.167	0.149	0.081	0.297	0.060	0.018	0.012	-0.204	0.283	0.072	0.066	0.000	-0.590	0.806	0.057	
$\alpha_{1,A3(L)-S}$	-0.114	-0.114	-0.209	-0.034	0.035	-0.046	-0.041	-0.290	0.283	0.062	-0.015	-0.030	-0.296	0.409	0.115	
σ	0.015	0.012	0.006	0.036	0.000	0.027	0.018	0.008	0.059	0.001	0.051	0.021	0.003	0.325	0.003	
P 00	0.817	0.814	0.749	0.891	0.021	0.794	0.790	0.708	0.886	0.037	0.822	0.851	0.655	0.911	0.050	
p ₁₁	0.159	0.146	0.091	0.317	0.028	0.143	0.127	0.000	0.457	0.048	0.235	0.186	0.028	0.497	0.093	
PIN	0.179	0.173	0.110	0.241	0.001	0.196	0.197	0.111	0.327	0.003	0.187	0.167	0.122	0.360	0.006	

Table 7 Order III Model

The table summarizes the parameter estimates (average value, median, maximum, minimum and asymptotic average standard error) from estimating the model with four categories of aggressiveness and the order direction (see equation (7) and the description in the main text) and the inferred probabilities of informed negotiation (PIN). The subindex 0 and 1 refers to the normal and excited state respectively. The subindeces refer to the degree of aggressiveness (A1,A2, A3(D) and A3(L)) and the direction (buy=B, sell=S) of the order.

	Group1							Group2			Group3				
	MEAN	MED.	MIN.	MAX.	S.E.	MEAN	MED.	MIN.	MAX.	S.E.	MEAN	MED.	MIN.	MAX.	S.E.
$\alpha_{0,A1-S}$	0.213	0.221	0.129	0.269	0.024	0.241	0.236	0.122	0.426	0.048	0.233	0.212	0.100	0.462	0.052
α _{0,A1-M}	0.520	0.514	0.351	0.641	0.047	0.488	0.469	0.300	0.734	0.074	0.439	0.446	0.224	0.579	0.088
$\alpha_{0,A1-L}$	1.383	1.238	0.966	2.143	0.185	1.406	1.168	0.685	4.528	0.313	1.307	1.000	0.087	5.530	0.205
$\alpha_{0,A2-S}$	1.059	1.105	0.828	1.156	0.041	0.940	0.959	0.133	1.523	0.059	0.940	1.103	0.070	1.227	0.093
α _{0,A2-M}	1.349	1.343	1.252	1.431	0.033	1.265	1.293	1.078	1.497	0.068	1.256	1.243	1.045	1.582	0.092
$\alpha_{0,A2-L}$	1.964	1.884	1.574	2.317	0.126	1.960	1.889	1.216	2.971	0.265	2.106	1.969	1.148	3.175	0.309
$\alpha_{0,A3-S}$	0.209	0.227	-0.068	0.354	0.048	0.171	0.161	0.010	0.285	0.063	0.069	0.061	-0.181	0.400	0.079
α _{0,A3-M}	0.428	0.429	0.237	0.644	0.032	0.379	0.406	0.140	0.563	0.079	0.277	0.284	0.054	0.520	0.065
$\alpha_{0,A3-L}$	0.715	0.686	0.466	1.035	0.079	0.641	0.630	0.181	1.321	0.185	0.565	0.663	-0.622	1.367	0.196
$\alpha_{1,A1-S}$	1.489	1.520	1.318	1.636	0.111	1.583	1.583	1.194	2.368	0.224	1.832	1.477	1.136	4.067	0.193
$\alpha_{1,A1-M}$	2.945	2.905	1.664	5.335	0.305	2.935	2.338	1.689	4.329	0.330	3.698	3.386	1.926	10.273	0.392
$\alpha_{1,A1-L}$	16.577	10.879	4.043	64.862	3.616	10.499	7.173	3.257	32.278	1.810	7.600	5.405	-5.468	31.363	0.819
$\alpha_{1,A2-S}$	1.603	1.454	0.988	3.904	0.307	0.965	0.887	0.559	1.573	0.191	0.987	1.126	-1.039	4.443	0.216
$\alpha_{1,A2-M}$	4.708	3.884	2.307	15.659	0.629	3.264	3.406	1.711	6.452	0.689	4.679	3.638	1.881	15.228	0.647
$\alpha_{1,A2-L}$	11.482	12.120	3.650	25.173	2.057	9.460	7.365	2.733	28.673	1.647	14.058	7.027	-0.010	48.481	1.960
$\alpha_{1,A3-S}$	1.504	1.431	0.754	2.352	0.172	1.414	1.268	0.822	2.289	0.324	1.078	1.038	-0.489	1.935	0.235
$\alpha_{1,A3-M}$	2.863	2.755	1.629	4.353	0.290	3.540	2.733	0.994	9.031	0.597	3.255	3.041	1.106	5.138	0.543
$\alpha_{1,A3-L}$	9.520	5.680	2.087	30.231	1.226	10.123	6.119	2.671	28.836	1.801	11.324	9.418	1.820	36.131	1.588
$\alpha_{0,A32}$	-0.011	-0.011	-0.026	-0.003	0.004	-0.017	-0.018	-0.061	0.006	0.011	-0.003	-0.006	-0.033	0.038	0.014
$\alpha_{1,A32}$	0.381	0.395	0.141	0.577	0.083	0.279	0.241	0.050	0.627	0.117	0.247	0.177	-0.190	0.800	0.159
σ	0.014	0.011	0.005	0.033	0.000	0.025	0.017	0.008	0.054	0.001	0.047	0.018	0.003	0.312	0.003
P 00	0.903	0.914	0.793	0.945	0.016	0.848	0.842	0.732	0.943	0.034	0.873	0.870	0.768	0.941	0.036
p ₁₁	0.158	0.150	0.084	0.293	0.022	0.254	0.204	0.146	0.538	0.055	0.277	0.210	0.131	0.518	0.075
PIN	0.103	0.092	0.057	0.199	0.001	0.172	0.156	0.064	0.328	0.004	0.153	0.167	0.067	0.328	0.007

Table 8 Order IV Model

The table summarizes the parameter estimates (average value, median, maximum, minimum and asymptotic average standard error) from estimating the model with four categories of aggressiveness and the order size (see equation (8) and the description in the main text) and the inferred probabilities of informed negotiation (PIN). The subindex 0 and 1 refers to the normal and excited state respectively. The subindeces refer to the degree of aggressiveness (A1,A2, A3(D) and A3(L)) and the size (small, medium, large) of the order.

		P	ANEL A: C	ROSS-AVE	RAGE PIN		
Trading Activity	Baseline	Size-ext.	Order1	Order2	Order3	Order4	EKOP
Group 1	12.7%	12.5%	6.0%	18.7%	17.9%	10.3%	17.9%
Group 2	16.5%	16.1%	7.0%	17.9%	19.6%	17.2%	21.8%
Group 3	16.7%	16.1%	7.0%	18.4%	18.7%	15.3%	26.8%
		PANEL B: I	BOOTSTRA	AP TESTS A	AND SIGNI	FICANCE	
t-tests: Mean eq.	Baseline	Size-ext.	Order1	Order2	Order3	Order4	EKOP
Group1 vs Group?	-3.485	-3.451	-1.174	0.420	-0.982	-2.689	-1.560
010up1 vs 010up2	[0.00]	[0.00]	[0.08]	[0.55]	[0.06]	[0.00]	[0.04]
Group? vs Group3	-0.196	0.036	-0.984	-0.198	0.343	0.655	-1.139
010up2 vs 010up5	[0.47]	[0.54]	[0.18]	[0.50]	[0.77]	[0.82]	[0.09]
Group1 vc Group3	-3.411	-2.973	-1.618	0.164	-0.39	-2.278	-2.278
Gloup1 vs Gloup5	[0.00]	[0.04]	[0.04]	[0.55]	[0.37]	[0.00]	[0.00]
	PANEL	C: CORRE	LATIONS	WITH SPR	EAD AND I	EKOP MEA	SURE
All groups	Baseline	Size-ext.	Order1	Order2	Order3	Order4	EKOP
SPREAD	25.8%	21.5%	-71.1%	7.2%	0.8%	26.7%	42.7%
EKOP	-20.5%	0.6%	-1.7%	2.6%	9.6%	15.4%	100%
Groups 1&2							
SPREAD	31.2%	29.9%	-71.1%	16.1%	1 4%	64 2%	54%

Table 9Model Performance Analysis

The table summarizes different results for all the estimated models. *Baseline* is the basic model in (2); *Size-ex* is the size-extended model in (6); *Order1 to Order4* are the models with i)three aggressiveness categories, ii) four aggressiveness categories, iii) four aggressiveness categories and order direction, iv) four aggressiveness categories and trade size. *EKOP* represents the estimates from the procedure of Easley et al. (1995). Panel A reports the cross-sectional mean values of the unconditional PIN estimates. Panel B tests presents the bootstrapped t-test (p-value between brackets) of the null hypothesis of equal mean values (i.e., the difference between the mean value of the i-th group and the j-th group is zero). Finally, Panel C presents the sample correlations between the PIN estimates of each model and both the relative spread (a time-weighted mean of the spread over the sample period) and the EKOP estimates. The correlation is computed by using the estimates and observations for each groups and excluding Group 3.

-43.4%

-7.8%

7.7%

30.0%

100%

EKOP

-33.7%

-31.2%

Figures



Figure 1 PIN and Pr(A2) Comparison

Pr(A2) denotes the probability of observing A2 orders for each asset in the sample, computed as the mean value of the indicator variable. PIN-base is the unconditional probability of being in excited state for any asset inferred from the baseline model.

Figure 2 Baseline and Size-extended Model Comparison



PIN-base and PIN-size denote, respectively, the cross-sectional unconditional probabilities of being in excited state inferred from the baseline and the size-extended models.

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