Order Submission: the Choice between Limit and Market Orders*

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Abstract:

Most financial markets allow investors to submit both limit and market orders but it is not always clear why agents choose one over the other. In this study we empirically investigate how several microstructure factors influence the choice and timing of submitting either limit or market orders using orders submitted to the Reuters 2000-2 system. Specifically we measure how these factors influence the expected time (duration) between successive orders using an autoregressive conditional duration (ACD) model. We find that the order submission process is not symmetric for market and limit orders. For example, we only find the lagged average volume, a proxy for market depth, affects the expected duration of market orders while the lagged market imbalance, quote intensity, average volume and bid-ask spread all shorten the expected duration of limit orders. We also find differences in the expected durations around the opening of different geographic markets on the expected duration, even after adjusting for the well-known time-of-day seasonalities. As a consequence our study provides empirical evidence in support of several market microstructure models of the order submission process.

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1. Introduction:

In most financial markets, traders can choose between submitting a market order for immediate execution or a limit order that specifies a price for execution but may take longer to execute. This provides traders with several alternatives with which to accomplish their goal of maximizing the expected value of terminal wealth. Consequently, the choice between these types of orders depends on both the trader's preferences and their beliefs regarding the market's current and future price generating process. As the market changes over the trading day and traders' preferences between the immediacy of trades and the cost of trading changes, we expect to see changes in traders' propensity to submit the different types of orders.

In this study we investigate the impact of various market microstructure factors on the market order and limit order submission decision (i.e. the type of order and timing of submission). Since it is typically assumed that market orders demand liquidity and limit orders provide liquidity, understanding what conditions influence the rate at which traders supply and demand liquidity can provide insight into the overall price formation process. This approach extends the existing microstructure studies in this area which have focused on comparing the overall costs of execution for limit and market orders. Starting with Demsetz (1968), Cohen, Maier, Schwartz and Whitcomb (1981), and Ho and Stoll (1983) and continuing in the more recent work of Handa and Schwartz (1996), Seppi (1997), Parlour (1998), Viswanathan and Wang (1998) and Foucault (1999) many factors have been hypothesized to influence the expected cost of each type of transaction. Empirical tests such as Biais, Hillion and Spatt (1995), Harris and Hasbrouck (1996), Kavajecz (1999), Ahn, Bae and Chan (2001) and Peterson and Sirri (2002), for example, have documented differences in the transaction costs across order types using intra-day data from equity markets[1].

We focus on the time between the submission of different orders because they arrive at irregular intervals and the timing of their submission may reveal important information about market conditions. Many models in the microstructure literature build on this intuition. Diamond and Verrechia (1987), for example, suggest that short-sale constraints may mean that a longer time between trades may signal bad news. On the other hand, Easley and O'Hara (1992) suggest that longer times between trades may signal an absence of information. The functional role for time implied by these models is investigated empirically by several authors including Engle and Russell (1997, 1998), Hasbrouck (1999), Cho and Nelling (2000) and Engle (2000). These authors find that the time between trades contains information in a manner consistent with Easley

[1] Note: whether market or limit orders have lower cost depends on the metrics used. This is discussed in more detail in Section 2.

and O'Hara (1992). For example Hasbrouck suggests that the clustering of trades, quotes and price changes is evidence a "fast market is not merely a normal market that is speeded up, but one in which the relationships between component events differs."

In this paper we extend these studies by examining the interaction between the frequency with which traders submit different types of orders (the order arrival process) and market conditions related to the cost and timing of order execution. We allow the arrival rates of market and limit orders to carry different information and ultimately impact the price formation process differently. This differs from existing studies which examine the role of time but consider only limit orders (e.g., Cho and Nelling (2000)), do not distinguish between market orders and limit orders (e.g., Engle and Russell (1997, 1998)) or have focused on the time between quote submission and execution (e.g., Melvin and Wen (2003)). Two notable exceptions are Hasbrouck (1999) and Hollifield, Miller, Sandas and Slive (2002). Hasbrouck performs a descriptive analysis of the arrival processes of the two types of orders and finds differences between them – they are negatively correlated over short intervals. Hollifield, Miller, Sandas and Slive explicitly model the arrival process and execution probability of the two order types to determine if traders submit the optimal type of order based on market conditions. They find differences in the conditions under which traders submit each order type, but they are not necessarily submitted optimally.

Our technique extends these studies because many of them implicitly assume the traders' arrival process and order submission decision are independent. We feel that there is valuable information in both the choice of order type and the timing of order submission and that these are not necessarily independent. Consequently we relax this assumption by employing an asymmetric autoregressive conditional duration (ACD) model similar to that of Engle and Russell (1998) and Bauwens and Giot (2000) to estimate the joint process of traders' arrival and order submission. This model allows for differences in the order arrival process and order submission decision across limit and market orders. Since prices are based on market conditions, especially information arrival, and the arrival process of these different types of orders provides valuable insight into the price formation process, our study extends the empirical microstructure literature in a very important dimension. We find that the information on the previous types of orders placed is important and ignoring it may lead to misspecification of the trade arrival process and thus of the price formation process as well.

For our study we investigate the order submission process in the context of the foreign exchange market using orders submitted on the Reuters 2000-2 electronic foreign exchange brokerage system. This complements the existing work using equity markets and allows us to investigate a wider variety of microstructure factors because the foreign exchange market is characterized by high liquidity, a twenty-four hour trading day, and it contains a large number of limit and market orders. Some of the main differences between our study and the majority of other high frequency studies are as follows. First, unlike the majority of studies in the foreign exchange market, we use data on firm quotes and not indicative quotes. The majority of studies use indicative quotes because this data is publicly available and studies such as Goodhart, Ito and Payne (1996) and Danielson and Payne (2001) suggest that it is a reasonable proxy for actual foreign exchange transaction data. Nevertheless Lyons (1995), Yao (1998), Evans (2002) and Evans and Lyons (2002a and 2002b) use actual transaction level data and find that microstructure factors influence the price formation process more than could be observed using indicative quotes. Second unlike most studies (regardless of the market used) we separate limit and market orders to investigate differences in what motivates investors to submit each order type. Finally, most microstructure studies aggregate the information over set intervals to enable the use of standard time series techniques. Our modeling of irregularly spaced data using the ACD model prevents the loss of information from such aggregation (see Muller et al (1990) and Dacrogna et al (2001) for a discussion).

For our investigation, we consider three models. In the first model, we use a simple version of the asymmetric ACD model developed by Bauwens and Giot (2000). We start with the simplest model – it assumes the arrival process depends on the type of order. The aim is to examine whether the history of the types of orders submitted provides information which affects the timing and type of the next quote. We find that the expected duration is dependent on the previous type of order submitted – previous limit orders decrease the duration for both market and limit orders. This is consistent with increased limit order activity as market volatility increases. Using the relationship between instantaneous volatility and duration from Engle and Russell (1998) we find a correlation between volatility and the type of order submitted. Since the relationships all depend on the current and past type of order, ignoring the information from the previous type of order submitted may lead to a misspecification of the arrival process of prices.

In the second model, we extend the first model by incorporating microstructure variables such as the volume traded, the balance between orders to buy and sell the currency, the frequency of quote submission and the bid-ask spread. The aim is to examine how variables related to market depth and information flow influence the arrival time and type of the next quote (or trade). We focus on these factors because they are among the most frequently proposed in market microstructure models of the dealers' order submission decision. We find that an increase in the average volume, a proxy for market depth, shortens the expected duration of market orders (the time between successive market orders), while increases in all of our proposed microstructure variables shorten the expected duration for limit orders. These findings suggest the existence of relationships between market depth, information flow and order type submission as suggested by the market microstructure literature.

The third model extends the previous models by focusing on some of the systematic intraday seasonalities documented in most intraday data. Specifically we focus on opening and closing effects for the London and New York markets since we believe changes in trading intensity at these hours can impose asymmetric effects on market and limit orders even after adjusting for intraday seasonalities. We find that the expected duration of market orders shrinks just before and after the opening of the New York market – as the New York market increases its involvement the duration decreases suggesting an increase (or expected increase) in market depth. For limit orders there is also a decrease in expected duration, but it is relatively small and concentrated before the opening of the London and New York markets. This is not surprising since the specific execution price of limit orders means increasing market depth plays less of a role for limit orders.

In summary, we find that several microstructure factors influence the arrival process of the different types of orders and thus trades. By explicitly investigating the time between the arrivals of different types of orders, we find that the duration processes of limit and market orders are different. Therefore a symmetric treatment of market and limit orders, as has been done previously in the literature, may lead to inconsistent estimation. The relationship between the duration processes of the two order types to the microstructure variables and peak trading hours are also different. In general the expected duration of market orders shortens only when measures of market depth increase whereas that of limit orders shortens when measures of market depth, market uncertainty and information arrival increase. Further, the impact of the information carried by our microstructure variables depends on the lag type of order, particularly when the lag type of order is a limit order. Limit orders appear to be used by traders to control for price risk, especially during periods of increased market uncertainty and the significance of lagged limit orders is due to the persistence of these periods. The primary risk for market orders is price risk, so they are submitted more frequently as market depth increases. This is consistent with the implications of many information based microstructure models of the order submission process discussed below.

The paper develops as follows. In section two we discuss some of the relevant theoretical and empirical studies in the market microstructure literature to motivate our different models. Section three describes the asymmetric ACD models we use. Section four discusses the data set, section five presents the results from the empirical analysis and the final section concludes.

2. Choice of Limit or Market Order

In this section we discuss some of the existing theoretical and empirical research on the order type decision in the market microstructure literature. These studies have taken a variety of perspectives to help explain the investors' order type and timing decisions. Combining the results from many of these studies we motivate several testable hypotheses which we investigate below.

A. Choice of Type of Order: Theory

Although traders are faced with the decision of whether to submit limit orders or market orders many times during the trading day, it is only recently that researchers have begun to investigate how different factors may influence the order type decision. Microstructure theory has focused most of its attention on limit-order trading. For example Glosten (1994), Kumar and Seppi (1994), Chakravarty and Holden (1996), Handa and Schwartz (1996), Seppi (1997), Parlour (1998), Parlour and Seppi (1998), Viswanathan and Wang (1998), and Foucault (1999) develop equilibrium models of the limit order book. Most of this literature builds on Glosten (1994) who examines an idealized electronic order book. Extensions such as Parlour and Seppi (1998) and Viswanathan and Wang (1998), for example, show how differences in trader characteristics influence their choice between transacting in a limit order or hybrid market.

Within hybrid markets where traders can submit both market and limit orders, the literature has focused on the interaction between market conditions, price changes and the type of order to submit. Specifically within the context of the tradeoff between execution certainty and transaction costs (e.g., Cohen et al (1981), Kumar and Seppi (1992), Chakravarty and Holden (1995), Harris and Hasbrouck (1996), and Harris (1997)). Handa and Schwartz (1996), for example, show that the perceived permanence of price changes is a key factor in traders' order form decision. Transitory volatility from inventory shocks or other short-term shocks attract limit orders more than market orders. Because trades made by informed traders are more likely to result in permanent price changes than liquidity trading, the order form choice depends on the probability the order will be executed against an informed trader. While executing limit orders against liquidity-driven or short-term price changes is profitable, executing limit orders against permanent price changes is undesirable. Parlour (1998) suggests that the current depth on each side of the market influences the choice of order type – limit orders being used when market depth is decreasing. Foucault (1999) shows that when the asset's volatility increases, market order trading becomes more costly so more traders find it optimal to submit limit orders at this time. As a result Foucault suggests that the proportion of limit orders should increase with asset volatility or market uncertainty. Finally many studies suggest a role for the time of day, especially the time to market closing, on order choice (e.g. Harris (1998) and Hollifield et al (2002).

B. Choice of Type of Order: Empirical Evidence

The empirical work has lagged behind the theoretical studies. Much of the empirical work has focused on limit order trading because it plays a crucial role in the trading mechanisms of so many of the world's stock exchanges. Domowitz (1993) documents that approximately 35 financial markets in 16 different countries contain elements of limit order mechanisms in their design. In order-driven markets, such as the Paris Bourse or the Tokyo Stock Exchange, all liquidity is provided by limit orders but in specialist markets, such as the New York Stock Exchange (NYSE), liquidity is supplied by both public limit orders and the specialist. Empirically the liquidity of the limit order book is supplemented the liquidity provided by the specialists in the NYSE. For example, Harris and Hasbrouck (1996) and Kavajecz (1999) find a dominant role for the limit order book in providing liquidity. As a consequence limit orders are some times referred to as liquidity orders.

Few empirical papers have investigated the behavior of limit-order traders in pure limit order markets (some exceptions are Biais, Hillion, and Spatt (1995) and Ahn, Bae and Chan (2001)). All of these studies find that limit order submission is impacted by market conditions especially market depth and volatility. Moving to hybrid markets, we continue to find a major role for limit orders. Harris and Hasbrouck (1996) document that 54 percent of SuperDot orders are limit orders, and Ross, Shapiro, and Smith (1996) report that limit orders account for 65 percent (75 percent) of all executed orders (executed shares). Among the important empirical results found in Harris and Hasbrouck (1996) are that limit orders perform better based on their ex ante performance measure and the most commonly used limit order placement strategies perform best. Extending these results, studies such as Harris and Hasbrouck (1996), Angel (1997), and Peterson and Sirri (2001) have identified significant differences in execution quality between market and limit orders.

There are very few studies which empirically investigate the order submission decision. Those that do such as Hollifield, Miller, Sandas and Slive (2002) and Ellul, Holden, Jain and Jennings (2003) model the probability of the arrival of different order types at specific times. Hollifield et al. go further by developing an econometric model to estimate the arrival process and execution probability of different orders using a sample from the Vancouver Stock Exchange. These studies indicate that there are differences in traders' submission strategies across market and limit orders. However an assumption in these studies is that the timing and order type decision are independent.

Since traders continue to submit both limit and market orders, these theoretical and empirical results suggest that many factors motivate dealers to submit each order type. First they suggest the market order and limit order submission processes are different so we use an asymmetric model to allow for differences across order type. This model also allows us to investigate the suggestions of the theoretical models that traders are more likely to submit limit orders as market uncertainty increases, market supply and demand imbalances increase and market depth decreases, but market orders are used more rapidly as market depth increases and as markets get closer to closing.

C. Timing of Different Orders: Theory

> "If market participants can learn from watching the timing of trades, then the adjustment of prices to information will also depend on time" (O'Hara (1995)).

The probability that a limit order will be executed and the expected time until its execution both play an important role in investors' decisions about the type of order they wish to submit. This probability has been carefully considered in the theoretical literature microstructure literature (starting with Cohen et al. (1981)). Cohen et al. showed that if an investor trades via a limit order, the investor's expected end of period wealth is an increasing function of the order execution probability. Extending this intuition, Diamond and Verrecciah (1987) develop a model in which short sale constraints impart information content to the time between trades. In their model traders learning bad news may be unable to short the stock, so longer times between trades may signal bad news. On the other hand, Easley and O'Hara (1992) show that if the existence of new information is uncertain then the time between trades carries information. Their idea is that when there has been an information event, orders arrive from both informed and uninformed traders resulting in a higher frequency of trades. As a result, when trades occur rapidly they are more informative and thus should have greater price impacts. This implies that the volume of trade and rapidity of quote submission may signal price relevant information.

Even though these models do not explicitly consider the order type, they suggest the time between trades conveys different information. Since the choice between market and limit orders is believed to be different, by extension the time between the submission of different types of orders should convey different information. The previous studies suggest that limit orders are used when market uncertainty is highest so we would expect to see more limit orders when there is little trading activity (Diamond and Verrecciah (1987)) or when there is heavy trading activity (Easley and O'Hara (1992)).

D. Time of Trade: Empirical Evidence

Most empirical studies of security price behavior rely on data aggregated over regular periods (e.g. hourly, daily etc.) since empirical analyses of trading are most conveniently set in a regular time scale. This aggregation into regular periods loses potentially important information. Although the majority of the literature has investigated microstructure data in this manner, studies should consider trades in real time to determine if there is information in the time between trades as suggested by the previous models. This role for time is investigated empirically by several authors including Engle and Russell (1998), Hasbrouck (1999), Cho and Nelling (2000) and Hollifield, Miller, Sandas and Slive (2002). Most relevant for our study is the approach developed by Engle and Russell (1998) to model irregularly spaced observations of real time data – the Autoregressive Conditional Duration (ACD) model. It focuses on the inter-temporal correlations of the time between events and "treats the arrival times of the data as a point process with an intensity defined conditional on past activity". The ACD model essentially estimates how long it will be until prices or quotes change given past quoting and trading activity.

With its focus on the characteristics of the time between price changes, the ACD model is related to models of volatility such as GARCH. Engle (2000) finds that, as suggested by the asymmetric information model, longer actual and longer expected times between trades are associated with lower price volatility. Engle and Russell (1997) apply the ACD technique to foreign exchange data and find that changes in the bid-ask spreads are predictive of future price changes. These future price changes are defined over a short horizon but these analyses show how patterns in trade and quote data can result in predictable price variation. Hasbrouck (1999) makes the point that trades, quotes and price changes tend to be clustered in time. He interprets this to mean that a "fast market is not merely a normal market that is speeded up, but one in which the relationships between component events differ". This is consistent with the model proposed by Easley and O'Hara (1992). Hollifield, Miller, Sandas and Slive (2002) extend the previous studies by estimating both the arrival process of investors and the execution probability of the two types of order. They find that the quoting behavior of investors does depend on market conditions, but they implicitly assume that the investor's decision to arrive at the market and the decision of which type of order to submit are independent.

In our study, we extend these previous studies by estimating a joint process for trader arrival and order submission. As suggested in the previous studies we allow market conditions related to market depth and information flow to influence the quote arrival process for market and limit orders differently.

3. Models

Our primary interest is in understanding the dynamics of the price formation process through the analysis of dealers' order submission strategies. Since prices are only observed when a trade occurs but orders can be submitted at any time, there may be price relevant information in the order submission times. These times are not equally spaced and many market conditions have changed between consecutive transactions, so the market microstructure literature has proposed several mechanisms through which these interact. Although there is evidence from work such as Engle and Russell (1998) suggesting that trades are intertemporally correlated, there has been little work investigating the arrival rates of limit and market orders. The studies discussed in the previous section suggest that the timing of the quotes may be related to market characteristics and may provide useful information. To investigate this we do not want to use the inter-temporally aggregated data used in many other high frequency studies. We want to investigate the dynamic impact of characteristics of individual trades and the quotes that were submitted between trades. As a consequence we treat the arrival times of trades as a point process jointly modeling the arrival times of the trades and the arrival times of different types of orders as a function of various market characteristics.

To focus on the impact of whether a quote was a market order or a limit order on the elapsed time between trades (duration) we use the asymmetric log-ACD model. In this framework, the conditional duration of the two types of orders are dependent on past information including order type. Specifically, let x_i be the duration between two trades at times t_{i-1} and t_i such that $x_i = t_i - t_{i-1}$ usually measured in seconds. The ACD model specifies the observed duration, x_i, as a mixing process such that

$$x_i = E[x_i|y_i, H_{i-1}]\,\varepsilon_i \qquad (1)$$

where the expected duration $E[x_i|y_i, H_{i-1}]$ is a function of whether a quote was a market or limit order, the state denoted by y_i, the information set available at time t_{i-1}, H_{i-1}, and the ε_i which are IID random variables with positive support. Because we are using the log ACD model, the expected duration takes the following form

$$E[x_i|y_i, H_{i-1}] = \Psi_i(y_i) = \exp(\psi_i(y_i)) \qquad (2)$$

where $\psi_i(y_i)$ depends on past information through a GARCH-like autoregressive process

$$\psi_i(y_i) = \omega(y_{i-1}) + \alpha(y_{i-1})\varepsilon_{i-1}(y_i) + \beta\psi_{i-1}(y_i) + \zeta(y_i)'z_{i-1}$$

where the intercepts, $\omega(y_{i-1})$, and ARCH effects, $\alpha(y_{i-1})$, depend on the lagged state (i.e. the lagged order type), z_{i-1} contains the lagged microstructure variables and $\zeta(y_i)$ their coefficients[2]. Thus expected duration of a certain order type can vary with the lag order type and other types of information such as market conditions.

The likelihood function we use is the Weibull distribution following the work of Engle and Russell (1997, 1998) and Bauwens and Giot (2002). Even though some other studies using the ACD model have used the Burr distribution because it is more general than the Weibull distribution (e.g. Melvin and Wen (2003)), we use the Weibull because it is simpler for large models such as those we consider. Our asymmetric models are larger than those used in many previous studies because we allow the quote submission process to differ across order types. This requires each order type to have its own autoregressive process and therefore doubles the number of parameters compared to the symmetric model. Further compounding the identification problem is our investigation of the influence of microstructure factors. The correspondingly large number of parameters makes the Burr distribution too complex for our study.

Three models are examined. The first is a basic model in which the autoregressive process on both market order and limit order depends only on the previous random errors and the type of orders. The second model incorporates market microstructure variables. The final model incorporates time effects of the peak trading hours.

A. Basic Model

The basic model we study follows that of Bauwens and Giot (2000). Specifically, let X_i be the raw duration between two trades at times t_{i-1} and t_i such that $X_i = t_i - t_{i-1}$. Since durations are known to vary over the day, we remove the intraday seasonalities in X_i, using the method proposed by Engle and Russell (1998). The corresponding adjusted duration, x_i, is defined as

$$x_i = \frac{X_i}{\phi(i)} \tag{3}$$

where $\phi(i)$ is the time-of-day effect. The time-of-day effect is formed by dividing each day into 48 half hour bins, averaging the durations within each bin and then smoothing the average durations by cubic splines. The choice of 30-minute time bins follows that in Bauwens and Giot (2000). Next we specify the state variable, y_i, which is the type of order. Let $y_i = 1$ if the quote is a limit order and $y_i = -1$ if the quote is a market order. For the asymmetric log ACD model the joint density function of x_i and y_i is given by

[2] Note: unlike the standard ACD model, the log ACD model does not require positivity constraints.

$$f(x_i, y_i \mid F_{i-1}) = \left[\frac{\gamma^{lmt}}{\Psi_i^+}\left(\frac{x_i}{\Psi_i^+}\right)^{\gamma^{lmt}-1}\right]^{I_i^+} e^{\left(\frac{x_i}{\Psi_i^+}\right)^{\gamma^{lmt}}} \left[\frac{\gamma^{mkt}}{\Psi_i^-}\left(\frac{x_i}{\Psi_i^-}\right)^{\gamma^{mkt}-1}\right]^{I_i^-} e^{\left(\frac{x_i}{\Psi_i^-}\right)^{\gamma^{mkt}}} \quad (4)$$

with $\Psi_i^+ = \exp\left(\psi_i^+\right)$ and $\Psi_i^- = \exp\left(\psi_i^-\right)$. The autoregressive process conditional on a limit order, ψ_i^+, is given by[3]

$$\psi_i^+ = \left(\omega_1 + \alpha_1 \varepsilon_{i-1}^+\right) I_{i-1}^+ + \left(\omega_2 + \alpha_2 \varepsilon_{i-1}^+\right) I_{i-1}^- + \beta^{lmt} \psi_{i-1}^+ \quad (5)$$

with $x_i = \exp(\psi_i^+)\varepsilon_i^+$ and I_{i-1}^+ is an indicator function which is equal to 1 if $y_i = 1$ and 0 otherwise. Similarly, the autoregressive process conditional on a market order, ψ_i^-, is given by

$$\psi_i^- = \left(\omega_3 + \alpha_3 \varepsilon_{i-1}^-\right) I_{i-1}^+ + \left(\omega_4 + \alpha_4 \varepsilon_{i-1}^-\right) I_{i-1}^- + \beta^{mkt} \psi_{i-1}^- \quad (6)$$

with $x_i = \exp\left(\psi_i^-\right)\varepsilon_i^-$ and I_{i-1}^- is an indicator function equal to 1 if $y_i = -1$ and 0 otherwise.

Equations (5) and (6) can be interpreted in an analogous fashion to a GARCH(1,1) model in the sense that the dependent variable is a function of its lagged value and a lagged random error term. The effect of the transition between states on duration is captured via the intercept, ω, and the coefficient on the previous random error, α. The values of ω represent the effect of the previous order type. For example, ω_1 and ω_3 are the impact of previous limit orders on the expected duration of current limit orders and market orders respectively. A negative value of ω_1 means that following a previous limit order, traders more rapidly submit limit orders (i.e. the duration decreases). The α's are the ARCH effects of the lagged disturbance based on the lagged order type on the expected duration. If these are different across α_1 and α_2, for example, the impact of the size of the disturbance from the last limit order on expected duration for current limit orders varies with the lagged order type. This setting allows us to test whether the expected durations, $\exp\left(\psi_i^+\right)$ and $\exp\left(\psi_i^-\right)$, are dependent upon the state variable – the type of order. If the expected duration until the next order, $\exp\left(\psi_i^+\right)$ or $\exp\left(\psi_i^-\right)$, does not depend on the type of the previous order, then the equalities $\omega_1=\omega_2$, $\omega_3=\omega_4$, $\alpha_1=\alpha_2$ and $\alpha_3=\alpha_4$ should hold and the arrival processes for the two order types are the same. This is the implicit assumption used in much of the literature, because it does not distinguish between the two order types. On the other

[3] For this and all subsequent models, we also consider more flexible versions of this model where the lagged duration is allowed to have an asymmetric impact on the duration based on the order type.

hand, if the equalities do not hold the models used in previous work which assume the processes are the same across order types are misspecified. This model helps us determine whether we need to distinguish between order types in modeling the quote arrival process.

To increase the information between observations we use a thinned price process. A thinned price process is constructed by selecting points at which the changes in price exceed a certain threshold. The practice of thinning the arrival of trades is commonly adopted when analyzing irregularly spaced data (for discussions see Engle and Russell (1997, 1998) and Bauwens and Giot (2000)). Under this construction, a more frequent arrival of quotes means that the time needed to achieve a certain price change shortens, thus there is a more rapid rate of change in price or a higher volatility. Consequently this setting also allows us to see how different order types affect the intensity of price changes or volatility of prices. An interesting conjecture which can be tested is whether the submission of limit orders is related to volatility as suggested by several models such as Foucault (1999). If ω_1 and ω_3 are negative, for example, then a lag limit order leads to a more rapid change in price, so limit orders are related to volatility.

B. Model with Microstructure Variables

We extend our basic model by allowing microstructure features to influence the autoregressive portion of our duration process. Various factors have been hypothesized to influence the choice between submitting limit or market orders in papers such as Demsetz (1968), Cohen and al. (1981), Ho and Stoll (1983) and are surveyed in both O'Hara (1995) and Madahvan (2000). The most commonly proposed factors are measures of market liquidity, dealers' inventory considerations and the possible presence of asymmetric information. The variables we use to control for some of these factors are the lagged quote intensity, the lagged average volume traded, the lagged market imbalance and the bid-ask spread.

The lagged quote intensity measures the rate at which information arrives at the market as discussed in Easley and O'Hara (1992). It is defined as the number of quotes between t-1 and t[4].

$$qint_t = nq_t - nq_{t-1} \quad (7)$$

where nq_t is the cumulative number of quotes until time t. The quote intensity is then adjusted by the time-of-day effect as in the case of adjusting the raw duration between trades.

The lagged average volume transacted is a measure of market depth. As discussed in Kyle (1985), a larger volume of transactions indicates a more liquid market – a market in which it

[4] In estimating the model, the trade arrival process is thinned such that the change in price from one observation to the next is greater than a constant, c. As a result, the number of quotes submitted and transactions between two observations can be greater than 1 (for discussion see Engle and Russell (1998)).

is possible to trade a larger volume at any given time. The submission of both types of orders is affected by market liquidity – the cost of placing a market order in a liquid market is lower both in terms of a higher probability of being fully filled and a lower premium for immediate execution; the cost of limit orders is also lower in a more liquid market as the execution risk decreases. The average volume used in this paper is defined as the quantity traded between t-1 and t divided by the number of transactions during that time. That is,

$$\mathrm{vol}_t = \frac{v_t - v_{t-1}}{ntrd_t - ntrd_{t-1}} \tag{8}$$

where v_t is the cumulative transacted volume and $ntrd_t$ is the cumulative number of transactions till time t. As in the case of adjusting raw trade duration, the average volume is scaled by the time-of-day effect to remove the intraday seasonality. This leaves the unexpected increase in the average size of trades or market depth.

The final measure of market depth we consider is market imbalance. It is defined as the relative difference in the depth on the bid side and ask side. In this context, market imbalance measures the relative liquidity provided on one side of the market compared to the other. Traders may believe that this indicates an imbalance between buyers and sellers so they may be anticipating a movement in one direction from which traders may want to either protect themselves or profit Since we are more concerned with the presence of an imbalance and what this implies about market conditions than on which side of the market there is an imbalance, the definition of market imbalance we use is the absolute value as in Peterson and Sirri (2002)

$$imb_t = 2x\left|\frac{bid\ size_t - ask\ size_t}{bid\ size_t + ask\ size_t}\right| \tag{9}$$

where the bid size_t is the aggregate quantity or aggregate size of orders on the bid side of the market from time t-1 to time t and the ask size_t is the aggregate quantity on the ask side. By incorporating lagged quote intensity, lagged traded volume and lagged market imbalance into the joint process of trade arrival and order type choice, we can examine how the two types of orders react to various measures of market depth

The final measure we consider is the bid-ask spread. The spread is a measure of both market depth and market uncertainty. It widens as market depth falls and uncertainty increases (see O'Hara (1995) and Madhavan (2000) for surveys). The measure for the spread used here is the difference between the lowest bid and the largest ask active in the market from time t-1 to time t. This provides us with a measure of the best bid-ask spread available in this period. As with our other measures, the spread is scaled by the time-of-day effect.

In the simplest form, adding these factors to our model, the autoregressive process with the microstructure variables conditional on a limit order, ψ_i^+, is given by

$$\begin{aligned}\psi_i^+ = \left(\omega_1 + \alpha_1\varepsilon_{i-1}^+\right)I_{i-1}^+ + \left(\omega_2 + \alpha_2\varepsilon_{i-1}^+\right)I_{i-1}^- + \beta^{lmt}\psi_{i-1}^+ \\ + \xi_{q\,\mathrm{int}}^{lmt} q\,\mathrm{int}_{t-1} + \xi_{vol}^{lmt} vol_{t-1} + \xi_{imb}^{lmt} imb_{t-1} + \xi_{spr}^{lmt} spr_{t-1}\end{aligned} \tag{10}$$

where $\xi_{q\,\mathrm{int}}^{lmt}$ is the coefficient of quote intensity given that the trade is a limit order, the average trade's coefficient is ξ_{vol}^{lmt}, the market imbalance coefficient is ξ_{imb}^{lmt}, and the coefficient on the best bid-ask spread is ξ_{spr}^{lmt}. These coefficients give us information on whether the microstructure variables affect the expected duration conditional on the submitted order being a limit order, exp $\left(\psi_i^+\right)$. Similarly, the autoregressive process conditional on a market order is given by

$$\begin{aligned}\psi_i^- = \left(\omega_3 + \alpha_3\varepsilon_{i-1}^-\right)I_{i-1}^+ + \left(\omega_4 + \alpha_4\varepsilon_{i-1}^-\right)I_{i-1}^- + \beta^{mkt}\psi_{i-1}^- \\ + \xi_{q\,\mathrm{int}}^{mkt} q\,\mathrm{int}_{t-1} + \xi_{vol}^{mkt} vol_{t-1} + \xi_{imb}^{mkt} imb_{t-1} + \xi_{spr}^{mkt} spr_{t-1}\end{aligned} \tag{11}$$

where $\xi_{q\,\mathrm{int}}^{mkt}$, ξ_{vol}^{mkt}, ξ_{imb}^{mkt} and ξ_{spr}^{mkt} are the coefficients of quote intensity, average volume, market imbalance and spread when the trade is a market order. As in the basic model, the microstructure variable coefficients in equation (10) and equation (11) can be interpreted both in the context of the order submission decision and asset volatilities. A negative coefficient indicates that an increase in the associated microstructure variable (i) induces market participants to place a certain type of order and (ii) leads to more rapid price change.

C. Model with Time Effects

As with all financial markets, there are clear trading patterns in the quoting and trading intensity of the foreign exchange market. The peak trading hours for foreign exchange can be clearly seen to fall into roughly three periods in Figure 1. Trading first peaks from 8:00a.m. to 10:00a.m. as markets open in London[5], trading drops slightly from 10:30a.m. to 12:30p.m. and trade intensity goes up again as the New York market opens at around 1:00p.m. Theoretically speaking, our adjusting of duration by expected duration discussed earlier should remove the influence of intraday seasonalities in foreign exchange trading. As specified in Equation (3), scaling frequent trading in peak hours by their expected duration and applying the same

[5] Note: all times are expressed as Greenwich Mean Time (GMT).

procedure to non-peak hour trading smoothes the clustering of intraday trading. However, it is possible that there is more to the hour-of-day effect for market orders and limit orders. Consequently we want to study whether the opening of the London and/or the New York markets have symmetric effects on the conditional expected duration of market orders and limit orders. The successful filling of an incoming order (whether it be a market or limit order) depends very much on the market depth. The opening of the New York market should deepen the existing market by introducing more possibilities of trade. This should shorten the expected duration of orders. For example the quoting frequency increases as markets open in New York, but more importantly the opening of markets in New York may increase the number of potential counter-parties. This possible increase in counter-parties may have a larger impact than can be captured by our smoothing process.

In our model, we include dummy variables to capture the effect of peak trading hours. Three time dummies are defined (one for each stage through the peak trading hours) such that the dummy takes on a value of 1 if a trade occurs in the respective period and 0 otherwise:

$d_1 = 1$ if the transaction occurs between 8:00 to 10:00 (GMT), $d_1 = 0$ otherwise

$d_2 = 1$ if the transaction occurs between 10:00 to 12:30 (GMT), $d_2 = 0$ otherwise

$d_3 = 1$ if the transaction occurs between 1:00 to 4:00 (GMT), $d_3 = 0$ otherwise

The autoregressive process for limit orders, ψ_i^+, with the time dummies incorporated is given by

$$\psi_i^+ = \left(\omega_1 + \alpha_1\varepsilon_{i-1}^+\right)I_{i-1}^+ + \left(\omega_2 + \alpha_2\varepsilon_{i-1}^+\right)I_{i-1}^- + \beta^{lmt}\psi_{i-1}^+ + \theta_1^{lmt}d_1 + \theta_2^{lmt}d_2 + \theta_3^{lmt}d_3 \quad (12)$$

where d_1, d_2 and d_3 are the qualitative variables which stand for the opening of the London market, the time period before the opening of the New York market and the time during the opening of the New York market respectively. The coefficients for limit orders are given by θ_1^{lmt}, θ_2^{lmt} and θ_3^{lmt}. Similarly, the autoregressive process for market orders with time dummies is

$$\psi_i^- = \left(\omega_3 + \alpha_3\varepsilon_{i-1}^-\right)I_{i-1}^+ + \left(\omega_4 + \alpha_4\varepsilon_{i-1}^-\right)I_{i-1}^- + \beta^{mkt}\psi_{i-1}^- + \theta_1^{mkt}d_1 + \theta_2^{mkt}d_2 + \theta_3^{mkt}d_3 \quad (13)$$

where θ_1^{mkt}, θ_2^{mkt} and θ_3^{mkt} are the coefficients of the time dummies when the transaction is a market order. By examining the θ's in equations (12) and (13), we can determine whether the order submission process of the two order types responds symmetrically to the peak trading hours. Even though several studies suggest that the time of day, especially the opening and closing of markets, influence trading and quoting strategies, few studies have considered it. It has potentially significant implications for the order type decision which have not been distinguished before. If we find that the peak trading hours impose asymmetric effects on the two order types, then work which does not distinguish between the two order types is not accurately adjusting for intraday seasonalities and estimation is no longer efficient.

4. Data

The data we use is for the Deutsche Mark - US dollar exchange rate and comes from the Reuters D2000-2 system. This system is an electronic brokerage system for foreign exchange transactions. Traders submit prices at which they would be willing to buy and sell a certain quantity of Deutsche Marks for US dollars. The data set covers trading activity in the electronic broker market from the evening of the 5th of October to midnight on the 10th of October 1997. The data set includes the price at which the submitter stands ready to buy or sell a set quantity of the currency, the exact time it arrived, whether the quote is a limit order or market order, whether the quote is bid side or ask side initiated, the entry and exit time of the quote, and the quantity to be traded. Although this data only covers the electronic broker market and not the interdealer market, the broker market has more transparent information flow than the direct interdealer market. The price, type of order and quantity submitted are observable by all market participants in this market whereas they are not in the interdealer market.[6] In the inter-dealer market traders contact other traders directly to arrange the transaction price and quantity. As a result little is known about these trades (notable exceptions being Lyons (1995), and Yao (1998)).

One of the most significant reasons we use the foreign exchange market is that it is the largest financial market in the world with trade occurring twenty-four hours a day. This limits problems due to illiquid trading, information asymmetries and errors in the measurement of microstructure characteristics. Finally it allows us to study how the supply and demand for a highly liquid asset develop over the trading day as liquidity increases and decreases with the opening and closing of different markets. Overall our data set consists of 130,526 submitted quotes and 63,617 trades. Of all of the submitted quotes, about one sixth are market orders and the rest are limit orders. The median time that a market order stays in the market till execution is much shorter than a limit order (0.06 seconds versus 12.15 seconds, respectively) and the variance is also much lower (0.002 versus over 960,000 seconds, respectively) since a market order is executed immediately. Although the time to execute an order is an interesting topic, this paper does not study the timing of orders being completed. Our focus is on the arrival process of

[6] Its relative importance is also increasing over time. In 1997 about 30 percent of all UK and US trading volume and 37 percent of all Japanese trading volume was conducted using electronic brokers (BIS (1998)) and by 2001 this had increased to over 67%, 54% and 48% respectively (BIS (2002)).

orders which according to Easley and O'Hara (1992) conveys information to market participants about the underlying state of the market.

The summary statistics for submitted quotes, trades, market orders, limit orders and their duration (defined as time elapsed between quote/trade in seconds) are given in Table 1. The average time between quotes is about 3.4 seconds and, not surprisingly, the time between trades is longer at 6.8 seconds. The variance of the time between trades is almost an order of magnitude larger suggesting that there are periods where there is a large time between trades but traders may still be submitting quotes. The average duration of a market order is much longer than a limit order (20.2 versus 4.8 seconds, respectively) and the variation of durations for market orders is much higher (almost twenty times larger) than that of the limit order.

Figure 1 shows the frequency[7] of quotes, trades, market orders and limit orders with a day divided into 48 time bins. Before 7:00 (GMT) and after 20:00 (GMT), intensities of all variables are very low. The market is most active from 8:00 (GMT) to 10:00 (GMT), dips from 10:30 to 12:30, and becomes active again during the opening hours of the London market around 13:00. Figure 2 shows the average waiting time until the next quote, trade, limit order and market order. For all the variables, the average duration is quite long before the opening of the London market. The average duration then shortens considerably after 7:00 (GMT) and remains so throughout the day, until just before the closing of the New York market. The average duration is longest after the closing of the New York market at 21:00 (GMT).

5. Results

In our analysis the observations from the 5th of October are used as the initial observations. We define "the arrival process of price" or "the price process" as the arrival of trades where a trade occurs once the cumulative price change (the threshold) between consecutive trades is at least 0.0001. As discussed in Bauwens and Giot (2001), there are a couple of reasons for thinning the trade process in this fashion. The first is that a thinned trade process, as shown in Engle and Russell (1998), is closely related to the instantaneous volatility which is discussed below. Second a thinned trade process allows microstructure variables to be more meaningfully defined by decreasing the impact of outliers on estimation results. Take average volume as an example. For the unthinned trade process, the average volume at time t is just the volume traded at time t. For the thinned process, trades are spaced by the cumulative price change so the

[7] The frequency of the quotes, trades, limit orders and market orders are created by averaging the number of observations for each variable falling into a particular time bin during the 5 trading days in the dataset.

number of trades occurring between observations can be larger than zero. Thus the average volume is the mean volume traded between observations, not just the volume traded at time t.

The summary statistics of the thinned trade process – the price at which trade occurs, the duration (time between trades) and the volume traded – are given in Table 2. Although the number of quotes is decreased substantially by the thinning process, the characteristics of the prices after thinning are close to the original. This is because the range of changes in price is relatively narrow and thus thinning does not greatly affect the characteristics of the traded prices. Not surprisingly the mean duration of the thinned trade process is longer and the variation is larger than for the raw data from Table 1. Figure 3 shows how closely the average frequency of thinned trades is to that of the original trade process. However, the interpretation is quite different: the frequency of thinned trades indicates the average number of trades for a given change in price, which implies the rate of price change. Thus prices are more volatile as more orders are submitted where the patterns of volatility closely follow the intensity of trading. Figure 4 shows the average duration of the thinned trade process. Since the change in price between two observations must be at least 0.0001, the average duration of the thinned trade process is longer than for the original price process as we had seen in Table 2. This figure also highlights that this pattern is stable over the entire trading day.

To understand how the different types of orders influence the trade process, we start with our basic model and use this to formally investigate many hypotheses below.

A. Basic Model

Table 3 shows the results for the estimation of our most basic model. We use this model to determine whether the order submission process is different for market and limit orders. Looking at the results in Table 3 we see that the ω-coefficients related to the previous limit order, ω_1 and ω_3, are significantly negative. This implies that (i) market participants place orders more intensively in response to previous limit orders and (ii) a previous limit order induces a more rapid price change for both order types. Thus our results are consistent with Foucault (1999) who conjectures that limit orders are related to asset volatilities. Another interesting result is that the market order submission decision only appears to be affected by lagged limit orders – the ω coefficient related to lagged market orders, ω_4, is not significantly different from zero. Turning to the ARCH effects, the α's are all significantly positive indicating that the size of the previous disturbance, independent of the lagged order type, lengthens the expected duration for all order types. Because of the differences in how previous limit or market orders influence the expected duration of the subsequent order, it would appear that using a symmetric model which does not allow for these differences would lead to model misspecification and inconsistent estimates.

To formally investigate if market orders and limit orders have different effects on the arrival of the next trade, we compare the results from restricted models to those from the basic unrestricted model in Table 3. We first investigate if market orders and limit orders have the same effect on the arrival of the next trade. A market order and a limit order have the same effect on the arrival of the next trade if all the parameters in their autoregressive process are the same. If the two types of orders have the same autoregressive process, then the density function can be simplified to the symmetric log-ACD model first estimated by Engle and Russell (1997) and used in many subsequent studies. In the symmetric model the order type plays no role in the arrival process of trade. The null hypothesis is thus given by

$$H_0 : \omega_1 = \omega_2 = \omega_3 = \omega_4,\ \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4,\ \beta^{lmt} = \beta^{mkt}\ and\ \gamma^{lmt} = \gamma^{mkt} \tag{14}$$

The hypothesis is tested via the likelihood ratio test. The constrained model is a model with the above restrictions imposed, so the corresponding test statistic follows a χ^2 distribution with 8 degrees of freedom. The test statistic is 6,534 which is highly significant so the hypothesis is rejected at all reasonable significance levels (Note: to conserve space we only present the null hypothesis and the value for the corresponding likelihood ratio test). This indicates that the conditional expected duration is different across order types.

Next we ask the question: do market participants extract information from the order type of the last trade? If they do, then the previous order type plays a role in the timing of the present trade. Formally, we investigate whether the expected duration depends on the previous order type by investigating whether the expected duration's autoregressive process for each order type is a function of the previous type of order. The effect of the previous order type is the same if the transition parameters in our autoregressive process are equal so our null hypothesis is

$$H_0 : \omega_1 = \omega_2,\ \omega_3 = \omega_4,\ \alpha_1 = \alpha_2\ \ and\ \ \alpha_3 = \alpha_4 \tag{15}$$

The likelihood ratio test statistic takes a value of 36, which means the null is rejected. This indicates that the conditional expected duration of a trade occurring is dependent on the previous type of order submitted. For market participants, the trading decision and the type of order submitted therefore depend on of the type of the last order submitted. The type of orders submitted in the past do contain information important to traders as suggested by the microstructure literature. Specifically if the previous order was a limit order the duration decreases for the next order, whether it is a market or limit order but there is little influence if the previous order was a market order. Traders may believe the volatility is liquidity driven so they persist in submitting limit orders until the short-term volatility decreases and it is no longer profitable to submit limit orders.

Building on the previous results, we examine the persistence of the expected duration for the two types of orders. In Table 3 we see that the t-statistics of both β^{lmt} and β^{mkt} are significant and the values for each β^{lmt} and β^{mkt} are above 0.9. This indicates the presence of strong autoregressive effects. We next investigate whether the autoregressive effects in expected duration are the same for market orders and limit orders. The null hypothesis is therefore

$$H_0 : \beta^{lmt} = \beta^{mkt} \tag{16}$$

The likelihood ratio test has a test statistic of 2.4 and thus cannot be rejected at conventional levels of significance. This indicates that the degree of autocorrelation is the same for both types of process, so there is a strong and similar persistence in duration across both processes. Consequently the patterns which favor the submission of one type of order over another appear to persist over time and the nature of this persistence appears to be similar across order types. We also estimated a model for which β^{lmt} and β^{mkt} are allowed to differ for lagged limit and market orders in the expected conditional duration of each order type but, not surprisingly, we did not find significant differences.

To investigate whether there are differences in other characteristics of the distribution across order types, we study the Weibull parameters, γ^{lmt} and γ^{mkt}, because they are related to the hazard of the trade process, x_i. We first check whether the Weibull parameters are less than 1. A Weibull parameter less than 1 means that the hazard is decreasing. For both order types the estimated coefficients are statistically less than 1 and statistically greater than 0. As a result, conditional on the present state, y_i, the hazard function of x_i is decreasing. The implication is that the longer the period without a price change, the less likely a trade will occur instantaneously. Since it is possible that the decreasing likelihood of a trade occurring is dependent on the type of order, we investigate whether limit orders and market orders have the same Weibull parameters. Beyond the importance for understanding how the hazard process depends on the submission of different types of orders, the issue is important because if

$$\gamma^{lmt} = \gamma^{mkt} = \gamma \tag{17}$$

then, as shown in Bauwens and Giot (2000), the marginal distribution of x_i follows a Weibull distribution with parameters γ and $\left[\left(\Psi_i^+\right)^{-\gamma}+\left(\Psi_i^-\right)^{-\gamma}\right]^{1/\gamma}$. The hazard of x_i can be simplified

$$h(x_i \mid F_{i-1})=\gamma\left[\left(\Psi_i^+\right)^{-\gamma}+\left(\Psi_i^-\right)^{-\gamma}\right]^{1/\gamma}\left(x_i\left[\left(\Psi_i^+\right)^{-\gamma}+\left(\Psi_i^-\right)^{-\gamma}\right]^{1/\gamma}\right)^{\gamma-1} \tag{18}$$

The likelihood ratio test, with equation (17) as the null hypothesis, has a test statistic of 0.4 so we can not reject this null hypothesis. Thus the Weibull parameters appear to be the same for both market orders and limit orders. This means that the relationship between price changes and trade occurring influences the traders' decision between submitting limit or market orders in a similar manner after considering the previous types of orders that were submitted.

We now examine the instantaneous volatility implied by the asymmetric ACD model. Engle and Russell (1997) showed that the instantaneous volatility is related to the threshold of price change, c, by the following equation

$$\sigma^2=\frac{c^2}{E[x_i \mid H_{i-1}]^2} \tag{19}$$

To understand the potential differences played by the different types of orders we compare the instantaneous volatility of the symmetric and asymmetric models. The equality of γ^{lmt} and γ^{mkt} simplifies the analysis so we can back out the conditional expectation of x_i under the asymmetric ACD model from equation (18) using

$$E[x_i \mid H_{i-1}]=\left[\left(\Psi_i^+\right)^{-\gamma}+\left(\Psi_i^-\right)^{-\gamma}\right]^{1/\gamma} \tag{20}$$

The value of γ in the asymmetric model is set to 0.77 from Table 3. For the resulting symmetric log ACD model, the conditional expectation of x_i is given by

$$E[x_i \mid H_{i-1}]=\Psi_i=\exp(\omega+\alpha\varepsilon_{i-1}+\beta x_{i-1}) \tag{21}$$

Table 4 shows the estimates of the symmetric model. The unit of σ for both models is adjusted from per second to percent of annual standard deviation. Table 5 compares different characteristics of the σ from both models. Both the mean and the variance of the instantaneous volatility of the asymmetric ACD model are 12% higher than for the symmetric ACD model. Figure 5 shows that the average volatility is highest between 13:00 (GMT) and 19:00 (GMT) for both models. This suggests that the most new information is flowing into the market when both the European and North American markets are open. Because the average volatility of the asymmetric model is uniformly higher than that of the symmetric model, it suggests that there is differential information incorporated into the limit and market orders. Consequently if the arrival process is estimated without allowing for differences across order types, we will underestimate the instantaneous volatility and not capture the most information possible. It therefore appears that the amount of information and the nature of volatility characterizing market and limit orders are different as hypothesized by many of the market microstructure models discussed earlier.

We lastly examine the performance of the model in terms of estimating the probability a dealer will submit a market order or limit order. We do this to compare our findings with those from the existing studies in this area. The main difference is that our analysis does not require the aggregation of observations into a fixed interval as is done in those studies. As shown in Bauwens and Giot (2000), the transition probability of y_i, the type of order, is independent of x_i if $\gamma^{lmt} = \gamma^{mkt}$. The transition probability of y_i is given by

$$f(y_i \mid H_i) = \frac{\left[\frac{\gamma^{lmt}}{\Psi_i^+}\left(\frac{1}{\Psi_i^+}\right)^{\gamma^{lmt}-1}\right]^{I_i^+}\left[\frac{\gamma^{mkt}}{\Psi_i^-}\left(\frac{1}{\Psi_i^-}\right)^{\gamma^{mkt}-1}\right]^{I_i^-}}{\frac{\gamma^{lmt}}{\Psi_i^+}\left(\frac{1}{\Psi_i^+}\right)^{\gamma^{lmt}-1}+\frac{\gamma^{mkt}}{\Psi_i^-}\left(\frac{1}{\Psi_i^-}\right)^{\gamma^{mkt}-1}} \tag{22}$$

Table 6 shows the summary statistics of the estimated probability of having a limit order and market order submitted. The sample mean of the transition probability of limit orders is 0.749 and for market orders is 0.252. The sample means are quite close to their empirical values: the proportion of limit orders and market orders are 0.750 and 0.250 respectively. To determine the role played by our factors in explaining the quote arrivals, we compare the conditional probability distribution of market orders and limit orders to the actual values through an average trading day. Figure 6 shows the difference in estimated and empirical probabilities of the two types of orders. The difference between estimated and empirical probabilities is relatively small during active trading hours. Divergence concentrates in the periods when both the London and New York markets are closed. It is also important to note the differences in Figure 6 across market and limit orders. The differences are most concentrated immediately before and after market openings and closings. This suggests that market depth across the trading day influences the order submission decision and simple models which do not account for these differences do not perform as well at predicting the arrival of limit and market orders. We investigate this in more detail below.

B. Model with Microstructure Variables

Table 7 shows the results for the unconstrained model including all of our microstructure variables. To understand how these different microstructure characteristics influence order submission process and the occurrence of trades, we examine the model under various parameter restrictions. The restrictions or hypotheses are designed to investigate whether quote intensity, average volume, market imbalance and spread in the previous period convey information to market participants and thus affect the arrival and type of the next trade. We also examine a model in which the influence of the microstructure variables on the order submission process is impacted by the order type in the previous period (i.e. the microstructure variables play a role in the transition density).

We first investigate whether the microstructure variables explain the expected duration of the price process given the type of order. To do this we test whether the microstructure variables are jointly significant using equations (10) and (11). That is, we test the null hypothesis

$$\xi_{t\,\mathrm{int}}^{lmt} = \xi_{vol}^{lmt} = \xi_{imb}^{lmt} = \xi_{spr}^{lmt} = \xi_{q\,\mathrm{int}}^{mkt} = \xi_{vol}^{mkt} = \xi_{imb}^{mkt} = \xi_{spr}^{mkt} = 0 \qquad (23)$$

The constrained model is the basic model described in Section 3 using the autoregressive processes defined in equations (5) and (6) and with results in Table 3. The likelihood ratio test statistic is 25.8, which is significant under $\chi_{(8)}^2$. Thus the four microstructure variables - average volume, quote intensity, market imbalance and spread– jointly have explanatory power in the arrival process of trades so market participants do appear to extract information from these variables in submitting their order.

We examine which of our set of four microstructure variables are valued by market participants by examining the t-statistic of the estimated coefficients on each variable. We will look at the two types of order separately. For limit orders, the coefficients for quote intensity, average volume and market imbalance all have the expected sign – they are all negative. Also the t-statistics for spread and market imbalance are significant at the 5% level while that of average volume and trade intensity are marginally significant at the 10% level. As discussed before, quote intensity proxies for the arrival rate of information in the market, average volume of trades proxies for market depth, market imbalance proxies for potential price uncertainty and market depth due to liquidity on only one side of the market and spread proxies both market depth and uncertainty. Consequently our results show that market participants submitting limit orders trade more intensively with increased information arrival, deeper markets, more liquidity on one side of market and less market uncertainty. The market imbalance result suggests that limit orders also provide a protective role[8]. Thus these four variables reduce the expected duration of the arrival of

[8] In results not presented, we investigate the differential impact of imbalances in which the depth is on the ask-side of the market versus on the bid-side of the market. The results were symmetric for market orders,

the next trade for trades based on limit orders. In the context of volatilities, the four microstructure variables lead to a more rapid price change in traded limit orders. These results are consistent with much of the microstructure literature suggesting limit orders are used during periods of increased volatility and uncertainty.

For market orders, only the average volume is significantly different from zero – it is smaller than zero. The absolute magnitude of the coefficient ξ_{vol}^{mkt} is nearly four times greater than ξ_{vol}^{lmt}. As a result the average volume traded shortens the expected duration of market orders more than that of limit orders. Thus our results are consistent with the conjecture of Admati and Pfleiderer (1988) among others that market participants submit market orders more intensively when there is a larger trading volume. The intuition of the result is that the immediacy of trade is important for market orders. As the volume transacted increases, the probability that an order will be filled immediately rises, so the volume transacted is important information for traders who need to trade immediately. This shortens the expected duration and thus the price risk for trades conditional on a market order.

Finally, we explore whether the expected duration reacts differently to the microstructure variables depending on the lagged order type by including them in the transition density for the different previous order types along with ω and α. This is important because it sheds light on how the previous order type carries information related to the microstructure variables. In this way, we can examine issues such as: what happens to the expected duration of a limit order/market order if the previous order was a limit order/ market order and the market depth / market imbalance / quote intensity increased? The corresponding autoregressive process we study conditional on limit orders, ψ_i^+, is given by

$$\psi_i^+ = \left(\omega_1 + \alpha_1 \varepsilon_{t-1}^+ + \zeta_1 z_{t-1}\right) I_{t-1}^+ + \left(\omega_2 + \alpha_2 \varepsilon_{t-1}^+ + \zeta_2 z_{t-1}\right) I_{t-1}^- + \beta^{lmt} \psi_{t-1}^+ \qquad (24)$$

in which $\zeta = (\zeta_{tint}, \zeta_{vol}, \zeta_{imb}, \zeta_{sprd})'$ and z represents the microstructure variables $z_{t-1} = (qint_{t-1}, vol_{t-1}, imb_{t-1}, sprd_{t-1})$. Similarly, the autoregressive process conditional on market orders is given by

$$\psi_i^- = \left(\omega_3 + \alpha_3 \varepsilon_{t-1}^- + \zeta_3 z_{t-1}\right) I_{t-1}^+ + \left(\omega_4 + \alpha_4 \varepsilon_{t-1}^- + \zeta_4 z_{t-1}\right) I_{t-1}^- + \beta^{mkt} \psi_{t-1}^- \qquad (25)$$

First, we test whether the microstructure variables appear to interact with the type of order by imposing the following constraints

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but the duration of limit orders decreased slightly as the number of ask orders exceeded the number of bid orders. This suggests a further difference in the order submission decision for market and limit orders.

$$\zeta_1 = \zeta_2, \ \zeta_3 = \zeta_4 \tag{26}$$

The two constraints impose symmetric microstructure effects on the two types of orders. The constrained model in this case is the model originally proposed in Section 3B. The value of the test statistic is 16, which is rejected at the 5% significance level. The effect of microstructure variables on expected duration and thus the rate of price change are therefore dependent on the previous type of order.

Next we investigate how microstructure variables interact with the previous order type in determining the expected duration and rate of price change (Table 8). We start by considering the autoregressive process for limit orders. For all of the estimated coefficients on the microstructure variables in the autoregressive process of limit orders, except for the spread, the t-statistics of the ζ_1 coefficients (the coefficients of the microstructure variables with the lagged limit orders) are all statistically significant and negative while those of the ζ_2 coefficients (the coefficients of the microstructure variables with lagged market orders) are not significant. Consequently with increasing trade intensity, market imbalances and volume traded, the expected duration is significantly shorter with a previous limit order but the expected duration does not respond to the microstructure variables with a previous market order. The implication is that market participants value information from these microstructure variables only if the previous order (the lagged order) was a limit order. These results indicated that limit orders are more actively submitted as market conditions are changing and previous limit orders contain valuable information for traders. Interestingly, the estimated coefficient for the spread is marginally significant at the 10% level with a previous market order but not significant with a previous limit order. This suggests that an increase in market uncertainty and the presence of a previous market order (which indicates a preference for rapid execution) signal possible changes in the underlying state so dealers place limit orders to protect their positions. Thus our results extend the empirical literature in an important dimension: previous literature (e.g. Biais, Hillion and Spatt (1995), Ahn, Bae and Chan (2001) and Bauwens and Giot (2000)) did not specify how market participants value information carried by the different order type and which order types carry information. We find that traders submit limit orders more intensively with more rapid information arrival, deeper markets and more liquidity on one side of the market along with a previous limit order. They also submit limit orders more rapidly when market uncertainty increases, especially following the earlier submission of market orders.

For the autoregressive process of market orders, the expected duration responds only to the average volume when there was a previous limit order: it is significantly shorter when lagged market depth increased and the previous order was a limit order. The expected duration of the market order does not appear to be influenced by the other microstructure variables. Thus it appears that market participants place market orders more intensively when the lagged market depth increases following the submission of limit orders which would also increase market liquidity. As a consequence it appears the lagged limit orders carry more information than lagged market orders. Unlike market orders which can arise out of liquidity needs, limit orders represent a willingness to trade at a specific price and traders can withdraw limit orders as market conditions change. Thus the existence of limit orders reflects a different willingness to trade and a different relationship between demand and market conditions. This information is valuable for the dealers' trade submission decision: the presence of limit orders reflects how market participants are interpreting current and future market conditions as captured by the microstructure variables.

C. Model with Time Effects

We first examine whether there is a time effect after removing the intraday seasonality. The existence of time effects are tested based on equations (12) and (13) with the hypothesis

$$\theta_1^{lmt} = \theta_2^{lmt} = \theta_3^{lmt} = \theta_1^{mkt} = \theta_2^{mkt} = \theta_3^{mkt} = 0 \qquad (27)$$

The likelihood test statistic has a value of 31.6 which rejects the null hypothesis. This suggests that time effects persist even after scaling the data to remove the time-of-day effect. Consequently it appears that peak trading hours, like the microstructure variables, carry information about the arrival of the next trade even after adjustment for time-of-day effects. A possible explanation for this would be the increase in the number of possible counter-parties as markets open over the day. This increases the depth of the market more than the time-of-day effects or other measures of market depth can capture.

To better understand the source of this result, we investigate the influence of each of the time dummies for the two types of orders (Table 9). For market orders, the time effects for the hours before and after the opening of New York market are statistically smaller than zero. This suggests an increase, or an expectated increase, in market depth at these times which would facilitate the execution of market orders. Thus consistent with our conjecture, the opening of the New York market shortens the price process's expected duration conditional on a market order. These time dummy variables, like the average volume between durations, proxy for market depth.

For the autoregressive process of the limit order, the time effects are evident only for the opening of the London market and the time before the opening of the New York market. Their t-statistics are significantly different from zero. The estimated coefficient corresponding to the opening of the New York market is very small and is not statistically different from zero.

D. Model with all Explanatory Variables incorporated

The final stage of our analysis is an estimation of model incorporating our microstructure variables and the qualitative variables for different trading periods[9]. The model serves as a robustness check for the results from the previous models since it is possible that some of these factors are measuring similar effects. The results are presented in Table 10 and generally confirm the findings from the previous, individual models. For limit orders, trade intensity and market imbalance impose a significantly negative impact on the arrival of limit orders while bid ask spread also has a marginally significant negative effect on limit order arrival process. For market orders, we find that lag market orders lengthen the expected duration of the next market order arriving at the market. The coefficient ω_3, which is the effect of a lag market order on the market order arrival process, is significantly positive. One possible explanation is that a lag market order dries up the liquidity of the market and thus discourages traders from placing future market orders, at least until more limit orders have been placed. Another finding is that the arrival process of market orders responds only to volume traded. The expected duration of market order shortens significantly with an increase in market depth, confirming the results in the microstructure variables model. The last finding is that, as in the time effect model, market orders arrive more rapidly before and after the opening of the New York market. The finding gives a clearer picture of the role played by the New York market: in this model, the variable traded volume already captures the effect of a deeper market. Thus it seems that the role of New York market lies in introducing more counter parties, which makes meeting matching trades easier.

6. Conclusion

We examine the impact of various factors on the market order and limit order submission process and investigate this question in the context of firm quotes in the foreign exchange market. Because of the potential differences in the characteristics of the submission process across order types and the irregular timing of order submissions and thus trades, we use the asymmetric log ACD model to analyze our data. We find that, conditional on the type of order, the expected duration until the arrival of the next quote (or trade) is dependent on the previous type of order that was submitted. As a consequence ignoring the type of orders submitted in the past may lead to a misspecification of the order submission process and similarly of the price formation process,

[9] For tractability the observations from 20:00 (GMT) to 6:00 (GMT) were removed. This exclusion dramatically decreases the time to convergence for these complex models and the results are robust to the inclusion or exclusion of these observations.

so estimation would no longer be consistent and measures such as the implied volatility would also be underestimated.

Extending our study to consider how the trading process depends on microstructure factors found to influence trading strategies in previous empirical and theoretical microstructure studies, we find that the expected duration differs across limit and market orders. Market orders react only to the average volume, a proxy of market depth, whereas limit order submissions are sensitive across several different measures of market depth and market uncertainty. We are able to see this more clearly than in other studies in the literature because previous studies tend to focus on one type of order or the other, do not distinguish between the two types of order or do not allow for the irregular spacing between quotes. Interestingly we also find that market participants' valuation of the information carried by microstructure variables is affected by the lagged order type. Information related to the microstructure variables carried by lagged limit orders appears to be more relevant than that carried by lagged market orders.

Since a common explanation for certain unusual findings in market microstructure studies is the time of day relative to the opening and closing of the market, the final stage of our study is to explicitly investigate how the opening and closing of different markets influences the order type decision. Unlike studies considering domestic equity markets, we are able to extensively study this because we are using twenty-four hour trading data from the foreign exchange market. Using time dummies for peak trading hours around the opening of the London and New York markets we find an impact on the expected duration of market orders even after the standard practice of adjusting the intraday seasonalities. The periods before and after the opening of the New York market act as proxies for market depth and significantly shrink the expected duration of market orders as the New York market increases its involvement in the market. We find little significant impact on limit orders except that there is a slight increase in activity and thus a decrease in duration before the opening of the London and New York markets. These findings suggest that traders expect an increase in informed trading at and immediately following the opening of these markets.

Having seen how the order type choice and trading process interact, one can start to extend the models we have considered to test a wider range of theoretical microstructure models. Our goal was to investigate some of the differences in market and limit orders based on the most widely known studies in the empirical and theoretical market microstructure literature. Having highlighted some of the areas where the order submission process is different across order types as well as where they are similar, further research can take this model and extend it to consider other hypotheses and use more general distributions for the random error.

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Table 1: Summary Statistics of Quote, Trade, Limit Order and Market Order

This table provides summary statistics describing the price and duration for both quotes and trades from the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997. Price is in Deutsche Marks per US dollar and duration is the time between the arrival of quotes and trade. For duration, the units of measurement are in seconds.

	quote price	Quote duration	trade price	trade duration	market order price	market order duration	limit order price	limit order duration
mean	1.75	3.35	1.75	6.77	1.75	20.21	1.75	4.7540
variance	0.0001	1,197.27	0.0001	9,763.52	0.0001	32,962.81	0.0001	1,696.35
median	1.75	0.99	1.753	1.59	1.75	3.9	1.75	1.15
max	2	5,367.57	1.77	10,390.27	1.77	12,729.22	2	5,367.57
min	1.70	0.01	1.73	0.01	1.73	0.01	1.70	0.01

Table 2: Summary Statistics of the Thinned Trading Process

This table provides summary statistics of the thinned trading process. This includes the duration, prices and volume of trade. The trade process is thinned such that the change in price between successive observations is at least 0.0001. Duration is the time between the arrival of trades with prices that differ by at least 0.0001. Price is the quoted price at which the exchange of currencies is executed. Volume is the transacted volume associated with the price process.

	duration	price	volume
Mean	17.3852	1.7505	1.7743
Variance	30,821.3	0.0001	1.9416
median	3	1.751	1
Max	10,472	1.7699	28
Min	0.01	1.7318	1

Table 3: Asymmetric Log- ACD Model

Maximum likelihood estimates of the asymmetric log-ACD models of duration. The model estimated is equation (5) and equation (6) using the data from the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997.

	Coefficient	Std Error	t-test
ω_1	-0.0201	0.0047	-4.2473
ω_2	-0.0630	0.0100	-6.2937
α_1	0.0876	0.0046	18.8789
α_2	0.0741	0.0095	7.8397
β_{lmt}	0.9656	0.0031	313.1685
γ_{lmt}	0.7677	0.0044	175.8330
ω_3	-0.0478	0.0121	-3.9381
ω_4	0.0031	0.0207	0.1472
α_3	0.5421	0.0406	13.3502
α_4	0.3643	0.0772	4.7171
β_{mkt}	0.9749	0.0048	203.8953
γ_{mkt}	0.7742	0.0076	101.7578
Likelihood	-58,297.7		

Table 4: Symmetric Log- ACD Model

Maximum likelihood estimates of the symmetric log-ACD models of duration. The autoregressive equation ψ_i is given by $\psi_i=\omega+\alpha\varepsilon_{i-1}+\beta x_{i-1}$ and the conditional duration is given by $\exp(\psi_i)$.

	Coefficient	Std Error	t-test
ω	-0.0280	0.0037	-7.6033
α	0.1609	0.0067	24.1328
β	0.9701	0.0025	383.3858
γ	0.7690	0.0038	203.1524
Likelihood	-61564.2		

Table 5: Statistics on Instantaneous Volatility

The table provides summary statistics of instantaneous volatility implied by the symmetric and asymmetric ACD model. Volatility is measured in annual standard deviation (%).

	Asymmetric ACD	Symmetric ACD
mean	33.5520	21.3558
variance	53.1133	21.4154
max	61.2224	38.8812
min	10.1015	6.4978

Table 6 Summary Statistics of Estimated Probability of Limit Order and Market Order

This table provides summary statistics of the percentage of all orders placed that are limit and market orders in each 30 minute bin.

	Limit order	Market order
Mean	74.8%	25.2%
Variance	0.0004	0.0004
Max	85.5%	33.8%
Min	50.0%	18.1%

Table 7: Asymmetric Log- ACD Model with Microstructure Variables

This table contains the maximum likelihood estimates of the asymmetric log-ACD models of duration. The model estimated is as in equation (10) and equation (11) using the data from the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997. This model corrects for some of the well-documented microstructure effects found in high-frequency studies in both equity and the foreign exchange markets. The variables used are quote intensity between trades, average volume between trades (equation (8)) and market imbalance between trades (equation (9)).

	coefficient	Std Error	t-test
ω_1	-0.0058	0.0083	-0.6975
ω_2	-0.0504	0.0120	-4.1862
α_1	0.0878	0.0047	18.7147
α_2	0.0730	0.0094	7.7352
β_{lmt}	0.9654	0.0031	313.8575
γ_{lmt}	0.7679	0.0044	175.8234
ζ^{lmt}_{imb}	-0.0047	0.0023	-2.0716
ζ^{lmt}_{qint}	-0.0478	0.0309	-1.5471
ζ^{lmt}_{vol}	-0.0095	0.0061	-1.5415
ζ^{lmt}_{sprd}	-0.0037	0.0021	-1.8111
ω_3	-0.0086	0.0190	-0.4545
ω_4	0.0477	0.0269	1.7761
α_3	0.5464	0.0412	13.2749
α_4	0.3636	0.0787	4.6194
β_{mkt}	0.9717	0.0050	192.5757
γ_{mkt}	0.7743	0.0076	101.7240
ζ^{mkt}_{imb}	0.0008	0.0041	0.1876
ζ^{mkt}_{qint}	0.0164	0.0615	0.2668
ζ^{mkt}_{vol}	-0.0386	0.0117	-3.2906
ζ^{mkt}_{sprd}	0.0047	0.0043	1.0958
likelihood	-58284.7962		

Table 8: Asymmetric Log- ACD Model with Asymmetric Effects of Microstructure Variables

This table contains the maximum likelihood estimates of the asymmetric log-ACD models of duration. The model estimated is as in equation (25) and equation (26) using the data from the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997. This model corrects for some of the well-documented microstructure effects found in high-frequency studies in the foreign exchange market. The variables used are quote intensity between trades (equation (7)), average volume between trades (equation (8)) and market imbalance between trades (equation (9)).

	coefficient	std	t-test
ω_1	-0.0058	0.0103	-0.5675
ω_2	-0.0458	0.0233	-1.9614
α_1	0.0869	0.0047	18.5106
α_2	0.0704	0.0092	7.6433
β_{lmt}	0.9652	0.0031	315.8003
γ_{lmt}	0.7680	0.0044	175.8029
ζ^1_{qint}	-0.0743	0.0176	-4.2309
ζ^2_{qint}	0.4031	0.3943	1.0223
ζ^1_{vol}	-0.0142	0.0071	-1.9925
ζ^2_{vol}	0.0054	0.0135	0.4027
ζ^1_{sprd}	0.0026	0.0057	0.4584
ζ^2_{sprd}	-0.0252	0.0168	-1.5015
ζ^1_{imb}	-0.0085	0.0029	-2.9582
ζ^2_{imb}	0.0014	0.0037	0.3797
ω_3	0.0042	0.0218	0.1944
ω_4	0.0026	0.0465	0.0557
α_3	0.5440	0.0405	13.4183
α_4	0.3524	0.0722	4.8792
β_{mkt}	0.9720	0.0049	198.4242
γ_{mkt}	0.7746	0.0076	101.6559
ζ^3_{qint}	0.0113	0.0619	0.1825
ζ^4_{qint}	0.1261	0.3027	0.4165
ζ^3_{vol}	-0.0528	0.0134	-3.9458
ζ^4_{vol}	0.0097	0.0256	0.3808
ζ^3_{sprd}	0.0044	0.0110	0.4004
ζ^4_{sprd}	0.0057	0.0320	0.1780
ζ^3_{imb}	0.0059	0.0053	1.1325
ζ^4_{imb}	-0.0083	0.0068	-1.2225
likelihood	-58276.8		

Table 9: Asymmetric Log- ACD Model with Time Dummies

This table contains the maximum likelihood estimates of the asymmetric log-ACD models of duration. The model estimated is as in equation (12) and equation (13) using the data from the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997. This model compensates for the differences in quoting intensity across the trading day by inserting time dummies in the peak trading hours. Trading level is low until the market in London opens and it peaks between 8:00 to 10:00 (GMT), it decreases somewhat between 10:30 and 12:30 (GMT) and peaks with the opening of the market in New York at 13:00 (GMT).

	Coefficient	Std Error	t-test
ω_1	-0.0166	0.0055	-3.0517
ω_2	-0.0625	0.0104	-5.9911
α_1	0.0873	0.0048	18.2554
α_2	0.0769	0.0097	7.9720
β_{lmt}	0.9627	0.0034	286.0924
γ_{lmt}	0.7681	0.0044	175.7491
$\theta_{lmt,1}$	0.0214	0.0091	2.3633
$\theta_{lmt,2}$	-0.0140	0.0071	-1.9747
$\theta_{lmt,3}$	0.0006	0.0077	0.0823
ω_1	-0.0278	0.0145	-1.9200
ω_2	0.0249	0.0234	1.0628
α_3	0.5332	0.0415	12.8379
α_4	0.3737	0.0831	4.4990
β_{mkt}	0.9688	0.0055	177.2440
γ_{mkt}	0.7751	0.0076	101.6357
$\theta_{mkt,1}$	0.0293	0.0179	1.6330
$\theta_{mkt,2}$	-0.0401	0.0144	-2.7812
$\theta_{mkt,3}$	-0.0335	0.0154	-2.1680
Likelihood	-58,281.9		

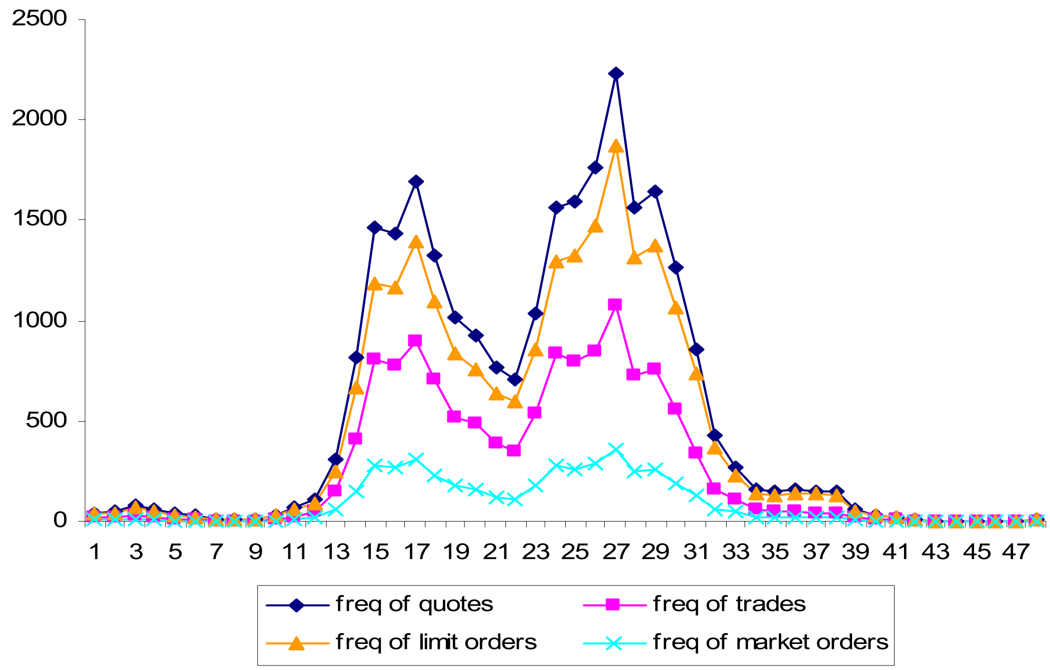
Table 10: Asymmetric Log- ACD Model with all Explanatory Variables

This table contains the maximum likelihood estimates of the asymmetric log-ACD models of duration. Using the data from the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997, this model incorporates both microstructure variables and time effects with overnight observations removed.

	coefficient	std	t-stat
ω_1	-0.0056	0.0089	-0.6341
ω_2	-0.0526	0.0127	-4.1336
α_1	0.0918	0.0050	18.4545
α_2	0.0773	0.0099	7.8429
β_{lmt}	0.9617	0.0034	282.8567
γ_{lmt}	0.7675	0.0044	174.1957
ζ^{lmt}_{qint}	-0.3379	0.1344	-2.5136
ζ^{lmt}_{vol}	-0.0077	0.0064	-1.2126
ζ^{lmt}_{sprd}	-0.1732	0.1166	-1.4848
ζ^{lmt}_{imb}	-0.0047	0.0024	-1.9868
$\theta_{lmt,1}$	0.0199	0.0095	2.0976
$\theta_{lmt,2}$	-0.0143	0.0075	-1.9062
$\theta_{lmt,3}$	-0.0006	0.0082	-0.0742
ω_1	0.0046	0.0201	0.2283
ω_2	0.0595	0.0279	2.1342
α_3	0.5256	0.0416	12.6288
α_4	0.3635	0.0790	4.6023
β_{mkt}	0.9680	0.0056	174.1359
γ_{mkt}	0.7773	0.0077	100.9604
ζ^{mkt}_{qint}	-0.0754	0.2605	-0.2895
ζ^{mkt}_{vol}	-0.0342	0.0118	-2.8978
ζ^{mkt}_{sprd}	0.2396	0.2346	1.0213
ζ^{mkt}_{imb}	0.0004	0.0042	0.0845
$\theta_{mkt,1}$	0.0279	0.0181	1.5381
$\theta_{mkt,2}$	-0.0387	0.0148	-2.6202
$\theta_{mkt,3}$	-0.0323	0.0158	-2.0518
likelihood	-57308.0997		

Figure 1: Frequency of Quotes, Prices (Trades), Limit Orders and Market Orders

This figure illustrates the frequency of quotes, prices (trades), limit orders and market orders based on the quotes submitted to the Reuters D-2002 electronic brokerage system for the week of October 6-10,1997. These are based on the consecutive 30 minute time bins across the twenty-four hour trading day.



<u>Figure 2: Duration (Arrival Process) of Quotes , Prices (Trades), Limit Orders and Market Orders</u>

This figure illustrates the duration of quotes, prices (trades), limit orders and market orders submitted to the Reuters D-2002 electronic brokerage system for the week of October 6-10,1997. Duration is defined as the time elapsed between quotes and trades. When the duration has a value of 1,800 seconds, it means either no trade occurs or the duration until next trade is longer than 1,800 seconds (the length of the 30-minute time bin). The observations are for the consecutive 30 minute time bins across the twenty-four hour trading day.

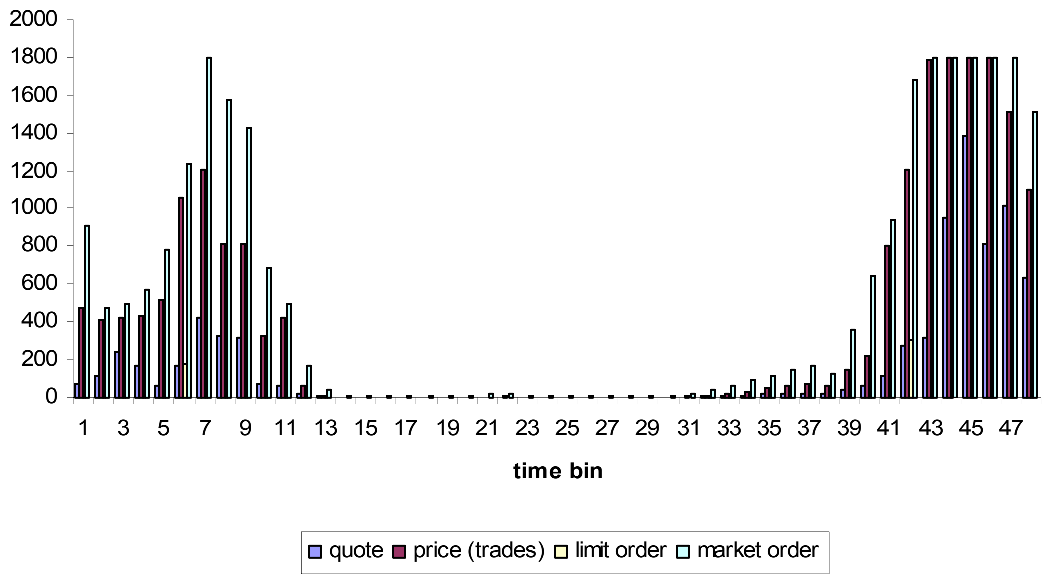


Figure 3: Frequency of Trades and Thinned Trades

This figure compares the frequency of all of the quotes submitted to the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997 to the quotes corresponding to the thinned trading process. The observations are for the consecutive 30 minute time bins across the twenty-four hour trading day.

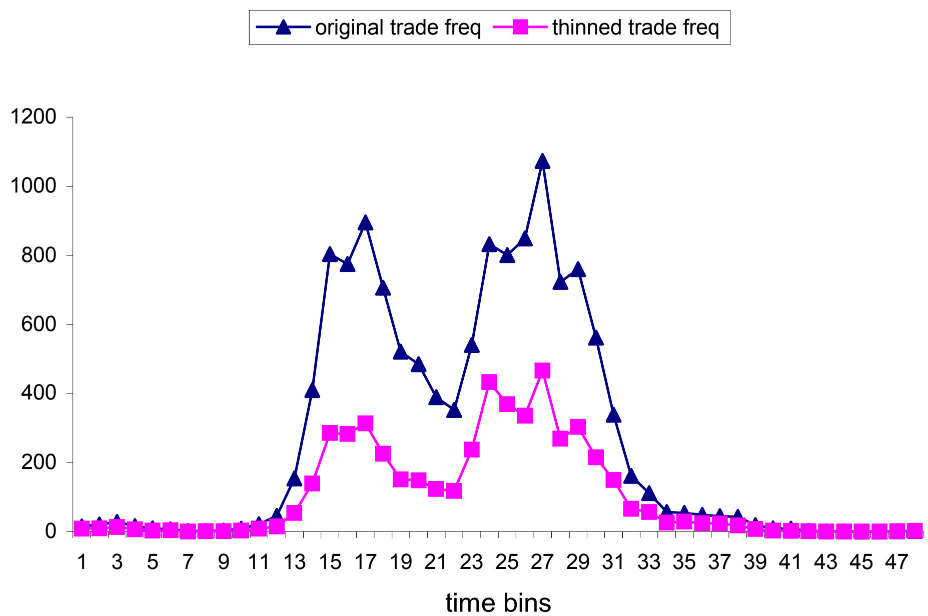


Figure 4: Duration (Arrival Process) of Trades and Thinned Trades

This figure compares the duration of all trades and of the trades in the thinned trading process from the quotes submitted to the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997. Duration is defined as the time elapsed between quotes and trades. For a duration hitting 1,800 seconds, it means that either no trade occurs or the duration until next trade is longer than 1,800 seconds. The observations are for the consecutive 30 minute time bins across the twenty-four hour trading day.

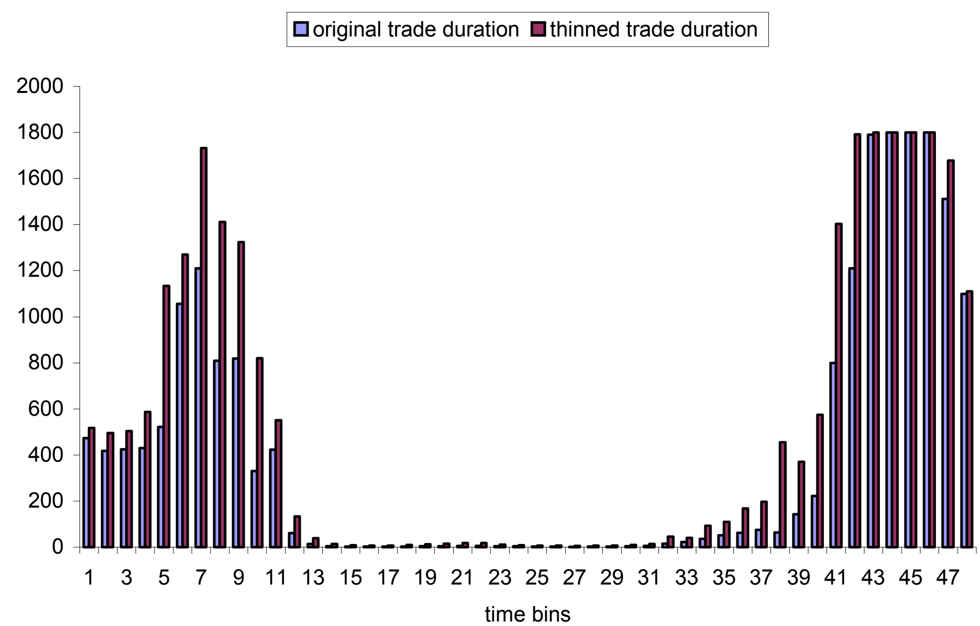


Figure 5: Average Instantaneous Volatility

This figure illustrates the average instantaneous volatility in a trading day implied by the symmetric ACD model and the asymmetric ACD model for the quotes submitted to the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997. The instantaneous volatility is presented in hours of the trading day.

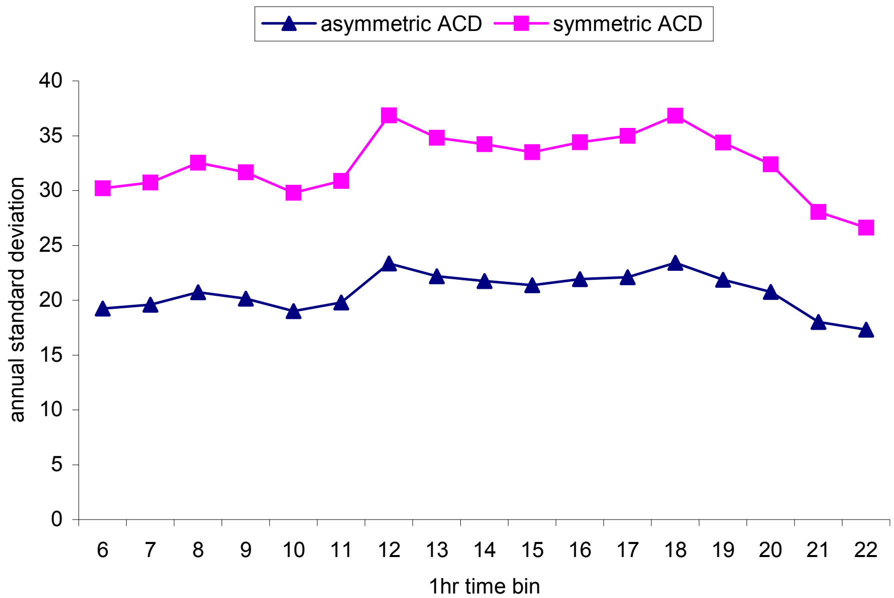


Figure 6: Difference in the Estimated and Empirical Probabilities of Limit Order and Market Orders

This figure shows the difference between the empirical and estimated distribution of the probability a submitted order was a limit order and market order for the quotes submitted to the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997. A day is divided into 24 time bins, each representing an hour of the day. The estimated probability is the sample mean of estimated probabilities within a particular hour.