The Choice of Direct Dealing or Electronic Brokerage in Foreign Exchange Trading

Michael Melvin*
Arizona State University

And

Lin Wen**
University of Redlands

Abstract

Central bank surveys indicate that the use of electronic brokerage systems account for the great majority of inter-dealer spot foreign exchange market trade execution. This share has grown from zero in the early 1990s and is up sharply from that reported in the surveys taken in 1998. While the surveys point out the rapid growth of electronic brokers as an important FX institution, there has been no research on the microstructure issues that lead traders to choose electronic brokerage (EB) over the historically dominant, and still quite relevant, institution of direct dealing where bilateral conversations (either telephone or electronic) occur between two FX traders and a deal is struck. We provide theory and empirical analysis to further our understanding of the choice of trading venue in foreign exchange.

Our theoretical model analyzes the choice of trading venue for "large" and "small" traders. The theory illustrates the importance of asymmetric information, transaction costs, and speed of execution. The most likely outcome has direct dealing used for large trades while the EB is used for small trades.

The empirical analysis utilizes data on orders submitted to the Reuters 2000-2 EB system. We focus on the duration of time between order submission and finding a match for trade execution. An autoregressive conditional duration (ACD) model is specified using the Burr distribution. Given the price competitiveness of an order, duration is increasing in order size. Because of this longer duration for large orders on the EB, large traders will prefer the direct dealing market to the brokerage. We also find that the greater the depth of the market, the shorter the duration of orders of all sizes. This result is consistent with traders clustering in time to submit orders so as to increase the probability of finding a match.

***W.P. Carey School of Business, Arizona State University, Tempe, AZ 85287-3806, mmelvin@asu.edu**
****Department of Business Administration, University of Redlands, Redlands, CA 92373-0999, lin_wen@redlands.edu**
We have benefited from the helpful suggestions of John Carlson, Hector Chade, Joachim Grammig, and Richard Lyons, and from comments received from seminar participants at Arizona State University, University of St. Gallen, and the Stockholm Conference on FX Microstructure.

December 2004

1. INTRODUCTION

One of the most dramatic shifts in the market structure of international financial markets has been the rise in the use of electronic brokerages to trade currencies. In the last triennial survey of foreign exchange trading taken in April 2001, the Federal Reserve Bank of New York (2001) reports that the use of electronic brokerage systems such as EBS or Reuters 2002 accounts for 54 percent of total turnover in U.S. inter-dealer spot foreign exchange market trading. This is up from less than a third of total spot market turnover in 1998. Prior to the 1998 survey, electronic brokerage volume was quite small. Similarly, the Bank of England (2001) reports that over 2/3 of U.K. inter-dealer spot trading volume is now conducted using electronic brokers, compared to about 30 percent in 1998; and the Bank of Japan (2001) reports that electronic brokers account for 48 percent of Japanese inter-dealer spot volume today compared to 37 percent in 1998. In all cases, the electronic brokers have grown to their current popularity while starting from a base of zero with their introduction in 1992.[1] While the recent survey points out the importance of electronic brokers as an institution, there has been very little research to date on the microstructure issues that lead traders to choose electronic brokerage over the historically dominant, and still quite relevant, institution of direct dealing where bilateral conversations (either telephone or electronic) occur between two traders and a deal is struck.

We seek to provide theory and empirical analysis of the issue in order to further our understanding regarding the choice of trading venue in foreign exchange. In equity

[1] A comprehensive review of electronic currency brokers is provided by Rime (2003). In April 2004, a new global survey was taken but the data on electronic broking were not fully available at the time of this draft.

trading, a literature has developed that addresses the choice of trading through a specialist or on an electronic crossing network (ECN).[2] There are significant differences between the equity trading environment and that for foreign exchange. The crossing networks for equity trading are part of a larger market with a great deal of transparency as trades are public information. However, the foreign exchange market, broadly speaking, is characterized by low transparency as the direct-dealing market generates proprietary information and the rest of the market does not know prices or quantities traded. The greater transparency provided by the foreign exchange electronic brokerages is one of the attractions of their use. To our knowledge, there has been no study that provides a theoretical model for the choice of inter-dealer foreign exchange trading venue and provides related empirical analysis.[3]

The paper is divided into four parts. Following the introduction, a theoretical model is developed in Section 2 that analyzes the choice of trading venue for large and small traders. The most likely optimal decision rule of the model has large traders using direct dealing while small traders utilize the electronic brokerage. Section 3 presents an empirical analysis utilizing data from the Reuters 2000-2 electronic brokerage system. The analysis focuses on the duration of the time between submitting an order and finding a match and a trade. An autoregressive conditional duration (ACD) model is specified using the Burr distribution rather than the usual exponential distribution assumed for the residual. The gain is that of moving from a flat, constant hazard function of the

[2] For examples see Katz & Shapiro (1985), Pagano (1989), Chowdhry & Nanda (1991), Glosten (1994), Parlour & Seppi (1998), and Hendershott & Mendelson (2000).

[3] Viswanathan and Wang (2000) compare theoretical models of a traditional dealer market and a multi-stage trading mechanism similar to an electronic limit order book and show that the adverse selection problem is lowered with the order book. This is analogous to an advantage associated with the electronic brokerage in foreign exchange and may be related to the popularity of trading on this platform.

exponential ACD to a non-monotonic hazard of the Burr ACD that allows the hazard to vary with duration time. The estimation results support the Burr functional form over the more common exponential or less common Weibull ACD models. In terms of the testable hypotheses suggested by the theory of Section 2, we find that it is important to condition inference on price competitiveness of orders. Given the price competitiveness of an order, duration is increasing in order size and decreasing in market depth. Finally, Section 4 offers a summary and concluding discussion.

2. CHOICE OF TRADING VENUE: THEORY

The direct dealership market and the electronic brokerage provide two trading venues competing for order flow in the inter-dealer foreign exchange market. An important benefit provided by the electronic brokerage is the lower transaction cost relative to the market-making dealer's bid-ask spread. A disadvantage is the lack of assurance of an immediate execution of transactions. So the transaction cost and immediacy of execution are the two key issues to be taken into account when a trader decides where to trade. In this section, we develop a model to describe the multi-market trading opportunities and the associated trader's choice problem. By examining the optimal decision rule, we can relate the model results to some of the stylized facts of foreign exchange trading.

2.a. Model Specification

We begin by assuming that there are two competing venues where currency can be traded: the direct dealing market where one trades with a market-maker (DD) and the electronic brokerage (EB). We construct a theoretical model of the market by specifying the players, the costs they face, available strategies, probabilities of order execution, and the equilibrium as follows:

2.a.1. Players:

The inter-bank foreign exchange market is made up of many traders associated with large financial institutions around the world. We abstract from the real world with assumptions that account for the reality that there are large and small players in this market. We assume that there are a large number of small traders who trade only one unit of the currency, as well as a larger trader who trades a large amount λ_l. Each trader receives a value from trading one unit of *u.* In general, *u* may be determined by a trader's liquidity preference, risk aversion, or other factors that determine a trader's demand for immediacy or urgency to trade.

2.a.2. Transaction Cost:

The cost of trading includes commissions, fees, taxes, the bid-ask spread, the price impact of a trade, and the cost associated with price movements if a trade cannot be executed immediately. Traders need to pay *s* per unit of currency for trades with a market-making dealer to have their orders executed with certainty. On the EB, traders trade among themselves without the intervention of market makers and pay a transaction cost per unit of *c* ($c<s$). Our focus is on limit orders submitted to the EB so that the duration between order submission and execution is an important consideration.[4] Traders would take into account the potential delay until a match is found on the EB by discounting the value of trading by a factor δ. So the net value of trading $u-c$ multiplied by δ reflects the value of trading on the EB adjusted for expected time to find a matching order. The determination of δ will be specified next.

2.a.3. Accounting for expected duration of orders on the electronic brokerage

After a trader submits his order to the EB, it may take some time to find a match. Duration is used to measure the "waiting time" on the EB and is the time between order submission and order execution for a filled order. For a failed order, it is the time between order entry and order removal. We specify duration as follows. Let β represent

[4] While market orders are executed immediately at the best price, there are related issues involving large and small orders for market order strategy. A large trade is likely to exhaust the limit orders with priority so that the order then trades at worse prices as the order is filled down the order book. So while market orders provide immediacy, since traders do not know what lies behind the best price, large market orders face price uncertainty relative to small market orders.

the common discount factor of the traders (0<β<1). Let t_s (t_l) be the (random) number of periods it takes for a small (large) trader to find a match on the EB. The effective discount rate for large traders is then $\delta_l = E\beta^{t_l}$ while for small traders it is $\delta_s = E\beta^{t_s}$.

Assume that t_s is distributed according to a cumulative distribution function $F_s(t) = P(t_s \leq t)$ and t_l is distributed according to $F_l(t) = P(t_l \leq t)$. Furthermore, assume that for any value t, $F_l(t) \leq F_s(t)$ or F_l dominates F_s in terms of first-order stochastic dominance. This implies that $Et_l \geq Et_s$ and $E\beta^{t_l} \leq E\beta^{t_s}$. Then the expected payoff for a small trader submitting an order is

$$E\left[\beta^{t_s}(u-c)\right] = (u-c)E\left[\beta^{t_s}\right] = (u-c)\delta_s \tag{1}$$

and the expected payoff for a large trader submitting an order is

$$E\left[\beta^{t_l}(u-c)\lambda_l\right] = (u-c)\lambda_l E\left[\beta^{t_l}\right] = (u-c)\lambda_l\delta_l . \tag{2}$$

The model just presented proposes that the duration for small traders, t_s, is less than the duration for large traders, t_l. We will test this proposition in the empirical section below. In particular, we estimate the conditional hazard function as a function of order size. Conditional on all available past information (all past duration times), the conditional hazard function measures the rate at which order durations are completed (matches are found and trades executed) after t_{i-1}, given that the order exists at t_{i-1}. In other words, the conditional hazard function gives the expected number of trades in the next time interval greater than t_{i-1} given that orders have been submitted to the EB at t_{i-1}. Since it takes several small orders on the other side of the market to fill one large order, we may expect the hazard rate for a large order, with duration t_l, to be lower than that for small orders, with duration t_s. However, this is really an empirical question as it is possible to observe hazard functions under reasonable parameterizations where the value of the hazard function is increasing in duration for a certain range.[5] Such hazard functions have the hazard increasing in small durations and decreasing in large durations. Given the possibility of such a hazard for trade on the EB, it is not possible to state, *a priori*, that large orders will have a smaller hazard than small orders. So even if large and small traders face the same hazard functions, the incidence of expected trades for large orders in the next time period could, theoretically, be smaller or larger than that for small orders. Our empirical work below will yield evidence on this issue.

2.a.4. Strategies:

Consider a simple situation where traders submit their orders to only one of the two markets. At this point the strategy set includes: 1) Go to DD, 2) Go to EB, or 3) Don't trade. The trader's decision depends on the expected payoff from trading on each market. The payoff from a direct-dealing transaction is $u - s$, while the expected payoff from the EB is: $(u - c)\delta$. In general, one goes to the market with the higher payoff from trading. If no positive payoff is attainable at any market, one may simply choose not to trade at all. Assume that the discount rate, δ, is the same for a group of traders. If a trader with u goes to the DD, it is easily shown that all the other traders in the group with a higher valuation of trade would go to the DD. On the other hand, if a trader with u goes

[5] Grammig and Maurer (2000) found that the hazard functions for 5 large stocks traded on the New York Stock Exchange were increasing in duration as duration increased from zero and then were decreasing in duration over the remainder of duration values. Based upon this finding, they argue that flexible hazard function specification is critical in successful duration models of financial markets.

to the EB, we know that all the traders with a lower valuation of trade would go to the EB. Cutoff values can be calculated by setting the payoffs at the two markets equal.

2.a.5. Optimal Decision Rules:

First we'll study the simplest version of the model by assuming value from trading, u, is the same among individual traders. Here we'll study optimal decision rules where given all the other traders' strategy, a trader would have no incentive to switch from one market to the other.

Optimal Strategies:

For any trader, at equilibrium he would:

Trade via DD, if $(u-s) > (u-c)\delta$ and $u-s > 0$

Trade via the EB, if $u-s < (u-c)\delta$ and $(u-c)\delta > 0$

Be indifferent between the two markets, if $u-s = (u-c)\delta > 0$

Decide not to trade, if $(u-c)\delta < 0$ and $(u-s) < 0$.

Different outcomes obtain for different values of u .

1) $u < c$, a trivial case since no one would trade.

2) $c < u < s$, exclusive EB trading.

3) $u > s$, the most interesting case because traders have to compare the payoffs from two competitive trading venues. We just focus on strategies when the direct-dealing market coexists with the EB because it is close to what we see in the FX market. Since all small traders have the same value from trading, their decisions would be the same. They will either all go to direct deals or else submit orders electronically all

together. Then we have two possible decision rules when the two trading venues coexist.

i) *Decision Rule 1: The large trader trades directly with market-making dealers and small traders go to the EB.*

For the large trader, we may expect that the payoff from direct dealing exceeds that on the EB. The condition under which large traders trade exclusively via direct-dealing is:

$$(u-s)\lambda_l > (u-c)\lambda_l\delta_l \text{, or } u > (s-\delta_l c)/(1-\delta_l). \tag{3}$$

Similarly small traders trade exclusively via the EB if:

$$(u-s) < (u-c)\delta_s \text{, or } u < (s-\delta_s c)/(1-\delta_s). \tag{4}$$

ii) *Decision Rule 2: The large trader trades on the EB and small traders trade directly with market-making dealers*.

This outcome can be easily ruled out since it requires the following condition:

$$(s-\delta_s c)/(1-\delta_s) < u < (s-\delta_l c)/(1-\delta_l). \tag{5}$$

If $\delta_s > \delta_l$, then this condition cannot be met.

So from the analysis above, we can see that the direct-dealing market and the electronic brokerage would coexist side by side when the valuation from trade u falls between $(s-\delta_l c)/(1-\delta_l)$ and $(s-\delta_s c)/(1-\delta_s)$. Since we expect the value of the hazard function facing the large traders to be lower than that facing the small traders, we then also expect $\delta_l < \delta_s$. The empirical analysis below will indicate whether the data support this belief. In this most likely strategy, the large trader chooses to trade via DD while the small traders go to the EB.[6]

2.b. Stylized Facts

2.b.1. Size Effect

The decision rule expected is consistent with the stylized fact in foreign exchange that large traders tend to trade with market-making dealers while small traders go to the EB. Within the framework developed above, we now discuss this fact.

Value from trading

As we have shown earlier, traders with higher valuations are more likely to trade via DD. Why might large traders have a higher trade valuation? Survey evidence has suggested that large traders are thought to possess private information about the value of the underlying asset, which, in terms of our model, would yield a higher value from trading.[7] Or it could be that the large trader is more risk averse so that a quick trade is strongly preferred to the uncertainty of the EB. Since our theoretical model has a common trade valuation for all traders, we will not devote our attention to this explanation.

Probability of execution

As we have argued above, the probability of execution is likely to be different for the small traders and the large trader. This is simply because it is more difficult for a large order to find a match on the EB. Since the expected payoff on the EB is $(u-c)\delta$, and we

---

[6] Note that the distribution of durations is not determined endogenously, as it would be in a general equilibrium model in which duration depends on the number of traders that go to the EB. However, the simplified model presented here is intended to shed light on the crucial trade-off that traders face.

[7] Cheung and Chinn (2001) report that surveyed foreign exchange dealers identify a competitive advantage to large traders stemming from their large customer base which provides better information on the order flow in the market. Gehrig and Menkhoff (forthcoming) also provide survey evidence on the role of order flow while Lyons (2001) provides a good overview of the topic and points out that large orders may have persistent price effects due to a portfolio-balance effect associated with the less than perfect substitutability across assets with different currency denominations (p. 32). A rapidly growing literature on order flow includes Bjonnes and Rime (2001), Evans and Lyons (2001), and Killeen, Lyons, and Moore (2002).

expect $\delta_l < \delta_s$, then with u the same, the large trader gets a smaller expected payoff value from trading on the EB than small traders. A corollary is that the transaction cost on the EB has to be lower to attract a large trader than to attract a small trader.

2.b.2. Failure of EB in high volatility periods

Another stylized fact about foreign exchange trading is that direct dealing seems to be preferred when exchange rate volatility is high. One striking result of the Federal Reserve Bank of New York survey on the impact of electronic broking in foreign exchange was the chief dealers' belief that "maintaining a viable interbank direct dealing market was prudent to ensure sufficient liquidity to handle large trades during periods of stress" (Federal Reserve Bank of New York, 1997, p. 6). The survey indicated that electronic broking systems were much less satisfactory for trading during periods of high volatility. In some extreme situations the EB may fail to attract a sufficient number of traders, so that it "dries up" in times of great uncertainty associated with high volatility. Price volatility might affect several variables in our model, such as the discount factor and transaction costs at both markets, thus changing the traders' behavior at the equilibrium. Since a long historical database of electronic brokerage activity is unavailable at this time, volatility effects are beyond the scope of this paper. However, as longer data sets, encompassing high volatility events, become available we hope to be able to address this issue.

Since it takes time for orders on the EB to be executed, there is a potential loss caused by price movement during the duration that an order sits without a match. This potential loss is due to an unfavorable exchange rate movement between the time an order is entered and the time the order is filled if the agent is unable to cancel the order before execution. This is a type of winner's curse, where a limit order is "picked-off" at a now-stale price in a fast-changing market. In times of high volatility, there is a higher probability of such an outcome. The theoretical model presented above has traders accounting for the delay on the EB by discounting the value of trading by a factor δ.

3. EMPIRICAL ANALYSIS

The theoretical model introduced in the previous section is used to motivate the empirical work that follows. In particular, the model generates testable hypotheses regarding the duration time of submitted orders on the EB and the probability of execution. We first describe the data set used for analysis and then turn to a description of the econometric methods employed before presenting estimation results.

3.a. Data Description

The data analyzed are Reuters D2000-2 electronic brokerage data on the Mark/Dollar exchange rate. The data set covers one week: October 6-10, 1997, and contains information on 130,535 orders.[8] The data include both limit orders and market orders. The following information about an order is available: type of order (market or limit); order date, entry and exit time; order removal codes for filled and cancelled orders; price; quantity ordered; and quantity dealt.

Reuters D2000-2 operates as an electronic limit order book with liquidity supply via limit order and liquidity demand via market order. Our data contain information not available to market participants since we can observe unexecuted orders submitted to the system. Participants just see the inside spread quotes but not the limit order book. Table1

[8] The data are described and analyzed in detail in Danielsson and Payne (2002).

provides some descriptive statistics for the original data. Table 1.a shows that the average price of an order was 1.75144 marks per dollar and the average order size was 2.283058 million dollars. The average quantity dealt was 0.883633 million, reflecting the fact that many orders are not filled and are withdrawn with no matching counterparty or are only partially filled. Tables 1.d and 1.e provide additional information in that 63,517 orders were successful in finding a counterparty and 67,018 were withdrawn before a match was found. In the empirical work below, we will document the role of competitive quotes in determining the probability of finding a match. If an agent submits a quote that is away from the current market price, that quote likely goes unfilled. Tables 1.b and 1.c show that there were 21,783 market orders, where orders are submitted for immediate execution at the best available price, and 108,752 limit orders, where quantity is accompanied by a reservation price which must be met for the order to be filled.

3.b. Duration Time of Orders

3.b.1. Definition and Construction

In order to examine the liquidity of the EB and the efficiency of its operation, we construct a variable (Duration), which measures the time from the entry of an order until its removal. Since Duration is computed as the time difference between the entry time and the removal time of an order, it provides a direct measure of the delay in a transaction on the EB.

Table 2 provides descriptive statistics on Duration. We break down the sample into different categories, for example, limit orders, market orders, cancelled orders, and the sample of limit orders used for estimation. Comparing all limit orders to all market orders, the noteworthy difference is the speed with which market orders are executed.

The average limit order duration is 2.855 minutes while the average market order duration is 0.0012 minutes. Since market orders are executed at the best available price, they are essentially executed immediately. However limit orders may sit in the order book for prolonged times and may be cancelled at any time. Note that the mean duration for cancelled orders is 3.5742 minutes. Some orders are cancelled in seconds after submission while others sit in the order book for hours before cancellation.

Since our theoretical model focuses on duration of successful limit orders, we construct a data set of completely filled limit orders. As will be discussed below, there is a pronounced intradaily pattern of activity in the Reuters EB. As a result, we focus on the active period of 8:00 to 17:00 London time. The data are then filtered to identify any extreme observations that would be unrepresentative of the market and would bias the analysis. We deleted any observations with a duration exceeding 80 minutes (61 observations). This leaves a sample of 29,740 orders with a mean duration of 1.2631 minutes. This is the data set used for estimation.

3.b.2. Time of Day Effect

As with all financial markets, we expect an intradaily pattern of duration time as markets tend to be deeper at certain times of day than at others. To illustrate the intradaily pattern, we average duration of the offers submitted to the network for each hour of the trading day over the five days in our sample. Table 3 reports the 24 average duration times and the number of orders submitted for each hour of the day. Traders have to wait longer on the network when the trading activity is low, as during hours 21-0 GMT, when North American trading has stopped and major Asian trading has not yet begun. Note the very low level of orders submitted during this time and the relatively long durations. Table 3 also shows the importance of the Reuters network for mark/dollar trading which is dominated by European and U.S. trading. The market is seen to be relatively thin during Asian trading hours. This reflects the fact that, while Hong Kong and Singapore both were active market-making centers for the mark (and now the euro), the rival electronic brokerage system offered by EBS is more popular for Asian trading. In addition, Tokyo trading is dominated by yen/dollar relative to any other currency pair.[9] In contrast to the thin market during Asian trading hours, note the depth of the market and associated short duration time during the peak European trading times from 8:00-17:00 GMT.

3.b.3. Autoregressive structure of duration time

The data suggest that there is a clustering of duration over time. This will surely be affected by the regular intradaily patterns, as well as any idiosyncratic patterns that emerge due to shocks. Long duration time tends to be followed by long duration and short duration followed by short duration time. The duration time of an order submitted to the network depends on the willingness of all other traders in the market to participate by contributing orders. As in the theoretical model presented earlier, if the market was liquid and the waiting time was short last period, people would be more likely to go to the EB this period, given their expectation conditional on past performance of the EB.

To document the presence of "clustering" in the duration data, we compute the average duration time of orders submitted within every 15-minute interval. A sample of 459 observations is constructed from 5 trading days. Autocorrelation coefficients are computed and the results are reported in Table 4. The statistics suggest that the duration

[9] A discussion of Asian trading practices in foreign exchange is provided in Ito, Lyons, and Melvin (1998) and Covrig and Melvin (2002).

time is highly autocorrelated with large and statistically significant coefficients even up to the fifth order.

3.c. Estimation of Duration Models

The theoretical model of section 2 suggests testable hypotheses regarding duration and the probability of execution on the EB. We examine the empirical evidence regarding the following three variables: order size, price competitiveness, and liquidity. We will discuss hypotheses related to each of these variables in turn before examining the evidence.

Hypothesis 1: Size effect

A stylized fact of the foreign exchange market is that large traders are more likely to use direct dealing than go to the EB. The intuitive explanation is that, in general, large orders have to wait longer on the network, which makes electronic trading riskier and less attractive. However, if the Burr distribution is a good representation of the foreign exchange market as Grammig and Maurer (2000) found for the stock market, then there may be a non-monotonic relationship between duration and the value of the hazard function. Rather than impose a particular shape on the hazard function, as is commonly done, we will specify a flexible function that will allow the data to identify the shape of the hazard function. It is possible to have a hazard function that is increasing in duration for small durations and decreasing in duration for large durations, so that one cannot be sure that large orders have a smaller hazard value than small orders. For instance, in an order book it could be the case that market order submission results in a short duration for limit orders with priority but also reduces the liquidity in the book so that following a clustering of market orders and short durations there is a lengthening of the duration process for newly submitted limit orders as market order submission slows while the depth of the book is rebuilt. In this case, the hazard function could be increasing for very short durations and then fall as the durations lengthen. The evidence presented here will allow the data to speak to this issue. We examine the relationship between durations and order size by incorporating an exogenous variable SIZE in our estimations below.

Hypothesis 2: Price Impact

Submission price of a limit order should affect the waiting time of the order on the EB. In general, we expect that an order with a competitive submission price, for example, a relatively high-priced buy order, or a relatively low-priced sell order, should get filled more quickly than other orders where price is farther away from the current transaction price of orders recently filled. This effect is explored by including in our estimation dummy variables for price competitiveness: *DummyBP,* switches to one for buy orders with a higher limit order price than the last transaction price; *DummyBN*, switches to one for buy orders with a submitted price lower than the last transaction price; *DummySP*, switches to one for sell orders with a submitted price higher than the last transaction price; and *DummySN*, switches to one for sell orders with a submitted price lower than the last transaction price. Competitive (uncompetitive) quotes with expected negative (positive) effects on duration are captured by *DummyBP* and *DummySN* (*DummyBN* and *DummySP*).

Hypothesis 3: Liquidity Effect

Duration should be negatively correlated with the total liquidity or depth of the market. The EB is characterized by a positive externality: An increase in the network's submitted order volume increases its liquidity, benefiting all trades. The duration should be smaller when the depth is large. There is a potential offsetting crowding effect of a negative externality associated with a large number of orders. As Hendershott & Mendelson (1999) point out, low value orders can compete with higher value orders on the same side of the market and there may be a greater chance of smaller orders being squeezed out of the queue. However the crowding effect can only dominate the liquidity effect after the EB becomes sufficiently liquid. We will explore the effect of liquidity by incorporating a variable *LDEPTH*, which measures the total quantity offered for purchase or sale on all active submitted limit orders. An additional measure of liquidity is a variable *MORDERS*, which is the number of market orders submitted in the period immediately preceding a limit order.

3.c.1. Econometric Methodology: the ACD Model

Since we are studying orders submitted in irregular time intervals, the standard econometric techniques based on fixed time interval are not appropriate analytical tools. If a short interval is chosen, there will be many intervals with no new information and heteroskedasticity will be introduced. On the other hand, the microstructure of the data will be lost if a long time interval is picked. Engel and Russell (1998) developed an autoregressive conditional duration (ACD) model to describe the point process of order arrival rates that is a natural approach to estimating the relationships of concern here.

The ACD model belongs to the family of self-exciting marked point processes of Cox and Lewis (1966). A point process is described as self-exciting when the past evolution impacts the probability of future events. Basically, the economic motivation behind the ACD and the ARCH model follows a similar logic: due to a clustering of news, financial market events occur in clusters. This implies that the waiting time between these events exhibits significant serial correlation.

Engel and Russell (1998) proposed the standard exponential ACD (EACD) model by specifying the observed duration x_i as a mixing process $x_i = \psi_i \varepsilon_i$. ψ_i is the conditional duration defined as $\psi_i = E(x_i \mid x_{i-1},...,x_1)$ and ε_i is an IID error sequence. For the EACD model, the density of error ε_i is assumed to be exponential.

A conditional density gives the forecast density for the next observation of order arrival conditional on all available past information (all past duration times). Given the current information set, the conditional hazard function measures the rate at which durations are completed after duration *t*, given that they last at least until *t*. Then for an EACD model, the Conditional Density of x_i is

$$f(x_i \mid x_{i-1},...,x_1) = \frac{1}{\psi_i} \exp(-\frac{x_i}{\psi_i}) \tag{6}$$

and the conditional hazard is

$$h(x_i \mid x_{i-1},...,x_1) = \frac{1}{\psi_i}. \tag{7}$$

In an ACD model, the conditional expectation is a linear function of the previous duration and conditional expectation. A simple EACD (1,1) is specified as

$$\psi_i = \omega + \alpha x_{i-1} + \beta \psi_{i-1}. \tag{8}$$

This equation has coefficient constraints $\omega > 0$, $\beta \geq 0$, $\alpha \geq 0$, and $\alpha + \beta < 1$. The first three constraints ensure the positivity of the conditional durations and the last ensures the existence of the unconditional mean of the durations. As will be discussed below, when additional explanatory variables are added to the model, the non-negativity constraints may be overly restrictive. For this reason, we will specify and estimate a log-ACD model below. First we will discuss implications of the particular distributional assumption made for the error term.

For EACD models, the hazard functions conditional on past duration are restricted to be a constant. The Weibull distribution is more flexible in that it nests the exponential and allows a non-flat hazard function $h(x_i \mid x_{i-1},...,x_1) = x_i^{\gamma-1}\gamma$ However, the hazard function is monotone: increasing if γ >1, decreasing if γ <1. As pointed out above, it is possible that the hazard function of financial transactions may be increasing for small durations and decreasing for long durations. The misspecification of the conditional hazard function can severely impact the estimation results. To avoid such problems, the Burr-distribution is proposed. This allows a hump shaped hazard and nests the Weibull distribution as a particular case. The Burr-distribution may be described by first defining

$$f(\psi_i) = \xi_i = \psi_i \cdot \frac{(\sigma^2)^{(1+\frac{1}{\kappa})} \cdot \Gamma(\frac{1}{\sigma^2}+1)}{\Gamma(1+\frac{1}{\kappa}) \cdot \Gamma(\frac{1}{\sigma^2}-\frac{1}{\kappa})}, \tag{9}$$

where κ and σ^2 are parameters, $0 < \sigma^2 < \kappa$ and Γ represents the gamma function. Then the conditional density is a Burr density

$$f(x_i \mid x_{i-1},...,x_1;\theta) = \frac{\kappa \cdot \xi_i^{-\kappa} \cdot x_i^{\kappa-1}}{(1+\sigma^2 \cdot \xi_i^{-\kappa} \cdot x_i^{\kappa})^{(\frac{1}{\sigma^2})+1}}, \tag{10}$$

and the conditional hazard function is

$$h(x_i \mid x_{i-1},...,x_1;\theta) = \frac{\kappa \cdot \xi_i^{-\kappa} \cdot x_i^{\kappa-1}}{1+\sigma^2 \cdot \xi_i^{-\kappa} \cdot x_i^{\kappa}}. \tag{11}$$

For $\sigma^2 \to 0$, the Burr-ACD reduces to the Weibull-ACD and if in addition $\kappa = 1$, it becomes the exponential-ACD. Since the Burr-ACD nests the Weibull and exponential specifications, by estimating the Burr model, we can test which specification is supported by the results. [10]

Figure 1 illustrates the shape of the hazard function for some alternative parameters. The monotonic function is parameterized as the Weibull with $\kappa = 0.5$ and $\sigma^2 = 0$. The hump-shaped hazard is a Burr with $\kappa = 2$ and $\sigma^2 = 0.5$. In general, for $\kappa > 1$ the Burr hazard has the hump-shape. Such hazard functions have the hazard increasing in small durations and decreasing in large durations. Given the possibility of such a hazard for trade on the EB, it is not possible to state, *a priori*, that large orders will have a smaller hazard than small orders. So even if large and small traders face the same hazard functions, the incidence of expected trades for large orders in the next time period could, theoretically, be smaller or larger than that for small orders. Our empirical work below will yield evidence on this issue.

As mentioned above, in order to test hypotheses suggested by our theoretical model, we want to include variables such as order size, price competitiveness, and market depth as explanatory variables in the conditional duration equation . When additional variables with negative coefficients are added linearly to the right-hand side of the equation, conditional duration ψ_i may become negative which is not admissible. If working with a standard ACD specification, we would have to impose non-negativity constraints on the coefficients of the variables so that the right-hand side of the ACD equation remains strictly positive. Since non-negativity constraints on the coefficients

[10] We acknowledge the generosity of Joachim Grammig in sharing his suite of ACD GAUSS programs, which greatly shortened the time spent in programming for the current study.

may be very restrictive, we work instead with a more flexible functional form provided by the log-ACD model as discussed by Bauwens and Giot (2000).

In a log-ACD model, duration x_i is defined as the mixing process $x_i = \exp(\psi_i)\varepsilon_i$, such that ψ_i is the logarithm of the conditional duration. ε_i is the same random variable as in the ACD model and we specify it as having a Burr distribution. The specification of the basic Log-ACD (1,1) model is:

$$\psi_i = \omega + \alpha\, ln(x_{i-1}) + \beta\psi_{i-1}. \tag{12}$$

With this specification, the only coefficient restriction is that $|\alpha + \beta| < 1$ for covariance stationarity of $ln(x_i)$. Estimation proceeds via maximum likelihood.

3.c.2. Censoring

The data include orders that are completely filled and those that are only partially filled or cancelled. Estimation using only the completely filled orders may result in a censoring bias due to the termination of the other orders prior to their full execution. Let c_i denote an observation being completely filled, $c_i = 1$, or censored, $c_i = 0$. If the pairs (x_i, c_i) are statistically independent, then the likelihood function for the sample of data may be written as:

$$\prod_{i=1}^{n} f(x_i; X_i)^{c_i} g(x_i; X_i)^{1-c_i} = \prod_F f(x_i; X_i) \prod_C g(x_i; X_i) \tag{13}$$

where $\prod_F$ and $\prod_C$ denote products taken over filled and censored orders, respectively, and X denotes the explanatory variables on which duration is conditioned. The independence assumption allows for the censoring mechanism to be related to past duration or the vector of variables contained in X. But at the time the order is submitted, the censoring decision (which is made later) is independent of the conditional duration or the likelihood that the order is executed.[11] We estimate the model parameters using the likelihood function as given in equation (13).

3.c.3 Estimation Results

Estimation is based on limit orders. The issue of duration for market orders is irrelevant since market orders get executed almost immediately after they are posted on the EB. As shown in Table 2, the mean duration for market orders is 0.0012 minutes, which is very small compared to the mean for filled limit orders of 1.7886 minutes. As discussed in the prior section, we estimate the parameters of the model for both filled limit orders and censored orders as manifested in cancelled orders. If only the filled orders were used, biased estimates may give us inaccurate information on model parameters related to the distribution of duration time. Finally, to avoid the problem of spurious results driven by thin trading periods, we estimate using data over the period of peak European business hours (8:00am—5:00pm GMT).[12]

As stated above, we seek to estimate ACD models which incorporate the following variables: *SIZE* (the quantity submitted in millions of dollars), dummy variables for competitiveness of submitted order (submission price – last transaction price), *LDEPTH* (total depth of the order book in millions of dollars), and *MDEPTH*, the number of market orders submitted over the prior 5 minutes preceding each limit order. Before proceeding to the results, some discussion of the price competitiveness dummies is in order. To determine the competitiveness of the submission price, we identify the

[11] See Lo, MacKinlay, and Zhang (2002) for a discussion of censoring in a limit-order setting.
[12] No "overnight" durations are utilized. We start each day with the duration from the first order after 8:00 GMT as our first available lag for that day.

transaction price of the last trade before each order is submitted and take the difference between the submission price and the last-trade transaction price. To avoid the bid-ask bounce, the trade must be of the same type as the submitted order. So for a buy limit order, the last transaction for a buy-order is found and the price difference between the submission price and the transaction price is computed. If the submission price is higher than the transaction price, we consider it a competitive order and expect it to get filled more quickly. By the same token, for a sell order, the submission price of a competitive order would be lower than the transaction price of the last filled sell-order. We constructed 4 dummy variables in order to capture the impact of price competitiveness on duration time: Define variable *Pricediff = submission price –last transaction price*, then

DummyBP = 1 for buy orders with *Pricediff>0;* 0 otherwise

DummyBN = 1 for buy orders with *Pricediff<0;* 0 otherwise

DummySP = 1 for sell orders with *Pricediff>0;* 0 otherwise

DummySN = 1 for sell orders with *Pricediff<0;* 0 otherwise.

The functional form of the Burr-log-ACD (1,1) model estimated is:

$$\begin{aligned}\psi_i = \omega + \alpha \ln(x_{i-1}) + \beta\psi_{i-1} + \delta_1 SIZE_i + \delta_2 DummyBP_i + \delta_3 DummyBN_i + \\ \delta_3 DummySP_i + \delta_4 DummySN_i + \delta_5 LDEPTH_i + \delta_6 MDEPTH_i\end{aligned} \quad (14)$$

where *i* indexes submitted orders and orders are arranged in calendar (clock) time. Note that there is no collinearity problem associated with including the four dummies for price competitiveness of quotes since about 30 percent of submitted orders have quotes equal to the last transaction price. Preliminary estimates indicated that one could not reject the hypothesis of equality of coefficients for the dummy variables for competitive bid and ask quotes and uncompetitive bad and ask quotes. As a result, we constrain the coefficients for each pair to be equal to reduce the number of coefficients to be estimated.

Estimates of the model are reported in Table 5. The estimation procedure employs the joint likelihood function for filled and unfilled orders as in equation (13). Estimates of the function for filled orders are given in part a) of Table 5. As expected, we get a positive significant coefficient for *SIZE*. This suggests that the bigger the order, the longer the duration time. In the theory presentation of section 2, the effect of *SIZE* was uncertain due to the possibility of a hump-shaped hazard function. However, the empirical results indicate that size of trade is a reason to expect big traders to prefer the dealer market over the EB. While not reported in the table, the shape and scale parameters associated with the Burr distribution are constrained to be equal for both the filled and censored samples. The estimated parameters of $\kappa = 0.6379$ and $\sigma^2 = 0.4652$ suggest that the appropriate hazard function for the electronic foreign exchange brokerage will have a shape like that portrayed in Figure 2. For these data, the hazard is monotonically decreasing in duration. The empirical results for filled orders suggest no ambiguity in the effect of *SIZE* on the value of the hazard function.

Both measures of market depth, *LDEPTH* and *MDEPTH*, have negative and statistically significant coefficients in part a) of Table 5. So the greater the quantity of outstanding orders, the shorter the duration time and the more market orders that were submitted prior to a limit order, the shorter the duration of the limit order. With regard to our price impact variables, results for the four dummies are also consistent with our priors. The negative coefficients of *DummyBP* and *DummySN* indicate that it takes less time to find a match for a limit order with a competitive price (a better price than the last transaction price). On the other hand, for buy orders with low prices and sell orders with high prices (relative to last transactions), the results suggest longer durations as indicated by the positive and significant coefficients estimated for *DummyBN* and *DummySP*. Without conditioning the estimation results on price competitiveness of quotes, one cannot properly infer the effects of other variables, like *SIZE* and *LDEPTH*. Our results for filled orders may be summarized as follows: given the price competitiveness of submitted orders, duration is increasing in order size and decreasing in market depth or liquidity.

Part b) of Table 5 reports the estimated parameters associated with the censored sample of cancelled orders. Interesting differences from the filled order results include a negative size coefficient and a positive and insignificant coefficient for the depth of the order book. The former indicates that large orders are more likely to be cancelled faster than small orders. Perhaps this reflects the more careful management of large orders by participants.

With regard to the proper functional form of ACD model, as mentioned above, the Burr model nests the Weibull and exponential. Referring back to the specification of the Burr ACD in Section 3.c.1, we can test whether the Weibull ACD is supported by a test of $\sigma^2 \to 0$. The results clearly reject the hypothesis that $\sigma^2 = 0$ (with a p-value of 0.000). Since we reject the Weibull in favor of the Burr specification, it is clear that the exponential is not supported (but we would also reject the additional restriction associated with the exponential, that is $\kappa = 1$).

4. SUMMARY

We begin by specifying a theoretical model of inter-dealer foreign exchange market participants facing a choice of trading directly with other dealers or submitting orders to an electronic brokerage (EB). The optimal decision rule of the model suggests that under normal conditions, we would expect large traders to prefer the direct-dealing market where certainty of quick execution is provided. A large order may be expected to have a longer duration on the EB in order to find a match. Smaller traders would prefer the EB due to lower transaction costs along with the greater likelihood of finding a match for a small order. The longer the expected duration of a submitted order, the lower the expected value from trading. This result is driven by the potential cost of having the market price move unfavorably and a limit order filled at an undesirable price before an order can be withdrawn.

Since a building block of the model is the longer duration for large orders, the empirical analysis focuses on estimating duration models of limit orders submitted to the Reuters D-2000-2 electronic brokerage system. We model the time from order submission to order fill (Duration) in an autoregressive conditional duration (ACD) framework where in addition to lagged conditional and unconditional duration, we include the size of the order (*SIZE*), the liquidity or depth of the market (*DEPTH*), and price competitiveness of the quote (*PRICEDIF*). The latter variable is measured by the difference between the price of the submitted order and the last transaction price on the same side of the market (buy or sell). It is important to condition the duration results on price competitiveness of quotes in order to make sensible inferences on other variables, like size of order submitted. We find that price competitiveness has the effects expected: uncompetitive quotes, as measured by relatively low buy prices or relatively high sell prices, are associated with longer durations while competitive quotes, as measured by relatively high buy prices or low sell prices are associated with shorter durations. Given these effects of price competitiveness, we find that the larger the size of order submitted, the longer the duration. Prior evidence for equity trades indicates that the hazard function may be increasing in duration for small durations and falling in duration for larger durations. In this case, we cannot say that large orders will have a lower value of the hazard function than small orders. However, our evidence suggests a hazard function that is monotonically decreasing in duration. So the longer duration, the lower the value of the hazard function and, in terms of the theory presented, the lower the value of order submission on the electronic brokerage. The empirical results support the theoretical model where big traders will prefer the dealer market over the EB due to the longer waiting time for big orders to find a match on the electronic brokerage. We also find that the greater the depth of the market, the shorter the duration. This is the expected result, as greater depth should increase the probability of finding a match for any submitted order.

This first look at theory and empirics on the choice of trading venue for foreign exchange pays due respect to the stylized facts of the market. The growth of electronic broking is the number one institutional FX development of the last decade and has revolutionized the way in which currencies are traded. The popularity of this innovation in trading protocol is associated with lower cost of transacting and the ability of smaller traders to compete on an equal footing with the big players in the market via anonymous order submission. In the future, if longer data sets become available, it will be instructive to analyze how trading migrates between the electronic broking network and the direct dealing network during times of stress. The theoretical model developed here can be extended by including a role for volatility to increase the probability of a regretted trade for submitted limit orders in times of great volatility. In such times of great price uncertainty, a limit order may be "picked off" and executed at an unfavorable price relative to the fast-moving current market values. As a result, we expect the electronic brokerage network to dry up during times of high volatility as even small traders migrate to the direct dealing market where immediate execution is offered. Analysis of such volatility effects awaits the availability of new and longer data sets.

References

Bank of England, 2001. The U.K. Foreign Exchange market and Over-The-Counter Derivatives Markets in April 2001 – Results Summary.

Bank of Japan, 2001. Central Bank Survey of Foreign Exchange and Derivatives Market Activity in April 2001: Turnover Data, Japan.

Bauwens, L., Giot, P., 2000, The logarithmic ACD model: an application to the bid-ask quote process of three NYSE stocks. Annales d'Economie et de Statistique 60, 117-149.

Bjonnes, G. H., Rime, D., 2001. Customer trading and information in foreign exchange markets. Working Paper, Stockholm Institute for Financial Research.

Cheung, Y.-W., Chinn, M.D., 2001. Currency traders and exchange rate dynamics: a survey of the U.S. market. Journal of International Money & Finance 20 (4), 439-472.

Chowdhry, B., Nanda, V., 1991. Multimarket trading and market liquidity. Review of Financial Studies 3, 483-511.

Cox, D.R., Lewis, P.A.W., 1966. The Statistical Analysis of Series of Events, London: Wiley.

Covrig, V., Melvin, M., 2002. Asymmetric information and price discovery in the FX market: does Tokyo know more about the yen? Journal of Empirical Finance 9, 271-285.

Danielsson, J., Payne, R., 2002. Real trading patterns and prices in spot foreign exchange markets. Journal of International Money and Finance 21, 203-222.

Donges, J., Heinemann, F., 2000. Competition for order flow as a coordination game, University of Frankfurt, Working paper .

Engle, R., Russell, J., 1998. Autoregressive conditional duration: a new model for irregularly spaced transaction data. Econometrica 66, 1127-1162.

Evans, M, Lyons, R., 2002. Order flow and exchange rate dynamics. Journal of Political Economy 110, 170-180.

Federal Reserve Bank of New York, 1997, A Survey Assessing the Impact of Electronic Broking on the Foreign Exchange Market.

Federal Reserve Bank of New York, 2001. The Foreign Exchange and Interest Rate Derivatives Markets Survey: Turnover in the United States.

Gehrig, Thomas and Lukas Menkhoff, forthcoming, "The Use of Flow Analysis in Foreign Exchange: Exploratory Evidence," Journal of International Money and Finance.

Glosten, L.R., 1994, Is the electronic order book inevitable? Journal of Finance 49, 1127-1161.

Grammig, J., Maurer, K.-O., 2000. Non-monotonic hazard functions and the autoregressive conditional duration model. The Econometrics Journal, 3, 16-38.

Hendershott, T., Mendelson, H., 2000. Crossing networks and dealer markets: competition and performances. Journal of Finance 55, 2071-2115.

Ito, T., Lyons, R.K., Melvin, M., 1998. Is there private information in the FX market? The Tokyo experiment. Journal of Finance 53, 111-1130.

Katz, M.L., Shapiro, C., 1985, Network externalities, competition, and compatibility, American Economic Review 75, 424-440.

Killeen, W., Lyons, R., Moore, M., 2002, Fixed versus flexible: lessons from EMS order flow. Working Paper, Queen's University, Belfast.

Lo, A. W., MacKinlay, A.C., Zhang, J., 2002, Econometric Models of Limit-Order Executions. Journal of Financial Economics 65, 31-71.

Lyons, Richard K., 2001, The Microstructure Approach to Exchange Rates, Cambridge: MIT Press.

Pagano, M., 1989, Trading volume and asset liquidity, Quarterly Journal of Economics 104, 255-274.

Parlour,C.A., Seppi, D.J., 1998, Liquidity-based competition for order flow, Working Paper, Carnegie-Mellon University.

Rime, D, 2003, New electronic trading systems in foreign exchange markets, in D. Jones (ed) New Economy Handbook, San Diego: Academic Press, 469-504.

Viswanathan, S., Wang, J.J.D., 2000, Inter-dealer trading in financial markets, Working Paper, Duke University.

Table 1

DESCRIPTIVE STATISTICS OF ELECTRONIC BROKERAGE DATA

The tables provide summary data from the Reuters D-2002 electronic brokerage system for the week of October 6-10, 1997. Price is marks per dollar and quantity is millions of dollars.

a. All submitted orders

	Price	Quantity	Quantity Dealt
Number of orders	130535	130535	130535
Mean	1.75144	2.283058	0.883633
Std Deviation	0.0163	3.58977	1.33644
Skewness	-85.55836	165.25713	3.224573
Kurtosis	9189.8112	45537.8361	22.7082

b. Market orders

	Price	Quantity	Quantity Dealt
Number of orders	21783	21783	21783
Mean	1.75145	3.236285	1.82132856
Std Deviation	0.00728	3.6032	1.35002
Skewness	-0.4863	3.15407	3.0855
Kurtosis	-0.79639	11.98166	17.6065

c. Limit orders

	Price	Quantity	Quantity Dealt
Number of orders	108752	108752	108752
Mean	1.75144	2.09213	0.6958
Std Deviation	0.001756	3.55651	1.2519
Skewness	-82.159	203.3116	3.7792
Kurtosis	8192.8236	56773.65	30.4539

Table 1 (cont.)

d. Orders with quantity dealt greater than 0 (successful orders)

	Price	Quantity	Quantity Dealt
Number of orders	63517	63517	63517
Mean	1.751419	2.468457	1.815971
Std Deviation	0.00731	2.63731	1.40623
Skewness	-0.4797	4.02832	3.66975
Kurtosis	-0.81644	23.2899	27.3741

e. Orders with 0 quantity dealt (withdrawn orders)

	Price	Quantity	Quantity Dealt
Number of orders	67018	67018	67018
Mean	1.751467	2.107344	0
Std Deviation	0.02161	4.29469	0
Skewness	-71.5303	187.17077	0
Kurtosis	5769.4977	43324.7019	0

Table 2

Descriptive Statistics for Duration

Duration is the time passing from the entry of an order until its removal. Order removal may be due to an order being filled or else cancelled. The units of measurement are in minutes. The sample used for estimation includes only filled limit orders.

	All Limit Orders	All Market Orders	All Cancelled Orders	Estimation Sample
Number of Orders	108683	21783	66517	29740
Mean (min)	2.855	0.0012	3.5742	1.2631
Std Deviation	16.334	0.0008	18.742	4.90
Range	802.67	0.0503	690.182	79.603
Skewness	15.956	14.269	13.374	8.169
Kurtosis	373.711	689.002	252.610	82.1344

Table 3

Intradaily Pattern of Duration

Duration is the time in minutes between the submission of an order and its removal from the Reuters electronic brokerage system. Time is measured as GMT (London time) so that 0 GMT is 9:00 in Tokyo and 19:00 in New York. The table shows a strong intradaily pattern where duration and number of orders is inversely related.

Time of Day	Average Duration	Number of Orders	Percentage
0	10.2146	477	0.37%
1	6.7147	692	0.53%
2	10.8359	317	0.24%
3	35.8062	64	0.05%
4	9.0134	200	0.15%
5	5.5536	891	0.68%
6	2.6893	5595	4.29%
7	2.3079	14491	11.10%
8	2.3178	15097	11.57%
9	3.0254	9696	7.43%
10	3.2417	7360	5.64%
11	2.1809	13006	9.96%
12	1.5406	16790	12.86%
13	1.4885	18976	14.54%
14	1.5596	14518	11.12%
15	2.391	6416	4.92%
16	4.7557	2139	1.64%
17	4.8778	1570	1.20%
18	3.1406	1510	1.16%
19	4.6772	446	0.34%
20	6.0416	143	0.11%
21	36.8439	43	0.03%
22	43.329	29	0.02%
23	44.7129	69	0.05%

Table 4

Autocorrelations of Average Duration Time

Duration times from order submission to order removal were averaged over 15 minute intervals over the 24-hour day. Autocorrelation coefficients were then estimated over this data set. The autocorrelation coefficients and associated standard errors reported below confirm the presence of duration clustering through time where periods of relatively long durations exist and then are followed by periods of relatively short durations.

<table>
<tr><th>Lag</th><th>Covariance</th><th>Correlation</th><th>-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1</th><th>Std Error</th></tr>
<tr><td>0</td><td>1636.742</td><td>1.00000</td><td>|********************|</td><td>0</td></tr>
<tr><td>1</td><td>519.214</td><td>0.31722</td><td>. |******</td><td>0.046676</td></tr>
<tr><td>2</td><td>353.370</td><td>0.21590</td><td>. |****</td><td>0.051158</td></tr>
<tr><td>3</td><td>159.369</td><td>0.09737</td><td>. |**</td><td>0.053106</td></tr>
<tr><td>4</td><td>282.972</td><td>0.17289</td><td>. |***</td><td>0.053493</td></tr>
<tr><td>5</td><td>256.431</td><td>0.15667</td><td>. |***</td><td>0.054697</td></tr>
<tr><td>6</td><td>63.954672</td><td>0.03907</td><td>. |*.</td><td>0.055666</td></tr>
<tr><td>7</td><td>102.902</td><td>0.06287</td><td>. |*.</td><td>0.055726</td></tr>
<tr><td>8</td><td>78.666688</td><td>0.04806</td><td>. |*.</td><td>0.055880</td></tr>
<tr><td>9</td><td>39.260038</td><td>0.02399</td><td>. | .</td><td>0.055970</td></tr>
<tr><td>10</td><td>6.685793</td><td>0.00408</td><td>. | .</td><td>0.055993</td></tr>
<tr><td>11</td><td>-11.446203</td><td>-.00699</td><td>. | .</td><td>0.055993</td></tr>
<tr><td>12</td><td>9.795678</td><td>0.00598</td><td>. | .</td><td>0.055995</td></tr>
<tr><td>13</td><td>9.432072</td><td>0.00576</td><td>. | .</td><td>0.055997</td></tr>
<tr><td>14</td><td>69.653841</td><td>0.04256</td><td>. |*.</td><td>0.055998</td></tr>
<tr><td>15</td><td>35.423853</td><td>0.02164</td><td>. | .</td><td>0.056068</td></tr>
<tr><td>16</td><td>18.549567</td><td>0.01133</td><td>. | .</td><td>0.056087</td></tr>
<tr><td>17</td><td>130.523</td><td>0.07975</td><td>. |**</td><td>0.056092</td></tr>
<tr><td>18</td><td>66.945660</td><td>0.04090</td><td>. |*.</td><td>0.056338</td></tr>
<tr><td>19</td><td>72.659411</td><td>0.04439</td><td>. |*.</td><td>0.056403</td></tr>
<tr><td>20</td><td>0.755464</td><td>0.00046</td><td>. | .</td><td>0.056479</td></tr>
<tr><td>21</td><td>10.467460</td><td>0.00640</td><td>. | .</td><td>0.056479</td></tr>
<tr><td>22</td><td>-7.547603</td><td>-.00461</td><td>. | .</td><td>0.056480</td></tr>
<tr><td>23</td><td>-41.758172</td><td>-.02551</td><td>.*| .</td><td>0.056481</td></tr>
<tr><td>24</td><td>-36.516871</td><td>-.02231</td><td>. | .</td><td>0.056506</td></tr>
</table>

Table 5

ACD Models of Duration: Estimates

Maximum likelihood estimates of Burr-log-ACD models of duration from time orders submitted until time orders are filled or cancelled are presented below. Joint estimation for filled orders and cancelled orders addresses the censoring problem associated with the latter
.

a. Filled Orders

	Coefficient	Std. Error	T-Stat	Prob
SIZE	0.0663	0.0094	7.051	0.0000
$DummyBP_i$	-1.0542	0.0347	-30.414	0.0000
$DummyBN_i$	1.9840	0.0331	60.026	0.0000
$DummySP_i$	1.9840	0.0331	60.026	0.0000
$DummySN_i$	-1.0542	0.0347	-30.414	0.0000
LDEPTH	-0.0023	0.0004	-5.559	0.0000
MDEPTH	-0.0073	0.0004	-16.551	0.0000

b. Cancelled Orders

	Coefficient	Std. Error	T-Stat	Prob
SIZE	-0.0490	0.0007	-67.583	0.0000
$DummyBP_i$	-0.3329	0.0371	-8.965	0.0000
$DummyBN_i$	1.4740	0.0374	39.417	0.0000
$DummySP_i$	1.4740	0.0374	39.417	0.0000
$DummySN_i$	-0.3329	0.0371	-8.965	0.0000
LDEPTH	0.0127	0.0064	1.990	0.0466
MDEPTH	-0.0054	0.0004	-13.151	0.0000

Figure 1: Representative Hazard Functions

The figure illustrates two alternative hazard functions derived from the general Burr distribution. The monotonically-decreasing function is parameterized to illustrate the Weibull hazard, which is nested in the Burr distribution, with $\kappa = 0.5$ and $\sigma^2 = 0$. The humped-shaped hazard occurs for Burr distributions with $\kappa > 1$. The figure depicts a Burr with $\kappa = 2$ and $\sigma^2 = 0.5$. Note that, depending on the parameters, the Burr hazard may be increasing in duration for small durations and decreasing in duration for larger durations.

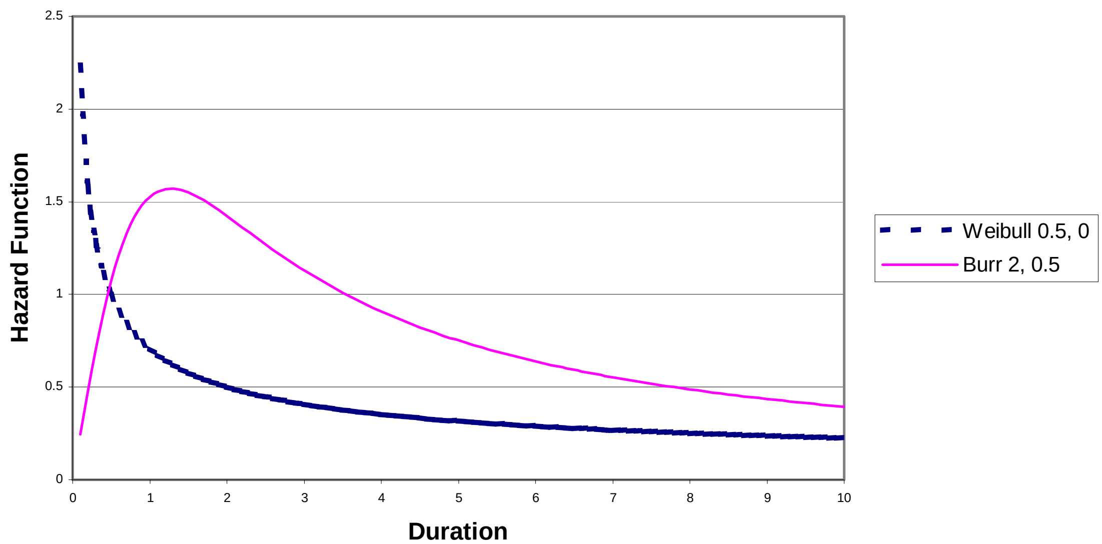

Figure 2: Shape of Estimated Hazard Function

The figure illustrates a hazard function with parameters equal to those estimated for the foreign exchange electronic brokerage data. The conditional hazard function is generated by a Burr distribution with $\kappa = 0.6379$ and $\sigma^2 = 0.4652$. Note that the hazard function is monotonically decreasing in duration, so that the longer the duration, the smaller the value of the hazard function. If large orders are associated with longer duration, then the associated value of the hazard function should be lower for large orders than small orders.