Abstract: This paper proposes a new model for limit order book dynamics. The limit order book consists of quantities available for trade at different prices so a dynamic model must describe the evolution of curves. The proposed model captures dependence in the curve using an autoregressive structure in two components of the curve that are simple to interpret from an economic perspective. The first term describes the average (weighted) distance that the depth on one side of the market (buy or sell) lies away from the midquote. The second term describes how spread out the depth is across prices. Maximum likelihood estimates are constructed using data from Archipelago Exchange (currently ARCA) and specification tests are described. By including additional explanatory variables, we test hypothesis about how market liquidity responds to information flow. We find that depth tends to move away from the midquote in periods of low volatility, high volume, and wide spreads. We find that the depth is more spread out across prices when volatility is high, trading volume is large, and spreads are wide.
I. Introduction

Nearly half the world’s stock exchanges are organized as order-driven markets such as ECN’s. The structure of the limit order book at any point in time determines the cost of any trade. The dynamics of the limit order book determine how this cost varies over time. Despite the prevalence of order driven markets there are remarkably few models for the determinants of the structure of the limit order book and its dynamics. This paper proposes a new dynamic model for the determinants of the structure of the limit order book as determined by the state of the market and asset characteristics.

Existing work on liquidity in order driven markets can be split into two groups. The first approach directly models the limit order placement strategies of individual traders. Examples include Biais, Hillioin, and Spatt (1998) Coppejans and Domowitz (2002), Ranaldo (2004), and Hall and Hautsch (2004). This approach provides insight into the micro behavior of decisions, but provides only indirect evidence about the overall structure of the limit order book. The second approach focuses on specific aspects of the limit order book such as bid ask spreads or the depth at the best bid or ask. This approach provides detailed statements about specific features of the limit order book but again, provides only indirect evidence about the overall structure of the limit order book. In the end, these approaches cannot provide direct answers to questions like “what is the expected cost of buying $1000 of IBM in one minute?” Answers to these questions require a more complete model of the limit order book that models the entire structure, not just a component. As a result, these approaches are focusing on narrow aspects of liquidity.

This paper takes a different approach. The limit order book is a set of quantities to be bought or sold at different prices. We propose directly modeling the time varying curves. The forecast of the model is therefore a function producing expected quantities over a range of prices as a function of the history of the limit order book and market and asset conditions. The model, therefore, can directly answer the questions regarding the expected cost of a purchase (or sale) in one minute.

The model is parameterized in a way that allows for easy interpretation and therefore the model is useful in assessing and interpreting how market conditions affect the shape of the limit order book and therefore liquidity. The distribution of depth across the limit order book is modeled by a time varying normal distribution and therefore depends on two time varying parameters. The first determines the average distance that the depth lies away from the midquote. As this parameter increases, market liquidity tends to decrease. The second parameter determines how spread out the depth is. Larger values of this parameter lead to a
flatter limit order book. These parameters are made time varying in an autoregressive manner so that the shape of the limit order book next period depends on the shape of the limit order book in the previous period and possibly other variables that characterize the market condition.

The model is applied to one month of limit order book data. The data come from Archipelago Exchange. Model estimates are presented for limit order book dynamics at one minute increments. We find that the limit order book exhibits very strong persistence suggesting that new limit orders are slow to replenish the book. We also find that depth tends to move away from the midquote, so that the market becomes less liquid, following larger spreads, smaller trade volume, higher transaction rates, and higher volatility. We also find that the book tends to become more disperse (flatter) when spreads are low, trade size is large, transaction rates are high, and volatility is high.

II. The model

This section presents a model for the distribution of the depth across multiple prices. Our approach decomposes the limit order book into two components; the total depth in the market and the distribution of that depth across the multiple prices.

We begin with some notation. Let the midquote at time $t$ be denoted by $m_t$. Next, we denote a grid for $N$ prices on the ask and bid sides. The $i^{th}$ ask price on the grid is denoted by $p_{i}^{a}$ and the $i^{th}$ bid price is denoted by $p_{i}^{b}$. $p_{i}^{a}$ is the first price at or above the midquote at which depth can be listed and similarly, $p_{i}^{b}$ is the first price below the midquote at which depth can be listed. We will treat the grid as being equally spaced so that each consecutive price on the ask side is a fixed unit above the previous price. The grid accounts for the fact that available prices in most markets are restricted to fall on values at fixed tick sizes. Hence the smallest increment considered would be that of the tick size. Larger increments could be considered as well. Finally, we define the total number of shares available in each price bin. On the ask side, $a_{it}$ denotes the total depth available in the $i^{th}$ bin. $a_{it}$ is the shares available in the limit order book at prices $p$ where $\left(p_{i}^{a} \leq p \leq p_{i+1}^{a}\right)$ and for $i>1$ $a_{it}$ denotes the shares available at prices $p$ where $\left(p_{i}^{a} < p \leq p_{i+1}^{a}\right)$. A similar notation is used for the bid side of the market where $b_{it}$ denotes the shares available in the limit order book on the bid side. The grid is anchored at the midquote so the grid has a time subscript. In both cases, larger values of $i$ are associated with prices further away from the midquote.
Our goal is to specify a model for the expected shares available in each bin given the state of the market and perhaps characteristics of the asset. For small number of bins (small N) the depth could be modeled by standard time series techniques such as a VAR. These approaches quickly become intractable when N is more than 1 or 2 since a large number of lags are likely needed introducing a very large number of parameters to be estimated. Additionally, it is difficult to interpret the individual parameters of VAR in the relevant context of liquidity and one would have to resort to impulse response functions. We take a different approach that decomposes the problem into two components. Define the total shares in the limit order book over the first N bins as \( D^s_t = \sum_{i=1}^{N} a_{it} \). We decompose the model for the limit order book into shape and level components. Given the total shares in the limit order book, define

1) \( \pi_{it} = E\left( \frac{a_{it}}{D^s_t} | D^s_t \right) \)

as the expected fraction of the depth \( D^s_t \) in bin i, at time t. Given the total shares, the expected depth in bin i at time t is given by

2) \( E\left( a_{it} | D^s_t \right) = \pi_{it} D^s_t \)

Differences in depth across bins are driven by the \( \pi \) terms. Hence, this decomposition separates the model for the limit order book into a shape component described by the \( \pi \)'s and a level given by the overall depth, \( D^s_t \). In general, both the shape of the limit order book and the total shares available, \( D^s_t \), will depend on characteristics of the asset and market conditions. Let \( F_{t-1} \) denote an information set available at time \( t-1 \), and let \( g\left( D^s_t | F_{t-1} \right) \) denote a model for the time-varying total shares. We now can generalize 1) and 2) to allow for time varying probabilities, time-varying total shares, \( D^s_t \), and a time varying limit order book:

3) \( \pi_{it} = E\left( \frac{a_{it}}{D^s_t} | D^s_t, F_{t-1} \right) \)

The one step ahead, predicted depth is then given by

4) \( E\left( a_{it} | F_{t-1} \right) = \int_D \pi_{it} g\left( D^s_t | F_{t-1} \right) dD \)

Hence, the limit order book can be modeled using a multinomial model for 3) and a univariate time series model for \( g\left( D^s_t | F_{t-1} \right) \). The latter is a univariate series that could be modeled with
standard time series time series models such as an ARMA model. The new part here is therefore to find a good model for the multinomial probabilities.

The goal in specifying the multinomial model is to find a model that fits the data well, is easily interpreted, and allows for \( N \) to be large without requiring a large number of parameters. The limit order book clearly exhibits dependence especially when viewed over short time periods. The model must therefore be specified in a flexible way so that the shape depends on the history of the limit order book.

Our model is formulated using a multinomial probit model. For the probit model, the multinomial probabilities are determined by areas under the normal density function. These probabilities are time varying when the mean and variance of the Normal density are time varying. Specifically, given a mean \( \mu_t \) and a variance \( \sigma^2_t \) the probability is given by:

\[
\pi_{it} = \Phi_t(p_{it} - m_i) - \Phi_t(p_{i,t-1} - m_i)
\]

Where \( \Phi_t \) is the cumulative distribution function for a Normal \((\mu_t, \sigma^2_t)\). If the grid is set on ticks, then this would correspond to the fraction of the depth that lies on the \( i \)th tick above the midquotes.

This parameterization is convenient to interpret. Clearly as \( \mu_t \) increases, the center of the distribution moves away from the midquote. Therefore, larger values of \( \mu_t \) are associated with depth over the modeled region lying, on average, further from the midquote. This would correspond to a less liquid market. As \( \sigma^2_t \) increases, the Normal density becomes flatter therefore spreading out the probability more evenly across the \( N \) bins. As \( \sigma^2_t \) goes to infinity the probabilities become equal. An increase or decrease in either the mean or the variance is therefore easily interpreted in terms of average distance that the depth lies from the midquote and how spread out the depth is across the \( N \) bins.

We now turn to dynamics of the distribution which are driven by the dynamics of the mean and variance. Since the shape of the limit order book will be highly dependent, especially over short time intervals, we begin with the simplest version of the model using an autoregressive structure for the mean and variance. At each time period \( t \), we can calculate the center of the empirical distribution of the depth. This is given by \( \bar{x}_t = \frac{1}{D_t} \sum_{i=1}^{n} (p_{it} - m_i) q_{it} \). The difference between the actual mean and the predicted mean is given by \( e_t = \bar{x}_t - \sum_{i=1}^{n} \pi_{it}(p_{it} - m_i) \).
Similarly, we can compute the variance of the depth across the bins as 
\[ s_t^2 = \frac{1}{D_t} \sum_{i=1}^{n} (p_{it} - \bar{x}_t)^2 \]
and the associated error is given by 
\[ \eta_t = \ln(s_t^2) - \ln\left( \sum_{i=1}^{n} \pi_{it} (p_{it} - \bar{x}_t)^2 \right) \]. If the model is correctly specified then both error terms will be uncorrelated, although the latter will not be mean zero.

These errors are used to build an autoregressive model for the time varying mean and variance that in turn dictate the time varying probabilities in the multinomial. Specifically, a simple model for the dynamic of the mean is given by:
\[ \mu_t = \beta_0 + \beta_1 \mu_{t-1} + \beta_2 \xi_{t-1} \]

Similarly, a simple model for the dynamics of the variance is given by:
\[ \ln(\sigma_t^2) = \gamma_0 + \gamma_1 \ln(\sigma_{t-1}^2) + \gamma_2 \eta_{t-1} \]

Clearly higher order models could be considered. Additionally, other variables that capture the state of the market could be included as well. The explicit dependence of the current mean and variance on the past mean and variance allows for potential persistence in the series. The error terms allow the updating to depend on the differences between the expected and actual mean and variance. In the next section, we turn to model estimation.

III. Model Estimation

The data on one side of the market consist of the number of shares available in each bin. We proceed to estimate parameters for the mean and variance dynamics via model by maximum likelihood. If each share submitted at each time period \( t \) could be viewed an iid draws from a multinomial distribution with probabilities given by the \( \pi_{it} \)'s then the likelihood associated with the \( t \)-th period is given by:
\[ l_t = \pi_{1t}^{a_{1t}} \pi_{2t}^{a_{2t}} \cdots \pi_{nt}^{a_{nt}} \]

This assumes that the shares are iid draws which is surely false. Orders are submitted in packets of multiple shares, typically in increments of 100 shares. If all orders were submitted in packets of 100 shares then the likelihood for the \( t \)th observation would be given by:
\[ l_t = \pi_{1t}^{\tilde{a}_{1t}} \pi_{2t}^{\tilde{a}_{2t}} \cdots \pi_{nt}^{\tilde{a}_{nt}} \]

where \( \tilde{a}_{it} = \frac{a_{it}}{100} \).
Hence we construct the log likelihood as:

\[ L = \sum_{t=1}^{T} \sum_{i=1}^{n} \tilde{a}_{it} \ln(\pi_{it}) \]

Given an initial value of \( \mu_0 \) and \( \sigma^2_0 \), the sequence multinomial probabilities can be sequentially updated and the likelihood evaluated for any set of parameters and maximized. Under the usual regularity conditions the estimates will be consistent and asymptotically normal.

IV. Data

The data consist of limit orders that were submitted through the Archipelago Exchange. This exchange has since been bought by NYSE and is now called ARCA. As of March, 2007, Archipelago is the second largest ECN in terms of shares traded (about 20% market share for NASDAQ stocks). Our data consists of one month of all limit orders submitted in January 2005. The data contains the type of order action; add, modify and delete. “Add” corresponds to a new order submission. “Modify” occurs when an order is modified either in its price, number of shares, or if an order is partially filled. “Delete” signifies that an order was cancelled, filled, or expires. The data also contains a time stamp down to the millisecond, the price and order size, and a buy or sell indicator, stock symbol, and exchange.

We extract orders for a single stock Google (GOOG). Only orders submitted during regular hours (9:30 to 4:00) are considered. From the order by order data we construct the complete limit order book at every minute. This results in 390 observations per day. For reference, the average trade price for Google over the month is close to $200. Figure 1 presents a plot of the depth at each cent moving away from the midquote from one cent to forty cents. The plot reveals a peaked distribution, with its peak around 15-20 cents away from the midquote. Of course this is an unconditional distribution.

The limit order book data is merged with Trades and Quotes (TAQ) data for the same time period. From this data we create several variables related to trading and volatility. Past order flow should be related to future order flow and therefore future limit order placement. For every minute, we construct the logarithm of the average trade size over the most recent 15 minute period. Additionally, we construct the total number of trades executed over the most recent 15 minute period. Both are indications of the degree of market activity. We also create a realized volatility measure constructed by summing squared, one-minute interval returns over the 15 most recent minutes. Finally, the bid-ask spread at transaction times is averaged over the 15 most recent minutes.
In principle, we could model depth out through any distance from the midquote. We focus our attention in this analysis to the depth out through 30 cents. We aggregate the shares within larger 5-cent bins and therefore have 6 bins on the bid side and 6 bins on the ask side. Our modeling strategy has separate models for the bid and ask side of the market. In our analysis, we focus on the ask side only.

V. Results

We begin with some summary statistics for the minute by minute data. At each minute, we have observed depth in the first 6, 5-cent bins, \( a_{1t}, a_{2t}, \ldots, a_{6t} \). It is interesting to assess the dependence structure in this vector time series. Specifically, if we stack the depth at time \( t \) into a vector \( x_t \) where the first element of \( x_t \) is \( a_{1t} \) and the last element is \( a_{6t} \), we construct the autocorrelations of the vector \( x_t \) for lags 0 through 3 minutes. The sample autocorrelations are presented in figure 2. The autocorrelations are statistically different from zero if larger than

\[
\frac{2}{\sqrt{T}} = .024 \text{ in absolute value.}
\]

All autocorrelations are positive indicating the depth at the prices tends to move together. Depth near the diagonal tends to be more highly correlated that depth away from the diagonal indicating that the correlation between close bins is larger than the correlation between bins that are far apart. The diagonal or autocorrelations of the same element of the vector \( x_t \) tend to have the highest of all correlations. Although not presented, the general positive and significant correlations structure continues out through lag 10 (or 10 minutes).

We now estimate the model for the distribution of the depth across the bins, the multinomial probit. We begin by estimating a simple, first order model presented in Section II, specifically \( \mu = \beta_0 + \beta_1 \mu_{t-1} + \beta_2 e_{t-1} \) and \( \ln(\sigma_i^2) = \gamma_0 + \gamma_1 \ln(\sigma_{i-1}^2) + \gamma_2 \eta_{i-1} \). The parameter estimates are given by \( \mu = .057 + .998 \mu_{t-1} -.93 e_{t-1} \) and \( \ln(\sigma_i^2) = .06 + .96 \ln(\sigma_{i-1}^2) + .06 \eta_{i-1} \). All parameters are significant at the 1% level. Both the mean and the variance exhibit very strong persistence indicating that the average distance of the depth from the midquote is highly persistent as is the degree spread of the depth across bins. The Autoregressive term is near 1 for both models. All coefficients are significant at the 1% level.

A natural test of the model is to check if the one step ahead forecast errors for the mean and variance equations (\( e_t \) and \( \eta_t \)) are uncorrelated. The null of a white noise series can be tested by examining the autocorrelations of these in sample errors. We perform a Ljung-Box test on the first 15 autocorrelations associated with the errors for the mean equation and the variance equation. The p-values are .53 and .06 respectively. Hence this simple first order model
appears to do a reasonably good job of capturing the dependence in the shape of the limit order book.

It is interesting to see that a simple first order version of the model can capture the substantial dependence in the shape of the limit order book. We now turn our attention to additional market factors that might influence the dynamics of the limit order book. Glosten (2000) predicts that higher trading rates should result in depth clustering around the midquote. Competition among traders in an active market leads to more limit orders being placed near the midquote. Similarly, Rosu (2008) proposes a theoretical model for the dynamics of the limit order book that suggests that also predicts that more depth should cluster around midquote when market activity is high. Following Glosten and Rosu, we should expect the mean to decrease, and the average distance of the depth move closer to the midquote in periods of high trading rates.

Periods of high volatility are associated with greater uncertainty. In periods of high uncertainty there might be a higher probability of trading against better informed agents. Classic microstructure theory predicts a widening of bid ask spreads when the probability of trading against better informed agents is higher. We might therefore expect that depth should move away from the midquote in periods of high volatility. At the same time, high volatility in the asset price increases the probability that a limit order far from the current price gets executed. This might also serve as an incentive for traders to seek superior execution by placing limit orders further from the current price. Both of the ideas imply that in periods of higher volatility, the mean average distance of the depth from the midquote should increase. We might also expect that the distribution of depth should flatten. Hence we might expect the mean and variance to increase in periods of high asset price volatility.

In light of these economic arguments, we next estimate models that condition on recent transaction history and volatility. Specifically, we use the transaction volume over the past 15 minutes, the number of trades over the last 15 minutes and the realized minute-by-minute volatility over the last 15 minutes. Additionally, we include some other economic variables that are of interest including the average spread over the last 15 minutes and the price change over the last 15 minutes. We include all these economic variables with in the first order time series model estimated above. The coefficients of the economic variables are presented in table 1. All variables are significant at the 1% level.

We begin with a discussion of the realized volatility. Realized variance has a positive coefficient in the mean equation indicating that when the volatility of the asset price increases the average distance of the depth tends to move away from the midquote. This is consistent with the both ideas, namely increased likelihood of trading against better informed agents moves depth to more conservative prices that account for this risk. It is also consistent with the idea that high
volatility increases the likelihood of depth further from the midquote getting executed at some point in the future. Similarly, the coefficient on the volatility is positive in the variance equation. This indicates a flattening of the distribution so that the depth is more evenly spread over the bins.

Next, consider the trade size and trading rate variables. We see that larger average trade size tends to move the depth closer to the midquote. Higher trading rates tend to move the depth further from the midquote, on average. The effect of trade size and trading rates are both positive on the variance. Larger trade size may be indicative of larger depth posted at the best bid and ask prices. Since the depth is correlated, this might simply be indicative of large depth at the ask following larger depth at the ask. The trading rates are a little easier to interpret because there is less of a direct link between trading rates and quantities at the best ask. The positive sign here indicates that depth tends to move away from the midquote during periods of high transaction rates. Additionally, the positive sign on both variables in the variance equation indicates that the depth is more evenly distributed during high trading rates and larger average size. Overall, the evidence does not support the predictions of Glosten or the model of Rosu.

Wider spreads are associated with more uncertainty. As with volatility, we might expect that depth should move away from the midquote in periods of greater uncertainty. Indeed, the sign on the spread is positive both for the mean equation and for the variance equation. Rising prices tend to be associated with depth moving away from the midquote and the distribution becoming more evenly distributed.

Next, we estimate a model for the second component of the model, namely the level of the depth $D^a_t$ on the ask side of the market. Specifically, we specify an ARMA(2,2) model for the logarithm of the depth:

$$\ln(D^a_t) = c + \alpha_1 \ln(D^a_{t-1}) + \alpha_2 \ln(D^a_{t-2}) + \theta_1 \xi_{t-1} + \theta_2 \xi_{t-2} + \lambda rv_{t-1} + \xi_t$$

where $\xi_t$ is white noise and $rv$ is the realized volatility over the last 15 minutes. The other economic variables are not significant so they are not included in the final model for the level. The estimated model is:

$$\ln(D^a_t) = 9.76 + 1.23 \ln(D^a_{t-1}) - .28 \ln(D^a_{t-2}) - .28 \xi_{t-1} - .81 \xi_{t-2} + 2.55 rv_{t-1} + \xi_t$$

The in-sample residuals pass a Ljung-Box test with 15 lags. The process is also highly persistent. Although the other economic variables are insignificant the realized volatility is significant at the 1% level and implies that the level of depth tends to increase following periods of higher volatility. Combining the results for the distribution and the level, we see that the total number
of shares in the first 30 cents tends to increase following high volatility periods, but that the distribution of the depth shifts away from the midquote and flattens out. Figure 3 presents a plot of the predicted depth under average conditions for all variables except the volatility which is varied from average to the 5th percentile (low) to 95th percentile (high).

VI. Conclusions.

We propose a model for limit order book dynamics. The model is formulated in a way that separates the modeling problem into a model for the level of the depth and a model for the distribution of the depth across specified bins. The decomposition combined with the use of a convenient probit model allows the dynamics to be interpreted in a particularly simple way. Specifically we model the level, average distance of the depth from the midquote, and the flatness or spread of the depth across the bins. The model for the level of the depth can be taken from off the shelf processes. The new part here is the model for the time varying multinomial distribution.

We show that a simple low order models for the probit are able to capture the strong temporal dependence in the shape of the distribution of the depth. More interestingly, we also consider several economic variables. We find that higher volatility predicts that the overall level of the depth will increase, but that depth moves away from the midquote and the distribution tends to flatten out, becoming more disperse.

Contrary to the predictions of Glosten (2000) and Rosu (2008) we find evidence that higher market activity, as measured by trading rates, tends to move depth away from the midquote and flatten the distribution.
References


Figure 1. Distribution of depth measured in cents away from midquote.
\[
\hat{\rho}_0 = \begin{bmatrix}
1.0 & 0.081 & 0.094 & 0.039 & 0.010 & 0.020 \\
0.081 & 1.00 & 0.190 & 0.167 & 0.090 & 0.075 \\
0.094 & 0.190 & 1.00 & 0.190 & 0.210 & 0.092 \\
0.039 & 0.167 & 0.190 & 1.00 & 0.185 & 0.033 \\
0.010 & 0.090 & 0.210 & 0.185 & 1.00 & 0.263 \\
0.020 & 0.075 & 0.092 & 0.133 & 0.263 & 1.00 
\end{bmatrix}
\]

\[
\hat{\rho}_1 = \begin{bmatrix}
0.049 & 0.136 & 0.082 & 0.074 & 0.087 & 0.053 \\
0.058 & 0.209 & 0.192 & 0.163 & 0.155 & 0.162 \\
0.111 & 0.164 & 0.228 & 0.207 & 0.184 & 0.219 \\
0.054 & 0.180 & 0.160 & 0.231 & 0.253 & 0.206 \\
0.116 & 0.146 & 0.210 & 0.230 & 0.311 & 0.276 \\
0.046 & 0.138 & 0.176 & 0.236 & 0.308 & 0.329 
\end{bmatrix}
\]

\[
\hat{\rho}_2 = \begin{bmatrix}
0.050 & 0.084 & 0.050 & 0.037 & 0.066 & 0.099 \\
0.088 & 0.123 & 0.085 & 0.108 & 0.105 & 0.106 \\
0.034 & 0.160 & 0.203 & 0.141 & 0.114 & 0.179 \\
0.059 & 0.132 & 0.142 & 0.184 & 0.174 & 0.200 \\
0.042 & 0.154 & 0.223 & 0.280 & 0.252 & \\
0.045 & 0.128 & 0.146 & 0.186 & 0.297 & 0.315 
\end{bmatrix}
\]

\[
\hat{\rho}_3 = \begin{bmatrix}
0.048 & 0.090 & 0.023 & 0.056 & 0.089 & 0.041 \\
0.092 & 0.145 & 0.116 & 0.097 & 0.140 & 0.099 \\
0.053 & 0.114 & 0.188 & 0.156 & 0.175 & 0.156 \\
0.026 & 0.105 & 0.103 & 0.170 & 0.143 & 0.152 \\
0.057 & 0.121 & 0.135 & 0.152 & 0.233 & 0.248 \\
0.058 & 0.125 & 0.145 & 0.177 & 0.222 & 0.269 
\end{bmatrix}
\]

Figure 2. Autocorrelations of depth in different bins on the ask side.
Figure 3. Predicted limit order book under average conditions as volatility varies from low to high.
<table>
<thead>
<tr>
<th></th>
<th>Model for Mean</th>
<th>Model for Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Realized Variance</td>
<td>.83</td>
<td>45.51</td>
</tr>
<tr>
<td>Trade Size</td>
<td>-.07</td>
<td>1.26</td>
</tr>
<tr>
<td>Spread</td>
<td>2.12</td>
<td>26.48</td>
</tr>
<tr>
<td>Trading Rate</td>
<td>.072</td>
<td>2.45</td>
</tr>
<tr>
<td>Price Change</td>
<td>.56</td>
<td>-10.08</td>
</tr>
</tbody>
</table>

Table 1. Estimated coefficients for economic variables.