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**DYNAMICS OF EFFECTIVE QUOTES AND SPREADS
BETWEEN CONSECUTIVE TRADES: A REAL-
TIME STRUCTURAL MODEL OF PRICE INFORMATION**

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April 3, 2001

Dynamics of Effective Quotes and Spreads between Consecutive Trades: A Real-time Structural Model of Price Formation*

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Current draft: April 3, 2001

Abstract

This paper develops a real-time structural model of price formation, and uses it to investigate the dynamics of effective quotes and bid-ask spreads between consecutive trades. There is some evidence that the effective bid-ask spreads increase over time when no orders arrive. The effective quotes are found to change over time when no orders arrive. The dynamics of bid and ask are different, and are related to the direction of previous transaction. Market makers act as though they believe that clustering trades with middle-range duration (coming one or two minutes after the last trades) are more likely to contain private information, while reversing trades with same duration are less likely to contain private information. Some stylized facts are also established regarding the average duration and frequency for clustering trades, reversing trades, upticks, and downticks.

JEL classification: C51, D82, G10.

Keywords: Price formation, Bid-ask spread, Trade duration, Quote dynamics.

* I thank William N. Goetzmann, Harry Mamaysky, Matthew Spiegel, and Werner Stanzl for their inspiration and numerous helpful comments and discussions. I also thank seminar participants at Yale University. All errors are mine.

1. Introduction

Price formation and bid-ask spread have long been of interest to traders, regulators, and researchers. Glosten and Harris (1988), Huang and Stoll (1994, 1997), Madhavan, Richardson, and Roomans (1997), among others, propose structural models - known as indicator regression models - to analyze price formation and volatility, estimate bid-ask spread components, and investigate trading costs. However, time is irrelevant in most structural models. The primary objective of this paper is to develop a real-time structural model of price formation. As an empirical application of the model, this paper investigates the dynamics of effective quotes and spreads between consecutive transactions.

Structural models of price formation are explicitly based on the market makers' quote-setting process. Theoretical analyses, such as those of Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987), Admati and Pfleiderer (1988), Foster and Viswanathan (1990, 1994), Franklin and Gorton (1992), and Blume, Easley, and O'Hara (1994), suggest that the price formation process is influenced by the market makers' learning process. Market makers collect information from the flow of orders and trades - the directions, sequences, duration, size, and other information as well. They infer a trader's motivation and private information about a stock's fundamental value, and then quote bid and ask prices at which they are willing to trade. Thus the evolution of a stock's price is driven not only by the public information, but also by the private information incorporated in market makers' inference based their observation of the trading process.

The measurement of the components of the bid-ask spread encompasses an extensive literature. Theoretical analyses show that the effective bid-ask spread consists of three components: asymmetric information, inventory carrying costs, and order processing costs. Many empirical studies investigate the relative importance of these components and provide valuable

insights into the difference of execution costs across different markets and stocks,¹ as well as the change of execution cost over the day [see e.g., Madhavan, Richardson, and Roomans (1997), McInish and Wood (1992)]. However, these papers do not address the issue of how execution costs change over time between consecutive transactions, which is of considerable practical and academic interests.

A fundamental feature of high-frequency data is that events occur at varying time intervals. Theoretical analyses, such as Garman (1976), Diamond and Verrecchia (1987), and Easley and O'Hara (1992), suggest an important information role for the trade arrival times. However, empirical works that investigate the role of time in trading are still in their infancy. Hausman, Lo, and Mackinlay (1992) estimate ordered probit models in which time interval between the current and the last trade serves as an explanatory variable. Engle and Russell (1998), Engle (2000), and Ghysels (2000), among others, propose various time relevant methods or find evidence of role of time in trading process. Dufour and Engle (2000) extend the VAR approach taken by Hasbrouck (1991). They show that the time interval between trades affects the behavior of market price. The extended VAR method, however, deals with the middle point of the bid-ask. It may not be suitable to investigate issues such as the intra-trade dynamics of the bid, the ask, and the bid-ask spread.

The dynamics of effective quotes between consecutive trades is of great interest to researchers. It may provide valuable insights into the learning process of market makers, and thus improve our understanding of the price formation process. It is also of great importance to portfolio managers and traders because of its direct and strong implications for the optimal trading strategy. The dynamics of the effective bid-ask spread, at the same time, is also of academic interest. As noted by Peterson and Fialkowski (1994), the effective spread, not the

¹ For example, Choi, Salandro, and Shastri (1988), George, Kaul, and Nimalendran (1991), Glosten (1987), Glosten and Harris (1988), Hasbrouck (1993), Huang and Stoll (1994), Roll (1984), and Stoll (1989), among many others.

posted spread, is the accurate measure of transaction cost to investors. The effective quotes, not the posted quotes, are the prices investors actually pay when they buy or sell stocks. When trades are executed inside the posted bid-ask spread,² the effective quotes do not equal the posted quotes, nor does the effective spread equal the posted spread.

This paper's contribution lies in its development and estimation of a structural model of price formation that not only captures many frictions in a unified setting but also explicitly incorporates the time interval between trades. The model follows indicator models, such as those developed by Madhavan, Richardson, and Roomans (1997), and Huang and Stoll (1997). It carefully describes market makers' quote-setting process through real time. It extends the conventional indicator models by allowing market makers to set quotes conditional upon not only the direction of the incoming order, but also the length of time between the last trade and the next one. This extension is justified by the fact that market makers are able to change their quotes through time.

This paper establishes some stylized facts about the duration and frequency of trades. A trade is called a *clustering (reversing)* trade if it has the same (opposite) direction with the previous trade. A trade is called an *uptick (downtick)* if its price is higher (lower) than the price of the previous trade. This paper finds that the average duration is the shortest for clustering upticks, followed by clustering downticks, and then by reversing downticks, and is the longest for reversing upticks. It also finds that the most frequently observed trades are clustering upticks, followed by reversing upticks, and then by reversing downticks, and the least frequently observed are clustering downticks. These findings are novel, and they are not predicted or satisfactorily explained by any available theories.

Estimating the real-time structural model reveals robust dynamic patterns of effective quotes between consecutive trades. First, the effective quotes change over time, but not

² Blume and Goldstein (1997) find that 12 to 31 % of the trades in their sample occur inside the spread.

monotonically. Moreover, the evolution of effective quotes depends on the direction of the preceding trade. After a buyer-initiated trade and before the coming of the next order, both the effective ask and bid increase at first, then decrease. However, after a seller-initiated trade and before the coming of the next order, both the effective ask and bid decrease at first, then increase. This pattern suggests the magnitude of the information content of clustering trade (buy after the last buy or sell after the last sell) and reversing trade (buy after the last sell or sell after the last buy) with the same duration may be different. Estimating the model also reveals the dynamics of effective bid-ask spreads. The effective spreads generally increase over time when no orders arrive. The magnitude of the difference between the largest spread and the smallest spread varies from about 0.13 cent to about 2.36 cents.

This paper proceeds as follows. Section 2 describes market makers' quote setting process, and develops the real-time structural model of price formation. Section 3 describes the data and provides some summary statistics. Section 4 establishes some empirical results about trade duration and frequency, and shows the dynamics of effective quotes and bid-ask spreads. Finally, Section 5 summarizes the main results and concludes.

2. A real-time structural model of price formation

2.1. The model

This section develops a real time structural model of price formation. In the model, price, direction, and duration characterize a trade. Let P_n denote the transaction price of trade n . Denote by I_n the direction of trade n , which equals 1 if the trade is buyer-initiated and -1 if it is seller-initiated. Denote by D_n the duration of trade n , which is defined as the length of time between the previous and the current trade. For example, a trade's duration equals one minute if it takes place one minute after the preceding trade.

Market makers are broadly defined here. They include the official market makers such as NYSE specialists, floor brokers who trade for liquidity reasons, and limit book orders as well. Market makers quote bid and ask prices at which they are willing to buy (at the bid) and sell (at the ask) the underlying stock. They continuously adjust the quotes so that the quotes are always consistent with their expectation of the stock's value at each moment. Thus when an order comes and triggers a trade, the transaction price is always consistent with market makers' expectation of the stock's value at that moment.

A transaction takes place when a market order comes and hits the prevailing quotes. Market makers receive the order, trade against it, and collect information from the order. After the trade, market makers continuously update their expectation of the underlying stock's value over time. Let V_n denote the market makers' expectation of the stock's value right before trade n . Thus the difference between V_{n+1} and V_n is determined by the information collected from trade n , new public information since trade n , the direction and duration of the order $n + 1$.

$$V_{n+1} - V_n = f(D_{n+1})(I_{n+1} + I_n) + g(D_{n+1})(I_{n+1} - I_n) + \mathbf{u}_{n+1} \quad (1)$$

The term I_{n+1} is the direction of trade $n + 1$. The function $f(D_{n+1})$ captures the information content of trade $n + 1$'s direction and duration given trade $n + 1$ being a clustering trade. Similarly, the function $g(D_{n+1})$ captures the information content of trade $n + 1$'s direction and duration given its being a reversing trade. The term \mathbf{u}_n is assumed to be independently and identically distributed with mean 0 and variance \mathbf{S}^2 . It captures information collected from trade n as well as new public information since trade n . The new public information is assumed to affect market makers' expectation of stock value but not through trading.

The information collected from trade n and new public information since trade n clearly contribute to the difference between V_{n+1} and V_n . Market makers are also able to condition their expectation of the underlying stock's value upon the direction and the duration of the next trade

because of several facts. First, they know that the next order is going to be either a buy or a sell, they therefore have an expectation corresponding to each scenario and make the bid and ask quotation *ex post* rational [see, e.g., Glosten and Milgrom (1985)]. Second, market makers are able to adjust their expectation of the underlying stock's value over time. Thus they are able to condition on the next trade's duration. Furthermore, previous research, such as Madhavan, Richardson, and Roomans (1997), shows that clustering trades are more likely to take place than reversing ones so they may have different impact on market makers' "belief revision". Following the same logic, equation (1) differentiates the information content of the direction and duration of a clustering trade from those of a reversing trade.

When market makers quote the bid and ask prices, they ask for fair compensation for their service in providing liquidity. Denote by Q_{n+1} the bid (ask) price at which market makers would like to buy (sell) the underlying stock when the trade $n + 1$ takes place. Thus the bid and ask quotes in the model are all effective ones. Assume market makers quote the ask and bid prices as follows,

$$Q_{n+1} = V_{n+1} + I_{n+1} \mathbf{I}. \quad (2)$$

The term $\mathbf{I} \geq 0$ represents market makers' cost per trade for supplying liquidity, which can be interpreted as market makers' compensation for transaction cost, inventory cost, and risk bearing. Note that the Q_{n+1} is a duo: the ask is $V_{n+1} + \mathbf{I}$, and the bid is $V_{n+1} - \mathbf{I}$.

Assume that an actual transaction price always equals the quoted ask (bid) plus stochastic rounding error. The price of trade $n + 1$ is denoted by P_{n+1} . Thus,

$$P_{n+1} = Q_{n+1} + \mathbf{x}_{n+1}. \quad (3)$$

The term \mathbf{x}_n captures the stochastic rounding errors due to price discreteness. Assume it is independently and identically distributed with mean 0 and variance \mathbf{y}^2 .

Combining equation (1), (2), and (3), produces

$$\begin{aligned}
P_{n+1} - P_n &= f(D_{n+1})(I_{n+1} + I_n) + g(D_{n+1})(I_{n+1} - I_n) \\
&+ (I_{n+1} - I_n)\mathbf{I} + \mathbf{u}_{n+1} + \mathbf{x}_{n+1} - \mathbf{x}_n.
\end{aligned} \tag{4}$$

The change of price from trade n to trade $n+1$ is a function of several variables: direction and duration of trade $n+1$, direction of trade n , and error terms. Equation (4) is the basis for the analysis of the impact of trade flow on price movement. Compared with previous structural models such as Huang and Stoll (1997) and Madhavan, Richardson, and Roomans (1997), equation (4) allows one to investigate not only the price impact of trade direction but also the price impact of trade duration.

2.2 Model specification

To implement the model, specify the functional forms of $f(D)$, and $g(D)$ in equation (4) as fourth order polynomials with intercepts.

$$\begin{aligned}
f(D) &= \mathbf{a}_0 + \mathbf{a}_1 D + \mathbf{a}_2 D^2 + \mathbf{a}_3 D^3 + \mathbf{a}_4 D^4, \\
g(D) &= \mathbf{b}_0 + \mathbf{b}_1 D + \mathbf{b}_2 D^2 + \mathbf{b}_3 D^3 + \mathbf{b}_4 D^4.
\end{aligned} \tag{5}$$

The equation (4) now equals

$$\begin{aligned}
&P_{n+1} - P_n \\
&= f(D_{n+1})(I_{n+1} + I_n) + g(D_{n+1})(I_{n+1} - I_n) \\
&+ (I_{n+1} - I_n)\mathbf{I} + \mathbf{u}_{n+1} + \mathbf{x}_{n+1} - \mathbf{x}_n \\
&= (\mathbf{a}_0 + \mathbf{a}_1 D_{n+1} + \mathbf{a}_2 D_{n+1}^2 + \mathbf{a}_3 D_{n+1}^3 + \mathbf{a}_4 D_{n+1}^4)(I_{n+1} + I_n) \\
&+ (\mathbf{b}_0 + \mathbf{I} + \mathbf{b}_1 D_{n+1} + \mathbf{b}_2 D_{n+1}^2 + \mathbf{b}_3 D_{n+1}^3 + \mathbf{b}_4 D_{n+1}^4)(I_{n+1} - I_n) \\
&+ \mathbf{u}_{n+1} + \mathbf{x}_{n+1} - \mathbf{x}_n.
\end{aligned} \tag{6}$$

Under the hypothesis that trade duration contains no information, $D_{n+1} = 0$, and equation (6)

reduces to

$$P_{n+1} - P_n = (\mathbf{a}_0 + \mathbf{b}_0 + \mathbf{I})I_{n+1} + (\mathbf{a}_0 - \mathbf{b}_0 - \mathbf{I})I_n + \mathbf{u}_{n+1} + \mathbf{x}_{n+1} - \mathbf{x}_n, \tag{7}$$

which is essentially equivalent to the price formation model of Madhavan, Richardson, and Roomans (1997).

2.3 Dynamics of quotations and spreads

Two examples help to illustrate the dynamics of the bid and ask prices described by equation (4). In the first example, assume trade n is buyer-initiated so $I_n = 1$. Therefore, trade $n + 1$ is a clustering trade (reversing trade) if it is buyer-initiated (seller-initiated). From equation (3) and (4), the expected ask price for the coming market buy with duration D_{n+1} is

$$P_n + 2f(D_{n+1}), \quad (8)$$

and the expected bid is

$$P_n - 2g(D_{n+1}) - 2\mathbf{I}. \quad (9)$$

The second example assumes trade n is seller-initiated so $I_n = -1$. Trade $n + 1$ is a reversing trade (clustering trade) if it is buyer-initiated (seller-initiated). Again, based on equation (3) and (4), the expected ask price for market order with duration D_{n+1} is

$$P_n + 2g(D_{n+1}) + 2\mathbf{I}, \quad (10)$$

and the expected bid price is

$$P_n - 2f(D_{n+1}). \quad (11)$$

From equation (8) and (9), or (10) and (11), D_{n+1} units of time after trade n and before the next trade takes place, the effective bid-ask spread equals

$$2f(D_{n+1}) + 2g(D_{n+1}) + 2\mathbf{I}. \quad (12)$$

The $2f(D_{n+1}) + 2g(D_{n+1})$ component corresponds to the information content of the direction and duration of the incoming trade. The $2\mathbf{I}$ part covers market makers' transaction cost and inventory cost. In equation (12), the bid-ask spread is a function of trade duration. This facilitates the investigation of its dynamics over time.

3. Data

This paper uses trade and quote data from the TAQ database provided by the NYSE. The sample periods are 253 trading days in year 1997, starting from January 2^d and ending on December 31st. This paper uses data for the whole year to make the results free from possible biases due to seasonal pattern of trading. The sample stocks consist of 10 arbitrarily selected NYSE-listed large (with market capitalization larger than 10 billion at the end of 1997) and actively traded stocks with no split taking place in 1997. The stocks are listed in the Appendix. The data set is restricted to NYSE trades and quotes.

Filters are imposed on the data to eliminate outliers or recording errors. First, drop all transactions occurring after 4:00PM, the official closing time of NYSE. Secondly, exclude the first and the last transactions on each day due to evidence that over-night returns are likely to come from a different distribution [see e.g., Amihud and Mendelson (1987)], and day-end transactions may not consistently represent stock values [see e.g. Harris (1989)]. Thirdly, treat recorded trades with the same time stamp and same price as one trade. Fourth, exclude following trades: trades involving correction, with negative price or size, and those with prices at least 20% higher (lower) than surrounding transaction prices. Additionally, exclude following quotes: those with a negative bid or ask, a bid higher than ask, a bid (ask) at least 20% higher (lower) than surrounding bids (asks), and those with a bid-ask spread greater than 20% of the bid-ask midpoint.

Each trade is identified as buyer- or seller-initiated by comparing the trade price to the prevailing bid and ask quotes. Quotes and transactions, although time stamped to the second, could be recorded out of sequence, as shown by Lee and Ready (1991). Thus for each trade, the prevailing quotes have to be at least five seconds before the trade. Also, to avoid the stale quote problem, the prevailing quotes need to be within thirty minutes of the trade. If there are more than one pair of admissible quotes, the latest one is chosen as the prevailing quote. When a trade takes

place at the ask, it is classified as buyer-initiated. When taking place at the bid, it is classified as seller-initiated. If it takes place within the spread, a trade is classified as buyer- (seller-) initiated if its price is closer to the prevailing ask (bid). When the trade takes place at the midpoint of the quotes or outside the spread, or no identified prevailing quotes, I resort to the tick test proposed by Lee and Ready (1991). The tick test classifies a trade as buyer- (seller-) initiated if it occurs on an uptick (downtick) or zero-uptick (zero-downtick).

Tale 1 presents descriptive statistics for the trades of 10 NYSE stocks used for the analysis. For each stock, statistics are reported for all trades as well as trades in sub-categories. The sub-categories are buyer-initiated trades, seller-initiated trades, and unidentifiable trades. The statistics are the number of transactions, mean and standard deviation of the transaction prices, mean and standard deviation of the transaction sizes. The total number of trades for the whole year (year 1997) ranges from a low of 73,222 (about 289 trades per day) for AA to a high of 231,118 (about 914 trades per day) for KO. The mean and standard deviation of transaction prices for all trades and the trades in three sub-categories are typically similar. Among trades whose directions are identified, there are more buyer-initiated trades than seller-initiated trades for each stock. For each stock, about 10 percent of the trades' directions are not identifiable. These trades have two basic properties. First, the average size of the unidentifiable trades is always larger than that of the buyer-and the seller-initiated trades. The difference between the average size of the unidentifiable trades and that of the buyer-initiated trades ranges from 487 shares (for JPM) to 1,617 shares (for GM). The difference between the average size of the unidentifiable trades and that of the seller-initiated trades ranges from 425 shares (for JPM) to 1,305 shares (for GM). Second, the standard deviation of unidentifiable trades is almost always (except for UTX) larger than that of buyer-initiated and seller-initiated trades. The first property may be related to pre-negotiated liquidity-driven transactions, which tends to take place within spread and have larger size, and thus perhaps more likely to be classified as unidentifiable.

In equation (7), the error term, $\mathbf{u}_{n+1} + \mathbf{x}_{n+1} - \mathbf{x}_n$, is serial correlated. This paper uses a simple method to deal with the serial correlation problem since there are enough observations in the data. Suppose there are N transactions in a day (after cleaning), then there are $N - 1$ observations of price change: $P_2 - P_1, P_3 - P_2, P_4 - P_3, \dots, P_N - P_{N-1}$. Obviously any two consecutive observations of price change contain correlated error terms, while any observations that are not next to each other do not. Thus, construct a data set of independent observations by picking out observations that are not next to each other, for example $P_2 - P_1, P_4 - P_3, P_6 - P_5$, and so on, as well as $(D_2, I_2, I_1), (D_4, I_4, I_3), (D_6, I_6, I_5)$, and so on. After that, remove all observations with trade direction unidentified. The new data set therefore contains roughly half of the observations in the original data set. Next section uses this data set to do empirical analysis.

4. Empirical analysis

4.1. Trade duration

Panel A in Table II presents descriptive statistics for the trade duration for all 10 stocks. The average duration of all trades ranges from 25 seconds (for KO) to 79 seconds (for AA). The standard deviation ranges from 32 seconds (for KO) to 105 seconds (for AA). Table II establishes three robust relations regarding the average trade duration. First, clustering trades have shorter average duration (and smaller standard deviation as well) than reversing trades. This relation holds for all 10 stocks in the sample. Across the sample stocks the average difference between the average duration of clustering trades and reversing trades is 18.1 seconds. The smallest difference is 5 seconds (for MMM). The biggest difference is 34 seconds (for AA). Second, upticks have shorter average duration (and smaller standard deviation as well) than downticks. This is also true for all 10 stocks. The difference between the average duration of upticks and downticks ranges from 3 seconds (for JNJ and KO) to 23 seconds (for MMM and UTX). Third, denoted by $D_{C,U}$,

$D_{C,D}$, $D_{R,D}$, and $D_{R,U}$ the average duration of clustering upticks, clustering downticks, the reversing downticks, and reversing upticks respectively, there is following relation,

$$D_{C,U} < D_{C,D} < D_{R,D} < D_{R,U} . \quad (13)$$

Equation (13) shows that the average trade duration is the shortest for the trades classified as clustering upticks, followed by the clustering downticks, and then by the reversing downticks, and is the longest for the reversing upticks. So far no theory predicts any relationship between the type of trades (clustering vs. reversing or upticks vs. downticks) and the average duration. Therefore it is unclear what causes these empirical relations and what the economic implications are. This obviously raises demand for more theoretical and empirical works.

Figure 1 plots the number of transactions based on their duration. Each picture is for a stock. In each picture, the horizontal axis is trade duration, and the vertical axis is the number of trades. There are 181 units in the horizontal axis. The first 180 units correspond to the first 180 seconds after the last transaction, the 181st unit corresponds to all time beyond the first 180 seconds. There are two curves in each picture: the upper one is for clustering trades; the lower one is for reversing trades. The number of trades, for both the clustering trades and reversing trades and for all stocks, reaches the highest number at the fourth second after last transactions. After that, the number generally decreases. At the same time, there is a clear and robust saw tooth pattern for all stocks, and for categories of clustering trades and reversing trades as well, which appears to be a four-second-cycle. Starting with the first second, for every four seconds, the number of transactions is almost always largest in the fourth second. For example, from the first to the fourth second, the number of transactions in the fourth second is the largest; for the fifth to the eighth second, the number of transactions in the eighth second is the largest; and so on. The four-second-cycle is intriguing because conversations with NYSE specialists do not suggest any rule of trading or recording that may account for this phenomenon.

4.2 Trade frequency

Panel B in Table II establishes three robust relations regarding the frequency for specific types of trades to take place in the sample. First, there are more clustering trades than reversing trades for all 10 stocks, which is obvious by looking at the second and the third columns of Panel B. The percentage of clustering trades ranges from 65% (for IP) to 71% (for GM). Second, there are more upticks than downticks, which is revealed by the fourth and fifth columns of Panel B. The percentage of upticks ranges from 79% (for JPM) to 84% (GM). Third, denote by $F_{C,U}$, $F_{C,D}$, $F_{R,D}$, and $F_{R,U}$ the frequency for clustering upticks, clustering downticks, reversing downticks, and reversing upticks respectively, Panel B establishes following relations:

$$F_{C,U} > F_{R,U} > F_{R,D} > F_{C,D}. \quad (14)$$

The most frequently observed trades are clustering upticks, followed by reversing upticks, and then by reversing downticks, and the least frequently observed are clustering downticks.

Inventory control models of dealer trading behavior [see, e.g., Stoll (1978), and Amihud and Mendelson (1980)] predict that there may be more reversing trades than clustering trades because dealers actively adjust the quotes to attract trades with opposite directions to keep their stock holdings within certain bounds. Asymmetric information models, on the other hand, imply that the number of clustering and reversing trades may be roughly the same because dealers set the quotes so that in expectation informed traders will not profit from trading. Therefore, the finding of more clustering trades is not supportive of the prediction of inventory models or satisfactorily explained by asymmetric information models. However, sequential trade models such as Easley and O'Hara (1992) could shed light on the issue. If investors become informed sequentially, when there is an information event, trades tend to take place with the same directions. Thus there should be more clustering trades than reversing trades.

The sequential trade models, however, may not be able to explain why there are more upticks than downticks. Suppose “Low” and “High signal” are equally likely and uninformed

traders are equally likely to buy or sell, there should be roughly the same number of upticks and downticks. The finding of more upticks than downticks therefore does not support Easley and O'Hara's (1992) prediction and does not have clear economic implications.

Suppose upticks are usually buyer-initiated and downticks are usually seller-initiated, the relation described by equation (14) implies that a buy more often follow a buy, while a sell less frequently follows a sell. This asymmetry is not consistent with the sequential trade models either. In the sequential trade models, if "High signal" ("Low signal") takes place, more trades would be buyer- (seller-) initiated, and thus more clustering upticks (downticks) should be observed. Suppose "Low" and "High signals" are equally likely to take place, a sell should follow a sell as often as a buy follows a buy. More work needs to be done to explore economically sensible explanations for these empirical relations.

4.3. Dynamics of Effective Spreads

Table III reports the results from estimation of equation (6) for all ten stocks. In general, equation (6) fits the data well. The R^2 ranges from 42.63% (for AA) to 72.13% (for KO). With the estimated parameters, one can easily show how the effective bid-ask spread varies through time according to equation (12). Figure 2 plots the dynamics of effective spreads within 180 seconds after the last trade for all 10 stocks. The spreads tend to increase over time. Specifically, for 8 out of 10 stocks, the spreads are wider at 180 seconds after the last trade. Table IV reports some descriptive statistics for the dynamic behavior of the bid-ask spreads. The differences between the maximum and the minimum of the spreads range from 0.13 cents (for IP) to 2.3 cents (for MMM). For 7 out of all 10 stocks, the difference is larger than 0.8 cents.

Easley and O'Hara (1992) predict that spreads will decrease as the time between transactions increases. The prediction is theoretically sensible because the absence of trades may imply that no news arrives, i.e. no informational event takes place, and therefore the likelihood of informed trading decreases. On the other hand, there may be alternative stories that are reasonable

as well yet have different empirical implications for the dynamics of spreads. For example, when market makers observe a trade long after the preceding trade, they may believe this trade takes place for a good reason, i.e. it is more likely driven by private information. They therefore increase the bid-ask spread over time to take account for that. The empirical findings in Table IV are not supportive of Easley and O'Hara's (1992) prediction. More theoretical work may be necessary to explain why effective spreads increase over time.

4.4. Dynamics of Effective Quotes

Table V summarizes the expected ask and bid quotes described by equations (8), (9), (10), and (11). The quotes are a function of the last trade price, duration of incoming order, direction of the last and incoming order, and compensation for liquidity providing. Subtracting the last trade price and controlling for the duration, the ask (bid) price following a buyer-initiated trade has the opposite sign but the same magnitude with the bid (ask) price following a seller-initiated trade.

Table VI reports the magnitude (absolute value) of the difference between quotes and the last transaction price for clustering and reversing trades. For a clustering trade, the magnitude starts from the minimum level (except for KO), reaches the maximum level after a while - from the 58th second after the last trade (for KO) to the 154th second (for AA) after it, then decreases. The difference of the minimum and maximum level ranges from 0.67 cents (for JNJ) to 3.05 cents (for MMM) with the average being 1.53 cents. For reversing trades, the magnitude tends to start from the maximum level (except for EK and KO), decreases and reaches the minimum level after a while - from the 48th second after the last trade (for KO) to the 165th second after the last trade (for UTX), then increases. The difference between the minimum and maximum level ranges from 0.6 cents (for MMM) to 1.47 cents (for JNJ) with an average of 1.01.

Figure 3 shows the dynamics of ask and bid prices after a buyer-initiated trade. The horizontal axis is the lapse of time since the last trade and without seeing an order coming. The

vertical axis is in cents, for the quotes minus the last trade price. Thus 0 corresponds to the last transaction price. This figure answers the following questions. First, by drawing a vertical line on the graph that corresponds to a specific moment after the last trade, one can answer the question, "What would be the ask and bid prices at this moment?" Second, by drawing a horizontal line, one can tell when, if ever, ask or bid price will hit that specific level. Both these two questions have direct implications for the optimal trading strategy.

In Figure 3, for all stocks, after a buyer-initiated trade, both ask and bid prices increase at first, then decrease after a while. Market makers tend to set higher ask (lower bid) for a market buy (sell) that more likely contains private information. Therefore, suggested by Figure 3, market makers seem to believe that the market buy coming within a middle range of time after the last buyer-initiated trade is more likely to contain private information. On the other hand, they seem to believe that the market sell coming within the same time-range is less likely to contain private information. The causes for these patterns are still unclear, and these patterns are not predicted by any theory.

5. Conclusions

This paper develops a real-time structural model of price formation. In the model, market makers are allowed to form expectation and quote ask and bid prices conditional upon the duration of the incoming order. This is justified by the fact that they are able to adjust the quotes through time. Thus the time interval between consecutive transactions enters the model naturally and has an impact on price formation.

This paper uses the model to investigate the dynamics of quotes and bid-ask spreads. It finds some evidence that the effective bid-ask spreads tend to increase over time when no orders arrive. Quotes are found changing through time when no orders arrive, but not monotonically or symmetrically. The dynamics of quotes is related to the direction of the last transaction: after a buyer-initiated (seller-initiated) trade, both ask and bid increase (decrease) first and then decrease

(increase). Market makers tend to set higher ask (lower bid) for coming order of market buy (sell) that are believed to contain private information. Therefore, the quote dynamics seem to show that market makers believe that the clustering trades with middle-range duration (coming one or two minutes after the last trades) are more likely to contain private information, while the reversing trades with same duration are less likely to contain private information.

This paper establishes some stylized facts about average duration of trades. Clustering trades have shorter average duration than reversing trades. Upticks have shorter average duration than downticks. The average trade duration is the shortest for the trades classified as clustering upticks, followed by the clustering downticks, and then by the reversing downticks, and is the longest for the reversing upticks. This paper also establishes stylized facts regarding frequency of trades. Clustering trades are more frequently observed than reversing trades. Upticks are more frequently observed than downticks. The most frequently observed trades are clustering upticks, followed by reversing upticks, and then by reversing downticks, and the least frequently observed are clustering downticks. These facts are either inconsistent with prevailing theoretical predictions or irrelevant to any available theory at all. More theoretical work seems to be needed to provide economically sound explanations.

References

- Admati, A., Pfleiderer, P., 1988. A theory of intraday trading patterns: Volume and price variability. *Review of Financial Studies* 1, 3-40.
- Amihud, Y., Mendelson, H., 1980. Dealership market: market making with inventory. *Journal of Financial Economics* 8, 31-53.
- Amihud, Y., Mendelson, H., 1987. Trading Mechanisms and Stock Returns: An Empirical Investigation. *Journal of Finance* 42 533-553.
- Blume, L., Easley, D., O'Hara, M., 1994. Market Statistics and technical analysis: the role of volume. *Journal of Finance* 49, 153-181.
- Blume, M., Goldstein, M., 1997. Quotes, order flow, and price discovery. *Journal of Finance* 52, 221-244.
- Choi, J., Salandro, D., Shastri, K., 1988. On the estimation of bid-ask spreads: Theory and evidence. *Journal of Financial and Quantitative Analysis* 23, 219-230.
- Diamond, D., Verrecchis, R., 1987. Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics* 18, 277-311.
- Dufour, A., Engle, R., 2000. Time and the price impact of a trade. *Journal of Finance* 55, 2467-2498.
- Easley, D., Kiefer, N., O'Hara, M., 1997. One day in the life of a very common stock. *Review of Financial Studies* 10, 805-835.
- Easley, D., O'Hara, M., 1987. Prices, trade size and information in security markets. *Journal of Financial Economics* 19, 69-90.
- Easley, D., O'Hara, M., 1992. Time and the process of security price adjustment. *Journal of Finance* 47, 577-604.
- Engle, R., 2000. The econometrics of ultra-high frequency data. *Econometrica* 68, 1-22.

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

Foster, D., Viswanathan, S., 1990. A theory of the intraday variations in volumes, variances and trading costs in security markets. *Review of Financial Studies* 3, 593-624.

Foster, D., Viswanathan, S., 1994. Strategic trading with asymmetrically informed traders and long-lived information. *Journal of Finance* 48, 187-211.

Franklin, A., Gorton, G., 1992. Stock price manipulation, market microstructure and asymmetric information. *European Economic Review* 36, 624-630.

Garman, M., 1976. Market microstructure. *Journal of Financial Economics* 3, 257-275.

George, T., Kaul, G., Nimalendran, M., 1991. Estimation of the bid-ask Spread and its components: A new approach. *Review of Financial Studies* 4, 623-656.

Ghysels, E., 2000. Some econometric recipes for high-frequency data cooking. *Journal of Business and Economic Statistics* 18, 54-163.

Glosten, L., 1987. Components of the bid-ask spread and the statistical properties of transaction prices. *Journal of Finance* 42, 1293-1307.

Glosten, L., Harris, L., 1988. Estimating the components of the bid-ask spread. *Journal of Financial Economics* 21, 123-142.

Glosten, L., Milgrom, P., 1985. Bid, ask, and transaction prices in a specialist market with heterogeneously informed agents. *Journal of Financial Economics* 14, 71-100.

Harris, L., 1989. A day-end transaction price anomaly. *Journal of Financial and Quantitative Analysis* 24, 29-45.

Hasbrouck, J., 1991. Measuring the information content of stock trades. *Journal of Finance* 46, 179-207.

Hasbrouck, J., Sofianos, G., 1993. The trades of market makers: An analysis of NYSE specialists. *Journal of Finance* 48, 1565-1595.

- Hausman, J., Lo, A., MacKinlay, C., 1992. An ordered probit analysis of transaction stock prices. *Journal of Financial Economics* 31, 319-379.
- Huang, R., Stoll, H., 1994. Market microstructure and stock return predictions. *Review of Financial Studies* 7, 179-213.
- Huang, R., Stoll, H., 1997. The components of the bid-ask spread: a general approach. *Review of Financial Studies* 10, 995-1034.
- Kyle, A., 1985. Continuous auctions and insider trading. *Econometrica* 53, 1315-1335.
- Lee, C., Ready, M., 1991. Inferring trade direction from intradaily data. *Journal of Finance* 46, 733-746.
- Madhavan, A., Richardson, M., Roomans, M., 1997. Why do security prices change? A transaction-level analysis of NYSE stocks. *Review of Financial Studies* 10, 1035-1064.
- McInish, T., Wood, R., 1992. An analysis of intraday patterns in bid/ask spreads for NYSE stocks. *Journal of Finance* 47, 753-764.
- Peterson, M., Fialkowski, D., 1994. Posted versus effective spreads: Good prices or bad quotes? *Journal of Financial Economics* 35, 269-292.
- Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39, 1127-1139.
- Stoll, H., 1978. The supply of dealer services in securities markets. *Journal of Finance* 33, 1133-1151.
- Stoll, H., 1989. Inferring the components of the bid-ask spread: Theory and empirical tests. *Journal of Finance* 44, 115-134.

Appendix: Sample of securities

Company Name	Symbol
Alcoa Inc.	AA
American Express Co.	AXP
Coca-Cola Co.	KO
Eastman Kodak Co.	EK
General Motors Corp.	GM
International Paper Co.	IP
J.P. Morgan & Co.	JPM
Johnson & Johnson	JNJ
Minnesota Mining & Manufacturing Co.	MMM
United Technologies Corp.	UTX

Table I. Descriptive Statistics for Trades

The table presents descriptive statistics of trades for 10 stocks over the sample period 1997. All trades and quotes are from NYSE. The directions of trades are determined by comparing the prices to the prevailing bid and ask quotes, or using tick test proposed by Lee and Ready (1991).

Company	Direction of trade	# of trades	Mean price	Std. Dev. price	Mean size	Std. Dev. size	Company	Direction of trade	# of trades	Mean price	Std. Dev. price	Mean size	Std. Dev. size
AA	All	73,222	74.75	6.20	2,310	6,302	JNJ	All	213,617	59.53	3.67	2,430	8,765
	Buy	35,097	74.90	6.14	2,138	5,115		Buy	104,991	59.43	3.70	2,177	4,877
	Sell	30,774	74.99	6.33	2,383	6,618		Sell	81,284	59.69	3.68	2,536	6,050
	Unknown	7,351	73.08	5.69	2,827	9,324		Unknown	27,342	59.47	3.50	3,086	19,985
AXP	All	137,003	73.72	9.21	2,209	10,556	JPM	All	117,262	109.03	6.79	1,358	4,575
	Buy	65,983	73.93	9.24	2,212	11,365		Buy	58,222	109.38	6.79	1,289	3,282
	Sell	57,788	73.83	9.13	2,036	6,614		Sell	48,574	109.16	6.74	1,351	5,225
	Unknown	13,232	72.15	9.26	2,955	17,830		Unknown	10,466	106.51	6.52	1,776	6,906
EK	All	163,853	70.47	10.39	2,168	7,768	KO	All	231,118	61.91	4.74	3,115	12,967
	Buy	75,565	70.41	10.28	1,970	4,902		Buy	105,573	61.89	4.72	3,137	6,982
	Sell	69,130	70.31	10.49	2,232	6,518		Sell	101,521	61.98	4.78	2,715	6,956
	Unknown	19,158	71.24	10.43	2,716	16,358		Unknown	24,024	61.70	4.63	4,711	34,579
GM	All	150,498	61.32	4.64	3,358	11,483	MMM	All	100,532	91.46	5.67	1,935	5,671
	Buy	67,940	61.31	4.63	3,005	7,618		Buy	44,553	91.64	5.63	1,982	4,079
	Sell	61,610	61.35	4.70	3,317	11,713		Sell	45,273	91.53	5.70	1,737	3,850
	Unknown	20,948	61.25	4.46	4,622	18,805		Unknown	10,706	90.39	5.61	2,577	13,018
IP	All	120,847	48.43	6.05	2,195	7,170	UTX	All	85,123	77.18	5.31	2,162	8,979
	Buy	57,001	48.08	5.93	2,087	5,456		Buy	39,873	77.23	5.32	2,039	7,279
	Sell	52,496	48.85	6.13	2,078	6,586		Sell	35,016	77.26	5.36	2,173	10,602
	Unknown	11,350	48.30	6.19	3,275	13,998		Unknown	10,234	76.66	5.05	2,607	8,908

Table II. Descriptive Statistics for Trade Duration & Frequency

The table presents descriptive statistics for trade duration and frequency. The duration of a trade is defined as the length of time between the last trade and the current trade. A trade is a clustering (reversing) trade if it has the same (opposite) direction with the last trade. A trade is an uptick (downtick) if its price is higher (lower) than the last transaction price. All numbers about trade duration are in second.

Panel A: Trade duration: mean (standard deviation)									
	All	Clustering	Reversing	Uptick	Downtick	Clustering -uptick	Clustering -downtick	Reversing -uptick	Reversing -downtick
AA	79 (105)	69 (99)	103(115)	75 (104)	95 (108)	67 (99)	85 (95)	103(115)	102(115)
AXP	43 (57)	37 (52)	56 (67)	40 (56)	54 (62)	35 (51)	52 (54)	56 (68)	55 (66)
EK	35 (49)	32 (46)	43 (54)	34 (49)	39 (50)	31 (46)	38 (46)	45 (57)	39 (52)
GM	39 (56)	36 (54)	45 (58)	37 (55)	45 (56)	35 (55)	47 (46)	46 (58)	45 (59)
IP	48 (64)	43 (60)	57 (68)	46 (62)	56 (67)	43 (60)	52 (59)	57 (67)	57 (70)
JNJ	27 (33)	25 (32)	31 (35)	26 (33)	29 (33)	25 (32)	31 (31)	32 (37)	29 (33)
JPM	50 (70)	43 (64)	64 (79)	47 (67)	60 (76)	41 (63)	56 (71)	65 (79)	63 (79)
KO	25 (32)	24 (31)	29 (34)	25 (32)	28 (33)	24 (31)	29 (30)	29 (35)	28 (33)
MMM	57 (73)	48 (66)	77 (83)	53 (71)	75 (80)	46 (65)	71 (74)	76 (83)	78 (84)
UTX	67 (93)	57 (84)	90 (106)	63 (91)	85 (98)	55 (83)	80 (89)	92 (108)	88 (103)

Panel B: Frequency of trade									
	All	Clustering	Reversing	Uptick	Downtick	Clustering -uptick	Clustering -downtick	Reversing -uptick	Reversing -downtick
AA	100%	69%	31%	81%	19%	62%	8%	19%	11%
AXP	100%	70%	30%	82%	18%	64%	6%	18%	12%
EK	100%	69%	31%	83%	17%	65%	5%	18%	12%
GM	100%	71%	29%	84%	16%	68%	3%	17%	12%
IP	100%	65%	35%	80%	20%	60%	4%	20%	16%
JNJ	100%	68%	32%	83%	17%	65%	3%	18%	14%
JPM	100%	69%	31%	79%	21%	60%	9%	19%	12%
KO	100%	67%	33%	83%	17%	64%	3%	19%	15%
MMM	100%	70%	30%	82%	18%	62%	7%	19%	11%
UTX	100%	70%	30%	80%	20%	62%	8%	19%	12%

Table III. Estimating the Real-time structural Model of Price Formation

$$P_n - P_{n-1} = c + f(D_n)(I_n + I_{n-1}) + [g(D_n) + \mathbf{I}](I_n - I_{n-1}) + \mathbf{e}_n$$

The P_n is the price (in cent) at which transaction n takes place. The D_n is the duration (in second) of trade n . The I_n is the direction of trade n , which equals 1 if transaction n is buyer-initiated and -1 if it is seller-initiated. The t -statistics are in parentheses. Functional forms of $f(D)$ and $g(D)$ are specified as:

$$f(D_n) = \mathbf{a}_0 + \mathbf{a}_1 D_n + \mathbf{a}_2 D_n^2 + \mathbf{a}_3 D_n^3 + \mathbf{a}_4 D_n^4; \quad g(D_n) = \mathbf{b}_0 + \mathbf{b}_1 D_n + \mathbf{b}_2 D_n^2 + \mathbf{b}_3 D_n^3 + \mathbf{b}_4 D_n^4.$$

	AA	AXP	EK	GM	IP	JNJ	JPM	KO	MMM	UTX
c	-0.1234 (-4.0)	-0.0742 (-4.3)	-0.0531 (-3.3)	-0.0242 (-1.9)	-0.0591 (-3.5)	-0.0861 (-8.0)	-0.2200 (-8.0)	-0.0022 (-0.2)	0.1055 (4.1)	-0.1493 (-5.4)
\mathbf{a}_0	0.5981 (20.0)	0.3185 (18.3)	0.2874 (18.0)	0.1657 (14.4)	0.3202 (18.6)	0.1642 (13.9)	0.9025 (35.4)	0.1185 (11.8)	0.2387 (9.1)	0.5087 (19.1)
\mathbf{a}_1	0.01357 (17.4)	0.02433 (28.8)	0.01322 (15.8)	0.00666 (16.9)	0.00957 (13.5)	0.01327 (14.1)	0.01561 (19.0)	0.01354 (17.4)	0.03317 (29.7)	0.01990 (22.7)
\mathbf{a}_2^*	-0.602 (-14.7)	-1.817 (-22.1)	-0.978 (-11.3)	-0.307 (-14.0)	-0.663 (-11.3)	-1.548 (-9.4)	-0.747 (-15.8)	-1.663 (-13.3)	-2.250 (-22.4)	-1.017 (-17.7)
\mathbf{a}_3^{**}	0.755 (12.0)	4.114 (17.5)	2.147 (8.4)	0.307 (11.5)	1.321 (9.3)	5.888 (6.7)	0.923 (12.5)	6.167 (10.5)	4.833 (17.7)	1.588 (14.1)
\mathbf{a}_4^{***}	-2.736 (-10.1)	-27.487 (-14.9)	-13.589 (-6.4)	-0.627 (-10.6)	-7.530 (-8.1)	-70.790 (-5.3)	-3.045 (-10.7)	-66.477 (-8.8)	-31.256 (-14.8)	-7.503 (-11.9)
$\mathbf{b}_0 + \mathbf{I}$	4.0663 (66.9)	4.0055 (132.8)	3.7014 (134.8)	3.7741 (172.7)	4.5132 (172.3)	4.5372 (239.9)	4.7007 (102.2)	4.2242 (283.0)	4.0735 (86.0)	4.1104 (87.2)
\mathbf{b}_1	-0.00603 (-4.2)	-0.01484 (-14.2)	-0.01471 (-11.4)	-0.01295 (-14.3)	-0.00899 (-9.6)	-0.03156 (-21.2)	-0.01008 (-7.4)	-0.01344 (-13.0)	-0.00692 (-5.7)	-0.00532 (-5.7)
\mathbf{b}_2^*	0.275 (3.4)	0.998 (12.4)	1.344 (9.9)	1.048 (13.1)	0.577 (7.7)	4.043 (14.6)	0.553 (6.4)	1.858 (11.8)	0.432 (6.2)	0.213 (5.4)
\mathbf{b}_3^{**}	-0.407 (-2.7)	-1.967 (-10.6)	-3.206 (-7.5)	-2.195 (-10.5)	-1.086 (-6.0)	-18.023 (-11.0)	-0.890 (-5.6)	-6.862 (-9.9)	-0.632 (-5.6)	-0.224 (-4.8)
\mathbf{b}_4^{***}	2.111 (2.5)	11.112 (9.5)	23.108 (6.1)	13.776 (8.9)	5.801 (4.9)	255.54 (9.0)	4.003 (5.0)	71.357 (8.7)	2.175 (5.3)	0.584 (4.4)
R^2	0.4263	0.5068	0.4753	0.6023	0.6502	0.6912	0.4356	0.7213	0.4462	0.4602

* In 0.0001. (1E-4)

** In 0.0000001.(1E-7)

*** In 0.00000000001.(1E-11)

Table IV. Dynamics of the Effective Bid-ask Spreads

This table reports descriptive statistics for the dynamics of the effective bid-ask spreads over 180 seconds after the last trade and when no orders arrive. All numbers (except the time) are in cent. The time is in second.

	Stocks														
	AA	AXP	EK	GM	IP	JNJ	JPM	KO	MMM	UTX					
Second 1	9.34	8.67	7.97	7.87	9.67	9.37	11.22	8.69	8.68	9.27					
Second 180	10.32	8.92	8.78	8.49	9.56	8.71	12.00	9.28	10.58	10.72					
Average	10.08	9.15	8.23	7.85	9.65	8.74	11.80	8.94	10.53	10.50					
Minimum	9.34	8.67	7.95	7.56	9.56	8.53	11.22	8.69	8.68	9.27					
time		1	1	22	52	180	59	1	1	1					
Maximum	10.35	9.32	8.78	8.49	9.69	9.37	12.02	9.28	11.03	10.87					
time		150	82	180	180	40	1	152	180	110					130
Maxi-Mini	1.00	0.66	0.83	0.92	0.13	0.84	0.81	0.59	2.36	1.60					

Table V. Value of Effective Quotes

This table reports the value of effective quotes, based on the real-time model of price formation, for the incoming clustering order and reversing order with duration D_{n+1} .

	Effective Bid (For incoming market sell)	Effective Ask (For incoming market buy)
If the last order is buy	$P_n - 2g(D_{n+1}) - 2\mathbf{I}$	$P_n + 2f(D_{n+1})$
If the last order is sell	$P_n - 2f(D_{n+1})$	$P_n + 2g(D_{n+1}) + 2\mathbf{I}$

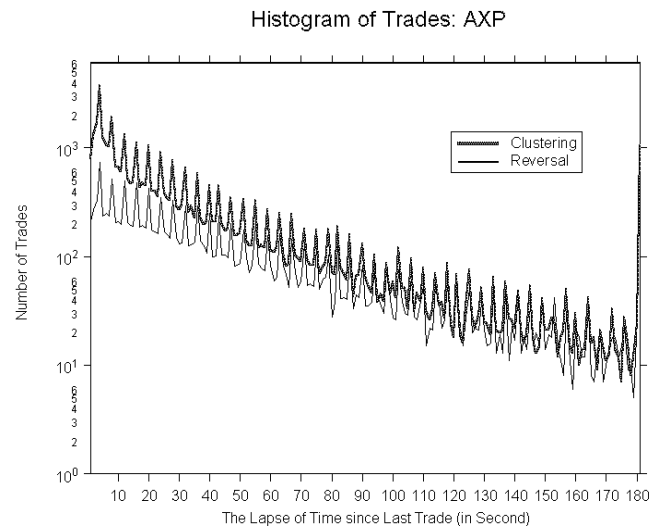
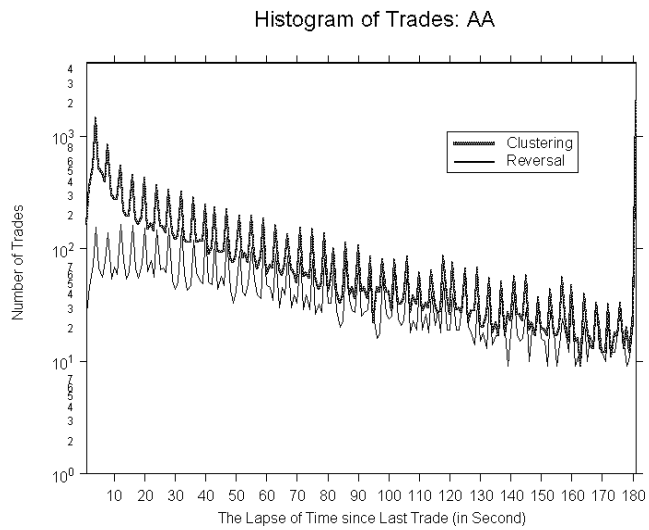
Table VI. Dynamics of the Effective Quotes

A trade is a clustering (reversing) trade if it has the same (opposite) direction with the last trade. A clustering trade could be a buy after a buy or a sell after a sell. The reversing trade could be a buy after a sell or a sell after a buy. The numbers in this table are magnitude of the difference between the ask (bid) and the last trade price. The quotes for a clustering buy and a clustering sell have symmetric dynamics. At the same time, the quotes for a reversing buy and a reversing sell have symmetric dynamics. Thus this table only reports the magnitude (absolute value) of the difference between quote for clustering and reversing trade and the last trade price.

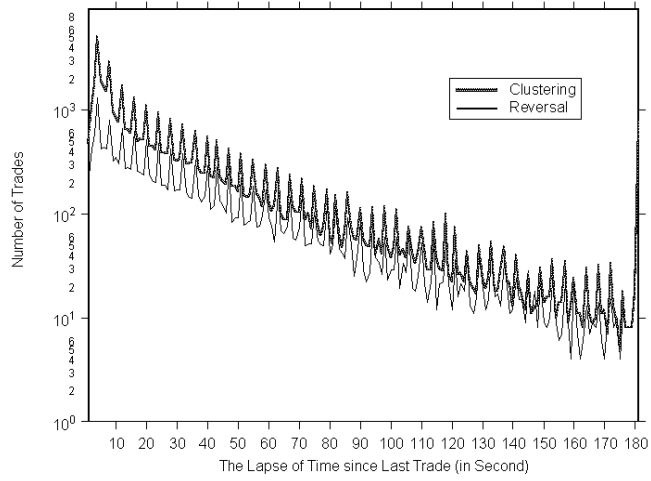
Magnitude of the Quote minus the Last Trade Price for a Clustering Trade													
	AA	AXP	EK	GM	IP	JNJ	JPM	KO	MMM	UTX			
Second 1	1.22	0.69	0.60	0.34	0.66	0.35	1.84	0.26	0.54	1.06			
Second 180	3.00	1.84	1.22	1.08	1.17	0.46	3.60	0.13	2.82	3.29			
Average	2.55	2.18	1.41	0.96	1.29	0.79	3.26	0.60	2.87	2.84			
Minimum	1.22	0.69	0.60	0.34	0.66	0.35	1.84	0.13	0.54	1.06			
time		1	1	1	1	1	1	1	180	1			1
Maximum	3.04	2.64	1.67	1.16	1.48	1.04	3.73	0.91	3.53	3.42			
time		154	95	95	135	100	64	137	58	107			139
Maxi-Mini	1.82	1.96	1.07	0.81	0.82	0.69	1.90	0.78	2.98	2.36			
Magnitude of the Quote minus the Last Trade Price for a Reversing Trade													
	AA	AXP	EK	GM	IP	JNJ	JPM	KO	MMM	UTX			
Second 1	8.12	7.98	7.37	7.52	9.01	9.01	9.38	8.42	8.13	8.21			
Second 180	7.31	7.07	7.56	7.41	8.38	8.25	8.40	9.14	7.76	7.44			
Average	7.53	6.97	6.82	6.90	8.36	7.94	8.54	8.34	7.66	7.66			
Minimum	7.30	6.67	6.45	6.60	8.17	7.49	8.28	7.87	7.50				
time		160	104	72	81	109	61	127	48	102			166
Maximum	8.12	7.98	7.56	7.52	9.01	9.01	9.38	9.14	8.13	8.21			
time		1	1	180	1	1	1	1	180	1			1
Maxi-mini	0.82	1.31	1.11	0.92	0.84	1.53	1.10	1.27	0.63	0.78			

Figure 1. Histogram of Trade Duration.

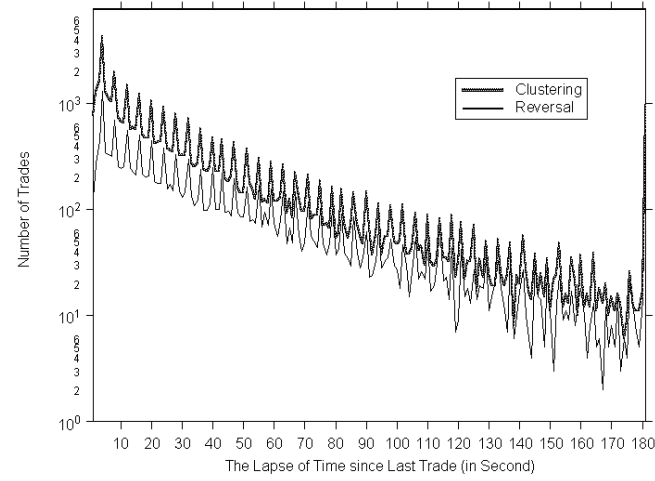
Each picture is for a stock. In each picture, the horizontal axis is trade duration, i.e. the time length since last transaction; the vertical axis is the number of trades. There are 181 units in the horizontal axis. The first 180 ones correspond to the first 180 seconds after the last transaction, the 181st unit corresponds to all time beyond the first 180 seconds. There are two curves in each picture: the upper one is for clustering trades, which have same directions with last transactions; the lower one is for reversing trades, which have opposite directions with last transactions.



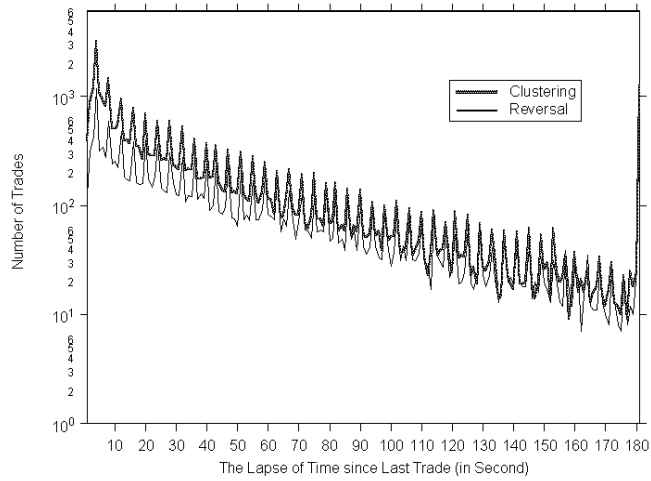
Histogram of Trades: EK



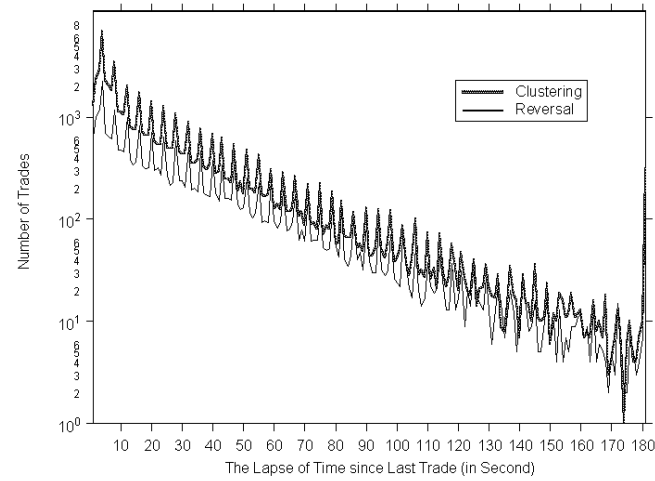
Histogram of Trades: GM



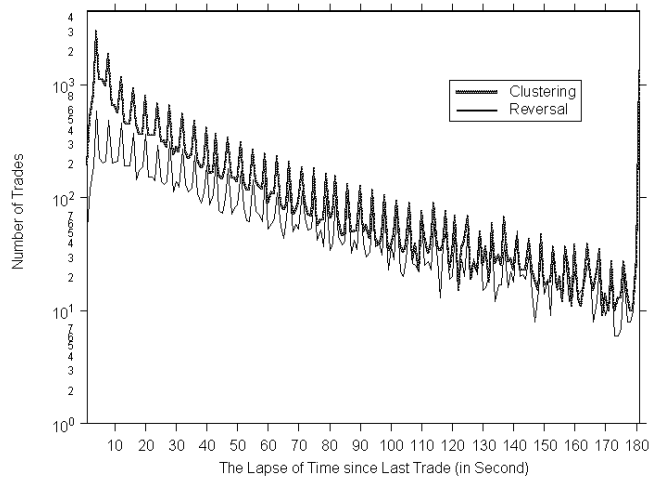
Histogram of Trades: IP



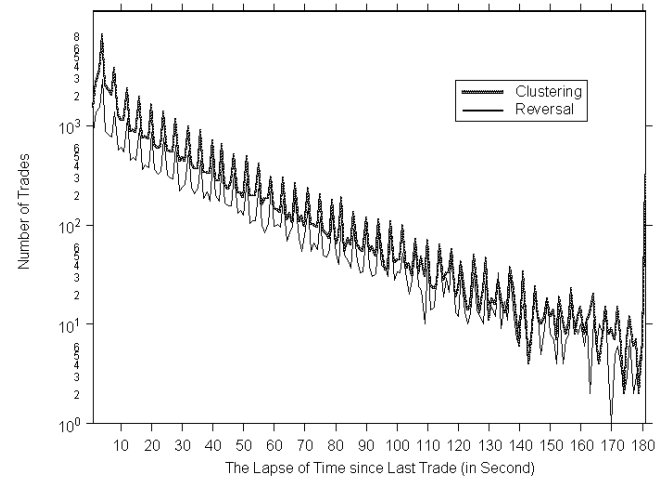
Histogram of Trades: JNJ



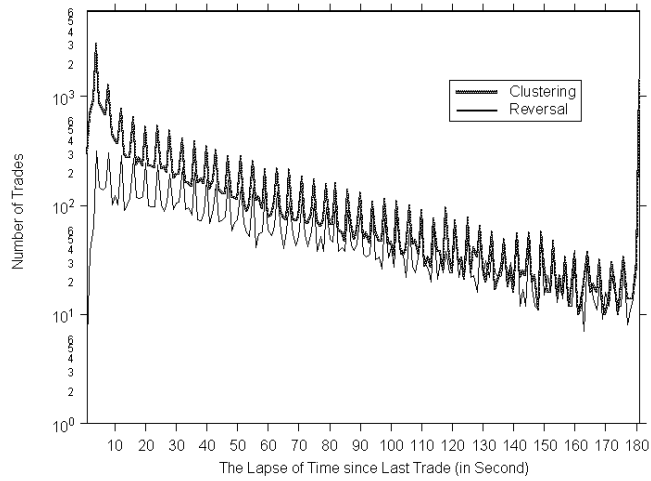
Histogram of Trades: JPM



Histogram of Trades: KO



Histogram of Trades: MMM



Histogram of Trades: UTX

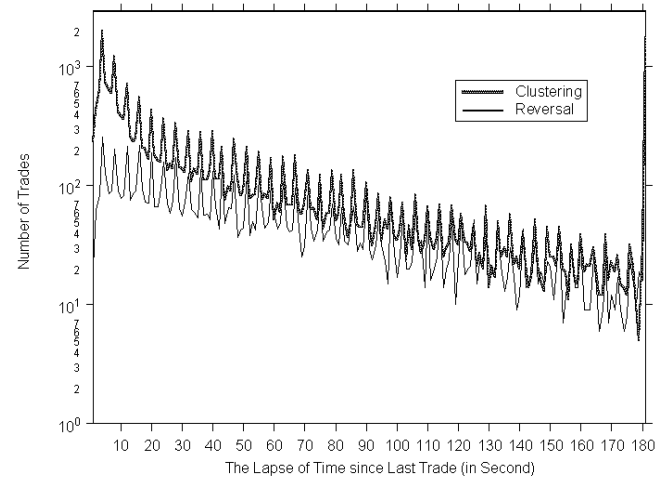


Figure 2. Dynamics of Effective Spreads

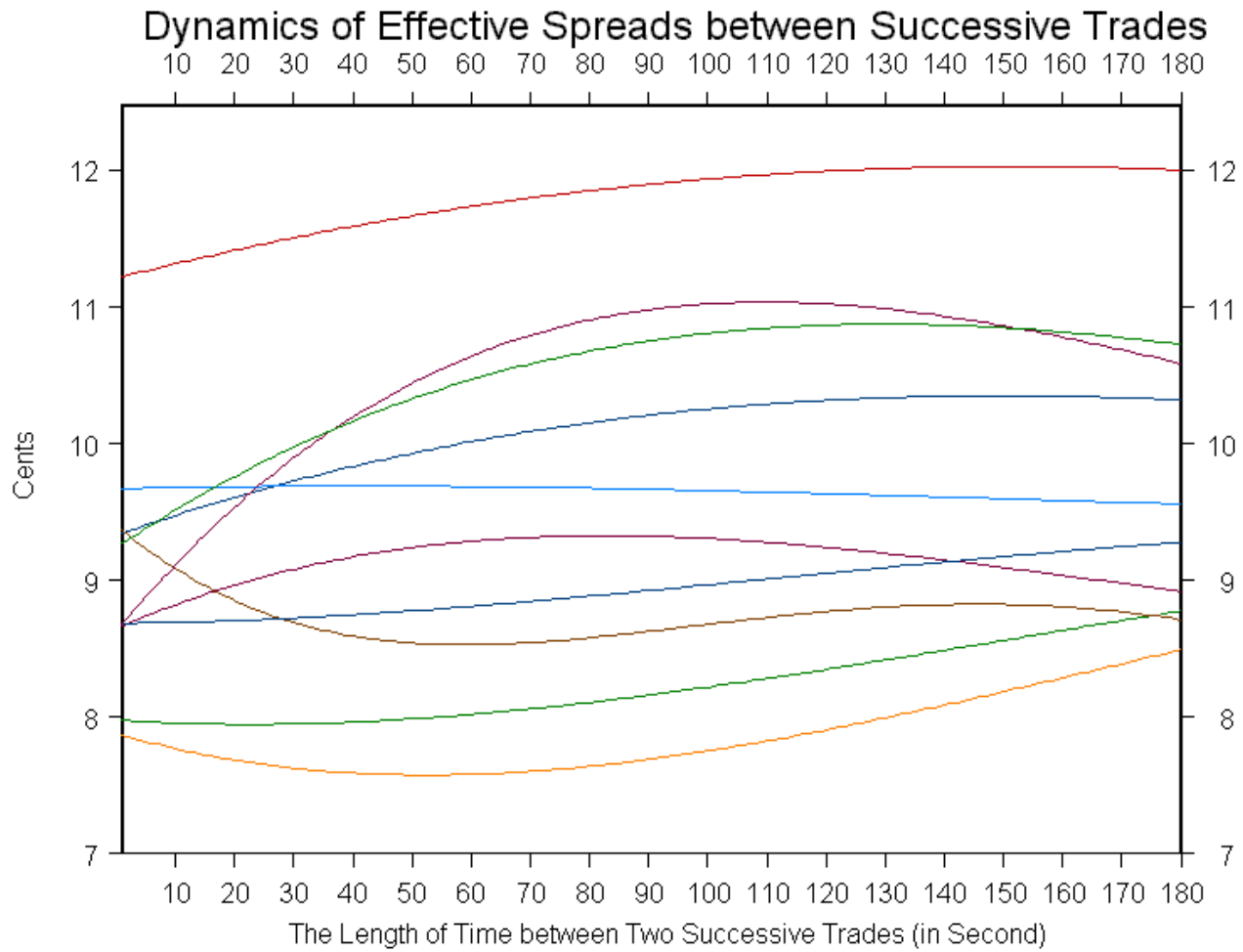
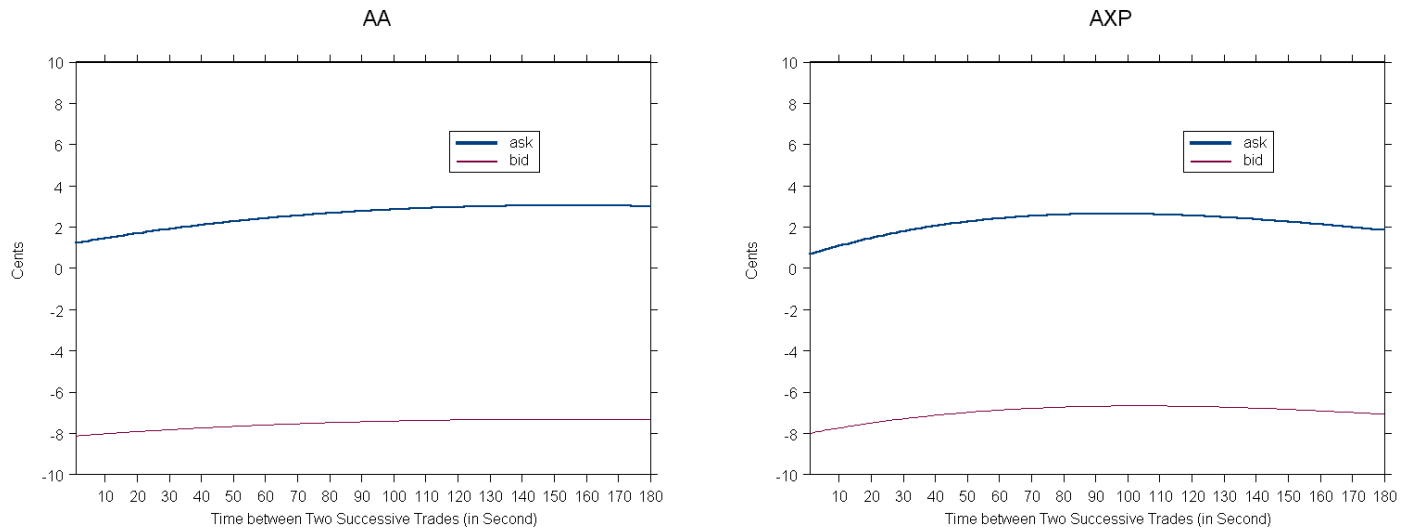
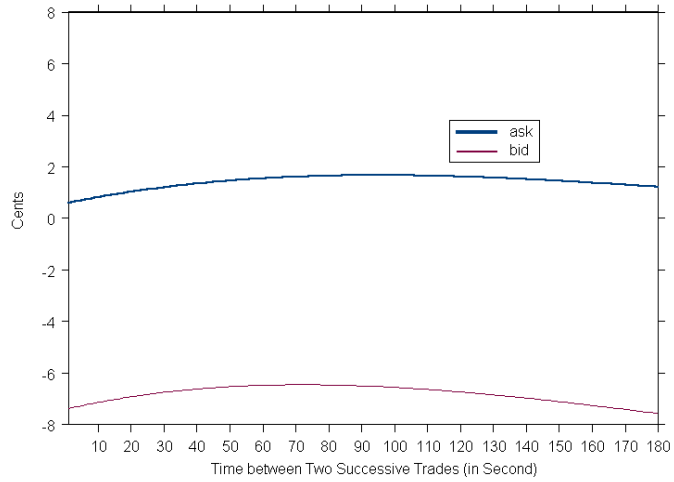


Figure 3. Dynamics of Quotes after a Buy

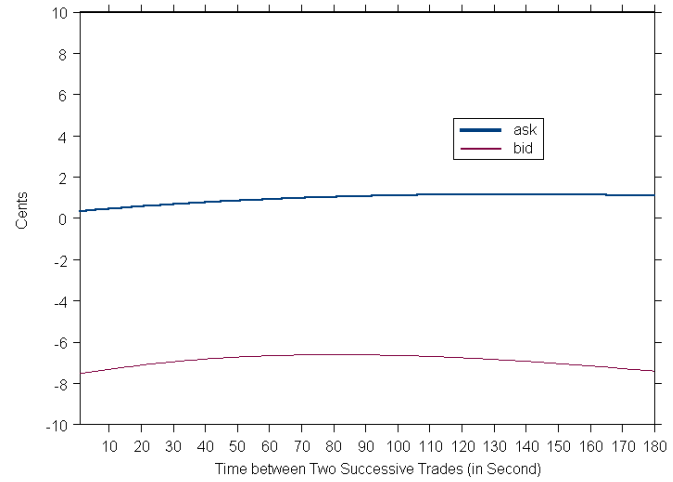
Each picture is for a stock. In each picture, the horizontal axis is the lapse of time since the last trade without seeing an order coming. The vertical axis is in cents, for the difference between quotes and the last trade price.



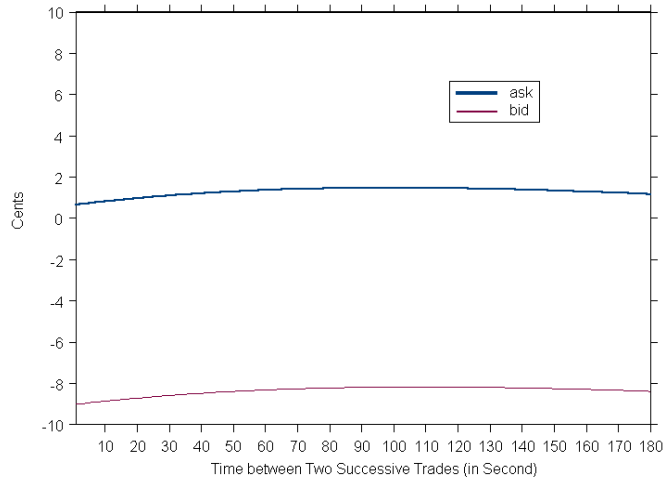
EK



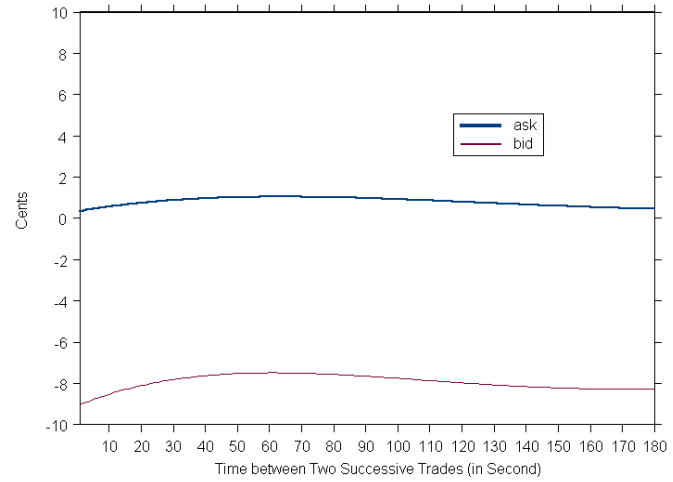
GM



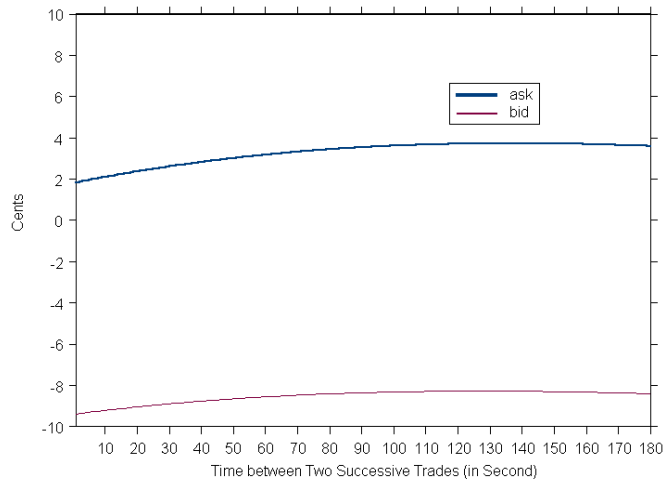
IP



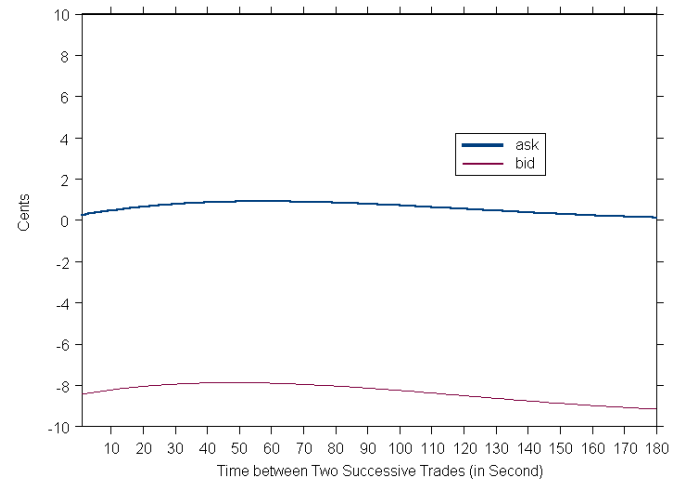
JNJ



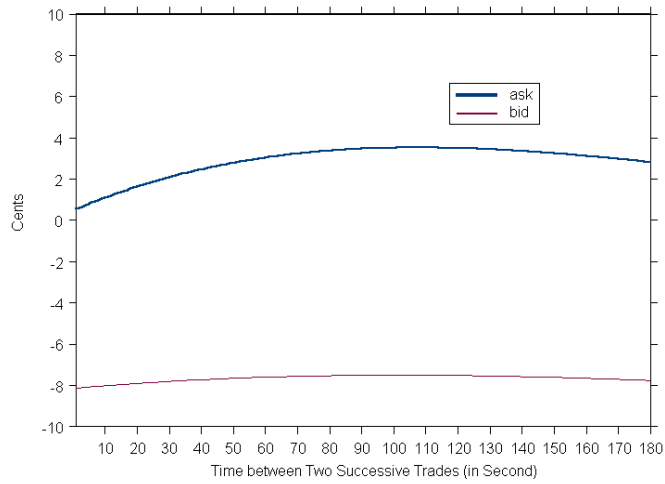
JPM



KO



MMM



UTX

