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IMPACTS OF TRADES IN AN ERROR-CORRECTION MODEL OF QUOTE PRICES*

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ABSTRACT

In this paper we analyze and interpret the quote price dynamics of 100 NYSE stocks with varying average trade frequencies. We specify an error-correction model for the log difference of the bid and the ask price, with the spread acting as the error-correction term, and include as regressors the characteristics of the trades occurring between quote observations, if any. We find that short duration and medium volume trades have the largest impacts on quote prices for all one hundred stocks, and that buyer initiated trades primarily move the ask price while seller initiated trades primarily move the bid price. Trades have a greater impact on quotes in both the short and the long run for the infrequently traded stocks than for the more actively traded stocks. Finally, we find strong evidence that the spread is mean reverting.

Keywords: market microstructure, error-correction, vector autoregression, price dynamics.

JEL Classification Codes : C32, G0, G1.

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1. INTRODUCTION

We propose an error-correction model for the bid and the ask prices, with the spread acting as the error-correction term. We use eighteen months of data on a selection of one hundred stocks from a range of trade frequency deciles to determine whether systematic differences in quote price behavior exist between deciles. One would not expect that a stock that averages just a few trades per day should exhibit the same dynamics as one, which averages hundreds or thousands of trades per day[1].

Modeling the bid and ask prices in a vector autoregressive system enables us to analyze any asymmetries in the impacts of trades on the bid or the ask price. For example, as market participants wishing to purchase a stock must do so at the ask price, we would expect that the impact of a buy is greater on the ask price than on the bid price. The converse should be true for a trade designated as a sell. Further, we are able to extract the implied models for the spread and the mid-quote from the model for the bid and ask prices, and analyze the impacts of various trade characteristics on these variables as well. We use the spread – mid-quote model to analyze the long run impacts of different types of trades.

The structure of the remainder of the paper is as follows: Section 2 provides an overview of the literature relevant to this study. In Section 3 we describe the trade and quote data used, and the methods employed in preparing it for analysis. Section 4 presents the model and the variables contained therein. Section 5 outlines some of the testable economic hypotheses relevant to this paper, and Section 6 relates the empirical results to these hypotheses. Finally, we conclude in Section 7.

2. BACKGROUND AND LITERATURE REVIEW

The ever-increasing availability of microstructure data and the computational technology necessary for its analysis mean that the empirical market microstructure literature is a fast growing one. This paper draws on and extends ideas presented in three previous studies: Jang and Venkatesh (1991), Easley, Kiefer, O'Hara and Paperman (1996) and Huang and Stoll (1994)

Huang and Stoll (1994) use an econometric specification that contains the quote revision and the transaction returns in a bivariate simultaneous equations system. They estimate their model via the generalised method of moments, using all transaction data during the calendar year 1988 on twenty of the most frequently traded stocks. Evidence that the amount of information present in a trade varies positively according to the size of the trade is found, and also that lagged returns on the S&P500 futures contract is a good predictor of both quote revisions and stock returns. In addition, they find that the depth at the ask price in excess of that at the bid price enters negatively into their model for the mid-quote, indicating that the asymmetric information effect dominates the inventory effect of depths.

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[1] The average number of trades per day in our sample ranges from 5.03 for International Aluminum Corp to 450.35 for Donaldson Luf Jenrette Inc.

Easley, Kiefer, O'Hara and Paperman (1996) examine empirically the difference in probabilities of informed trading between less frequently traded stocks and frequently traded stocks. The authors used trade volume to sort the stocks into deciles, and based their sample on a random selection from the 10th, 6th and 3rd deciles (where the 10th decile contains the stocks with the highest trade volume, and the 1st decile contains the lowest trade volume stocks).[2] A theoretical model for the market maker's price-setting decision problem is specified as a Bayesian learning model, the parameters of which are then estimated from the data. They find that the risk of trading with an informed agent is lower for the more actively traded stocks, implying that larger spreads for less frequently traded stocks are to be expected.

Jang and Venkatesh (1991) use descriptive statistics to draw inferences about quote price behavior. The authors use quote and trade data on all stocks listed on the NYSE, for the period March 1985 to April 1985 to analyze the changes in the posted bid and ask prices in the context of the various market microstructure theories. Amongst other results, they report that over three-quarters of the quote changes in their data set are inconsistent with the predictions of the models of the specialist, which state that following a trade at the bid (ask) *both* quote prices should be revised down (up) by the same amount. The asymmetry in impact of a transaction at the bid versus that at the ask for each of the quote prices is one of the subjects under analysis in our paper. Jang and Venkatesh also report that quote price behavior is different for times with a large spread from those

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[2] In this paper we used the total number of trades, rather than the total number of shares traded, to sort the stocks into trade frequency deciles. While the two measures are probably highly correlated, they are not identical.

with a small spread. Specifically, the spread is much more likely to decrease than increase at the following observation if it is greater than three-eighths, with the converse being true if the spread is at or below two-eighths. This is another feature we attempt to capture in our model.

3. THE DATA

The data used in this paper were taken from the Trades and Quotes (TAQ) dataset, produced by the New York Stock Exchange. This dataset contains every trade and quote posted on the NYSE, the American Stock Exchange and the NASDAQ National Market System for all securities listed on the NYSE. Further information about this dataset can be found in NYSE Inc (1999).

In order to obtain a sample of stocks with a range of trade frequencies, we first used data on the total number of trades in the 1997 calendar year on all NYSE listed stocks to determine trade frequency deciles. The average number of trades ranged from 1,090 for Decile 1 to 174,825 for Decile 10. We then randomly selected 25 stocks from each of the second, fourth, sixth and eighth deciles, checking that each stock traded continuously for the entire sample period, and excluding American Depositary Receipts and Real Estate Investment Trusts. The 100 stocks selected via this procedure became the sample for this study. Table A.1 in the Appendix contains a list of the stocks selected, and Table 3.1 presents some summary statistics of the data over the sample period.

One of the main attractions of market microstructure data is also one of its main drawbacks: it is *very* detailed. This detail allows us to closely examine the behavior of stock prices, but also requires us to carefully prepare the data for analysis. Such things as stock splits and dividends must be accounted for, as well as exchange enforced trade halts and the like. We deal with the above situations by removing any trades that occur immediately after the payment of a dividend, or the resumption of trade after a trade halt of some kind. In the case of the former, we do so to remove the impact of the drop in price that occurs following the payment of a dividend, which is essentially a deterministic part of the price dynamics. In the case of the latter, we do so to reflect the fact that the first price after such a halt is probably not generated by the same dynamics as the other prices. As a filter for recording or transcription errors, we exclude any observations that represent a change of more than 50% from the previous observation, if followed by another change of a similar magnitude in the opposite direction.

3.1. Trade Data

Although we do not actually model transaction prices in this paper, we do use the characteristics of transactions in our model of quote prices. As such it was necessary to prepare the trade data set as though it were to be modelled.

We first removed any trades that occurred with non-standard correction or G127 codes (both of these are fields in the trades data base on the TAQ CDs), such as trades that were cancelled, trades that were recorded out of time sequence, and trades that called for the delivery of the stock at some later date. We then cumulated any trades that were recorded with the same time stamp into one trade[3]. To do this we summed the total volume of the trades, attributed it to the first trade, and then removed the other trades from the sample.

Any trades that were recorded to have occurred before 9:30am (the official start of trading on the NYSE) or after 4pm (the official close of trading) were removed. Trade durations were calculated as the difference in seconds between two successive trade time stamps, except for the overnight period. For the overnight period, we calculated the duration as the time between the last trade of the previous day and 4pm plus the time between 9:30am and the time of the first trade on the next day, thus ignoring the entire overnight (and weekend) period.

We constructed BUY and SELL indicator variables for the trades according to a procedure proposed and tested by Lee and Ready (1991) that is now common in the empirical market microstructure literature, see Hasbrouck (1991) and Easley *et al.* (1996). This procedure identifies the standing quote at a given trade, calculates the mid-quote, and compares the price at which the trade occurred with the mid-quote. If the trade price was higher than the mid-quote, the trade is considered “buyer-initiated”. If the trade price was lower than the mid-quote then it is considered “seller-initiated”. If the trade price was exactly at the mid-quote, then we consider it to be indeterminate. We also consider all trades that occur before the first quote of the day to be indeterminate.

[3] Simultaneous trading of a stock on two or more exchanges is possible. Such trades are guaranteed to execute at the same price, as all trades must take place at the national best bid or offer price.

Due to problems in the trade and quote recording process, Lee and Ready suggest that using quotes that are at least five seconds old as the standing quote for a trade is preferable to using quotes immediately prior to a trade.

3.2. Quote Data

We use only quotes that were posted at the NYSE in this study, rather than all quotes posted at all exchanges. Blume and Goldstein (1997) used one year of data from the TAQ CDs (from July 1994 to June 1995) on all U.S. domiciled companies that reported at least one trade in the twelve month period; a total of 2023 stocks. They find that the NYSE quote, on average, determines or matches the national best quote around 95% of the time, compared with the next best exchange (the Cincinnati exchange) with 11 to 12%. As all trades on any exchange must be executed at the national best quote, those quotes that are not at the national best are not relevant to traders.

In a similar fashion to the formatting of the trade data, we removed any observations that appeared with non-standard quote modes (a field in the TAQ quote data base) or that were recorded as occurring before 9:30am or after 4pm.

A common feature of microstructure data is the high ratio of the number of quotes in a period to the number of trades. A large proportion of these additional quotes are adjustments to the quote depths at a particular price, and not changes in actual quote prices, see Table 3.1 for the proportions of quotes with no price changes. In the present study, we are primarily focused on quote *price* dynamics, and as such, we discard any quotes that do not reflect a change in either the bid or the ask price.

4. THE MODEL

One of the unique features of this study is that it models the bid and ask prices as a system, rather than just the mid-quote as is done is some previous studies, see Dufour and Engle (2000) and Hasbrouck (1991). By modeling the two quote prices explicitly we are able to obtain models for the mid-quote and the spread, and are also able to capture any asymmetries in the dynamics of the two series.

Below we present the model used in the analysis of the bid and ask prices. As expected, the log levels of the bid and ask prices were found to be integrated of order one in most cases[4], and so the models are specified in terms of log-differences. We estimate the models on the bid and ask series as tenth order vector autoregression, as below. The variables in the model are described in Table 4.1.

Quote observations are indexed $t = 1, 2, \ldots, T$, while trades are indexed according to the quote they precede: $\tau(t)\text{-}j$ indexes the j^{th} most recent trade to quote observation t. As the equation below indicates, we include information on the five most recent trades as exogenous regressors in our model. $k(t)$ is a function that counts the number of trades occurring between quote t-1 and quote t. The bottom two rows of Table 3.1 show the median and mean of $k(t)$ for the four deciles.

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[4] We used an Augmented Dickey-Fuller test to determine whether we could reject the null hypothesis of a unit root in the log level of the quote prices, using 10 lags of the change in the variable to remove any serial correlation. For 92 bid series and 91 ask series we could not reject the null hypothesis of the presence of a unit root, using an alpha level of 1%. The higher than

$$
\begin{bmatrix} \Delta\log(\mathrm{ASK}_t) \\ \Delta\log(\mathrm{BID}_t) \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \beta_0 \end{bmatrix} + \sum_{i=1}^{10} \begin{bmatrix} \alpha_i & \alpha_{i+10} \\ \beta_i & \beta_{i+10} \end{bmatrix} \cdot \begin{bmatrix} \Delta\log(\mathrm{ASK}_{t-i}) \\ \Delta\log(\mathrm{BID}_{t-i}) \end{bmatrix} + \begin{bmatrix} \alpha_{21} \\ \beta_{21} \end{bmatrix} \cdot \mathrm{SPR}_{t-1} +
$$

$$
\begin{bmatrix} \alpha_{22} \\ \beta_{22} \end{bmatrix} \cdot (\mathrm{DPTH}^{\mathrm{ASK}}_{t-1} - \mathrm{DPTH}^{\mathrm{BID}}_{t-1}) + \sum_{j=1}^{5} (\Psi \cdot \mathrm{BUY}_{\tau(t)-j} + \Phi \cdot \mathrm{SELL}_{\tau(t)-j}) \cdot \begin{bmatrix} 1 \\ V^{\mathrm{med}}_{\tau(t)-j} \\ V^{\mathrm{big}}_{\tau(t)-j} \\ D^{\mathrm{sht}}_{\tau(t)-j} \\ D^{\mathrm{lng}}_{\tau(t)-j} \end{bmatrix} +
$$

$$
\begin{bmatrix} \alpha_{73} & \alpha_{74} \\ \beta_{73} & \beta_{74} \end{bmatrix} \cdot \begin{bmatrix} \sum_{j=1}^{k(t)} \mathrm{BUY}_{\tau(t)-j} \\ \sum_{j=1}^{k(t)} \mathrm{SELL}_{\tau(t)-j} \end{bmatrix} + \sum_{d=1}^{8} \begin{bmatrix} \alpha_{74+d} \\ \beta_{74+d} \end{bmatrix} \cdot \mathrm{DIURN}^{d}_{t}
$$

where
$$
\Psi = \begin{bmatrix} \alpha_{22+j} & \alpha_{27+j} & \alpha_{32+j} & \alpha_{37+j} & \alpha_{42+j} \\ \beta_{22+j} & \beta_{27+j} & \beta_{32+j} & \beta_{37+j} & \beta_{42+j} \end{bmatrix}
$$

$$
\Phi = \begin{bmatrix} \alpha_{47+j} & \alpha_{52+j} & \alpha_{57+j} & \alpha_{62+j} & \alpha_{67+j} \\ \beta_{47+j} & \beta_{52+j} & \beta_{57+j} & \beta_{562+j} & \beta_{67+j} \end{bmatrix}
$$

The equation above was estimated using ordinary least squares. We anticipated the presence of heteroscedasticity in the residuals and so estimated the standard errors of the estimators in each equation using White's (1980) method. This method provides standard errors that are robust to a wide variety of forms of heteroscedasticity. We also used White's method to estimate the covariance between the estimators in the ask price equation and the estimators in the bid price equation. Having obtained this we are able to derive the coefficient estimates and standard errors of the implied model for the spread and mid-quote by applying the appropriate rotation.

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expected rejection rate found may reflect a change in the power of the ADF test in the face of the

5. SOME TESTABLE ECONOMIC HYPOTHESES

5.1. Evidence of error-correction behavior

We include as a regressor in the vector autoregression the lagged log spread, defined as the difference between the log ask price and the log bid price, which would behave as the error-correction term if the two series were cointegrated. That is, we would expect large spread at the previous quote to lead to a rise in the bid price and a fall in the ask price at the following quote, to restore the spread to its long-run equilibrium value. Similarly, a small spread should do the opposite. Augmented Dickey Fuller tests on the log spread, including 10 lags of the change in the spread to account for serial correlation, indicate that we can reject the null hypothesis that the spread is I(1) for all 100 stocks, at the 1% alpha level. This fact, combined with the fact that the bid and ask series are integrated, suggests that the quote price series are cointegrated.

Easley and O'Hara (1992) suggest something similar to this, in their second proposition. They assert that the bid and ask price will converge toward the equilibrium stock price in periods with no trades, which implies that the equilibrium spread in the absence of trades is zero. Jang and Venkatesh (1991) also allude to error-correcting behavior, when they write that a decrease in the spread is more likely than an increase when the spread is greater than some threshold (three-eighths of a dollar), and more likely to increase when it is below some threshold (one-quarter of a dollar).

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discrete dependent variable.

5.2. *Asymmetric impact of BUYs and SELLs*

Economic theory suggests that a BUY should have a positive impact on both the bid and the ask prices, while a SELL should have a negative impact. It does *not* suggest, however, that the impacts of BUYs and SELLs need be the same. When a market participant wishes to take a long position in a stock, he/she must purchase that stock from the market maker, at the posted ask price. Conversely, if the trader wishes to reduce a long position or go short, he/she must trade at the bid price. Thus it would seem logical that a BUY has a larger impact on the ask price than a SELL, and that a SELL has a larger impact on the bid price than a BUY. The above logic suggests that the ask price leads the bid price when the stock price is rising, while the bid price leads the ask price when the stock price is falling.

5.3. *Does size matter?*

Does the size of the trade affect the impact it has on the quote prices? In order to answer this question we introduce two indicator variables designed to reflect the size of the trade. The V^{med} variable is one if the trade volume was between 1,000 and 10,000 shares and zero otherwise, while the V^{big} variable is one if the trade volume is greater than 10,000 shares and zero otherwise. The literature is not unanimous on the effect of trade size on price impacts. Hasbrouck (1991) finds that larger trade volumes increase the spread more than smaller volumes, while Barclay and Warner (1993) and Keim and Madhavan (1996) suggest that a quadratic relation may be more appropriate. Barclay and Warner (1993) find that medium volume trades (defined as those with volume between 500 and 9900 shares; very similar to our definition) drive most of the cumulative stock price movements, and suggest that informed traders break up their trades so as to remain less conspicuous. Keim and Madhavan provide evidence of information leakage as block trades are 'shopped' in the upstairs market. The "downstairs" market is the regular stock market, where trades are accomplished via buying or selling through the market maker. The upstairs market, on the other hand, is a market for very high volume trades (minimum 10,000 shares) where the transaction is carried out by a broker or intermediary, who locates (potentially many) counter-parties to the trade. Information leakage occurs when the price of the stock rises or falls prior to the execution of the block trade as the broker "shops" the block trade, thus revealing some of the information the block trade carries *before* it is actually executed.

5.4. What kind of news is no news?

In addition to considering the volume of a trade, we also examine the impact of the duration of a trade, defined as the time between two trades. Theoretical studies by Diamond and Verrecchia (1987) and Easley and O'Hara (1992) suggest that the time between trades conveys information about the type of news a trade carries. Diamond and Verrecchia suggest that long times between trades reflect bad news, as short selling restrictions prevent traders from selling a stock on the basis of bad news. Easley and O'Hara, on the other hand, propose that long durations signal neither bad nor good news. Empirical studies by Dufour and Engle (2000) and Engle (2000) have found evidence to support the Easley and O'Hara hypothesis that long durations imply no news. We include a short duration indicator variable for durations of less than 60 seconds and a long duration indicator for durations longer than 5 minutes to capture the effects documented in the above studies.

5.5. *Inventory balance vs. Asymmetric information effects*

In our model above we include a variable first suggested by Huang and Stoll (1994) to determine which of the inventory balance and asymmetric information effects is the strongest. This variable is the difference between the log of the quote depth at the ask price and the log of the quote depth at the bid price. The inventory effect asserts that a market maker with excess inventory will simultaneously lower the ask price and raise the ask depth, in order to attract buyers. At the next quote the ask price is raised back to its previous level. A similar argument for the bid price holds in the case when the market maker has too small an inventory. Thus the inventory effect suggests that the coefficient on the difference between the ask depth and the bid depth will be positive: excess depth at the ask will lead to a rise in the ask price, while excess depth at the bid will lead to a fall.

The asymmetric information effect, on the other hand, asserts that the impact on quote prices of an excess of supply at the ask over that at the bid is negative. High depth at the ask price potentially indicates a number of sellers on the limit order book, suggesting to the market that the stock is overpriced. Huang and Stoll also note that the presence of the barrier effect would have the same impact as that of the asymmetric information effect[5]. Higher depth at the ask price than at the bid price means less trade volume is required before a downward movement than an upward movement. Thus the *barrier* to a downward movement is weaker than that to an upward movement, making a

[5] See O'Hara (1995) for more detail on these three market microstructure theories.

downward movement more likely. The same logic applies when the depth at the bid price is greater than that at the ask price.

5.6. *Deterministic Time-of-Day Effects*

In a manner similar to seasonality in macroeconomic variables, intra-daily data may exhibit "intra-daily seasonality", which is more accurately called *diurnality*. In an effort to capture any deterministic component of the intra-day dynamics of the variables under analysis, we use piece-wise linear splines to reflect the time of trade day that the observation appeared. Previous studies, see Engle and Russell (1998) and Dufour and Engle (2000), have also used a similar method of diurnal adjustment. The nodes of the splines are the start of the trade day, 9:30am, and then 10am, 11am, noon, 1pm, 2pm, 3pm, 3:30pm and the close of the trade day, 4pm.

Chen, Chung and Johnson (1995) report that the spread on frequently traded NYSE stocks display a U-shape, that is, that spreads are larger at the beginning and end of the trade day than they are in the middle. We can determine whether this holds when controlling for the regressors described in Table 4.1, and also look for any systematic patterns that emerge between stocks with different average trade frequencies. The significance of the diurnal variables in our model will indicate whether time-of-day effects are important for quote price revisions.

6. IMPLICATIONS OF THE RESULTS FOR QUOTE PRICE DYNAMICS

The model presented in the above equation was estimated on all 100 stocks. For ease of exposition, we selected one stock from each decile for presentation as a representative of the entire decile. A summary of the results of the econometric estimation on the quote price series for the four representative stocks is presented in Table 6.1. This table contains only the variables of economic interest to us. The complete set of results for these stocks is presented in the Appendix, in Table A.2. The results for a particular variable for the entire sample of stocks are presented in the form of the median coefficient for each decile, along with a count of the number of times the coefficient was positive and significant, and negative and significant. This format enables us to draw general conclusions as the significance and magnitude of coefficients across deciles.

6.1. Specification Tests

The summary statistics presented at the bottom on Table 6.1 indicate that the regressions are very significant, with all F-statistics (testing for the joint significance of the variables in the model) being large. The R^2 statistics for the representative stocks range from 0.248 to 0.337, all quite high. We tested for two forms of misspecification: serial correlation and heteroscedasticity.

A common test for serial correlation is the Breusch-Pagan Lagrange Multiplier (or LM) test, which involves regressing the residuals on lags of themselves, and on the regressors in the model. Due to the large number of regressors in our model, we found that this was computationally infeasible for the most frequently traded stocks. We instead look at Ljung-Box's (1978) statistic for the residuals, which is asymptotically equivalent to the LM test, but involves only the finding of the autocorrelation function of the residuals.

For all but one stock, we find no evidence of serial correlation in the residuals at the 1% alpha level, using ten lags. This indicates that the inclusion of ten lags of the dependent variables and five lags of the trade indicator variables was sufficient to capture the commonly observed negative serial correlation in microstructure data.

Although we needed five lags of the trade indicator variables in the model to remove the presence of serial correlation[6], we found that very few of the second or further lags of the trade variables were significant. This implies that although the second through fifth lags of the trade variables are jointly significant, they are not usually individually significant. To conserve space, and simplify the presentation of the results, we present only the coefficients on the most recent trade indicator. The complete set of results for the representative stocks is presented in Table A.2, and the results for the entire sample of stocks may be obtained from the authors on request.

The time varying volatility of financial time series has been widely documented, see Black (1976), Bollerslev, Chou and Kroner (1992) and Schwert (1989) for examples, and so we should expect that the data used in this paper also exhibit this characteristic. We again use the Ljung-Box statistic to test for heteroscedasticity, this time on the squared residuals. Using ten lags of the squared residuals and an alpha level of 1%, we find evidence of heteroscedasticity in 192 of the 200 series. This means that the usual

[6] We previously estimated the same model with only one lag of the trade indicator variables, and found substantial evidence of serial correlation. Stoll (2000) also finds substantial evidence of negative serial correlation in quote price changes.

standard errors of the estimators are inconsistent for the true standard errors, and so the use of White's robust standard errors is necessary.

In the subsections below we relate the results obtained to the economic hypotheses discussed in section 5.

6.2. Error-correction behavior

In all eight of the series' results presented in Table 6.1 we find that the coefficient on the lagged spread is significant, and of the correct sign. As hypothesized, a high spread leads to a decrease in the ask price and an increase in the bid price, moving the spread toward its equilibrium value. This result complements the descriptive results presented in Jang and Venkatesh (1991), and supports Easley and O'Hara's (1992) proposition.

In the entire sample of 100 stocks (and thus 200 quote price series) we find that that the coefficient on the spread is significant and of the correct sign 187 times. This is very strong support for the importance of this variable in describing quote price dynamics.

Table 6.2: Coefficients on the SPR_{t-1} Variable.

	Decile 2		Decile 4		Decile 6		Decile 8	
	Ask	*Bid*	*Ask*	*Bid*	*Ask*	*Bid*	*Ask*	*Bid*
Median	-.1333	0.1220	-0.1342	0.1640	-0.1446	0.1444	-0.1569	0.1359
Signif pos	0	22	0	23	0	25	0	25
Signif neg	19	0	23	0	25	0	25	0

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25.

The magnitudes of the coefficients are approximately the same across stocks and deciles, as can be seen in Table 6.2 above. The similar magnitudes of these coefficients across the deciles indicate that the speed (in event time) of adjustment of quote prices from a large or small spread is not affected by average trade frequency. However, as fewer events happen per day for the lower deciles, the calendar time taken for the quotes to adjust is greater for infrequently traded stocks than frequently traded stocks.

6.3. *Asymmetric Impacts of BUYs and SELLs*

From the results for the representative stocks in Table 6.1 we observe that both the BUY variables and the SELL variables all have the *a priori* expected signs: the BUY variables all have positive signs, indicating that a buyer-initiated trade raises the price, while a seller-initiated trade lowers the price. Further, we can see that the coefficients on the BUY variables are more significant and greater in magnitude that the SELL variables in the models for the ask price. The reverse is true for the models for the bid price. Table 6.3 shows that this holds for the entire sample.

Table 6.3: Coefficients on the $BUY_{t\ (t)-1}$ and $SELL_{t\ (t)-1}$ Variables.

BUY_t	ASK				BID			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.2146	0.1179	0.0904	0.0624	0.1192	0.0637	0.0431	0.0290
Signif pos	21	24	25	25	18	22	24	25
Signif neg	0	0	0	0	0	0	0	0

$SELL_{t\ (t)-1}$	ASK				BID			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	-0.0844	-0.0504	-0.0399	-0.0297	-0.1822	-0.0940	-0.0743	-0.0525
Signif pos	0	0	0	0	0	0	0	0
Signif neg	18	22	24	25	17	24	25	25

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25.

The results for the $BUY_{\tau(t)-1}$ and $SELL_{\tau(t)-1}$ variables extend to the other signed trade indicator variables in the results for the representative stocks, with a couple of exceptions (the large volume sell variable is significant in the Decile 2 stock's ask price model, and the long duration sell variable is significant in the Decile 8 stock's ask price model). For the entire sample we find that the BUY variables are more often significant in the ask price model than SELL variables, with the opposite holding true in the model for the bid price, sound evidence in support of the assertion that a buyer-initiated trade has a greater influence on the ask price than a seller-initiated trade, which is what economic intuition suggests should happen. This asymmetry in the impacts of BUYs and SELLs on the ask and bid prices would not have been as easily detectable in a model for the spread and mid-quote.

In presenting the results for the remaining coefficients, we will present only those multiplied by a BUY in the ask price model, and only those multiplied by a SELL in the bid price model, in the interests of parsimony.

6.4. Does trade size matter?

Yes, but only up to a point. In all four representative stocks we find that the coefficient on the V^{med} variable is significant, when multiplied by the appropriate trade indicator variable. This indicates that a trade with volume between 1,000 shares and 10,000 shares carries more quote price relevant information than a trade of less than 1,000 shares. This finding is consistent with many previous studies: Easley and O'Hara (1987), Hasbrouck (1991), and Barclay and Warner (1993), amongst others. The results for the entire 100 stocks are summarized in Table 6.4 below. Notice that the magnitude of the coefficient on the medium volume variable decreases as we increase the trade frequency, indicating reduced liquidity in the market for less frequently traded stocks.

Table 6.4: Coefficients on the V^{med} Variable.

	Ask models: BUY*V^{med}				Bid models: SELL*V^{med}			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.1049	0.0757	0.0515	0.0465	-0.1650	-0.0759	-0.0651	-0.0454
Signif pos	15	24	25	25	0	0	0	0
Signif neg	0	0	0	0	20	25	25	25

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25.

Table 6.5 presents the results for the coefficients on the large volume trade indicator. The reader can observe that the coefficients on this variable are less often significant than those on the medium volume trade indicator, particularly for the less frequently traded stocks. Recall that the proportion of trades with very large volumes is only slightly larger for deciles 6 and 8, as reported in Table 3.1, but that the total number of trades for stocks in these deciles is also larger. Thus there are many more large volume trades for the frequently traded stocks than for the infrequently traded stocks. This larger number provides a possible reason for the increased significance of the V^{big} variable in the higher deciles: a larger number of trades makes precise estimates of this coefficient possible, that is, the coefficient may in truth be different from zero in the lower deciles also, but we do not have enough observations of such large trades to estimate it accurately[7].

[7] In fact, for one stock (Fort Dearborn Income Securities) we did not observe *any* SELLs with volume greater than 10,000 in the sample period, meaning that for this stock we had to force the impact of a large trade to be symmetric – we used the variable (BUY-SELL)*V^{big} rather than each variable separately.

The magnitudes of the coefficients on the medium and large volume trade indicators are roughly equal; certainly close enough that we cannot detect a significant statistical difference between the two. Thus we can reject the hypothesis that quote price impacts are monotonic in trade volume.

Table 6.5: Coefficients on the V^{big} Variable.

	Ask models: BUY*V^{big}				Bid models: SELL*V^{big}			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.1028	0.0827	0.0615	0.0587	-0.1126	-0.0670	-0.0601	-0.0526
Signif pos	7	10	19	25	0	0	0	0
Signif neg	0	0	0	0	7	9	18	25

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25 for all deciles except Decile 2, which has a potential maximum of 24 (see footnote 7).

6.5. *What kind of news is no news?*

No news is no news, it seems. The coefficient on D^{lng}, indicating a trade with duration greater than five minutes, was not significant at all in the stocks from the second and fourth decile, and only significant in one of the quote price series of each of the sixth and eighth decile stocks. For the full sample we find that the long duration variable is significant only 14 times out of a potential 200. The few times that we do find it significant, the coefficient is usually of the opposite sign to the coefficient on the lagged BUY and lagged SELL variables.

This indicates that a trade occurring after a period longer than five minutes with no trades has either the same impact (coefficient not significant) or slightly less impact (coefficient significant and of the opposite sign to the lagged BUY/SELL variable) than a medium duration trade; one which occurred after one to five minute period of no trades. These findings add further support to the theoretical assertion of Easley and O'Hara (1992) that long durations mean no news, and so a trade that occurs after a long duration is likely to be liquidity trade rather than one based on valuable information.

Short durations, on the other hand, are significant in most of the four representative stocks' results (short duration BUYs were not significant for the Decile 2 and 4 stocks), when multiplied by the appropriate trade indicator variable. In all cases we find that the sign of the coefficient is such that a short duration trade has a larger impact than a medium or long duration trade, consistent with the findings of Dufour and Engle (2000). The results for the entire data set for this variable are presented in Table 6.6.

Table 6.6: Coefficients on the D^{sht} Variable.

	Ask models: BUY*D^{sht}				Bid models: SELL*D^{sht}			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.0660	0.0308	0.0206	0.0112	-0.0850	-0.0457	-0.0239	-0.0125
Signif pos	6	13	19	23	0	0	0	0
Signif neg	0	0	0	0	12	16	20	20

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25.

As the above table shows, the coefficient on the short duration variable (multiplied by the appropriate BUY/SELL indicator) decreases in magnitude, but increases in significance as we increase the average trade frequency. Short durations are more rare in the lower deciles than in the higher deciles, by construction, and so we would expect trades with short durations to have a larger impact on the price of infrequently traded stocks than they do on frequently traded stocks.

An alternative explanation of the increased magnitudes of the coefficients on short duration trades in the lower deciles is provided by Easley *et al.* (1996) who find evidence that the risk of trading with an informed agent is higher for infrequently traded stocks than it is for frequently traded stocks. Such an increase would explain why trades have a larger quote price impact for less frequently traded stocks.

6.6. Inventory Balance vs. Asymmetric Information Effects

The question of which of the inventory balance or the asymmetric information effects is strongest can be answered by looking at the sign and significance of the coefficient on the lagged difference in depths posted at the previous quote[8]. A significant positive coefficient would indicate that the inventory balance effect is stronger than the asymmetric information effect, and a negative coefficient the opposite. In all eight of the quote price models presented in Table 6.1, and for 170 out of the 200 quote price models estimated in total, we find that the coefficient on this variable is negative and significant. This is consistent with the asymmetric information hypothesis dominating the inventory balance effect.

While the sign and significance of this variable is consistent across the deciles studied, the magnitude of the variable exhibits some variation. Table 6.7 below presents some summary statistics on this coefficient across the deciles.

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[8] Note that the quote from which we take the depths for this variable was the last quote *with* a change in one of the quoted prices, that is, the previous quote in the thinned quote price data set. This may not be the most recently posted quote. We also estimated the model with the most

Table 6.7: Coefficients on the DPTH_DIFF Variable.

	Decile 2	Decile 4	Decile 6	Decile 8
Median	-0.0670	-0.0402	-0.0289	-0.0238
Signif pos	4	8	10	6
Signif neg	45	41	40	44

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 50.

The above results indicate that the magnitude of this coefficient decreases as we increase the average trade frequency. The median coefficient in the second decile is 2.8 times larger than that coefficient in the eighth decile. The decrease in the magnitude of this coefficient as we move upwards through the trade frequency deciles suggests that the strength of the asymmetric information (or barrier effect) relative to the inventory balance effect is greater for less frequently traded stocks. As mentioned above, Easley *et al.* (1996) report evidence suggesting that the risk of trading with an informed trader is higher for infrequently traded stocks, which could serve as an explanation for the above observation that the coefficient on the quote depths difference variable is larger for these stocks than for frequently traded stocks.

6.7. Deterministic Time-of-Day Effects

The results of the estimation of the coefficients on the diurnal variables can be found at the bottom of Table A.2. As one can see from this table, very few of these coefficients are significant. The spline coefficient corresponding to the opening thirty minutes of trading is generally significant (132 times out of 200), but very few others, suggesting that a deterministic time-of-day effect is not an important source of variation in the quote price

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recent difference in quote depths, and the results were (somewhat surprisingly) very similar to those presented above.

series. Dufour and Engle (2000) and Hasbrouck (1999) conclude similarly that only the beginning of the trade day displays a significant deterministic component.

7. THE IMPLIED MODELS FOR THE SPREAD AND MID-QUOTE

Having a model for each of the bid and the ask prices enables us to extract a model for the spread and mid-quote, two of the more commonly modeled market microstructure variables. Obtaining the estimates of the coefficients and their standard errors in the implied model for the spread and mid-quote is straightforward once the complete covariance matrix of the coefficients in the models for the ask and the bid is determined: we simply pre-multiply by a rotation matrix (with a 1 and –1 in the first row, and a ½ and ½ in the bottom row) to find the coefficient matrix. To obtain the variance-covariance matrix of these coefficients we pre-multiply by the same rotation matrix, and post-multiply by the transpose of the rotation matrix.

The results for implied models for the spread and the mid-quote are presented in Table 7.1, below. The model for the spread is presented in the (log) level, as this variable is stationary, while the model for the mid-quote is presented in log-differences. From the results for the spread and mid-quote models we can look at many of the above hypotheses, and in addition, the spread and the mid-quote are the natural variables to look at when examining long-run impacts.

The model for the spread is particularly interesting as the spread is a common measure of friction in the market. A large spread indicates a high cost to a trader wishing to execute a trade quickly; a high cost of *immediacy* in Stoll's (2000) terminology.

7.1. *Asymmetric Impacts of BUYs and SELLs*

The results presented in Table 7.2 indicate that BUYs and SELLs both have a positive impact on the spread, while the former has a positive impact, and the latter a negative impact, on the mid-quote. That both types of trades have a positive impact on the spread is in accordance with economic intuition: both a buy and a sell involve a trader initiating a trade with the market maker that they cannot immediately reverse without incurring a loss (due to the positive bid-ask spread). Such a trade is a signal to the market maker, and as such we would expect the spread to increase. This finding, combined with the results of Easley and O'Hara (1992), suggests that there is more than one information event per day – not an unexpected result.

As expected, we find that a BUY increases the mid-quote on average, while a SELL decreases it.

Table 7.2: Coefficients on $BUY_{t\,(t)-1}$ and $SELL_{t\,(t)-1}$ Variables in the models for the Spread and Mid-Quote

Spread	BUY				SELL			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.0782	0.0589	0.0480	0.0325	0.0376	0.0481	0.0352	0.0236
Signif pos	9	22	24	25	7	17	24	23
Signif neg	0	0	0	0	2	0	0	0

Mid-Quote	BUY				SELL			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.1639	0.0917	0.0668	0.0468	-0.1473	-0.0687	-0.0566	-0.0403
Signif pos	21	24	25	25	0	0	0	0
Signif neg	0	0	0	0	20	24	25	25

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25.

For the four representative stocks we find that all of the coefficients on lagged BUYs and SELLs in both the models for the spread and the mid-quote are significant, and of the signs suggested in the above paragraph, except for the coefficient on $SELL_{\tau(t)-1}$ in the Decile 2 stock's spread model. When expand this to the full sample of 100 stocks, strong evidence of this is found for all but the second decile.

In the model for the mid-quote, on the other hand, we find that the coefficient on BUYs is significant and positive and the coefficient on SELLs is significant and negative for almost all stocks in all deciles. The coefficients in the lower deciles tend to be larger (in absolute value) and more variable than those in the higher deciles.

We find little evidence of asymmetry in the impacts of BUYs and SELLs on the spread and the change in the mid-quote. In the models of the mid-quote we find no significant evidence, and in the models for the spread we find some weak evidence that a BUY has a larger impact than a SELL. For the other trade variables (those including indicator variables for the volume or the duration of the trade) we find no evidence of asymmetry in the impacts of BUYs or SELLs on either the spread or the mid-quote.

7.2. Does Trade Size Matter?

The results for the implied models for both the spread and the mid-quote indicate that trade size is important for both. Again we find that medium volume trades generally have significant coefficients in all deciles, with the expected signs, see Table 7.3. The significance increases as we increase the average trade frequency, a feature that seems common to all of our results.

Table 7.3: Coefficients on the BUY*V^{med} and SELL*V^{med} variable in the model for the Spread

	BUY				SELL			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.0743	0.0503	0.0382	0.0349	0.1148	0.0484	0.0459	0.0390
Signif pos	9	18	25	25	16	20	25	25
Signif neg	1	0	0	0	0	0	0	0

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25.

As Table 7.4 shows, the decrease in the magnitude and increase in significance of the coefficients on medium volume trades are also present in the model for the mid-quote.

Table 7.4: Coefficients on the BUY*V^{med} and SELL*V^{med} variable in the model for the Mid-Quote

	BUY				SELL			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.0677	0.0469	0.0398	0.0280	-0.1076	-0.0515	-0.0399	-0.0259
Signif pos	13	22	25	25	0	0	0	0
Signif neg	0	0	0	0	19	24	25	25

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25.

The coefficients on the large volume trades, presented in summary form in Table 7.5, were only rarely significant in the lower two deciles, and only marginally significant in decile six. Decile 8 again had the highest significance rate. The magnitudes of the coefficients on large volume trades indicate that large volume trades have roughly the same short-run impact as medium volume trades on both the spread and the mid-quote.

Table 7.5: Coefficients on the BUY*V^{big} and SELL*V^{big} variable in the models for the Spread and Mid-Quote

Spread	BUY				SELL			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.1127	0.0444	0.0319	0.0462	0.0120	0.0362	0.0269	0.0382
Signif pos	6	6	14	22	6	4	12	23
Signif neg	1	0	0	0	0	0	0	0

Mid-Quote	BUY				SELL			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.0705	0.0578	0.0398	0.0387	-0.0980	-0.0402	-0.0409	-0.0317
Signif pos	5	4	18	24	0	0	0	0
Signif neg	0	0	0	0	7	7	18	23

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25 for all deciles except Decile 2, which has a potential maximum of 24 (see footnote 7).

7.3. What kind of news is no news?

Again we find that no news is no news – just a handful of the coefficients on the long duration indicator are significant, out of a possible 200, in both the model for the spread and the model for the mid-quote. This implies that a trade with duration longer than 5 minutes has the same impact on the spread and the mid-quote that a trade with duration of between 60 seconds and 5 minutes.

Table 7.6: Coefficients on the BUY*D^{sht} and SELL*D^{sht} variable in the models for the Spread and Mid-Quote

Spread	BUY				SELL			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.0433	0.0199	0.0158	0.0145	0.0776	0.0317	0.0189	0.0131
Signif pos	4	7	15	23	6	12	15	21
Signif neg	0	0	0	0	0	0	0	0

Mid-Quote	BUY				SELL			
	Dec 2	*Dec 4*	*Dec 6*	*Dec 8*	*Dec 2*	*Dec 4*	*Dec 6*	*Dec 8*
Median	0.0352	0.0245	0.0122	0.0070	-0.0450	-0.0284	-0.0127	-0.0056
Signif pos	4	10	12	18	0	0	0	0
Signif neg	0	0	0	0	7	16	12	15

NOTE: *Signif pos* and *Signif neg* count the number of times this variable was significant at the 1% level, and of the indicated sign. The maximum possible is 25.

Short duration trades, those with durations shorter than 60 seconds, exhibit the same trends that we observed in the models for the bid and the ask: the magnitude of the coefficients decreases as we increase the average trade frequency, but the significance increases.

7.4. *Inventory Balance vs. Asymmetric Information Effects*

As discussed above, the coefficient on the lagged difference in quote depths indicates the relative strengths of the impacts of the inventory balance and asymmetric information effects. (The model for the spread is not relevant in answering this question.) For 86 of the 100 stocks we find that this coefficient is negative and significant; substantial evidence indicating that the asymmetric information effect dominates the inventory effect. The same result was found in the models for the bid and the ask prices, and related to the results of Huang and Stoll (1994), though the result in this section relates more directly, as the aforementioned authors examined the mid-quote and not the individual quote prices separately.

7.5. *Deterministic Time-of-Day Effects*

A number of previous studies, see Chan *et al.* (1995), and Wei (1992), amongst others, have reported the presence of a U-shaped time-of-day pattern in the spread. We find substantial evidence of increased spreads at the beginning of the trade day (all but four stocks have a significant negative coefficient on the first diurnal adjustment variable) but we find no evidence of an increase in average spreads towards the end of the trade day. Thus, by conditioning on the lagged quote and trade variables we are able to explain the increase in spreads towards the end of the trade day, but we are not able to do so for the beginning of the trade day.

As in the bid and ask price models, the deterministic diurnal effect is not significant for the mid-quote.

7.6. Long-Run Impact of a Trade

Estimating a model comprised of the bid and ask prices appeared to be a neat way to capture short-run asymmetries, but the natural variables to look at for long-run impacts are the spread and the mid-quote. We are able to back out the long run impacts on the bid and ask price by performing the inverse of the rotation applied to obtain the spread and the mid-quote in the first place, if so desired.

In calculating the long-run impacts of a trade we need to determine an appropriate value for $k(t)$, the number of trades between quote t-1 and quote t. Table 3.1 suggests that a reasonable figure is one, as for all deciles this is the integer nearest both the mean and median of $k(t)$.

In Tables 7.7 and 7.8 we present the long-run impacts of a variety of types of trades on the spread and the mid-quote. The figures reported are the median long-run impacts for each decile.

Table 7.7 shows that there is substantial variation in the impacts on the spread of trades with different characteristics. Short duration, medium volume trades have the largest impacts on the spread, while the type of trade with the smallest impact seems to vary. In general medium to long duration, small volume trades have the smallest impacts.

Turning now to the long-run impacts of trades on the mid-quote, we present Table 7.8. Similar to the results presented for the spread, we find that short duration trades with medium to large volumes have the largest long-run impacts on the mid-quote. Small volume trades with medium to long durations have the smallest long-run impacts.

The fact that all but one of the trades with the largest impacts on both the spread and the mid-quote are those with short durations indicates the importance of the time between trades in explaining the impact of a trade on quote prices, supporting the findings of Dufour and Engle (2000). That medium and large volume trades have the largest impacts also supports the findings of Hasbrouck (1991).

8. CONCLUSIONS

In this paper we conducted an empirical investigation of the quote price dynamics of a range of NYSE-listed stocks. We used 1997 data to sort stocks into trade frequency deciles, and then selected 25 stocks from each of the second, fourth, sixth and eighth deciles (where the first decile contains the least frequently traded and the tenth decile contains the most frequently traded stocks). We estimated a vector autoregression on the log-difference of the bid and the ask prices with the lagged log spread as the error-correction term, and including as regressors the lagged difference in the depths posted at the ask and bid prices and indicator variables for the volume and duration characteristics of the most recent trade.

We find that the lagged spread is very significant in all of the stocks' models, and has a sign indicating that it behaves as an error-correction term for the bid and the ask price. Large spreads lead to falls in the ask price and rises in the bid price, moving the spread toward its equilibrium level. Conversely, small spreads lead to increases in the ask price and falls in the bid price. To the authors' knowledge the error-correcting behaviour of the spread has not been explicitly modeled before.

Strong evidence of asymmetry in the impacts of buyer-initiated trades versus seller-initiated trades on the bid and the ask prices are found. Agents wishing to purchase the stock must do so at the ask, and those wishing to sell must do so at the bid, providing a solid reason to expect that a BUY has a larger impact on the ask price than does a SELL, with the opposite holding true for the bid price.

We constructed indicator variables for trade durations and volumes, breaking them into short, medium and long, and small, medium and large, respectively. Short durations and medium volume trades were found to be the most significant, and to generally have the largest long-run impacts, a finding that was consistent across the deciles. Large volume trades had a significant impact on the bid and ask prices of the frequently traded stocks, but not on the infrequently traded stocks. Long durations were not found to have a significantly different impact than medium durations. A consistent finding for all coefficients and long-run impacts was that the magnitudes of coefficients in the lower deciles tended to be greater, the significance of these coefficients were reduced.

Finally, we allowed for deterministic time-of-day effects in quoted prices, through the inclusion of eight diurnal adjustment indicator variables. These variables were generally not significant in the models for the bid, ask and mid-quote, though some significance was found for them in the model for the spread. Specifically, spreads seem to be higher at the start of the trade day.

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TABLES

TABLE 3.1: Description of the Data

		Decile 2	Decile 4	Decile 6	Decile 8
Representative stocks:		*GBX*	*TEC*	*OC*	*GAP*
Panel A: Trades					
Data size:	Min	1,903	4,514	13,818	29,275
	Max	18,203	34,162	54,411	170,232
	Median	3,663	10,549	26,737	56,733
	Mean	4,624	11,543	27,298	60,633
	Representative stock	5,366	13,995	27,912	48,344
Mean Proportions:	BUYS	0.3872	0.4058	0.4278	0.4388
	SELLS	0.5018	0.4961	0.4654	0.4731
	Mid-quote	0.1110	0.0981	0.1068	0.0880
	V(small)	0.7522	0.8085	0.7704	0.7452
	V(medium)	0.2297	0.1815	0.2112	0.2310
	V(big)	0.0181	0.0100	0.0184	0.0238
	D(short)	0.2589	0.2932	0.3558	0.4744
	D(medium)	0.1303	0.2023	0.3011	0.3425
	D(long)	0.6108	0.5044	0.3430	0.1831
Panel B: Quotes					
Data size:	Min	3,141	5,083	19,439	33,463
	Max	96,380	42,044	77,100	172,800
	Median	6,427	21,022	43,467	90,465
	Mean	12,981	20,780	44,638	90,676
	Representative stock	12,333	23,309	56,270	108,734
No price change (%)		0.5601	0.5925	0.4973	0.4519
Panel C: Thinned Quotes					
Data size:	Min	758	2,656	8,893	18,462
	Max	25,589	24,281	39,034	96,817
	Median	3,898	12,934	20,427	37,597
	Mean	6,216	12,264	21,920	40,682
	Representative stock	7,561	14,840	30,252	46,021
Proportions	Change <= -2 ticks	0.0561	0.0712	0.0507	0.0431
	Change = -1 tick	0.0895	0.0893	0.0797	0.0781
	Change = 0 ticks	0.7120	0.6819	0.7409	0.7592
	Change = +1 tick	0.0872	0.0871	0.0785	0.0764
	Change >= +2 ticks	0.0553	0.0705	0.0503	0.0432
Median number of trades between quotes		0.7697	0.8624	1.1776	1.4686
Mean number of trades between quotes		1.2137	0.9884	1.2818	1.4397

TABLE 4.1: Description of the Variables

Variable	Description
Quote variables	
$\Delta\log(ASK_t)$	Log difference of the ask price between quote *t* and quote *t-1*.
$\Delta\log(BID_t)$	Log difference of the bid price between quote *t* and quote *t-1*.
SPR_t	The spread in logs: $\log(ASK_t) - \log(BID_t)$.
$DEPTH\_DIFF_t$	The difference between the log of the quote depth at the ask price and the log of the quote depth at the bid price at quote *t*.
Trade variables	
k(t)	The number of trades between quote *t* and quote *t-1*.
$\tau(t)$-j	Denotes the *j*th most recent trade at quote *t*.
$BUY_{\tau(t)-j}$	Buy indicator: equals 1 if $k(t) \geq j$ and the *j*th most recent trade at quote *t* was identified as a buy, else this variable equals 0.
$SELL_{\tau(t)-j}$	Sell indicator: equals 1 if $k(t) \geq j$ and the *j*th most recent trade at quote *t* was identified as a sell, else this variable equals 0.
$V^{med}_{\tau(t)-j}$	Medium volume trade indicator: equals 1 if the *j*th most recent trade at quote *t* had volume between 1,000 and 10,000 shares, else this variable equals 0.
$V^{big}_{\tau(t)-j}$	Large volume trade indicator: : equals 1 if the *j*th most recent trade at quote *t* had volume of over 10,000 shares, else this variable equals 0.
$D^{sht}_{\tau(t)-j}$	Short duration trade indicator: equals 1 if the *j*th most recent trade at quote *t* had a duration less than 60 seconds, else this variable equals 0.
$D^{lng}_{\tau(t)-j}$	Long duration trade indicator: : equals 1 if the *j*th most recent trade at quote *t* had duration longer than 5 minutes, else this variable equals 0.
Deterministic variables	
$DIURN^{d}_{t}$	Diurnal adjustment variable: The value of the *d*th diurnal indicator variable at quote *t*.

Table 6.1: Summary of results for the representative stocks.

13/10/00 3:39 *Variable*	Decile 2 - GBX *Ask*	*Bid*	Decile 4 - TEC *Ask*	*Bid*	Decile 6 - OC *Ask*	*Bid*	Decile 8 - GAP *Ask*	*Bid*
SPR_{t-1}	-0.1329*	0.1592*	-0.1150*	0.1640*	-0.1200*	0.1552*	-0.1836*	0.1474*
	(0.0198)	(0.0178)	(0.0143)	(0.0145)	(0.0145)	(0.0240)	(0.0162)	(0.0093)
$DEPTH\_DIFF_{t-1}$	-0.0672*	-0.0409*	-0.0562*	-0.0449*	-0.0245*	-0.0257*	-0.0257*	-0.0265*
	(0.0056)	(0.0054)	(0.0034)	(0.0035)	(0.0013)	(0.0014)	(0.001)	(0.0008)
$BUY_{\tau(t)-1}$	0.1816*	0.1208*	0.1416*	0.0586*	0.0774*	0.0251*	0.0624*	0.0313*
	(0.0207)	(0.0186)	(0.0119)	(0.0103)	(0.0036)	(0.0032)	(0.0034)	(0.0022)
$SELL_{\tau(t)-1}$	-0.1310*	-0.1822*	-0.0699*	-0.134*	-0.0214*	-0.0591*	-0.0248*	-0.0390*
	(0.0229)	(0.0239)	(0.0095)	(0.0114)	(0.0028)	(0.0046)	(0.0024)	(0.0021)
$\Sigma\ (BUY)_{\tau(t)-1}$	-0.0015	-0.0053	0.0092	-0.0012	0.0018	0.0021	0.0031*	-0.0003
	(0.0058)	(0.0037)	(0.0040)	(0.0044)	(0.0015)	(0.0014)	(0.0010)	(0.0008)
$\Sigma\ (SELL)_{\tau(t)-1}$	0.0183	0.0130	-0.0066	-0.0077	0.0009	-0.0011	-0.0021*	-0.0030*
	(0.0090)	(0.0081)	(0.0032)	(0.0035)	(0.0012)	(0.0017)	(0.0007)	(0.0007)
$BUY_{\tau(t)-1}*V_{\tau(t)-1}^{med}$	0.1049*	0.0306	0.1042*	0.0455*	0.0481*	0.0152*	0.0494*	0.0097*
	(0.0216)	(0.0181)	(0.0117)	(0.0099)	(0.0035)	(0.0035)	(0.0033)	(0.0021)
$SEL_{\tau(t)-1}*V_{\tau(t)-1}^{med}$	-0.0384	-0.1532*	-0.0418*	-0.1102*	-0.0086*	-0.0546*	-0.0092*	-0.0526*
	(0.0191)	(0.0218)	(0.0110)	(0.0137)	(0.0026)	(0.0041)	(0.0025)	(0.0029)
$BUY_{\tau(t)-1}*V_{\tau(t)-1}^{big}$	0.0988	-0.0713	0.0393	0.0076	0.0663*	0.0028	0.0769*	0.0082
	(0.0481)	(0.0372)	(0.056)	(0.0366)	(0.0137)	(0.0089)	(0.0127)	(0.0071)
$SEL_{\tau(t)-1}*V_{\tau(t)-1}^{big}$	-0.1071*	-0.1064	-0.0904	-0.1056	0.0041	-0.0181	-0.0015	-0.0397*
	(0.0403)	(0.0534)	(0.0380)	(0.0529)	(0.0091)	(0.0128)	(0.0093)	(0.0107)
$BUY_{\tau(t)-1}*D_{\tau(t)-1}^{sht}$	0.0453	0.0020	0.0320	0.0224	0.0224*	-0.0025	0.0105*	-0.0040
	(0.0243)	(0.0242)	(0.0128)	(0.0101)	(0.0042)	(0.0032)	(0.0030)	(0.002)
$SEL_{\tau(t)-1}*D_{\tau(t)-1}^{sht}$	-0.0303	-0.1115*	-0.0083	-0.0597*	-0.0021	-0.0284*	0.0017	-0.0087*
	(0.0260)	(0.0272)	(0.0112)	(0.0142)	(0.0031)	(0.0055)	(0.0021)	(0.0023)
$BUY_{\tau(t)-1}*D_{\tau(t)-1}^{lng}$	-0.0224	-0.0301	0.0085	0.0225	-0.0091*	-0.0076	-0.0031	-0.0016
	(0.0200)	(0.0187)	(0.0124)	(0.0092)	(0.0034)	(0.0054)	(0.0032)	(0.0023)
$SEL_{\tau(t)-1}*D_{\tau(t)-1}^{lng}$	0.0089	-0.0285	0.0138	-0.0165	-0.0026	0.0077	-0.0089*	0.0011
	(0.0209)	(0.0231)	(0.0093)	(0.0128)	(0.0026)	(0.0041)	(0.0024)	(0.0026)
F-stat	41.88	39.61	70.10	69.67	126.95	126.46	217.65	167.76
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.337	0.325	0.300	0.299	0.275	0.274	0.299	0.248

Table 7.1: Implied models for the spread and the mid-quote: summary of results for the representative stocks.

Variable	Decile 2 – GBX		Decile 4 – TEC		Decile 6 – OC		Decile 8 - GAP	
	Spread	*Mid-Quote*	*Spread*	*Mid-Quote*	*Spread*	*Mid-Quote*	*Spread*	*Mid-Quote*
$DEPTH\_DIFF_{t-1}$	-0.0263*	-0.0541*	-0.0114*	-0.0505*	0.0012	-0.0251*	0.0008	-0.0261*
	(0.0061)	(0.0046)	(0.0040)	(0.0028)	(0.0016)	(0.0010)	(0.0010)	(0.0007)
$BUY_{\tau(t)-1}$	0.0608*	0.1512*	0.0830*	0.1001*	0.0523*	0.0512*	0.0311*	0.0468*
	(0.0221)	(0.0163)	(0.0125)	(0.0092)	(0.0040)	(0.0027)	(0.0031)	(0.0024)
$SELL_{\tau(t)-1}$	0.0512	-0.1566*	0.0641*	-0.1020*	0.0377*	-0.0402*	0.0142*	-0.0319*
	(0.0251)	(0.0197)	(0.0125)	(0.0084)	(0.0045)	(0.0031)	(0.0028)	(0.0018)
$\Sigma\ (BUY)_{\tau(t)-1}$	0.0038	-0.0034	0.0104	0.0040	-0.0002	0.0020	0.0034*	0.0014
	(0.0051)	(0.0041)	(0.0044)	(0.0036)	(0.0017)	(0.0012)	(0.0010)	(0.0008)
$\Sigma\ (SELL)_{\tau(t)-1}$	0.0053	0.0157	0.0011	-0.0072*	0.0020	-0.0001	0.0010	-0.0026*
	(0.0094)	(0.0072)	(0.0038)	(0.0027)	(0.0016)	(0.0012)	(0.0009)	(0.0005)
$BUY_{\tau(t)-1}{*}V_{\tau(t)-1}^{med}$	0.0743*	0.0677*	0.0586*	0.0748*	0.0329*	0.0317*	0.0397*	0.0296*
	(0.0235)	(0.0161)	(0.0126)	(0.0088)	(0.0046)	(0.0027)	(0.0038)	(0.0021)
$SEL_{\tau(t)-1}{*}V_{\tau(t)-1}^{med}$	0.1148*	-0.0958*	0.0685*	-0.0760*	0.0459*	-0.0316*	0.0434*	-0.0309*
	(0.0242)	(0.0165)	(0.0135)	(0.0104)	(0.0046)	(0.0025)	(0.0037)	(0.0020)
$BUY_{\tau(t)-1}{*}V_{\tau(t)-1}^{big}$	0.1701*	0.0138	0.0318	0.0235	0.0635*	0.0346*	0.0687*	0.0426*
	(0.0561)	(0.0325)	(0.0439)	(0.0419)	(0.0157)	(0.0085)	(0.0148)	(0.0072)
$SEL_{\tau(t)-1}{*}V_{\tau(t)-1}^{big}$	-0.0007	-0.1067*	0.0152	-0.0980	0.0222	-0.0070	0.0382*	-0.0206*
	(0.0541)	(0.0388)	(0.0449)	(0.0402)	(0.0144)	(0.0084)	(0.0144)	(0.0070)
$BUY_{\tau(t)-1}{*}D_{\tau(t)-1}^{sht}$	0.0433	0.0237	0.0096	0.0272*	0.0249*	0.0100*	0.0145*	0.0032
	(0.0277)	(0.0200)	(0.0136)	(0.0093)	(0.0045)	(0.0030)	(0.0032)	(0.0020)
$SEL_{\tau(t)-1}{*}D_{\tau(t)-1}^{sht}$	0.0812*	-0.0709*	0.0513*	-0.0340*	0.0263*	-0.0152*	0.0104*	-0.0035
	(0.0285)	(0.0224)	(0.0146)	(0.0105)	(0.0051)	(0.0037)	(0.0029)	(0.0017)
$BUY_{\tau(t)-1}{*}D_{\tau(t)-1}^{long}$	0.0077	-0.0263	-0.0140	0.0155	-0.0014	-0.0084	-0.0015	-0.0024
	(0.0221)	(0.0159)	(0.0130)	(0.0087)	(0.0061)	(0.0033)	(0.0037)	(0.0021)
$SEL_{\tau(t)-1}{*}D_{\tau(t)-1}^{long}$	0.0375	-0.0098	0.0303	-0.0013	-0.0103	0.0026	-0.0100*	-0.0039
	(0.0238)	(0.0185)	(0.0136)	(0.0089)	(0.0045)	(0.0026)	(0.0033)	(0.0019)

Table 7.7: Long-Run Impacts of Various Types of Trades on the Spread

Panel A: Decile 2

BUY	D_{short}	D_{medium}	D_{long}	*SELL*	D_{short}	D_{medium}	D_{long}
V_{small}	0.3291	0.1348	0.1657	V_{small}	0.4007	0.2410	0.2157
V_{medium}	0.5400	0.1592	0.2943	V_{medium}	1.0139	0.8088	0.4616
V_{large}	0.3209	0.0303	0.1357	V_{large}	0.4815	0.1258	0.2617

Panel B: Decile 4

BUY	D_{short}	D_{medium}	D_{long}	*SELL*	D_{short}	D_{medium}	D_{long}
V_{small}	0.2366	0.2031	0.1395	V_{small}	0.3071	0.1417	0.1702
V_{medium}	0.2670	0.2709	0.2159	V_{medium}	0.3402	0.1912	0.2065
V_{large}	0.2663	0.2145	0.2873	V_{large}	0.3508	0.1547	0.1623

Panel C: Decile 6

BUY	D_{short}	D_{medium}	D_{long}	*SELL*	D_{short}	D_{medium}	D_{long}
V_{small}	0.2271	0.1418	0.1746	V_{small}	0.2282	0.1637	0.1502
V_{medium}	0.3230	0.2448	0.2731	V_{medium}	0.3099	0.2340	0.2784
V_{large}	0.2466	0.1965	0.1745	V_{large}	0.1759	0.1055	0.1169

Panel D: Decile 8

BUY	D_{short}	D_{medium}	D_{long}	*SELL*	D_{short}	D_{medium}	D_{long}
V_{small}	0.1912	0.1164	0.1024	V_{small}	0.1365	0.0583	0.0544
V_{medium}	0.2857	0.2202	0.2047	V_{medium}	0.2329	0.1839	0.1963
V_{large}	0.2089	0.1796	0.1562	V_{large}	0.2001	0.1294	0.1158

NOTE: This table presents the median long-run impact of nine different types of trades for each decile. The reader is referred to Table 4.1 for definitions of the various trade characteristic indicator variables.

Table 7.8: Long-Run Impacts of Various Types of Trades on the Mid-Quote

Panel A: Decile 2							
BUY	D_{short}	D_{medium}	D_{long}	*SELL*	D_{short}	D_{medium}	D_{long}
V_{small}	0.3445	0.1869	0.1592	V_{small}	-0.2994	-0.1224	-0.1777
V_{medium}	0.4424	0.2713	0.2419	V_{medium}	-0.4424	-0.2835	-0.2769
V_{large}	0.4343	0.3047	0.2815	V_{large}	-0.2768	-0.1180	-0.1872
Panel B: Decile 4							
BUY	D_{short}	D_{medium}	D_{long}	*SELL*	D_{short}	D_{medium}	D_{long}
V_{small}	0.1834	0.1346	0.1162	V_{small}	-0.1470	-0.0737	-0.0946
V_{medium}	0.2601	0.1932	0.1862	V_{medium}	-0.2145	-0.1454	-0.1729
V_{large}	0.2529	0.2061	0.1882	V_{large}	-0.2000	-0.1247	-0.1370
Panel C: Decile 6							
BUY	D_{short}	D_{medium}	D_{long}	*SELL*	D_{short}	D_{medium}	D_{long}
V_{small}	0.1177	0.0804	0.0778	V_{small}	-0.0855	-0.0601	-0.0633
V_{medium}	0.1545	0.1426	0.1296	V_{medium}	-0.1395	-0.1152	-0.1115
V_{large}	0.1681	0.1362	0.1294	V_{large}	-0.1138	-0.1069	-0.1097
Panel D: Decile 8							
BUY	D_{short}	D_{medium}	D_{long}	*SELL*	D_{short}	D_{medium}	D_{long}
V_{small}	0.0725	0.0583	0.0544	V_{small}	-0.0673	-0.0443	-0.0494
V_{medium}	0.1206	0.0982	0.0912	V_{medium}	-0.0920	-0.0811	-0.0880
V_{large}	0.1309	0.1181	0.1117	V_{large}	-0.0912	-0.0729	-0.0748

NOTE: This table presents the median long-run impact of nine different types of trades for each decile. The reader is referred to Table 4.1 for definitions of the various trade characteristic indicator variables.

A1. Appendix 1

Table A.1: Companies included in the sample. (An asterix indicates that this is a representative stock.)

Ticker	Company Name	Mean number of trades / day: Jan 1997 to Dec 1997	Jan 1998 to June 1999
Panel A: Decile 2			
HTD	HUNTINGDON LIFE SCIENCE GP	8.38	7.04
BE	BENGUET CORP	11.54	15.68
PDC	PRESLEY COMPANIES	8.45	14.53
ABG	GROUPE AB S A ADS	11.55	5.62
LSB	LSB INDUSTRIES INC	8.52	8.47
GBX*	GREENBRIER COMPANIES INC	9.89	14.20
STC	STEWART INFORMATION SVCS CORP	8.00	48.16
DTC	DOMTAR INC	10.17	11.34
PCZ	PETRO-CANADA VARIABLE VTG SHS	12.35	12.89
TGN	TRIGEN ENERGY CORP COMMON	7.29	8.78
SGD	SCOTTS LIQUID GOLD INC	12.52	11.31
OFG	ORIENTAL FINL GRP HOLD CO.	10.93	19.69
JNS	CHIC BY H.I.S. INC	9.45	10.74
JAX	J ALEXANDER S CORP.	7.55	7.46
HUN	HUNT CORP	11.29	16.13
TPR	TRANSPRO INC.	11.79	8.40
VHI	VALHI INC	10.08	9.47
MIG	MEADOWBROOK INSURANCE GRP INC	10.30	14.33
PIC	PICCADILLY CAFETERIAS INC	12.19	9.42
GOT	GOTTSCHALKS INC	12.05	9.63
GSE	GUNDLE/SLT ENVIROMENTAL INC.	8.91	5.32
CSS	CSS INDUSTRIES INC	9.42	9.68
SAJ	ST JOSEPH LIGHT POWER CO	10.81	12.84
FTD	FORT DEARBORN INCOME SECS	10.44	9.69
IAL	INTERNATIONAL ALUMINUM CORP	7.27	5.03
Panel B: Decile 4			
CNE	CONNECTICUT ENERGY CORP	21.04	27.46
TEC*	COMMERCIAL INTERTECH CORP	25.69	37.02
JC	JENNY CRAIG INC	24.07	16.67
NRD	NORD RESOURCES CORP	20.36	17.28
LSH	LASALLE RE HOLDINGS LTD	20.09	33.54
PCU	SOUTHERN PERU COPPER CORP	23.75	27.91
BOR	BORG WARNER SECURITIES CORP	19.47	26.93
FC	FRANKLIN COVEY CO.	20.93	38.63
CHP	C D TECHNOLOGIES INC.	20.88	34.25

Ticker	Company Name	Mean number of trades / day: Jan 1997 – Dec 1997	Jan 1998 - June 1999
Panel B (continued): Decile 4			
CGI	COMMERCE GROUP INC	19.80	31.71
XTR	XTRA CORP	21.44	34.52
FIC	FAIR ISAAC AND CO INC	23.13	46.62
FED	FIRSTFED FINANCIAL CORP	19.65	39.73
OSG	OVERSEAS SHIPHOLDING GROUP	26.86	33.58
BKE	BUCKLE INC	19.63	90.38
BNK	CNB BANCSHARES INC	20.64	56.11
UAH	UNITED AMER HEALTHCARE CORP	24.61	13.12
RGC	REPUBLIC GROUP INC	25.29	26.62
RDO	RDO EQUIPMENT CO	19.79	17.64
OXM	OXFORD INDUSTRIES INC	25.48	21.30
FMN	F M NATIONAL CORP	24.09	31.68
FEP	FRANKLIN ELECTRONIC PUBLISHER	19.56	11.94
PTC	PAR TECHNOLOGY CORP	25.63	15.81
TSY	TECH SYM CORP	20.02	13.44
BBR	BUTLER MANUFACTURING CO	22.58	19.56
Panel C: Decile 6			
TBY	TCBY ENTERPRISE INC	50.12	65.69
OMM	OMI CORPORATION NEW	39.50	41.27
FUN	CEDAR FAIR DEP R L.P.	51.73	63.46
GRO	MISSISSIPPI CHEMICAL CORP.	50.53	38.43
DGX	QUEST DIAGNOSTICS INC.	48.44	36.56
WSO	WATSCO INC	41.11	47.00
ASL	ASHANTI GOLDFLDS	48.50	89.55
FA	FAIRCHILD CORP CL	46.21	54.12
MPP	GENERAL CIGAR HOLDINGS CL	55.33	57.34
CDI	C D I CORP	44.04	52.00
IEI	INDIANA ENERGY INC HLDG CO	49.79	51.53
LUK	LEUCADIA NATIONAL CORP	45.63	77.59
CWC	CARIBINER INTERNATIONAL INC	43.85	81.12
RDK	RUDDICK CORP	51.71	70.73
WRC	WORLD COLOR PRESS INC	46.54	76.68
BUR	BURLINGTON INDS INC	48.82	83.88
CSL	CARLISLE COMPANIES INC	51.63	91.04
OC*	ORION CAPITAL CORP	40.04	73.84
PNM	PUBLIC SERVICE NEW MEXICO	49.12	69.56
CNA	CNA FINANCIAL CORP	39.26	70.38

Ticker	Company Name	Mean number of trades / day: Jan 1997 – Dec 1997	Jan 1998 - June 1999
Panel C (continued): Decile 6			
PNR	PENTAIR INC	39.09	77.13
ZLC	ZALE CORP	55.55	102.04
RYN	RAYONIER INC	49.24	73.17
LIN	LINENS N THINGS INC.	44.01	143.94
PMS	POLICY MANAGEMENT SYSTEMS CORP	41.46	117.37
Panel D: Decile 8			
RGR	STURM RUGER CO INC	83.23	77.47
AVX	AVX CORP	96.50	77.45
WNC	WABASH NATIONAL CORP	86.97	86.39
SEI	SEITEL INC	113.66	97.97
ARG	AIRGAS INC	111.91	93.31
FLM	FLEMING COS INC	83.88	93.11
BRR	BARRETT RESOURCES CORP	84.71	85.16
LTV	LTV CORP NEW	113.90	131.87
PMI	PREMARK INTERNATIONAL INC	84.12	95.89
TRN	TRINITY INDUSTRIES	111.73	152.31
ASD	AMERICAN STANDARD COS INC	119.90	120.76
TCB	TCF FINANCIAL CORP	83.14	150.09
R	RYDER SYSTEM INC	117.41	173.02
VTS	VERITAS DGC INC.	122.57	232.06
SNC	SNYDER COMMUNICATIONS INC.	82.61	197.24
GAS	NICOR INCORPORATED	86.63	112.22
AVT	AVNET INC	110.48	159.55
GAP*	GREAT ATLANTIC PAC TEA	92.77	127.89
DLP	DELTA AND PINE LAND COMPANY	91.20	176.24
COX	COX COMMUNICATIONS INC	82.94	245.96
FMO	FEDERAL-MOGUL CORP	86.08	191.18
CTX	CENTEX CORP	107.34	212.75
CP	CANADIAN PACIFIC LTD ORD NEW	123.38	194.47
CNS	CONSOLIDATED STORES CORP	106.44	275.42
DLJ	DONALDSON LUF JENRETTE INC	93.45	450.35

Table A.2: Complete results for the representative stocks.

	Decile 2 - GBX		Decile 4 - TEC		Decile 6 - OC		Decile 8 - GAP	
Variable	*Ask*	*Bid*	*Ask*	*Bid*	*Ask*	*Bid*	*Ask*	*Bid*
ASK_{t-1}	-0.4277*	0.0978*	-0.283*	0.1405*	-0.2376*	0.1297*	-0.2688*	0.0727*
	(0.0331)	(0.0248)	(0.0198)	(0.0173)	(0.05)	(0.0256)	(0.0438)	(0.019)
ASK_{t-2}	-0.2409*	0.0943*	-0.1708*	0.1006*	-0.1053*	0.1446*	-0.1403*	0.0797*
	(0.0284)	(0.0221)	(0.0293)	(0.0191)	(0.0213)	(0.0242)	(0.0185)	(0.0097)
ASK_{t-3}	-0.2165*	0.0716*	-0.1492*	0.1101*	-0.0762*	0.1151*	-0.1074*	0.0628*
	(0.0259)	(0.0218)	(0.0199)	(0.0167)	(0.0146)	(0.0193)	(0.0118)	(0.0081)
ASK_{t-4}	-0.1713*	0.0531	-0.1089*	0.0814*	-0.0636*	0.0843*	-0.0869*	0.0573*
	(0.0259)	(0.0219)	(0.0161)	(0.0158)	(0.0122)	(0.0179)	(0.0101)	(0.0073)
ASK_{t-5}	-0.1658*	0.0287	-0.0884*	0.0646*	-0.0594*	0.0873*	-0.0641*	0.0529*
	(0.0232)	(0.0205)	(0.0145)	(0.0137)	(0.0104)	(0.0144)	(0.0094)	(0.0067)
ASK_{t-6}	-0.1162*	0.0121	-0.0569*	0.0541*	-0.0593*	0.0579*	-0.0525*	0.0485*
	(0.0213)	(0.0189)	(0.013)	(0.0133)	(0.01)	(0.0123)	(0.0083)	(0.006)
ASK_{t-7}	-0.0992*	0.0164	-0.047*	0.0417*	-0.0452*	0.0681*	-0.044*	0.0357*
	(0.0199)	(0.0179)	(0.0124)	(0.0133)	(0.009)	(0.0123)	(0.0077)	(0.0059)
ASK_{t-8}	-0.0927*	0.0076	-0.0335*	0.0273	-0.0506*	0.0381*	-0.028*	0.0282*
	(0.0195)	(0.0172)	(0.0115)	(0.0116)	(0.0088)	(0.0114)	(0.0064)	(0.0052)
ASK_{t-9}	-0.0743*	0.0261	-0.0226	0.0283*	-0.0303*	0.0261*	-0.0192*	0.0168*
	(0.0175)	(0.015)	(0.0107)	(0.0105)	(0.008)	(0.0082)	(0.0059)	(0.0047)
ASK_{t-10}	-0.0215	0.0265	-0.0023	0.0286*	-0.0156	0.0078	-0.0183*	0.0037
	(0.0134)	(0.0117)	(0.0086)	(0.0086)	(0.0064)	(0.0065)	(0.0055)	(0.0037)
BID_{t-1}	0.2336*	-0.319*	0.1677*	-0.2872*	0.0895*	-0.3084*	0.1487*	-0.1756*
	(0.0227)	(0.023)	(0.0197)	(0.0322)	(0.0326)	(0.0814)	(0.0103)	(0.0101)
BID_{t-2}	0.2379*	-0.0676*	0.1557*	-0.1311*	0.106*	-0.174*	0.1344*	-0.0813*
	(0.0264)	(0.023)	(0.0173)	(0.0214)	(0.0175)	(0.0387)	(0.0141)	(0.01)
BID_{t-3}	0.1979*	-0.0774*	0.1302*	-0.0978*	0.1002*	-0.1285*	0.1146*	-0.0795*
	(0.0263)	(0.0222)	(0.0176)	(0.0172)	(0.0141)	(0.0237)	(0.0116)	(0.0111)
BID_{t-4}	0.1832*	-0.0344	0.1026*	-0.0749*	0.091*	-0.0844*	0.0915*	-0.0563*
	(0.0248)	(0.022)	(0.0152)	(0.015)	(0.013)	(0.0175)	(0.0099)	(0.0086)
BID_{t-5}	0.1562*	-0.038	0.0775*	-0.063*	0.0713*	-0.0701*	0.0692*	-0.0468*
	(0.0241)	(0.0215)	(0.0139)	(0.0142)	(0.0114)	(0.0139)	(0.0095)	(0.0074)
BID_{t-6}	0.1181*	-0.0073	0.0661*	-0.0432*	0.0525*	-0.0584*	0.0587*	-0.0405*
	(0.022)	(0.0205)	(0.0133)	(0.0132)	(0.0098)	(0.0119)	(0.0085)	(0.0067)
BID_{t-7}	0.0936*	-0.0083	0.052*	-0.0482*	0.0552*	-0.0446*	0.0489*	-0.0466*
	(0.0213)	(0.0188)	(0.0118)	(0.0123)	(0.009)	(0.0098)	(0.0072)	(0.006)
BID_{t-8}	0.0938*	0.0083	0.0377*	-0.0175	0.0542*	-0.0337*	0.039*	-0.0341*
	(0.0197)	(0.018)	(0.0106)	(0.012)	(0.0077)	(0.0088)	(0.0073)	(0.0061)

Variable	Decile 2 - GBX Ask	Decile 2 - GBX Bid	Decile 4 - TEC Ask	Decile 4 - TEC Bid	Decile 6 - OC Ask	Decile 6 - OC Bid	Decile 8 - GAP Ask	Decile 8 - GAP Bid
BID_{t-9}	0.0796*	-0.0175	0.0027	-0.0251	0.0264*	-0.0159	0.031*	-0.0202*
	(0.0178)	(0.0158)	(0.01)	(0.0105)	(0.0073)	(0.0075)	(0.0062)	(0.0058)
BID_{t-10}	0.0381	0.0076	0.0054	-0.0173	0.0277*	-0.0094	0.0142	0.0037
	(0.0154)	(0.014)	(0.0084)	(0.0087)	(0.0068)	(0.0056)	(0.0061)	(0.0056)
constant	0.2523*	-0.083*	0.1734*	-0.1291*	0.0704*	-0.0542*	0.0719*	-0.075*
	(0.0229)	(0.0202)	(0.0165)	(0.0174)	(0.0083)	(0.0104)	(0.0083)	(0.0056)
SPR_{t-1}	-0.1329*	0.1592*	-0.115*	0.164*	-0.12*	0.1552*	-0.1836*	0.1474*
	(0.0198)	(0.0178)	(0.0143)	(0.0145)	(0.0145)	(0.024)	(0.0162)	(0.0093)
$DPTH\_DIFF_{t-1}$	-0.0672*	-0.0409*	-0.0562*	-0.0449*	-0.0245*	-0.0257*	-0.0257*	-0.0265*
	(0.0056)	(0.0054)	(0.0034)	(0.0035)	(0.0013)	(0.0014)	(0.001)	(0.0008)
$BUY_{\tau(t)-1}$	0.1816*	0.1208*	0.1416*	0.0586*	0.0774*	0.0251*	0.0624*	0.0313*
	(0.0207)	(0.0186)	(0.0119)	(0.0103)	(0.0036)	(0.0032)	(0.0034)	(0.0022)
$BUY_{\tau(t)-2}$	0.0525	-0.0004	0.0092	0.0058	0.0173*	0.0102	0.0168*	0.0104*
	(0.0227)	(0.0179)	(0.0112)	(0.0111)	(0.0056)	(0.004)	(0.0042)	(0.0025)
$BUY_{\tau(t)-3}$	-0.016	0.0046	0.0015	0.0159	0.0033	-0.0041	0.0047	0.0026
	(0.0299)	(0.0202)	(0.0141)	(0.0106)	(0.0037)	(0.0035)	(0.0027)	(0.0022)
$BUY_{\tau(t)-4}$	-0.007	-0.0236	0.0041	0.0041	0.0022	-0.0036	0.001	-0.0036
	(0.0197)	(0.0188)	(0.0108)	(0.0107)	(0.0048)	(0.0033)	(0.0024)	(0.0021)
$BUY_{\tau(t)-5}$	-0.0181	-0.0222	0.0097	0.0005	-0.0094	-0.0042	0.0035	-0.0015
	(0.0196)	(0.0182)	(0.0115)	(0.0103)	(0.0037)	(0.0046)	(0.0025)	(0.0022)
$SELL_{\tau(t)-1}$	-0.131*	-0.1822*	-0.0699*	-0.134*	-0.0214*	-0.0591*	-0.0248*	-0.039*
	(0.0229)	(0.0239)	(0.0095)	(0.0114)	(0.0028)	(0.0046)	(0.0024)	(0.0021)
$SELL_{\tau(t)-2}$	-0.0457	-0.043	-0.005	-0.0186	-0.008	-0.014	-0.0057	-0.0068*
	(0.0225)	(0.0226)	(0.0109)	(0.0122)	(0.0034)	(0.0061)	(0.0023)	(0.002)
$SELL_{\tau(t)-3}$	-0.0312	-0.0163	0.0163	0.0151	-0.0013	0.0021	-0.0052	-0.002
	(0.0246)	(0.0209)	(0.0106)	(0.0114)	(0.0029)	(0.0035)	(0.0023)	(0.0022)
$SELL_{\tau(t)-4}$	-0.036	0.0018	0.0293*	0.0148	0.0031	-0.0003	-0.0016	-0.0028
	(0.0211)	(0.0211)	(0.0104)	(0.0111)	(0.0035)	(0.0032)	(0.0023)	(0.0021)
$SELL_{\tau(t)-5}$	-0.0114	-0.0355	0.0086	0.0021	0.0026	-0.0024	0.0064	0.0035
	(0.0292)	(0.0287)	(0.013)	(0.0101)	(0.0033)	(0.0031)	(0.0025)	(0.0019)
$\Sigma BUY_{\tau(t)-1}$	-0.0015	-0.0053	0.0092	-0.0012	0.0018	0.0021	0.0031*	-0.0003
	(0.0058)	(0.0037)	(0.004)	(0.0044)	(0.0015)	(0.0014)	(0.001)	(0.0008)
$\Sigma BUY_{\tau(t)-2}$	-0.0052	0.0025	0.0036	0.0027	-0.0003	0.0017	0.0002	0.0031*
	(0.0034)	(0.0033)	(0.0035)	(0.0038)	(0.0013)	(0.0011)	(0.0009)	(0.0007)
$\Sigma BUY_{\tau(t)-3}$	0.0103	0.0036	0.001	0.0016	-0.0013	0.0006	-0.0012	0.0001
	(0.0131)	(0.004)	(0.0031)	(0.0031)	(0.0013)	(0.0012)	(0.0008)	(0.0007)
$\Sigma BUY_{\tau(t)-4}$	-0.0075	-0.0047	0.0035	0.0015	-0.0015	0.0011	-0.0016	0.0014
	(0.0044)	(0.005)	(0.0031)	(0.0031)	(0.0012)	(0.0011)	(0.0007)	(0.0007)

Variable	Decile 2 - GBX		Decile 4 - TEC		Decile 6 - OC		Decile 8 - GAP	
	Ask	*Bid*	*Ask*	*Bid*	*Ask*	*Bid*	*Ask*	*Bid*
$\Sigma BUY_{\tau(t)-5}$	-0.0009	-0.0016	-0.0004	0.0012	0.001	-0.0014	-0.0004	0.0003
	(0.0047)	(0.0034)	(0.0029)	(0.0031)	(0.0012)	(0.0012)	(0.0008)	(0.0007)
$\Sigma SELL_{\tau(t)-1}$	0.0183	0.013	-0.0066	-0.0077	0.0009	-0.0011	-0.0021*	-0.003*
	(0.009)	(0.0081)	(0.0032)	(0.0035)	(0.0012)	(0.0017)	(0.0007)	(0.0007)
$\Sigma SELL_{\tau(t)-2}$	0.0001	-0.0022	-0.0047	-0.0038	-0.0028*	-0.0026	-0.0014	-0.0006
	(0.0068)	(0.0069)	(0.003)	(0.0032)	(0.0011)	(0.0011)	(0.0007)	(0.0006)
$\Sigma SELL_{\tau(t)-3}$	0.0109	0.0149	-0.002	-0.0032	-0.0003	-0.0003	-0.0007	0.0007
	(0.0099)	(0.0084)	(0.003)	(0.0035)	(0.001)	(0.0012)	(0.0006)	(0.0006)
$\Sigma SELL_{\tau(t)-4}$	0.0096	0.0007	-0.0005	-0.0005	0.0004	0.0008	-0.0003	0.0004
	(0.0076)	(0.0064)	(0.003)	(0.0038)	(0.0016)	(0.0014)	(0.0008)	(0.0008)
$\Sigma SELL_{\tau(t)-5}$	-0.0005	0.0086	0.0006	0.0019	-0.001	0.0019	-0.0006	0.0009
	(0.0074)	(0.0067)	(0.0032)	(0.0033)	(0.0012)	(0.0013)	(0.0006)	(0.0006)
$BUY_{\tau(t)-1}*V_{\tau(t)-1}^{med}$	0.1049*	0.0306	0.1042*	0.0455*	0.0481*	0.0152*	0.0494*	0.0097*
	(0.0216)	(0.0181)	(0.0117)	(0.0099)	(0.0035)	(0.0035)	(0.0033)	(0.0021)
$BUY_{\tau(t)-2}*V_{\tau(t)-2}^{med}$	0.0143	0.0346	-0.002	0.0294*	0.0134*	0.0056	0.0109*	0.0133*
	(0.0208)	(0.019)	(0.0113)	(0.0111)	(0.0041)	(0.0034)	(0.0038)	(0.0028)
$BUY_{\tau(t)-3}*V_{\tau(t)-3}^{med}$	-0.0375	-0.0144	0.0046	0.0186	0.0042	0.0026	0.002	0.0058
	(0.0199)	(0.0187)	(0.0106)	(0.0102)	(0.0033)	(0.0038)	(0.0031)	(0.0027)
$BUY_{\tau(t)-4}*V_{\tau(t)-4}^{med}$	-0.0038	-0.054*	0.0006	0.0036	0.003	-0.001	-0.001	0.0026
	(0.0221)	(0.0179)	(0.0114)	(0.0107)	(0.0032)	(0.0032)	(0.0029)	(0.003)
$BUY_{\tau(t)-5}*V_{\tau(t)-5}^{med}$	0.0167	-0.0339	0.001	0.0198	0.0095*	0.0077	0.0067	0.0051
	(0.0192)	(0.0174)	(0.0111)	(0.0102)	(0.0033)	(0.0036)	(0.0032)	(0.0025)
$SEL_{\tau(t)-1}*V_{\tau(t)-1}^{med}$	-0.0384	-0.1532*	-0.0418*	-0.1102*	-0.0086*	-0.0546*	-0.0092*	-0.0526*
	(0.0191)	(0.0218)	(0.011)	(0.0137)	(0.0026)	(0.0041)	(0.0025)	(0.0029)
$SEL_{\tau(t)-2}*V_{\tau(t)-2}^{med}$	-0.0221	-0.0282	-0.019	-0.0105	-0.0099*	-0.0138	-0.0083*	-0.0082*
	(0.0198)	(0.0202)	(0.0107)	(0.013)	(0.0036)	(0.006)	(0.0026)	(0.0027)
$SEL_{\tau(t)-3}*V_{\tau(t)-3}^{med}$	0.0312	0.0323	-0.0112	0.0228	-0.0039	-0.0014	0.001	0.0026
	(0.0203)	(0.0194)	(0.0108)	(0.011)	(0.0034)	(0.0035)	(0.0032)	(0.003)
$SEL_{\tau(t)-4}*V_{\tau(t)-4}^{med}$	-0.0221	0.0037	-0.0033	-0.0082	-0.0011	-0.0073	-0.0021	-0.0019
	(0.0206)	(0.0204)	(0.0112)	(0.0114)	(0.0035)	(0.0031)	(0.0027)	(0.0027)
$SEL_{\tau(t)-5}*V_{\tau(t)-5}^{med}$	0.0271	0.0008	0.0134	-0.0033	0.0027	0	-0.0005	-0.0009
	(0.0209)	(0.0182)	(0.0102)	(0.0121)	(0.0033)	(0.0037)	(0.005)	(0.0026)
$BUY_{\tau(t)-1}*V_{\tau(t)-1}^{big}$	0.0988	-0.0713	0.0393	0.0076	0.0663*	0.0028	0.0769*	0.0082
	(0.0481)	(0.0372)	(0.056)	(0.0366)	(0.0137)	(0.0089)	(0.0127)	(0.0071)
$BUY_{\tau(t)-2}*V_{\tau(t)-2}^{big}$	0.0458	0.1186	-0.0983	-0.0269	-0.0052	-0.0096	0.0083	0.0343*
	(0.042)	(0.0534)	(0.0888)	(0.1175)	(0.013)	(0.0112)	(0.0097)	(0.01)
$BUY_{\tau(t)-3}*V_{\tau(t)-3}^{big}$	-0.021	0.0761	0.0492	-0.0015	0.0077	0.0091	-0.03*	0.0016
	(0.0541)	(0.0507)	(0.0339)	(0.0602)	(0.015)	(0.0143)	(0.0096)	(0.0082)

Variable	Decile 2 - GBX Ask	Decile 2 - GBX Bid	Decile 4 - TEC Ask	Decile 4 - TEC Bid	Decile 6 - OC Ask	Decile 6 - OC Bid	Decile 8 - GAP Ask	Decile 8 - GAP Bid
$BUY_{\tau(t)-4}*V_{\tau(t)-4}^{big}$	0.0107	-0.0153	0.04	0.0796	0.0039	0.0087	-0.0135	0.0177
	(0.0493)	(0.0296)	(0.0609)	(0.0558)	(0.0101)	(0.0099)	(0.0107)	(0.0088)
$BUY_{\tau(t)-5}*V_{\tau(t)-5}^{big}$	0.0286	0.0167	-0.0088	-0.0058	-0.0113	0.0029	0.0064	0.0088
	(0.0444)	(0.0542)	(0.0421)	(0.0765)	(0.0102)	(0.0111)	(0.0144)	(0.0139)
$SEL_{\tau(t)-1}*V_{\tau(t)-1}^{big}$	-0.1071*	-0.1064	-0.0904	-0.1056	0.0041	-0.0181	-0.0015	-0.0397*
	(0.0403)	(0.0534)	(0.038)	(0.0529)	(0.0091)	(0.0128)	(0.0093)	(0.0107)
$SEL_{\tau(t)-2}*V_{\tau(t)-2}^{big}$	0.0447	0.0088	-0.0953	0.0111	-0.0057	-0.0204	-0.0148	-0.0061
	(0.0298)	(0.0402)	(0.0438)	(0.0501)	(0.0085)	(0.0113)	(0.0083)	(0.0099)
$SEL_{\tau(t)-3}*V_{\tau(t)-3}^{big}$	-0.0468	0.0535	0.0868	-0.0131	0.0086	-0.0063	0.0068	0.0079
	(0.0474)	(0.0404)	(0.0533)	(0.0281)	(0.0096)	(0.01)	(0.0096)	(0.0085)
$SEL_{\tau(t)-4}*V_{\tau(t)-4}^{big}$	0.0034	-0.0244	0.0493	-0.0044	-0.001	-0.0073	0.003	0.0008
	(0.05)	(0.0478)	(0.0552)	(0.0423)	(0.0109)	(0.0105)	(0.0099)	(0.0103)
$SEL_{\tau(t)-5}*V_{\tau(t)-5}^{big}$	0.0389	0.0349	0.0444	0.0262	-0.0134	-0.0026	-0.0024	-0.0045
	(0.0553)	(0.0599)	(0.0578)	(0.0431)	(0.0096)	(0.0091)	(0.0088)	(0.01)
$BUY_{\tau(t)-1}*D_{\tau(t)-1}^{sht}$	0.0453	0.002	0.032	0.0224	0.0224*	-0.0025	0.0105*	-0.004
	(0.0243)	(0.0242)	(0.0128)	(0.0101)	(0.0042)	(0.0032)	(0.003)	(0.002)
$BUY_{\tau(t)-2}*D_{\tau(t)-2}^{sht}$	0.0405	0.0743*	0.0177	0.0243	0.0141*	0.0045	0.0097*	0.0029
	(0.0269)	(0.0221)	(0.0119)	(0.0115)	(0.004)	(0.0035)	(0.0028)	(0.0023)
$BUY_{\tau(t)-3}*D_{\tau(t)-3}^{sht}$	0.0092	0.0027	-0.0016	-0.0099	0.005	0.0049	0.0018	0.0022
	(0.026)	(0.0235)	(0.0137)	(0.0114)	(0.0038)	(0.0036)	(0.0027)	(0.0023)
$BUY_{\tau(t)-4}*D_{\tau(t)-4}^{sht}$	0.0382	0.0486	-0.0117	-0.0124	-0.0027	0.0036	0.0007	0.0044
	(0.0254)	(0.0236)	(0.0118)	(0.0113)	(0.0044)	(0.0036)	(0.0026)	(0.0024)
$BUY_{\tau(t)-5}*D_{\tau(t)-5}^{sht}$	-0.0046	0.0307	0.0039	0.0021	0.0014	0.0026	-0.0024	0.001
	(0.0225)	(0.0227)	(0.0121)	(0.0109)	(0.0036)	(0.0045)	(0.0027)	(0.0023)
$SEL_{\tau(t)-1}*D_{\tau(t)-1}^{sht}$	-0.0303	-0.1115*	-0.0083	-0.0597*	-0.0021	-0.0284*	0.0017	-0.0087*
	(0.026)	(0.0272)	(0.0112)	(0.0142)	(0.0031)	(0.0055)	(0.0021)	(0.0023)
$SEL_{\tau(t)-2}*D_{\tau(t)-2}^{sht}$	-0.0175	-0.0085	-0.0348*	-0.0248	-0.001	-0.018*	-0.001	-0.0077*
	(0.0262)	(0.0264)	(0.0119)	(0.0128)	(0.0033)	(0.0046)	(0.0021)	(0.0021)
$SEL_{\tau(t)-3}*D_{\tau(t)-3}^{sht}$	-0.0324	-0.0432	0.0013	-0.0195	-0.0016	-0.0136*	0.0026	-0.0008
	(0.0276)	(0.0278)	(0.0114)	(0.0123)	(0.0032)	(0.0037)	(0.0023)	(0.0022)
$SEL_{\tau(t)-4}*D_{\tau(t)-4}^{sht}$	0.0193	-0.0221	-0.0253	-0.0175	-0.0014	-0.0057	0.0051	0.0016
	(0.0279)	(0.0246)	(0.0116)	(0.0121)	(0.0034)	(0.0035)	(0.0025)	(0.0021)
$SEL_{\tau(t)-5}*D_{\tau(t)-5}^{sht}$	0.0213	0.0211	-0.0155	-0.0134	-0.0019	-0.0038	-0.0038	-0.0035
	(0.0313)	(0.0303)	(0.0131)	(0.0121)	(0.0033)	(0.0033)	(0.0031)	(0.0021)
$BUY_{\tau(t)-1}*D_{\tau(t)-1}^{lng}$	-0.0224	-0.0301	0.0085	0.0225	-0.0091*	-0.0076	-0.0031	-0.0016
	(0.02)	(0.0187)	(0.0124)	(0.0092)	(0.0034)	(0.0054)	(0.0032)	(0.0023)
$BUY_{\tau(t)-2}*D_{\tau(t)-2}^{lng}$	-0.012	0.0392	0.0128	0.0053	-0.0072	0.0023	-0.0043	-0.0016
	(0.0227)	(0.0185)	(0.0112)	(0.0112)	(0.0036)	(0.0037)	(0.003)	(0.0026)

Variable	Decile 2 - GBX Ask	Decile 2 - GBX Bid	Decile 4 - TEC Ask	Decile 4 - TEC Bid	Decile 6 - OC Ask	Decile 6 - OC Bid	Decile 8 - GAP Ask	Decile 8 - GAP Bid
$BUY_{\tau(t)-3}*D_{\tau(t)-3}^{lng}$	-0.0008	0.0023	-0.0053	-0.0114	-0.0002	-0.0003	-0.0014	-0.0006
	(0.0224)	(0.0204)	(0.0138)	(0.0107)	(0.0036)	(0.0053)	(0.0032)	(0.0028)
$BUY_{\tau(t)-4}*D_{\tau(t)-4}^{lng}$	0.0112	0.0394	-0.0196	-0.0143	-0.0027	0.0041	-0.0006	0.0032
	(0.0206)	(0.0184)	(0.011)	(0.0108)	(0.0047)	(0.0039)	(0.003)	(0.0028)
$BUY_{\tau(t)-5}*D_{\tau(t)-5}^{lng}$	0.0048	0.0219	-0.0066	-0.018	0.0095*	0.0065	-0.0043	-0.0004
	(0.0196)	(0.0188)	(0.0117)	(0.0102)	(0.0037)	(0.0046)	(0.003)	(0.0027)
$SEL_{\tau(t)-1}*D_{\tau(t)-1}^{lng}$	0.0089	-0.0285	0.0138	-0.0165	-0.0026	0.0077	-0.0089*	0.0011
	(0.0209)	(0.0231)	(0.0093)	(0.0128)	(0.0026)	(0.0041)	(0.0024)	(0.0026)
$SEL_{\tau(t)-2}*D_{\tau(t)-2}^{lng}$	0.0081	-0.0127	-0.0069	-0.0002	0.002	0.0021	-0.0034	0.0007
	(0.0218)	(0.0218)	(0.0108)	(0.0116)	(0.0028)	(0.0038)	(0.0024)	(0.0025)
$SEL_{\tau(t)-3}*D_{\tau(t)-3}^{lng}$	0.0258	0.0106	-0.0105	-0.0172	0.006	-0.0025	0.0001	-0.0017
	(0.021)	(0.0201)	(0.0106)	(0.0114)	(0.004)	(0.0033)	(0.0027)	(0.0025)
$SEL_{\tau(t)-4}*D_{\tau(t)-4}^{lng}$	0.0304	0.002	-0.0288*	-0.0068	-0.0042	0.0002	0.0035	0.0019
	(0.0205)	(0.0207)	(0.0104)	(0.0109)	(0.0036)	(0.0031)	(0.0026)	(0.0025)
$SEL_{\tau(t)-5}*D_{\tau(t)-5}^{lng}$	0.0163	0.037	-0.0005	0.0051	-0.0004	-0.0053	-0.0038	-0.0074*
	(0.0278)	(0.0273)	(0.0125)	(0.0103)	(0.0033)	(0.0048)	(0.0031)	(0.0025)
$DIURN_1$	-0.114*	0.0061	-0.0821*	0.04*	-0.0363*	0.0171*	-0.0219*	0.0241*
	(0.0142)	(0.013)	(0.0099)	(0.0114)	(0.0045)	(0.0045)	(0.0048)	(0.0031)
$DIURN_2$	0.0061	-0.0011	0.0041	-0.0018	0.0012	0.0008	0.0023*	-0.0015
	(0.0045)	(0.0043)	(0.0029)	(0.0038)	(0.0009)	(0.001)	(0.0009)	(0.0007)
$DIURN_3$	-0.0009	0.0025	-0.0008	-0.003	0.0008	0.0001	-0.0005	0.0008
	(0.0037)	(0.0038)	(0.0031)	(0.0029)	(0.001)	(0.0012)	(0.0007)	(0.0007)
$DIURN_4$	-0.0022	-0.0023	0.0006	0.004	-0.0012	-0.0013	0.0003	0
	(0.0041)	(0.004)	(0.0033)	(0.0028)	(0.001)	(0.0011)	(0.0007)	(0.0007)
$DIURN_5$	0.0029	-0.0025	-0.0031	-0.0009	0.0002	0.0007	-0.0009	-0.0005
	(0.0047)	(0.0042)	(0.0029)	(0.0027)	(0.001)	(0.001)	(0.0007)	(0.0007)
$DIURN_6$	-0.0038	0.0001	-0.0011	-0.0022	-0.0008	-0.0004	0	0.0006
	(0.0053)	(0.004)	(0.0028)	(0.0029)	(0.0009)	(0.0015)	(0.0007)	(0.0007)
$DIURN_7$	0.0059	0.0005	0.0145	0.0068	0.0056	0.0023	0.0006	-0.0026
	(0.0106)	(0.0098)	(0.0063)	(0.0065)	(0.0022)	(0.0028)	(0.0016)	(0.0015)
$DIURN_8$	-0.0148	0.0054	-0.0144	-0.0174	-0.0013	-0.0021	-0.0037	0.0078*
	(0.0122)	(0.0119)	(0.0081)	(0.0085)	(0.0029)	(0.0026)	(0.0022)	(0.0019)