Title

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Publication Date

2000-04-12

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April 12, 2001

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This paper owes a significant debt to Charles Lee and Mark Ready for developing the trade signing algorithm. For helpful comments, we owe a debt of gratitude to an anonymous referee, Hank Bessembinder, Jeff Busee, Clifton Green, Paul Irvine, Jonathan Karpoff, Olivier Ledoit, Ross Valkanov, and Sunil Wahal.

Order Imbalance, Liquidity, and Market Returns

Abstract

Traditionally, volume has provided the link between trading activity and returns. We focus on a hitherto unexplored but intuitive measure of trading activity: the aggregate daily order imbalance on the New York Stock Exchange. Signed order imbalances increase (decrease) following market declines (rises), which reveals that investors are contrarians on aggregate. Order imbalances in either direction, either excess buy or sell orders, reduce liquidity. Market-wide returns are strongly affected by contemporaneous and lagged order imbalances. Market-wide returns reverse themselves after high negative imbalance, large negative return days; the magnitude of this reversal is partially predictable from the level of the imbalance and return. Even after controlling for aggregate market volume and liquidity, market returns are affected by order imbalance.

1. Introduction

A large literature has studied the association between trading activity and stock market returns; (e.g., see Benston and Hagerman, 1974; Gallant, Rossi, and Tauchen, 1992; Hiemstra and Jones, 1994; Lo and Wang, 2000; and also the studies summarized in Karpoff, 1987). Stock trading volume is also linked inextricably to liquidity (Benston and Hagerman, 1974; Stoll, 1978b). Our aim here is to shed further light on the tri-partite association among trading activity, liquidity, and stock market returns using a lengthy and recent set of high frequency data.

In most existing studies, trading activity is measured by volume. But volume alone is absolutely guaranteed to conceal some important aspects of trading. Consider, for example, a reported volume of one million shares. At one extreme, this might be a million shares sold to the market maker while at the other extreme it could be a million shares purchased. Perhaps more typically, it would be roughly split, about 500,000 shares sold to and 500,000 shares bought from the market maker. Clearly, each possibility has its own unique implications for prices and liquidity.

Intuition suggests that prices <u>and</u> liquidity should be more strongly affected by more extreme order imbalances, regardless of volume, for two reasons. First, order imbalances sometimes signal private information, which should reduce liquidity at least temporarily and could also move the market price permanently, as also suggested by the well-known Kyle (1985) theory of price formation. Second, even a <u>random</u> large order imbalance exacerbates the inventory problem faced by the market maker, who can be expected to respond by changing bid-ask spreads and revising price quotations. Hence, order imbalances should be important influences on stock returns and liquidity, conceivably even more important than volume. Indeed, the inventory models of Stoll (1978a), Ho and Stoll (1981), and Spiegel and Subrahmanyam (1995) involve market makers accommodating buying and selling by outside investors, and liquidity as well as returns are influenced by inventory concerns in this paradigm.

Most existing studies analyze order imbalances around specific events or over short periods of time. Thus, Sias (1997) analyzes order imbalances in the context of institutional buying and selling of closed-end funds; Lauterbach and Ben-Zion (1993) and Blume, MacKinlay, and Terker, (1989) analyze order imbalances around the October 1987 crash; and Lee (1992) does the same around earnings announcements. Chan and Fong (2000) analyze how order imbalance changes the contemporaneous relation between stock volatility and volume using data for about six months. Hasbrouck and Seppi (2001) and Brown, Walsh, and Yuen (1997) study order imbalances for thirty and twenty stocks, over one and two years, respectively.

A long-term study using order imbalances for a broad cross-section has not been performed primarily because transactions databases do not identify buyers and sellers. Thus, the investigator is obliged to undertake an arduous task: assigning hundreds of millions of transactions to either the buyer-initiated or seller-initiated categories. Happily, assignment algorithms are available for this purpose.

Our first contribution is to construct a database of estimated market-wide order imbalances for a comprehensive sample of NYSE stocks during the period 1988-1998 inclusive. Using data from the Institute for the Study of Security Markets (1988-1992) and the TAQ database provided by the NYSE, every transaction is assigned using the Lee/Ready (1991) algorithm.[1] Of course,

[1] The Lee/Ready algorithm is basically quite simple; a trade is classified as buyer (seller) initiated if it is closer to the ask (bid) of the prevailing quote. The quote must be at least five seconds old. If the trade is exactly at the mid-

there is inevitably some assignment error, so the resulting order imbalances are *estimates*. Yet, as shown in Lee and Radhakrishna (2000), and Odders-White (2000), the Lee/Ready algorithm is accurate enough as to not pose serious problems in our large sample study.

Our empirical study focuses in sequence on (1) characterizing properties and determinants of market-wide daily order imbalances (2) investigating the relation between order imbalance and an aggregate measure of liquidity,[2] and (3) investigating the extent to which daily stock market returns are related to order imbalances after controlling for the effects of market liquidity. To our knowledge, this is the first paper to consider daily order imbalances for a comprehensive sample of stocks over a long sample period.

For the aggregate market, asymmetric information is not likely to be an issue, and we expect the inventory paradigm to be more relevant in the interplay between imbalances, liquidity, and returns. For example, in this paradigm, after a large inventory imbalance, market makers position their quotes to encourage trading on the other side of the market in order to stabilize their inventory. This strategy, if successful, will cause a direct relation between past returns and future order imbalances. Further, in this paradigm, imbalances cause price pressures that have a direct effect on returns. Finally, increased return fluctuations cause a widening of the bid-ask spread due to an increase in inventory risk. While the intention of our study is mainly to examine the relation between imbalances, spreads, and returns from a purely empirical standpoint, the inventory paradigm serves as the theoretical underpinning of our analysis. As

point of the quote, a "tick test" is used whereby the trade is classified as buyer (seller) initiated if the last price change prior to the trade is positive (negative.)

[2] Liquidity is measured by the daily value-weighted quoted spread associated with each transaction during the day. The weights are proportional to market capitalization of each stock at the beginning of the calendar year.

we describe below, our results are broadly supportive of the central implications of this paradigm of price formation.

We find that the daily levels of order imbalances are persistent, though their first differences are negatively autocorrelated. In addition, there is evidence that aggregate order imbalance is contrarian; buying activity is more pronounced following market crashes, and selling activity is more pronounced following market rises. This evidence is consistent with the notion that temporary inventory imbalances and consequent price pressures are countervailed effectively by astute traders.[3]

Our analysis also indicates that order imbalances are significantly associated with daily changes in liquidity and with contemporaneous market returns, after controlling for the level of unsigned trading activity. The latter result underscores the role of excess buying and selling activity, as opposed to just trading volume, as a determinant of fluctuations in market returns.

In contrast to market returns, we find liquidity is highly predictable not only by its own past values, but also by past market returns. This result is consistent with the notion that increased asset price fluctuations cause a decrease in liquidity owing to an increase in inventory risk.

Notwithstanding the daily serial dependence in both order imbalances and liquidity, there is no evidence they can predict one-day ahead stock market returns. Thus, the aggregate market is resilient to market microstructure effects; in general, there is no evidence that the effects of illiquidity and order imbalance on market returns persist beyond a single day. (The S&P 500

[3] Harris and Gurel (1986) and Shleifer (1986) document price pressures when stocks are added to the S&P500 index.

return series was selected as the object to be predicted because its unconditional daily serial correlation was virtually zero during the 1988-1998 sample period and we wanted a difficult objective.) However, there is evidence that large negative order imbalance, large negative return days are accompanied by strong reversals, consistent with the block trading literature for individual stocks (e.g., Kraus and Stoll, 1972), which suggests that large block sells are accompanied by reversals in stock prices. Our results underscore the point that price pressures caused by imbalances in inventory are an issue not just for individual stocks, but for the aggregate market as well. This finding has direct implications for agents wishing to trade a diversified market portfolio.

Our decision to analyze liquidity, order imbalances, and returns over daily intervals is to some extent arbitrary (one could have chosen hourly intervals, or for that matter, monthly intervals). Our justification is, first, the inventory paradigm that motivates our interplay between liquidity, order imbalances, and returns is most likely to be manifest itself over rather short horizons, i.e., daily as opposed to weekly or monthly; and second, higher than daily frequency poses problems of inter-asset synchronicity which could make it more difficult to detect market-wide relations.

This paper is organized as follows. Section 2 describes the data. Section 3 discusses the determinants of order imbalance. Section 4 discusses the relation between liquidity and order imbalances while Section 5 discusses the relation between returns and order imbalances. Section 6 concludes.

2. Data

The S&P500 is our representative stock market index. It was selected because the serial correlation in its return series is close to zero (its first-order autocorrelation coefficient was

0.005, p-value=0.78; higher-order coefficients are also close to zero), and we wanted a difficult object to be predicted.[4] The transactions data sources are the Institute for the Study of Securities Markets (ISSM) and the New York Stock Exchange TAQ (trades and automated quotations). The ISSM data cover 1988-1992 inclusive while the TAQ data are for 1993-1998.

2.1 Inclusion Requirements

Stocks are included or excluded during a calendar year depending on the following criteria:

- To be included, a stock had to be present at the beginning and at the end of the year in both the CRSP and the intraday databases, and in the S&P 500 at the beginning of the year.
- To keep the size of our sample manageable, and also because signing trades for Nasdaq stocks is problematic (see, e.g., Christie and Schultz, 1999), and also, we include only NYSE stocks in the calculation of aggregate order imbalance.
- If the firm changed exchanges from Nasdaq to NYSE during the year (no firms switched from the NYSE to the Nasdaq during our sample period), it was dropped from the sample for that year.
- Because their trading characteristics might differ from ordinary equities, assets in the following categories were also expunged: certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks and REITs.
- To avoid the influence of unduly high-priced stocks, if the price at any month-end during the year was greater than $999, the stock was deleted from the sample for the year.

[4] We also performed regressions using value-weighted and equally-weighted order imbalances for all NYSE stocks, and value-weighted imbalances for NYSE stocks in the top size decile. The results were broadly consistent with those reported in this paper for the S&P500 index, and are available upon request from the authors.

Given that a stock is included in the sample, its transaction data are included or excluded according to the following criteria:

- A trade is excluded if it is out of sequence, recorded before the open or after the closing time, or has special settlement conditions (because it might then be subject to distinct liquidity considerations).
- Quotes established before the opening of the market or after the close are excluded.
- Negative bid-ask spreads are discarded.
- Only BBO (best bid or offer)-eligible primary market (NYSE) quotes are retained (Chordia, Roll, and Subrahmanyam, 2001, provide a justification for using only NYSE quotes).
- Following Lee and Ready (1991), any quote less than five seconds prior to the trade is ignored and the first one at least five seconds prior to the trade is retained.

2.2 Order Imbalance Variables

Each transaction is designated as either buyer-initiated or seller-initiated according to the Lee and Ready (1991) algorithm. For each stock-day we compute

- $OIBNUM_t$: the number of buyer-initiated less the number of seller-initiated trades on day t.
- $OIBSH_t$: the buyer-initiated shares purchased less the seller-initiated shares sold on day t.
- $OIBDOL_t$: the buyer-initiated dollars paid less the seller-initiated dollars received on day t.

In addition to the order imbalance measures, we also computed the following measures of trading activity and liquidity:

- $QSPR_t$: the quoted bid-ask spread averaged across all trades on day t.
- $NUMTRANS_t$: the total number of transactions on day t
- $\$VOL_t$: the total dollar volume for day t

From this point, our analysis focuses on the order imbalance, liquidity, and trading activity measures aggregated in a value-weighted manner over all stocks in our sample each day. (The value-weights were computed based on market capitalization as of the end of the previous year.)

2.3 Summary Statistics

Table 1, Panel A presents descriptive statistics for market-wide order imbalance measures, and other measures of liquidity and trading activity used in this study. The mean/standard deviation ratios are of similar magnitude for all three measures of order imbalance. The average quoted spread is about 18 cents, and the average number of transactions is about 658. Interestingly, the order imbalance measures have positive means and medians. This finding relates to the fact that we sign market orders in our analysis, which suggests that the excess of buy market orders over sell market orders is accommodated by the limit order book, provided specialists succeed in maintaining zero inventory levels on average. Since returns have been overwhelmingly positive over our sample period, this suggests that limit orders have generally been on the wrong side of the trades in the 1990s.

Panel B gives correlations among the three measures of the order imbalance, the concurrent daily return on the S&P500 index, dollar volume, and the total number of transactions. All variables are strongly positively correlated, with the exception of the correlations between the S&P500 return and NUMTRANS, and the S&P500 return and $VOL, which are virtually zero. This points to the notion that the variable which relates trading activity to returns is order imbalance, rather than aggregate trading volume.

Panel C reports autocorrelations. Market order imbalances are persistent up to five daily lags but the S&P500 return has no autocorrelation of any significance. Thus, the market appears to take immediate account of the forecastable portion of the persistence in imbalance.[5] Changes in the quoted spread are significantly negatively autocorrelated at lags of one and two days and are positively autocorrelated at a lag of five days; the latter reveals a weekly seasonal in the quoted spread.

Henceforth we will report regression results measuring order imbalance in transactions only. We made this choice for the following reasons. First, the share measure of order imbalance is influenced by stock splits and reverse splits, whereas the number of transactions is not directly influenced by these events. Further, the dollar measure of order imbalance includes the price level, and return and liquidity forecasts using a variable that includes the past price level may lead to misleading conclusions. Thus, given the high correlations among different measures of order imbalance, and based on the work of Jones et al. (1994) mentioned earlier, we perform our regressions using OIBNUM; all three measures yield qualitatively similar results.

3. What Causes Order Imbalance?

On a given day, market-wide order imbalance could conceivably be caused by many factors. Market returns and changes in macroeconomic variables such as interest rates immediately come to mind. There is also some reason to expect weekly regularities in order imbalance, given the regularities in daily returns (see, e.g., Gibbons and Hess, 1981) and the weekly regularities in market liquidity documented by Chordia, Roll, and Subrahmanyam (2001). Finally, if temporary

[5] An interesting feature of the OIBNUM series is that its first differences exhibit strong negative autocorrelation which decays quickly.

price pressures caused by imbalance are reversed by other traders, one would expect this to manifest itself in the order imbalance series.

Based on the above arguments, in this section we ask whether order imbalance can be predicted using past market returns after controlling for weekly regularities and past lagged values of order imbalance. Thus, the daily order imbalance in number of transactions (OIBNUM) is regressed on day-of-the-week dummies and variables designed to capture past up-market and down-market moves, and on past values of order imbalance.

3.1 Regression Results

The time-series regression described above is reported in Table 2. The results show that, in aggregate, investors act as contrarians. They buy after market declines and sell after market advances. This behavior is particularly significant for market declines. For both market advances and declines, the behavior persists for up to three days.

Although order imbalances are highly predictable, returns on the S&P500 index are virtually uncorrelated. During our sample period, the first-order autocorrelation coefficient of the S&P500 daily return is 0.005 (p-value=0.78), and higher-order coefficients are also close to zero. Hence, order imbalances respond to past market moves in a manner that makes the S&P500 close to a random walk. The order imbalance pattern is consistent with price pressure caused by inventory imbalances on a given day which is corrected by some investors taking the opposite side of the market on the succeeding day. This phenomenon will be examined further in Section 5.

As Table 2 also reveals, there appears to be a significant Wednesday regularity in order imbalance. However, from Chordia et al. (2001), trading activity itself tends to be higher during mid-week. To ascertain whether the above results are driven by trading activity per se, we scaled the dependent variable OIBNUM by the total number of transactions (see Panel B of Table 2). There remains strong evidence of a contrarian pattern in investor trading. The weekly seasonals are now insignificant, suggesting that there is no significant seasonality in order imbalance after controlling for the overall level of trading activity.

3.2 Summary of Results

The central results in this section are consistent with the inventory paradigm. In particular, the paradigm suggests that after an event that causes a large inventory imbalance on one side of the market, market makers set quotes to elicit trading on the other side of the market. Our evidence that investors are contrarians on aggregate, i.e., they are net sellers after market rises, and vice versa, indicates that they are successful in this endeavor and that temporary price pressures are, in general countervailed effectively by financial market investors.

4. The Relation Between Liquidity and Order Imbalance

Theoretical paradigms of price formation predict that liquidity is influenced by inventory concerns caused by an imbalance between buyer- and seller-initiated trades. For an individual stock, a large order imbalance could be random or induced by either public or private information. Regardless of the cause, market makers can be expected to respond by worsening their offered terms of trade. At the market level, it seems unlikely that asymmetric information is behind aggregate order imbalances, yet market maker inventories still experience periodic strain. Such inventory problems could persist beyond a trading day and thus have extended effects on liquidity. The next sub-sections provide empirical evidence about these possibilities.

4.1 Order Imbalance and Contemporaneous Changes in Liquidity

To measure liquidity, we first average each individual stock's quoted spread over all daily transactions, and then value-weight across stocks (as explained in Section 2 above). The daily percentage change in the resulting market-average quoted spread is regressed on (1) a non-linear function of the contemporaneous daily change in the absolute order imbalance between the number of buyer- and seller-initiated trades, (2) the simultaneous daily percentage change in the number of transactions, (3) concurrent return, and (4) concurrent market volatility (measured by the absolute return on the S&P 500). Both the order imbalance and the number of transactions are value-weight averaged over NYSE stocks in the S&P500 index.

The controls (2)-(4) are inserted to account for aggregate trading activity and market movements. Order imbalance itself could be associated with greater trading activity as well as with large market movements; however, our aim is untangle the incremental effect, if any, of order imbalance on liquidity above and beyond its association with trading and price moves.

There is no theoretical guide to the functional form of the relation between liquidity and order imbalance, so the extent of non-linearity was estimated empirically by employing a Box/Cox transformation, $F(x)=(x^{\lambda}-1)/\lambda$; (see Judge, *et. al.*, 1985, ch. 20.) Since the absolute value of order imbalance is taken prior to the non-linear transformation, the results (Table 3, second column) indicate that higher spreads occur when orders are more unbalanced in either direction. The effect turns out to be highly significant and non-linear, with a t-statistic of about 12 and a curvature between cubic and quartic; the maximum likelihood estimate of λ being 3.19.

The change in the number of transactions has a separate and very significant positive impact on spreads. This is a bit surprising in that order imbalance has already been taken into account. One possible explanation is measurement error in the order imbalance variable thereby leaving some explanatory scope for the number of trades. Another possibility is that changes in the sheer volume of trading, without any imbalance in orders, makes it more difficult for market makers to control inventory and induces them to respond by increasing quoted spreads. An alternative explanation is that during periods of increased trading volume, the inside limit orders are picked off, widening the difference between posted bid and ask quotes. In addition, market volatility as measure by the absolute value of the contemporaneous market return, is positively associated with changes in spreads, and, as in Chordia et al. (2001), market returns are negatively associated with changes in spreads. As reported in the second column of Table 3, approximately 26% of the average daily variation in quoted spreads is explained by these variables.

The overall implication is that contemporaneous changes in liquidity are strongly and non-linearly associated with order imbalances , after controlling for both trading activity and for the sign and magnitude of the market return. To some extent, the contemporaneous association between the quoted spread and order imbalance could arise because of the inability of specialists to adjust quotes on both sides of the market during periods of large imbalances. In particular, if orders tend to occur on one side of the market during a period, then the specialist has to rapidly adjust quotes or clear the limit order book on that side of the market. If the book on the other side is not adjusted quickly enough, the spread will widen. Nevertheless, the widening of the spread does reflect an increase in trading costs when order imbalances are high.

4.2 The Predictability of Liquidity

We use the same variables as in the previous subsection to predict the next day's percentage change in the market-wide quoted spread. The ensuing results are reported in the third column of Table 3. While order imbalance appears to have no forecasting ability, there is evidence that both the number of trades and the market return can predict future changes in liquidity. Controlling for the market return, the predictive power of volatility is only marginal. To further disentangle the role of market moves, instead of the return and its absolute value, separate variables for up and down market moves are used in the regression reported in the last column of Table 3. We find that liquidity persistently follows previous market moves. A down market predicts low liquidity (higher spreads) *the next day*. An up-market also predicts higher liquidity the next day though the magnitude of the effect is much smaller than for a previous down market.

Table 3 shows also that an increase in transactions is associated with a spread increase on the following day (as well as on the same day). The R^2 of this forecasting regression is about 13% which, not surprisingly, is lower than that for the contemporaneous spread regression reported in the second column of the Table. These results are consistent with inventory models of the spread (e.g., Stoll, 1978a). In such models, imbalances cause a shift in quotes but do not affect liquidity. However, market movements do affect liquidity, and our results show that it is down markets where the effects of index movements exert the strongest effects on liquidity. A plausible explanation for this finding is that inventory financing constraints are more binding in falling markets where specialist inventory levels might become very high.

4.3 Summary of Results

The data reveal a very strong contemporaneous association between changes in the absolute level of market-wide order imbalance and market-wide liquidity. There is also strong evidence that changes in liquidity can be predicted using market returns. In particular, liquidity falls following market declines. For academics, these results are consistent with the notion that inventory risk increases during periods of large price fluctuations. From a practical standpoint, they have important implications for the design of trading strategies. For example, it would seem unwise to trade on days immediately following a down-market if waiting costs are not very high. Similarly, portfolio managers would do well to avoid trading on days when the preponderance of trades is on one side of the market.

5. Daily Market Returns, Order Imbalance, and Liquidity

Inventory concerns could influence risk premia and thus alter required returns (Stoll, 1978a, and Spiegel and Subrahmanyam, 1995). Empirical studies of block trading dating back to Kraus and Stoll (1972) find that large trades induce price pressures. In either case, there is reason to expect that aggregate market order imbalances can exert pressure on market returns; so this section provides information on the phenomenon by estimating the directional impact of order imbalances on contemporaneous and future market returns.

In such an empirical investigation one would ideally use a market index unaffected by non-synchronous trading and the concomitant nuisance of spurious serial dependence. The S&P500

is actually quite appropriate. As mentioned in Section 3, during our January 1988 through December 1998 sample period, it displayed virtually no unconditional serial dependence (see Table 1, Panel C). Returns on the S&P500 appear to be unpredictable by their own past values.

5.1 Returns, Order Imbalance, and Liquidity

To examine the relation between S&P500 returns and order imbalances, a signed measure of order imbalance is desirable (in contrast to the absolute value used in the liquidity regression of Table 3). So, order imbalance is split into positive and negative parts and included as separate regressors. This allows for a differential impact of excess buy and sell orders.

The second column of Table 4, Panel A shows that contemporaneous order imbalance (as measured by OIBNUM) exerts an extremely significant impact on market returns in the expected direction; the positive coefficients imply that excess buy (sell) orders drive up (down) prices.

Interestingly, lagged order imbalance exert a significant negative effect on the current day's return after controlling for the contemporaneous order imbalance. This is consistent with inventory stabilization, wherein the previous day's imbalance is reversed and hence exerts a negative effect on the contemporaneous return. Given the well-known noise in daily returns, the explanatory power is good: an adjusted R-square of 28%. A significant portion of daily stock market movement can be explained by the buying and selling activity of the general public. These results reveal that microstructure effects are not restricted to the level of the individual stocks; they influence the price process at the aggregate market level.

The third column of Table 4, Panel A adds lagged negative and positive market returns. Surprisingly, even though the S&P500 has virtually zero unconditional serial correlation, these lagged returns are highly significant. Controlling for order imbalances, both positive returns and negative returns exhibit continuation. The explanatory power is impressive: 33%. However, it seems unlikely that these results reveal a profit opportunity because only specialists know order imbalances in real time for individual stocks and no specialist knows it for all stocks in aggregate.

To check whether predictability is present without contemporaneous order imbalance knowledge, we estimated the regression reported in the fourth column of Table 4. Lagged order imbalances become insignificant when not accompanied by their contemporaneous counterparts. The lagged market returns also fall in magnitude, but remain significant. However, given the difficulty of procuring aggregate order imbalance data even with a one-day lag, there might be some doubt that these results represent a profit opportunity based on publicly available information.

At this point, the reader may wonder whether any of our results in this section are driven by the relation between returns and unsigned trading volume. We did not include unsigned volume as an explanatory variable in Table 4, Panel A because there is no strong a priori reason for volume to be related to signed returns. However, inclusion of trading volume (dollar volume or number of transactions) does not alter any of the results of Panel A. The regressions including unsigned volume are available from the authors upon request.

The fifth column of Table 4, Panel A reports a forecasting model for the next day's market index return using past returns alone, which would of course be publicly available information. As might have been expected, the predictive power is minimal (adjusted R-square: 0.00772.) However, the signed lagged market returns have surprisingly large significance levels. Despite the virtual complete absence of ordinary serial dependence for the S&P500 index, the signed lagged returns are both significant. A positive return tends to be followed by a continuation (as revealed by the positive coefficient) while a negative return tends to be reversed. We thought this surprising result, to our knowledge never before noticed, deserved mention and further discussion.

Given the results of Atkins and Dyl (1990) and Cox and Peterson (1994), who find reversals in individual stocks following large stock price declines, there is ample reason to believe that market-wide reversals genuinely follow market crashes and that the phenomenon is not an artifact of the data. To investigate further, we calculated the correlation $\text{corr}(R_t, R_{t-1}|R_{t-1}<-1\%)$ and $\text{corr}(R_t, R_{t-1}|R_{t-1}<-0.1\%)$. The values for the two correlations respectively are -0.304 (126 observations - p-value<0.0001) and -0.126 (1087 observations - p-value<0.0001). Thus, the reversal effect is most pronounced after larger market declines. We also calculated the corresponding correlations for up-markets, $\text{corr}(R_t, R_{t-1}|R_{t-1}>+1\%)$ and $\text{corr}(R_t, R_{t-1}|R_{t-1}>+0.1\%)$. The values for the two correlations respectively are -0.033 (296 observations - p-value 0.57) and +0.067 (1313 observations - p-value 0.02). Evidently, the continuation in up-markets is not dependent on the size of the up-move.

Previous studies of block trading find that large block sales are followed by price reversals while large buys are not (see Kraus and Stoll, 1972). To relate this empirical finding for individual stocks to our market-wide data, we sorted all days by order imbalance and S&P500 return. We then calculated the serial correlation for those days t (a) that fell into the top quintiles of both the order imbalance and return sorts and (b) that fell into the bottom top quintiles of both the order imbalance and return sorts. The serial correlation for days falling into category (b) was -0.290 (sample size=235) whereas that for those falling in category (a) was only -0.084 (sample size=233). Hence, there is evidence of strong reversals following large negative return, large negative imbalance days, but only weak reversals following large positive return, positive imbalance days.

In Panel B of Table 4 reports a predictive regression using observations belonging to categories (a) and (b). There is significant evidence that returns are predictable using past imbalances and past returns following large negative order imbalance, large negative return days, but there is no predictive power following high positive order imbalance, high positive return days. Two of the four regressions reported in Panel B also control for aggregate trading volume, to ensure that the predictability for high negative imbalance, large negative return days is not driven by the level of unsigned trading volume. As can be seen, inclusion of dollar trading volume does not materially alter the results,[6] underscoring the importance of imbalance in the predictive results.

5.2 Volatility, Volume, and Imbalance

Previous literature has focused extensively on the relation between volume and volatility (see, e.g., Gallant, Rossi, and Tauchen, 1992). However, daily imbalances could provide information about stock price movements in addition that provided by aggregate daily volume. For example, if aggregate daily volume is driven by equal amounts of buying and selling activity, the impact

[6] Trading volume measured in number of transactions does not change the qualitative results of Panel B either.

of volume on price movements may be minimal, while if volume is driven by a large imbalance, it could have a large impact. Note that the exercise of disentangling the role of volume vis a vis imbalance in explaining stock price fluctuations is best done using *volatility* as the dependent variable. This is because, as we mentioned in the previous subsection, there is no a priori reason to believe that unsigned volume would have an effect on signed returns. We therefore explore the role of unsigned order imbalances in explaining return volatility over and above the influence of trading volume.

Table 5 provides some information about this issue. The first regression, reported in the second column, regresses the absolute value of the S&P500 contemporaneous return on dollar volume, the positive and negative parts of order imbalance, the average quoted spread, and the lagged absolute market return. The quoted spread is included to control for any liquidity effect on volatility while the lagged absolute return is included to account for the well-documented persistence in volatility.

Sure enough, order imbalance is significant. The effect is asymmetric; excess sell orders have an impact four times that of excess buy orders; this result is consistent with that in Table 4, Panel B, wherein large sell orders have a greater price impact. Both volume and quoted spreads are also significant. Thus, considerable improvement in explanatory power for contemporaneous daily volatility can be obtained by accounting for the joint and several influences of all these variables. Notice that the lagged absolute market return has a negative coefficient. Its persistence is, therefore, fully offset by the other variables.

In the third column of Table 5, the same variables are used to predict volatility on the following day. Here, order imbalance disappears as a significant explanatory factor while dollar volume and the lagged quoted spread retain their significance. The lagged volatility proxy $|R_t|$ now has a significant positive impact on $|R_{t+1}|$, thereby verifying the usual finding. Evidently, the persistence in volatility is induced partly by persistent levels of volume and liquidity. In contrast, but perhaps not surprisingly, order imbalance has only a fleeting influence on volatility. So the effect of imbalance on future volatility is subsumed by the influences of lagged liquidity and past volatility.

5.4 Summary of Results

There is a strong contemporaneous association between stock returns and order imbalance. There is evidence that market prices tend to reverse following declines and continue following previous up-moves. Reversal effects are particularly pronounced after large down-market, large negative imbalance days. Our results are consistent with the inventory paradigm, which suggests that imbalances cause price pressures, and with the block trading literature for individual stocks, which indicates that price pressures caused by large sell orders are greater than those for buy orders. Order imbalance also has an impact on contemporaneous volatility above and beyond the well-known influence of trading volume. Our results underscore the point that price pressures caused by imbalances are not an artifact of price formation at the individual stock level; they also manifest themselves at the aggregate market level. This finding has direct implications for agents wishing to trade the aggregate market portfolio.

6. Conclusion

The relations between trading activity and liquidity and between trading activity and market returns have been explored extensively. Trading activity has usually been measured by volume, but the inventory paradigm, (developed, for example, in Stoll, 1978a, and Spiegel and Subrahmanyam, 1995) suggests that the imbalance between buyer- and seller-initiated orders could be a powerful determinant of liquidity and price movements beyond trading volume per se. This turns out to be empirically upheld by a daily index of aggregate market order imbalance for NYSE stocks.

Our analysis of the determinants and properties of market-wide order imbalances, and of the relation between order imbalances, liquidity, and daily stock market returns is generally consistent with the inventory paradigm and yields the following empirical stylized facts:

- Order imbalances are strongly related to past market returns. There is evidence of aggregate contrarian behavior; signed order imbalances are high following market crashes and low following market increases. Since returns on the S&P500 are virtually uncorrelated, this is evidence that price pressures and inventory imbalances are countervailed efficiently by the market participants.
- Liquidity is predictable from market returns, but not from past imbalances. In particular, down market days tend to be followed by days of decreased liquidity. These findings are consistent with inventory models of liquidity such as Stoll (1978a), where imbalance affects the placement of quotes but not the size of the bid-ask spread, and with the notion that spreads depend on the costs of holding inventory, which arise from risk and financing constraints. Our results indicate that such costs are particularly high in down markets.

- There is some evidence that reversals tend to follow negative market returns while positive returns tend to be continued. Returns following large negative order imbalance, large negative return days are partially predictable using order imbalance and return, but the same is not true for large positive imbalance, large positive return days. This result is consistent with the block trading literature for individual stocks dating back to Kraus and Stoll (1972), wherein large block sells are followed by reversals but large block buys are not. Our results indicate that price pressure effects of large trades are not restricted to individual stocks but also influence returns at the aggregate market level; this has implications for agents wishing to trade large dollar amounts of a diversified market portfolio.
- Order imbalances are strongly related to contemporaneous absolute returns after controlling for market volume and market liquidity. This underscores the importance of accounting for order imbalance, in addition to volume, as a determinant of return volatility.

To our knowledge, this is the first study to analyze daily order imbalances for a comprehensive sample of stocks over a long sample period. Our results generally indicate that imbalances affect liquidity and returns not just at the individual stock level but at the aggregate market level as well. Since private information is not likely to be an issue at the aggregate market level, the results generally support the notion that the inventory paradigm, wherein market makers accommodate uninformed imbalances from outside agents, plays an important role in price formation in the stock market.

Data for order imbalance open arenas of research beyond those in this paper. For example, analyzing order imbalances over longer horizons could shed light on growth/value effects in returns and how they relate to investor trading patterns. In addition, order imbalances around major macroeconomic announcements could help shed additional light on the information paradigm by ascertaining whether agents are able to predict the sign of the impending announcement. These and other possible topics are left for future research.

References

Atkins, A., and E. Dyl, 1990, Price reversals, bid-ask spreads, and market efficiency, *Journal of Financial and Quantitative Analysis* 25, 535-547.

Benston, G., and R. Hagerman, 1974, Determinants of bid-asked spreads in the over-the-counter market, *Journal of Financial Economics* 1, 353-364.

Blume, M., A. MacKinlay, and B. Terker, 1989, Order imbalances and stock price movements on October 19 and 20, 1987, *Journal of Finance* 44, 827-848.

Judge, George G., W. E. Griffiths, R. Carter Hill, Helmut Lütkepohl, and Tsoung-Chao Lee, 1985, *The Theory and Practice of Econometrics*, (New York: Wiley).

Brown, P., D., Walsh, and A. Yuen, 1997, The interaction between order imbalance and stock price, *Pacific-Basin Finance Journal* 5, 539-557.

Chan, K., and W. Fong, 2000, Trade size, order imbalance, and the volatility-volume relation, *Journal Of Financial Economics* 57, 247-273.

Christie, W., and Schultz, P., 1999, The initiation and withdrawal of odd-eighth quotes among Nasdaq stocks: An empirical analysis, *Journal of Financial Economics* 52, 409-442.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, Market liquidity and trading activity, *Journal of Finance*, forthcoming.

Cox, D., and D. Peterson, 1994, Stock returns following large one-day declines: Evidence on short-term reversals and longer-term performance, *Journal of Finance* 49, 255-267.

Gallant, A., P. Rossi, and G. Tauchen, 1992, Stock prices and volume, *Review of Financial Studies* 5, 199-242.

Gibbons, M., and P. Hess, 1981, Day of the week effects and asset returns, *Journal of Business* 54, 579-596.

Harris, L., and E. Gurel, 1986, Price and volume effects associated with changes in the S&P 500 list: New evidence for the existence of price pressures, *Journal of Finance* 41, 815-829.

Hasbrouck, J., and D. Seppi, 2001, Common factors in prices, order flows and liquidity, *Journal of Financial Economics* 59, 383-411.

Hiemstra, C., and J. Jones, 1994, Testing for linear and nonlinear Granger causality in the stock price-volume relation, *Journal of Finance* 49, 1639-1664.

Ho, T., and H. Stoll, 1983, The dynamics of dealer markets under competition, *Journal of Finance* 38, 1053-1074.

Jones, C., G. Kaul, and M. Lipson, 1994, Transactions, volume, and volatility, *Review of Financial Studies* 7, 631-651.

Karpoff, J., 1987, The relation between price changes and trading volume: A survey, *Journal of Financial and Quantitative Analysis* 22, 109-125.

Kraus, A., and H. Stoll, 1972, Parallel trading by institutional investors, *Journal of Financial and Quantitative Analysis* 7, 2107-2138.

Kyle, A., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Lauterbach, B., and U. Ben-Zion, 1993, Stock market crashes and the performance of circuit breakers: Empirical evidence, *Journal of Finance* 48, 1909-1925.

Lee, C., 1992, Earnings news and small traders: An intraday analysis, *Journal of Accounting and Economics* 15, 265-302.

Lee, C., and B. Radhakrishna, 2000, Inferring investor behavior: Evidence from TORQ data, *Journal of Financial Markets* 3, 83-111.

Lee, C., and M. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-747.

Lo A., and J. Wang, 2000, Trading volume: definitions, data analysis, and implications of portfolio theory, *Review of Financial Studies* 13, 257-300.

Odders-White, Elizabeth R., 2000, On the occurrence and consequences of inaccurate trade classification, *Journal of Financial Markets* 3, 205-332.

Shleifer, A., 1986, Do demand curves for stocks slope down?, *Journal of Finance* 41, 579-590.

Sias, R., 1997, Price pressure and the role of institutional investors in closed-end funds, *Journal of Financial Research* 20, 211-229.

Spiegel, M., and A. Subrahmanyam, 1995, On intraday risk premia, *Journal of Finance* 50, 319-339.

Stoll, H., 1978a, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133-1151.

Stoll, H., 1978b, The pricing of security dealer services: An empirical study of NASDAQ stocks, *Journal of Finance* 33, 1153-1172.

Table 1

Market-wide Order Imbalance – Summary statistics and correlations

Descriptive statistics are given for average daily order imbalance measures from NYSE stocks belonging to the S&P 500 over 1988-1998 inclusive, 2,779 observations. Trades are signed using the Lee and Ready (1991) algorithm. OIBNUM, OIBSH, and OIBDOL measure the value-weighted[7] order imbalance in number of transactions, shares, and dollars, respectively. $VOL, NUMTRANS, and QSPR are the value-weighted averages of dollar volume (in millions of dollars), number of transactions, and the average daily quoted spread, respectively. The variables DQSPR and DOIBNUM denote the daily percentages and the daily first differences in QSPR and OIBNUM, respectively. S&P500 is the daily return on the Standard & Poor's 500 Index.

Panel A: Summary statistics

	Mean	Median	Standard Deviation
OIBNUM	34.89	27.22	57.48
OIBSH/1 x 10^3	59.71	45.40	97.12
OIBDOL/1 x 10^6	4.167	2.830	6.498
|OIBNUM|	90.33	78.61	52.71
|OIBSH|/1 x 10^3	168.0	147.0	86.04
|OIBDOL|/1 x 10^9	9.628	7.560	6.165
QSPR	0.182	0.187	0.030
NUMTRANS	658.0	534	399.0
$VOL	58.37	40.17	42.17
DQSPR(%)	2.66	1.98	2.63

Panel B: Correlations

	OIBNUM	OIBSH	OIBDOL	NUMTRANS	$VOL
OIBSH	0.523				
OIBDOL	0.531	0.961			
NUMTRANS	0.533	0.468	0.563		
$VOL	0.476	0.509	0.609	0.971	
S&P500	0.408	0.599	0.528	0.012	0.024

Panel C. Autocorrelations[8]

Lag (Days)	OIBNUM	OIBSH	OIBDOL	S&P500	Quoted Spread	DOIBNUM
1	**0.539**	**0.376**	**0.465**	0.005	**-0.321**	**-0.420**
2	**0.470**	**0.322**	**0.421**	-0.023	**-0.096**	**-0.074**
3	**0.469**	**0.297**	**0.400**	-0.032	-0.022	**-0.037**
4	**0.434**	**0.290**	**0.399**	-0.018	-0.022	-0.016
5	**0.414**	**0.271**	**0.384**	-0.023	-0.023	**0.034**

7 The value weights are proportional to market capitalization at the end of the previous calendar year.
8 Values in bold face are significantly non-zero with an asymptotic p-value less than 0.00001.

Table 2

What causes Market-wide Order Imbalance?

The dependent variable is the daily order imbalance measured in number of transactions ($OIBNUM_t$) on trading day t. It is regressed on day-of-the-week dummies and past positive and negative parts of S&P500 returns; R_t denotes the S&P500 index return on day t. The Cochrane/Orcutt procedure was applied to correct for first-order serial dependence in the residuals. In Panel A, the dependent variable is the value-weighted order imbalance for NYSE-listed stocks in the S&P 500 index. In Panel B the dependent variable is $OIBNUM_t/NUMTRANS_t$, where NUMTRANS is total number of transactions (again value-weighted for NYSE stocks in the S&P500). 1988-98 inclusive, 2779 observations. T-statistics are in parentheses.

Panel A: Dependent variable is the value-weighted order imbalance for NYSE stocks in the S&P 500

Explanatory variable	Coefficient (t-statistic)
Intercept	-0.992 (-0.43)
Monday	-1.80 (-0.70)
Tuesday	6.60 (2.64)
Wednesday	5.85 (2.33)
Thursday	0.020 (0.01)
Min(0, R_{t-1})	-30.06 (-17.70)
Min(0, R_{t-2})	-2.80 (-1.59)
Min(0, R_{t-3})	-6.25 (-3.52)
Min(0, R_{t-4})	-1.92 (-1.08)
Min(0, R_{t-5})	-1.16 (-0.66)
Max(0, R_{t-1})	-8.93 (-4.94)
Max(0, R_{t-2})	0.465 (0.26)
Max(0, R_{t-3})	-6.75 (-3.71)
Max(0, R_{t-4})	-2.47 (-1.36)
Max(0, R_{t-5})	-1.57 (-0.88)
$OIBNUM_{t-1}$	0.464 (20.18)
$OIBNUM_{t-2}$	0.047 (1.83)
$OIBNUM_{t-3}$	0.178 (7.04)
$OIBNUM_{t-4}$	0.067 (2.62)
$OIBNUM_{t-5}$	0.064 (2.85)
Durbin Watson	2.01
Cochrane-Orcutt autocorrelation	-0.011
Adjusted R^2	0.477

Panel B: Dependent variable is OIBNUM/NUMTRANS

Explanatory variable	Coefficient (t-statistic)
Intercept	0.544 (1.68)
Monday	-0.372 (-1.06)
Tuesday	0.161 (0.47)
Wednesday	0.605 (1.76)
Thursday	-0.345 (-1.00)
$Min(0, R_{t-1})$	-2.319 (-9.58)
$Min(0, R_{t-2})$	-1.225 (-5.05)
$Min(0, R_{t-3})$	-0.535 (-2.17)
$Min(0, R_{t-4})$	-0.546 (-2.22)
$Min(0, R_{t-5})$	0.828 (-3.43)
$Max(0, R_{t-1})$	-1.750 (-7.04)
$Max(0, R_{t-2})$	-0.369 (-1.46)
$Max(0, R_{t-3})$	-0.877 (-3.48)
$Max(0, R_{t-4})$	-0.449 (-1.79)
$Max(0, R_{t-5})$	-0.530 (-2.14)
$OIBNUM_{t-1}$	0.387 (15.99)
$OIBNUM_{t-2}$	0.121 (4.67)
$OIBNUM_{t-3}$	0.120 (4.63)
$OIBNUM_{t-4}$	0.093 (3.59)
$OIBNUM_{t-5}$	0.120 (4.96)
Durbin Watson	2.01
Cochrane-Orcutt autocorrelation	-0.014
Adjusted R^2	0.408

Table 3

Changes in Market Liquidity, Contemporaneous Changes in Order Imbalance and the Number of Transactions, and Market Up and Down Moves

The dependent variables are the contemporaneous and next-day's daily percentage change in the value-weighted[9] quoted spread for NYSE-listed stocks in the S&P500. Explanatory variables include the daily first difference in a Box/Cox transformation of the absolute value of the value-weighted order imbalance for NYSE stocks in the S&P500 measured in number of shares (OIBNUM), the daily percentage change in the number of transactions for NYSE stocks in the S&P 500, the S&P 500 return if it is positive, and zero otherwise (S&P500+), and the S&P 500 return if it is negative, and zero otherwise (S&P500-). The Cochrane/Orcutt procedure was applied to correct for first-order serial dependence in the residuals. The Box/Cox transformation's λ is estimated by maximizing the explanatory power of the contemporaneous regression using the original variables and the Cochrane/Orcutt coefficient estimates. 2778 observations, 1988-98 inclusive. T-statistics are in parentheses

	Percentage change in value-weighted quoted spread (contemporaneous)	Percentage change in value-weighted quoted spread (next day)	Percentage change in value-weighted quoted spread (next day)
Explanatory variable	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
$(\lvert OIBNUM_t\rvert^{\lambda}-\lvert OIBNUM_{t-1}\rvert^{\lambda})/\lambda$	75.63 (11.83)	-10.77 (-1.59)	-10.77 (-1.59)
% Change in Number of Trades	0.036 (10.80)	0.011 (3.11)	0.011 (3.11)
S&P500	-0.931 (-14.14)	-0.425 (-5.50)	
|S&P500|	0.654 (7.06)	0.177 (1.64)	
S&P500+			-0.248 (-1.87)
S&P500-			-0.602 (-4.52)
Lagged (one-day)dependent variable		-0.264 (-11.04)	-0.264 (-11.04)
Intercept	-0.484 (-4.97)	-0.054 (0.54)	-0.054 (-0.54)
Adjusted R^2	0.261	0.129	0.129
λ	3.19	3.19	3.19
Durbin-Watson	2.16	2.08	2.08
Cochrane/Orcutt autocorrelation	-0.353	-0.182	-0.182

[9] The value weights are proportional to market capitalization at the end of the previous calendar year.

Table 4

Returns on the S&P500 Stock Market Index, Contemporaneous and Lagged Order Imbalances and Lagged Returns

The dependent variable is the daily return on the S&P500 index, denoted R_t. Explanatory variables include contemporaneous and lagged positive and negative daily order imbalances measured in number of trades and lagged positive and negative index returns. Order imbalances are value-weighted averages for NYSE stocks in the S&P500. For Panel B, days are sorted separately by OIBNUM and by the S&P500 return. Then a predictive regression is fit using observations that are common to the top 20% of days with high imbalance *as well as* the top 20% of days with high returns. Another predictive regression is run for high sell order imbalance, large negative return days (i.e., days that are common to the bottom 20% of *both* variables). The results for these two regressions are reported respectively in the second and third columns of Panel B. Data cover 1988-98 inclusive. T-statistics are in parentheses.

Panel A: Dependent variable: R_t

Excess Buy Orders, $\text{Max}[0,\text{OIBNUM}_t]$	6.83 (19.88)	8.63 (24.03)		
Excess Sell Orders, $-\lvert\text{Min}[0,\text{OIBNUM}_t]\rvert$	22.44 (19.85)	23.59 (21.57)		
Excess Buy Orders, $\text{Max}[0,\text{OIBNUM}_{t-1}]$	-4.56 (-13.13)	-7.01 (-18.61)	-0.218 (-0.60)	
Excess Sell Orders, $-\lvert\text{Min}[0,\text{OIBNUM}_{t-1}]\rvert$	-5.83 (-5.12)	-10.42 (-8.72)	-2.69 (-1.90)	
Lagged Positive Return, $\max[0,R_{t-1}]$		0.314 (10.59)	0.148 (4.16)	0.135 (4.12)
Lagged Negative Return, $\min[0,R_{t-1}]$		0.235 (7.61)	-0.094 (-2.67)	-0.122 (-3.77)
Intercept	0.058 (2.63)	0.024 (1.06)	-0.021 (-0.82)	-0.0187 (-0.807)
Adjusted R^2	0.281	0.332	0.00882	0.00772
Number of Observations	2778	2778	2778	2778

Panel B: Dependent variable: R_{t+1}

	Days with $OIBNUM_t$ in top quintile and R_t in top quintile		Days with $OIBNUM_t$ in bottom quintile and R_t in bottom quintile	
Lagged order imbalance ($OIBNUM_t$)	-0.408 (-0.53)	-0.914 (-1.08)	-7.59 (-2.36)	-8.42 (-2.59)
Lagged return (R_t)	-0.086 (-0.90)	-0.103 (-1.07)	-0.233 (-2.88)	-0.267 (-3.19)
Lagged volume ($\$VOL_t$)		0.182 (1.36)		-0.263 (-1.52)
Intercept	0.360 (2.56)	0.273 (1.77)	-0.390 (-3.25)	-0.329 (-2.62)
Adjusted R^2	-0.001	0.003	0.098	0.103
Number of Observations	233	233	235	235

Table 5

Absolute Returns on the S&P500 Stock Market Index, Order Imbalance, Volume and Liquidity

The dependent variable is the absolute value of the daily return on the S&P500 index, denoted $|R_t|$. Explanatory variables include contemporaneous and lagged positive and negative daily order imbalances measured in number of trades, dollar volume, and quoted spreads. Order imbalances, volume, and spreads are value-weighted averages for NYSE stocks in the S&P500. Data cover 1988-98 inclusive. T-statistics are in parentheses.

	Dependent Variable	
	$\|R_t\|$	$\|R_{t+1}\|$
Explanatory Variable	Coefficient (t-statistic)	
Excess Buy Orders, $Max[0,OIBNUM_t]$	2.40 (9.67)	-0.474 (-1.71)
Excess Sell Orders, $\|Min[0,OIBNUM_t]\|$	10.7 (13.1)	0.0542 (0.0577)
Dollar Volume ($\$VOL_t/100$)	0.825 (19.0)	0.552 (11.4)
Quoted $Spread_t$	10.1 (18.1)	4.95 (7.98)
One-day lagged $\|R\|$	-0.0556 (-3.07)	0.0481 (2.28)
Intercept	-1.82 (-15.5)	-0.620 (-4.74)
Adjusted R-Square	0.247	0.0664
Number of Observations	2778	2778