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Order imbalance, liquidity, and market returns ☆

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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, buy orders less sell orders, on the New York Stock Exchange. Order imbalance increases following market declines and vice versa, which reveals that investors are contrarians on aggregate. Order imbalances in either direction, excess buy *or* sell orders, reduce liquidity. Market-wide returns are strongly affected by contemporaneous and lagged order imbalances. Market returns reverse themselves after high-negative-imbalance, large-negative-return days. Even after controlling for aggregate volume and liquidity, market returns are affected by order imbalance.

JEL classification: G10; G82

Keywords: Liquidity; Trading volume; 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 et al., 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 tripartite

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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 *and* 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 *random* 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 (1983), 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 et al. (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 imbalances change the contemporaneous relation between stock volatility and volume using data for about six months. Hasbrouck and Seppi (2001) and Brown et al. (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 marketwide 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 trades and automated quotations (TAQ) database provided by the NYSE, every transaction is assigned using the Lee and Ready (1991) algorithm. The 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 midpoint of the quote, a ‘‘tick test’’ classifies the trade as buyer (seller) initiated if the last price change prior to the trade is positive (negative). Of course, 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 and Ready algorithm is accurate enough not to pose serious problems.

This paper studies in sequence (1) properties and determinants of marketwide daily order imbalances, (2) the relation between order imbalance and an aggregate measure of liquidity, and (3) the extent to which daily stock market returns are related to order imbalances after controlling for market liquidity. Liquidity is measured by the daily value-weighted quoted spread associated with each transaction during the day. The weights are proportional to the market capitalization of each stock at the beginning of the calendar year. To our knowledge, this is the first paper to consider daily order imbalances for a comprehensive sample of stocks over an extended time period.

For the aggregate market, asymmetric information seems unlikely, so the inventory paradigm provides a more cogent explanation of the interplay between imbalances, liquidity, and returns. For example, after a large inventory accumulation, market makers position their quotes to encourage trading on the other side of the market. This strategy, if successful, will cause a direct relation between past returns and future order imbalances. Further, 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 the increased inventory risk. While the intention of this study is to examine the relation among imbalances, spreads, and returns from a purely empirical standpoint, the inventory paradigm serves as the theoretical underpinning. The results are broadly supportive of its theoretical implications.

We find that daily order imbalances are highly persistent, though first differences are negatively autocorrelated. In addition, aggregate order imbalance is contrarian in the sense that buying activity is more pronounced following market crashes, and selling activity is more pronounced following market rises. This evidence is consistent with temporary inventory imbalances and price pressures being countervailed effectively by astute traders.[1]

Order imbalances are significantly associated with daily changes in liquidity and with contemporaneous market returns, after controlling for volume. This reveals that excess buying or selling, as opposed to undifferentiated trading activity, is an additional determinant of market price movements.

In contrast to market returns, we find that liquidity is highly predictable not only by its own past values, but also by past market returns. This result is consistent with increased asset price fluctuations causing a decrease in liquidity because of increased 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

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

returns persist beyond a single day. (The S&P500 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-imbalance, large-negative-return days are accompanied by strong reversals, consistent with the block trading literature for individual stocks (e.g., Kraus and Stoll, 1972b), which suggests that large block sells are accompanied by reversals in stock prices. Our results suggest that price pressures caused by imbalances in inventory are an issue not just for individual stocks, but for the aggregate market as well. This has obvious implications for agents managing diversified portfolios.

Our decision to analyze liquidity, order imbalances, and returns over daily intervals is to some extent arbitrary (we could have chosen hourly intervals, or for that matter, monthly intervals). The daily interval is justified on the one hand because inventory effects are most likely to be manifested over rather short horizons, while on the other hand very high frequency data is plagued by inter-asset synchronicity.

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

We selected the S&P500 as our representative stock market index 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.[2] 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 Center for Research in Security Prices (CRSP) and the intraday databases, and in the S&P500 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), we include only NYSE stocks in the calculation of aggregate order imbalance.

[2] We also performed regressions using value-weighted and equal-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.

- If the firm switched from Nasdaq to NYSE during the year (no firms switched from the NYSE to 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.

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 et al. (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 the following:

- OIBNUM_t: the number of buyer-initiated trades 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; and
- 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; and
- $\$\text{VOL}_t$: the total dollar volume for day t.

From this point, order imbalance, liquidity, and trading activity measures are value-weighted averages over all stocks in the 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 marketwide 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

Table 1
Marketwide order imbalance—summary statistics and correlations
Descriptive statistics are given for average daily order imbalance measures from NYSE stocks belonging to the S&P500 over 1988–1998 inclusive (2779 observations). Trades are signed using the Lee and Ready (1991) algorithm. OIBNUM, OIBSH, and OIBDOL measure the value-weighted 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 value weights are proportional to market capitalization at the end of the previous calendar year. 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. Values in bold face (Panel C) are significantly nonzero with an asymptotic p-value less than 0.00001.

Panel A: Summary statistics

	Mean	Median	Standard deviation
OIBNUM	34.89	27.22	57.48
OIBSH/1×10^3	59.71	45.40	97.12
OIBDOL/1×10^6	4.167	2.830	6.498
|OIBNUM|	90.33	78.61	52.71
|OIBSH|/1×10^3	168.0	147.0	86.04
|OIBDOL|/1×10^9	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	0.522				
OIBDOL	0.531	0.966			
NUMTRANS	0.533	0.468	0.562		
$VOL	0.476	0.509	0.608	0.971	
S&P500	0.408	0.599	0.528	0.012	0.024

Panel C. Autocorrelations

Lag (days)	OIBNUM	OIBSH	OIBDOL	S&P500	DQSPR	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	−0.018	**0.034**

order imbalance. The average quoted spread is about 18 cents, and the average number of transactions is about 658. All three order imbalance measures have positive means and medians. Provided that specialists maintain zero inventory levels on average, our signed market orders (buys less sells) are accommodated by the limit order book. Market returns have been strongly positive from 1988 through 1998, which suggests that limit orders have typically been on the wrong side of trades during this period.

Panel B reports correlations among the three measures of 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. The pattern suggests that trading activity and returns are related through order imbalances, rather than through sheer trading volume.

Panel C reports autocorrelations. Market order imbalances are persistent up to at least 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. (An interesting feature of the OIBNUM series is that its first differences exhibit strong negative autocorrelation which decays quickly.) Changes in the quoted spread are significantly negatively autocorrelated at lags of one and two days.

Henceforth, the empirical results are reported for order imbalance measured in number of transactions only. We made this choice for several reasons. First, the share measure of order imbalance is influenced by stock splits and reverse splits, whereas the number of transactions is not directly affected. Second, the dollar measure of order imbalance includes the price level, and return and liquidity forecasts using a variable that includes the past price level could conceivably give a misleading impression. Hence, given the high correlations among different measures of order imbalance and the work of Jones et al. (1994), our main regressions use only OIBNUM. All three measures yield qualitatively similar results.

3. What causes order imbalance?

On a given day, marketwide 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 et al. (2001). Finally, if temporary price pressures caused by imbalance are reversed by other traders, one would expect this to manifest itself in the order imbalance series.

This section asks if 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 the 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, as noted earlier. 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 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 at 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 the third column 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, specialists set quotes to elicit trading on the other side of the market. The evidence that investors are contrarians on aggregate, i.e., they are net sellers after market rises and vice versa, indicates that specialists are successful in this endeavor and that temporary price pressures are countervailed effectively by astute traders.

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

Table 2

What causes marketwide order imbalance?

Dependent variables are the daily order imbalance measured in number of transactions, $OIBNUM_t$, on trading day t and $OIBNUM_t/NUMTRANS_t$, where NUMTRANS is total number of transactions. Both are value-weighted averages for NYSE stocks in the S&P500. The value weights are proportional to market capitalization at the end of the previous calendar year. They are 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 adjust for first-order serial dependence in the residuals. Data are from 1988–1998 inclusive (2779 observations, t-statistics in parentheses).

Dependent variable→	$OIBNUM_t$	$\frac{OIBNUM_t}{NUMTRANS_t}$
Explanatory variable	Coefficient (t-statistic)	
Intercept	−0.992	0.544
	(−0.43)	(1.68)
Monday	−1.80	−0.372
	(−0.70)	(−1.06)
Tuesday	6.60	0.161
	(2.64)	(0.47)
Wednesday	5.85	0.605
	(2.33)	(1.76)
Thursday	0.020	−0.345
	(0.01)	(−1.00)
Min(0, R_{t-1})	−30.06	−2.319
	(−17.70)	(−9.58)
Min(0, R_{t-2})	−2.80	−1.225
	(−1.59)	(−5.05)
Min(0, R_{t-3})	−6.25	−0.535
	(−3.52)	(−2.17)
Min(0, R_{t-4})	−1.92	−0.546
	(−1.08)	(−2.22)
Min(0, R_{t-5})	−1.16	0.828
	(−0.66)	(−3.43)
Max(0, R_{t-1})	−8.93	−1.750
	(−4.94)	(−7.04)
Max(0, R_{t-2})	0.465	−0.369
	(0.26)	(−1.46)
Max(0, R_{t-3})	−6.75	−0.877
	(−3.71)	(−3.48)
Max(0, R_{t-4})	−2.47	−0.449
	(−1.36)	(−1.79)
Max(0, R_{t-5})	−1.57	−0.530
	(−0.88)	(−2.14)
$OIBNUM_{t-1}$	0.464	0.387
	(20.18)	(15.99)
$OIBNUM_{t-2}$	0.047	0.121
	(1.83)	(4.67)
$OIBNUM_{t-3}$	0.178	0.120
	(7.04)	(4.63)
$OIBNUM_{t-4}$	0.067	0.093
	(2.62)	(3.59)
$OIBNUM_{t-5}$	0.064	0.120
	(2.85)	(4.96)
Durbin-Watson	2.01	2.01
Adjusted R^2	0.477	0.408

inventory problems could persist beyond a trading day and thus have extended effects on liquidity. The next subsections provide empirical evidence about these possibilities.

4.1. Order imbalance and contemporaneous changes in liquidity

To measure liquidity, each individual stock's quoted spreads are averaged over all daily transactions, and then the average daily spreads are value-weighted across stocks. The daily percentage change in the resulting market-average quoted spread is regressed on (1) a nonlinear 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&P500). 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 intended 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 to 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, Chapter 20). Since the absolute value of order imbalance is taken prior to the nonlinear 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 nonlinear, with a *t*-statistic of about 12 and a curvature between cubic and quartic; the maximum likelihood estimate of λ is 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, make it more difficult for market makers to control inventory and induce 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 measured 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.

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 quoted spread for NYSE-listed stocks in the S&P500. The value weights are proportional to market capitalization at the end of the previous calendar year. 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&P500, the S&P500 return if it is positive, and zero otherwise (S&P500+), and the S&P500 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. The data are for 1988–1998 inclusive (2778 observations, t-statistics 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	−10.77	−10.77
	(11.83)	(−1.59)	(−1.59)
% Change in number of trades	0.036	0.011	0.011
	(10.80)	(3.11)	(3.11)
S&P500	−0.931	−0.425	
	(−14.14)	(−5.50)	
|S&P500|	0.654	0.177	
	(7.06)	(1.64)	
S&P500+			−0.248
			(−1.87)
S&P500−			−0.602
			(−4.52)
Lagged (one-day) dependent variable		−0.264	−0.264
		(−11.04)	(−11.04)
Intercept	−0.484	−0.054	−0.054
	(−4.97)	(0.54)	(−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

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 reflects an increase in trading costs when order imbalances are high.

4.2. The predictability of liquidity

The same variables as in the previous subsection are used here to predict the next day's percentage change in the marketwide 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, we use separate variables for up and down market moves (instead of the return and its absolute value) in the regression reported in the last column of Table 3. Liquidity persistently follows previous market moves. A down market predicts low liquidity (higher spreads) *the next day*. An up market also predicts higher liquidity (lower spreads) the next day, although the magnitude of the effect is much smaller than for a previous down market.

Table 3 also shows 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 in down markets when 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 marketwide order imbalance and marketwide liquidity. There is also strong evidence that changes in liquidity can be predicted using market returns. In particular, liquidity falls following market declines. The results are consistent with inventory risk increasing during periods of large price fluctuations. From a practical standpoint, it would appear unwise to trade on days immediately following a down market if waiting costs are not very high. Similarly, portfolio managers would be well advised 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; Spiegel and Subrahmanyam, 1995). Empirical studies of parallel trading and block trading dating back to Kraus and Stoll (1972a, b) find that large trades induce temporary 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 nonsynchronous trading and the concomitant nuisance of spurious serial dependence. The S&P500 is actually quite appropriate. As mentioned in Section 3, from January 1988 through December 1998, 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 exerts 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^2 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
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 buy order imbalance *as well as* the top 20% of days with high returns. Another predictive regression is run for observations on days with high sell order imbalance and large negative returns (i.e., days that are common to the bottom 20% of *both* imbalance and return variables). The results for these two regressions are reported respectively in the second and third columns of Panel B. Data cover 1988–1998 inclusive (t-statistics are in parentheses).

Panel A: Dependent variable: R_t

Excess buy orders,	6.83	8.63		
Max[0,OIBNUM$_t$]	(19.88)	(24.03)		
Excess sell orders,	22.44	23.59		
$-\lvert$Min[0,OIBNUM$_t$]$\rvert$	(19.85)	(21.57)		
Excess buy orders,	−4.56	−7.01	−0.218	
Max[0,OIBNUM$_{t-1}$]	(−13.13)	(−18.61)	(−0.60)	
Excess sell orders,	−5.83	−10.42	−2.69	
$-\lvert$Min[0,OIBNUM$_{t-1}$]$\rvert$	(−5.12)	(−8.72)	(−1.90)	
Lagged positive return, max[0, R_{t-1}]		0.314	0.148	0.135
		(10.59)	(4.16)	(4.12)
Lagged negative return, min[0, R_{t-1}]		0.235	−0.094	−0.122
		(7.61)	(−2.67)	(−3.77)
Intercept	0.058	0.024	−0.021	−0.0187
	(2.63)	(1.06)	(−0.82)	(−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	−0.914	−7.59	−8.42
	(−0.53)	(−1.08)	(−2.36)	(−2.59)
Lagged return (R_t)	−0.086	−0.103	−0.233	−0.267
	(−0.90)	(−1.07)	(−2.88)	(−3.19)
Lagged volume (VOL_t$)		0.182		−0.263
		(1.36)		(−1.52)
Intercept	0.360	0.273	−0.390	−0.329
	(2.56)	(1.77)	(−3.25)	(−2.62)
Adjusted R^2	−0.001	0.003	0.098	0.103
Number of observations	233	233	235	235

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 might wonder whether any results in this section are driven by the relation between returns and unsigned trading volume. Unsigned volume was not included 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 $R^2 = 0.00772$). 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 that 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 marketwide 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. The corresponding correlations for up markets, $\text{corr}(R_t, R_{t-1}|R_{t-1} > +1\%)$ and $\text{corr}(R_t, R_{t-1}|R_{t-1} > +0.1\%)$, turn out to be, respectively, -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 individual stock block sales are followed by price reversals while large buys are not (see Kraus and Stoll, 1972b); we wondered if the same phenomenon would be found in marketwide data. To investigate this question, all days were sorted by order imbalance and by S&P500 return. Then the serial correlation was calculated 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 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-imbalance, large-negative-return days, but there is no predictive power following high-positive-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, underscoring the importance of controlling for imbalance. Trading volume measured in number of transactions does not change the qualitative results of Panel B either.

5.2. Volatility, volume, and imbalance

Previous literature has focused extensively on the relation between volume and volatility (see, e.g., Gallant et al., 1992). However, daily imbalances could provide information about stock price movements in addition to that provided by aggregate daily volume. For example, if aggregate daily volume is driven by equal amounts of buying and selling activity, the impact of volume on price movements could 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 with regard to imbalance in explaining stock price fluctuations is best done using *volatility* as the dependent variable. This is because, as mentioned in the previous subsection, there is no a priori reason to think that unsigned volume might affect signed returns.

Table 5 provides some evidence. 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. Daily volatility seems to depend on 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.

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. The value weights are proportional to market capitalization at the end of the previous calendar year. Data cover 1988–1998 inclusive (2778 observations, *t*-statistics are in parentheses).

	Dependent variable	
	$\|R_t\|$	$\|R_{t+1}\|$
Explanatory variable	Coefficient (*t*-statistic)	
Excess buy orders,	2.40	−0.474
Max[0,OIBNUM$_t$]	(9.67)	(−1.71)
Excess sell orders,	10.7	0.0542
|Min[0,OIBNUM$_t$]|	(13.1)	(0.0577)
Dollar volume (VOL_t$/100)	0.825	0.552
	(19.0)	(11.4)
Quoted spread$_t$	10.1	4.95
	(18.1)	(7.98)
One-day lagged $\|R\|$	−0.0556	0.0481
	(−3.07)	(2.28)
Intercept	−1.82	−0.620
	(−15.5)	(−4.74)
Adjusted R^2	0.247	0.0664

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. These results are consistent with the inventory paradigm, which suggests that imbalances cause price pressures, as well as 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. Price pressures caused by imbalances go beyond the level of individual stocks; they also influence the aggregate market.

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 as 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 marketwide order imbalances, and of the relation among 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 declines and low following market advances. Since returns on the S&P500 are virtually uncorrelated, this constitutes evidence that price pressures and inventory imbalances are countervailed efficiently by astute traders.
- 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), in which imbalance affects the placement of quotes but not the size of the bid–ask spread, as well as with the notion that spreads depend on inventory holding costs, which arise from risk and financing constraints. Such costs appear to be 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-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 parallel and block trading literature for individual stocks dating back to Kraus and Stoll (1972a, b), wherein large sales are followed by reversals but large buys are not. The results reveal that price pressure is not limited to individual stocks but also influences returns at the aggregate market level.
- Order imbalances are strongly related to contemporaneous absolute returns after controlling for market volume and market liquidity. To explain volatility, it is imperative to account for order imbalance in addition to volume.

To our knowledge, this is the first study to analyze daily order imbalances for a comprehensive sample of stocks over an extended time period. The results indicate that order imbalances affect liquidity and returns at the aggregate market level. Since private information is not likely to be an issue at the market level, the results are broadly consistent with an inventory explanation whereby market makers accommodate uninformed actions by outside agents.

Order imbalance data 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.

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