Variations in Stock Returns : Asymmetries and Other Patterns

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Abstract

This paper documents several properties of stock return data which are not directly related to neoclassical models of price determination. These properties are important to document for several reasons. First, if they are ignored, then improper inference may result. This is demonstrated by analyzing the effect of option introduction on the underlying stock's volatility. Second, many empirical investigations of non-neoclassical models of price formation (focusing on the market making process) are just-identified. They may be fit to data and look reasonable even if the properties of the data suggest that they are inappropriate. Finally, these findings may provide a challenge to theorists to develop models which are consistent with the data. The cross-sectional dispersion of daily returns is found to be asymmetric between large up and down moves in the market. We demonstrate that the drop in residual variance which is generally ascribed to option listing is spurious in that it is due to not controlling for market wide shifts in residual variance. Using transactions data, it is demonstrated that price is very unresponsive to order flow, which has implications for attempts at the decomposition of the spread using just-identified models.

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1 Introduction

Empirical research in finance has increasingly paid heed to the fact that observed security prices may mean different things in different settings. Theoretical models of the determinants of the size and location of the bid-ask spread have sparked empirical investigation into these issues. In spite of these trends, little is known about certain features of stock return behavior because much of empirical research is focused on testing sharp null hypotheses from specific theories. We know, from Lo and MacKinlay (1990) for example, that weekly portfolio returns exhibit strong positive autocorrelations. This fact represents a rejection of a martingale model of price behavior. We know, from French and Roll (1988), that return variances are higher in trading periods than in non-trading periods – a fact that rejects the hypothesis that returns evolve in calendar time (noted generally by Lamoureux and Lastrapes 1990). The purpose of this paper is to document features of stock market data – on both an intra- and interday basis, using both individual stocks and large portfolios – that are not suggested by any theories of price determination – either neoclassical or informationally (liquidity) motivated. Highlighting these patterns is timely precisely because of the proliferation of theories of the price formation process. Many of the empirical analyses of these models are just-identified, in the sense that they do not generate over-identifying restrictions relative to an alternative model.[1]

First we examine the properties of cross-sectional dispersion within the stock market. This variable is not addressed by neoclassical finance, with its emphasis on systematic variance. The cross-sectional dispersion is a measure of the reward for diversification, in the sense that the market variance equals the total variability within the market less cross-sectional dispersion. We provide a concrete example of how not being

[1]A recent empirical paper which also addresses patterns in the data rather than performing tests of sharp hypotheses or fitting just-identified models is Boudoukh, Richardson, and Whitelaw (1994). Their focus is on the extent to which non-trading may generate the positive (cross-) serial dependencies in small stock portfolios.

aware of properties of this variable has led to an erroneous conclusion in the empirical finance literature.

Next we turn to the asymmetry between buying and selling in the stock market. There is a tradition in empirical finance to isolate different properties of speculative price increases from those of price decreases. Examples include the "leverage effect" that variances tend to increase following price declines, and decrease following price increases (Black 1976 and Christie 1982). Another example is the asymmetric relationship between trading volume and absolute price change depending on the sign of the price change (Karpoff 1987). More recently, studies looking at intra-day data find differences between the impact of sales and buys. For example, in a study of a specialist's transactions over the period February - December, 1987, Madhavan and Smidt (1991) find that block buys have a greater price impact than block sells. In their data, block sells are more common than block buys. Chan and Lakonishok (1993) examine the transactions of 37 large institutional money managers over a two and one-half year period. They find that, "purchases of a stock are accompanied by an increase in its price, which continues to rise after the trade; sales of a stock are accompanied by a drop in its price, but there is subsequently an almost complete price recovery" (Chan and Lakonishok 1993, p. 184).

Historically, the purported reasons for these asymmetries have varied. In the early volume literature, the asymmetry was attributed to costly short selling. Presumably, the specialist associates a higher probability to an order reflecting private information if it is a sale relative to a buy.[2] The intra-day data suggests the opposite may be true. Lakonishok and Chan speculate that, "information effects might ... be stronger for purchases than for sales" (p.184). The "leverage effect" is so named because of speculation that after a stock price decline the firm's capital structure has relatively more debt than before, and the stock is therefore more volatile.

[2]Although studies on the relationship between futures price changes and volume revealed the same asymmetry as with stocks, there are no "short selling" costs in the futures markets. (Karpoff 1987)

This paper adds several such facts documenting the relative properties of buying and selling in both intra-day individual stock data as well as inter-day market-wide data. We find that the cross sectional dispersion is larger when the market has large up moves than when it has large down moves. In other words, stock tend to move much closer together on large down moves than on large up moves. Conditioning on the direction of yesterday's market move also explains the cross autocovariance structure of portfolio returns. We find, for example, that following days when the market dropped by more than two standard deviations, the daily correlation between the lagged return on the largest decile portfolio and today's return on the smallest portfolio is 44%. Following days when the market rise is more than two standard deviations above its mean, the same cross autocorrelation is statistically insignificant. The properties of cross-sectional dispersion within the stock market may provide insights about the implications of (non-neoclassical) frictions for the evolution of stock prices.

Using intra-day data, we find no significant differences between the price impact of buying relative to selling. Similarly, when we look at significant price moves within a day, there is no difference in the preceding volume whether the price move is up or down. Strikingly, we find very little price impacts from any kind of transaction. As previously noted by Jang and Venkatesh (1991) the order flow seems to have very little effect on price formation. This is an important finding as most empirical studies of the price formation process do not allow for a test of an underlying model: They *fit* a model to the data to make estimates about components of the spread. With interday data, we note that large drops in price tend to be reversed over the next two trading days, while there is no such reversal for large price increases.

Finally, we examine the serial correlation properties of individual daily stock returns in light of the sign of the market. We find that in the 1987–1992 period, after large positive market returns, individual stock returns are negatively serially correlated, and also negatively correlated with the lagged market return. However, following large negative returns on the market portfolio, stock return autocorrelation is low, and positive, although correlation with the lagged market portfolio is large and positive.

The remainder of this paper is organized as follows. Section 2 contains the results on dispersion. Section 3 looks at the asymmetries between buying and selling behavior. Section 4 concludes the paper.

2 Dispersion

Thanks largely to the GARCH-related literature, the time-series behavior of squared market returns is well documented. This literature indicates that there is some serial correlation at low lags (ARCH effects), but that the in-sample fit (as determined using a likelihood ratio test, for example), is dramatically improved by including moving average-type terms in the conditional variance equation. Out-of-sample forecasts, however, (as in Lamoureux and Lastrapes 1993) indicate that such a term results in an overstatement of the persistence of shocks to the variance. This suggests that the underlying variance process is slowly evolving (see Nelson and Foster 1994). GARCH characterizes the time-series properties of squared returns. The squared market return in any period can be decomposed into two parts:

$$r_{m,t}^2 = \sum_{i=1}^{n} r_i^2 \; - \; \sum_{i=1}^{n} (r_i - r_m)^2. \tag{1}$$

The variance of the market return is the total variability in the stock market less the reward to diversification. Neoclassical finance, which focuses on the role of non-diversifiable risk, has no reason to evaluate this decomposition. Recent empirical research in finance has focused on the role that frictions – which result from taxes and liquidity provision – play in the generation of observed stock market data.[3] This vari-

[3]An early paper in which recognizes the relevance of microstructure to the data generating process is Cohen, Hawawini, Maier, Schwartz and Whitcomb (1980). More recent papers have looked at specific events which may be colored by the microstructure of the market. For example Lamoureux and Wansley

ance decomposition may similarly help us to develop an understanding of the neutrality (or lack thereof) of frictions in the evolution of stock prices.

Table 1 reports the correlations between daily market return and dispersion on consecutive days. The correlations are not significant in the overall sample. However, when there is a large up or down move in the market, identified as a daily return of more than two standard deviations above or below the mean, the correlations are very strong. Dispersion is highly contemporaneously correlated with the market return on both up and down moves. The mean dispersion is also about 25% more (and significant) on large up moves than on the overall sample. The crosscorrelations between the market return on large moves and the dispersion on the next day also are very strong and asymmetric. The crosscorrelation is 23% on up moves and -70% on down moves. Dispersion is also strongly autocorrelated following large market moves: 79% on up moves and 83% on down moves. These results suggest two broad patterns. Stocks move more closely together on large down moves than on large up moves. Further, they take more time to sort themselves out on large down moves than following large up moves.

Price dispersion of real goods and services has been analyzed by macroeconomists, such as Cukierman (1983). There it has been observed that prices tend to be more disperse when price levels are changing rapidly, (empirically, inflation and relative price dispersion are positively correlated). Since there have been no sustained periods of deflation during the post-war era in the US, there is no direct analog to the asymmetry documented here. In the macro literature, dispersion is often used as a measure of heterogeneity of information about system-wide shocks.

Fama (1980) and Schwert and Seguin (1992) have noted that squared returns on individual stocks may move together over time. Schwert and Seguin (1992) suggest that the squared return on the market may capture most of these patterns. This also was

(1987) look at additions to and deletions from the S&P 500 Index. Lamoureux and Wansley (1989) look at the pricing of when-issued securities on NYSE. Lamoureux and Sanger (1989) look at the seasonal returns on NASDAQ stocks in light of bid-ask spreads. Lamoureux and Poon (1987) tie in micrsostructure and tax implications to explain the market's reaction to stock splits.

the focus of an earlier literature on modeling heteroskedasticty in the market model (see Barone-Adesi and Talwar 1983). From (1) it is not clear that the squared market return would pick up patterns in total market variation. In fact from Figure 1, we note that market variation was high in 1975, although the market variance was not. Contrast this period to 1987, where the market variance is high, market variation is also high, but not as high as in 1975. As noted in the introduction, this phenomenon is not part of any model – either statistical or theoretical – of financial markets. Nevertheless, it is of interest for several reasons. First, identifying the source of the dramatic spike to the within market variation of 1975 may help to develop an understanding of market phenomena. Second, ignoring this feature in the data (even without identifying its source) is perilous. An example of a literature in finance which has ignored the phenomenon is the options listing literature. This literature evolved originally atheoretically, however a recent paper by Back (1993) gives a theoretical underpinning to the issue.

2.1 Option listing: An empirical caveat

In a recent study, Skinner (1989, p. 77) concludes that, "The listing of options on common stocks is associated with a decline in the variance of returns on these stocks. This decline is not fully explained by contemporaneous changes in market volatility." Skinner feels that the change is due (in part) to a reduction in the volatility of the cash flows of the underlying firm. Conrad (1989), Damodaran and Lim (1988), Klemkosky and Maness (1980), Nabar and Park (1988), Nathan (1974), Trennepohl and Dukes (1979), and Whiteside, Dukes and Dunne (1983), all document a reduction in the volatility of the underlying stock's returns pursuant to the introduction of publicly traded options on that stock. On the other hand, Ma and Rao (1988) document a non-uniformity in the impact of option listing on volatility: in particular, those stocks with low variances exhibit an increase, whereas those stocks with high variances tend to exhibit a decrease.[4]

The point here is that it is now virtually a stylized fact that the introduction of option trading causes a decrease in the variance of the underlying stock's returns.[5] There seems to be an empirical challenge to explain this result. On the theoretical front, Back (1992) examines the effect of the introduction of public trading in options on the stochastic process that generates stock returns. He uses a Kyle (1985) model of a competitive specialist confronting informed and liquidity traders, in continuous time. He shows that arbitrage opportunities will exist if stock volatility does not become stochastic following the introduction of options (with asymmetric information, the option will not be a redundant asset). Moreover, the average variance of the stock return process is the same as the variance prior to the introduction of options. This result has strong intuitive appeal: the (average) variance of the stock return process is a function of the cash flows of the underlying firm. Thus the extant empirical evidence appears at odds with the theoretical result.

2.2 Results

The CBOE supplied a list of all option introductions from 1973 (when public trading in listed options originated in the U.S.) until 1988. There are 778 introductions (for which we could identify a CUSIP); of these, 718 are unique companies. (The other 70 represent multiple listings.) In some cases involving the Philadelphia, Pacific, and American Option Exchanges, only a month of listing was provided.

Define LD as the listing date. To qualify for the final sample, the stock must have an exact date, no missing returns from the CRSP tape(s) for the period (LD - 300)

[4]Ma and Rao attribute this result to the effect that options have on the composition of traders in a particular stock. It would be natural to attribute these results to mean reversion (i.e., a purely statistical phenomenon, void of economic content), but here we show that these results make sense in light of market-wide movements in market model residual variance.

[5]Taking a lead from Lamoureux (1992), Freund, McCann, and Webb (1994) conclude that the earlier papers do overstate the significance of the variance drop pursuant to option introduction, although they detect a small drop in the sub-period from 1973 through 1982.

through (LD - 50) and (LD + 50) through (LD + 300). Only the first date of option listing is used. The final sample consists of 439 NYSE-AMEX stocks and 88 NASDAQ stocks. We estimate the market model using the CRSP equally weighted index (with dividends). Of the 439 NYSE-AMEX stocks, 252 exhibit a decrease in the daily market model residual variance. The mean residual variance drops from 0.00049 to 0.00042 (a percentage drop of 14.3%). Now, it is plausible that this result may be affected by the serial correlation in the daily residuals (as documented by Lo and MacKinlay (1988)). To examine this, we formed 3 day cumulated returns on each stock and the market. Here 247 of the 439 exhibit a decline in residual variance, and the mean falls from .00145 to .00129 (a drop of 11.7%). These results almost perfectly replicate those of Skinner. Furthermore, to the extent that patterns of serial correlation change around the option introduction, these cause the inference of a drop in residual variance to be slightly biased upward.[6]

The 88 NASDAQ stocks tell a different story. Of these, 21 experience a drop in residual variance after option listing. The mean rises from .00068 to .00098. This is not because NASDAQ firms are different from NYSE-AMEX firms. Rather, the first introduction of options on NASDAQ stocks did not occur until June 3, 1985.

Table 2 provides the results for the 439 NYSE-AMEX stocks by year. Note that in the first year of option trading, 1973, 27 events are in the sample; none of these stocks had a drop in residual variance. In contrast, there were 87 events in 1975, and all of these experienced a drop in the market model residual variance from the pre test period to the post test period. During the NASDAQ era (post 1984), 117 NYSE-AMEX firms had (new) option listings; 83 experienced an increase in residual variance, and the mean rose from .00031 to .00048. This experience is virtually identical to the NASDAQ results.

[6]We regressed the change in residual standard deviation on the change in first order serial correlation (cross sectionally). The coefficient on the difference in the first order autoregressive term (of the market model residuals) is -.011 with a standard error of .0027. The r^2 of this regression is 3.4%.

In Table 3, we provide results analogous to those presented in Table 2 for all NYSE-AMEX firms for which data is available on the CRSP tapes, and which through the end of 1988 do not have options. In a move toward a controlled experiment, we repeat the analysis conducted for the options listing sample on all stocks. All NYSE-AMEX with no missing returns on the CRSP tape in the pre and post option listing periods are used in the control sample. The market model is estimated pre and post, for each separate option listing date, and the mean residual variances around each date are multiplied by the number of option listings on that date. The numbers for 1974 to 1976 clearly demonstrate that the drop in residual variance is not confined to the option listing sample.[7]

Note that in 1975, of the roughly 1428 firms evaluated, roughly 1246 experience a drop in residual variance, with the mean falling from 0.00143 to 0.00090. The market-wide results for 1976 are equally compelling. Of the roughly 1287 firms in the test sample, about 1178 experienced a decline in residual variance. The mean falls from 0.00106 to 0.00060. The 1985 - 1987 era is characterized by an opposite trend (as is also the case for the optioned stock sample).

These results are not visible from observing the variance in a well diversified (market) portfolio. Over the event period (in event time), the variance of the CRSP equally-weighted portfolio actually increases from 0.0000714 to 0.0000869. Thus, there were market-wide forces which affected the size of market model residual variances over time. On average, the period of time in which options have been introduced was characterized by an economy-wide drop in residual variances: hence the spurious conclusion that the introduction of options causes residual variance to fall. The options introduction literature has essentially detected the spike in market variation in 1975, but drew an improper inference.

It is not surprising that the residuals from a daily market model are not cross-

[7]Note the options sample includes both the 439 NYSE-AMEX firms as reported in Table 2 as well as the 88 NASDAQ firms as reported in the text.

sectionally independent. Problems in the measurement of β, for example will result in a dependence between the average market model residual variance and the market variance. The correlation between the market variance and the mean residual variance shown in Figure 1 is 49.6%.[8] In a similar vein, Fama (1976, pp. 128-131) notes that the variance of market model residuals estimated from monthly returns is markedly lower, both on average and for all but one company, in the 1963-1968 period than the 1934-1938 period.

3 Buying vs. Selling

3.1 Inter-Day differences

One of the ways non-neoclassical methods have affected empirical analysis of financial markets is in the context of serial dependencies in stock returns and across stock returns. Lo and MacKinlay (1990), for example document large cross-autocorrelations in weekly returns of size-ranked portfolios. The explanations for this dependency include non-trading, which would mean that the observed market price often deviates from the latent true price; and time-varying expected returns, which would give rise to predictable return patterns.

Further evidence on this phenomenon is contained in Table 4. Here we condition on the size and sign of the market return on day $t-1$. Consider the results for the 1962-92 period at the bottom of Panels A and B of Table 4. Note that autocorrelation is always negative, and does not depend on the sign of lagged market return (from Panel A). On a daily basis, positive cross-serial correlation occurs after a large market drop, and is most pronounced for smaller firms (from Panel B).

There is no evidence of this serial covariance following up moves by the market.

[8]For example, consider that the market model is mis-specified. The average β in cross section may be unbiased, but it is the average squared beta which will link the market variance and the average residual variance.

Table 4 also provides these results for 5 six-year sub-periods. Here we see that all of this asymmetry results exclusively from the 1987–1992 period. On a daily basis, market returns lead the smallest portfolio's stocks with a 34% average correlation following market down moves. For all portfolios, the average cross correlation with the market is negative following market up moves. In this period, we also observe fairly large **positive** autocorrelations – for portfolio 6, for example it is 14%. An interesting exception to this is the largest portfolio, where the average autocorrelation following a market down move is -17%. Recall that the market used is value weighted, so this is capturing a reversal of large price moves, a phenomenon which has been documented by Bremer and Sweeney (1991).

Bremer and Sweeney (1991) show that on days following large negative returns, Fortune 500 firms tend to have significant positive returns.[9] Cox and Peterson (1994) note that this reversal is larger for smaller firms, and that the reversal itself tends to be reversed over longer horizons (beyond 4 trading days). We extend their analysis to examine both positive and negative returns, and isolate the effects by size. This information is contained in Table 5. Like Bremer and Sweeney, we note that most firms have large positive returns on days subsequent to returns below -10%. While the effect seems smallest in decile portfolios 7, 8 and 9, even these portfolios show large positive returns 2 trading days following the large price drop. We also note the striking asymmetry between days following large price drops versus days following large price increases. Even in the smallest decile portfolio, where there is a 5% reversal on the day following large price drops, there is no evidence of price reversal following price increases. Panel B of Table 5 provides a summary of results that are similar when the large move is identified as 5%, rather than 10%. There is much less tendency toward reversal in this case, and hence a smaller asymmetry.

[9] The fact that the literature contains results documenting the reversals following downturns, but nothing about corresponding upturns is a manifestation of what statisticians call "file drawer bias." This is a selection bias where non-results are not published.

3.2 Intra-Day differences

The interday asymmetries between positive and negative price moves suggest a fundamental difference between the reasons that stocks go up and fall. In this section, we investigate intraday price moves. We might expect that sellers have less substitution elasticity than buyers. Knowing this, specialists may respond to sell orders with greater price elasticity than to buy orders. Thus, we might expect that buyers have relatively little price impact on the market, as they have chosen which stocks to buy based on where price pressure will be the smallest. We might speculate that sellers have no such flexibility.

In order to examine this, we identify all blocks of 30 trades – from within the same day– on the set of all NYSE-listed stocks on the third of the four 1988 ISSM tapes. To eliminate warrants, multiple-issue preferreds, and when-issueds, we require that an issue have at least 5,500 trades and quotes for 1988, to be included in the sample. This results in a sample of 424 companies (whose ticker symbols fall alphabetically between LIG and SFX) and 4,536,667 (within-day, overlapping) trade blocks. The first cut on the data isolates instances where it appears from the outside that there exists either selling or buying pressure. Thus, we isolate those cases where 75% of the trading volume in the 30 trade block is at one end of the spread or the other. If the volume is at the bid, we refer to the situation as selling pressure, and if the volume is at the ask, we say that the block exhibits buying pressure. Here, we find 257,867 blocks with buying pressure and 248,550 blocks with selling pressure. Next, we ask whether the specialist responds to the selling or buying pressure by examining whether the ask at the end of buying pressure, (or the bid at the end of selling pressure), is any higher (lower) than the ask (bid) at the beginning of the block. If the ask (bid) is no higher (no lower) at the end of the block than at the beginning of the block we say that the specialist is unresponsive to the order flow. Here, the specialist was unresponsive to the order flow when confronted with buying pressure 64% of the time. The specialist was unresponsive to the order flow when confronted with selling pressure 67% of the time.

Next, change the definitions of selling and buying pressure to require that, in addition to 75% of the volume being at the appropriate end of the spread, 25 of the within-day 30 trades must be at that end of the spread. Now there are 22,608 instances of buying pressure and 34,886 instances of selling pressure. The specialist is unresponsive to this buying pressure 89% of the time and unresponsive to selling pressure 91% of the time. We perform similar sets of analyses for filters with 25 trades and 90% of the volume, and all of these are repeated using within-day trade blocks of size 10. There are 5,874,757 overlapping, within-day trade blocks of size 10 for this sample of 424 firms.

In addition, for all of the trade blocks and filters described above, the analysis is repeated on a company-by-company basis, where a company must have at least one instance of each type of order pressure to qualify for inclusion. This stratification is motivated by the vast differences in activity within the sample of 424 issues. The most active issue in the sample is MRK (Merck) with 223,924 trades and quotes in 1988. To prevent the properties of the few giants from swamping the results, we weight each company equally in addition to weighting each trade block equally. This allows us to examine the distribution of the responsiveness to trade across companies. All of these results are reported in Table 6.

To further isolate possible order imbalances from the empirical order flow, we rank all of the within-day 30 (and 10) trade blocks, for each company. In Table 6, all results are reported adding requirements that the identification of a block as one with selling or buying pressure be restricted to blocks which are in the top 50th, 75th, 85th, 90th, and 95th percentile of block volume for that issue in 1988. Thus, for example from Panel A, we have a row which identifies all within-day 30 trade blocks where 90% of the volume within the block was at the bid (ask) and 20 of the thirty trades were at the bid (ask) and the trade-block is in the top 75%ile of volume for all 30-trade blocks in 1988 for the relevant issue. Reading across that row, there were 17,985 blocks which met the criteria where the bid is the appropriate end-point of the spread. Of these, the bid at the end of the 30-trade block was no lower than the bid at the beginning 88% of the time. There were 9025 30-trade blocks where the action was taking place at the ask. Of these the ask at the end was no higher than the ask at the beginning 74% of the time. When companies are weighted equally, the average across-issue unresponsiveness to selling pressure is 61% (with a 3.4% standard error). At the ask side of the spread, similarly the average unresponsiveness across companies is 61%, with a standard error of 3.6%. The last 2 columns in Table 6 report that 93 issues were used to obtain the cross-issue averages, and that only 1 of these 94 issues had at least one of the two measures of unresponsiveness below .5.

The results using 10-trade blocks, additional block-volume filters, as well as those done on a company-by-company basis are virtually identical to those already discussed. Note that for both the 10-trade and 30-trade blocks, and for both the 75% and 90% volume filter, the unresponsiveness to order flow is uniformly increasing in the number-of-trades filter. Thus, consider 10-trade blocks (Panel B), and the 75% volume filter, the least responsiveness to order flow is realized when buying (selling) pressure is defined by 75% of the volume *and* 8 of the 10 trades at the bid (ask), 91% (90%). Compare to the case where there is no minimum trade filter and the corresponding measures of non-responsiveness are 75% (74%). This pattern suggests that very large trades have a price impact, since the effect of adding a number of trade filter to the volume filter is to lessen the role of a very large trade.[10]

These results are consistent with those reported in Jang and Venkatesh (1991). They report that a quote revision followed a trade at one end of the spread only 23%

[10]Consider, for example a 30-trade block where there is one transaction at the bid of 300,000 shares, and 29 100-share trades not at the bid. This block will meet the first filter, but will be excluded by adding the number-of-trade filters.

of the time for a sample of 250 NYSE-listed firms during a 42 day period in 1985.

Next, we look at the converse of the above. We ask of times when the price went up or down by a large amount over a 30 trade block, what was the pattern of buying / selling within the block. We define "a large amount" by being in the top (or bottom) 5% of the empirical distribution of the returns on within-day 30-trade blocks, (defined specifically for each company). On average, over the 30 trades preceding a large upward return, 38.2% of the volume and 10.2 trades were at the ask. Symmetrically, over the 30 trades constituting a large downward return, 38.0% of the volume and 10.1 of the 30 trades were at the bid. Over the 30 trades constituting a large upward return, 18.0% of the volume and 6.8 trades were at the bid. Symmetrically, over the 30 trades constituting a large downward return, 18.3% of the volume and 7.0 of the 30 trades were at the ask. This set of results suggests that large price moves – either up or down – are preceded by the same kind of trading activity. During these periods, 18 - 19% of the volume and 7 of 30 trades takes place against the market movement. It is clear that the specialist is not inundated with orders on only one side of the market. As in the previous analysis, we repeat this experiment with 10-trade blocks. Here, preceding large up moves, we find 37% of the volume and 3.4 of the 10 trades at the ask, and 20.0% of the volume and 2.4 of the 10 trades at the bid. Preceding large down moves (over 10-trade blocks), we find that 37.3% of the volume and 3.4 of the 10 trades are at the bid, while 20% of the volume and 2.4 trades are at the ask.

Taken together, these results suggest that there is no difference in the trading activity preceding up or down moves, or that buying has a different price impact than selling. Furthermore, the results suggest that the "empirical order flow" is uninformative. Given the general unresponsiveness of price to the empirical order flow, inferences about the decomposition of the spread (e.g., Hasbrouck 1991) are placed in doubt. When there is no public information release, there may be a large number of trades which trade against the limit order book without affecting the location of the spread.

Conversely, when there is a public information release, the limit order book (coupled with exchange guidelines) limit the specialist's ability to move the price quickly to its new level, the gradual price move through the limit order book may give the false impression that the price is responsive to order flow, (recall that limit orders are by their nature not contingent on states of nature). Since major public information releases are not the norm, we find here that prices are unresponsive to the order flow.[11]

4 Conclusion

This paper presents a series of patterns in high frequency financial market data which have heretofore gone unnoticed. One of the reasons that these patterns have not been identified is that neoclassical finance theories place restrictions on the relationships between returns and systematic risk. Total variance – and its components and time series properties – is not material. On the other hand, non-neoclassical methods which emphasize informational asymmetries and other frictions have not been successful at generating sharp null hypothesis tests. Much of the empirical work in the area of microstructure has been directed at exploiting a structure suggested by a model to estimate components of the spread. The process which generates the data may look wildly different from that suggested by the model, but the fitting can not identify this tension. The analysis reported here shows that price is very unresponsive to the order flow, as can be observed by an outsider.

Another implication of increased emphasis on frictions in the market place is apt to be additional empirical studies of the effect of a certain event on the stock's variance. Our patterns suggest that simply controlling for the market's variance will be an inadequate means of conducting inference. One by-product of this paper may be an

[11]This discussion also highlights the importance of knowing who are the counterparties to a trade. It may well be that trades involving the specialist have a greater price impact than trades which do not involve the specialist. A problem with estimating spread components from the order flow is that it is generally not possible to identify the counterparties.

attempt to identify the reasons for the spike in the market-wide variability in 1975.

Finally, as in Boudoukh, Richardson, and Whitelaw (1994), frictions are a likely source for serial dependencies in returns. We show that serial dependencies in daily returns – both autocorrelations, and cross-correlations – depend on the sign and size of the market move. We also show that stocks tend to down together, but are dispersed when the market is moving up.

This set of results provides warnings for future empirical work in the non-neoclassical areas of finance. We hope too, that they will deepen our understanding of market processes, and spur theoretical work which is consistent with these patterns.

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Table 1

The sample is all stocks on the CRSP NYSE/AMEX daily files and the period is from July 1962 to December 1992. The correlations between market return(MR) and dispersion(Δ)on day t and day $t+1$ are reported for the whole sample and for subsamples when there were large up or down moves in the market on day t. A large move is identified as a move of more than 2 standard deviations above or below the mean. P-values are in parentheses.

		MR_t	Δ_{t+1}	Δ_t
Overall	MR_{t+1}	0.17973	0.00055	0.00386
(T=7674)		(0.0001)	(0.9616)	(0.7353)
	MR_t		-0.00609	0.00056
			(0.5940)	(0.9612)
	Δ_{t+1}			0.00390
				(0.7330)
Down more than	MR_{t+1}	-0.04193	-0.13275	0.11856
2 SD		(0.5795)	(0.0773)	(0.1160)
(T=178)	MR_t		-0.69836	-0.69864
			(0.0001)	(0.0001)
	Δ_{t+1}			0.82382
				(0.0001)
Up more than	MR_{t+1}	-0.01204	0.44049	0.22879
2 SD		(0.8697)	(0.0001)	(0.0016)
(T=188)	MR_t		0.23863	0.52181
			(0.0010)	(0.0001)
	Δ_{t+1}			0.79322
				(0.0001)

Table 2

Define LD as the option listing date. The pre period is the LD - 300 trading days through LD - 50 trading days. The post listing period is LD + 50 through LD + 300. Companies are sorted simply by the year in which the option listing occurred. Note that the sample contains no observations for 1979. The CRSP equally weighted index (with dividends) is used as the market proxy.

Year	Sample Size Size	Mean Resid σ^2 pre	Mean Resid σ^2 post	Number of Stocks with drop in resid σ^2
1973	27	0.00022	0.00046	0
1974	7	0.00042	0.00024	7
1975	87	0.00063	0.00027	87
1976	44	0.00054	0.00024	43
1977	13	0.00046	0.00026	11
1978	3	0.00058	0.00064	1
1980	50	0.00044	0.00047	17
1981	7	0.00087	0.00087	5
1982	54	0.00051	0.00056	21
1983	24	0.00076	0.00067	20
1984	6	0.00039	0.00024	6
1985	29	0.00025	0.00029	13
1986	25	0.00035	0.00050	7
1987	63	0.00033	0.00056	14

Table 3

For any day t in which there was an option listing, average market model residual variances are calculated by using market model residual variances for a t-300 to t-50 "pre" period and a t+50 to t+300 "post" period for all stocks which never had options introduced. Weighted averages by year are reported by weighting each day's values by the number of listings on the day.

Year	Number of of stocks	Mean Resid σ^2 "pre"	Mean Resid σ^2 "post"	Number with drop in resid σ^2
73	1700.7	0.00068	0.00139	143.1
74	1661.0	0.00133	0.00123	1096.8
75	1428.2	0.00143	0.00090	1246.3
76	1287.6	0.00106	0.00060	1178.4
77	1154.9	0.00068	0.00054	847.9
78	1233.3	0.00060	0.00064	455.0
80	1321.1	0.00071	0.00064	678.3
81	1287.8	0.00067	0.00067	715.4
82	1304.7	0.00064	0.00073	556.5
83	1283.1	0.00080	0.00058	1008.1
84	1230.2	0.00057	0.00067	769.7
85	1237.2	0.00060	0.00086	476.4
86	1307.8	0.00069	0.00090	432.9
87	1408.7	0.00085	0.00129	416.0

Table 4

Panel A reports the (averaged by size decile) correlation of a stock's return on a day in which the market moved up or down, as the case may be, by more than than two standard deviations, with the same stock's return on the next trading day. Panel B reports the (averaged by size decile) correlation of the market return on a day in which there was a more than two standard deviation move in the market, with a stock's return on the next trading day. The results are for all stocks which had returns available on the CRSP NYSE/AMEX daily files for the relevant time period. Decile 1 is the small firm decile.

Panel A : Autocorrelations

Period	Move	Dec 1	Dec 2	Dec 3	Dec 4	Dec 5	Dec 6	Dec 7	Dec 8	Dec 9	Dec 10	Mkt
1962-68	up	-0.130	-0.120	-0.113	-0.099	-0.100	-0.075	-0.080	-0.092	-0.065	-0.093	-0.095
1962-68	dn	-0.173	-0.178	-0.188	-0.158	-0.163	-0.179	-0.156	-0.165	-0.155	-0.161	-0.166
1969-74	up	-0.097	-0.071	-0.081	-0.031	-0.019	-0.001	-0.001	0.009	0.033	0.068	-0.012
1969-74	dn	-0.155	-0.146	-0.130	-0.117	-0.109	-0.107	-0.079	-0.112	-0.100	-0.032	-0.104
1975-80	up	-0.080	-0.019	-0.054	-0.017	-0.017	-0.001	0.006	0.021	0.017	0.026	-0.008
1975-80	dn	-0.116	-0.083	-0.035	-0.057	-0.051	-0.048	-0.051	-0.082	-0.057	-0.069	-0.064
1981-86	up	-0.044	-0.028	-0.057	-0.038	-0.017	0.010	0.009	0.008	0.007	-0.001	-0.012
1981-86	dn	-0.093	-0.096	-0.070	-0.047	-0.091	-0.087	-0.052	-0.081	-0.044	-0.025	-0.066
1987-92	up	-0.179	-0.156	-0.151	-0.104	-0.114	-0.097	-0.097	-0.155	-0.115	-0.127	-0.129
1987-92	dn	-0.038	0.068	0.066	0.123	0.070	0.143	0.103	0.047	-0.023	-0.173	0.026
1962-92	up	-0.147	-0.127	-0.090	-0.090	-0.107	-0.081	-0.072	-0.073	-0.016	-0.030	-0.083
1962-92	dn	-0.116	-0.114	-0.040	-0.062	-0.055	-0.047	-0.079	-0.091	-0.037	-0.112	-0.076

Table 4

Panel B : Cross serial correlations with the market

Period	Move	Dec 1	Dec 2	Dec 3	Dec 4	Dec 5	Dec 6	Dec 7	Dec 8	Dec 9	Dec 10	Mkt
1962-68	up	-0.013	-0.002	0.007	0.010	-0.004	-0.004	0.009	-0.008	-0.005	-0.045	-0.008
1962-68	dn	0.022	-0.014	-0.035	-0.042	-0.088	-0.118	-0.120	-0.128	-0.156	-0.259	-0.110
1969-74	up	0.078	0.087	0.098	0.122	0.143	0.117	0.107	0.113	0.111	0.134	0.112
1969-74	dn	0.061	0.054	0.051	0.051	0.035	0.064	0.049	0.035	0.054	0.044	0.049
1975-80	up	0.072	0.069	0.067	0.068	0.068	0.044	0.031	0.034	-0.018	-0.032	0.036
1975-80	dn	0.082	0.091	0.096	0.075	0.055	0.071	0.079	0.037	0.010	-0.027	0.053
1981-86	up	0.050	0.063	0.040	0.069	0.085	0.108	0.079	0.107	0.083	0.070	0.077
1981-86	dn	0.070	0.060	0.083	0.085	0.080	0.085	0.116	0.088	0.036	0.050	0.074
1987-92	up	-0.074	-0.109	-0.127	-0.137	-0.185	-0.164	-0.159	-0.238	-0.242	-0.288	-0.183
1987-92	dn	0.344	0.393	0.321	0.363	0.261	0.336	0.276	0.185	0.083	-0.080	0.225
1962-92	up	-0.021	-0.008	-0.041	-0.008	-0.022	-0.052	0.004	-0.024	-0.014	-0.037	-0.022
1962-92	dn	0.166	0.174	0.126	0.118	0.143	0.136	0.069	0.068	0.071	-0.053	0.100

Table 5

Averages, by size decile, are reported for percentage returns on a stock, one, two and three days after any day on which there was a large up or down move in the stock. Large is identified by a more than 10 % move in Panel A and by a 5 % move in Panel B. The percentage of positive returns in each category is also reported. The results are for all stocks on the CRSP NYSE/AMEX daily files, a period from July 1962 to December 1992. Decile 1 is the small firm decile.

Panel A : 10 % moves							
Day	Decile	Up			Down		
		Smp. Size	Average	Percent > 0	Smp. Size	Average	Percent > 0
1	1	53	0.44	41.50	16	5.03	68.70
	2	90	0.88	48.80	16	2.17	50.00
	3	261	0.31	43.30	63	2.85	71.40
	4	324	0.33	46.60	78	2.11	57.60
	5	461	0.23	44.20	164	1.54	56.70
	6	695	0.41	46.70	233	1.12	52.30
	7	815	-0.04	41.40	368	0.32	46.70
	8	845	0.21	44.20	479	0.83	53.80
	9	973	-0.11	41.00	642	0.80	51.70
	10	777	0.04	45.60	670	2.39	63.20
2	1	50	0.17	38.00	16	0.23	43.70
	2	89	-0.72	30.30	16	-0.34	50.00
	3	260	-0.51	34.60	64	1.85	56.20
	4	323	-0.09	39.60	78	0.44	44.80
	5	463	-0.10	41.20	166	1.44	55.40
	6	694	-0.46	37.30	234	0.84	53.80
	7	813	0.08	41.40	369	1.68	54.20
	8	850	-0.23	40.10	479	1.86	53.40
	9	974	0.02	41.70	640	1.78	54.50
	10	780	-0.51	39.10	670	2.47	61.10
3	1	53	-0.94	39.60	14	1.64	35.70
	2	89	0.00	40.40	16	0.59	37.50
	3	259	0.03	37.80	64	-0.38	35.90
	4	322	0.06	42.20	79	0.98	45.50
	5	460	-0.24	39.70	165	0.06	47.20
	6	693	-0.33	38.30	235	0.99	48.90
	7	816	-0.49	36.60	369	0.25	45.50
	8	850	-0.67	39.50	480	0.16	45.80
	9	977	-0.51	39.90	641	-0.17	42.40
	10	779	-0.72	40.10	671	-0.10	45.10

Panel B : 5 % moves							
Day	Decile	Up			Down		
		Smp. Size	Average	Percent > 0	Smp. Size	Average	Percent > 0
1	1	270	0.28	47.00	121	1.62	62.80
	2	545	0.73	48.80	229	0.29	48.00
	3	1570	0.64	49.50	700	0.40	49.10
	4	2787	0.62	48.90	1149	0.61	52.30
	5	4434	0.58	48.80	1994	0.41	51.50
	6	6425	0.54	49.00	3136	0.37	52.90
	7	9298	0.41	47.50	4899	0.35	51.60
	8	10963	0.33	47.20	6095	0.23	50.90
	9	13552	0.32	47.50	8228	0.11	50.10
	10	13362	0.24	47.50	8668	0.18	51.60
2	1	268	-0.18	37.30	121	0.37	46.20
	2	544	-0.11	37.30	228	0.22	43.80
	3	1569	-0.13	39.20	700	0.55	47.40
	4	2781	0.00	39.70	1147	0.41	49.00
	5	4438	-0.02	40.00	1995	0.53	51.10
	6	6420	-0.13	39.80	3135	0.50	51.30
	7	9301	-0.07	41.00	4897	0.45	49.30
	8	10962	-0.09	41.50	6094	0.47	50.80
	9	13554	-0.09	42.00	8224	0.46	51.70
	10	13358	-0.07	43.00	8670	0.52	53.10
3	1	271	-0.08	38.70	118	0.08	35.50
	2	544	-0.09	37.10	229	0.01	41.40
	3	1564	-0.05	40.30	701	0.26	45.00
	4	2782	-0.08	38.90	1149	0.30	46.50
	5	4438	-0.18	39.40	1991	0.20	46.60
	6	6420	-0.15	39.80	3137	0.27	47.00
	7	9303	-0.10	41.80	4894	0.31	46.70
	8	10961	-0.15	41.70	6097	0.23	48.30
	9	13554	-0.18	41.80	8224	0.15	46.80
	10	13360	-0.16	42.80	8673	0.26	49.90

Table 6

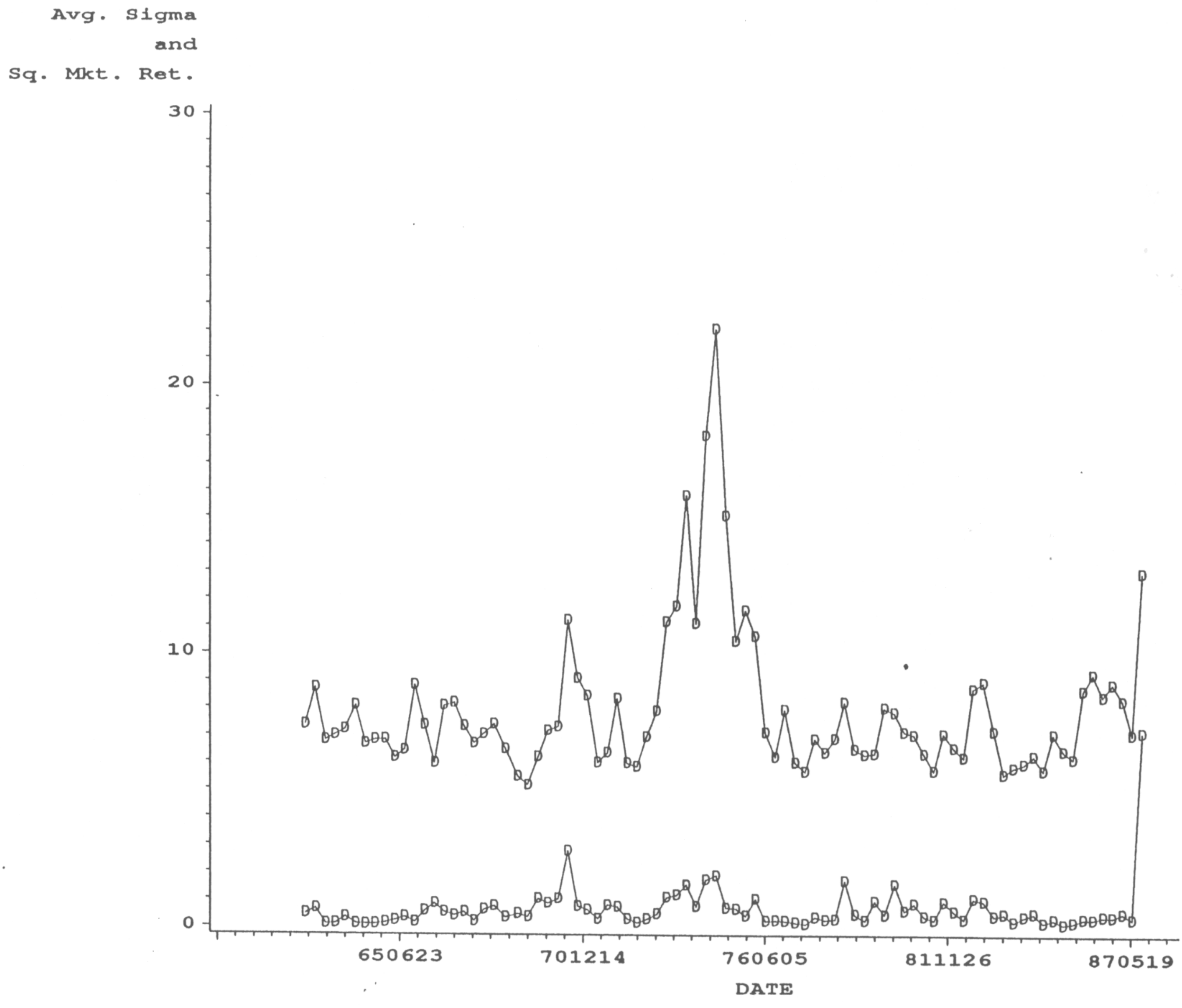
The unresponsiveness of the relevant side of the spread to buying and selling pressure is reported from transactions data for 424 companies on the third of four ISSM tapes for 1988. A company had to have at least 5500 trades plus quotes for the year to qualify for inclusion. N1 is the number of companies that had nonzero number of blocks with both buying and selling pressure and therefore qualified for the averages over companies. N2 is the number of companies which had at least one of the unresponsiveness ratios below 0.5.

Panel A: 30-trade blocks												
Def. of Buying/Selling Pressure			Selling Press. (Overall)		Buying Press. (Overall)		Selling Press. (Avg. over companies)		Buying Press. (Avg. over companies)		N1	N2
% Vol. at Bid/Ask	No. of Trades Bid/Ask	Percentile Rank of Block Vol.	No. of Blocks	Ratio Unresp.	No. of Blocks	Ratio Unresp.	Ratio Unresp.	S.E. of Prev. col.	Ratio Unresp.	S.E. of Prev. col.		
0.750	-	-	248550	0.66873	257867	0.64505	0.50389	(0.01586)	0.48120	(0.01414)	300	91
0.750	-	50th pc	156657	0.62002	159428	0.57792	0.46311	(0.01579)	0.45806	(0.01454)	276	81
0.750	-	75th pc	98793	0.60062	97977	0.54359	0.46959	(0.01646)	0.45018	(0.01560)	251	75
0.750	-	85th pc	69351	0.58759	67054	0.52517	0.47181	(0.01723)	0.43586	(0.01687)	236	66
0.750	-	90th pc	51650	0.57839	49108	0.51941	0.46785	(0.01808)	0.43656	(0.01770)	218	54
0.750	-	95th pc	30139	0.56784	27200	0.51441	0.48855	(0.01928)	0.46666	(0.02169)	187	34
0.750	20	-	97761	0.81080	90209	0.79375	0.58108	(0.02073)	0.57811	(0.01913)	229	19
0.750	20	50th pc	44900	0.80425	35455	0.73330	0.59207	(0.02394)	0.51860	(0.02457)	176	7
0.750	20	75th pc	24664	0.82290	15451	0.69672	0.56262	(0.02981)	0.53567	(0.03064)	130	4
0.750	20	85th pc	15741	0.83978	8682	0.68222	0.56532	(0.03465)	0.54948	(0.03526)	98	2
0.750	20	90th pc	11146	0.85313	5899	0.67537	0.55484	(0.03922)	0.59343	(0.03781)	80	1
0.750	20	95th pc	6141	0.86712	2932	0.69816	0.66082	(0.04450)	0.64166	(0.04836)	53	0
0.750	25	-	34886	0.90784	22608	0.88712	0.75118	(0.02530)	0.75580	(0.02635)	133	0
0.750	25	50th pc	17366	0.92439	7750	0.86774	0.76710	(0.03162)	0.70251	(0.04115)	73	0
0.750	25	75th pc	11447	0.94400	3220	0.84752	0.79724	(0.04374)	0.76769	(0.04956)	44	0
0.750	25	85th pc	8250	0.95564	1838	0.81882	0.90734	(0.02675)	0.76539	(0.05982)	30	0
0.750	25	90th pc	6302	0.95763	1244	0.81511	0.92295	(0.03034)	0.81849	(0.05587)	21	0
0.750	25	95th pc	3795	0.96864	657	0.85236	0.92905	(0.03970)	0.77489	(0.09246)	13	0
0.900	-	-	65243	0.77145	53554	0.73744	0.55482	(0.02151)	0.60029	(0.01913)	212	26
0.900	-	50th pc	46070	0.73866	36669	0.68041	0.50482	(0.02239)	0.55241	(0.02124)	191	18
0.900	-	75th pc	34350	0.72277	25885	0.64300	0.47512	(0.02355)	0.55289	(0.02320)	168	12
0.900	-	85th pc	26721	0.70132	20209	0.62863	0.46442	(0.02476)	0.51868	(0.02467)	155	10
0.900	-	90th pc	21511	0.68328	16550	0.62018	0.46317	(0.02601)	0.51259	(0.02624)	143	10
0.900	-	95th pc	14038	0.64838	10510	0.61532	0.46739	(0.02834)	0.51923	(0.02918)	113	7
0.900	20	-	45655	0.86251	33477	0.82086	0.64639	(0.02476)	0.64171	(0.02398)	173	3
0.900	20	50th pc	27463	0.86429	17529	0.77557	0.63129	(0.02907)	0.58719	(0.02942)	131	3
0.900	20	75th pc	17985	0.87996	9025	0.74205	0.61405	(0.03424)	0.61099	(0.03589)	94	1
0.900	20	85th pc	12513	0.88540	5677	0.72239	0.59910	(0.04146)	0.60766	(0.03949)	78	1
0.900	20	90th pc	9196	0.89441	4135	0.72019	0.61065	(0.04562)	0.58447	(0.04501)	63	0
0.900	20	95th pc	5234	0.89950	2228	0.74641	0.68351	(0.05493)	0.70808	(0.05176)	43	0
0.900	25	-	27337	0.92519	16335	0.89795	0.77833	(0.02700)	0.77586	(0.02895)	117	0
0.900	25	50th pc	15212	0.94149	6444	0.88532	0.78663	(0.03359)	0.74468	(0.04118)	65	0
0.900	25	75th pc	10453	0.95886	2754	0.86855	0.84944	(0.03737)	0.81087	(0.04982)	37	0
0.900	25	85th pc	7695	0.96621	1623	0.84350	0.92365	(0.02355)	0.78474	(0.06128)	28	0
0.900	25	90th pc	5874	0.96731	1103	0.84950	0.91388	(0.03299)	0.84988	(0.06461)	18	0
0.900	25	95th pc	3533	0.97453	586	0.88567	0.91059	(0.04800)	0.94858	(0.02607)	10	0

Table 6 (Contd.)

Panel B: 10-trade blocks												
Def. of Buying/Selling Pressure			Selling Press. (Overall)		Buying Press. (Overall)		Selling Press. (Avg. over companies)		Buying Press. (Avg. over companies)		N1	N2
% Vol. at Bid/Ask	No. of Trades Bid/Ask	Percentile Rank of Block Vol.	No. of Blocks	Ratio Unresp.	No. of Blocks	Ratio Unresp.	Ratio Unresp.	S.E. of Prev. col.	Ratio Unresp.	S.E. of Prev. col.		
75	-	-	677202	0.75138	701513	0.73845	0.64469	(0.00844)	0.62380	(0.00819)	424	72
75	-	50th pc	383174	0.69269	404279	0.66668	0.58850	(0.00866)	0.55552	(0.00854)	420	107
75	-	75th pc	217697	0.66397	226146	0.62712	0.56013	(0.00936)	0.52838	(0.00897)	417	93
75	-	85th pc	142244	0.65120	145321	0.60658	0.55395	(0.00989)	0.52449	(0.00993)	411	81
75	-	90th pc	100859	0.63894	100786	0.59370	0.55798	(0.01036)	0.51301	(0.01099)	402	71
75	-	95th pc	56128	0.62113	53674	0.57710	0.55282	(0.01157)	0.50254	(0.01204)	366	50
75	6	-	376559	0.83421	369002	0.82502	0.70849	(0.00942)	0.68185	(0.00960)	420	25
75	6	50th pc	166421	0.79382	163711	0.76231	0.64460	(0.01097)	0.58748	(0.01116)	408	41
75	6	75th pc	80729	0.78397	77036	0.72801	0.60802	(0.01279)	0.55979	(0.01253)	386	21
75	6	85th pc	48289	0.78513	44978	0.70957	0.59723	(0.01465)	0.56021	(0.01441)	356	9
75	6	90th pc	32285	0.78557	28970	0.70107	0.60454	(0.01556)	0.57385	(0.01544)	329	5
75	6	95th pc	16355	0.78765	14034	0.69282	0.61067	(0.01769)	0.57152	(0.01791)	263	0
75	8	-	148765	0.90868	125855	0.90276	0.79633	(0.01030)	0.78455	(0.01032)	386	2
75	8	50th pc	62633	0.89140	49018	0.86501	0.73735	(0.01383)	0.70875	(0.01390)	336	2
75	8	75th pc	31096	0.89909	21581	0.84621	0.73166	(0.01644)	0.68857	(0.01677)	283	0
75	8	85th pc	19449	0.90627	12256	0.83559	0.73320	(0.01923)	0.70426	(0.01911)	239	0
75	8	90th pc	13481	0.91240	7748	0.83080	0.73254	(0.02193)	0.72388	(0.02077)	198	0
75	8	95th pc	7245	0.92767	3639	0.82797	0.77861	(0.02441)	0.73957	(0.02416)	132	0
90	-	-	290193	0.80102	281940	0.78700	0.68294	(0.01006)	0.66831	(0.00951)	412	33
90	-	50th pc	178373	0.74611	177223	0.72395	0.61603	(0.01112)	0.59005	(0.01078)	405	52
90	-	75th pc	113487	0.71346	111173	0.68292	0.58657	(0.01147)	0.56254	(0.01177)	393	49
90	-	85th pc	80811	0.69559	77678	0.65907	0.57518	(0.01241)	0.55282	(0.01241)	377	42
90	-	90th pc	60818	0.67995	57363	0.64301	0.56910	(0.01225)	0.54850	(0.01326)	366	33
90	-	95th pc	37125	0.65662	33550	0.62003	0.55882	(0.01405)	0.54678	(0.01396)	325	20
90	6	-	222615	0.85846	206272	0.84359	0.73835	(0.01067)	0.70233	(0.01024)	406	17
90	6	50th pc	115826	0.82285	107772	0.78975	0.66880	(0.01246)	0.60888	(0.01231)	390	21
90	6	75th pc	62388	0.81413	56035	0.75862	0.63787	(0.01402)	0.59512	(0.01400)	359	9
90	6	85th pc	39502	0.81252	34475	0.74071	0.62900	(0.01595)	0.59506	(0.01567)	324	6
90	6	90th pc	27160	0.81130	22934	0.73171	0.63287	(0.01635)	0.60460	(0.01681)	299	0
90	6	95th pc	14411	0.81216	11647	0.72165	0.64472	(0.01880)	0.60782	(0.01924)	241	0
90	8	-	128902	0.91619	106637	0.90848	0.80393	(0.01081)	0.78765	(0.01124)	377	2
90	8	50th pc	57538	0.89949	43938	0.87437	0.74334	(0.01436)	0.72278	(0.01442)	327	2
90	8	75th pc	29351	0.90627	19965	0.85590	0.73499	(0.01714)	0.69926	(0.01767)	278	0
90	8	85th pc	18599	0.91268	11496	0.84612	0.75115	(0.01872)	0.72461	(0.01926)	225	0
90	8	90th pc	12957	0.91819	7304	0.84064	0.73839	(0.02222)	0.73365	(0.02162)	191	0
90	8	95th pc	7057	0.93212	3494	0.83572	0.78520	(0.02401)	0.75699	(0.02405)	124	0

Average Residual Variance and Squared Market Return
for 75 day intervals



Higher Series is Avg. Res. Var. when Returns are in %
Lower Series is Square of % Market Return