Stock Returns and Trading at the Close

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Abstract

This paper analyzes empirically the behavior of stock returns at the close across the stocks of the Russell 1000 using (a) Transaction-level data for the period June 1997 to July 1998, and (b) The complete record of all Market On Close (MOC) order imbalance indications issued by NYSE specialists. We show that the last five minutes of the trading day explains a disproportionate fraction of the variation in daily returns, consistent with the hypothesis that institutional trading interest induces a common component to stock returns at the end of the day. This return phenomenon reflects a higher demand for immediacy in the closing period. We find systematic return reversals following order imbalance publications consistent with temporary price pressure related to liquidity trading.

Keywords: Institutional trading, closing prices, stock returns, volatility

1. Introduction

Traders place enormous importance on closing stock prices as benchmarks of value. Portfolio returns and mutual fund net asset values are computed using closing prices. In addition, some contracts and after-hours trading on various Alternative Trading Systems (ATS) and Electronic Communications Networks (ECNs) are based on closing prices.[1] For these reasons, many traders, especially institutions such as passive index funds, try to trade at or near the day's close. Increasingly, large trading volumes at the end of the trading day have in turn complicated the task of price discovery and led to growing concern about the ability of markets to provide liquidity in this critical period.

A recent case involving Safeway stock offers an interesting, albeit extreme, example of these issues. On November 12, 1998, Safeway stock was to be added as of the close to the S&P 500, following an announcement made the previous week.[2] High demand by index funds seeking to add Safeway stock to their portfolios at the closing price on this day resulted in a large order imbalance at the close. To accommodate the excess demand, the NYSE specialist for Safeway, Spear Leeds, set a closing price of $55, up 11% from the *previous* trade. In subsequent overnight trading Safeway stock fell in price, closing at $51.1875 the following day.

Many institutional investors who paid large premiums to acquire Safeway at the close on November 12 were highly critical of the manner in which the closing price was determined. The Safeway case spurred (Ip, 1999) "intensive debate over how the close, the most critical time of the day, should be handled." Investors argued that closing imbalances in Safeway should have been widely publicized to alert potential buyers that they would trade at a substantial premium while simultaneously attracting counterparty interest to dampen the temporary price pressure at the close. Similarly chaotic closings for other S&P 500 additions and deletions including Amoco Corporation and America Online Inc. on December 31, 1998 also illustrate the difficulties in de-

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[1] Examples include Instinet's and the NYSE's after-hours (Session I) crossing systems.
[2] See Ip (1998). Safeway replaced Chrysler Corporation which was dropped from the S&P 500 index because of its merger with Daimler-Benz, A.G., a foreign firm.

termining efficient closing prices and the importance of widely disseminating information on order imbalances.

The problems associated with trading at the close discussed above have led to various new policy initiatives. Exchanges have imposed various rules on the submission of market and limit-on-close orders to alleviate problems associated with day-end order imbalances.[3] Similarly, the Standard & Poor's Corporation announced on December 30, 1998 that it would delay announcement of additions and deletions from its stock indexes after the close of trading, noting that "We don't want our announcements to affect a stock's official closing price for the day."[4] Yet, it is difficult to assess the nature and impact of such initiatives without further data on how closing prices are actually determined. The objective of this paper is to further our understanding of the process of price formation at the close.

A considerable body of research has documented various anomalies in intraday returns, volumes, and volatility.[5] However, research on how closing prices are determined is relatively recent. Hillion and Suominen (1998a) study the closing prices of the CAC 40 stocks of the Paris Bourse. They find evidence of reversals in the overnight period and also higher volatility and spreads at the close.[6] The problems documented by Hillion and Suominen (1998a) prompted the Paris Bourse to implement a closing call auction. Thomas (1998) finds that orders are larger and there are fewer cancellations after the closing call was implemented. She concludes that these findings provide evidence that the call auction procedure leads to more efficient price discovery and less gaming at the close.[7]

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[3] Meier (1998) surveys 49 leading stock markets including the NYSE, Nasdaq, London Stock Exchange, Paris Bourse, and Frankfurt Stock Exchange. He finds that at year-end 1997, 35 (71%) exchanges used special procedures to open while 12 (25%) use special closing procedures.

[4] The change was prompted by large movements in shares of America Online Inc. following the announcement on December 22, 1998 that the stock would be added to the S&P 500 index. See, e.g., "S&P is Changing an Index Procedure," New York Times, December 31, 1998, page C6.

[5] See, e.g., Jain and Joh (1988) and Harris (1986, 1989).

[6] Hillion and Suominen (1998b) develop a theoretical model to explain this finding, showing that this evidence is consistent with brokers manipulating closing prices to provide the appearance of favorable execution for large customers.

[7] Madhavan (1992) provides a theoretical justification for the use of call auctions in times of market stress.

While these studies advance our understanding of how closing prices are set, there are still many questions that remain unanswered. First, is the closing period disproportionately "important" in a return sense, as many believe? And if so, is there any evidence that end of day returns reflect systematic factors common to a broad cross-section of stocks? This question naturally leads to an examination of order flow patterns towards the close. Specifically, is there a higher demand for immediacy at the close, and can this explain the known "anomalies" in returns? Are closing prices more responsive to order flows? The answers to these questions can shed light on both the return anomalies noted in the previous literature and the possibility of market manipulation or gaming at the close. A closely related question is whether the higher demand for immediacy induces transitory shocks to closing prices? This question is interesting because it implies that there are predictable price reversals following large order imbalances or, in other words, that closing prices are possibly biased.

This paper examines these three sets of issues across the stocks of the Russell 1000 index using: (a) Transaction-level data for the period June 1997 to July 1998, and (b) The complete record of all Market On Close (MOC) order imbalance indications issued by the NYSE. Our study yields several new results. We show that the last five minutes of the trading day explains a disproportionate fraction of the variation in daily returns. Indeed, this fraction is almost 18% in portfolios although the closing period constitutes only 1.3% of trade time.[8] By contrast, the corresponding fraction is only 4% in individual stocks. This finding is consistent with the hypothesis that institutional trading interest induces a common component to stock returns at the end of the day.

We examine the cause of the disproportionately large closing period returns using a model of the return generating process. Our results suggest that the closing return phenomena can be explained by: (a) A shift downward in the percentage of large-block (presumably upstairs-intermediated) trades at the end of the day, consistent with a greater demand for immediacy by

[8] The closing period accounts for a disproportionate share of volume and volatility relative to trade time, but of a far smaller magnitude. See Harris (1986, 1989) and Jain and Joh (1988).

institutions unwilling to bear the delays associated with upstairs intermediation, (b) Higher sensitivity of prices to *non*-block order flow relative to block order flow, and (c) A higher sensitivity of prices to *non-block* order flow at the close relative to other times of the day.

Additional evidence that the demand for immediacy can explain the sharp price movements at the close comes from our analysis of new data on market-on-close order imbalance publications. We find positive (negative) overnight returns following publicized sell (buy) imbalances. Return reversals are especially strong on index expiration days where the imbalances arise primarily from liquidity trading. Interestingly, the same pattern of reversals is observed in next-day returns as well. This phenomenon does not reflect negative autocorrelation in order flow. Rather, our evidence suggests that prices over-react to order imbalances at the close. The return reversal the following day occurs because the opening price the next day is "sticky" in the sense that it is a weighted average of the previous day's close and the price implied by overnight flows. These results demonstrate that transitory order imbalances bias closing prices, consistent with anecdotal evidence. We discuss the implications of our results in terms of the effectiveness of imbalance publications, and explore alternatives to enhance price efficiency and lower volatility at the close.

The paper proceeds as follows: Section 2 describes our data sources and procedures. Section 3 outlines our empirical hypotheses. Section 4 provides evidence on the relative contribution of closing period returns to the daily return. Section 5 examines the determinants of closing returns across stocks focusing on the role of order flow. Section 6 discusses the properties of returns following publication of order imbalances and Section 7 concludes by summarizing our results and their policy implications.

2. Data Sources and Procedures

2.1. Sample Universe and Data Sources

The primary source of our data is the NYSE's Trades and Quotes (TAQ) files for the period June 1997-July 1998. The TAQ files record, on a stock-by-stock basis, transaction level data on prices, quotes, and volumes, time-stamped to the second. Our sample universe is the

Russell 1000. The Frank Russell Company equity indexes are popular benchmarks of US stock market performance. The Russell 1000 Index(R) consists of the top 1000 US stocks by market capitalization. The universe of stocks from which Russell chooses index constituents includes domestic common stocks and REITs but excludes certain issue types such as royalty trusts and closed-end mutual funds. In order to restore its capitalization-based definition and replace stocks that drop out over time due to corporate actions and bankruptcies, the Russell 1000 is re-constituted annually at the end of June. This fact accounts for our choice of July 1 as the starting date of the data set. We restrict attention to common stocks that were continuously present in the Russell 1000 universe during the sample period and for which all study data was available.

We gathered additional data for each stock from various sources, as follows: (a) Membership in the S&P 500 index (Standard & Poors), (b) Options traded on the stock (Factset), (c) Dividend amount, type, and ex date (Reuters), (d) Split Factor (Reuters), (e) Earnings Surprise (I/B/E/S), (f) Stock subject to NYSE MOC regulations (NYSE), and (g) Exchange-listed (CRSP). From the NYSE we obtained information on whether there was a publicized market-on-close buy or sell imbalance for each stock for each of the 252 days in the sample period.

To verify the accuracy of the return data we imposed filters to detect outliers including those related to dropped digits, missing quotes, or split-related price recording errors. As an additional check, we matched daily returns for the stocks computed using TAQ data with the CRSP daily return file. Some of our analyses require information on the net order flow. We use the procedure suggested by Lee and Ready (1991) to classify trades as buyer- or seller-initiated. Specifically, we compare the trade price to the midpoint of the "prevailing" bid and ask quotes; we use a 15-second lag on quotes to correct for differences in the clock speed with which trades and quotes are reported. Trades whose prices are above (below) the midpoint are classified as "positive" ("negative") volume. Trades at the quote midpoint (e.g., upstairs crosses) generally cannot be classified in this manner, and are classified as "zero" volume trades. We define net order flow as positive share volume less negative share volume. In addition to the filters reported above, we eliminated from the sample those stocks for which volume data was incomplete (e.g., because of difficulties in matching quotes and trades) and stocks that did not trade at least once per day, leaving us with a sample of 769 stocks.

2.2. Market-on-Close Imbalance Indicators

As of June 5, 1995 (see NYSE Memo 95-21), the NYSE adopted certain rules designed to reduce problems associated with Market-on-Close (MOC) orders. The rules imposed certain order entry cutoff times. Specifically, no MOC orders were accepted after 3:50 p.m., except to offset a published imbalance. The cutoff time for expiration days was 3:40 p.m. Imbalance publication was subject to the following rule: On expiration days, for a list of pilot stocks and for any stock being added to or deleted from an index, the specialist must publish any MOC imbalance of 50,000 shares or more, or a "no imbalance" status as soon after 3:40 p.m. as practicable. Publication is at the specialist's discretion for other stocks, after consultation with a Floor Official. On non-expiration days, the rules are the same, except that publication time is as soon after 3:50 p.m. as practicable and there is no requirement to publish a "no imbalance" message for pilot stocks not having an imbalance.[9] Thus, specialists in stocks on the list must publish their order imbalances *on expiration days*, whereas publishing imbalances is not required for other stocks (and for stocks on the list on non-expiration dates). On June 24, 1998, the rules were amended so that all market-on-close had to be entered by 3:40 p.m., except to offset a published imbalance. In addition, other changes were implemented to facilitate disclosure of imbalances. For this reason, we focus on the pre-June 1998 period in our analyses.

In our sample period, the MOC restrictions applied to all stocks. The file we obtained from the NYSE contains all published imbalances, i.e., those that were made public in NYSE stocks.[10] The data contain the following fields: *Buy MOC imbalance*, *Sell MOC imbalance*, *No MOC imbalance*, and *No Trading* status messages for a given day. The time of the publication of the MOC imbalance message is the Consolidated Trade System (CTS) dissemination time and is

[9] Sofianos (1994) documents the high prevalence of MOC imbalances on days with index expirations.

[10] We thank Jeff Bacidore and George Sofianos for their help in providing us with these data.

recorded to the second. Other fields indicate whether the MOC imbalance was eligible to be published that day for that stock.

3. Empirical Hypotheses

Before turning to the analysis, it is useful to explicitly formulate the empirical hypotheses we seek to test in the paper. Consider a set of *N* assets that are traded in a trading day consisting of c trading sessions. Let $p_{i,t}^{k}$ denote the (midquote) price in trading session $k = 1,\dots, c$ for stock *i*, on day *t*. In each session, prices are set by competitive market makers who observe the net order flow in each stock, $x_{i,t}^{k}$. Formally, the (midquote) price for stock *i* on day *t* in session *k* is $p_{i,t}^{k} = E[p_i^* | x_{i,t}^{k}, \Omega_{i,t}]$ where p_i^* represents the intrinsic value of the stock and $\Omega_{i,t}$ denotes public information. Define by $r_{i,t}^{k} = p_{i,t}^{k} - p_{i,t-1}^{k}$ the (midquote) price change for stock *i* in session *k*. We assume that returns reflect both net order flow and public information flows, and model intraday returns as

$$r_{i,t}^{k} = \mu_i + \lambda_i^k x_{i,t}^{k} + \varepsilon_{i,t}^{k}, \tag{1}$$

where the coefficient $\lambda_i^k > 0$ reflects the sensitivity to order flow (which can vary across stocks and sessions), μ_i is the mean return per period, and $\varepsilon_{i,t}^{k}$ captures the effect of public information flows. Both order flows and information may be correlated across assets but in time-invariant ways. The model can be interpreted as a reduced-form equation from a more complex microstructure model where prices are set by competitive market makers who face an adverse selection problem because some traders possess private information. The actual price in session *k*, denoted by $P_{i,t}^{k}$, is the midquote price plus a microstructure induced shock, $s_{i,t}^{k}$ that can take on positive or negative values that reflect temporary liquidity pressures. Within this simple structure we formulate three empirical hypotheses.

3.1. Correlation in Institutional Order Flows at Day End

In the *final* trading period *c* of the day, we assume the net order flow $x_{i,t}^{c}$ consists of a base-level order flow $\omega_{i,t}^{c}$ (assumed for simplicity to have the same distributional properties for all periods) and additional institutional trading, denoted by $z_{i,t}$. Institutional trading across stocks is correlated and takes the form $z_{i,t} = z_t + \xi_{i,t}$, where z_t is a common term across stocks and $\xi_{i,t}$ is an i.i.d. shock. The common term may reflect herding by institutional traders and portfolio based strategies, or it may reflect common response to new information. Alternatively, if institutional traders place closing orders that are systematically related to the day's movement in the index, z_t will be a function of the average cross-sectional daily return.

From this specification, it follows that returns during the day will exhibit an *increase in correlation across stocks* at the end of the day induced by institutional trading. In particular, consider two stocks *i* and *j*. Denote by $\rho_{i,j}$ the correlation in midquote returns for periods prior to the close (i.e., *k* = 1, .., *c*-1) between these two stocks. In the closing period this correlation is

$$\rho(r_{i,t}^c, r_{j,t}^c) = \left[\frac{\lambda_i^c \lambda_j^c \ \sigma^2(z_t^c)}{\sigma(r_{i,t}^c)\sigma(r_{j,t}^c)} \right] + \rho_{i,j}. \tag{2}$$

If $\rho_{i,j}$ is positive (which is likely to be the case for most stocks) then the correlation is higher in the closing period; if it is negative, it is less negative at the close or perhaps even positive.

3.2. Information and the Responsiveness of Returns to Order Flow

Another set of hypotheses we test concerns whether the responsiveness of price to order flow is different towards the close than at other times. If institutional investors are viewed as trading at the close primarily for liquidity reasons, the responsiveness of prices to order flow would be less at this time so that $\lambda_i^c < \lambda_i^k$ for *k* = 1, .., *c*-1. However, if institutional traders trade on private information and also concentrate their trading at the close, order flows at the close will be especially informative and we would expect the opposite, i.e., $\lambda_i^c > \lambda_i^k$ for *k* = 1, .., *c*-1. Finally, the existence of differences in order flow responsiveness may induce strategic trading by discretionary traders or those with long-lived information so that the responsiveness of prices to order flow is constant across sessions for a given stock. Thus, estimation of equation (1) at different times would allow us to assess the effect of trading on closing prices.

3.3. Publication of Order Imbalances

We are also concerned with the efficiency of prices at the close. Suppose that exchange rules allow market makers to broadcast indications of imbalances at the close with a view toward attracting counterparty interest. If such interest does not materialize, specialists may offset the imbalance, but at a premium to the expected value of the asset. Recall that the closing price reflects not only expectations of value (which are related to order flows as above) but also a transitory component that capture the price of liquidity. During "normal" trading periods, this temporary component (or spread) is economically small because of competition from liquidity providers. However, liquidity providers may be able to extract a large temporary premium if there are large imbalances and the market is closing soon. This suggests that the size of the temporary component (like the permanent revision in beliefs) is also related to the order flow imbalance.

Specifically, let $s_{i,t}^c(x_{i,t}^c)$ denote the price of liquidity which we model as a function of the imbalance such that when $x_{i,t}^c > 0$ then $s_{i,t}^c > 0$ and vice versa. The logic of this specification is that $s_{i,t}^c(x_{i,t}^c)$ distinguishes between permanent revisions in beliefs (as already modeled above as a function of net order flow) and additional temporary price pressure caused by imbalances. This is a form of a non-linearity, i.e., a temporary – and possibly economically large – spread element that arises when there are imbalances at the close.

To the extent that $s_{i,t}^c(x_{i,t}^c)$ is transitory (i.e., not associated with a change in beliefs) there should be a price reversal the following day in the opposite direction of the imbalance. Formally, if $x_{i,t}^c > 0$, the expected overnight trading return is $E[P_{i,t+1}^1 - P_{i,t}^c] = -s_{i,t}^c$. This term is negative because the transitory spread element is reversed; the opposite is true of sell imbalances. If imbalance publications succeed in attracting counterparty interest, $P_{i,t+1}^1 - P_{i,t}^c$ is zero on average for both buy and sell imbalance publications at the close. Thus, the returns following imbalance publications provide clues as to the extent to which closing prices incorporate transitory shocks.

4. Analysis of Returns

4.1. Descriptive Statistics

We begin our empirical analysis by summarizing some of the characteristics of the sample, focusing on the patterns in returns towards the end of the day. These characteristics confirm that the patterns observed by previous authors are also present in our sample. In the following section, we turn to a more formal analysis of the factors affecting returns at the end of the day.

Table 1 presents descriptive statistics on the stocks in the sample, for all stocks and broken down by deciles of daily dollar trading volume.[11] We first calculate daily means for each

[11] We use dollar-trading volume – as opposed to market capitalization – because our focus is on trading activity rather than size.

statistic for each stock and then average these statistics across stocks. A wide range of trading activity is represented, with average daily volume ranging from \$0.80 to \$3.77 million. However, percentage bid-ask spreads (computed using the 3 p.m. price and expressed as a percentage of the midquote price) are relatively small and exhibit less variation across activity deciles. Spreads range from 0.24% in the most active decile to 0.44% in the least active decile. There is also little variation in prices across trading volume deciles. The majority of stocks, about 56.44%, are also in the S&P 500 index. Interestingly, although 84.53% of stocks are exchange-listed (i.e., listed on the NYSE or AMEX), the most active stock category (decile 10) actually has the lowest percentage of listed stocks, just 62.34%. This reflects the presence of some Nasdaq stocks – such as Microsoft – that have much larger volumes than the average exchange-listed stock.

4.2. Day-End Returns and Common Factors

4.2.1. Individual and Portfolio Regressions

We begin our analysis by asking whether returns towards the end of the day are "important" in the sense that they represent a large fraction of the day's return. We decompose the open-to-close period from 9:30 a.m. to 4:00 p.m. into 13 half-hour intervals or trading sessions.

Let $r_{i,t}^{k}$ denote the (logarithmic) return in trading session $k = 1,\ldots,13$ for stock i, on day t. As a purely descriptive exercise, we regress the daily return on: (a) the return in the last half-hour, and (b) the return in the last 5 minutes, for each stock in the sample. Specifically, for each stock $i = 1,\ldots,769$, we estimate two regressions:

$$\left(\sum_{k=1}^{13} r_{i,t}^{k}\right) = \alpha + \beta r_{i,t}^{13} + \varepsilon_{i,t}\ , \tag{3}$$

$$\left(\sum_{k=1}^{13} r_{i,t}^{k}\right) = \alpha + \beta r_{i,t}^{c} + \varepsilon_{i,t}\ , \tag{4}$$

where $r_{i,t}^{c}$ is the return from 3:55 to 4:00 p.m. To focus attention on factors common to all the sample stocks we estimate portfolio analogues to equations (3) and (4). We group stocks into portfolios by trading activity deciles and compute equally-weighted returns for decile portfolios and for all stocks in the sample. Then, for each decile portfolio and for a portfolio of all stocks, we estimate two regressions of the form

$$\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{13} r_{i,t}^{k}\right) = \alpha + \beta\left(\frac{1}{N}\sum_{i=1}^{N} r_{i,t}^{13}\right) + \varepsilon_{i,t}\,, \tag{5}$$

$$\left(\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{13} r_{i,t}^{k}\right) = \alpha + \beta\left(\frac{1}{N}\sum_{i=1}^{N} r_{i,t}^{c}\right) + \varepsilon_{i,t}\,, \tag{6}$$

where N is the number of stocks in the portfolio. Observe that we are making no assumptions about the statistical properties of returns which could exhibit autocorrelation and heteroskedasticity. Rather, our goal is simply to illustrate the extent to which the closing period is important in a return sense.

The results of the estimation are summarized in Figures 1 and 2, which illustrate the importance of the closing period. Figure 1 plots the coefficient of determination from the individual and portfolio regressions using the last half-hour of returns, i.e., equations (3) and (5). In the individual regressions, the mean adjusted R^2 is 7.7%, ranging from 6.79% in decile 1 to 9.79% in decile 10. (By way of comparison, if returns follow a classical random walk across trading sessions, the coefficient of determination (regression R-squared) should be approximately 1/13 or 7.69%.) In the portfolio regressions, the adjusted R-squared is generally similar except in the most active deciles where it is generally higher. Indeed, in the largest decile the coefficient of determination is 15.8% in portfolios versus 9.8% for the individual regressions. This is consistent with our hypothesis of a common trading factor in the largest cap stocks.

More striking is Figure 2 which documents the results for regressions of individual and portfolio daily returns on returns in the last 5 minutes of trading, i.e., from equations (4) and (6). In the individual stocks, the regression R-squared is 3.81% overall, compared to approximately 1/78 (or 1.28%) under a naïve random walk model. (This difference is also statistically significant using an F-test.) But for portfolios, in all deciles, the adjusted R-squared is much higher than the corresponding figure for the individual regressions, and overall it is 17.55%. This shows that the abnormal returns in the last 5 minutes tend to be common across stocks, i.e., market-wide in nature. These systematic factors are not averaged out in the portfolio formation process unlike the idiosyncratic returns in the previous 25 minutes, consistent with the concentration of institutional trading at the close. It is worth noting that this result is unlikely to be driven solely by *Fisher* effects (i.e., non-synchronous trading) since the stocks in the sample trade frequently. This is especially so for the stocks in the active deciles that trade very frequently, often several times in a minute.[12] Also worthy of note is that the estimates of β for the portfolio regressions (5) and (6) are much higher – 1.45 and 2.66 – than the corresponding average estimates – 0.89 and 0.92 – for the individual regressions (3) and (4), a point we discuss in detail below.

While these findings might reflect inventory rebalancing by market makers, empirical evidence using inventory data suggests that the effects of inventory on stock prices are relatively weak.[13] A more likely explanation for this finding would be the actions of institutional traders who seek to trade at the close. A common component to institutional trading in the closing period would increase the correlation among stock returns in the closing period.

In summary, our results show that: (a) The last half-hour is disproportionately important for the most active decile of stocks but not for other stocks (suggesting that this is not a problem with non-synchronous trading), and (b) the last part of the closing period is disproportionately important in a return sense for all stocks. Of course, it should be kept in mind that the naïve benchmark is just that; a considerable body of research documents autocorrelation in short-horizon returns and higher day-end volatility, factors which affect the computed R-squared.[14]

[12] Harris (1989) noted a much higher likelihood of the last trade of the day occurring at the ask rather than the bid. We calculated, for each stock, the frequency at which the closing price was (a) equal to or below the closing bid, (b) equal to or above the closing ask, (c) not at the closing bid or the ask. For all stocks, corresponding figures are 21.15%, 31.29%, and 47.56%. Thus, the phenomenon noted by Harris over a decade ago is still present at the close.

[13] See, e.g., Madhavan and Sofianos (1997).

[14] We also regressed the return from 3:55 to 4:00 p.m. on the return from 3:30-3:55 p.m. individually for all 769 stocks in the sample. Some negative autocorrelation is present but is not economically significant.

4.2.2. Discussion

To better understand these results, note that the slope coefficient in the regressions estimated above is $\beta = \frac{\rho_{d,c}\sigma_r}{\sigma_c}$, where (suppressing subscripts for notational ease) $\rho_{d,c}$ denotes the correlation between the *whole* day's return (for either the stock or portfolio) and the appropriate closing period return, σ_r is the standard deviation of the whole day's return, and σ_c is the standard deviation of the closing return. The regression R-square reported in Tables 2 and 3 is simply $\rho_{d,c}^2$. We can write $\rho_{d,c} = (1+\rho)$, where ρ is the correlation between returns in the first and second parts of the day. Thus, higher values of β can result from higher correlations between the day's return and the closing return $\rho_{d,c}$ in portfolios. Why is the R-squared higher in portfolios? Obviously, the autocorrelation between daily returns and the close is higher in portfolios. One possibility is that this represents non-synchronous trading. If our mid-quotes are based on stale prices, portfolio returns will exhibit spurious autocorrelation, possibly explaining the higher β in portfolio regressions. However, as shown in Figure 1, the effects are concentrated in Decile 10, containing the most active stocks, so this explanation appears unlikely, although we cannot rule it out completely.

An alternative explanation, one that we favor, is that the results are driven by a common factor – specifically, institutional trading towards the close that is correlated positively with the return in the market that day. Anecdotal evidence indicates that institutions often concentrate their trades in the largest stocks, which is consistent with our evidence. Without more detailed data on institutional trading, we cannot conclusively verify this conjecture, but it remains the most likely explanation for our findings. This is an interesting topic for future research.

5. Order Flow and Returns at the Close

5.1. The Composition of Trading Volume

The previous section demonstrates that the closing period return is important. Our theoretical hypotheses suggest that the observed return behavior may reflect the effects of a common factor in order flows at the close, perhaps arising from institutional trading. Accordingly, we begin our analysis by asking if there is evidence of a change in institutional trading at the end of the day.

Figure 3 plots the average daily block-trading volume as a percentage of total trading volume (where a block is defined as 10,000 or more shares), the average daily block-trading volume 30 minutes before closing as a percentage of total trading volume 30 minutes before closing, and the average daily trading volume 5 minutes before closing as a percentage of total trading volume 5 minutes before closing. Overall, the volume of trading done in blocks was 31.3% of total trading.[15]

Two new findings are apparent from the figure. First, more active stocks tend to have a larger fraction of volume in large-block trades in all time periods. This is perhaps not surprising because liquidity is greatest in the most active stocks. Second, the frequency of block trading diminishes uniformly towards the close. For all stocks, the percentage of block volume in the last half-hour is 19.6% and just 10.8% in the last five minutes of trading. These results are consistent with a high demand for immediacy at day-end from institutional traders seeking to trade at or near the closing price. Specifically, many large-block trades (which typically are initiated by institutional traders) originate in the so-called “upstairs” market where block brokers facilitate large trades by locating counterparties.[16] This process takes time and consequently institutional traders seeking immediacy might seek to trade in the regular “downstairs” markets rather than run the risk of failing to execute because of the difficulty in locating counterparties is towards the end of the day. To investigate the impact of the high demand for immediacy at day-end on returns, we turn now to a more formal analysis of trading at the close.

5.2. A Model of the Returns Generating Process

In the classical model of an efficient security market, prices move in response to new public information that causes traders to simultaneously revise their beliefs. The process of trading itself may generate price movements because of frictions such as inventory control by market makers or because order flow is motivated by private information. Madhavan,

[15] The fraction of large-block volume to total volume for all NYSE stocks was 50.9% in 1998.
[16] See Keim and Madhavan (1996).

Richardson, and Roomans (1997) show that price movements reflect both public information and order flows.

To investigate the effects of order flow on closing returns, we propose a trading model where prices respond to public information flows and to net order flows. Specifically, we model the open-to-close return $r_{i,t}$ as

$$r_{i,t} = \mu + \lambda_{nb}\, x_{i,t}^{nb} + \lambda_b\, x_{i,t}^{b} + \theta_{nb}\, z_{i,t}^{nb} + \theta_b\, z_{i,t}^{b} + \eta_{i,t}\,, \tag{7}$$

where $x_{i,t}^{nb}$ is the signed non-block order flow from the opening to 3:30 p.m. (expressed as a percentage of average daily volume in stock *i*), $x_{i,t}^{b}$ is the corresponding signed block order flow in the period prior to 3:30 p.m., $z_{i,t}^{nb}$ is the signed non-block order flow (as a percentage of average daily volume in stock *i*) from 3:30 p.m. to the close, $z_{i,t}^{b}$ is the signed block volume in the period from 3:30 p.m. to the close, λ_{nb} , λ_b , θ_{nb} and θ_b are *order flow sensitivities* that capture the price impacts of non-block and block volume in the period prior to and during the last half-hour of trading, μ is the intercept, and $\eta_{i,t}$ captures the revision in share prices associated with public information flows unrelated to net order flow. For notational convenience, we suppress the subscript *i* on the coefficients μ , λ_{nb} , λ_b , θ_{nb} and θ_b which are estimated on a stock-by-stock or portfolio basis.

Two questions are of interest given our theoretical discussion. First, is the reaction of prices to block and non-block order flows similar? Our model suggests that anomalous day-end returns can be explained by a greater demand for immediacy. The summary statistics presented in Section 5.1 above suggest such a shift among institutional traders, but for this to have an effect on returns, the responsiveness of prices to block and non-block flows should be different.

The second question of interest is whether there are differences in the responsiveness of stock prices to order flow (both block and non-block) at different times of the day. Our argument of a common factor arising from institutional trading suggests that the responsiveness of prices to order flows is larger at the day's end. Why? A common factor in institutional trading implies that market maker inventories will move in the same direction across a wide range of stocks at the day's end. This might induce a larger price impact at the close because risk averse market makers demand a premium to carry large inventories overnight. There might also be information revealed by order flows if these anticipate future flows or imbalances.

Thus, the null hypotheses to be tested are

$$H_0^A: \quad \lambda_{nb} = \lambda_b = \theta_{nb} = \theta_b \ , \tag{8}$$

$$H_0^B: \quad \lambda_{nb} = \theta_{nb} \text{ and } \lambda_b = \theta_b \ . \tag{9}$$

Table 2 reports the results of estimation of the regression model (7) with order flow variables for individual regressions for all 769 stocks in the sample. We report for all stocks and for dollar volume deciles, the average coefficient estimate, the average t-ratios, and the average adjusted R-squared. The model performs very well; the coefficient estimates on volume are of the predicted positive sign and significance levels are generally high.

Several interesting points are worth noting. First, observe that the coefficients on non-block volume are much larger in magnitude than the corresponding coefficients on block volume. For the average stock, the coefficient on non-block volume is 7.57 in the time before the last half-hour but the corresponding coefficient on block volume is only 0.78. This is consistent with the hypotheses advanced in previous work that large-block trades have lower price impacts because they originate in the upstairs markets. This finding is consistent with the hypothesis that a common factor, manifested in greater demand for immediacy at the close, can explain the importance of closing period returns documented in the previous section.

Second, the average sensitivities to block and non-block order flow are *higher* in the closing period than in the rest of the day. The coefficients on non-block and block volumes at the close are 10.29 and 2.24, respectively, as opposed to 7.57 and 0.78 in the period prior to 3:30. Third, there is a general tendency for the order flow sensitivities to increase with trading activity deciles, as does the adjusted R-square. We would expect the order flow sensitivities to be greater for more thinly traded stocks where adverse selection might be more of a problem. However, we know from other research (Keim and Madhavan, 1997) that there are systematic differences in order flow sensitivities across auction and dealer markets. Indeed, as shown in Table 1, the fraction of listed stocks is far from monotonic in trading activity, with the highest activity decile having the lowest fraction of listed stocks. This factor might explain the seemingly anomalous pattern in coefficient estimates.[17]

Table 3 contains the details of the tests of the null hypotheses concerning block and non-block order flow, for all stocks and for dollar trading volume decile. Each cell in the table re-

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[17] It may also reflect other factors such as variation in float and market capitalization.

ports the average F-value for a test of the appropriate null hypothesis and (in parentheses) the percentage of stocks in that cell for which the F-test was statistically significant at the 1-percent significance level. The results confirm the intuition from the previous table. In particular, in 93.37% of stocks, we can reject (at the 1% significance level) the null hypothesis that the composition of order flow does not matter. This is not surprising given the differences between block trades in upstairs and downstairs markets. More interesting are the results of the tests on whether the order flow sensitivities for the volume components are constant across periods. The results here are weaker, and over all stocks we reject the null in 13.65% of cases. However, the significance levels are higher in more active deciles. Indeed, in the most active decile, the percentage of stocks for which the *F*-test rejects the null hypothesis of equal sensitivities across periods is 35.07%. It is worth noting that these results are not driven by autocorrelation in order flow, which although positive, is weak for both the block and non-block components.

Our results suggest that the closing return phenomena described in the previous section can be explained by: (a) A shift downward in the percentage of large-block trades at the end of the day, consistent with a greater demand for immediacy by institutions unwilling to bear the delays associated with upstairs intermediation, (b) Higher sensitivity of prices to *non*-block order flow relative to block order flow, and (c) A higher sensitivity of prices to *non-block* order flow at the close relative to other times of the day. Thus, the end of day return “anomalies” have a partial explanation in terms of the demand for immediacy and the sensitivity of returns to order flows.

We now turn to the consequences of large order imbalances at the close. We investigate this question using our data on MOC imbalances.

6. Evidence on MOC Imbalances

6.1. Characteristics of MOC Imbalances

We essentially have two distinct data sets, the Imbalance Publications (IPs) prior to and those on or after the rule change of June 24, 1998. Since our study ends in July 1998, we focus on the pre-rule change set. As our focus is on the impact of liquidity trading, we treat index expiration days as a separate population, because imbalances associated with expirations are almost surely liquidity-driven.

Given the absence of formal investigations of MOC imbalances, it is useful to provide an overview of the data. The pre-rule change set contains 1,910 stock-date events, with much of the activity on expirations. Virtually all of the pre-June 24 are published on or after 3:50, again as the rules then required. Most of the stocks in this set are blue chip, and certain names, such as RD and WMT, appear with higher frequency. There is a clear tendency for the frequency of imbalance indications to increase with trading volume. This is interesting since it suggests that the largest and most active stocks are those with the most severe problems at the close, perhaps because those stocks are the ones where institutional trading interest is concentrated.

To assess the relative importance of imbalance indications, we computed the size of disclosed imbalances relative to average daily volume in the stock over the entire sample of imbalances. There are 1,126 buy imbalances (there may be more than one publicized imbalance on a given day) with a mean ratio to average daily volume of 13.29% (the median is 4.30%) and 728 sell imbalances with a mean ratio of 10.59% (median of 5.49%). Thus, the publicized size of imbalances is relatively large compared to average daily volume and the distribution is strongly right-skewed indicative of some extreme observations.

6.2. Returns Following MOC Imbalance Publications

To understand the effectiveness of imbalance publications, we investigated the pattern of returns and volume following MOC imbalances focusing on the pre-June 24 period. Table 4 reports statistics on returns following market-on-close (MOC) imbalance indications. Two returns are reported: (a) close to next-day open returns, and (b) next-day open to close returns, all in percent. We report statistics separately for MOC buy and sell imbalance indications and for index expiration and non-expiration related imbalances. Figures in parentheses are *t*-values for a test of the null hypothesis that the statistic in question is zero.

Focusing first on expiration related imbalances, there is clear evidence that closing prices reflect temporary price pressure that is reversed in subsequent trading. For example, on days following *sell* imbalances, returns both overnight and in the next day are *positive* and significantly different from zero. For *buy* imbalances, there is an opposite effect, with next day overnight and daily returns significantly *negative*. Since expiration related imbalances are unlikely to reflect fundamental information, the conclusion that emerges is that temporary liquidity effects bias closing prices. Turning now to non-expiration related imbalance publications, we see the same pattern returns consistent with temporary pressure at the close that is reversed in subsequent trading. However, only the returns following sell imbalances are significant. This is consistent with Wall Street lore where sellers often seek to “get out” at any price whereas buyers are more cautious.

6.3. Interpretation of Results

The results above are interesting but require some caution in their interpretation. Our finding that next day open to close returns are positive (negative) following sell (buy) imbalances merits further comment. One explanation for the documented return behavior on the next day after the imbalance is that it simply reflects negative autocorrelation in order flow. However, our evidence suggests otherwise. Rather, we believe that this pattern can be explained by the fact that closing prices over-react to order imbalances and that the opening price the next day is biased towards the previous day’s close as shown by Madhavan and Panchapagesan (1999).

Of course, our findings do not mean that imbalance publications are ineffective – rather, it suggests that they are not entirely successful in eliminating temporary price pressure. For exchange officials and regulators concerned with excess volatility, these results suggest that imbalance publications be supplemented with other measures or that they be modified to increase their effectiveness. This could be achieved in several ways. For example, exchanges could hold closing call auctions in stocks with large imbalance publications. Alternatively, imbalance publication times might be made earlier (or the closing period extended) for stocks experiencing difficulties. Finally, steps could be taken to enhance the transparency of markets by publicizing imbalances more widely. In any event, our results show that closing prices are biased by non-informative order flows.

7. Conclusions

Institutional traders place enormous importance on closing stock prices as benchmarks of value. Closing prices are used to calculate portfolio returns, tally the net asset values of mutual funds, and as a basis for certain types contracts and for after-hours trading. This paper analyzes empirically the behavior of stock returns at the close across the stocks of the Russell 1000.

Consistent with anecdotal evidence, we demonstrate that the closing period accounts for a disproportionate fraction of a stock’s daily return. The effect is significantly stronger in portfolios where almost 18% of the variation in daily returns is explained by the return in the last five minutes of trading, despite the fact that this period only accounts for 1.3% of the trading day. This result is consistent with the hypothesis that institutional trading interest induces a common component to stock returns at the day end. We find that the ratio of volume in large-block trades to total volume falls sharply in the last five minutes of the day, consistent with higher demand for immediacy by institutional traders. This shift partly explains the closing return phenomenon because prices are more responsive to non-block order flows. Compounding this effect, we also show that the sensitivity of returns to order flow is greater in the closing period. Additional evidence that the demand for immediacy can explain the sharp price movements at the end of the day comes from our analysis of new data on market-on-close order imbalance publications. We find systematic return reversals, especially on days related to index expirations.

Our analysis has several implications for practitioners and academics. First, the results support the view that end of day return anomalies may be explained in terms of concentrated trading at the close together with changes in the composition of volume. Second, the evidence presented suggests that institutional trading is correlated across stocks towards the day's end and that this may explain some of the observed return phenomena. Third, closing prices are affected by transitory order imbalances associated with index expirations.

Given these results, it is natural to ask how we can reduce the volatility induced by transitory order flows and improve price efficiency at the close. One possibility is to disseminate information on order flows at the close in a more timely manner, in greater detail, and to a wider audience. Greater transparency might attract counterparties to take the opposite side of order imbalances, while simultaneously serving to alert potential traders that their orders may be executed at substantial premiums over previous trades. A more radical approach is to adopt special trading protocols at the close, for example, by replacing the current continuous trading with a formal closing call auction. Indeed, many other exchanges (e.g., the Paris Bourse) have implemented special closing procedures for exactly this reason. For NYSE stocks, a closing call can be modeled on the opening protocols at the NYSE. For Nasdaq stocks, the integration of a call market into the dealer structure is more difficult. The OptiMark™ system that Nasdaq plans to use to open trading could also be used as a closing mechanism as well. Given the growing concern over price volatility at the close, a more detailed investigation of these and other options will undoubtedly prove to be valuable.

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Table 1
Descriptive Statistics

The table provides summary statistics based on daily trading data from July 1, 1997 to June 30, 1998 for 769 stocks in the Russell 1000 index. We restrict attention to common stocks that were continuously in the index, traded at least once per day, and for which trades and quotes could be matched using TAQ data. For each of 769 sample stocks, we first compute the mean statistic of interest and then compute the average values of these statistics across stocks for each decile of average daily dollar trading volume and for the entire sample. The table reports the mean dollar trading volume (millions), mean opening price, mean bid-ask spread (computed at as a percentage of the midquote using 3 p.m. quotes), the percentage of stocks in the S&P 500 index, and the percentage of stocks listed on the NYSE or AMEX.

Dollar Trading Volume Decile	Daily Trading Volume ($ million)	Average Stock Price	Percentage Bid-Ask Spread	Percentage in the S&P 500 Index	Percentage Exchange-Listed
All Stocks	**0.80**	**48.91**	**0.34**	**56.44**	**84.53**
1 (Low)	0.07	53.12	0.44	11.84	92.11
2	0.14	49.89	0.39	29.87	87.01
3	0.20	45.92	0.35	38.96	97.40
4	0.26	49.93	0.36	50.65	80.52
5	0.33	42.67	0.39	63.64	85.71
6	0.42	49.59	0.34	64.94	89.61
7	0.57	47.45	0.33	75.33	88.31
8	0.86	46.83	0.31	71.43	80.52
9	1.37	50.59	0.27	72.73	81.82
10 (High)	3.77	53.18	0.24	84.42	62.34

Table 2
Regressions of Daily Returns on Block and Non-Block Order Flows

The table presents the results of 769 individual stock regressions of daily returns on block and non-block order flows. The regression model is specified as

$$r_{i,t} = \mu + \lambda_{nb}\, x_{i,t}^{nb} + \lambda_b\, x_{i,t}^{b} + \theta_{nb}\, z_{i,t}^{nb} + \theta_b\, z_{i,t}^{b} + \eta_{i,t}$$

where $x_{i,t}^{nb}$ is the signed non-block order flow from the opening to 3:30 p.m. (expressed as a percentage of average daily volume in stock i), $x_{i,t}^{b}$ is the corresponding signed block volume in the period prior to 3:30 p.m., $z_{i,t}^{nb}$ is the signed non-block order flow (as a percentage of average daily volume in stock i) from 3:30 p.m. to the close, $z_{i,t}^{b}$ is the signed block volume in the period from 3:30 p.m. to the close, λ_{nb} , λ_b , θ_{nb} and θ_b capture the price impacts of non-block and block volume in the period prior to and during the last half-hour of trading, μ is the intercept, and $\eta_{i,t}$ is the error term. Volume data are obtained from the TAQ database and signed using the procedure of Lee and Ready (1991). The table reports the average coefficient estimate, the average t-statistics for each coefficient, and the average adjusted R-squared for stocks within each trading volume decile and all stocks.

Dollar Trading Volume Decile	μ	**T**μ	λ_{nb}	**T**λ_{nb}	λ_b	**T**λ_b	θ_{nb}	**T**θ_{nb}	θ_b	**T**θ_b	Adjusted R Square
All Stocks	**-0.24**	**-1.82**	**7.57**	**7.00**	**0.78**	**1.41**	**10.29**	**2.30**	**2.24**	**0.85**	**24.24**
1	-0.03	-0.21	2.22	5.20	0.10	0.37	2.32	1.57	0.84	0.54	13.30
2	-0.05	-0.33	3.65	6.21	0.19	0.79	3.43	1.73	0.67	0.52	17.08
3	-0.11	-0.98	4.27	6.11	0.29	1.11	3.98	1.61	0.86	0.77	18.35
4	-0.14	-1.25	5.37	7.06	0.31	1.01	5.86	2.02	0.71	0.59	22.40
5	-0.13	-1.05	6.20	6.70	0.42	1.23	7.56	2.19	0.98	0.55	21.05
6	-0.17	-1.48	7.42	7.61	0.61	1.69	8.47	2.26	1.29	0.88	25.36
7	-0.28	-2.25	8.71	7.50	0.67	1.73	11.52	2.61	1.73	0.85	26.43
8	-0.35	-2.58	11.48	8.27	1.19	2.23	14.68	2.69	2.42	0.81	30.65
9	-0.54	-4.09	12.81	8.19	1.03	1.61	18.17	2.99	4.24	1.43	34.03
10	-0.55	-3.98	13.48	7.18	3.04	2.26	26.77	3.30	8.67	1.57	33.58

Table 3
***F*-tests on the Coefficients in the Regressions of Daily Returns on Order Flows**

The table provides summary statistics on individual stock *F*-tests on the estimated coefficients from regressions of daily returns on order flows in the previous panel. The two null hypotheses tested are:

$$H_0^A: \quad \lambda_{nb} = \lambda_b = \theta_{nb} = \theta_b$$
$$H_0^B: \quad \lambda_{nb} = \theta_{nb} \text{ and } \lambda_b = \theta_b$$

Each cell reports the average *F*-value for a test of the appropriate null hypothesis and (in parentheses) the percentage of stocks in that cell for which the *F*-test is statistically significant at the 1-percent significance level.

Dollar Trading Volume Decile	Mean Value of F_A	Percentage of F_A Significant at 1% Level	Mean Value of F_B	Percentage of F_B Significant at 1% Level
All Stocks	**14.96**	**93.37**	**2.51**	**13.65**
1	9.10	78.95	2.03	13.16
2	12.48	87.01	2.04	7.79
3	12.01	92.21	1.97	7.79
4	15.08	93.51	2.41	6.49
5	14.43	97.40	2.32	12.99
6	17.14	96.10	2.04	10.39
7	17.54	98.70	2.21	11.69
8	18.38	97.40	2.15	9.09
9	19.20	100.00	3.21	22.08
10	14.20	92.21	4.69	35.07

Table 4
Returns Following Market-On-Close Imbalance

The table reports statistics returns following market-on-close (MOC) imbalance indications. Two returns are reported: (a) close to next-day open returns, and (b) next-day open to close returns, all in percent. We report statistics separately for MOC buy and sell imbalance indications and for index expiration and non-expiration related imbalances. Figures in parentheses are t-values for a test of the null hypothesis that the statistic in question is zero.

	Sell Indications		**Buy Indications**	
	Expiration Related	**Non-Expiration Related**	**Expiration Related**	**Non-Expiration Related**
Return from Close to Next-Day Open	0.366 (3.616)	0.397 (3.970)	-0.150 (-2.441)	-0.053 (-1.227)
Next-Day Daily Return	0.824 (5.695)	0.355 (4.025)	-0.304 (-2.846)	-0.094 (-1.395)
Number of Observations	142	437	260	771

Figure 1
Coefficient of Determination From Regressions of Daily Returns on Returns in the Last Half-Hour

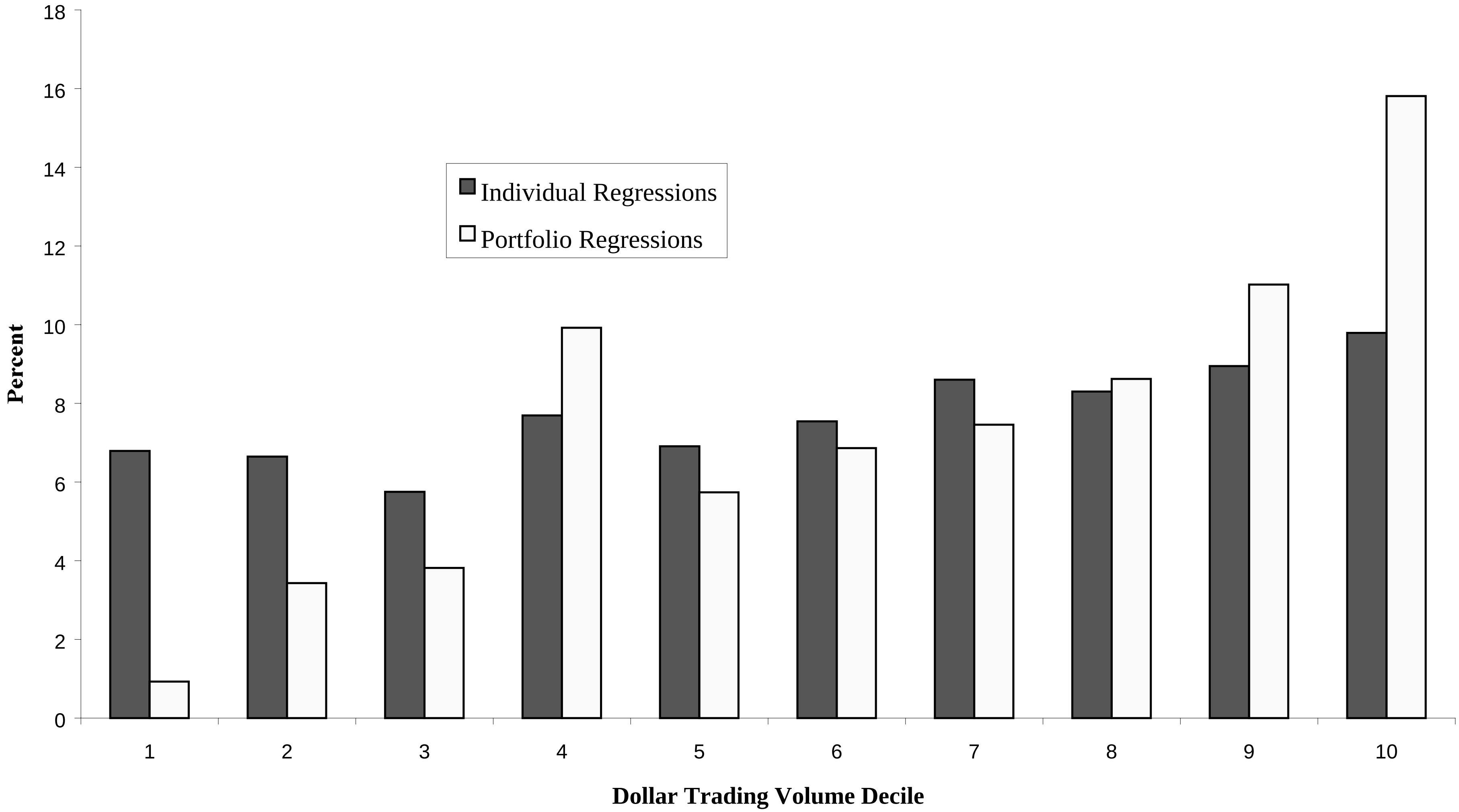

Figure 2
Coefficient of Determination from Regressions of Daily Returns on Returns in the Last Five Minutes

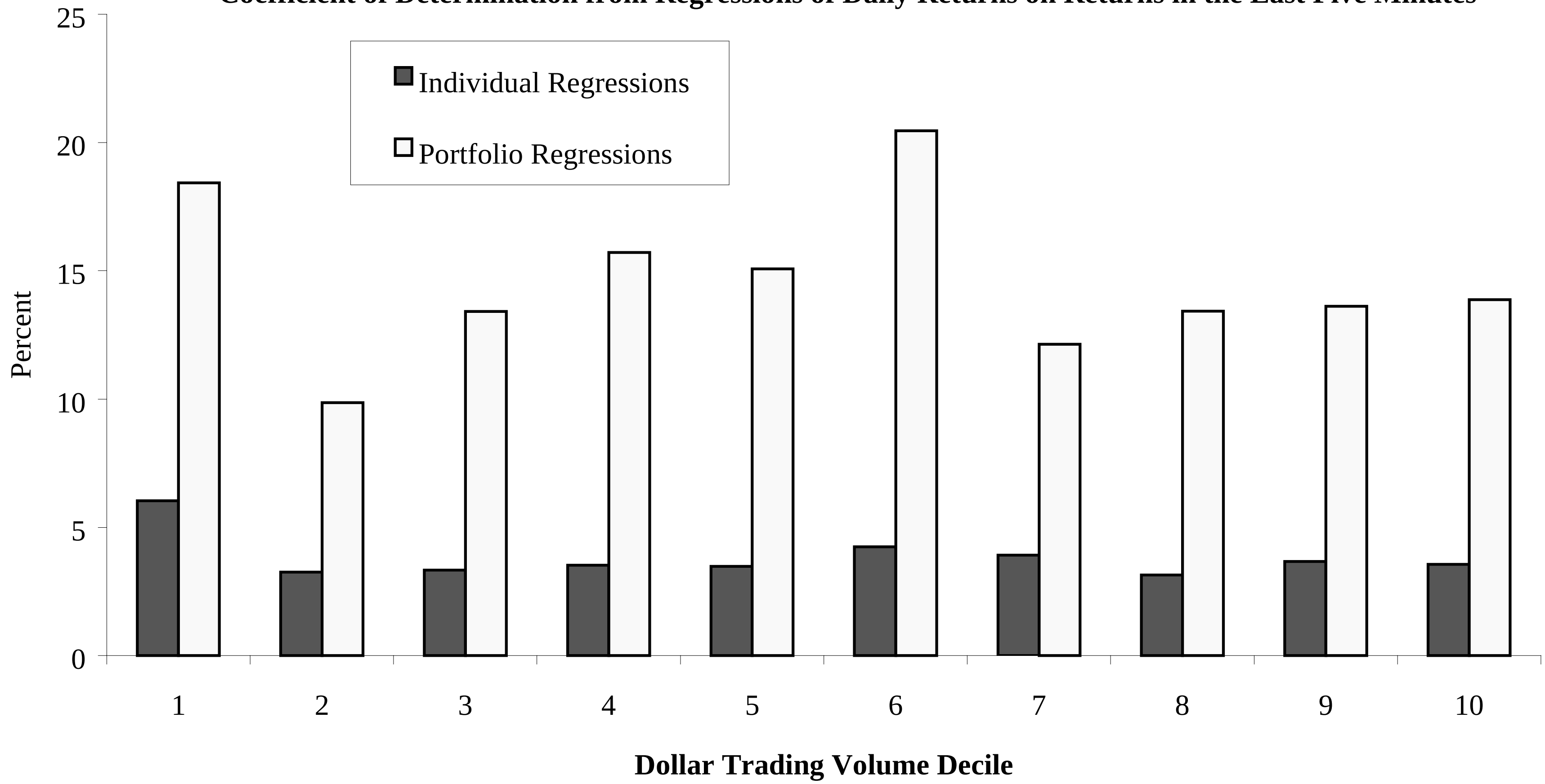

Figure 3
Percentage of Volume in Blocks by Time of Day