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HOW IMPORTANT ARE BLOCK TRADES IN THE PRICE DISCOVERY PROCESS?

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How Important Are Block Trades in the Price Discovery Process?

by

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Abstract

This paper develops a new technique for estimating the permanent component of block trade returns (i.e., that part potentially due to information revelation or long-term price pressure). For a sample of block trades from 1989, permanent block price changes appear to be economically important in that they account for a disproportionate share of the variation of daily stock prices. Evidence of potentially important "leakage" of block information in pre-block prices is also found.

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Statistically large price changes have been widely documented on block trades executed on the NYSE.[1] However, in assessing their economic importance the focus has been on price impact costs for large investors. This paper takes a different approach by trying to measure how important block trades are in the "price discovery" process. By this metric, block trades do indeed appear to be economically important in the sense that they account for a disproportionate share of the variation of daily stock prices.[2]

Thus the focus here is on so-called "permanent" rather than "temporary" block price changes (i.e., that part which contributes to daily returns). These permanent changes may reflect either information revelation or possibly interday price pressure.[3] For my purposes, however, the source of permanent block price changes is irrelevant.

Previous studies have used the following methodology to measure permanent block price changes: A sample of block trades is first sorted using a price tick classification rule into subsamples of uptick trades (sometimes interpreted as buyer-initiated), downtick trades (seller-initiated) and zero tick trades (crossed buy and sell orders).[4] The difference between the subsequent closing price (or other post-block price) and the previous trade price (or other pre-trade price) is then averaged for each tick subsample as a measure of the mean permanent component.

In this study the permanent component is instead measured by regressing a stock's daily return on the block return. The permanent block component is estimated via its correlation with the daily permanent return (of which it is part). No tick classification is needed although tick-sorted samples can be used if desired (since the block return is the explanatory variable). The slope coefficient in this regression is shown to be a downward biased estimate of the mean ratio of the permanent block return to the observed block return.

This regression approach has five advantages: First, the slope coefficient includes an estimate of that part of the full permanent block price change which may (for institutional reasons discussed below) already have been impounded in previous transaction prices. Second, it excludes permanent price changes from earlier and later in the day which are unrelated to (or more precisely uncorrelated with) the block. Third, the regression R^2 measures the economic importance of block trades in terms of the proportion of daily price variance they explain relative to *all* sources of price variation. This is a natural alternative to measures based on a block's price impact on investment returns. Fourth, there is no danger of misclassification of buys and sells. And fifth, it avoids a possible bias in tick-sorted samples due to the fact in uptick (downtick) samples the previous transaction is more likely to be at the bid (ask) thereby under (over) estimating the pre-block price level if the preceeding trade is used for this purpose.

The sample used here is panel data for the first 200 firms (in alphabetic ticker symbol order) satisfying certain selection criteria (discussed below). The sample period is the 1989 calender year. A block is taken here to be simply the largest trade on each day for a particular stock. This avoids any need to formulate an absolute definition of a "block" (e.g., number of shares, fraction of shares outstanding traded, etc.) which must be applied across different stocks. For each stock, the largest daily trades are then subdivided into two samples of above- and below-median blocks (i.e., above or below the median largest daily trade for the stock in question). OLS regressions are then estimated individually for each stock using its time series of daily and block returns. The distribution of various regression estimates across the different stocks are then reported.

For above-median blocks the estimated slope coefficients average .82 cross-sectionally (i.e., the mean permanent block return is 82 percent of the block return) with a maximum of 3.04 (or 304 percent). With regard to economic importance, the regression R^2s indicate that the block return explains an average of 5.6 percent (maximum of 46 percent) of the daily return variance on days with above-median blocks. This seems high given that the average time elapsed between block and previous trades ranges between 1 and 35 minutes.

The slope coefficients for below-median blocks are typically somewhat lower with an average of .57 (or 57% of the block return is permanent) and the corresponding average R^2 drops to 3.6 with a maximum of 25. At the other extreme of size, a cross-sectional regression pooling the 10 largest blocks for each of the 200 stocks has a slope coefficient of .95 and an R^2 of 11.5 percent.

The number of slope estimates close to or above 1 (i.e., the mean permanent block return equals or exceeds the block return itself) together with evidence of temporary block price pressure of around 20 percent of the block return suggests that for many individual stocks (and for "top 10" trades for all stocks) a significant portion of the permanent price impact of large blocks is already impounded in previous prices. This pre-block informational leakage - it is argued - can have important implications for empirical estimates of the price/trade-size relation (as in Glosten and Harris (1988) or Hasbrouck (1991)). In particular, it can reduce the apparent information (i.e., permanent) content of large relative to small trades.

This paper is organized as follows: Section 1 describes a regression-based technique for measuring permanent block price changes. Section 2 describes the data used to estimate these regressions. Section 3 reports and interprets the empirical estimates. Section 4 provides a short summary.

1. Measurement of Permanent Price Changes

This section explains how regressions of daily returns on block returns can be used to measure the permanent component of block price changes.[5] Estimates of the permanent component are of interest because they can be interpreted as indirect measures of information revelation (or long-term price pressure) and, as a practical investment issue, because they represent a price impact cost of block trading for large institutional investors. These estimates also have implications for the size of the temporary component of block trade price changes.[6]

For each day T with a block trade, the relevant price changes are defined using the closing trades on day T and day T-1, the block trade t, its previous transaction t-1, and a trade $t*$. The index $t*$ is a random variable equal to the index of the last trade executed at a price independent of information about the block trade t. The chronology of these trades is illustrated in Figure 1.

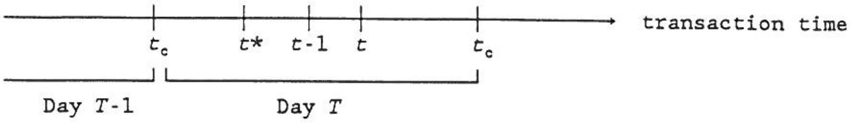

Figure 1
Chronology of trades.

The log price $ln[P_i(T,s)]$ observed on each trade s of firm i's stock on day T is assumed, as in Hasbrouck (1991), to consist of the sum of two stochastic processes

$$(1) \qquad ln[P_i(T,s)] = p_i(T,s) + \eta_i(T,s)$$

where $p_i(T,s)$ is the permanent price process and $\eta_i(T,s)$ is a temporary price process. Innovations in the permanent price $p_i(T,s)$ are assumed to be serially uncorrelated. The temporary process $\eta_i(T,s)$ is a mean-reverting process due to non-informational bid-ask spreads arising from inventory/immediacy/liquidity effects and market maker cost recovery and profit effects.

Using (1) the log return between a block trade t and the previous transaction t-1 is the sum of an innovation in the permanent price plus the change in the level of the temporary price process

$$(2) \qquad \begin{aligned} r_{ibT} &= ln[P_i(T,t)/P_i(T,t-1)] \\ &= [p_i(T,t) - p_i(T,t-1)] + [\eta_i(T,t) - \eta_i(T,t-1)]. \end{aligned}$$

The observed block return measures the permanent block return with two types of error. First, r_{ibT} includes the change in the level of the temporary process $\eta_i(T,t) - \eta_i(T,t-1)$. Second, unless $t* = t-1$ (i.e., the previous price is independent of the following block) the difference $p_i(T,t) - p_i(T,t-1)$ understates the full innovation in the permanent price process due to the block trade

$$(3) \qquad \Delta p_b = p_i(T,t) - p_i(T,t*).$$

Certain institutional features of the "upstairs" block market make it unlikely that $t^* = t-1$. In particular, the previous transaction price will not be independent of information about a subsequent block if either (i) knowledge of the block becomes public before the block is officially crossed on the exchange floor (e.g., if the dealer "shops" the block) or (ii) the previous transaction is a limit order executed in advance of the block (thereby circumventing NYSE rule 127). Consequently, the difference $p_i(T,t) - p_i(T,t-1)$ implicit in the block return r_{ibT} may understate the block's full permanent price impact. This is referred to here as "informational leakage."

An equivalent way to write (2) is

$$(4) \qquad r_{ibT} = \begin{cases} [1 - \gamma_i(T,t) + \alpha_i(T,t)]\ \Delta p_b & \text{if } \Delta p_b \neq 0 \\ \eta_i(T,t) - \eta_i(T,t-1) & \text{otherwise} \end{cases}$$

where $\alpha_i(T,t)$ and $\gamma_i(T,t)$ are formally defined by

$$\alpha_i(T,t) = \frac{\eta_i(T,t) - \eta_i(T,t-1)}{\Delta p_b}$$

$$\gamma_i(T,t) = \frac{p_i(T,t-1) - p_i(T,t^*)}{\Delta p_b}.$$

The variable $\alpha_i(T,t)$ is the ratio of the temporary price change to the full permanent return associated with the block t. The variable $\gamma_i(T,t)$ is the proportion of the full permanent change Δp_b already impounded in the permanent price for the previous trade $p_i(T,t-1)$. Equation (4) is a convenient way of representing the fact that permanent and temporary price changes on block trades are likely to be correlated. For example, block sells which lead to a decrease in the permanent price are also likely to be executed at bid prices which reflect downward price pressure.

The ratio $\alpha_i(T,t)$ is treated here as one of the underlying random variables (rather than $\eta_i(T,t) - \eta_i(T,t-1)$ itself). The leakage ratio $\gamma_i(T,t)$ is also treated as a random variable with a probability distribution on [0,1]. Two cases are encompassed in the following analysis: first, $\alpha_i(T,t)$ and $\gamma_i(T,t)$ are constants and second, $\alpha_i(T,t)$, $\gamma_i(T,t)$ and Δp_b are independent random variables.

Daily returns can also be decomposed into permanent and temporary components

$$(5) \qquad r_{idT} = \ln[P_i(T,t_c)/P_i(T-1,t_c)] = \Delta p_1 + \Delta p_b + \Delta p_2 + \Delta\eta_T$$

where t_c is a closing trade and (in addition to Δp_b above)

$$\Delta p_1 = p_i(T,t*) - p_i(T-1,t_c)$$

$$\Delta p_2 = p_i(T,t_c) - p_i(T,t)$$

$$\Delta\eta_T = \eta_i(T,t_c) - \eta_i(T-1,t_c).$$

Under the assumption that Δp_1, Δp_b, Δp_2, $\Delta\eta_T$, α and γ are independent,[7] the linear projection of the daily return on the observed block return is

$$(6) \qquad \mathrm{LP}(r_{idT} : r_{ibT}) = a_0 + a_1 r_{ibT}$$

where

$$a_0 = \mathrm{E}(\Delta p_1) + \mathrm{E}(\Delta p_2) + \mathrm{E}(\Delta\eta_T) + [1 - a_1 \mathrm{E}(1-\gamma+\alpha)] \mathrm{E}(\Delta p_b)$$

$$a_1 = \cfrac{1}{\mathrm{E}(1-\gamma+\alpha) + \cfrac{\sigma^2(1-\gamma+\alpha)\mathrm{E}(\Delta p_b{}^2)}{\mathrm{E}(1-\gamma+\alpha)\sigma^2(\Delta p_b)}} .$$

If the usual assumptions for stochastic regressors are met,[8] the OLS coefficients $\hat{a}_0$ and $\hat{a}_1$ are consistent estimates of a_0 and a_1. The estimated slope coefficient $\hat{a}_1$ is of interest because a_1 is (from (6)) a downward biased estimate of the the expected ratio of the full permanent block price change Δp_b to the observed block return r_{ibT}. Using (4), (6) and Jensen's inequality

$$\text{(7)} \qquad \text{plim } \hat{a}_1 - a_1 \leq \frac{1}{E(1-\gamma+\alpha)} < E\left[\frac{1}{1-\gamma+\alpha}\right] - E\left[\frac{\Delta p_b}{r_{ibT}}\right]$$

where the equalities hold in the special case in which $\alpha_i(T,t)$ and $\gamma_i(T,t)$ are constants.

This regression-based approach has five advantages over the standard methodology for measuring permanent price changes (i.e., calculating mean price changes for tick-sorted samples). First, the slope coefficient $\hat{a}_{i1}$ includes an estimate of the portion of the permanent block price change already impounded in the previous price $P_i(T,t-1)$. Mean price changes between closing and previous transaction prices may underestimate the permanent component for this reason. Second, permanent price changes Δp_1 and Δp_2 from earlier and later in the day (unrelated to the block trade) are excluded. Mean price changes calculated from closing prices incorrectly include these price effects. Third, the regression R^2, as the proportion of daily variance explained by the observed block return, is a natural metric for economic importance of block trading in the daily price discovery process. Fourth, there is no danger of misclassification of buys and sells. And fifth, because there is no need to sign blocks as "buys" or "sells" it thereby avoids a possible bias that in uptick (downtick) samples the previous transaction is more likely to be at the bid (ask) thereby causing the previous trade price $P_i(T,t-1)$ to under (over) estimate the pre-block permanent price level.

A potential econometric problem with this approach is spurious correlation which can arise if some blocks are traded in reaction to (or are triggered by) old information already reflected in pre-block prices. For example, stop-loss, portfolio insurance and filter rule trading strategies can lead to "reactive" trades.[9] Under these conditions, even if the block return is entirely temporary, it would still (given its correlation with the triggering pre-block return) appear to have explanatory power.

Thus, there is an identification problem in determining whether prior returns cause blocks or whether (due to the institutional reasons alluded to earlier) impending blocks (partially) cause prior returns. One check for spurious correlation pursued in Section 3 is to test whether block returns retain explanatory power when the pre-block return itself is included as a second explanatory variable in the regression.

2. The Data

The data used in this paper are panel data consisting of a time series of transaction prices for a cross-section of stocks which traded in 1989. The data were obtained from the Institute for the Study of Security Markets (ISSM) at Memphis State University.

Block trades are defined separately for each stock as the largest daily trade on each trading day of that stock. Defining blocks relative to a stock's own trading history avoids (as Holthausen, Leftwich and Mayers (1990) note) comparisons *across* firms and thereby avoids complications due to differences in "normal" trade size (which may differ substantially between say Alcoa and Alaska Air). One possible problem with this admittedly *ad hoc* rule is that economically large blocks (as opposed to routine "vanilla" blocks) may not occur every day. Thus the block sample is further divided into two subsamples of "above-median" and "below-median" blocks (i.e., using the median largest daily trades for the stock in question).

The sample studied here was formed by processing the 1992 ISSM tape sequentially in alphabetic ticker symbol order until 200 "common stocks" (as opposed to say preferred stock or warrants) were found each of which had at least 101 days with a largest daily trade or block[10] satisfying the following criteria.

1. *Low price screens*: The previous closing price, the price on the trade preceding the block and the block price were all at least \$5.
2. *Data entry error screens*: The absolute value of the dollar differences between the prices of (i) the previous close $P_i(T-1, t_c)$ and the trade before the block $P_i(T, t-1)$, (ii) the previous trade and the block $P_i(T, t)$, (iii) the block and the first post-block trade $P_i(T, t+1)$, (iv) the first and the second post-block trade $P_i(T, t+2)$ and (v) the second post-block trade and the closing trade $P_i(T, t_c)$ are all less than \$10.
3. *Temporary price reversal screen*: The closing price was at least 3 trades after the block.
4. *Market open screen*: The first and second trades of the day are ineligible as blocks.[11]

The resulting sample runs from Alcoa (AA) through Crown Cork (CCK).

Four returns were then calculated for each day included in the sample. The first is simply the "transactional" return r_{ibT} between the block t and the previous trade t-1 given in (2). The second is the daily return r_{idT} given in (5).

The third is the pre-block return up through the previous trade t-1 from the previous day's close

(8) $$r_{iprv,T} = ln[P_i(T, t-1)/P_i(T-1, t_c)].$$

The last is the post-block return from the block through the second trade after the block

(9) $$r_{ipost,T} = ln[P_i(T, t+2)/P_i(T, t)].$$

Holthausen, Leftwich and Mayers (1990) find no detectible further price reversion after trade $t+2$ (hence also screen 3 above). The temporary block price change $\eta_i(T,t) - \eta_i(T,t-1)$ should thus be negatively correlated with the post block return $r_{ipost,T}$.

3. Estimates of Permanent Price Change Components

This section reports estimates of the permanent component of block returns for the sample described in Section 2. For each of the 200 stocks a separate OLS regression corresponding to (6) is estimated using time series data for that stock. The distribution of these estimates across the 200 stocks is then reported. In the current version of this paper these cross-sectional distributions are simply suggestive of differences in block pricing between stocks. Work is currently in progress to test whether the observed dispersion represents genuine cross-sectional heterogeneity (and if so, is it related to factors like firm size?) or simply estimation error.

Table 1 reports the cross-sectional mean, median, minimum, maximum and inter-quartile range for the distribution of the individual firms' (i) market values of outstanding stock at the start of 1989, (ii) corresponding shares outstanding, (iii) total trades during 1989 and (iv) median number of shares in the largest daily trades for that stock. In addition, for each of the above- and below-median block subsamples, Table 1 also reports the distribution of the stocks' (i) median largest daily trade sizes in the subsample, (ii) median block prices, (iii) time elapsed between the block and previous trades and (iv) standard deviations of the daily return.

Noteworthy is that the mean time elapsed between blocks and previous trades is very short for most firms (about 11 minutes on average). Consequently, it is likely that information about impending block trades is already impounded in previous transaction prices. It is also likely that any public information (other than the execution of the block itself) arriving between t-1 and t is typically negligible. The market values of the 200 particular stocks studied here range from small ($1.9 million for Ati Med Inc.) to large ($1.9 billion for Amoco). Lastly, although not formally tested, the cross-sectional distribution of the daily return's standard deviations $s(r_{idT})$ for above-average blocks appears to lie to the right of the distribution for below-average blocks.

Table 2 reports the cross-sectional mean, median, minimum, maximum and inter-quartile range for the distribution of individual stocks' (i) coefficient estimates, (ii) White (1980) t-statistics[12] and (iii) adjusted R^2s from three different OLS regressions for the above-median blocks. Table 3 provides the analogous statistics for below-median blocks.

Panel A in Table 2 gives results from the regression

(10) $$r_{idT} = a_{i0} + a_{i1} r_{ibT} + e_{iT}.$$

Two features of these regressions are noteworthy. First, the R^2 statistics suggest that above-median blocks are indeed economically important in the sense that they account for a disproportionate share of the daily return variance. Although the (cross-sectional) median of the average time between blocks and previous trades is only 11 minutes, the R^2s in Table 2 average 5.6 percent with a maximum of 46.5 percent. Thus large blocks do appear to play a significant role in the price discovery process on days in which they occur.

The second noteworthy feature is that the estimated slopes $\hat{a}_{i1}$ for above-median blocks are also quite large. The cross-sectional average is .82

with over a quarter of the estimates being greater than 1 and with a maximum of 3.04. That is, the mean permanent block return is a a full 82 percent of the observed block return r_{ibT}. The reported $t_0(a_{i1})$ statistics allow the null ($H_0 : a_{i1} = 0$) to be rejected at the 5% level for over half of the sample.

The corresponding R^2s and slopes $\hat{a}_{i1}$ for below-median blocks in Table 3 are somewhat lower than for above-median blocks (although the difference is not statistically significant for most individual firms).[13] The role of trade size is considered further at the end of this section.

A. **Informational Leakage.** From Section 1, the slope $\hat{a}_{i1}$ can be interpreted as a downward biased estimate of the expected proportion of the observed block return which is permanent. The reported slope estimates suggest that for a number of stocks the full permanent block returns may be close (or even larger in some cases) than the observed block returns. Indeed, over half of the reported $t_1(a_{i1})$ statistics (null $H_0 : a_{i1} = 1$) do not reject this possibility at the 5% level.

More interestingly, these slope estimates also provide indirect evidence that informational leakage (or alternately spurious correlation) is a significant factor in block pricing. Again from Section 1, there are two factors tending to make the slope a_{i1} be less than 1. The first is an errors-in-variable" term $\sigma^2(1-\gamma+\alpha)E(\Delta p_b{}^2)/E(1-\gamma+\alpha)\sigma^2(\Delta p_b)$ due to randomness in the ratios $\alpha_i(T,t)$ and $\gamma_i(T,t)$. The second is expected temporary price pressure $E[\alpha_i(T,t)]$. If both factors are present, then (in the context of the model in Section 1) a slope coefficient a_{i1} of 1 or more is possible only if the expected leakage ratio $E[\gamma_i(T,t)]$ is greater than 0 -- that is, if on average pre-block prices already re f lect some of the block's full permanent price innovation.

Although the magnitude of the errors-in-variable problem is hard to assess, it is clear from Panel C that most stocks (consistent with other studies' findings) have significant temporary price pressure on block trades. In particular, Panel C reports results from the regression

$$r_{ipost,T} = c_{i0} + c_{i1}r_{ibT} + e_{iT}. \tag{11}$$

The slope coefficient c_{i1} should be negative if the block return r_{ibT} includes temporary price pressure $\eta_i(T,t) - \eta_i(T,t\text{-}1)$ which is reversed in the post-block return $r_{ipost,T}$. The actual estimates $\hat{c}_{i1}$ average -.23 so that (in words) the reversed temporary price pressure averages 23 percent of the block return r_{ibT}.

Given then the prevalence of price pressure -- as well as the likely errors-in-variable bias -- pre-block informational leakage thus appears probable for many stocks.

Leakage of permanent block returns into previous prices has a number of empirical implications. First, large trades will appear less informative and small trades preceding large trades will appear more informative. Thus, in regressions of transactional price changes on trade size (e.g., Glosten and Harris (1988)), leakage biases the "trade sign" coefficient upward and biases the "signed volume" coefficient downward. Leakage (by diminishing the apparent informational content of price changes on large trades) can also lead to a concave estimated price/trade-size relation even if the true relation is linear. Lastly, it is also a possible explanation for the positive post-trade price impulse response (rather than negative as one would expect given temporary price reversion) to order flow innovations reported in Hasbrouck (1991).

B. The Identification Problem. As discussed in Section 1, high slope estimates $\hat{a}_{i1}$ are consistent with both informational leakage and with the alternate "spurious correlation from reactive block trading" hypothesis. These two hypotheses would seem, however, to have differing implications for the *partial* correlation between block returns r_{ibT} and daily returns r_{idT} after controlling for the daily return's correlation with the pre-block return $r_{iprv,T}$. If the slope estimates in Panel A overstate the permanent return of reactive blocks then the increase in R^2 for the Panel B regression

(12) $$r_{idT} = b_{i0} + b_{i1}r_{ibT} + b_{i2}r_{iprv,T} + e_{iT}$$

should be small when compared to the R^2 from an (unreported) regression[14]

(13) $$r_{idT} = d_{i0} + d_{i2}r_{iprv,T} + e_{iT}.$$

The ΔR^2 in Panel B is this change in the adjusted R^2 due to the addition of the block return as an explanatory variable. In general the ΔR^2s in Panel B are comparable to the R^2 in Panel A for both above- and below-median blocks. Further, at least half of the $t_0(b_{i1})$ statistics are greater than 2 in each sample suggesting that the ΔR^2s are statistically large as well. Thus, the partial correlation evidence appears to be more consistent with the informational leakage than the "reactive" block hypothesis.

C. "Top 10" Trades and the Role of Block Size. A natural conjecture is that "larger" blocks are informationally more important (reveal more information) than "smaller" blocks. Larger blocks may also be "shopped" more intensively leading to possibly greater pre-block informational leakage.

The comparison between above- and below-median blocks was one attempt to address these issues. As a second pass the three regressions discussed above were reestimated using a pooled cross-sectional sample of the "top 10" largest trades for each of the 200 stocks. The estimated regressions were:

(14a) $$r_{idT} = .003 + .947\, r_{ibT} + e_{iT}$$
$$\quad\ (3.85)\quad (8.42)$$

$$\text{Adj. } R^2 = .115$$

(14b) $$r_{idT} = .003 + .796\, r_{ibT} + .919\, r_{iprv,T} + e_{iT}$$
$$\quad\ (8.25)\quad (10.13)\quad (26.66)$$

$$\text{Adj. } R^2 = .736, \quad \Delta R^2 = .081$$

(14c) $$r_{ipost,T} = .0007 - .235\, r_{ibT} + e_{iT}$$
$$\quad\ (3.45)\quad (-4.36)$$

$$\text{Adj. } R^2 = .140$$

Briefly, the results (when compared with Tables 2 or 3) seem consistent with our conjectures. From (14a) the return on just these very large "top 10" blocks explains a full 11.5 percent of the daily return on days on which they occurred. The partial correlation from (14b) still does not support a spurious correlation interpretation of (14a). Lastly, the estimated mean permanent price change of 94.7 percent of the block return (from (14a)) together with continued temporary block price pressure of around 23 percent of block return (from (14c) and unchanged from Table 2) suggest significant pre-block leakage precedes the crossing of these blocks on the exchange floor.

4. Summary

This paper examines the empirical importance of block trading in the price discovery process based on estimates of the permanent component of block returns. Using a new regression-based technique I found that block trades account for a disproportionate share of daily price changes. In addition, the regressions suggest that leakage of permanent block returns into pre-block prices occurs for a number of stocks in the sample. This informational leakage can have important consequences for empirical estimates of the price/trade-size relation including inducing apparent non-linearities.

Endnotes

1 See Kraus and Stoll (1972) and Holthausen, Leftwich and Mayers (1987,1990).

2 Clearly blocks are an important part of the transactions process *per se* since in recent years roughly half of the NYSE trading volume was in blocks of over 10,000 shares. See NYSE *Fact Book 1991*.

3 The linkage between information and prices via orders, referred to here as "information revelation," was initially proposed by Scholes (1972). See Easley and O'Hara (1987), Gammill (1985) and Seppi (1990) for formal models of information revelation through block trading. The term "price pressure" is often restricted to mean short-term price inducements paid to market makers for providing liquidity. However, absent explicit links between block prices and fundamental information, the possibility of inter-day price adjustments can not be ruled out *a priori*. See Seppi (1992) for evidence of information revelation about unexpected quarterly earnings.

4 A tick rule classifies trades in terms of the difference between the block price and the previous transaction price. See Kraus and Stoll (1972) and Holthausen, Leftwich and Mayers (1987) for evidence supporting the buy/sell/cross interpretation of this classification for large trades.

5 An early version of this analysis can be found in Seppi (1988) along with some limited empirical analysis for blocks around quarterly earnings announcements.

6 See Dann, Mayers and Raab (1977) and Holthausen, Leftwich and Mayers (1990) for evidence on how long temporary price pressure persists and whether there are implementable trading strategies exploiting post-block price reversals which are profitable.

7 The assumption that α and $\Delta\eta_T$ are independent can be justified by evidence in Dann, Mayers and Raab (1977) and Holthausen, Leftwich and Mayers (1990) that the speed of adjustment of the temporary price process is rapid.

8 The sample estimates of $E(\alpha)$, $E(\gamma)$, $\sigma^2(1-\gamma+\alpha)$, $E(\Delta p_b)$, $\sigma^2(\Delta p_b)$ and $cov[\Delta p_1+\Delta p_2+\Delta\eta_T,\ (1-\gamma+\alpha)\Delta p_b]$ must converge to their true values $E(\alpha)$, $E(\gamma)$, $\sigma^2(1-\gamma+\alpha)$, $E(\Delta p_b)$, $\sigma^2(\Delta p_b)$ and 0.

9 Beebower and Priest (1980) find evidence that block trades are negatively correlated with past stock price residuals relative to the return on a portfolio of stocks with similar variance. Dependence of this sort would lead to a negative bias in the estimated slope coefficient.

10 A total of 8 trades of over 3.2 million shares each are omitted from the current sample. They will be included in the next version of this paper.

11 The NYSE market opening procedure can cause the the first trade of the day to be a large transaction "batching" multiple independent orders.

12 These t-statistics correct for heteroscedasticity without specific restrictions on its form.

13 To check whether the above- and below-median block differences are statistically significant, (10) was reestimated for each stock pooling both block sizes and including a slope dummy variable for above-median blocks

$$r_{idT} = a'_{i0} + a'_{i1} r_{ibT} + a'_{i2} r_{ibT} * D_{i\,above,T} + e_{iT}.$$

The average t-statistic for a'_{i2} was only .51. However, 21 stocks had t values of more than 2 and only 5 had t values of less than 2.

14 As can be inferred, the pre-block return explains a significant portion of the daily return. Although not surprising, this need not hold by construction since intraday return variance is lower when exchanges are closed (see French and Roll (1986)) and at midday (vs. at open/close - see Wood, McInish and Ord (1985)).

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Table 1
Cross-Sectional Sample Characteristics[a]

Variable	mean	min	Q1	median	Q3	max
1. Market Value ($ mil.)	192	2	20	59	191	1906
2. Shs. Outs. (mil.)	5.8	.3	1.3	3.0	7.4	47.8
3. No. Trades (000)	22	2	6	13	29	153
4. Median Vol. (100)	285	16	89	207	433	946
Above-median largest daily trades sample:						
5. Median Vol. (100)	326	20	100	250	500	1000
6. Median Price ($)	29.7	5.5	14.0	23.5	35.0	427.0
7. Ave. Time (sec.)	657	53	244	519	998	2073
8. $s(r_{idT})$	.022	.007	.015	.019	.026	.059
Below-median largest daily trades sample:						
9. Median Vol. (100)	100	5	22	66	150	500
10. Median Price ($)	30.4	5.4	13.8	22.8	35.4	489.0
11. Ave. Time (sec.)	875	62	281	628	1301	3426
12. $s(r_{idT})$	.015	.005	.011	.015	.018	.028

[a] The sample consists of the first 200 stocks satisfying the sample section criteria. The sample period is 1989. Market Value and Shs. Outs. are respectively the beginning of year value of each firm's outstanding stock and the number of shares. No. Trades is the total number of reported transactions for a stock during 1989. Median Vol. is the median shares in a stock's largest daily trades in each sample. Above- and below-median refer to its median in the full sample. Median price is the median block price for a firm's largest daily trades. Ave. Time is the average time between the block and the preceding transaction in seconds. $s(r_{idT})$ is the standard deviation of a stock's daily log return.

Table 2
Regression Results for Above-Median Largest Daily Trades[a]

Variable	mean	min	Q1	median	Q3	max
1. Sample size	100	44	90	106	115	121
A. Regression model: $r_{idT} = a_{i0} + a_{i1}r_{ibT} + e_{iT}$						
1. a_{i0}	.002	-.005	.001	.001	.003	.02
2. $t_0(a_{i0})$	.93	-2.27	.26	.98	1.59	3.61
3. a_{i1}	.82	-.30	.46	.78	1.07	3.04
4. $t_0(a_{i1})$	2.37	-.62	1.34	2.33	3.07	14.06
5. $t_1(a_{i1})$	-1.02	-25.56	-1.94	-.60	.17	4.77
6. R^2	.056	-.018	.011	.040	.084	.465
B. Regression model: $r_{idT} = b_{i0} + b_{i1}r_{ibT} + b_{i2}r_{iprv,T} + e_{iT}$						
1. b_{i0}	.002	-.002	.000	.001	.002	.02
2. $t_0(b_{i0})$	1.11	-1.85	.33	1.09	1.81	6.08
3. b_{i1}	.80	.07	.61	.79	1.03	1.68
4. $t_0(b_{i1})$	3.97	.18	2.86	3.88	4.94	8.96
5. $t_1(b_{i1})$	-1.22	-8.84	-2.14	-1.11	.16	1.84
6. b_{i2}	.96	.60	.89	.97	1.04	1.35
7. $t_0(b_{i2})$	12.67	3.61	9.30	11.56	13.78	80.63
8. R^2	.624	.339	.537	.634	.700	.958
9. ΔR^2	.069	-.008	.025	.049	.083	.319

Table 2 (cont)
Regression Results for Above-Median Largest Daily Trades[a]

Variable	mean	min	Q1	median	Q3	max
C. Regression model: $r_{ipost,T} = c_{i0} + c_{i1} r_{ibT} + e_{iT}$						
1. c_{i0}	.000	-.002	.000	.000	.001	.008
2. $t_0(c_{i0})$	.47	-3.37	-.47	.48	1.45	4.36
3. c_{i1}	-.23	-.88	-.31	-.22	-.14	.10
4. $t_0(c_{i1})$	-2.68	-8.73	-3.65	-2.57	-1.63	1.05
5. R^2	.095	-.017	.022	.068	.129	.795

[a] The sample consists of the first 200 stocks satisfying the sample section criteria. The sample period is 1989. Above-median refers to the stocks' median largest daily trade in the full sample. The first subscript in the White (1980) t-statistic $t_n(x_{ij})$ refers to the null $(H_0: x_{ij} = n)$. All R^2s are adjusted R^2s. ΔR^2 refers to the difference between the regression R^2 in Panel B and the R^2 in an unreported regression omitting the block return r_{ibT}.

Table 3
Regression Results for Below-Median Largest Daily Trades[a]

Variable	mean	min	Q1	median	Q3	max
1. Sample size	99	35	89	105	115	121
A. Regression model: $r_{idT} = a_{i0} + a_{i1}r_{ibT} + e_{iT}$						
1. a_{i0}	.000	-.007	-.001	.000	.001	.004
2. $t_0(a_{i0})$	-.11	-2.81	-.85	-.14	.68	3.10
3. a_{i1}	.57	-.91	.25	.50	.89	2.37
4. $t_0(a_{i1})$	1.76	-1.71	.86	1.66	2.61	4.95
5. $t_1(a_{i1})$	-1.86	-11.55	-3.00	-1.49	-.37	2.40
6. R^2	.036	-.021	-.001	.019	.057	.249
B. Regression model: $r_{idT} = b_{i0} + b_{i1}r_{ibT} + b_{i2}r_{iprv,T} + e_{iT}$						
1. b_{i0}	.000	-.006	-.001	.000	.001	.009
2. $t_0(b_{i0})$	.18	-3.47	-.55	.21	.89	4.10
3. b_{i1}	.69	-.10	.49	.65	.90	1.64
4. $t_0(b_{i1})$	3.45	-.025	2.42	3.44	4.43	10.27
5. $t_1(b_{i1})$	-1.76	-7.82	-2.92	-1.53	-.47	1.04
6. b_{i2}	.92	.46	.85	.93	1.02	1.23
7. $t_0(b_{i2})$	11.26	1.23	8.54	10.74	13.85	22.02
8. R^2	.559	.109	.49	.565	.64	.815
9. ΔR^2	.059	-.016	.023	.044	.086	.289

Table 3 (cont)
Regression Results for Below-Median Largest Daily Trades[a]

Variable	mean	min	Q1	median	Q3	max
C. Regression model: $r_{ipost,T} = c_{i0} + c_{i1} r_{ibT} + e_{iT}$						
1. c_{i0}	.000	-.002	.000	.000	.000	.004
2. $t_0(c_{i0})$	-.10	-3.40	-.99	-.17	.76	3.56
3. c_{i1}	-.29	-.66	-.36	-.28	-.20	.09
4. $t_0(c_{i1})$	-3.00	-7.07	-3.86	-2.96	-2.03	.35
5. R^2	.095	-.024	.035	.077	.140	.490

[a] The sample consists of the first 200 stocks satisfying the sample section criteria. The sample period is 1989. Below-median refers to the stocks' median largest daily trade in the full sample. The first subscript in the White (1980) t-statistic $t_n(x_{ij})$ refers to the null ($H_0: x_{ij} = n$). All R^2s are adjusted R^2s. ΔR^2 refers to the difference between the regression R^2 in Panel B and the R^2 in an unreported regression omitting the block return r_{ibT}.

Hur viktig är handeln med stora aktieposter för prisbildningen?

Här utvecklas en ny teknik för skattning av den permanenta komponenten i avkastningen på handel med stora aktieposter (dvs. den del som potentiellt kunde bero på ny information eller långsiktigt pristryck). På basen av ett stickprov från 1989 kunde man dra slutsatsen att permanenta förändringar i priserna på stora poster är viktiga såtillvida, att de står för en oproportionerligt stor del av variationen i de dagliga aktiekurserna. Det finns också belägg för för att det "läcker" potentiellt viktigt information till priser noterade före den stora transaktionen.

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