Block Trading and Information Revelation around Quarterly Earnings Announcements

Duane J. Seppi
Carnegie Mellon University

I investigate the empirical importance of information revelation in the pricing of block trades. In particular, I examine whether block prices are correlated with the unexpected part of firms' quarterly earnings. For my sample of block trades, information revelation does indeed appear to be a significant factor shortly before earnings announcements.

Do block trade price changes reflect the revelation of investors' private information?[1] And if so, what role does trade size play? Answering such questions is complicated by the potential presence of a variety of "price pressure" effects. These include market-maker inventory control problems, intraday discounts or premiums compensating for execution "immediacy," and also possibly longer-lived adjustments due to changes in the price of risk or perhaps trading-induced fads.

This article is based on the third chapter of my dissertation from the University of Chicago. This research benefited greatly from the advice of my dissertation committee: Douglas Diamond (chairman), Robert Holthausen, Merton Miller, George Constantinides, Kenneth French, and Robert Vishny. I also thank Elizabeth Cammack, Richard Green, David Mayers, Konduru Sivaramakrishnan, Fallaw Sowell, Chester Spatt seminar participants at Yale and Carnegie Mellon, and particularly Michael Gibbons (the editor) and Michael Barclay (the referee) for many helpful suggestions. Address reprint requests to Duane Seppi, Graduate School of Industrial Administration, Carnegie Mellon University, Pittsburgh, PA 15213.

[1] The linkage between information and prices via orders, referred to here as "information revelation," was initially proposed by Scholes (1972). Formal models of information revelation through block trading can be found in Easley and O'Hara (1987). Gammill (1985), and Seppi (1990).

The Review of Financial Studies 1992 Volume 5, number 2, pp. 281-305

Beginning with Scholes (1972), previous attempts to distinguish information revelation from price pressure have decomposed block prices (and more recently transaction prices generally) into "permanent" and "transitory" components and then interpreted the "permanent" part as information revelation.[2] Unfortunately, the *intraday* (price) time-series properties of "permanent" price changes due to information revelation are observationally indistinguishable from those of *interday* noninformational price pressure. Thus, tests based on price data alone will have low power in distinguishing between these two hypotheses.

A more direct test of information revelation involves explicitly identifying variables about which blocks are informative. If block trades reveal private information about a variable, then (under fairly weak conditions) block price changes will be correlated with the (pre-block) unexpected component of that variable. In contrast, price pressure on liquidity-motivated trades will be uncorrelated with these surprises.

Using this idea, we investigate the extent to which block price changes around quarterly earnings announcements in 1982 are explained by unexpected earnings. As a proxy for unexpected earnings, we use forecast errors relative to the last *Value Line* forecast of earnings-per-share. The strongest evidence in support of information revelation is found in a sample of "large" blocks (over 0.5 percent of shares outstanding) traded between days -6 and -2 before a quarterly earnings announcement. Unexpected earnings explain between 4.6 and 19.8 percent of the variance of different measures of price change for these trades. The mean price increase is between 18 and 74 cents for each additional $1 of unforecasted earnings.

There is also evidence that information content is increasing in block size. For "small" blocks (between 0.1 and 0.3 percent of shares outstanding) the regression R^2*'s* drop to between 0.3 and 2 percent. The mean price increase falls to between 2 and 13 cents per dollar of unforecasted earnings. Block trades executed earlier in event time also have less earnings information content than do blocks closer to the announcement.

This article is organized as follows: In Section 1, a test of the link between block prices and private information is developed. In Section 2, the idea is illustrated in the context of a simple theoretical model. In Section 3, advantages and disadvantages of the proposed tests are considered. In Section 4, the earnings and block trade data are described. The empirical results are presented in Sections 5 and 6. A short summary is provided in Section 7.

[2] For block trades, see Kraus and Stoll (1972) and Holthausen, Leftwich, and Mayers (1987, 1990). For transactions in general, see Glosten and Harris (1988) and Hasbrouck (1991).

1. A Test of Information Revelation

In a noisy securities market with asymmetric information, the price $P_i(T, t)$ at which a block of shares in firm *i* trades at time *t* on day *T* depends in general on the signed size of the block $B_i(T, t)$ (i.e., where $B < 0$ for block sells). Block size is given in turn by a trading correspondence mapping an investor's private information and other noninformational reasons for trade into orders. If block size is increasing in good news and block prices are increasing in (signed) block size, then block prices will be increasing in good news.

This relation between information and block prices provides a simple and direct way to test for information revelation. In this study, quarterly earnings is our candidate information variable and scaled forecast errors,

$$\mathrm{FE}_{iT} = [\mathrm{EPS}_{iT} - \mathrm{FEPS}_{iT}]/P_i(T-1, t_c),$$

serve as our proxy for investors' private information, where EPS_{iT} is the next announced earnings-per-share after the block on day T, FEPS_{iT} is the preceding *Value Line* forecast (i.e., FEPS_{iT} is conditioned on a *preblock* information set), and $P_i(T-1, t_c)$ is the closing price from the day before the block.

Suppose both informed and uninformed investors trade blocks. Investors who are informed about earnings should buy (sell) at the ask (bid) when unexpected earnings are positive (negative). Hence, if the forecast error FE_{iT} is a good proxy for unexpected earnings, prices on informed investors' blocks should be positively correlated with FE_{iT}. Uninformed investors, however, trade blocks independently of unexpected earnings. Thus, even if uninformed blocks are ex ante indistinguishable from informed blocks (i.e., they face identical bid and ask quotes), the realized transaction prices on uninformed blocks will be uncorrelated with FE_{iT}. Pooling informed and uninformed trades, block prices and forecast errors should be positively correlated overall.[3]

This correlation can take a variety of functional forms. Block price changes and forecast errors are tested here for *sign consistency* using a χ^2-statistic[4] and for *monotonicity* using Spearman rank correlation. If the relation is linear (e.g., as in Section 2), we can estimate regressions:

[3] For other applications of this idea, see French, Leftwich, and Uhrig (1985), Ofer and Siegel (1987). and Pound (1986).

[4] Such a restriction arises in its starkest form in Easley and O'Hara (1987) and in Seppi (1990). Our test statistic is the sum $\sum_{i=1}^{4} (O_i - E_i)^2/E_i$, where O_i and E_i are the actual and the expected number of observations in a 2 × 2 sign contingency table for nonzero price changes and forecast errors. It is distributed χ^2 with 1 degree of freedom. See Daniel (1978), pages 163-169.

$$\frac{P_t(T, t) - P_t(T, t-1)}{P_t(T-1, t_c)} = a_0 + a_1 \mathrm{FE}_{tT} + e_{tT}, \tag{2}$$

where t - 1 is the index for the trade preceding block trade t. Price changes and forecast errors throughout this article are "weighted" by $P_t(T - 1, t_c)$ as a partial control for heteroskedasticity.

The slope coefficient a, gives the mean dollar price change per $1 of unforecasted earnings. The error e_{tT} includes, first, the price impact of any new public (nonearnings) information arriving between trades t - 1 and t; second, the price impact of "trading noise" if some blocks are liquidity motivated; third, measurement error since FE_{tT} proxies only imperfectly for actual private earnings information; and, fourth, any information revealed by blocks about variables uncorrelated with current earnings.

Positive correlation between block prices and forecast errors, while consistent with information revelation, should be interpreted cautiously, however, as evidence only that informed block trades were *executed.* The systematic execution of informed block sells at the bid and buys at the ask still induces positive correlation even if the bid-ask spread is *unchanging* over time (i.e., if the market is inefficient). In this case, although informed blocks are traded, no new information is *impounded* in postblock prices. Thus, we would like to distinguish between "correlation due to the execution of information-based trades" and "correlation due to the impounding of private information."

Given positive correlation in (2), we test if postblock prices reflect new earnings information in the following regression (and the corresponding nonparametric tests):[5]

$$\frac{P_t(T, t_c) - P_t(T, t-1)}{P_t(T-1, t_c)} = a_0' + a_1' \mathrm{FE}_{tT} + e_{tT}', \tag{3}$$

where $P_t(T, t_c)$ is the closing price on day T and t - 1 is the index of the trade preceding the block trade t. The dependent variable includes the "permanent" component, but excludes any intraday "temporary" component in the block price change.[6] If no new information is impounded in postblock prices, then (in the absence of other postblock public earningsnews, which would also be reflected in the closing price) the slope coefficient a'_1 should be zero.

The R^2 -statistics for regressions (2) and (3) have an interesting economic interpretation in that they measure how much of block

[5] This presupposes, of course, that the block trade t is not also the closing trade t_c. See note 18.

[6] Prices rebound from "temporary" price pressure on blocks within 15 minutes in Dann, Mayers, and Raab (1977) and within three trades in Holthausen, Leftwich, and Mayers (1990).

price variance is statistically related to current earnings information. Thus, they can be used to assess claims from some practitioners that block trading causes prices to be "too" volatile compared to the flow of information about firms' underlying cash flows. Of course, these R^2's are only a rough measure since (i) without an explicit model of market equilibrium it is not possible to test if the information content of block trades is *properly* impounded in stock prices; and (ii) current earnings are only one (albeit significant) piece of fundamental information.

2. A Simple Model

Equations (2) and (3) are "reduced-form" regressions in that their coefficients depend both on the correspondence between information and orders and on the relation between orders and prices. It may thus be useful to consider a simple model in which Equation (2) has an explicit "structural" interpretation. This is, however, only an illustration.

Let earning-per-share be $A = \mu + \eta$, where μ is the expected EPS and η is an earnings surprise that is distributed $N(0, \sigma_\eta^2)$. For simplicity, assume that the postannouncement stock price is $v = \gamma A + \xi$, where γ is an expected "local" price/earnings ratio[7] and where the price impact of other public information ξ has a mean of zero. Thus, in a risk-neutral market with zero interest rates, the ex ante (preblock) price $P_t(T, t-1)$ is $\gamma\mu$.

Suppose an investor wishes to trade a block with a risk-neutral competitive dealer before earnings are announced. Since blocks are executed individually, it is unrealistic to introduce trading "noise" via a Kyle (1985) trading protocol in which orders are anonymously "batched."[8] As an alternative, assume the investor knows the earnings surprise η), but is also subject to an exogenous liquidity shock u distributed $N(0, \sigma_u^2)$. The block size B is picked strategically (with $B > 0$ for buys and $B < 0$ for sells) to maximize expected profits from the private information η less a quadratic penalty for deviating from the shock u. In particular, if $P_t(T, t) = q(B)$ is the block pricing rule, then the investor's objective is

$$\max_B [\gamma(\mu + \eta) - q(B)]B - \phi(u - B)^2. \tag{4}$$

[7] To avoid confusion, note that the p/e ratio γ applies only for some "window" around the earnings announcement (i.e., this does not imply a constant p/e ratio γ at *all* times). Furthermore, the model is easily modified to accommodate different p/e ratios for expected versus unexpected earnings.

[8] Hughson (1990) makes this same point with regard to intraday transactions in general.

If the price rule is linear, $q(B) = \gamma\mu + \lambda B$, the first-order condition from (4) gives, as the optimal block order,

$$B = \frac{\gamma}{2(\phi + \lambda)}\eta + \frac{\phi}{\phi + \lambda}u, \tag{5}$$

where the second-order condition is satisfied if $\lambda > -\phi$.

Dealers are assumed to know the *p/e* ratio γ and (because of past experience) the parameters ϕ and σ_u^2 of the investor's problem (4), although not the realizations η and u motivating the trade B. Since η and u are jointly normal, conditional expectations given Bare indeed linear. Solving for the linear projection gives the price rule

$$q(B) = \gamma\mu + \frac{2\phi\gamma^2\sigma_\eta^2}{4\phi^2\sigma_u^2 - \gamma^2\sigma_\eta^2}B. \tag{6}$$

The price parameter λ is positive (and thus greater than $-\phi$) provided that, analogously to Glosten (1989) and Madhavan (1987), the liquidity shock is sufficiently noisy with $\sigma_u^2 > \gamma^2\sigma_\eta^2/4\phi^2$.

Substituting for λ in (5) gives the optimal block order to be

$$B = \frac{\gamma(4\phi^2\sigma_u^2 - \gamma^2\sigma_\eta^2)}{8\phi^3\sigma_u^2 + 2\phi\gamma^2\sigma_\eta^2}\eta + \frac{4\phi^2\sigma_u^2 - \gamma^2\sigma_\eta^2}{4\phi^2\sigma_u^2 + \gamma^2\sigma_\eta^2}u. \tag{7}$$

The reduced-form equation corresponding to (2) is obtained by using (7) to substitute out for B in (6), which gives

$$\frac{P_i(T, t) - P_i(T, t-1)}{P_i(T-1, t_c)} = a_1\left(\frac{\eta}{P_i(T-1, t_c)}\right) + \frac{2\phi\gamma^2\sigma_\eta^2}{4\phi^2\sigma_u^2 + \gamma^2\sigma_\eta^2}\left(\frac{u}{P_i(T-1, t_c)}\right), \tag{8a}$$

where

$$a_1 = \gamma\frac{\gamma^2\sigma_\eta^2}{4\phi^2\sigma_u^2 + \gamma^2\sigma_\eta^2}. \tag{8b}$$

Thus, the slope coefficient a, can be interpreted here as an estimate of the *p/e* ratio γ biased downward by the presence of liquidity shocks in block trading. However, far from being a nuisance, this "bias" is of independent interest since from (7) it equals the fraction of the variance of the block size σ^2 *(B)* due to earnings information η.

In practice, however, available proxies for private earnings information are also likely-for reasons discussed in Section 3-to include measurement error. Thus, the estimated coefficient $\hat{a}_1$ is itself a biased estimate of a_1. As will be seen, the combined effect of these two sources of bias is substantial since the estimates of $\hat{a}_1$ reported in

Section 5 are all under 1, which is much smaller than typical *p/e* ratios.

3. Econometric Issues

The chief advantage of "reduced-form" tests of information revelation is that it is not necessary to specify the exact *mechanism* (i.e., trade characteristics such as size, urgency, broker/investor reputation) through which information is revealed. In particular, unsigned volume data do not need to be "signed" by identifying trades as buys or sells. The question is *whether* information is revealed, not *how* it is revealed.

There are, however, still some potential econometric problems, two of which are discussed here along with corrective steps and checks on robustness. The first problem is that OLS regressions of (2) and (3) almost surely misspecify the relation between prices and earnings. For example, even if individual blocks are generated as in Section 2, most samples used in practice to estimate (2) and (3) are likely to include trades from different types of investors-some who are highly informed, others who are purely liquidity-motivated, and others with "noisy" (rather than perfect) information. Thus, our sample will inevitably pool data generated by different "models" (e.g., different values of ϕ and σ_u^2) -a problem that is worsened by cross-sectional heterogeneity in firms' "information structures" (e.g., earnings uncertainty σ_η^2 and *p/e* ratio γ; as well as possible dealer uncertainty about ϕ and σ_u^2) and differences in the size of any noninformational component of the bid-ask spread in richer models. Hence, it is important to check regression results against the more robust comparatively "model-free" nonparametric tests.

The second problem, for both the regression and nonparametric tests, is measurement error when earnings forecast errors proxy for private information. In particular, $\mathbf{FE}_{tT}$ can be decomposed into the desired private information component plus three uncorrelated errors: (i) a prediction error due to the fact that (unlike in Section 2) even informed traders may not know the actual earnings; (ii) misestimation of the market's preblock expectation due to the intervening arrival of new public information between the previous trade $t - 1$ and the block t (or subsequent close t_c); and (iii) misestimation of preblock expectations due to the arrival of information between the analyst forecast date and the previous trade $t - 1$.

The prediction error (i) leads to a standard errors-in-variable problem biasing the estimated slope coefficients in regressions (2) and (3) toward zero (i.e., *against* information revelation). In contrast, the forecast error (ii) due to the intratrade arrival of public information will be positively correlated with observed price changes. The resulting positive bias in the estimated slope coefficient reduces the power of the proposed tests to reject the information revelation hypothesis.

Foster (1977) and Foster, Olsen, and Shevlin (1984) document a positive correlation between forecast errors and preannouncement price changes. Although perfectly consistent with (trade-based) information revelation, it is important to guard against the danger that prices on *any* preannouncement transactions may be positively associated with forecast errors even if the trades themselves revealed no new information. Consequently, "matched" samples of small trades are formed below and used to check whether the association for small trades is weaker than for block trades. In addition, this bias might be expected to decrease as the price observation interval (during which new information can arrive) is shortened. Hence, in analyzing regression results, greater weight is placed on inferences made with respect to narrower price changes measured over shorter observation intervals.

The last forecast error (iii) also leads to a standard errors-in-variables problem, unless block-trading decisions are made in reaction to (or are triggered by) information arriving after the analyst's forecast. For example, "reactive" trades from "stop-loss" strategies (e.g., portfolio insurance), "window dressing," and "filter" rules can lead to a positive or negative bias in the slope coefficient depending on the direction of the dependence between orders and past information. For example, Beebower and Priest (1980) find that block trades are negatively correlated with lagged price residuals. Dependence of this type would lead to a negative bias in the estimated slope coefficient.

One check for a "reactive trading" bias is to repeat the analysis for a sample of postannouncement block trades. Once earnings are known, forecast errors, when used as a measure of (now nonexistent) private information about *past* reported earnings, consist entirely of measurement error due to the use of an outdated forecast as a proxy for the market's expectation. Thus, one can test whether these later blocks are traded "reactively" in response to the earnings announcement itself. If *postannouncement* blocks are not positively correlated with forecast errors, this would tend to cast doubt on the significance of a "reactive trading" bias in the *preannouncement* tests.

In coping with measurement error in $\mathbf{FE}_{iT}$, one alternative to the regressions specified here in (2) and (3) is to reverse the dependent and independent variables. This is not done here, however, for the following reasons: first, one objective of this study is to measure "how much" of block price changes are explained by information revelation about current earnings. No such. R^2 is available in the "reverse regression." Second, price changes themselves measure the block's *price* *impact* with "error" because of (i) randomness in the bid-ask spread reflected in our proxies for preblock and postblock price levels $P_i(T, t-1)$ and $P_i(T, t_c)$, (ii) the arrival of other public news which also affects prices, and (iii) "leakage" of the block price impact in preblock prices (see Section 4). Thus, a "reverse regression" replaces earnings measurement error with price impact measurement error. Third, correlation between earnings measurement error and prices (e.g., due to the intratrade arrival of public news or to "reactive trading") still biases the slope coefficient even in the "reverse regression."

4. The Data

In this study, I use earnings and block trade data from 1982. The earnings data were collected from the *Value Line Investment Survey* and the *Wall Street Journal Index*. The *Investment Survey* is the source for actual and forecasted quarterly earnings-per-share for a set of approximately 1700 firms regularly followed by *Value Line*. The last forecast prior to the earnings announcement date proxies for the market's expectation.[9] Nonoperational gains and losses due to tax benefit sales, subsidiary sales, asset write-offs, and changes in accounting rules[10] were excluded from actual earnings unless *Value Line* specifically stated that estimates of these nonoperational items were included in their forecast.

The *Wall Street Journal Index* was used to identify the publication date of the earliest report that appeared to entail a significant resolution of uncertainty about quarterly earnings relative to the *Value Line* forecast. Typically, this was the publication date of the earnings announcement itself. In 75 instances, however, unofficial notices in advance of official announcements, preliminary management forecasts, or earlier reports about an important subsidiary's earnings appeared to resolve most of the uncertainty. In these cases, the earlier date was treated as the relevant publication date in order to reduce the measurement error in *Value Line* forecast errors due to the arrival of new public information.

Earnings data were collected for all firms for all fiscal quarters announced during 1982 (i.e., the fourth quarter of 1981 through the third quarter of 1982), which satisfied the following criteria:

---

[9] Analyst forecasts were used rather than time-series predictions because of evidence that analyst forecasts (and *Value Line's* in particular) are superior predictors. See Brown and Rozeff (1978). Fried and Givoly (1982). and Givoly and Lakonishok (1984).

[10] For example, switches from FIFO to LIFO. changes in pension fund accounting, and changes in the treatment of gains and losses from foreign currency transactions due to the adoption of FASB 52 in place of FASB 8. *Value Line* was the source of information about such nonoperational items.

1. A forecast of earnings-per-share was available in the last *Value Line* report before the earnings announcement and actual earnings-per-share could be obtained from subsequent reports. Firms with reports in the third and fourth weeks of the 13-week *Value Line* reporting cycle were excluded along with firms listed as "Unassigned Stocks," "Foreign Stocks," "Utilities," and passenger airlines listed in the "Air Transport Industry." American Depository Receipts (ADRs), Real Estate Investment Trusts (REITs), and Share Beneficial Interests (SBIs) were also excluded.[11]
2. The firm's stock was traded on the NYSE.
3. The firm's fiscal year ended in December or January.
4. Actual earnings data were available for all previous quarters on the date of the last forecast.
5. Fully diluted shares outstanding (as reported in *Value Line)* did not change by more than 1 percent between the issues containing the last forecast and the announced earnings. One exception was changes due to stock splits and stock dividends. In such cases, earnings-per-share were adjusted to be consistent.
6. Sufficient data were reported to net out nonoperational items from actual earnings when such items were not explicitly included in the last *Value Line* forecast.
7. The publication date of the firm's earnings announcement (or a prior announcement significantly reducing earnings uncertainty) could be obtained from the *Wall Street Journal Index.*

An initial sample of 1779 announcements satisfied these criteria. These earnings data were then compared with block trade data for 1982 to identify firms with block trades around earnings announcements.

The block trade data used in this study are a subset of the data used in Holthausen, Leftwich, and Mayers (1987).[12] The database derives from two sources, Francis Emory Fitch, Inc. and the Center

[11] All decisions about sample composition were made *before* looking at the price data. The difficulty with reports in the third and fourth weeks is that many quarterly earnings announcements are also made during that time. Consequently, the last forecast may be almost 13 weeks old. These old forecasts are also often disqualified by criterion 4 if the firm was slow in reporting earnings for the previous quarter. In addition, these *Value Line* forecasts may postdate the earnings announcement because the announcement was made while the report was being printed or mailed. Hence, identifying the last forecast before the announcement can be a time-consuming process. "Unassigned Stocks" were excluded because these are typically first reports for firms that *Value Line* is adding to its roster. "Foreign Stocks" were excluded because the "information structure" for those stocks is likely to be different than for domestic stocks. "Utilities" were excluded because of possible differences in earnings induced by the regulatory process. Passenger airlines were excluded because structural changes in the airline industry appeared to be showing up in earnings in the form of onetime gains and losses (i.e., a gain from the sale of a significant portion of an airline's Beet). ADRs, REITs. and SBIs were excluded because block trade data were not available.

[12] I thank Robert Holthausen, Richard Leftwich, and David Mayers for making their data available to me.

for Research in Security Prices at the University of Chicago (CRSP). For all trades of 5000 shares or more executed on the New York Stock Exchange in 1982, the Fitch file contains the following information: the time and date of the trade, the price at which the trade was executed, and the number of shares traded.[13] It also contains the same information for the previous transaction regardless of the number of shares involved. The CRSP Daily Master file is the source of two additional pieces of information: the adjacent closing prices before and after each trade on the Fitch tape, and the number of shares outstanding. These data were then screened to exclude trades for which any of the following were true:

1. The closing price from CRSP for the day before the trade or for the day of the trade was an average of bid and ask quotes.
2. The number of shares outstanding was not available from CRSP.
3. A change of over 2.5 percent in the number of shares outstanding occurred (for any reason) within either 21 days before or 5 days after the block trade.
4. The block trade was the first trade of the day and thus no previous transaction price was available from Fitch.
5. There appeared to be an error in the trade times reported by Fitch (i.e., the "previous" transaction was time-stamped after the block trade).
6. The block trade predated the corresponding last *Value Line* earnings forecast.

Trades were then sorted into six samples based on size and timing relative to the earnings announcement. This allows us to focus on trades for which information revelation about earnings is a priori more likely to be important. In particular, we can then test if empirically it is important. Also, while recognizing our ignorance of exact functional forms, sorting does provide a robust way of investigating the information content of block size as well as the timing of earnings information revelation. The role of size is then studied further in Section 6.

Block size is measured by the percentage of shares outstanding traded. "Small" blocks are trades of between 0.1 and 0.3 percent of shares outstanding and "large" blocks involved over 0.5 percent of shares outstanding. Although ad hoc, Holthausen, Leftwich, and Mayers (1987) find "large" blocks (by this definition) did have significant price changes. In addition, there are theoretical predictions in Easley and O'Hara (1987) and Seppi (1990) that the frequency of information-based blocks increases in size.

[13] There is a lacuna in the Fitch file from May 10 through June 15 due to a lost tape.

Blocks were also grouped into three "event time" weeks [-11, -7], [-6, -2], and [0, +4], where day 0 is the *Wall Street Journal* publication date. The prediction is that block trades just before a quarterly earnings announcement should be more informative than earlier blocks. This will occur if the frequency of informed blocks increases (e.g., perhaps because of "leaks") and the frequency of "uninformed" blocks does not increase.

Four price variables were constructed on each day for each firm with a qualifying block trade. The first variable ΔP (Prv, Blk) is the dependent variable from Equation (2), calculated for the first block t_1 for firm i that satisfied the sample selection criterion for size on day T

$$\Delta P(\text{Prv, Blk}) = [P_i(T, t_1) - P_i(T, t_1 - 1)]/P_i(T - 1, t_c). \qquad (9)$$

Because the time between price observations is minimized, the probability of false rejection of the null hypothesis (i.e., no informed trading $a_1 = 0$) due to the intervening arrival of public information is minimized. First trades alone are used to avoid possible differences in the predictability of first and any subsequent block trades.

The second variable ΔP (Prv, Clo) is the dependent variable from regression (3),

$$\Delta P(\text{Prv, Clo}) = [P_i(T, t_c) - P_i(T, t_1 - 1)]/P_i(T - 1, t_c), \qquad (10)$$

which includes the permanent component in ΔP (Prv, Blk). However, because more time elapses between price observations, the probability of false rejection of the null (i.e., no impounding $a_1 = 0$) is greater.

A problem common to both ΔP (Prv, Blk) and ΔP (Prv, Clo) is the use of previous transaction prices to measure preblock price levels. For institutional reasons, the previous transaction price may already reflect much of the price impact of a block trade. Under NYSE Rule 127, a block trade negotiated off the exchange floor can be crossed on the floor only after any outstanding limit orders at prices between the current price and the block price are executed.[14] In addition, the time a block is officially crossed may lag the time that knowledge of an impending block trade becomes public (e.g., if the broker "shops" the block).

"Leakage" of block price impact into previous transaction prices is problematic because it biases both the slope coefficients a, and a_1' and the R^2's in regressions (2) and (3) downward. One correction is to measure price changes relative to the closing price from the

[14] Under Rule 127, intervening limit orders should be executed at the block price. However, from conversations with practitioners it appears that sometimes the limit order book is cleared out in advance of the block at the limit prices.

Table 1
Descriptive statistics for price changes and earnings on days with block trades during weeks [−11, −7], [−6, −2], and [0, +4] around a quarterly earnings announcement

Variable	Mean	Median	SD	SR
A: Small blocks (n = 2567)				
1. ΔP(Prv, Blk)	−.001	.000	.010	16.7
2. ΔP(Prv, Clo)	.002	.000	.023	13.1
3. ΔP(Pclo, Blk)	.003	.000	.031	23.7
4. ΔP(Pclo, Clo)	.006	.003	.037	20.6
5. EPS	.011	.022	.075	19.7
6. FE	−.007	−.001	.036	15.5
B: Large blocks (n = 326)				
1. ΔP(Prv, Blk)	−.006	.000	.018	8.5
2. ΔP(Prv, Clo)	.000	.000	.025	7.2
3. ΔP(Pclo, Blk)	−.003	.000	.038	8.5
4. ΔP(Pclo, Clo)	.003	.000	.039	7.5
5. EPS	.011	.022	.062	13.4
6. FE	−.009	−.003	.030	15.8

"Small" blocks involved between 0.1% and 0.3% of shares outstanding. "Large" blocks involved over 0.5% of shares outstanding. Price and earnings variables are scaled by the closing price from the preceding day. ΔP(Prv, Blk) is the scaled price change between the first qualifying block of the day and the previous transaction. ΔP(Prv, Clo) is the scaled price change between the close on the day of a block and the transaction preceding the first block. ΔP(Pclo, Blk) is the scaled price change between the first block and the previous close. ΔP(Pclo, Clo) is the scaled price change between the close on the day of a block and the preceding close. EPS is scaled earnings per share. FE is the scaled forecast error from the last *Value Line* forecast of earnings per share. SD is the standard deviation and SR is the studentized range statistic.

preceding day. The variable ΔP (Pclo, Blk), a broader measure of the total block price change, is the scaled difference between the price on block trade t_1, and the previous closing price:

$$\Delta P(\text{Pclo, Blk}) = [P_i(T, t_1) - P_i(T-1, t_c)]/P_i(T-1, t_c). \quad (11)$$

The corresponding measure of the permanent price change ΔP (Pclo, Clo) is the scaled difference between closing prices:

$$\Delta P(\text{Pclo, Clo}) = [P_i(T, t_c) - P_i(T-1, t_c)]/P_i(T-1, t_c). \quad (12)$$

Again, however, the problem of possible false rejections due to the arrival of public information is more serious for these broader measures than for their narrower counterparts.

For each qualifying block observation, the scaled *Value Line* earnings forecast error $\mathbf{FE}_{iT}$ is calculated as in (1).

5. Results

Summary statistics on prices and earnings over the full pooled interval are reported in Table 1. Qualitatively similar values (not reported) were found in the three subperiods. First, as might be expected, the standard deviations of ΔP (Prv, Clo), ΔP (Pclo, Blk), and ΔP (Pclo, Clo)

Table 2
Descriptive statistics for the time between block and previous trades, forecast age, trade size, and market value

Block sample	Sample size	Time		Forecast age		Median trade size		Median firm equity ($mil.)
		Median	Max	Median	Max	Shares traded (000)	Value ($mil.)	
1. Small	2567	9	349	7	17	24	0.53	347
2. Large	326	10	360	8	12	91	1.85	198

The time between block trades and previous transactions is measured in minutes. The forecast age is measured in 5-day "trading" weeks between the publication date of a firm's quarterly earnings announcements in the *Wall Street Journal* and the date of the last *Value Line* forecast. Firm equity market value is shares outstanding on the block trade date multiplied by the closing price on the preceding day.

"Small" blocks involved between 0.1% and 0.3% of shares outstanding. "Large" blocks involved over 0.5% of shares outstanding.

are consistently greater than those of the narrower measure ΔP (Prv, Blk). This reflects both the arrival of nonblock information and any precrossing "leakage" of block information.

Second, the mean of the forecast error $\mathbf{FE}_{iT}$ should not be compared with its standard deviation as a check on the unbiasedness of the *Value Line* forecasts. Contemporaneous forecast errors are likely to be cross-sectionally correlated, causing the true standard deviation to be underestimated. In addition, these samples suffer from a selection bias. If some block trades are based on private information and if blocks are more easily sold than bought,[15] then these samples may be biased toward firms for which the forecast, although ex ante unbiased, was ex post too high. Evidence on the accuracy of the *Value Line* forecasts is better sought in time-series studies such as Brown and Rozeff (1978), which shows that *Value Line* forecasts have smaller prediction errors than several alternative time-series models of earnings.

Third, price changes and earnings are somewhat kurtotic, as evidenced by their high studentized ranges (SR). Sample deviations from normality are another reason to include the nonparametric rank correlation and x^2 -tests.

The time elapsed between blocks and previous transactions, the age of the *Value Line* forecasts, other measures of trade size, and firm equity market value are reported in Table 2. The median time elapsed between block trades and previous transactions is very short (about 10 minutes). Consequently, given the widespread "shopping" of blocks, together with the temptation to circumvent NYSE Rule 127,

[15] Holthausen, Leftwich, and Mayers (1987) find that for "large" blocks the frequency of sells exceeds that of buys.

Table 3
Block trades in week [−11, −7] before a quarterly earnings announcement

Dependent variable	a_0	a_1	SD	Adj. R^2	SR(e)	Spear-man	χ^2
A: Small blocks (n = 811)							
1. ΔP(Prv, Blk)	−.001	.013	.010	.001	12.0	.043	.24
	(−2.59)	(1.35)					
	[−2.66]	[.58]					
2. ΔP(Prv, Clo)	.002	−.003	.022	.000	10.3	−.012	4.45
	(2.32)	(−.16)					
	[2.35]	[−.11]					
3. ΔP(Pclo, Blk)	.005	.096	.033	.009	19.6	.082	6.73
	(4.45)	(2.94)					
	[4.26]	[2.10]					
4. ΔP(Pclo, Clo)	.008	.080	.038	.004	16.4	.046	1.38
	(5.87)	(2.11)					
	[5.70]	[1.56]					
B: Large blocks (n = 90)							
1. ΔP(Prv, Blk)	−.005	.027	.017	.000	7.1	−.023	.01
	(−2.76)	(.39)					
	[−2.87]	[.39]					
2. ΔP(Prv, Clo)	.002	.023	.027	.000	5.7	−.001	.00
	(.64)	(.21)					
	[.66]	[.21]					
3. ΔP(Pclo, Blk)	−.002	.075	.037	.000	6.5	.082	1.24
	(−.37)	(.49)					
	[−.35]	[.67]					
4. ΔP(Pclo, Clo)	.06	.072	.040	.000	5.6	.056	.05
	(1.24)	(.44)					
	[1.20]	[.44]					

The regression model is $\Delta P_{iT} = a_0 + a_1 \mathrm{FE}_{iT} + e_{iT}$. *T*-statistics for the null hypothesis that the coefficient is 0 are reported in parentheses using OLS standard errors and in brackets using White (1980) standard errors. SR(e) is the studentized range of the regression residuals. The critical value for the Spearman rank correlation at the .05 level is .069 with n = 811 and .208 with n = 90. The χ^2-statistic is from a 2 × 2 sign contingency table for ΔP and FE. The .05 critical value is 3.84.

"Small" blocks involved between 0.1% and 0.3% of shares outstanding. "Large" blocks involved over 0.5% of shares outstanding. Price changes ΔP and *Value Line* forecast errors FE are scaled by the closing price from the preceding day.

it is likely that previous transaction prices already reflect information about subsequent block trades. Also, the short time lag makes less likely correlation between ΔP (Prv, Blk) and forecast errors due to the intervening arrival of public information. The median forecast age is about seven weeks on the day of the block trade. Consequently, the unexpected earnings proxy $\mathbf{FE}_{iT}$ is likely to contain a substantial amount of measurement error.

The regression results are presented in Tables 3-6. T-statistics are reported using both OLS standard errors (in parentheses) and White (1980) heteroskedasticity-corrected standard errors (in brackets).[16]

[16] Heteroskedasticity also makes the interpretation of the regression R^2's problematic. However, because of the lack of alternatives, they are reported to provide some measure of goodness of fit.

The two nonparametric statistics, the Spearman rank correlation and the χ^2 -test for independence, are also reported.

Results for block trades executed during the second-to-last "trading week" before a quarterly earnings announcement are reported in Table 3. All but one of the estimated slope coefficients are positive, as predicted by the information revelation hypothesis. However, only for price changes measured over longer observation intervals [i.e., ΔP (Pclo, Blk) and ΔP (Pclo, Clo)] are any coefficients statistically large. The regression R^2's are also small. Forecast errors explain less than 1 percent of the variance of any measure of block price change. The nonparametric tests are also consistent with this pattern. Given the weakness of the association between the narrow measure ΔP (Prv, Blk) and $\mathbf{FE}_{iT}$, it is reasonable to attribute any weak correlation between the longer price change variables and earnings to the arrival of new public information.

Results for block trades during the last "trading week" before a quarterly earnings announcement are reported in Table 4. Over this interval, all of the estimated slope coefficients are positive. Compared with the slope coefficients for the prior "week," these estimates are [with the exception of ΔP (Pclo, Blk) for "small" blocks] larger both in absolute magnitude and relative to their respective standard errors.[17] In particular, both the regression and nonparametric tests confirm a positive relation between $\mathbf{FE}_{iT}$ and the narrow price change ΔP (Prv, Blk) on "large" blocks.

Not only does it appear that "large" information-based blocks are traded, but "the market" also appears to learn from these blocks. The estimated slope coefficients in the ΔP (Prv, Clo) and ΔP (Pclo, Clo) regressions (which measure new earnings information impounded in postblock prices) are equal to the slope coefficients in the corresponding ΔP (Prv, Blk) and ΔP (Pclo, Blk) regressions (which test for the execution of information-based blocks).[18]

Using previous closing prices rather than previous transaction prices

---

[17] To test formally whether the slope coefficients differ across the two weeks, we estimated the regression

$$\Delta P_{iT} = a_0 + a_1 \mathrm{FE}_{iT} + a_2 \mathrm{FE}_{iT} \cdot D_{iT} + e_{iT},$$

where $D_{iT} = 1$ if T is in $[-6, -2]$ and 0 if T is in $[-11, -7]$. For "large" blocks (using a r-test based on White standard errors), the null $a_2 = 0$ is rejected at the 5 percent level for ΔP (Pclo, Blk) and ΔP (Pclo, Clo) but not for ΔP (Prv, Blk) and ΔP (Prv, Clo). However, the standard errors are so large (from Table 3) that we also cannot reject that the slopes in [-11, -7] are 0.

[18] Unfortunately, given our limited data, it is not possible to tell when the block trade is also the closing trade. As a conservative test for robustness to this problem, the analysis was repeated for 77 "large" blocks in [-6, -2], where the block and closing prices were not equal. Significance levels are lower, but the slope coefficients for ΔP (Pclo, Blk) and ΔP (Pclo, Clo) are still roughly equal (i.e.. about 8) as are the point estimates for ΔP (Prv, Blk) and ΔP (Prv, Clo) [although the t -statistics in the ΔP (Prv, Clo) regression are less than 2].

Table 4
Block trades in week [−6, −2] before a quarterly earnings announcement

Dependent variable	a_0	a_1	SD	Adj. R^2	SR(e)	Spear-man	χ^2
A: Small blocks (n = 821)							
1. ΔP(Prv, Blk)	.0002	.019	.010	.003	10.7	.047	1.07
	(.52)	(1.75)					
	[.54]	[1.15]					
2. ΔP(Prv, Clo)	.003	.064	.021	.009	7.6	.076	1.77
	(4.19)	(2.85)					
	[4.21]	[2.65]					
3. ΔP(Pclo, Blk)	.005	.088	.026	.010	12.7	.084	4.00
	(5.54)	(3.09)					
	[5.67]	[2.54]					
4. ΔP(Pclo, Clo)	.008	.133	.032	.017	12.0	.11	4.33
	(7.13)	(3.84)					
	[7.33]	[3.51]					
B: Large blocks (n = 107)							
1. ΔP(Prv, Blk)	−.005	.183	.016	.046	5.8	.216	7.41
	(−2.99)	(2.48)					
	[−3.20]	[2.56]					
2. ΔP(Prv, Clo)	−.001	.183	.021	.022	6.6	.100	1.09
	(−.23)	(1.85)					
	[−.24]	[2.49]					
3. ΔP(Pclo, Blk)	.0001	.736	.030	.198	5.4	.278	6.55
	(.03)	(5.21)					
	[.03]	[3.32]					
4. ΔP(Pclo, Clo)	.004	.736	.032	.179	5.0	.242	5.77
	(1.35)	(4.91)					
	[1.43]	[3.50]					

The regression model is $\Delta P_{iT} = a_0 + a_1 \mathrm{FE}_{iT} + e_{iT}$. T-statistics for the null hypothesis that the coefficient is 0 are reported in parentheses using OLS standard errors and in brackets using White (1980) standard errors. SR(e) is the studentized range of the regression residuals. The critical value for the Spearman rank correlation at the .05 level is .068 with n = 821 and .190 with n = 107. The χ^2-statistic is from a 2 × 2 sign contingency table for ΔP and FE. The .05 critical value is 3.84.

"Small" blocks involved between 0.1% and 0.3% of shares outstanding. "Large" blocks involved over 0.5% of shares outstanding. Price changes ΔP and *Value Line* forecast errors FE are scaled by the closing price from the preceding day.

to measure the preblock price level makes a dramatic difference in the magnitude of the information revelation price effects. For example, when the previous day's closing price is used in the "large" block regressions, the slope coefficients jump by about .55 (i.e., 55 cents per dollar unforecasted earnings) and the R^2's indicate an extra 15 percent of price variation is explained. This jump is consistent with the "leakage" of information about impending block trades into previous transaction prices as well as the alternate "reactive" trading explanation.[19]

[19] As further evidence of "leakage" or "reactive" trading, the preblock price change ΔP (Pclo, Blk) - ΔP (Prv, Blk) and ΔP (Prv, Blk) are strongly associated. For "large" blocks in [-6, -2], the correlation is .319 and the rank correlation is .304, although the x^2 -statistic is only 3.19. For "small" blocks, the correlation is only ,023, but the rank correlation is .122 and the x^2 -statistic is 15.46.

Comparing results across block size samples also supports predictions that information revelation increases in block size. One interpretation of this prediction is that the magnitude of the associated revision in expectations should increase with size. A second interpretation is that the informational component of block prices should explain a greater proportion of block price change variance. Both interpretations are supported. First, the slope coefficients for each price variable are increasing in block size.[20] For example, the price of a "small" block is on average only 2 cents higher than the previous transaction price per dollar unforecasted earnings. The price of a "large" block is 18 cents higher. Second, the regression R^2's are also increasing. Forecast errors explain only 0.3 percent of the variance of the difference between "small" block and previous transaction prices versus 4.6 percent for "large" block trades.

As a check on whether these results are simply statistical artifacts of using transactions taken from a time when the probability of new public information arriving is high, the same regressions and nonparametric tests were reestimated for samples of "matched" small trades which were constructed as follows. For each qualifying "large" block trade observation, the corresponding "matched" sample includes the smallest trade[21] from the same week [-6, -2] that satisfied the following criteria:

1. The small trade satisfied the conditions previously given for inclusion in the block trade sample.
2. The trade involved less than 0.1 percent of shares outstanding.
3. No trade executed on the same day was included in the corresponding block trade sample for this firm.

A similar process was used to obtain a "matched" sample for "small" blocks. The variables ΔP (Prv, Match), ΔP (Prv, Clo), ΔP (Pclo, Match), ΔP (Pclo, Clo), and $\mathbf{FE}_{iT}$ are defined analogously to their block trade counterparts.

The "matched" sample results are reported in Table 5. In contrast to the block trade results, there is little evidence of positive correlation between "matched" price changes and unforecasted earnings. The estimated slope coefficients are sometimes negative, although their t -statistics are all less than 2. In addition, none of the nonparametric tests reject the independence of "matched" price changes and

[20] Using a t -test, the null hypothesis of equal slope coefficients for "large" and "small" blocks during the week [-6, -2] is rejected at the 5 percent level for all four price variables.

[21] In the event of "ties" for the smallest trade, the last such trade is used. Typically, ties occurred because of the 5000 share floor. At most one "matched" trade is found per interval in which a firm has a block trade. Only about half of the "large" blocks could be matched-with fewer matches found for smaller firms as is reflected in the median market value of firms in the two samples (e.g., $230 million for "large" blocks versus $363 million for the corresponding "matched" trades).

Table 5
"Matched" small trades in week [−6, −2] before a quarterly earnings announcement

Dependent variable	a_0	a_1	SD	Adj. R^2	SR(e)	Spear-man	χ^2
A: "Matched" sample for small blocks ($n = 412$)							
1. ΔP(Prv, Match)	.0001	−.010	.007	.000	12.5	.039	.49
	(.18)	(−.83)					
	[.18]	[−.74]					
2. ΔP(Prv, Clo)	.001	−.035	.016	.001	8.2	.038	.05
	(1.31)	(−1.27)					
	[1.32]	[−.88]					
3. ΔP(Pclo, Match)	.006	.047	.030	.000	12.2	.091	2.44
	(3.99)	(.94)					
	[3.97]	[.45]					
4. ΔP(Pclo, Clo)	.007	.022	.032	.000	11.1	.072	2.38
	(4.26)	(.40)					
	[4.25]	[.20]					
B: "Matched" sample for large blocks ($n = 53$)							
1. ΔP(Prv, Match)	−.001	−.089	.007	.047	4.9	−.041	—[1]
	(−1.07)	(−1.89)					
	[−1.08]	[−1.14]					
2. ΔP(Prv, Clo)	.0005	.050	.015	.000	7.3	.167	—[1]
	(.20)	(.47)					
	[.18]	[.61]					
3. ΔP(Pclo, Match)	.001	.20	.024	.008	6.4	.148	.19
	(.17)	(1.19)					
	[.19]	[.88]					
4. ΔP(Pclo, Clo)	.002	.335	.027	.039	5.8	.217	.05
	(.52)	(1.76)					
	[.56]	[1.54]					

The regression model is $\Delta P_{iT} = a_0 + a_1 FE_{iT} + e_{iT}$. T-statistics for the null hypothesis that the coefficient is 0 are reported in parentheses using OLS standard errors and in brackets using White (1980) standard errors. SR(e) is the studentized range of the regression residuals. The critical value for the Spearman rank correlation at the .05 level is .097 with $n = 412$ and .272 with $n = 53$. The χ^2-statistic is from a 2 × 2 sign contingency table for ΔP and FE. The .05 critical value is 3.84.

"Small" blocks involved between 0.1% and 0.3% of shares outstanding. "Large" blocks involved over 0.5% of shares outstanding. Each "matched" sample comprises the smallest trade (greater than 5000 shares but less than 0.1% of shares outstanding) in each interval [−6, −2] before a quarterly earnings announcement in which a firm had a trade in the corresponding block trade sample. Price and earnings variables are scaled by the closing price from the preceding day. ΔP(Prv, Match) is the scaled price change between the matched and previous trades. ΔP(Prv, Clo) is the scaled price change between the close and the transaction preceding the matched trade. ΔP(Pclo, Match) is the scaled price change between the matched trade and the previous close. ΔP(Pclo, Clo) is the scaled price change between the close and the preceding close. FE is the scaled forecast error from the last *Value Line* forecast of earnings per share.

[1] χ^2-statistic not reported because of inadequate sample size.

earnings at the 5 percent level. The weakness of the association between earnings and the "matched" price changes (and, in particular, those measured over longer time periods) further supports the information revelation interpretation of the block trade results.[22]

[22] Using a t-test. the null of equal slope coefficients for "large" blocks and "matched' small trades during [-6, -2] is rejected at the 5 percent level for ΔP (Prv, Blk) and at the 10 percent level for ΔP (Pclo, Blk).

Table 6
Block trades in week [0, +4] after a quarterly earnings announcement

Dependent variable	a_0	a_1	SD	Adj. R^2	SR(e)	Spear-man	χ^2
A: Small blocks (n = 935)							
1. ΔP(Prv, Blk)	−.0005	.017	.011	.003	14.6	.082	.97
	(−1.25)	(1.86)					
	[−1.26]	[1.20]					
2. ΔP(Prv, Clo)	.003	.010	.025	.000	11.9	.042	.09
	(3.28)	(.47)					
	[3.27]	[.46]					
3. ΔP(Pclo, Blk)	.002	.039	.032	.001	16.8	.080	.40
	(1.70)	(1.40)					
	[1.73]	[1.10]					
4. ΔP(Pclo, Clo)	.005	.031	.039	.000	15.8	.077	1.47
	(3.84)	(.94)					
	[3.84]	[.79]					
B: Large blocks (n = 129)							
1. ΔP(Prv, Blk)	−.006	.074	.020	.013	7.7	.300	5.19
	(−3.13)	(1.65)					
	[−3.21]	[1.78]					
2. ΔP(Prv, Clo)	.002	.068	.027	.002	6.8	.081	1.26
	(.70)	(1.12)					
	[.72]	[1.09]					
3. ΔP(Pclo, Blk)	−.0005	.024	.042	.000	7.6	.234	4.30
	(−.12)	(.25)					
	[−.12]	[.32]					
4. ΔP(Pclo, Clo)	.007	.018	.043	.000	6.8	.136	1.29
	(1.76)	(.19)					
	[1.79]	[.22]					

The regression model is $\Delta P_{iT} = a_0 + a_1 \mathrm{FE}_{iT} + e_{iT}$. T-statistics for the null hypothesis that the coefficient is 0 are reported in parentheses using OLS standard errors and in brackets using White (1980) standard errors. SR(e) is the studentized range of the regression residuals. The critical value for the Spearman rank correlation at the .05 level is .064 with $n = 935$ and .173 with $n = 129$. The χ^2-statistic is from a 2 × 2 sign contingency table for ΔP and FE. The .05 critical value is 3.84. "Small" blocks involved between 0.1% and 0.3% of shares outstanding. "Large" blocks involved over 0.5% of shares outstanding. Price changes ΔP and *Value Line* forecast errors FE are scaled by the closing price from the preceding day.

Results for block trades executed during the first "trading week" after a quarterly earnings announcement (including the publication date itself) are reported in Table 6. This postannouncement sample is used to test an alternate explanation for the preannouncement results-namely, that block trades only *appear* to reveal information because of "spurious" correlation between (i) blocks that were traded "reactively" in response to past earnings information, and (ii) measurement error in FE_{iT} due to the same information. In the postannouncement period, true unexpected earnings (for the past quarter) are identically zero because any uncertainty about reported earnings has been resolved by the announcement itself. Thus, the forecast error FE_{iT}, when used to proxy for unexpected earnings, is pure measurement error. Thus, an indirect way to assess the influence of "spurious" correlation on the *preannouncement* results is to reestimate the tests over this *postannouncement* period.

In the OLS regressions, $\mathbf{FE}_{iT}$ is not significantly correlated with the different price changes,[23] although the x^2 -test and rank correlation test do reject independence at the 5 percent level for "large" blocks using ΔP (Pclo, Blk) and ΔP (Prv, Blk). In the case of ΔP (Pclo, Blk), however, these nonparametric rejections are due more to observations with $\mathbf{FE}_{iT}$ close to 0 than the extreme (i.e., potentially profitable) $\mathbf{FE}_{iT}$ observations that lead to rejection in the preannouncement samples.

The ambiguous evidence for ΔP (Prv, Blk) and earnings is more problematic, preventing, as it does, definitive conclusions on the bias contributed by "reactive" trading to the preannouncement results. In future work with larger sample sizes, it may be possible to make sharper inferences. In particular, it would be interesting to disentangle the effects of any quick-response "reactive" trading on day 0 from lagged "reactive" trading on days +1 through +4.

6. The Role of Block Size

The results in Section 5 can be viewed as "reduced-form" evidence on the composite relation between block prices and information. In this section, I present "structural" evidence on whether trade size itself is a variable which reveals earnings information. If trade size does convey information, then it is reasonable to expect (i) earnings forecast errors and (ii) block prices each to be correlated with trade size.

These predictions are tested nonparametrically using Spearman rank correlations between *unsigned* measures of trade size and the *absolute values* of scaled forecast errors and price changes. The chief merit of this procedure is again that unsigned Fitch volume data does not need to be signed. Furthermore, the x^2 -tests from Table 4 already indicate that the *signs* of block price changes and forecast errors are correlated. Thus, the focus here is on *magnitude* rather than sign-that is, whether extreme forecast errors are associated with extreme block size and whether extreme block size is associated with extreme price changes.

Rank correlations for week [-6, -2] before earnings announcements (i.e., the period for which evidence of information revelation is uncovered in Section 5 are reported in Table 7). Two measures of trade size are used: (i) percent of shares outstanding traded, and (ii) number of shares traded. The second measure is included as a robust-

[23] Using a t -test. the null of equal slope coefficients for "large" blocks in [-6, -2] and [0, +4] is rejected at the 5 percent level for ΔP (Pclo, Blk) and ΔP (Pclo, Clo).

Table 7
Spearman rank correlations for trade size in week [−6, −2]

Variable	"Large" blocks only		"Large" and "small" blocks	
	% Outstanding	No. of shares	% Outstanding	No. of shares
$\lvert \Delta P(\text{Prv, Blk}) \rvert$	−.043	.116	.074	.054
$\lvert \Delta P(\text{Prv, Clo}) \rvert$	−.129	−.110	.007	.025
$\lvert \Delta P(\text{Pclo, Blk}) \rvert$	−.049	.091	.102	.033
$\lvert \Delta P(\text{Pclo, Clo}) \rvert$	−.035	−.133	.043	.024
$\lvert FE \rvert$	.101	.063	.037	−.090

The .05 critical values for rank correlations are .190 for "large" blocks ($n = 107$) and .064 for pooled "large" and "small" blocks ($n = 928$).

The same samples (sorted based on percent of shares outstanding traded) are used for rank correlations with percent of shares outstanding and with number of shares traded. "Small" blocks involved between 0.1% and 0.3% of shares outstanding. "Large" blocks involved over 0.5% of shares outstanding. Price changes ΔP and *Value Line* forecast errors FE are scaled by the closing price on the preceding day.

ness check. Unlike in Section 5 (where size is used only for a coarse sorting), size here is hypothesized to have a more structured (monotone) relation with price and earnings across the sample of firms.

When the sample is limited to "large" blocks of at least 0.5 percent of shares outstanding, little correlation is detected between prices or earnings and either size measure. When the range of trade sizes is expanded to include both "large" and "small" blocks, the percentage of shares traded is (rank) correlated with the absolute total price change $\lvert \Delta P(\text{Prv, Blk}) \rvert$. However, surprisingly, the percentage of shares traded is not (rank) correlated with either of the absolute "permanent" price changes $\lvert \Delta P(\text{Prv, Clo}) \rvert$ and $\lvert \Delta P(\text{Pclo, Clo}) \rvert$ or with the absolute forecast error $\lvert FE \rvert$. Taken at face value, this lack of correlation is inconsistent with the percentage of shares traded being a *mechanism* revealing private information about the magnitude of unexpected earnings.

Size as measured by the number of shares traded is also an unlikely candidate mechanism during the last week. The number of shares traded is not significantly (rank) correlated with absolute price change and is negatively correlated with earnings forecast errors.

There are several possible explanations for the weakness of the "structural" versus the "reduced-form" evidence. First, since "large" blocks do appear (from Table 4) to be more informative than "small" blocks, it is possible that "large" blocks are informative only about the *sign* and not the *magnitude* of unexpected earnings.[24] Second, trade size alone may be less informative than investor urgency, rep-

[24] There is some empirical support for this first explanation. Calculating rank correlations between $\lvert FE \rvert$ and each of the four absolute price changes, we found in this week that all were below the .05 critical value except for $\lvert \Delta P(\text{Prv, Blk}) \rvert$ in the pooled "large" and "small" block sample. However, caveats about cross-sectional heterogeneity also apply to these tests.

utation, and other trade characteristics. However, if "large" size signals that dealers should condition on these other variables, then "large" blocks will still be more informative about earnings even if "size" itself is not directly informative. Third, heterogeneity across firms (e.g., in the price impact of a given size trade) may confound "structural" tests using cross-sectional data. Time-series data is clearly preferable for this reason. However, the relative infrequency of block trades around earnings announcements (i.e., 107 "large" blocks during week [-6, -2] for 1779 quarterly announcements) may make the use of cross-sectional data unavoidable.

As a final methodological comment, even with time-series data on block trades, the "reduced form" evidence would not be redundant. In particular, "structural" tests based on pairwise correlations (with price changes and with forecast errors) may indicate that size (or some other variable) is informative about earnings when actually it is not.

For example, assume (i) all traders are uninformed about true unexpected earnings, (ii) certain blocks are known by dealers (e.g., because of investor reputations) to be "reactive" trades in response to lagged public earnings information, but (iii) no other blocks are "reactive," (iv) that forecast errors $\mathbf{FE}_{iT}$ include measurement error due to this lagged public information, and lastly (v) some traders are informed about a possible tender offer and that the market is aware of this possibility. Under these conditions, "structural" tests will incorrectly support earnings information revelation, while "reduced form" tests will correctly reject it. In particular, assumptions (ii) and (iv) induce positive correlation between trades and FE while assumption (v) leads to positive correlation between trades and price changes (i.e., as a result of information revelation about the tender offer, not earnings). In contrast, given assumptions (i)-(iii), FE will be correlated with ΔP (Prv, Blk) only if there is price pressure (i.e., on the uninformed "reactive" trades) and will be uncorrelated with ΔP (Prv, Clo) (i.e., after the price pressure has abated).

7. Summary

Do block price changes reflect the revelation of private information about unexpected quarterly earnings? From "reduced-form" tests of the composite relation between earnings and prices, the answer appears to be yes. In particular, prices on "large" blocks (of over 0.5 percent of share outstanding) shortly before earnings announcements are positively correlated with *Value Line* forecast errors, our proxy for unexpected earnings. However, the magnitude of these price effects depends dramatically on whether the preblock price level is measured by the preceding closing or the previous transaction price.

Turning to our second question, is block size itself (as one of many descriptive characteristics of a trade) informative about earnings? Here the answer is less clear. "Large" blocks do appear to be more informative than "small" blocks or randomly "matched" small trades. However, we do not find significant (positive) Spearman rank correlation between *unsigned* block size and the absolute values of either earnings forecast errors or "permanent" price change. Hence, blocks may be more informative about the *sign* than the *magnitude* of unexpected earnings. However, a likely problem with these more "structural" tests is that the "market" may interpret our two size measures differently across sample firms. Another possibility is that, although not directly informative about earnings, trade size may indirectly signal dealers that they should condition prices on other trade characteristics (e.g., investor urgency and reputation) that are informative.

This study suggests several avenues for future work. First, in the regression analysis, information revelation about current earnings explains at most 20 percent of block price variance for a sample constructed a priori to maximize the importance of this effect. Thus, there clearly is a need for further work identifying other variables (e.g., earnings further in the future or the split of firm value between stock and bond holders) about which block trades-and transactions generally-are informative.

Second, there is a need for work-both theoretical and empirical-on standardized ways to measure trade size so that its informational interpretation is consistent in cross-sectional samples, and on the role trade characteristics other than size (e.g., investor urgency, reputation) play in the process of information revelation.

References

Beebower, G., and W. Priest, 1980, "The Tricks of the Trade," *Journal of Portfolio Management,* 6, 36-42.

Brown, L.. and M. Rozeff, 1978, "The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings," *Journal of Finance,* 33, 1-16.

Daniel, W., 1978, *Applied Nonparametric Statistics,* Houghton Mifflin, Boston.

Dann, L., D. Mayers, and R. Raab, 1977, "Trading Rules, Large Blocks and the Speed of Adjustment," *Journal of Financial Economics,* 4, 3-22.

Easley, D., and M. O'Hara, 1987, "Prices, Trade Size and Information in Security Markets." *Journal of Financial Economics,* 19, 69-90.

Foster, G.. 1977. "Quarterly Accounting Data: Time-Series Properties and Predictive-Ability Results," *Accounting Review,* 52, 1-21.

Foster, G., C. Olsen. and T. Shevlin, 1984, "Earnings Releases, Anomalies and the Behavior of Security Returns." *Accounting Review,* 59, 574-599.

French. K., R. Leftwich, and W. Uhrig, 1985, "The Effect of Scheduled Money Supply Announcements and Crop Forecasts on Future Prices," working paper, University of Chicago.

Fried, D., and D. Givoly, 1982, "Financial Analysts' Forecasts of Earnings," *Journal of Accounting and Economics* 4, 85-107.

Gammill, J., 1985. *The Design of Financial Markets,* Ph.D. dissertation, Massachusetts Institute of Technology (unpublished).

Givoly, D., and J. Lakonishok, 1984, "Properties of Analysts' Forecasts of Earnings: A Review and Analysis of the Research," *Journal of Accounting Literature,* 3, 117-152.

Glosten, L., 1989. "Insider Trading, Liquidity and the Role of the Monopoly Specialist," *Journal of Business,* 62, 211-235.

Glosten, L., and L. Harris, 1988. "Estimating the Components of the Bid/Ask Spread," *Journal of Financial Economics,* 21, 123-144.

Hasbrouck, J., 1991, "The Summary Informativeness of Stock Trades: An Econometric Analysis." *Review of Financial Studies,* 4, 571-595.

Holthausen, R., R. Leftwich, and D. Mayers, 1987, "The Effect of Large Block Transactions on Security Prices," *Journal of Financial Economics,* 19, 237-267.

Holthausen, R., R. Leftwich, and D. Mayers, 1990. "Large Block Transactions, the Speed of Response, and Temporary and Permanent Stock-Price Effects," *Journal of Financial Economics,* 26, 71-95.

Hughson, E., 1990, "Intraday Trade in Dealership Markets," working paper, California Institute of Technology.

Kraus, A., and H. Stoll, 1972, "Price Impacts of Block Trading on the New York Stock Exchange," *Journal of Finance,* 27, 569-580.

Kyle, A., 1985, "Continuous Auctions and Insider Trading," *Econometrica,* 53, 1315-1335

Madhavan, A., 1987, "Trading Mechanisms in Security Markets," working paper, University of Pennsylvania.

Ofer, A., and D. Siegel, 1987, "Corporate Financial Policy, Information and Market Expectations: An Empirical Investigation of Dividends," *Journal of Finance,* 42, 889-911.

Pound, J.. 1986, "The Signalling Content of Takeover Bids and Managerial Resistence: Empirical Evidence," working paper, Yale University.

Scholes, M., 1972. "The Market for Securities: Substitution versus Price Pressure and the Effects of Information on Share Prices," *Journal of Business,* 45, 179-211.

Seppi, D., 1990, "Equilibrium Block Trading and Asymmetric Information," *Journal of Finance,* 45,73-94.

White; H., 1980, "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica,* 48, 817-828.