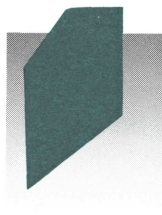# Does program trading cause stock prices to overreact?

James T. Moser

Program trading constitutes a substantial fraction of the trading activity in the New York Stock Exchange. The volume of stocks exchanged in orders labeled program trades typically averages 10 percent of total volume. This article investigates the claim that program trading causes stock prices to overreact. Stock price overreaction is important because investors are thought to use stock prices as guides to the best uses of their capital. If prices overreact to new information, they cannot provide accurate guidance. Evidence of such stock price overreaction would be indicative of excessive volatility.

Previous researchers have considered the possible effect of program trading on volatility, a proposition which requires a model for the natural evolution of volatility. Because such a model lacks general acceptance, this article offers an alternative approach. I investigate whether program trades increase the odds of price reversions.

Prices reverse when previously encountered price decreases are immediately followed by an increase in price; or when a previously encountered price increase is immediately followed by a price decrease. Price reversions can be expected to occur when price changes are larger than the value changes warranted by new information, that is, when prices overreact to new information. In instances of overreaction, informed traders will find current prices out of line with their valuations. The trades of these informed traders will then bring prices

back toward their original levels. This depiction follows that of Black (1985).

This article examines whether program trading should be classified as a type of noise trading or as a type of information trading. If levels of program trading increase the likelihood that a price reversal will occur, we can conclude that program trading is a type of noise trading. On the other hand, if program trading is unrelated to the likelihood of encountering a price reversal, then program trading should be categorized as information trading. I examine a 34-month period of daily program trading activity and stock prices and use a logit specification to consider the proposition that trading activity changes the probability of stock price reversals. The results do not support the claim that program trading causes stock price overreactions.

Literature review

Much of the literature on program trading considers its effect on stock price volatility. Stoll and Whaley (1986, 1987, 1988, 1990) examine the consequences of program trading occurring on "triple-witching days," that is, dates when multiple derivative contracts on stocks simultaneously expire. As heavy program trading frequently occurs on these expiration dates, Stoll and Whaley's evidence of higher volatility suggests that program trading can be linked to increased volatility. Edwards (1988) studies the impact of stock-index futures and finds that volatility does not increase

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after the introduction of multiple derivative contracts. Since these contracts are frequently involved in program trading strategies, an increase in stock price volatility would be consistent with a program trading effect. Maberly, Allen, and Gilbert (1989) note that this result depends on the sample period. Harris (1989) finds only a slight increase in volatility during the 1980s, suggesting that the increased program trading activity that was facilitated by futures trading had, at most, a very modest effect on volatility. Martin and Senchack (1989, 1991) find that the volatility of stocks included in the Major Market Index (MMI) rose after the MMI futures contract was introduced. Their risk decomposition indicates that the systematic risk of these stocks rose. Since the MMI futures contract is frequently involved in program trading, this finding suggests that program trading led to higher volatility.

Program trading grew rapidly during the 1980s. If this activity increases volatility, then the 1980s should have shown higher than usual volatility. Several investigators have examined the period for changes in volatility. Froot, Perold, and Stein (1991) investigate returns on the Standard and Poor 500 since the 1930s. They find that changes in volatility are conditional on the length of the holding period. There is strong evidence of an increase in return volatility during the 1980s for 15-minute holding periods. When longer holding periods are examined, it is much less evident that volatility has changed. Miller (1990) suggests a conceptual distinction between the volatility of price changes and price-change velocity. While statistical tests frequently demonstrate no change in volatility levels, the speed of price adjustments does appear to have increased during the 1980s. Froot and Perold (1990) decompose price changes into bid-ask bounce, nontrading effects, and noncontemporaneous cross-stock correlations. They demonstrate that price adjustments occurred more rapidly during the 1980s.

Direct investigation of the effects of program trading finds temporary increases in volatility which are most prominent in index arbitrage activities. Much of this evidence is reviewed by Duffee, Kupiec, and White (1990). Grossman (1988) regresses various measures of daily price volatility on program trading intensity, finding no significant effect. A Securities and Exchange Commission study (1989) finds a positive association between daily volatility of

changes in the Dow Jones Index and levels of program trading activity. Furbush (1989) finds a significant relationship between price volatility and program trading activity in the three days prior to the October 19, 1987, market break. Harris, Sofianos, and Shapiro (1990) and Neal (1991) investigate intraday program trading, finding that responses to program trades are similar to those found for block trades. Using "GARCH" estimation procedures, Moser (1994) finds a modest increase in the volatility of returns for one-day holding periods associated with sell program activity. Thus, the evidence is inconclusive. The logit specification developed in the next section offers an alternative approach to examining this question.

Data sets and sample description

Trading activity data for this study are from the New York Stock Exchange (NYSE).[1] The data set includes aggregate trading volume and share volumes involved in programmed trades. The sample consists of 717 daily observations from the period January 1, 1988, through October 31, 1990. Program trades are presently classified as buys, sells, and short sales.

Program trading activity is the number of shares included in orders identified as program trades. The NYSE defines program trades as orders involving 15 or more stocks having a combined market value in excess of one million dollars. The program trades of this sample include shares exchanged through SuperDOT.[2]

Price reversals are constructed from a data set of percentage changes, denoted R_t, in the Dow Jones Industrial Averages. This stock index is useful in that it is computed from prices for heavily traded stocks which are frequently involved in program trades. Thus, if program trading does lead to price overreaction, this effect should be most pronounced in these stocks. Reversals, denoted r_t, are computed for the stock return sample as follows:

$$(1) \quad r_{t-j} = \begin{cases} 1 \ if \ \widetilde{\varepsilon}_{t-j} \cdot \widetilde{\varepsilon}_{t-j-1} < 0 \\ \\ 0 \ otherwise \end{cases}$$

where

$$(2) \quad \widetilde{\varepsilon}_t = \widetilde{R}_t - E(\widetilde{R}_t \mid \phi_t) .$$

Equation 1 specifies an indicator variable assigned a value of one on sample dates when the unanticipated portion of the return at $t–j–1$ has the opposite sign as that of the unanticipated return realized at $t–j$ for the holding period from $t–j–1$ through $t–j$; on other dates, the indicator variable is set to zero. Equation 2 states that unanticipated returns are computed as actual returns minus their corresponding expectations. Expected returns are generated assuming that stock prices can be described by a martingale; that is, $E(R_t) = 0$. As the next section points out, considering various values of the lag j permits longer intervals for prices to correct following a price overreaction.

Estimating reversal probabilities conditional on trading activity

Let Z represent a vector of index values with each element measuring the propensity of the market to produce a reversal. The proposition that program trading encourages overreaction as demonstrated by stock price reversals, implies that the index should be related to levels of program trading activity. If this is true, the data should allow us to reject the null hypothesis that program trading has no effect. Defining X as a matrix of k measures of the trading activity variables, we write

$$Z = X\beta ,$$

so that levels of the index are predicted by activity levels and their coefficients. The over-reaction null predicts that β will differ from zero. The level of this index can also be described as determining the probability of encountering a reversal conditional on trading activity. The vector of these probabilities can be written as $P=F(Z)$. Taking $F(\ )$ to be the cumulative logistic probability function, these probabilities of reversals are given by

$$P_t = F(Z_t) = \frac{1}{1 + e^{-z_t}} = \frac{1}{1 + e^{-x_t\beta}} .$$

Taking logs and rearranging gives the following logit specification:

$$(3) \quad \log \frac{P_t}{1-P_t} = X_t\beta + \tilde{e}_t .$$

Equation 3 is estimated using the method of maximum likelihood. The expression for the log likelihood is

$$\log l = \sum_{t=1}^{T} r_t \log[F(x'_{t-j}b)]$$
$$+ (1 - r_t) \log[1 - F(x'_{t-j}b)],$$

where T is the number of observed changes in returns and x_{t-j} are the activity variables observed at dates $t–j$. Lagging the activity variables coincides with the null under investigation. When $j=1$, the null hypothesis under investigation asks, does heavy trading activity at date $t–1$ consistently cause stock prices to overreact? If program trading activity caused an overreaction on this date, and if a price correction occurred in the one trading period since the overreaction, then a price reversal is realized, provided the information arriving at t does not overwhelm the amount of price correction. If these conditions hold, then the coefficients on the activity variables will differ from zero, reflecting the average impact from trading activity. Thus, the test specification jointly considers three questions:

1) Does overreaction occur?

2) Are price corrections realized the following day?

3) Is the amount of the price correction masked by the value of newly arriving information?

The null hypothesis of no effect can be rejected only if the answer to each of these questions is yes.

The third of these conditions is addressed *a priori*. Amounts of price corrections are masked by valuations of new information only if the value of new information is larger and has the same price change implications as the previous overreaction. As the distribution of value changes based on new information is likely to be symmetric, it is not likely that more than half of the overreactions will be masked by value changes attributable to new information. Further, if price changes due to overreactions are generally smaller than those caused by value changes due to new information, then the problem of overreaction may not be as large as often portrayed. These considerations reduce the problem of new information

masking overreactions to an efficiency concern rather than a bias concern. This leaves two conditions. As the inferences that can be drawn regarding the primary question of overreaction depend on the answer to the second question, I attempted to lessen the dependence on the length of the correction interval. I did this by examining longer correction intervals. Specifically, I extended the hypothesis to consider whether trading activity at $t–j$ produces overreactions on that date which are corrected over the interval from $t–j$ to t. Thus I considered the possibility that correction intervals last longer than one day. This still left open the possibility that corrections occur in less than one day.

Table 1 reports estimates of the logit specification given in equation 3 for price correction intervals of one through five trading days. Coefficients on the activity variables are generally small. Evidence of price reversals attributable to buy program activity is present for correction intervals of four trading days. Though statistically significant, the impact on price reversal probabilities is small. To gauge the relevance of this coefficient, I evaluated it at average levels of trading activity. Price reversals for this correction interval occur in

19.69 per cent of the sampled trading days. Taking this as the unconditional probability of a reversal, the conditional probability of a reversal increases by approximately .00037 for each increment of 1,000 shares executed in buy programs above the sample-average level of 8,044,000. At one standard deviation above this average level of trading activity—17.5 million shares—buy programs increase the probability of a reversal by 3.49 percent, with the reversal from this activity being realized over the succeeding four trading days.

Comparing the coefficients across the three categories of trading activity included in these regressions, nonprogram trading appears to be a more reliable cause of price reversals. Coefficients on nonprogram trading differ reliably from zero for the two-, three-, and five-day correction intervals. Again the magnitudes of these effects are small. At one standard deviation above average nonprogram trading activity, the probability of a reversal increases by 3.4 percent for the three-day correction interval. The magnitudes of impacts on reversal probabilities for the four- and five-day correction intervals are similar.

Pseudo R^2 values are computed following Judge *et al.* (1985) for each specification. The

TABLE 1					
Maximum likelihood estimates of logit specifications for price correction intervals of one to five days January 1, 1988 - October 31, 1990					
Parameter	**Price correction intervals**				
(x10,000)	1	2	3	4	5
Constant	3,242.5 (0.324)	−15,179** (−3.724)	−18,823** (−4.340)	−18,738** (−4.048)	−24,817** (−5.261)
Buy program	−0.07746 (−0.782)	0.00178 (0.017)	0.17976 (1.640)	0.23766* (2.075)	0.07580 (0.626)
Sell program	0.12082 (1.098)	0.16371 (1.444)	−0.16985 (−1.354)	−0.20134 (−1.509)	−0.03613 (−0.267)
Nonprogram	−0.02039 (−0.803)	0.05158* (1.942)	0.05740* (2.033)	0.03795 (1.262)	0.07042* (2.311)
Pseudo R^2	0.0021	0.0074	0.0095	0.0088	0.0084
Log l	−494.24	−457.66	−408.40	−371.07	−349.74

Note: t-statistics in parentheses.
 *p < .05.
**p < .01.

low values of these R^2 values implies that trading activity explains a very small portion of the overall variation in reversals. To consider the explanatory power of our specifications, I conducted a likelihood ratio test. Under the null hypothesis of no effect, the maximum value of the likelihood function is

$$\log l = n\log (n/T) + (T - n)\log (T - n/T),$$

where n is the number of reversals and T the number of sample dates. Specifications can be tested using a likelihood ratio test for the difference between this maximum log likelihood and the log likelihood obtained from the estimation procedure. For the sample of one-period correction intervals, the maximum log likelihood under the null hypothesis is –495.29, which is only slightly smaller than the actual value of –494.24. The critical value of twice this difference is 7.81 for the 95 percent level of confidence. Thus, the data fails to reject the null hypothesis; that is, the results for the one-day correction interval do not support an association between trading activity and price reversals. These differences are 6.85, 7.85, 6.56, and 5.96 for the two-, three-, four-, and five-day correction intervals, respectively. The critical value is exceeded only at the three-day correction interval. This implies that trading activity does lead to price overreactions which are subsequently corrected in three trading days. The individual coefficients indicate that it is nonprogram trading which produces these overreac-tions rather than buy or sell trading activity.

Recall that the price correction intervals considered in this paper are whole trading days. Fractional trading days are not considered. Thus, overreactions with a subsequent correction within the same trading day cannot be detected using a sample of daily returns as in this article. Previous research does investigate within-day reversals. Harris, Sofianos, and Shapiro (1990) and Neal (1991) find that the price impact of an average program trade is similar to that found for block trades. We conclude that price reversals, where found, are generally small. This implies that current trading mechanisms are usually quick to resolve those price overreactions attributable to program trading. Given the current effectiveness of these mechanisms, changes such as the imposition of transaction taxes or other institutional arrangements appear to be unwarranted.

Conclusion

Descriptions of stock market results frequently give the impression that program trading causes prices to overreact to current information. Some have proposed policy changes intended to dampen the effects of the extent of these overreactions. This article introduces a procedure to test the proposition that program trading causes price overreactions. Given the evidence presented, it appears that program trading activity does not cause price overreactions.

NOTES

[1] I am indebted to Deborah Sosebee and her staff at the NYSE. They provided the data on program trading and patiently answered many questions.

[2] Most but not all program trades at the NYSE are routed through SuperDOT, a computerized routing system. Large brokerage houses can arrange to have their program trades executed by floor brokers, but this method is more costly and slower. The weekly summaries of program trading reported in the financial press include program trades executed off the SuperDOT system. These data are unavailable on a daily basis. Program trading reported in the weekly summaries for the period 1/1/88 through 9/22/90 averaged 16.4 million shares per day. Program trades in this sample over the same period averaged 15.9 million shares. This suggests that program trades executed off the SuperDOT system account for only about 3 percent of program trading activity.

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