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Trading Activity, Program Trading, and the Volatility of Stock Returns

by

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Trading Activity, Program Trading, and the Volatility of Stock Returns

Abstract

Relationships between trading activity and the volatility of stock returns are investigated. Trading activity appears to explain the persistence of return volatility. GARCH specifications suggested by Lamoreaux and Lastrapes (1990a) are extended to include conditional variance and a moving-average term which captures the effects of nontrading within the stock indexes I examine. Trading activity is decomposed into predicted and unpredicted activity. Comparison of alternative specifications indicates that trading activity is jointly determined with volatility. Coefficients on conditional variance are positive in specifications which include trading activity variables. Magnitudes of the MA coefficients are consistent with nontrading effects. Average levels of sell program activity appear to increase annual return variance by 4.08% in the Standard and Poor's 500. Average levels of sell program activity raise volatility of the broader Wilshire 5000 index by 2.33%. The possibility that these volatility increases are not warranted by changes in fundamentals is investigated by examining for price reversals. Two methods are employed. The first is the procedure used by Stoll and Whaley (1986, 1987). The second approach estimates a nonlinear AR model, conditioning the autoregressive parameter on trading activity. Both approaches reject price reversals due to trading activity.

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I. Introduction

This paper investigates the link between trading activity and volatility using several GARCH specifications and price-reversal tests. Trading activity is tied to volatility in a variety of models for financial activity. The findings of many empirical investigations support the existence of such a fundamental relationship. Recently, program trading has come to be regarded as having a unique effect on volatility. The claims that volatility is induced by program trading are supported by economic intuition provided by Grossman (1987) and Gennotte and Leland (1990).

The GARCH specification introduced by Lamoureux and Lastrapes (1990a) is extended to conform with specifications examined by French, Schwert and Stambaugh (1987). This extension incorporates conditional volatility and an MA(1) parameter as testable restrictions. These restrictions are used as diagnostic aids which presume positive prices for risk bearing and autoregressive returns for stock indexes which is consistent with nontrading of stocks included in these indexes. This diagnostic approach has an important implication for the results of the study. Namely, results for the trading-activity hypotheses examined here must be stated as conditional on the appropriateness of these restrictions.

I find that, like Lamoureux and Lastrapes, inclusion of aggregate trading activity reduces volatility persistence; however, this specification rejects both risk pricing and the nontrading effect. In specifications which separate volume into nonprogram trading activity, program-buy activity and program-sell activity, neither the risk-pricing or the nontrading hypotheses are rejected. Coefficients on trading activity used in this specification imply that buy programs increase volatility and sell programs decrease volatility.

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Noting that these specifications rely on the level of trading activity being exogenously determined, trading activity is further decomposed into its predictable and unpredictable components using an AR(1) process. Predicted values from the AR(1) are used as instruments for trading activity. This decomposition significantly increases log likelihoods over those obtained from specifications imposing equality on the decomposed parameters. This result is consistent with joint determination of volatility and trading activity. Results for these specifications indicate increased persistence in volatility which induces a negative bias on the trading activity coefficients. The nature of this bias is investigated. The results indicate that sell program activity increases volatility. Comparison of the effects for several indexes suggests that stocks not included in program trading are less affected by program trading.

The positive association between program-trading activity and volatility is further examined. Excess volatility is defined here as volatility which is unrelated to changes in fundamentals. The paper posits that price reversals associated with prior trading activity indicates prior price over-reaction thus constituting evidence of excessive volatility. I test for reversals to determine if trading activity induces excess volatility. Two methods are employed to examine for price reversals. The first is the procedure introduced by Stoll and Whaley (1986,1987). The second is a nonlinear AR model which conditions the autoregressive parameter on trading activity and the incidence of circuit breakers. Both methods reject price reversals. Hence, the higher conditional volatility associated with sell program activity cannot be characterized as temporary price reversals. Eliminating price reversals as an explanation for increased volatility suggests the impact on risk is somewhat

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permanent.

The literature addressing the issues of this paper relates trading activity to volatility. Karpoff (1987) reviews the explanations and evidence of the relationship between volume and volatility. The relationship between program trading and volatility is indirectly examined in several papers. Stoll and Whaley (1986,1987,1988,1990) examine the effect of simultaneous expiration of multiple derivative contracts on stocks. Program trading activity is frequently heavy on these "triple-witching days." They find evidence of price reversals indicating excessive volatility. Edwards (1988) studies the impact of stock-index futures, finding no increase in volatility following the introduction of stock-index futures 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 the dependence of this result on the sample period. However, Harris (1989) finds only a slight increase in volatility during the 1980's, suggesting that the increase in program trading activity during this period 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 following the introduction of the MMI futures contract. Their decomposition of risk indicates that the systematic risk of these stocks rose. Since this contract is frequently involved in program trading, this suggests program trading led to higher volatility.

Froot, Perold and Stein (1991) investigate returns on the S&P 500 since the 1930's. They find that evidence of volatility changes is conditional on holding-period length. There is strong evidence of an increase in return volatility during the 1980's for fifteen-minute holding periods. It is much less evident that volatility has changed when longer holding

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periods are examined. 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 1980's. Froot and Perold (1990) decompose price changes into bid-ask bounce, nontrading effects and noncontemporaneous cross-stock correlations. They demonstrate an increased speed of price adjustment during the period.

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 (1988a) regresses various measures of daily volatility on program trading intensity, finding no significant effect. An SEC (1989) study 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 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.

Section II describes the data set used in the paper. Section III introduces the GARCH specification for contemporaneous trading activity. Section IV separates trading activity into its predictable and unpredictable components. Section V covers the price-reversal tests. Section VI concludes the paper.

II. Data sets and sample description

A. Data

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Trading activity data for this study are from the New York Stock Exchange (NYSE).[1] The data set includes aggregate trading volume and trading activity in programmed trades. The data are 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 fifteen or more stocks having a combined market value exceeding one million dollars. The program trades of this sample include only shares exchanged through SuperDOT.[2] In the early part of the sample period (104 observations), program short sales were combined with shares exchanged in program sell orders. The remainder of the sample (613 observations) separates sell orders from short-sell orders. These two categories are combined in this study.[3]

Stock indexes matching the period of the trading activity data are for the Dow-Jones Industrials, the Standard and Poor's 500 and the Wilshire 5000. These indexes differ in their construction. An important difference for the purposes of this paper is the range of stocks included in each. The thirty stocks included in the Dow Jones are actively traded and very

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

[2] Most, but not all, program trades at the NYSE are routed through SuperDOT. Large brokerage houses can arrange to have their program trades executed by floor brokers. 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% of program trading activity.

[3] Estimates for the latter sample period found the effects of short-sell program and sell programs were similar.

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likely to be included in program trade orders. The likelihood that stocks are involved in program trades can be inferred by examining the use of the various stock index futures contracts in index-arbitrage programs. These contracts trade baskets of stocks which closely approximate cash-market indexes: the Major Market Index (MMI) futures contract approximates the Dow Jones Industrial index and the S&P 500 futures contract replicates the Standard and Poor's 500. Neal (1991) studies index arbitrage activity during the period January 3, 1989 through March 31, 1989. He finds that programs involving the MMI futures contract made up 23.5% of the volume of stocks traded in the sample, averaging 23.42 stocks per program-trade order. The 500 stocks constituting the S&P also include many stocks likely to be included in program trades. Neal (1991) reports that 35.5% of his sample involved the S&P 500 futures contract, averaging 375.2 stocks per program. The Neal study suggests that program trading activity is concentrated in the stocks included in these broad market indexes. Stocks less likely to be involved in program trades are the 38 stocks included in the S&P 500 but not listed at NYSE and stocks which are included but are thinly traded. Other evidence suggests that less than half of the S&P 500 stocks are frequently involved in program trades. For example, Harris, Sofianos and Shapiro (1990) examine 2,346 program trades on the NYSE during June 1989. Their sample of program trades averaged 210,000 shares in 176 stocks for buy programs and 199,000 shares in 179 stocks for sell programs. Similar reasoning leads to the conclusion that the majority of stocks included in the Wilshire 5000 are unlikely to be included in program trades.[4] These inclusion differences

[4] The Wilshire 5000 includes the NYSE and AMEX stocks plus the major NASDAQ stocks. The index includes about 5,000 stocks and is value weighted.

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offer insight into the question of whether trading activity effects extend beyond the stocks most often involved in program trades.[5]

B. Sample description

Table 1 reports summary statistics for the trading activity variables and returns for the respective indexes. Panel A summarizes trading activity. Trading activity amounts are reported in thousands of shares traded. Shares traded in transactions classified as buy programs average just over eight million shares daily or 5.0% percent of all shares traded. Sell programs average 7.8 million shares or 4.8% of all shares traded. Combined program trading is consistent with other evidence indicating that program trades account for 10% of daily trading activity.[6] Standard deviations, minimums and maximums suggest that program trading activity is more variable than total trading volume.

Continuously compounded, annualized returns on the stock indexes are analyzed in the paper.[7] Panel B of Table I reports autocorrelations for portfolio returns and their squares. Examining the autocorrelations of portfolio returns indicates no trends. The Box-Ljung test confirms this, detecting no significant autoregressive trends in the data through the twelfth lag. Bollerslev (1986) suggests that autoregressive trends in squares of data series can be evidence of ARCH effects. Autocorrelations of squared returns tend to be positive and largest

[5] Martin and Senchack (1991) find that program trading effects are limited to stocks likely to be included in this activity.

[6] NYSE (1990) reports 10%.

[7] This usage follows convention. Returns on the portfolio of stocks included in the Dow would not match the percentage rate of change in the index itself. This is due to the weights used in constructing the Dow. Similarly, none of the indexes include dividends. Thus, actual portfolio returns would differ from rates of change in these indexes.

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around the fifth through eighth lags for each of the portfolios. Q(12) statistics also indicate the presence of autoregressive trends in the squared return series. This suggests the presence of ARCH effects in these series. This result is consistent with well-known evidence of excessive kurtosis in security returns:[8] autoregression in the variance being one explanation for this evidence.

Correlations of trading activity and returns are consistent with those reported elsewhere. Correlations of volume levels and index returns are: .06 for the Dow, .05 for the S&P and .04 for the Wilshire index. The magnitudes of these correlations are consistent with the ranges of regression coefficients reported by Epps and Epps (1976) and Tauchen and Pitts (1983). The correlations between the number of shares exchanged in buy program trades and returns on the index are much higher. These correlations are: .28 for the Dow, .29 for the S&P and .27 for the Wilshire index. In contrast, shares traded in sell programs are negatively correlated with returns as follows: -.30 for the Dow, -.30 for the S&P, and -.31 for the Wilshire. These correlations of returns with measures of program trading activity indicate that program trading activity is generally contemporaneous with large price changes.[9]

Nonprogram trades, defined as total trading volume minus the volume of stocks included in program trades, are not significantly correlated with either buy or sell-program activity. Admati and Pfleiderer (1989) offer a trade-execution explanation for the observed

[8] Fama (1965) is the customary citation.

[9] An SEC (1989) study reports a correlation of .31 between the number of shares involved in program trading activity and return volatility. The study measures daily volatility as the standard deviation of price change at the open, close, and six equally spaced intervals during the day.

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"clumping" of trading activity. The low correlations between program and nonprogram trading activity indicate that incentives to initiate program trades may not depend on market depth.

III. The effect of trading activity on the volatility of portfolio returns

A. Specification

The Generalized GARCH-in-mean model of Engle, Lilien, and Robbins (1987) and Bollerslev, Engle and Wooldridge (1988) permits joint estimation of a conditional mean as a function of volatility jointly estimated as a time series dependent on conditional volatility and past squared residuals from the process. Such a model for daily stock returns is given as:

$$R_{pt} = \alpha + \beta\sigma_t^2 + \varepsilon_t - \theta\varepsilon_{t-1} \tag{1}$$

$$\sigma_t^2 = a + b\sigma_{t-1}^2 + c\varepsilon_{t-1}^2 + d_1 V_t \tag{2}$$

$$\varepsilon_t \sim N(0,\sigma_t) \tag{3}$$

where R_{pt} is the return on a portfolio of stocks. Expected returns on stocks are conditional on volatility included in the specification as a jointly estimated conditional variance of returns. As noted by Bollerslev, Chou, Jayaraman and Kroner (1990, hereinafter BCJK), the parameter ß corresponds to the coefficient of relative risk aversion. A positive risk-return tradeoff implies ß>0. Nonsynchronous trading of individual securities included in an index induces first-order autocorrelation in index returns [see Fisher (1966) and Scholes and Williams (1977)] which is incorporated into this specification by including a first-order moving average process for the errors. Nonsynchronicity implies $\Theta>0$ with the further expectation that the magnitude of Θ increases as the extent of nontrading of the stocks contained in the index

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rises.[10] Examination of coefficients on conditional volatility and the moving average parameters attributable to nontrading aids in the diagnosis of the specification. Thus, evidence that risk is incorrectly priced or lack of nontrading evidence is interpreted as an indication of miss-specification.

If the sum of the parameters b and c of equation (2) are positive, then volatility shocks persist. The degree of this persistence for a non-explosive volatility series is determined by the proximity of the sum of these parameters to unity. BCJK document the extent of the evidence for stock return persistence. Lamoureux and Lastrapes (1990b) suggest that failure to account for structural changes in return variance may explain this evidence of persistence. The inclusion of volume in the conditional volatility, denoted V_t, is motivated by models suggesting that trading activity might explain structural shifts in volatility. These models suggest that the sum of the parameters b and c should be sensitive to a restriction of the coefficient on V_t to zero.

The estimation procedures of this paper rely on the normality assumption expressed in equation (3). The results of Baillie and DeGennaro (1990) indicate that this assumption may not hold exactly in the data, however previous research finds that quasi-maximum likelihood estimates of these parameters are generally consistent and asymptotically normally distributed, provided that the conditional mean [equation (1)] and conditional variance [equation (2)] are

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[10] The intuition for this result is that common components of all securities are contemporaneously correlated with underlying market factors. Thus, price changes realized for thinly traded securities are frequently correlated with previously realized changes in the broad market. This autoregressive component has an MA(1) representation. Lo and MacKinlay (1988,1990) demonstrate that autocorrelations of index returns may be too high to be satisfactorily explained by nontrading.

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correctly specified.[11]

The motivation for including volume in the volatility specification follows Lamoureux and Lastrapes (1990a). Let δ_{it} denote the ith intraday equilibrium price increment in day t with δ_{it} assumed to be i.i.d. with mean zero and variance σ_t^2. This implies that returns over fixed intervals can be construed as mixtures of distributions for the equilibrium price changes occurring throughout the interval. The sum of these intraday price changes,

$$\varepsilon_t = \sum_{i=1}^{n_t} \delta_{it} \tag{4}$$

defines the equilibrium price change over the period. The distribution of ε_t is subordinate to δ_{it}. Further, the number of distributions encompassed by ε_t is directed by n_t. The directing variable, n_t, approximates the stochastic rate of the flow of information into the market. High values of n_t imply a high rate of information arrival. The model of Ross (1989) augments this intuition by linking the variation in asset prices to variation in the rate of information arrival. Since trading activity is indicative of uncertainty changes affecting the distribution of expected cash flows, then current values are affected. Thus, high values of n_t also imply high

[11] See Domowitz and White (1982), Weiss (1986) and Bollerslev and Wooldridge (1991).

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return variances.[12]

Further insight requires parameterization of the information arrival process. A natural candidate for information arrival is trading volume. Epps and Epps (1976) suggest trading volume represents the extent of heterogeneity in the expectations of traders. In their model, trades are motivated by divergences between the reservation prices of individual traders and the prevailing market price. Thus, high volume, indicative of disagreement, is positively related to volatility. Similarly, Roll (1988) conjectures that trading volume is positively related to the arrival rate of idiosyncratic information.

Tauchen and Pitts (1983) derive a model which jointly determines trading activity and return volatility. In their model, both volume and price change depend on an underlying common factor. Although price changes conditional on the underlying factor are independent of volume conditional on the same factor, unconditional volume and price changes are positively related. As Karpoff (1987) notes, simultaneous determination of volume and volatility requires a model for volume. The specification developed in this section takes

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[12] To demonstrate their point that evidence of persistence in return variances in GARCH specifications can be due to shifts in the structure of variance, Lamoreaux and Lastrapes assume that the daily number of information arrivals is serially correlated, expressed as follows:

$$n_t = k + b(L)n_{t-1} + u_t \tag{5}$$

where k is a constant, b(L) is a lag polynomial of order q, and u_t is white noise. Innovations to the mixing variable persist according to the autoregressive structure of b(L). Define $\Omega_t = E(\varepsilon_t^2 | n_t)$. Validity of the mixture model implies $\Omega_t = \sigma^2 n_t$ and substituting from (5) under this null yields

$$\Omega_t = \sigma^2 k + b(L)\Omega_{t-1} + \sigma^2 u_t \tag{6}$$

Equation (6) demonstrates how persistence in conditional variance can be picked up in a GARCH model. Innovations to the information process lead to a momentum in the squared residuals of daily returns which can, mistakenly, be construed as persistence in variance.

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volume as exogenous. Later sections of this paper further address this issue.

B. Results

Equations (1)-(2) are estimated using the Berndt, Hall, Hall and Hausman algorithm. Starting values for α and a are, respectively, the sample means and standard deviations of returns on the indexes for the sample period. Other starting values set to zero. Attempts using alternate starting values suggest the conclusions of the paper are insensitive to the choice of starting values. Experiments using additional lags of the conditional variance and squared residuals suggest a GARCH(1,1) adequately summarizes the sample. The criterion for convergence of the algorithm is an R square of .001.

Table II reports results for the three stock indexes: the Dow-Jones 30 Industrials, the Standard and Poor's 500, and the Wilshire 5000. Columns labelled "Excluding Volume" restrict the coefficient on volume to zero. Asymptotic standard errors are in parentheses below their associated coefficient estimates.

Coefficients on the conditional variances included in the mean do not differ reliably from zero. This suggests that risk premia do not reflect the level of volatility conditional on either specification for volatility. This is in contrast to the results of prior research examining longer periods which generally find a positive relationship,[13] but conforms to the results of Baillie and DeGennaro (1989) and Campbell and Shiller (1989) who find coefficients on conditional volatility do not differ reliably from zero. Estimates of the moving average

[13] Researchers finding a significant positive coefficient on conditional volatility included in the means are: French, Schwert and Stambaugh (1987) for the daily S&P over the period 1928-1985, Chou (1988) for weekly NYSE value-weighted returns for 1962-1985, Attanasio and Wadhwani (1989) for monthly and annual returns, and Friedman and Kuttner (1988) for quarterly US stock return over the period 1960-1985.

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parameters also do not differ reliably from zero. Thus, results from the specification for conditional mean are suggestive of specification error.

Results for the volatility equation accord with expectations. First, as expected, the sums of coefficients on lagged conditional volatility and lagged squared residuals decline when trading activity is included in the specification. For the Dow, the sum declines from .94 to -.12; for the S&P 500, the sum declines from .95 to -.07; and for the Wilshire 5000, the sum declines from .88 to -.13. Evidence of the impact of restricting the coefficient on volume to zero can be seen by comparing their log likelihoods. For each index, log likelihoods rise substantially when the restriction on the volume coefficient is dropped. The significance of these declines is obtained with a likelihood ratio test. The negative of twice the difference in log likelihoods for the specification restricting the volume coefficient to zero and the unrestricted-coefficient specification is distributed chi square with one degree of freedom. Log likelihoods differ by 68.0 for the Dow specifications, by 52.2 for the S&P specifications, and by 34.2 for the Wilshire specifications. Each of these differences are much greater than the one-percent critical level of 6.63. Thus, the restriction that the coefficient on volume is zero can be rejected at better than the one-percent level.

Lamoureaux and Lastrapes (1990a) find a strong positive relationship between volatility and trading activity in their sample of twenty actively traded stocks. Further, they find that ARCH effects disappear when volume is included in the specification for conditional volatility. Similarly, Najan and Yung (1991) find a positive relationship between the conditional volatility of returns for CBOT-traded futures contracts on U.S. Treasury Bonds and levels of trading activity, both contemporaneous and one-period lags. This result is

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interpreted as evidence that volatility and trading activity are jointly determined. Unlike Lamoureaux and Lastrapes (1990a), Najan and Yung find substantial evidence of volatility persistence in specifications which include trading activity in the expression for volatility.

Results from this section accord with the idea that trading activity can explain the variance persistence observed in previous research. The results of the specification for the conditional mean indicate the need for further examination of this specification.

IV. Separating program and nonprogram trading activity

One interpretation of the results of the previous section is that trading volume miss-represents the directing variable, n_t. For example, if the rate of information arrival differs between program trades and nonprogram trades, then the coefficient on trading volume previously examined may vary according to the portion of trading activity due to program trades. This section examines the relationship between volatility and trading activity separated by their classification as program or nonprogram trading.

A. Specification using contemporaneous trading activity

The sum of equilibrium price changes denoted in equation (4) can be re-written as follows:

$$\varepsilon_t = \sum_{i=1}^{n_{bp,t}} \delta_{it} + \sum_{j=1}^{n_{sp,t}} \delta_{jt} + \sum_{k=1}^{n_t - n_{bp,t} - n_{sp,t}} \delta_{kt} \qquad (7)$$

where $n_{bp,t}$ is the number of buy-program trades, $n_{sp,t}$ is the number of sell-program trades and n_t-$n_{bp,t}$-$n_{sp,t}$ is the number of nonprogram trades. Equation (7) implies that the distribution of ε_t is subordinate to the distributions of the δ_i, δ_j, δ_k. These distributions are directed by their respective numbers of trades. The indices i, j, and k for the equilibrium price changes leave

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open the possibility that the variance added by additional trades in one category may differ from the variance added by additional trades in the remaining categories.[14] Incorporating these separate trading categories into a GARCH specification enables a test of differences in return variation for each of the classifications of trading activity. The GARCH specification is

$$R_{pt} = \alpha + \beta\sigma_t^2 + \varepsilon_t - \theta\varepsilon_{t-1} \tag{8}$$

$$\sigma_t^2 = a + b\sigma_{t-1}^2 + c\varepsilon_{t-1}^2 + d_1V_{N,t} + d_2V_{bp,t} + d_3V_{sp,t} \tag{9}$$

$$\varepsilon_t \sim N(0,\sigma_t) \tag{10}$$

where $V_{N,t}$ is volume net of program trades, $V_{bp,t}$ is trading volume involved in buy programs and $V_{sp,t}$ is trading volume involved in sell programs. Starting values for the estimation procedure are from the estimates for equations (1) and (2) with the additional parameter starting values set to zero. Experiments with starting values suggest results are robust to alternate starting values. Additional experiments adding lags of the conditional variance and squared residuals suggest a GARCH(1,1) adequately summarizes the sample.

Table III reports results for the three stock indexes: the Dow-Jones 30 Industrials, the Standard and Poor's 500, and the Wilshire 5000. Asymptotic standard errors are in parentheses below their associated coefficient estimates. Coefficients on conditional volatility

[14] This interpretation relies on two assumptions, both consistent with the conditions on equation (4). First, that trades are sequential. Second, that the return distributions for equilibrium price changes are independent. These assumptions preclude the possibility that, for example, the volatility of buy-program price changes affects the volatility of price changes for either of the other trading categories.

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are positive and reliably differ from zero. Estimates of the moving average parameters differ reliably from zero as is consistent with the nontrading explanation. Comparison of the magnitudes of the moving average parameters for each index indicates consistency with the nontrading explanation. As the extent of nontrading in the stocks included in an index rises, the magnitude of the moving average parameter should increase. The blue chip stocks included in the Dow index are consistently the heaviest traded, the stocks included in the S&P 500 are less heavily traded, and the Wilshire 5000 includes the least heavily traded stocks. Consistent with this pattern of nontrading, the magnitude of the moving-average parameter increases as the extent of nontrading within each index rises. Also, ß is significantly positive, thus, the specification for the mean appears to be consistent with the intuition that expected returns are positively related to their conditional variances and that nontrading of the stocks composing an index leads to autoregressive disturbances.

Coefficients on lagged conditional volatility and residual squares are similar to those reported in Table II. Signs of the coefficients on the trading activity variables are consistent across the three indices. Comparison of coefficient magnitudes across the three indices suggests that they decline as the number of stocks included in the index rises. The coefficients on nonprogram trading are positive, but are well within two standard errors of zero. Thus, nonprogram trading activity does not reliably influence return volatility. In terms of the model, this result suggests that nonprogram trades do not alter the amount of information arriving at the market. In contrast, coefficients on buy and sell program activity are reliably different from zero. Buy programs are associated with increased volatility and sell programs with decreased volatility. This result implies that buy and sell program activity

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conveys information, provided trading activity is exogenous.

B. Specifications separating expected and unexpected trading activity

Bessembinder (1991) and the evidence of Schwert (1989) suggest decomposition of volume into its predictable and unpredictable components. Bessembinder's decomposition is partially motivated by the idea that coefficients on unpredictable volume reflect the impact of information flows. In the context of the present paper, volume which can be predicted on the basis of past trading activity cannot be jointly determined with volatility. Should trading activity and volatility be jointly determined as suggested by Tauchen and Pitts (1983), the unpredictable portion of volume may not be exogenous as presumed in the previous specifications of this paper. Alternately, implementation of circuit breaker rules may induce a contemporaneous bi-directional association between volume and volatility.[15] This possibility is explored by decomposing each of the trading activity variables into their predictable and unpredictable components. Specifically, the following AR(1) representations for trading activity are employed:

$$V_{N,t} = \rho_N V_{N,t-1} + u_{N,t} \qquad \textbf{(11a)}$$

$$V_{bp,t} = \rho_B V_{bp,t-1} + u_{bp,t} \qquad \textbf{(11b)}$$

$$V_{sp,t} = \rho_S V_{sp,t-1} + u_{sp,t} \qquad \textbf{(11a)}$$

Thus, deviations from expected share volumes in each trading category are denoted $u_{N,t}$, $u_{bp,t}$, and $u_{sp,t}$. The realized trading activity variables used in equation (9) are replaced by their

[15] Circuit breakers are rules designed to alter order flows when changes in a stock index exceed some benchmark. Thus, volatility and order flow are simultaneously determined.

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corresponding predicted values and residuals from the AR(1) specification. This substitution gives the following GARCH specification:

$$R_{pt} = \alpha + \beta\sigma_t^2 + \varepsilon_t - \theta\varepsilon_{t-1} \tag{12}$$

$$\sigma_t^2 = a + b\sigma_{t-1}^2 + c\varepsilon_{t-1}^2 + d_1 v_{N,t} + d_2 u_{N,t} + d_3 v_{bp,t} + d_4 u_{bp,t} + d_5 v_{sp,t} + d_6 u_{sp,t} \tag{13}$$

$$\varepsilon_t \sim N(0,\sigma_t) \tag{14}$$

where $v_{N,t}$ is the predicted volume of stock trades net of shares traded in programs, $v_{bp,t}$ and $v_{sp,t}$ are, respectively, the predicted volumes of shares traded in buy and sell programs. Expected volumes are the predictions from the respective AR(1) process.

Table IV reports results for unrestricted estimates of equations (12) and (13) and estimates which restrict coefficients on unpredicted activity to zero. The log likelihoods from the unrestricted specifications in Table IV are larger than the corresponding log likelihoods in Table III. Comparing these quantities examines the possibility that the coefficients on the predicted activity variables differ from the coefficients on the unpredicted activity variables. Rejection of equal coefficients is consistent with joint determination of trading activity and volatility. The increases in log likelihood ratios are: 9.2 for the Dow; 13.3 for the S&P; and, 4.9 for the Wilshire. The unrestricted specifications of Table IV relax three coefficient restrictions from their counterparts in Table III. The critical value is 7.82 for the negative of twice the difference between log likelihoods. Each comparison indicates a reliable difference at the 95% level. The test suggests a simultaneous equations bias to the coefficients in Table III and to the coefficients on unpredicted trading activity from the unrestricted specifications reported in Table IV. This inference lessens our reliance on the coefficients from the

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unrestricted specification and prompts increased attention to the restricted specification.

Parameter estimates for the mean equation are sensitive to restricting coefficients on the unpredictable trading activity variables to zero. Coefficients on conditional volatility decline considerably when the restriction is imposed. In particular, the restricted estimate for the Dow index implies that the coefficient of relative risk aversion does not differ reliably from zero. The S&P 500 and Wilshire results indicate a reliably positive, but modest risk-return relationship. Comparison of the moving average parameters indicates little change due to the coefficient restrictions and their rankings remain consistent with the nontrading explanation.

Results for the volatility equation indicate persistence. The sum of the coefficients on lagged conditional variance and squared residuals rise, in two cases considerably, when unexpected volume coefficients are restricted to zero. The sum rises from .20 to .24 for the Dow, from .22 to .57 for the S&P, and from .19 to .79 for the Wilshire. These increases are indicative of the loss of information due to the reliance on instrumental variables to represent trading activity. Recognizing this, the coefficients on predicted trading activity are cautiously interpreted. The conclusions tentatively made in this section are further investigated in the following section.

Coefficients on predicted volume net of program trading activity are generally negative; differing reliably from zero in the unrestricted specifications. Bessembinder and Seguin (1992) interpret predictable volume as a proxy for market depth. Their specifications also detect a negative association between predictable volume and volatility. This negative association is consistent with Kyle's (1985) intuition: as market depth increases, the price

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effect of trades reaching the market is reduced.

Coefficients on predicted buy-program activity are reliably negative for each index. This holds regardless of the coefficient restrictions. Predicted sell-program coefficients for the S&P and Wilshire indexes are positive regardless of the coefficient restriction. Incorporating the coefficient restriction has an impact on the significance levels of these coefficients. Both are slightly less than two standard errors from zero; at conventional levels, they are not significant. The coefficient on predicted sell-program activity in the Dow specification switches from positive to negative when the coefficients on unpredicted trading activity are restricted to zero. Both of these coefficients are more than two standard errors from zero.

Interpretation of these results relies importantly on the time paths of volatility and trading activity in each of these specifications. It is useful to compare these time paths. The half-life of a shock to a continuous process is: $1 - \log_e(2)/\log_e(\phi)$ where ϕ is the observed discrete response to previous levels of the shocked variable. The GARCH specification estimated by equation 13 implies the response to a volatility shock is the sum of the b and c parameters so that $\phi = b + c$. Thus, from Table IV the half lives for volatility shocks are: 1.48 days for the Dow specification, 2.26 days for the S&P specification, and 3.39 days for the Wilshire specification.[16]

To understand this bias, first presume that program trading activity follows a similar time path. In this instance, interpretation of the above coefficients is straightforward: buy-

[16] Approximate standard errors for these halflives are: .13 for the Dow, .23 for the S&P, .18 for the Wilshire. Approximate standard errors are obtained using a first-order Taylor series expansion of the half-life formula.

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program activity lowers volatility; sell-program activity lowers volatility for the heavily traded stocks included in the Dow while possibly raising it for stocks included in the broader S&P and Wilshire indexes.

Suppose, however, that trading activity quickly reverts to normal levels. Thus, an episode of high volatility accompanied by heavy program trading will have the following time path: volatility declines gradually over subsequent trading periods while trading activity immediately falls to its normal level. This combination of time paths induces a negative bias to the coefficients on trading activity because high volatility levels are observed during periods when program trading activity is low.[17] Thus, evidence that the time path of program trading activity is shorter than the time path for volatility shocks implies a negative bias for the trading-activity coefficients. Alternatively, suppose volatility quickly returns to its normal level while trading activity only gradually returns to its normal level. This also implies a negative bias because volatility is low during periods when program trading activity was high. Such evidence would, however, be inconsistent with the idea that program trading produces volatility. This is because volatility declines despite persistent levels of program trading. Thus, mismatches in the time paths of volatility and trading activity shocks impart a negative bias to the trading activity coefficients.

To investigate these possibilities, estimates of the mean-reversion parameter for each of the trading activity variables are obtained using the following regression specification where VOL_t is the trading activity variable and the number of lagged changes in VOL_t are

[17] Although simultaneous downward shocks to volatility and program trading activity don't make the news, the bias is the same.

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$$\Delta VOL_t = \pi_0 + \pi_1 VOL_{t-1} + \sum_{j=1}^{J} \pi_{j+1} \Delta VOL_{t-j} + \varepsilon_t \tag{15}$$

determined by choosing the specification which maximizes AIC.[18] The regression coefficient on lagged activity levels can be applied to the half life formula by recognizing that response to a trading activity shock is given by $1+\pi_1$ so that $\phi = 1+\pi_1$. Thus, the coefficient estimates for the trading activity variables in the half life formula imply half lives as follows: 1.36 days for buy-program activity, 1.72 days for sell-program activity and 2.75 days for nonprogram trading activity.[19]

Comparing the time paths of volatility with trading activity begins with an assumption that both are simultaneously shocked. This assumption is consistent with the idea that program trading causes volatility or that program trading is more likely when volatility is high. The half life of volatility shocks on the S&P and Wilshire specifications are considerably longer than those for program-trading activity. This implies a negative bias to these coefficients. Thus, the negative coefficients on buy-program activity in these specifications cannot be interpreted. However, the positive coefficients on sell-program activity may be understated. This interpretation suggests volatility is positively associated

[18] This specification is that of the Augmented Dickey-Fuller test. To reject the null of no mean reversion, t statistics for the coefficients on lagged volume levels must be negative. Fuller (1976) tabulates the critical values for this test, they are -1.95 for the five percent level and -2.58 for the one-percent level. Results are: -5.627 for nonprogram volume, -7.663 for buy-program volume, and -6.337 for sell program volume. The results indicate that trading activity does revert to a long-run mean.

[19] Approximate standard errors for these half lives are: .13 for buy-program activity, .14 for sell program activity, and .15 for nonprogram activity. Approximate standard errors are obtained using a first-order Taylor series expansion of the half life formula.

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with program selling activity. The small coefficients on conditional volatility in the mean equations of these specifications are of concern. Nevertheless, the S&P and Wilshire specifications pass the diagnostic tests of a significant risk-return relationship and consistency with the nontrading explanation. In addition, the coefficient bias implied by persistent variance suggests the positive association between volatility and predicted program-selling activity may be understated. Comparison of the coefficients on sell program activity for the S&P and Wilshire specifications indicates that sell-program activity has a relatively larger impact on the S&P than on the Wilshire. For example, the impact of sell program activity at its mean level of 7.8 million shares to the intercept of the S&P specification indicates that sell programs increase the volatility of the S&P 500 by 4.08%. The impact of shares traded in sell programs on the Wilshire amount to a volatility increase of 2.33%. This difference is consistent with a volatility impact which is limited to stocks included in program trading activity.

The half life of volatility shocks on the Dow matches the half life from shocks to buy-program activity and is shorter than the half-life from sell-program activity. This suggests no bias for the buy-program coefficient and a negative bias for the sell-program coefficient. Unfortunately, as previously pointed out, the specification for returns on the Dow does not pass the risk-pricing diagnostic test.

V. Examination of price trends conditional on trading activity

A. Examination of reversals

A potential explanation for the volatility increases of the previous section might be that trading activity induces excess volatility, defined here as price changes which are

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unrelated to changes in fundamentals. For example, Stoll and Whaley (1986,1987) examine returns for the S&P 500 index following incidences of "triple witching days." They find that prices reverse and conclude that these reversals are due to temporary trading imbalances.[20] Since these imbalances are likely to be unrelated to changes in fundamentals, their results implicate order imbalances as a cause of excess volatility.

This section examines returns for evidence that program trading activity contributes to excess volatility by increasing the incidence of return reversals. Reversals imply prices over-react to information becoming available at t-1, returning at t toward their t-2 levels. For example, a traditional interpretation applied to program trading is that heavy trading activity induces price pressures. This pressure implies that buy programs cause prices to be bid "too high" and sell programs cause prices to be bid "too low." Thus, program trading leads to over-reactions. Relaxation of this pressure on prices results in reversals as conjectured premiums or discounts disappear when trading activity returns to its normal level.[21] Thus, evidence that program activity leads to excessive volatility might be inferred from a pattern of return reversals. This question is examined by defining reversals, denoted $REV_{p,t}$, as follows:

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[20] In a subsequent examination of return changes for individual stocks, Stoll and Whaley (1990, Table 7) find a positive, but not significant, relationship between returns at t+1 the product of time-t returns and trading volume. They suggest that elevated levels of trading activity during these periods leads to lower price reversals.

[21] Following the Stoll and Whaley procedure, this pressure on prices is relaxed on the first trading day following a "triple witching day."

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$$REV_{p,t} = \begin{cases} R_{p,t} & \text{if } R_{p,t-1} < 0 \\ -R_{p,t} & \text{if } R_{p,t-1} \geq 0 \end{cases} \tag{15}$$

The null of no reversals due to trading activity is rejected by evidence of positive values for $REV_{p,t}$ when trading activity is high. To investigate this possibility, values of $REV_{p,t}$ are categorized into activity quintiles using the level of trading activity at t-1. Student's t statistics are computed based on the means and standard deviations of the reversal measures within each quintile.

Table V reports results for these reversal tests. Evidence of reversals is found in the lowest quintile of nonprogram trading activity for the Dow and S&P indexes. While reversals at low levels of activity does not bear on the excess-volatility question of this paper, the issue is of some interest. Fifty-four of the 143 reversals included in this quintile grouping are incidences of low net volume occurring on mondays. This is well above the expected number of monday observations suggesting a "monday effect" explanation. This possibility is explored by restricting the sample to trading days following mondays and repeating the procedure. The t statistic for reversals based on the net-trading activity of mondays only is .72, rejecting the null that low net trading activity on monday is likely to be followed by a reversal. Indeed, partitioning the reversals in the low-activity quintile by day of the week indicates that the "low net-activity effect" implied by Table V stems, for the most part, from reversals following low trading on tuesdays. The large number of monday observations does not appear to explain reversals in this low-activity quintile.

Student's t statistics of reversals for the buy and sell program classifications do not support reversals. This does not contradict the inference drawn from the GARCH estimates

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supporting higher volatility associated with sell program activity. The tests of this section seek to detect excess volatility.

B. A nonlinear AR specification for return changes

The reversals examined in the previous subsection can also be detected by testing for negative autocorrelation of returns. This approach has the advantage of enabling specifications which include the possibility that buy and sell activity in combination affect volatility as well as incorporating the effects of trading rules. This subsection introduces a nonlinear AR approach to further examine the effect of trading activity.[22] The idea is to investigate an AR model of returns which conditions the autoregressive parameter on prior trading activity. The specification is:

$$R_{pt} = \alpha_{p,0} + \alpha_{p,1} R_{pt-1} + \varepsilon_t \qquad \varepsilon_t = \mu_t - \theta \varepsilon_{t-1} \tag{16}$$

$$\alpha_{p,1} = a_0 + a_1 \pi_{bp,t-1} + a_2 \pi_{sp,t-1} + a_3 cb_{t-1} \pi_{bp,t-1} + a_4 cb_{t-1} \pi_{sp,t-1} + a_5 cb_{t-1}$$

$$\pi_{i,t-1} = \exp\left(-\frac{\bar{V}_i}{V_{i,t-1}}\right) \qquad i = (bp, sp)$$

$$cb_{t-1} = \begin{cases} 1 & \textit{if circuit breakers activated at } t\text{-}1 \\ 0 & \textit{otherwise} \end{cases}$$

[22] I am indebted to Greg Duffee who initially suggested this approach.

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where $\pi_{i,t-1}$ is a metric for buy-program (i=bp) or sell-program (i=sp) activity at time t-1, bars over trading activity levels indicate the sample means for the respective categories, and cb_{t-1} is an indicator variable for the incidence of a circuit breaker at t-1. Within this sample $\pi_{bp,t}$ ranges from near zero at the minimum buy-activity level to .915 at maximum buy-activity and is .368 at mean buy-program activity. The range of the sell program measure, $\pi_{sp,t}$, is similar. The moving average component of this specification is included to capture nontrading effects which would otherwise bias $\alpha_{p,1}$ downward. The nonlinear specification is estimated using conditional least squares which incorporates bounds for $\alpha_{p,1}$ at -1 and 1. A Gaussian minimization procedure was used over a range of starting values and convergence criteria with no important differences, an indication of the robustness of results reported in Table VI.

The specification incorporates trading rules which may affect the execution of large orders, obscuring the effect of program trades. The sample period of this paper includes three trading rules intended to control program trading activity when price changes become large. These are: the Collar rule, Sidecar processing, and Rule 80A. The Collar Rule, which was activated nine times during the sample period, prevents use of SuperDOT for index-arbitrage orders.[23] Sidecar processing re-prioritizes program orders following large price declines.[24] Rule 80A imposes a price-tick criterion for execution of index arbitrage orders following

[23] Mann and Sofianos (1990) describe the Collar rule and provide evidence of its effects. Collar rules were activated on the following dates: April 6, 1988; April 14, 1988; May 31, 1988; June 8, 1988; June 22, 1988; August 10, 1988; and September 2, 1988.

[24] Moser (1990) describes Sidecar processing. Sidecar rules were activated on: October 13, 1989; October 24, 1989; January 12, 1990; July 23, 1990; August 3, 1990; August 6, 1990; and August 21, 1990.

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large changes in the Dow Industrials. During the sample period, Rule 80A was activated more frequently.[25]

The parameter a_0 is the relation of returns at t with returns one period earlier after controlling for trading activity. A zero value for this parameter is indicative of a market which continuously and fully incorporates available information into prices. Froot and Perold (1990) document a decline in return autocorrelations for the S&P stock index during the 1980s, concluding that the increased trading activity in derivative markets during that period enhanced the informational efficiency of stock prices. The estimates for a_0 in Table VI support their conclusion. None of these parameter estimates differ importantly from zero.

The parameters a_1 and a_2 estimate the direct effects of trading activity on the autocorrelation of returns: positive values for these parameters indicate increases in the autocorrelation of returns, negative values indicate decreases in return autocorrelations. Since return reversals imply that returns are negatively autocorrelated, excess volatility is affirmed by negative values for a_1, a_2 or for their sum. Taking these parameters separately, each is positive but not reliably different from zero. Testing the sums of these coefficients is a test of the joint effects of buy and sell programs on return autocorrelations. The asymptotic t values for these sums are: 0.82 for the Dow, 0.49 for the S&P, and 0.78 for the Wilshire.

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[25] Description and analysis of Rule 80A are in the following: McDonald, O'Callahan, Petzel and Shalen (1991); McMillan and Overdahl (1991); and NYSE (1991). Activations of Rule 80a occurred on the following dates: August 3, 1990; August 6, 1990; August 10, 1990; August 16, 1990; August 17, 1990; August 21, 1990; August 23, 1990; August 24, 1990; August 27, 1990; August 30, 1990; September 20, 1990; September 24, 1990; September 27, 1990; October 1, 1990; October 5, 1990; October 9, 1990; October 10, 1990; October 18, 1990; October 19, 1990; October 30, 1990; November 12, 1990.

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Again, in each case, we reject a direct impact from program trading on the autocorrelation of returns. This, in turn, implies that program trading does not contribute to excess volatility; indeed, these coefficient signs are inconsistent with an excess volatility explanation.

The a_3 and a_4 parameters consider the possibility of interactions between program trading and the incidence of circuit breaker procedures. This portion of the specification has two interpretations. First, as an examination of the effects from program trading at periods when the exchange has intervened. Presumably, these represent incidences when any effects from program trading will be most pronounced. Should program trading lead to price reversals, these are periods when this effect should be most apparent. However, a second interpretation mitigates the first. This is that intervention by the exchange prevents reversals. Inclusion of these interaction effects is therefore warranted not so much by their direct interpretation, but by the increased efficiency obtained for the a_1 and a_2 coefficients. The coefficients in each case are negative, suggestive of reversals, but they are not reliably different from zero. Asymptotic t statistics for the sum of these coefficients differing from zero are: -1.06 for the Dow, -0.87 for the S&P, and -1.16 for the Wilshire. While the signs of these coefficients are consistent with reversals, and therefore with excess volatility, they lack the significance to support this inference.

The a_5 coefficients examine the impact of circuit breakers on return autocorrelations. If circuit breakers impede the assimilation of information into prices, return autocorrelations should be positive. This would be indicated by reliably positive coefficients on the cb_{t-1} variables. Each specification rejects this. The coefficient in the Wilshire specification comes closest to failing to reject this, possibly indicating that circuit breakers reduce the

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informational efficiency of markets for thinly traded securities.

The results of this section do not support excess volatility attributable to program trading rules. This suggests that GARCH estimates indicating a positive association between sell program activity and volatility cannot be explained as increases in excess volatility. The tests for excess volatility indicate that the apparent increase in volatility owing to sell-program activity is not temporary. Further, trading rules intended to restrict the impact of program trading do not appear to impede the informational efficiency of markets.

VI. Conclusion

GARCH specifications are used to investigate the relationship between trading activity and volatility. These specifications incorporate risk pricing and the effects of nontrading of stocks contained in these indexes as diagnostic aids. Specifications incorporating overall trading volume are rejected on the basis of these diagnostic tests. Specifications which separate volume into buy and sell program activity and nonprogram trading activity pass the diagnostic tests and suggest that buy program activity raises volatility while sell program activity lowers it. Since volume may be jointly determined with volatility, trading activity is decomposed into its predictable and unpredictable components. The use of predictable trading activity as an instrument leads to an increase of volatility persistence. This increase is shown to lead to a negative bias in the trading activity coefficients in the S&P and Wilshire specifications. This precludes an interpretation of the negative coefficients on buy-program activity, but implies that the positive coefficients on sell-program activity are probably understated.

Tests for price reversals are conducted to investigate the possibility that the positive

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association between sell program activity and volatility might be attributed to excess volatility. Univariate and multivariate tests for reversals are employed. The univariate tests employ the Stoll and Whaley (1986, 1987) procedure. Multivariate tests use a nonlinear AR estimation procedure, conditioning the autoregressive parameter on trading activity. Both procedures reject price reversals as the cause of the volatility associated with sell program trades. The evidence indicates that these volatility increases are more permanent than would be implied by a price-reversal explanation.

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Table I
Summary Statistics

Sample Period: 1/4/1988-10/31/1990

Panel A
Trading activity

Trading Activity	Mean	Standard Deviation	Minimum	Maximum
Program-Buy Executions	8044	9419	459	90676
Program-Sell Executions	7836	8503	510	92596
NYSE Volume	161723	33928	68869	416290

Trading activity amounts are shares traded (in thousands). Program-buy executions are shares traded in SuperDOT orders classified as program trades. Program-sell executions are shares traded in SuperDOT orders classified as program trades. Program-sell executions include both shares sold and shares sold short. NYSE volume is the number of shares exchanged.

Panel B
Autocorrelations of returns and squared returns

	Return series			Squared Return Series		
Lag	*Dow Jones Industrial Average*	*Standard & Poors 500*	*Wilshire 5000*	*Dow Jones Industrial Average*	*Standard & Poors 500*	*Wilshire 5000*
1	.029	.030	.071	.003	-.001	.005
2	-.022	-.012	.026	-.012	-.012	.009
3	-.023	-.050	-.050	-.015	-.008	.003
4	-.020	-.022	-.005	.006	.007	.015
5	.007	.006	-.003	.033	.063	.074
6	-.080	-.071	-.071	.028	.024	.019
7	-.038	-.052	-.038	.012	.006	.000
8	-.021	-.012	-.009	.073	.066	.063
9	.046	.048	.051	.002	.006	.012
10	.013	.009	.017	.015	.020	.021
11	-.008	-.013	-.006	-.011	-.006	-.003
12	.056	.050	.055	.002	.001	.001
Q(12)	12.9	13.7	16.7	61.1	67.9	75.7
	(.38)	(.32)	(.16)	(.00)	(.00)	(.00)

Q(12) is the Box-Ljung (1978) statistic for autoregressive disturbances in 12 lags of the respective series. Values in parentheses are significance probabilities.

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Table II
Generalized autoregressive conditional heteroskedasticity-in-mean (GARCH-in-mean) specifications of daily returns for various stock price indexes on levels of trading activity

Sample period: January 2, 1988 through October 31, 1990

$$R_{pt} = \alpha + \beta\sigma_t^2 + \varepsilon_t - \theta\varepsilon_{t-1}$$

$$\sigma_t^2 = a + b\sigma_{t-1}^2 + c\varepsilon_{t-1}^2 + d_1 V_t$$

$$\varepsilon_t \sim N(0,\sigma_t)$$

	Dow Jones Industrial Average		*Standard & Poor's 500*		*Wilshire 5000*	
	Excluding Volume	Including Volume	Excluding Volume	Including Volume	Excluding Volume	Including Volume
α	-0.349	0.134	0.274	0.130	-0.140	0.292
	(1.789)	(0.310)	(0.713)	(0.348)	(1.000)	(0.345)
β	0.034	-0.020	-0.018	-0.021	0.025	-0.040
	(0.161)	(0.026)	(0.080)	(0.028)	(0.133)	(0.031)
Θ	-0.040	0.015	-0.034	0.022	-0.070	0.009
	(0.039)	(0.044)	(0.038)	(0.050)	(0.042)	(0.059)
a	0.662	-12.705	0.382	-13.316	0.866	-11.512
	(0.767)	(0.882)	(0.198)	(0.931)	(0.793)	(0.995)
b	0.933	-0.110	0.942	-0.067	0.867	-0.121
	(0.076)	(0.094)	(0.028)	(0.091)	(0.119)	(0.116)
c	0.007	-0.010	0.013	-0.006	0.017	-0.006
	(0.007)	(0.022)	(0.006)	(0.017)	(0.013)	(0.027)
d_1		0.162		0.164		0.147
		(0.006)		(0.008)		(0.008)
log L	-1880.9	-1812.9	-1838.4	-1786.2	-1730.4	-1696.2

R_{pt} is the annualized, continuously compounded rate of return on the respective stock index. V_t is the volume of NYSE stock trades at t. Share volumes are in millions. Asymptotic standard errors are in parenthesis under the coefficient estimates.

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Table III
Generalized autoregressive conditional heteroskedasticity-in-mean (GARCH-in-mean) specifications of daily returns for various stock price indexes on levels of nonprogram and program-trading activity

Sample period: January 2, 1988 through October 31, 1990

$$R_{pt} = \alpha + \beta\sigma_t^2 + \varepsilon_t - \theta\varepsilon_{t-1}$$

$$\sigma_t^2 = a + b\sigma_{t-1}^2 + c\varepsilon_{t-1}^2 + d_1 V_{N,t} + d_2 V_{bp,t} + d_3 V_{sp,t}$$

$$\varepsilon_t \sim N(0,\sigma_t)$$

	Dow Jones Industrial Average	*Standard & Poor's 500*	*Wilshire 5000*
α	-22.384	-20.194	-18.413
	(0.923)	(0.757)	(0.849)
β	3.363	3.569	4.235
	(0.147)	(0.146)	(0.208)
Θ	-0.089	-0.118	-0.158
	(0.045)	(0.045)	(0.045)
a	7.798	6.755	5.089
	(0.375)	(0.289)	(0.222)
b	-0.196	-0.210	-0.184
	(0.049)	(0.044)	(0.044)
c	0.006	0.007	0.007
	(0.002)	(0.001)	(0.001)
d_1 X 10^5	0.123	0.076	0.054
	(0.113)	(0.095)	(0.069)
d_2 X 10^5	7.524	6.941	4.851
	(0.557)	(0.478)	(0.377)
d_3 X 10^5	-8.052	-7.445	-5.312
	(0.611)	(0.530)	(0.423)
log L	-1706.7	-1650.9	-1556.3

R_{pt} is the annualized, continuously compounded rate of return on the respective stock index. $V_{N,t}$ is the volume of stock trades net of shares traded in programs. $V_{bp,t}$ and $V_{sp,t}$ are, respectively, the volume of shares traded in buy and sell programs. Share volumes are in thousands and sell programs include shares sold and shares sold short. Asymptotic standard errors are in parenthesis under the coefficient estimates.

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Table IV
Generalized autoregressive conditional heteroskedasticity-in-mean (GARCH-in-mean) specifications of daily returns for various stock price indexes on levels of nonprogram and program-trading activity

Sample period: January 2, 1988 through October 31, 1990

$$R_{pt} = \alpha + \beta\sigma_t^2 + \varepsilon_t - \theta\varepsilon_{t-1}$$

$$\sigma_t^2 = a + b\sigma_{t-1}^2 + c\varepsilon_{t-1}^2 + d_1 v_{N,t} + d_2 u_{N,t} + d_3 v_{bp,t} + d_4 u_{bp,t} + d_5 v_{sp,t} + d_6 u_{sp,t}$$

$$\varepsilon_t \sim N(0,\sigma_t)$$

	Dow Jones Industrial Average		*Standard & Poor's 500*		*Wilshire 5000*	
	Unrestricted	Restricted	Unrestricted	Restricted	Unrestricted	Restricted
α	-21.968	-0.823	-20.684	-2.253	-17.871	-0.965
	(0.883)	(0.771)	(0.796)	(0.818)	(0.773)	(0.345)
ß	3.340	0.075	3.605	0.263	4.172	0.162
	(0.140)	(0.065)	(0.146)	(0.094)	(0.195)	(0.053)
Θ	-0.069	-0.065	-0.093	-0.107	-0.138	-0.124
	(0.049)	(0.037)	(0.050)	(0.043)	(0.046)	(0.043)
a	8.675	48.368	7.760	23.403	5.659	17.685
	(0.686)	(7.936)	(0.563)	(5.530)	(0.439)	(2.120)
b	0.195	0.239	0.209	0.558	0.179	0.708
	(0.096)	(0.110)	(0.084)	(0.113)	(0.087)	(0.054)
c	0.005	-0.001	0.006	0.018	0.007	0.040
	(0.002)	(0.012)	(0.002)	(0.014)	(0.001)	(0.012)
$d_1 \times 10^5$	-0.676	6.277	-0.607	-0.995	-0.405	-0.580
	(0.254)	(4.079)	(0.224)	(1.732)	(0.174)	(0.980)
$d_2 \times 10^5$	0.245		0.176		0.113	
	(0.120)		(0.101)		(0.073)	
$d_3 \times 10^5$	-55.504	-512.63	-55.433	-282.91	-33.386	-220.98
	(15.808)	(126.86)	(13.135)	(70.527)	(9.762)	(36.51)
$d_4 \times 10^5$	7.408		6.781		4.801	
	(0.581)		(0.508)		(0.387)	
$d_5 \times 10^5$	27.551	-113.31	28.056	60.365	15.093	34.452
	(7.986)	(38.558)	(6.716)	(31.119)	(4.933)	(19.27)
$d_6 \times 10^5$	-8.414		-7.633		-5.516	
	(0.622)		(0.555)		(0.425)	
log L	-1697.5	-1876.3	-1637.6	-1832.3	-1551.4	-1721.6

R_{pt} is the annualized, continuously compounded rate of return on the respective stock index. $v_{N,t}$ is the predicted volume of stock trades net of shares traded in programs. $v_{bp,t}$ and $v_{sp,t}$ are, respectively, the predicted volumes of shares traded in buy and sell programs. Deviations from predicted volume levels are denoted: $u_{N,t}$, $u_{bp,t}$, and $u_{sp,t}$. Share volumes are in thousands and sell programs include shares sold and shares sold short. Asymptotic standard errors are in parenthesis under the coefficient estimates.

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Table V
Student t statistics for one-day changes in stock-index returns categorized by quintiles of the trading activity variables

Sample period: January 2, 1988 through October 31, 1990

Trading Activity	*Activity Quintile*	*Dow Jones Industrial Average*	*Standard & Poor's 500*	*Wilshire 5000*
Nonprogram Activity				
lowest	1	1.81	1.92	1.36
	2	0.10	-0.62	-0.49
	3	-1.14	-0.95	-1.24
	4	0.04	-0.17	-0.95
highest	5	-1.46	-1.08	-1.92
Buy Program Activity				
lowest	1	1.07	0.08	0.54
	2	0.55	0.85	-0.04
	3	-0.59	-1.35	-1.02
	4	-1.76	-0.70	-1.51
highest	5	0.82	0.70	-0.86
Sell Program Activity				
lowest	1	-0.17	0.68	-0.52
	2	-0.64	-1.49	-0.70
	3	1.03	0.15	-0.73
	4	-1.35	-0.39	-0.87
highest	5	0.34	0.13	-0.48

Return reversals are defined as:

$$REV_{p,t} = \begin{cases} R_{p,t} & \text{if } R_{p,t-1} < 0 \\ -R_{p,t} & \text{if } R_{p,t-1} \geq 0 \end{cases}$$

where $R_{p,t}$ is the annualized continuously compounded return on the respective stock index. Quintiles are formed based on the level of the trading activity variables at t-1 with the lowest quintile listed as 1, highest as 5. Student's t statistics are computed as follows:

$$\textit{Student's } t = \frac{\sqrt{N}\mu_p}{\sigma_p}$$

$$\textit{where } \mu_p = \frac{1}{N}\sum_{t=1}^{N} REV_{p,t}$$

$$\sigma_p^2 = \frac{1}{N-1}\sum_{t=1}^{N}(REV_{p,t} - \mu_p)^2$$

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Table VI
Autoregressive parameters of stock-index returns conditional on trading variables

Sample period: January 2, 1988 through October 31, 1990

$$R_{pt} = \alpha_{p,0} + \alpha_{p,1} R_{pt-1} + \varepsilon_t \qquad \varepsilon_t = \mu_t - \theta\varepsilon_{t-1}$$

$$\alpha_{p,1} = a_0 + a_1\pi_{bp,t-1} + a_2\pi_{sp,t-1} + a_3 cb_{t-1}\pi_{bp,t-1} + a_4 cb_{t-1}\pi_{sp,t-1} + a_5 cb_{t-1}$$

$$\pi_{i,t-1} = \exp(-\frac{\bar{V}_i}{V_{i,t-1}}) \qquad i = (bp,sp)$$

$$cb_{t-1} = \begin{cases} 1 & \textit{if circuit breakers activated at } t\text{-}1 \\ 0 & \textit{otherwise} \end{cases}$$

	Dow Jones Industrial Average	Standard & Poor's 500	Wilshire 5000
α_0	0.0275	0.0271	0.0501
	(0.19)	(0.20)	(0.40)
a_0	-0.1971	-0.0347	0.0970
	(-0.35)	(-0.05)	(0.22)
a_1	0.2173	0.1436	0.1636
	(1.15)	(0.77)	(0.86)
a_2	0.0400	0.0067	0.0801
	(0.21)	(0.04)	(0.41)
a_3	-0.3084	-0.2411	-0.2722
	(-0.86)	(-0.63)	(-0.74)
a_4	-0.3537	-0.3360	-0.4667
	(-0.95)	(-0.85)	(-1.18)
a_5	0.2482	0.2434	0.3565
	(0.91)	(0.90)	(1.23)
Θ	0.1580	0.0178	0.1133

(t statistics in parentheses)

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