PROGRAM TRADING, NONPROGRAM TRADING, AND MARKET VOLATILITY

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INTRODUCTION

The popular financial press often implicates program trading as a menacing contributor to fluctuations in the stock market. Generalizations often follow that accuse program trading of facilitating market overreactions, resulting in excess market volatility. For example, *Newsweek* [The Villain in . . . , (1989)] reports

> Stock market investors are generally a forgiving lot, except when it comes to one thing: volatility. Wild, erratic market swings . . . always provoke their fury. Now they're on the warpath again, and they've found a familiar villain to blame for the volatility: program trading (p. 58)

Statements like this make it clear that investors believe there is a strong detrimental relationship between program trading volume and volatility. This article estimates the joint distribution of spot and futures market returns to test the following hypotheses regarding the relationship between program trading, nonprogram trading, and market volatility:

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H1: Does a unit change in program trading volume result in the same change in market volatility as a one unit change in nonprogram trading?

H2: Are buy-program trades associated with the same increase in market volatility as sell-program trades?

H3: Does program trading have the same relationship with futures market volatility as it does with cash market volatility?

H4: Is the impact of program trading and nonprogram trading on market volatility greater in down markets?

Possible regulatory implications based on the findings of this study will not be addressed for the following two reasons. First, an assessment would need to be made as to whether market volatility is excessive. Market volatility is excessive only to the extent that it is attributable to some form of market imperfection. This study does not identify any source of market imperfection and, hence, no such claim can be made. Second, there is sufficient evidence, such as in Hasbrouck (1996), that program trades are informationally based. Hence, it seems best to view volatility and program trades as being endogenous to information flows.

The bivariate error correction GARCH model chosen to address these hypotheses offers several potential benefits. First, the bivariate model offers a unique opportunity to study the effects of program trading on both the cash and futures markets. For example, because much of program trading exploits the mispricing between cash and futures markets, there is no reason to expect that program trading should affect only one of these markets.[1] Also, institutional differences between cash and futures markets may lead to different price dynamics in response to program trading. Specifically, the ability to undertake short positions in the cash market is impeded by the uptick rule, whereas no such impedance exists in the futures market. Therefore, any program trade that requires short positions in the spot market will lead to different price dynamics than trades that require short positions in the futures market. Also, Samuelson (1965) suggested that news, which is often proxied by trading volume, can have different impacts on cash markets than on futures markets, depending on the assumptions made about the generating process of the underlying asset. Further, the Cascade theory[2] says that spot and

[1]This will be discussed in more detail in subsection II.A.

[2]The Cascade theory, according to the Brady report, can be described as follows: During falling markets, portfolio insurers liquidate their equity exposure by selling stock index futures. As futures prices fall below their equilibrium, reverse cash-and-carry arbitrage ensues. Now, the index arbitragers buy futures and sell stocks, driving equity prices lower and futures prices higher. This leads to reverse cash-and-carry arbitrage, in which portfolio insurers sell futures and buy equity. Therefore, this cascading of prices downwards leads to the futures and cash markets undergoing nonsynchronous periods of rising and falling volatility.

futures market volatility might be nonsynchronous. This implies that the relationship between volume and volatility might be different in these two markets.

Second, the bivariate GARCH model assumes that the relationship between the cash market volatility and trading volume is not independent of the relationship between the futures market volatility and trading volume. The bivariate GARCH model allows one to formally test these ideas by permitting the effect of trading volume to be different in the spot market than in the futures market. Furthermore, this specification will produce more efficient parameter estimates than single-equation estimation, and hence more powerful tests about the impact of program trading on volatility.

Third, this study's model accounts for cointegration between the cash and futures markets. Brenner and Kroner (1995) demonstrate that cointegration is a theoretical implication of arbitraging between any two markets that are fundamentally linked, that is, cash and futures on a commodity. To account for cointegration, an error correction model is used, which permits the change in cash and futures prices to respond to recent arbitrage opportunities. Failure to incorporate cointegration into the model would result in a misspecified model from which statistical inference may be invalid [Engle and Granger (1987)]. Furthermore, the cash market volatility is allowed to interact with the futures market returns, and vice versa, to address the possibility [see Koutmos and Tucker (1996)] that the cash and the futures returns may not be independent of volatilities across markets.

Fourth, the model and data set allow testing to determine whether the relationship between program buy orders and volatility differs from the relationship between program sell orders and volatility. This is an important question because any theoretical models of the relationship between program trading and volatility should address the differential relationships of buy and sell trades, if it exists.

Finally, the program trading volume–volatility relationship in this article could be a manifestation of the nonprogram volume–volatility relationship in down markets (when both the cash and the futures returns are negative). The bivariate GARCH model used here allows this hypothesis to be tested.

The remainder of the article is organized as follows: Section II briefly summarizes the pertinent literature on the volume–volatility relationship. Section III describes the data and empirical model. Section IV presents the model estimates and the results from several hypotheses tests regarding the link between program trading and volatility. The final section concludes the study.

NONPROGRAM TRADING, PROGRAM TRADING, AND MARKET VOLATILITY

Some Theoretical Considerations

Up to half of program trading[3] is motivated by "index arbitrage trading" [Neal (1992)]. Index arbitrage trades are trades that attempt to exploit potential arbitrage opportunities. To illustrate, program trading will occur when the following no-arbitrage condition (ignoring transaction costs) is violated:

$$\ln F_{t,T} = \ln S_t + \ln(1 + r_{t,T}) - \ln D_{t,T}, \tag{1}$$

where $F_{t,T}$ is the price of an index futures at time t that expires at time T. S_t denotes the stock index price at time t and $r_{t,T}$ is the appropriate interest rate. $D_{t,T}$ is the future value of dividends between t and T on a portfolio that mimics the index. If for some reason

$$\ln F_{t,T} > [\ln S_t + \ln(1 + r_{t,T}) - \ln D_{t,T}], \tag{2}$$

then the index arbitrage mechanism has the investor borrowing and purchasing the portfolio that mimics the index while selling short the index futures. One important implication of this is that, to the extent that program trades are index arbitrage based, the effect of program trading on spot market volatility will not be independent of its effect on futures market volatility. Therefore, a bivariate model should yield more efficient parameter estimates and test statistics because it assumes that the cash and futures markets are not independent of one another with respect to their ties to program trading. Also, to the extent that the uptick rule makes short selling stocks in response to arbitrage opportunities more difficult than selling futures, the relationship between program trading volume and volatility is expected to be different in the cash market than in the futures market.

There is an additional reason to expect the relationship between program trading and cash market volatility to be different from the relationship between program trading and futures market volatility. Before the advent of program trading, macroinformation got impounded into stock prices through nonprogram trades: Investors bought and sold baskets of stocks directly. However, with the introduction of the futures market, information gets incorporated first in futures prices, because futures con-

[3]Other kinds of program trades include [see Neal (1992)] portfolio rebalancing and asset allocation, and attempt to limit portfolio losses while allowing for upside gains. This often requires selling during times of declining prices and buying during times of increasing prices.

tracts are a cheaper way of buying and selling a basket of stocks as the futures prices move out of line with the cash market prices. In this context, it is not unlikely that program trading has a bigger impact on the futures market volatility than on the cash market.

The literature relating trading volume to volatility is large compared to the literature relating program trading volume to volatility. For example, Clark (1973) suggests that increases in the rate of information flow simultaneously cause increases in both price variance and trading volume. Asset prices are modeled as a subordinate processes in which the rate of information flow acts as the directing variable. More recent models have emphasized the role of asymmetric information on asset price volatility and trading volume. Within a Walrasian equilibrium setting, Epps and Epps (1976) argue that the effect of information flows on asset volatility and trading volume increases with the degree of heterogeneous expectations. Tauchen and Pitts (1983) argue that the number of traders also influences the joint distribution of asset volatility and trading volume. Specifically, as the number of traders increases, price volatility declines while volume increases. Models of Admati and Pfleiderer (1988) and Kyle (1985) also predict a positive relationship between trading volume and price volatility within a noisy rational expectations equilibrium framework.

In summary, the existing literature suggests that trading volume and price volatility are jointly determined by information flows and the degree of dispersion of information. If program trading is not fundamentally different from nonprogram trading, then one should find a similar positive relationship between program trading volume and price volatility as between nonprogram trading volume and price volatility [see Karpoff (1987)]. However, program trading volume may contain information that is not correlated with the information contained in aggregate market volume. As Harris, Sofianos, and Shapiro (1990) claim, program trades are indicative of fundamental changes in information yet to be reflected in the marketplace. Therefore, it is possible that the response of financial markets to an increase in program trading may differ from the response to an increase in aggregate volume. Grossman (1988b) specifically links portfolio insurance program trades to price volatility. He argues that when prices are falling, speculators are not informed about the extent to which insurance related trades will hit the market. Without such information, speculators might have inadequate funds available to offset program-related sell orders, so prices fall in excess of what they would have if speculators had been informed. The shortage of speculative capital creates a positive net demand for insurance and hence an increase in market vol-ability in times of declining markets.[4] Brennan and Schwartz (1989) also link portfolio insurance to market volatility. They claim that in a declining market, portfolio-insurance–related orders increase the market risk premium and the returns volatility. Finally, according to Harris et al. (1990), market participants are sensitive to program sells. Hence, program sells could promote more nonprogram selling, leading to an increase in overall volatility in the cash and futures markets.

Previous Empirical Evidence

On October 19, 1987 the Dow Jones Industrial Average fell almost 25% from the previous close. The Brady Commission Report and the Securities and Exchange Commission both cited index arbitrage and portfolio insurance as factors responsible for the stock market crash. In contrast, the Chicago Mercantile Exchange and the Commodity Futures Trading Commission both failed to detect evidence of the effects of index arbitrage on market volatility. The empirical evidence from academia has been mixed as well. Grossman (1988a), using program trading data from January, 1987–October, 1987, finds no systematic link between program trading and market volatility. Furbush (1989), using 5-minute–interval data from October 14–20, 1987, finds that on October 14, program trading explains 50% of the variation in the S&P500, whereas on October 19 and 20 its impact was less. Harris et al. (1990), using minute-by-minute data, found that program trading affects the market volatility. Chung (1991) uses transaction data and provides some evidence of the link between index arbitrage and spot and futures market volatility.

This article presents new evidence based on the GARCH model. The bivariate GARCH model allows the conditional variance–covariance matrix of the stock and futures returns to vary over time. To capture the effects of program trading on the time-varying volatility in each market, various types of daily program trading volume are included as exogenous variables in the time-varying covariance matrix, permitting new insights into the link between program trading and stock returns volatility.

In a related article, Hasbrouck (1996) concludes that the informational content of program trades/orders are similar to that of nonprogram trades. This follows from his finding that program trades, nonprogram trades, and index-arbitrage trades have similar impact on stock prices. Although this study does not investigate the relationship between pro-

[4]Equally plausible is the possibility of excess speculative capital in rising markets. In this case, a net supply of portfolio insurance exists, which leads to a decrease in market volatility. Only in the case when net portfolio demand is zero will portfolio-related trades not influence market volatility.

gram trades and market volatility, the relationship does have some important implications for this study. Specifically, because program trades are found to be informationally based, statements about whether program trades create excess market volatility simply are not justified.

EMPIRICAL MODEL AND DATA

The Empirical Model

The conditional first moments of the bivariate distribution of the S&P500 cash and near-term futures returns are parametrized as a bivariate error correction model, as in Kroner and Sultan (1993) and Chan, Chan, and Karolyi (1991):

$$\Delta \ln S_t = \beta_{s,0} + \beta_{s,vol}\,\mathrm{NYSE}_t + \sum_{i=1}^{4} \beta_{s,i} D_{i,t} + \gamma_s (\ln S_{t-1} - \ln F_{t-1}) + \varepsilon_{s,t} \tag{3a}$$

$$\Delta \ln F_t = \beta_{f,0} + \beta_{f,vol}\,\mathrm{NYSE}_t + \sum_{i=1}^{4} \beta_{f,i} D_{i,t} + \gamma_f (\ln S_{t-1} - \ln F_{t-1}) + \varepsilon_{f,t} \tag{3b}$$

$$\begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{bmatrix} \mid \psi_{t-1} \sim D(0, H_t) \tag{4}$$

where $\Delta \ln S_t$, and $\Delta \ln F_t$ denote the change in the natural log of daily cash and futures prices, respectively, NYSE_t is total NYSE trading volume (in millions of shares), $D_{i,t}$ are day-of-the-week dummies, ψ_{t-1} is the information set at time $t-1$, and $D(0, H_t)$ refers to an as-yet-unspecified bivariate conditional distribution with mean zero and covariance matrix H_t.

Volume is allowed to be a regressor in the mean equations to avoid the possibility of finding a spurious volume/volatility relationship in the variance equations. The term $(\ln S_{t-1} - \ln F_{t-1})$, often referred to as an error-correction term (ECT), is included in the mean to account for the fact that cash and futures markets are cointegrated. In the event that these two markets are cointegrated, omitting the ECT from the mean equations leads to model misspecification. So the ECT term measures the amount of short-run disequilibrium in the long-run relationship between these markets.

Unfortunately, intraday transactions data are not available for this study. If transaction data were used, then the ECT could be thought of as measuring the impact of index arbitrage opportunities on returns. Intuitively, γ_s and γ_f measure the speed with which each market responds to deviations from the no-arbitrage equilibrium condition given in eq. (1). For example, if γ_s is large and negative, then deviations that have the spot underpriced, as in eq. (2), will result in a large increase in the spot price next period.[5]

The conditional second moments of the bivariate distribution of spot and futures returns are parametrized as a bivariate GARCH(1,1) model. To distinguish the effects of program trading volume and nonprogram trading volume, the following specification for the covariance matrix is used:

$$H_t = \begin{bmatrix} h_{ss,t} & h_{sf,t} \\ & h_{ff,t} \end{bmatrix}, \tag{5}$$

where the elements of the H_t matrix are

$$\begin{bmatrix} h_{ss,t} = w_{ss} + \alpha_{ss}\varepsilon^2_{s,t-1} + \beta_{ss}h_{ss,t-1} \\ \quad + \delta^h_{ss}\mathrm{BUY}_t + \delta^s_{ss}\mathrm{SELL}_t + \delta^p_{ss}\mathrm{PT}_t + \delta^{np}_{ss}\mathrm{NPT}_t \\ h_{sf,t} = w_{sf} + \alpha_{sf}\varepsilon_{s,t-1}\varepsilon_{f,t-1} + \beta_{sf}h_{sf,t-1} \\ \quad + \delta^b_{sf}\mathrm{BUY}_t + \delta^s_{sf}\mathrm{SELL}_t + \delta^p_{sf}\mathrm{PT}_t + \delta^{np}_{sf}\mathrm{NPT}_t \\ h_{ff,t} = w_{ff} + \alpha_{ff}\varepsilon^2_{f,t-1} + \beta_{ff}h_{ff,t-1} \\ \quad + \delta^b_{ff}\mathrm{BUY}_t + \delta^s_{ff}\mathrm{SELL}_t + \delta^p_{ff}\mathrm{PT}_t + \delta^{np}_{ff}\mathrm{NPT}_t \end{bmatrix}$$

The volume variables are

BUY_t = volume of executed buy program trade orders
SELL_t = volume of executed sell program trade orders
PT_t = total program trade orders ($\mathrm{BUY}_t + \mathrm{SELL}_t$)
NPT_t = total nonprogram trade volume ($\mathrm{NYSE}_t - \mathrm{PT}_t$).

In this model, current volatility ($h_{ii,t}$) is parametrized as a function of past shocks to the asset ($\varepsilon_{i,t-1}$ and $h_{ii,t-1}$) and a set of volume variables. See Engle and Kroner (1994) for the properties of this model. Of course, not all the volume variables are put into the model at the same time, because that would generate perfect multicollinearity.

Preliminary estimation with a conditional normal distribution in (4) reveals substantial excess conditional kurtosis. As demonstrated in Bollerslev and Wooldridge (1992), this invalidates traditional inference procedures. Therefore, the conditional elliptical t distribution is used in place of the normal, and the degrees of freedom is treated as another parameter

[5]Clearly, the error-correction term is only an approximation to the no-arbitrage mechanism. It is not exact because the error-correction model results in an adjustment for any index arbitrage deviation, even though there is no arbitrage pressure from deviations within transactions bounds. Nonetheless, the error-correction model still captures the essential features of the index arbitrage mechanism.

to be estimated.[6] The likelihood function is maximized as in [see Muirhead (1982, pp. 48–49)]

$$f(\varepsilon_t) = \frac{\Gamma[(n + \nu)/2]}{\Gamma(\nu/2)(\sqrt{\pi(\nu - 2)})^n} \mid H_t \mid^{-1/2} \left[1 + \frac{1}{\nu - 2} \varepsilon_t' H_t^{-1} \varepsilon_t\right]^{[(n+\nu)/2]} \tag{6}$$

where n is the number of variables, ν denotes the degrees of freedom, H_t is the $n \times n$ covariance matrix, and ε_t is an $n \times 1$ vector. This distribution converges to the multivariate normal as $\nu \rightarrow \infty$. In this application, $n = 2$, $\varepsilon_t' = (\varepsilon_{s,t}, \varepsilon_{f,t})$ from eq. (3), and H_t is given by eq. (5) above.

The Data

Daily returns for January 3, 1988 to December 31, 1991 are computed from closing prices of the S&P500 cash and the CME S&P500 near-term futures contracts, giving 1010 observations. Daily volume data for the same period are from the New York Stock Exchange, including data on program trades that were executed through the SuperDot system. The New York Stock Exchange defines program trading volume as the sum of shares purchased, sold, and sold short for various trading strategies involving 15 or more stocks worth at least 1 million dollars. Because of data limitations, it is not possible to separate index arbitrage from non-index-arbitrage volume, even though the relationship between these kinds of volume and volatility might be different. However, as Neal (1992) suggests, both types of trades respond to violations of eq. (1), suggesting that the differences might not be large.

Descriptive statistics for daily S&P500 cash and futures returns are reported in Panel (A) of Table I. The average daily returns for S&P500 cash and futures are 0.0483% and 0.0481%, respectively. Both returns are leptokurtic and their Bera–Jarque statistics reject the null hypothesis of normality. Engle's (1982) LM test for ARCH is significant for both series, suggesting that the GARCH equations in (5) are appropriate. The Phillips and Perron (1988) test for unit roots with a drift indicates that both series have a unit root. The Engle and Granger (1987) test for cointegration (not reported in the table) gives a test statistic of -6.59, which is less than the 95% critical value of -3.69, indicating rejection of the null hypothesis that the two series are not cointegrated. These final two results support Brenner and Kroner (1995), and imply that the bivariate error-correction model in eq. (3) may be appropriate.

[6]The elliptical t distribution is the distribution of ε_t, under the assumption that the standardized residuals $\eta_t = H_t^{-1/2} \varepsilon_t$ are bivariate t.

TABLE I

Descriptive Statistics

	Mean	*Standard Deviation*	*Skewness*	*Excess Kurtosis*	*B–J*	*ARCH*	*P–P*
			Panel A: Summary Statistics				
S&P cash	0.05	0.95	−0.74	5.79	1505.36	16.61	−2.97
S&P futures	0.05	1.06	−1.17	10.63	4982.00	28.08	−2.59
NYSE	165.81	35.75	1.09	3.92	844.97		−49.85
PT	19.09	18.22	4.77	30.04	41799.32		−25.94
NPT	146.73	30.92	0.85	3.32	585.55		−13.88
BUY	9.87	11.05	4.31	25.51	30509.91		−25.59
SELL	9.22	7.86	4.63	31.13	44387.73		−23.79
			Panel B: Correlation Coefficients				
		NYSE	PT	NPT	Buy	Sell	
NYSE		1.000	0.502	0.860	0.482	0.421	
PT			1.000	−0.009	0.923	0.884	
NPT				1.000	0.014	−0.035	
Buy					1.000	0.636	
Sell						1.000	

Note: Daily returns for the S&P500 cash and near-term futures contracts are computed with the use of log differences of daily closing prices from January 3, 1988 to December 31, 1991. NYSE indicates that shares are traded on the New York Stock Exchange (including program trading). PT is the total number of program trading shares. NPT is the total nonprogram trading in millions of shares (NYSE-PT). BUY indicates shares purchased in program trades and SELL represents shares sold in program trades. Volume data are measured in millions of shares. Bera–Jarque (B–J) statistic is a test for normality that is distributed as χ^2_2. The null hypothesis is normality, which is calculated as follows:

$$B\text{–}J = T\left(\frac{skewness^2}{6} + \frac{Excess\ kurtosis^2}{24}\right).$$

ARCH is Engle's (1982) LM test for eighth-order ARCH effects. It is distributed χ^2_8 under the null hypothesis of no ARCH and 95% critical value, 15.51. No test for ARCH is made on the volume data because it is not relevant for this study. P–P is the Phillips and Perron (1988) test for unit roots. The null hypothesis of a unit root is rejected at the 95% level if the test statistic is less than −3.37.

Descriptive statistics for total program trading volume (PT), buy-program trading volume (BUY), sell-program trading volume (SELL) and nonprogram trading volume (NPT) (i.e., total NYSE volume minus total program trading volume), are also reported in Panel A of Table I. Average daily program trading volume was 19.09 million shares, of which 9.87 million shares were buy orders and 9.21 million shares were sell orders. Average nonprogram trading volume was 146.72 million shares, almost eight times larger than program trading volume. Program trade volume is much more skewed and leptokurtic than nonprogram trade volume, and does not have a unit root. The correlation coefficients between the various measures of program trading and nonprogram trading volume are reported in Panel B of Table I. The correlation between program trading volume and nonprogram trading volume is surprisingly low (ρ =

−0.089). Similarly, the correlations between NPT and both BUY and SELL are low, 0.014 and −0.035, respectively. These low correlations support the notion that the information content of these two indicators of market activity are different.

EMPIRICAL RESULTS

Model Estimation

The maximum-likelihood parameter estimates from the benchmark bivariate GARCH model are presented in the first two columns of Table II, with asymptotic t statistics in parentheses.[7] The benchmark model includes eqs. (3)–(5) without any volume variables in the covariance matrix. Consider first the estimates of the mean equations (3a) and (3b).

Several observations merit mention. First, the coefficients on total NYSE volume in both mean equations are positive and significant, indicating that volume is higher in rising markets than in declining markets. This confirms the findings of several studies, dating as far back as Ying (1966). Several explanations have been proposed for this result. For example, it could be caused by the high costs of short selling [Jennings, Starks, and Fellingham (1981), Karpoff (1988)], by the disposition effect [Shefrin and Statman (1985), Thaler (1984)], and by positive feedback trading strategies [Delong, Shleifer, Summers, and Waldmann (1990)]. See Karpoff (1987) for a survey. Second, though not reported in Table II, the likelihood-ratio test for joint significance of day-of-the-week dummies is 38.60. This statistic is distributed χ^2_8 and has 95% critical value, 15.51. Thus, the null hypothesis that the dummies are jointly zero is rejected even though many of the individual dummies are insignificant. Therefore, day-of-the-week dummies are included in the mean equation in all subsequent models.

Third, the error-correction term (ECT) is negative in the cash equation and positive in the futures equation, suggesting that if the no-arbitrage condition [i.e., eq. (1)] is violated because the cash price is too high (low), the market will react by decreasing (increasing) the cash price next period and increasing (decreasing) the futures price. Although the individual ECT parameters are not significant, the likelihood-ratio test for their joint significance is 95.05. This is distributed χ^2_2 with 95% critical value 5.99. Thus, the error-correction term is included in all subsequent estimations. Note too that this result is expected if cash and futures are

[7]Because the estimation of the coefficients associated with the conditional covariance equations add little to the discussion, they are not reported. They are available on request.

TABLE II

Model Estimates

	Benchmark Model		*Volume Model*		*Full Model*		*Down-Market Model*	
	Cash	*Futures*	*Cash*	*Futures*	*Cash*	*Futures*	*Cash*	*Futures*
Mean equations								
Constant	−0.649	−0.595	−0.491	−0.438	−0.428	−0.384	−.419	−.356
	(−4.76)	(−4.10)	(−3.79)	(−3.11)	(−3.36)	(−2.87)	(−3.88)	(3.10)
NYSE	0.042	0.041	0.034	0.033	0.033	0.033	.039	.038
	(6.23)	(5.56)	(4.71)	(4.23)	(4.55)	(4.20)	(6.28)	(5.91)
Monday	0.049	0.183	0.012	0.144	−0.002	0.133	−.006	.124
	(0.63)	(2.12)	(0.16)	(1.70)	(−0.03)	(1.64)	−.097	(1.82)
Tuesday	−0.019	0.055	−0.032	0.046	−0.057	0.020.	−.084	−.003
	(−0.25)	(0.68)	(−.43)	(0.56)	(−0.77)	(0.25)	(−1.32)	(−.05)
Wednesday	−0.049	0.009	−0.054	0.005	−0.070	−0.011	−.089	−.033
	(0.64)	(0.11)	(−0.69)	(0.06)	(−0.92)	(−0.13)	(−1.34)	(−.48)
Thursday	−0.129	−0.064	−0.148	−0.083	−0.163	−0.098	−.180	−.110
	(−1.68)	−0.77	(−1.91)	(−0.99)	(−2.14)	(−1.18)	(−2.77)	(−1.59)
ECT	−0.089	0.066	−0.090	0.070	−0.082	0.075	−.039	.1299
	(−1.52)	(1.06)	(−1.64)	(1.16)	(−1.54)	(1.29)	(−.88)	(2.63)
Variance equations								
Constant	0.276	0.631	−0.067	0.078	−0.120	0.011	−.09	.037
	(4.34)	(5.54)	(−0.34)	(0.35)	(−0.70)	(0.06)	(−.79)	(.31)
ε^2_{t-1}	0.032	0.052	0.053	0.078	0.039	0.066	.030	.058
	(1.84)	(2.78)	(2.19)	(3.13)	(1.79)	(2.89)	(1.64)	(2.91)
h_{t-1}	0.627	0.253	0.028	−0.013	0.038	0.005	−.008	−.043
	(7.21)	(2.21)	(0.39)	(−0.19)	(0.57)	(0.08)	−.26	(1.46)

TABLE II (Continued)

Model Estimates

	Benchmark Model		*Volume Model*		*Full Model*		*Down-Market Model*	
	Cash	*Futures*	*Cash*	*Futures*	*Cash*	*Futures*	*Cash*	*Futures*
PT			0.248	0.239			.170	.138
			(5.84)	(5.22)			(20.94)	(16.86)
NPT			0.027	0.027	0.025	0.025	.021	.020
			(1.88)	(1.68)	(1.97)	(1.74)	(2.52)	(2.38)
BUY					0.178	0.133		
					(2.24)	(1.69)		
SELL					0.388	0.471		
					(4.75)	(4.81)		
Down* PT							.409	.404
							(1.66)	(1.19)
Down* NPT							.125	.168
							(1.67)	(1.81)
Diagnostics								
$1/\nu$	0.197		0.187		0.181		.157	
	(11.00)		(9.58)		(8.99)		(7.89)	
κ	10.41	15.06	6.57	9.53	5.49	7.51	3.31	3.69
κ^*	8.57		7.45		6.9		5.53	
$Q(12)$	12.73	11.24	9.78	8.11	10.76	8.95	13.78	12.72
$Q^2(12)$	7.73	4.09	13.62	4.80	17.26	8.18	12.20	6.50
L	−1346.4		−1291.5		−1283.9		−1186.99	

Note: This table gives the model estimates from Eqs. (3)–(6) in the text. ν is the estimated degree of freedom in the conditional t distribution. Asymptotic t-statistics are in parentheses. The sample kurtosis is given by κ, and the theoretical kurtosis from a t distribution with $1/\hat{\nu}$ degree of freedom is denoted κ^*. $Q(12)$ and $Q^2(12)$ are the Ljung–Box test statistics for up to twelve order serial correlation in the standardized level and squared residuals, respectively. They are distributed χ^2_{12} under the null of no serial correlation, and have a 95% critical value, 21.03. L is the log-likelihood value.

cointegrated, because as Engle and Granger (1987) demonstrate, co-integration implies that the ECT should belong.

Consider next the estimates of the variance equations (5). The parameter estimates are generally significant, suggesting that previous shocks can help to explain current volatility. The term $1/\hat{\nu}$ is the estimate of the reciprocal of the degrees of freedom in the conditional distribution. It suggests that the degree of freedom is about 5.1, implying that conditional normality would have been an incorrect conditional distribution for this data set.[8] To demonstrate that this model adequately captures leptokurtosis, the theoretical kurtosis implied by a t distribution is presented in Table II. In the benchmark model, $1/\hat{\nu} = 0.197$, which implies a kurtosis of 8.57. This is denoted κ^* in Table II. The actual kurtosises in the residuals, given by k in Table II, are 10.41 and 15.06 for the spot and futures equations, respectively. Thus, the benchmark model adequately captures the leptokurtosis in the spot equation, but falls a little short in the futures equation. Finally, the $Q(12)$ statistic, which is the Ljung–Box test for up to 12th-order serial correlation in ε_t, is 12.73. This is distributed χ^2_{12} with a 95% critical value, 21.03. Therefore, the model adequately captures the dynamics in the first moments of spot and futures returns. The $Q^2(12)$ statistic is the Ljung–Box test for up to 12th-order serial correlation in the squared standardized residuals ($\varepsilon^2_{it}/h_{ii,t}$), and is distributed χ^2_{12}. It is insignificant, which suggests that the GARCH model adequately captures the dynamics in the second moments of spot and futures returns.

The middle two columns of Table II report estimates from a bivariate GARCH model with program trading volume and nonprogram trading volume included in the variance equations. The coefficients in the conditional mean equations are essentially the same as those reported in the benchmark model, and diagnostics again reveal that the conditional mean equations are adequately specified. In the variance equations, the inclusion of program trading and nonprogram trading volume reduces the parameters on $h_{ii,t-1}$ and $\varepsilon^2_{i,t-1}$ to insignificant levels. This is consistent with the findings of Lamoureux and Lastrapes (1991), who found that the inclusion of overall trading volume in the conditional variance equation for individual securities reduced GARCH parameters to insignificant levels. Diagnostic statistics indicate that this model adequately characterizes the serial correlation in conditional means and variances of spot and futures returns. Also, the theoretical kurtosis implied by a t distribution

[8]The null hypothesis that $1/\nu = 0$ is the boundary of the parameter space, implying that standard hypothesis tests are not appropriate for this parameter. However, based on the simulations in Bollerslev (1987), the estimate of $1/\nu$ is significantly different from 0.

with 1/.187 degrees of freedom is 7.45, which is close to the observed kurtosis of 6.57 and 9.53 for the spot and futures equations, respectively. Therefore, this model adequately captures the leptokurtosis in the data, suggesting that hypothesis testing from this model should not be affected by incorrect distributional assumptions.

Coefficients for nonprogram trading volume are positive (though marginally insignificant) in the conditional variance equations for the cash and futures markets, whereas coefficients on program trading are large and strongly significant. The likelihood-ratio test for the joint significance of the volume variables is 109.8. This is distributed χ_6^2 with a 95% critical value, 12.59. Therefore, the evidence that trading volume in aggregate is correlated with volatility is very strong. These results provide clear evidence of a strong positive relationship between program trading and market volatility, even while nonprogram trading is controlled for. This is not surprising, and is consistent with Harris, Sofiano, and Shapiro (1990), and Neal (1992), among others, who find a positive correlation between program trading volume and price volatility. Several explanations are mentioned in section subsection II.A.

A potential shortcoming of the preceding model is that it fails to account for intermarket volatility–returns relationship, as demonstrated in Koutmos and Tucker (1996), who show that volatility innovations in futures markets spill over into the spot market. However, the cause of such spillovers is not directly addressed. In light of their finding, this study investigates the extent to which program trading volume is a driving force behind the temporal relationships between spot and future market second moments. The cash market volatility is allowed to impact the futures market returns, and vice versa. The failure to include the link between volatility and returns in the bivariate setting could be misleading, as it would suggest that they are not related. One way to correct for this misspecification is to formally test that there is no intermarket volatility spillover; that is, cash market returns are not affected by futures market volatility, and vice versa. To test for this intermarket relationship, the mean equations are specified in the following way:

$$\Delta \ln S_t = \beta_{s,0} + \beta_{s,\mathrm{vol}}\,\mathrm{NYSE}_t + \sum_{i=1}^{4} \beta_{s,i} D_{i,t} + \gamma_s (\ln S_{t-1} - \ln F_{t-1})$$

$$+ \delta_1 h_{ss,t-1} + \delta_2 h_{sf,t-1} + \delta_3 h_{ff,t-1} + \varepsilon_{s,t} \tag{3a}$$

$$\Delta \ln F_t = \beta_{f,0} + \beta_{f,\mathrm{vol}}\,\mathrm{NYSE}_t + \sum_{i=1}^{4} \beta_{f,i} D_{i,t} + \gamma_f (\ln S_{t-1} - \ln F_{t-1})$$

$$+ \delta_1 h_{ss,t-1} + \delta_2 h_{sf,t-1} + \delta_3 h_{ff,t-1} + \varepsilon_{f,t} \tag{3b}$$

where eqs. (3a′) and (3b′) include three additional conditional volatility terms. Note that to avoid high multicollinearity, δ_1 and δ_2 in eq. (3a′) and δ_2 and δ_3 in eq. (3b′) are set to zero. This specification thus allows an examination of the issue of volatility spillover to the mean equations. No changes are needed in the conditional covariance matrix.

The model is jointly estimated with the conditional variance equations and the results, though not reported here, suggest that there is no volatility spillover to the mean equations. The log-likelihood value from this model is -1325.87, and the likelihood ratio statistic, χ^2, with two degrees of freedom is 2.18, which is not significant at any conventional level. Several alternative models are evaluated also, with no major changes in the results.

Hypothesis Tests

It is evident from the volume model in Table II that program trading has a stronger relationship with volatility than nonprogram trading. Several hypotheses are tested to evaluate this and related questions. First, the link between program trading and volatility is examined to determine if it differs from the link between nonprogram trading and volatility. This is formalized as hypothesis H_1:

> **H_1:** A one-unit change in program trading volume is associated with the same change in market volatility as a one-unit change in nonprogram trading volume. That is,

$$H_1 : \delta^{P}_{ss} = \delta^{np}_{ss}; \qquad \delta^{P}_{ff} = \delta^{np}_{ff}$$

The results reported in Table II indicate that the program trading volume coefficients are approximately *nine* times larger than nonprogram trading volume coefficients. The likelihood-ratio test statistic is 20.73, which is distributed χ^2_2 with 95% critical value, 5.99. Thus, H_1 is rejected.[9]

Several explanations for this result are available.

1. This could be interpreted as support for the hypothesis that program trades reflect different information than the information contained in aggregate market volume. To further support this hypothesis, the au-

[9]Note that the elasticity of volatility with respect to program trading volume is not statistically different from the elasticity of volatility with respect to nonprogram trading volume, measured on an average trading day. In other words, on a typical trading day, a 1% change in program trading volume is associated with the same percentage change in volatility as is a 1% change in nonprogram trading volume. The likelihood-ratio test for this restriction gives a test statistic of 1.68. It is distributed χ^2_2 with a 95% critical value, 5.99.

tocorrelation coefficients for daily program trading and daily nonprogram trading are computed. The first-order correlation coefficient for program trading is only 0.114, whereas for nonprogram trading it is 0.470. This dramatic difference in persistence continues at higher lags. Therefore, in terms of informational content, program trading volume data seems to be fundamentally different than nonprogram trading volume data. There are several reasons for this. For example, index arbitrage program trades are likely to be based on marketwide information, in contrast to nonprogram trades, which are more likely (than program trades) to be based on firm-specific information.

2. The relationship between trading volume and volatility is tempered by both short-selling restrictions and disagreement among investors over the implications of incoming information [see, for example, Jennings et al. (1981)]. For program trading volume, however, a relatively small percentage of trades are subject to short-sell restrictions [Harris et al., (1990)].[10] Furthermore, unlike nonprogram trades, there is little disagreement among program traders. Program trades usually convey either pessimistic views or optimistic views, but not both. Therefore, it is not surprising that program trades have a stronger correlation with volatility than nonprogram trades.
3. The two major driving forces behind any kind of trade (whether program trade or nonprogram trade) are information and liquidity motives. If trades are more information (liquidity) based, then the volume-volatility relationship will be stronger (weaker). The evidence suggests that program trades are more information based, whereas nonprogram trades are more liquidity based. This would be inconsistent with the previously mentioned conclusions of Hasbrouck (1996), who argues that the informational content of program trades is very similar to that of nonprogram trades.

The important conclusion from this result is that the program trading/volatility relationship is substantially different than the nonprogram trading/volatility relationship. Therefore, care must be taken when applying the existing volume/volatility models to program trading, and perhaps the theoretical models of the relationship between nonprogram trading volume and volatility must be modified to describe the relationship between program trading volume and volatility.

[10]There are other restrictions on program trading, however. For example, Rule 80A restricts program trades on days when the Dow Jones moves 50 points from the previous close, and the 5-minute Sidecar restricts trades on days when the Dow Jones moves 100 points from the previous close.

Another important and closely related result is that the relationship between overall trading volume and volatility seems to be caused almost entirely by the strong relationship between program trading volume and volatility. Though the results are not reported in Table II, putting overall NYSE volume (= PT + NPT) into the variance equations in place of PT and NPT gives a coefficient on NYSE of 0.049 in the spot variance equation (t statistic is 3.76) and 0.048 (3.41) in the futures variance equation. In other words, overall volume is strongly positively correlated with market volatility. This is not surprising, and is consistent with a large and growing empirical literature; see Gallant, Rossi, and Tauchen (1992) for a recent comprehensive study. Several explanations are available. Very briefly, it could be caused by: new information reaching investors with heterogeneous beliefs [Beaver (1968)]; "price pressure" or liquidity effects [Krause and Stoll (1972)]; the mixture of distributions hypothesis with volume as the mixing variable [Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983), Anderson (1992)]; or positive feedback trading strategies, in which investors base trading decisions on price movements [Delong et al. (1990)]. However, as shown in Table II, including PT and NPT *separately* gives much lower coefficients and insignificant parameters on NPT. This surprising result suggests that the positive correlations between overall volume and volatility that permeate the literature might be caused by the program trading/volatility relationship. At the very least, it suggests that empirical tests of the volume/volatility relationship should first purge program trades from the volume data. The results of this study indicate that the relationship will disappear if this is done.

Next, program trading is disaggregated into program buys and program sells to draw inferences regarding the response of volatility to program buys and program sells. In the last two columns of Table II estimates are reported of the full model, which includes buy-program trading volume, sell-program trading volume, and nonprogram trading volume in the volatility equations. Postestimation diagnostics reported at the bottom of the table show that the standardized residuals and squared standardized residuals are free of serial correlation. Also, the conditional t distribution captures the leptokurtosis in the data. The likelihood ratio statistic for including the three volume variables in the conditional covariance matrix is 125.00. The test is distributed χ^2_9, and has a 95% critical value of 16.92. Therefore, the hypothesis that program trading and nonprogram trading volume do not belong in the conditional covariance matrix can be rejected.

The parameters in the mean equations are qualitatively similar to those from the other models. In the conditional variance equations, notice first that the coefficients on NPT are still positive, but borderline insignificant, suggesting again that the volume/volatility relationship found in the literature might be specific to program trading volume. Next, notice that the coefficient on program buying is *seven* times as large as the coefficient on nonprogram volume, which supports both the hypotheses that program trading exacerbates market volatility and that program trading imparts different information from nonprogram trading. Finally, notice that the coefficients on program selling are 15 times as large as the coefficients on NPT, and twice as large as those on program buying, which indicates that program selling imparts different information than program buying or nonprogram trading.

Although these estimates suggest that both buy- and sell-program trading volume are positively linked to market volatility, the sizes of the estimated coefficients differ considerably. It is useful to test if the difference in size is statistically significant. This may be formally stated as H_2:

H_2: Buy-program trades are associated with the same increase in market volatility as sell-program trades. That is,

$$H_2 : \delta_{ss}^{b} = \delta_{ss}^{s}; \qquad \delta_{ff}^{b} = \delta_{ff}^{s}.$$

The likelihood-ratio test statistic for H_2 is 15.01. It is distributed χ_2^2 and has a 95% critical value, 5.99. Therefore, H_2 is rejected. In other words, although both kinds of trades are positively correlated with volatility, the relationship is stronger for sell-program trades than for buy-program trades. The results are consistent with the analysis in Harris et al. (1990), who argue that program sells might contribute to widespread selling, whereas program buys are less likely to lead to widespread buying. This will lead to a greater overall volatility with program sells than with program buys. The implication of this result is that any theoretical model of the relationship between program trading and volatility should account for this differential relationship.

The bivariate framework allows one to test whether the stock market response to program trading differs from that of the futures market. As discussed previously, there are several reasons why this hypothesis is interesting. For example, the uptick rule, the Samuelson hypothesis, and the Cascade theory all suggest a different relationship between volume and volatility in the cash market than in the futures market. In terms of this study's model, the hypothesis is

H_3: Program trading has the same relationship with futures market volatility as it does with cash market volatility. That is,

$$H_3 : \delta^b_{ss} = \delta^b_{ss}; \qquad \delta^s_{ss} = \delta^s_{ff}.$$

The likelihood-ratio statistic for H_3 is 3.48. This is distributed χ^2_2 and has a 95% critical value, 5.99. Therefore, H_3 is not rejected—the relationship between program trading and volatility is the same in the cash market as it is in the futures market. Thus, at least at the daily frequency, the uptick rule, the Samuelson hypothesis, and the Cascade theory do not have a significant impact on the relationship between program trading and market volatility. Abstracting from institutional differences between the markets, to the extent that program trading is index arbitrage based, this is not surprising. Index-arbitrage-based program trades (and some other portfolio trades) involve taking opposite positions in the cash and futures markets, so the volatility induced in each market will be the same.

Finally, one plausible explanation as to why sell-program trades have a larger impact on market volatility than buy-program trades is that the latter is more likely to occur during a down market. To investigate this possibility, the variance equations are augmented with two additional variables representing program and nonprogram volumes during down markets. Down markets are defined as those days during which both cash and futures markets returns decline by at least 1% from the previous day's returns. So the dummy variable *Down* is set equal to 1 when the above condition is true, and zero otherwise. Finally, the dummy variable (Down) is premultiplied by program and nonprogram volumes separately to create these two additional volume variables. The new variance equations are

$$\begin{bmatrix} h_{ss,t} = w_{ss} + \alpha_{ss}\varepsilon^2_{s,t-1} + \beta_{ss}h_{ss,t-1} + \delta^b_{ss}\,\mathrm{BUY}_t + \delta^s_{ss}\,\mathrm{SELL}_t + \delta^p_{ss}\,\mathrm{PT}_t \\ \quad + \delta^{np}_{ss}\,\mathrm{NPT}_t + \Theta_1\,\mathrm{Down*PT}_t + \Theta_2\,\mathrm{Down*NPT}_t \\ h_{sf,t} = w_{sf} + \alpha_{sf}\,\varepsilon_{s,t-1}\varepsilon_{f,t-1} + \beta_{sf}h_{sf,t-1} + \delta^b_{sf}\,\mathrm{BUY}_t + \delta^s_{sf}\,\mathrm{SELL}_t + \delta^p_{sf}\,\mathrm{PT}_t \\ \quad + \delta^{np}_{sf}\,\mathrm{NPT}_t + \Theta_1\,\mathrm{Down*PT}_t + \Theta_2\,\mathrm{Down*NPT}_t \\ h_{ff,t} = w_{ff} + \alpha_{ff}\,\varepsilon^2_{f,t-1} + \beta_{ff}h_{ff,t-1} + \delta^b_{ff}\,\mathrm{BUY}_t + \delta^s_{ff}\,\mathrm{SELL}_t + \delta^p_{ff} \\ \quad \mathrm{PT}_t + \delta^{np}_{ff}\,\mathrm{NPT}_t + \Theta_1\,\mathrm{Down*PT}_t + \Theta_2\,\mathrm{Down*NPT}_t \end{bmatrix}$$

These results are reported in the last two columns of Table II. The down market program trading variable is found to be marginally significant and positive in the cash market variance equation. Hence, program trades have a larger impact on cash market volatility during a down market. In contrast, nonprogram volume tends to have positive and significant (at 10% level) relationships with both the cash and futures market volatility. Interestingly, the size of the coefficients on program trading volume is twice as large as the coefficients for the nonprogram trading volumes during down markets. Overall, these results further illustrate that the program trading volume and market volatility relationship documented in this study is not a manifestation of the down-market artifacts.

CONCLUSIONS

This article examines the relationship between program trading and volatility in the S&P500 cash and futures markets. A bivariate error-correction model with GARCH error structure extends the literature in several key respects. First, it examines the effects of program trading simultaneously on the stock and futures markets. Second, the GARCH model allows the joint distribution of stock and futures returns to vary over time as a function of the information set. Finally, the impact of program trading on volatility in each market is examined by including program trading volume in the relevant information set.

Empirical support is found for many of the findings of Grossman (1988a, 1988b), Harris et al. (1990), Neal (1992), and others, who study the relationship between program trading volume and market volatility. In addition, the relationship between program trades and volatility differs from the relationship between nonprogram trades and volatility, and the relationship between volume and volatility disappears when program trades are held constant. The results can be summarized as follows.

1. Nonprogram trading is only weakly related to volatility, suggesting that the strong correlation between aggregate market volume and volatility is due to the relationship between program trading and volatility.
2. The positive relationship between program trading volume and volatility is much stronger than the positive relationship between nonprogram trading and volatility.
3. Sell-program trades are associated with higher market volatility than buy-program trades.
4. Program trading has the same effect on futures market volatility as it has on cash market volatility.

In conclusion, it appears that the existing models on nonprogram trading volume and market volatility are not adequate to describe the relationship between program trading volume and market volatility, because these relationships are substantially different. These results also suggest that program trading does lead to a higher market volatility, which confirms that the media's characterization of the role of program trading in contributing to a higher market volatility may be accurate. The difference is more pronounced in down markets. However, as suggested earlier in the article, we make no policy recommendations based upon our results. The extent to which these results justify regulatory comment is highly circumspect. The objective of this article is to show that the relationship between program trading volume and market volatility differs from that of the relationship between nonprogram trading volume and market volatility. Policy recommendations regarding program trading must be based upon evidence that program trading causes excess market volatility, an issue that has not been investigated in this article.

Many interesting questions remain for continued research. For example, this article demonstrates a dramatically different relationship between buy-program trades and volatility than the relationship between sell trades and volatility. Much more can be done to analyze why these relationships are so different. Could the size of the orders be related to their differential impacts on market volatility? Future work could also examine causality between program trading and volatility [as in Harris et al. (1990)], or seek to make welfare inferences. But perhaps the biggest question relates to the relationship between nonprogram trading and volatility. Does this relationship disappear after controlling for program trading volume, even with higher-frequency data? If so, why does the relationship between volume and volatility disappear when controlling for program trades?

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