[The Journal of Entrepreneurial Finance](https://digitalcommons.pepperdine.edu/jef)

Volume 8
Issue 1 *Spring 2003*

Article 6

12-2003

Dynamic Linkages Between Trading Volume and Price Movements: Evidence for Small Firm Stocks

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Recent theoretical and empirical studies suggest that volume conveys useful information to forecast stock price movements. We investigate the information content of volume for the stock indices of small-capitalization firms in the US and France. Information asymmetry problems tend to be more important for small-capitalization firms and it can be argued that the information content of volume should be more significant. We find that volume does indeed forecast returns of the small-capitalization stock indices. We also detect a positive contemporaneous relation between volume and absolute value of returns. The findings are qualitatively the same for data from the US and France.

Introduction

Many studies argue that stock price movements and trading volume are closely associated. Early models of Clark (1973) and Copeland (1976) suggest that a latent variable, representing the rate of information arrival to the market, jointly affects price variance and volume, causing contemporaneous movements between absolute value of returns and trading volume. Empirical work, surveyed in Karpoff (1987), has generally found support for this prediction in both equity and futures markets.

Blume, Easely and O'Hara (BEO, 1994) and Suominen (2001), in theoretical papers, also investigate the role of volume on asset markets and show that volume conveys information about future price movements to market participants. BEO and Suominen (2001) suggest that stock prices are noisy and cannot reflect all available information that reaches the market. Trading volume, in their models, emerges as a useful statistic because it provides information that cannot be obtained from price alone. In BEO, volume conveys information about the precision of the informative signal that reaches the market. Suominen (2001) suggests that volume is helpful to

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Acknowledgements: I am grateful to the late Craig Hiemstra for generously sharing his software to calculate nonlinear causality tests used in this paper.

determine the extent of informational asymmetry in the market. The prediction of both of these models is that there is an association between volume and subsequent price movements and traders that include volume information in their strategies obtain better trading results.[1]

In this paper, we rely on the motivation by these models and investigate the predictive power of volume for the small capitalization stock indices of the S&P 600 and the Nouvaue Marche (NM) Index of the NM exchange of France. The S&P 600 includes domestic small capitalization firms and the NM, a part of the Paris Stock Exchange, lists stocks of small, high-growth firms. While numerous papers have investigated the stock price-volume relation for market-wide stock indices, such as Hiemstra and Jones (1994), Gallant, Rossi and Tauchen (1992) and Lee and Rui (2002), this is the first study, to the best of our knowledge, to focus on the stock price-volume dynamics for small firms. This investigation should be of interest to market participants since small firms tend to be less widely followed by analysts, and more affected by informational asymmetry problems. Considering that volume conveys information to the market in BEO and Suominen (2001) because prices are noisy, it can be argued that, as BEO point out, informational content of volume should be more pronounced for small firm stocks. An investigation of the stock price-volume relation for small firms should also be of interest to entrepreneurs, who use the stock market to take their ventures to public.

We test for the predictive power of volume for both the magnitude and direction of stock price movements, i.e. absolute value of returns and returns per se. While testing for the linkages between volume and absolute returns, it is important to account for the simultaneous relation between the variables, which is sometimes ignored in the literature (see, Hiemstra and Jones, 1994, for a discussion of this point). We construct a structural model and estimate the relation between volume and absolute returns simultaneously, using instrumental variables (IV) based generalized method moments (GMM) estimation. Our approach treats both variables as endogenous and eliminates the simultaneity bias.

We use linear and nonlinear methods to test for the relation between volume and returns. We estimate vector autoregression (VAR) models to calculate conventional linear Granger causality tests. Gallant, Rossi and Tauchen (1992) and Hiemstra and Jones (1994) show that volume and returns could have nonlinear linkages that cannot be detected by linear tests. We use the modified Baek and Brock (1992) test to examine nonlinear causal dynamics. The modified Beak and Brock test, fully developed in Hiemstra and Jones (1994), is a nonparametric test, designed to detect linkages that cannot be uncovered by conventional linear test statistics.

Our results suggest that a positive contemporaneous relation exists between volume and absolute value of returns for both of the stock indices, consistent with evidence from prior studies. We find no evidence to support that lagged volume predicts absolute returns, contrary to the predictions of BEO and Suominen (2001). However, we report strong evidence suggesting that past volume could be used to forecast returns, again on both of the markets examined.

We provide a brief review of the literature in the next section and discuss the hypotheses and the empirical method of analysis of the study in Section 3. We present the data set in Section 4, discuss the empirical findings in Section 5 and offer the concluding remarks of the paper in the final section.

[1] It should be mentioned that their analysis is also consistent with the manner volume is viewed by practitioners. For example, technical traders believe that price movements accompanied with high trading volume are more important than price changes with low volume. In fact, “It takes volume to move prices” is a widely quoted adage on Wall Street.

I. Prior Work

Early work on stock price-volume linkages were mainly motivated by the mixture of distributions hypothesis (MDM) of Clark (1973) and the sequential information flow hypothesis (SIF) of Copeland (1976).[2] As surveyed by Karpoff (1987), a common conclusion of these studies is that a positive simultaneous relation exists between trading volume and absolute value of returns, on both equity and futures markets. This finding is consistent with Clark's (1973) interpretations that volume may act as a proxy for the rate of information arrival at the market.

More recent studies examine the dynamic linkages between volume and returns. Notably, Gallant, Rossi and Tauchen (1992) and Hiemstra and Jones (1994) both find significant interactions between volume and returns on the major indices of the New York Stock Exchange (NYSE). While Gallant, Rossi and Tauchen (1992) argue that returns univariately impact volume, Hiemstra and Jones (1994) find that a feedback relationship exists between the variables. It is noteworthy that Hiemstra and Jones (1994) show that there are nonlinear linkages between volume and stock return, undetected by linear causality tests.

Some studies examine the stock price-volume relation on international equity markets. Saatcioglu and Starks (1988) investigate Latin American markets and report that volume leads returns. Lee and Rui (2000) examine the predictive power of volume on China's four stock exchanges and find little supportive evidence. Silvapulle and Choi (1999) use linear and nonlinear causality tests to investigate linkages between returns and volume on the Korean stock exchange. Lee and Rui (2002) find that trading volume does not Granger cause returns on main stock indices of the stock exchanges of New York, Tokyo and London. It should be mentioned, however, that they focus solely on linear linkages and do not test for nonlinear predictive power.

Campbell, Grossman and Wang (1993) and Llorente et al. (2001) provide equilibrium models on the interaction between volume and return autocorrelations. Their models suggest that volume is informative about future stock price movements. Specifically, they show that days with high trading volume are followed by negative return autocorrelations if hedging (risk allocation) is the main motive to trade. However, positive return autocorrelations will be observed when speculation is the primary motive. Llorente et al. (2001) provide a detailed investigation of this theory for the US individual stocks and report empirical results consistent with their predictions. Conrad, Hameed and Niden (1994) and Cooper (1999) also test the predictions of these two models within the context of short-horizon contrarian trading strategies. Conrad, Hameed and Niden (1994) argue that trading volume induces negative return autocorrelations, while Cooper (1999) finds that trading volume decreases them. Cooper (1999) suggests that the different results are caused by size of the stock samples used in the two papers.

In articles constituting the theoretical motivation for the current study, BEO and Suominen (2001) also investigate the role of trading volume in financial markets. As argued in introduction, the main contribution of these models is that rather than describing the correlation

[2] The *sequential information flow* model of Copeland (1976) postulates that new information that reaches the market is not disseminated to all participants simultaneously, but to one investor at a time. Final information equilibrium is reached only after a sequence of transitional equilibria. Hence, due to the sequential information flow, lagged trading volume may have predictive power for current absolute stock returns and lagged absolute stock returns could have predictive power for current trading volume. The *mixture of distributions* model of Clark (1973) argues that returns and trading volume are positively correlated because the variance of returns is conditional upon the volume of that transaction. In Clark’s (1973) model, trading volume is a proxy for the speed of information flow, which is regarded as a latent common factor that affects prices and volume synchronously. No causal relation from trading volume to returns is predicted in this model.

between price and volume, they study how volume could affect market behavior. BEO show that traders learn from volume and use it in their decision-making because volume conveys information about the precision of the informative signal that reaches the market. In Suominen (2001), volume is informative because it helps to resolve information asymmetries. He shows that traders estimate the availability of private information on the market using past volume and adjust their strategies. Both of these studies argue that volume conveys information to the market that cannot be obtained from price alone and significant linkages are suggested between lagged volume and subsequent price movements.

II. Statistical Method of Analysis

In this section, we discuss the hypotheses of the study and our econometric approach. In the first part of the empirical analysis, we examine the linkages between volume and absolute value of returns on the S&P 600 and the NM Index. The MDH and SIF suggest that a positive simultaneous relation exists between volume and absolute returns, which is also supported by previous empirical studies. Hence, it is important point to account for this simultaneous relation in empirical modeling. We construct the following structural model, adopted from Foster (1995) and estimate it using an IV-based GMM estimator.

$$\begin{aligned} V_t &= a_0 + a_1 |R_t| + a_2 V_{t-1} + a_3 V_{t-2} + u_{1t} \\ |R_t| &= b_0 + b_1 V_t + b_2 V_{t-1} + b_3 |R_{t-1}| + u_{2t} \end{aligned} \qquad (1)$$

This model treats volume and absolute returns as endogenous and IV-estimation accounts for the simultaneity bias, while the GMM approach accounts for heteroscedasticity in residuals. Significance of coefficients a_1 and b_1 would indicate a contemporaneous relation between volume and absolute returns and significance of b_2 would indicate that lagged volume has predictive power for future absolute returns, as suggested by BEO and Suominen (2001).

In the second part of the empirical analysis, we test whether trading volume has forecasting power for future returns. This investigation has implications for market efficiency, which states that direction of price changes should not be predicted using public information, like trading volume. We conduct linear and nonlinear Granger causality tests of volume-return relation. Granger causality testing investigates whether the past or present of a variable improves the forecast of another economic variable. Linear causality tests can be conducted using vector autoregresssion (VAR) models. The VAR approach is ideally suited to detect stylized facts in the data without imposing a priori restrictions. We estimate the following VAR model to test for dynamic linkages between volume and returns

$$R_t = a_r + \sum_{i=1}^{l} b_{r,i} R_{t-i} + \sum_{i=1}^{l} c_{r,i} V_{t-i} + \sum_{i=1}^{k} D_i + u_{r,t} \qquad (2)$$

$$V_t = a_v + \sum_{i=1}^{l} b_{v,i} R_{t-i} + \sum_{i=1}^{l} c_{v,i} V_{t-i} + \sum_{i=1}^{k} D_i + u_{v,t} \qquad (3)$$

in which R_t denotes returns, calculated as log price changes, V_t denotes trading volume, Di's are dummy variables to account for the day of the week and month of the year effects in stock returns, $u_{r,t}$, $u_{v,t}$ are error terms and l denotes the autoregressive lag length.

We formulate the linear Granger causality restrictions as follows: If the null hypothesis that all c_r's jointly equal zero is rejected, it is argued that volume Granger causes returns, which is the main hypothesis of interest. If the null hypothesis that all b_v's jointly equal zero is rejected, it is argued that returns Granger cause volume. If both of the null hypotheses are rejected, it is said that bivariate causality (feedback) exists between volume and returns. Although several

Granger causality tests have been offered, we use the conventional χ^2-test for joint exclusion restrictions. Evidence reported in the literature suggests that this simplest form of linear causality testing is the most powerful (see, Geweke, Meese and Dent, 1983, among others).

In addition to linear linkages, volume and returns could have nonlinear linkages. The models by Campbell, Grossman and Wang (1993) and Wang (1994) predict a nonlinear relationship between returns and volume. LeBaron (1992) and Duffee (1992) provide empirical evidence of significant nonlinear interactions between stock returns and trading volume. Hiemstra and Jones (1994) and Fujihara and Mougoue (1997) show that bidirectional nonlinear Granger causality exists between trading volume and returns in US equity and futures markets, respectively, although linear Granger causality tests cannot capture it.[3] Following these articles, we also examine whether there exists nonlinear causality dynamics between volume and returns of the S&P 600 and the NM Index.

We use the modified Baek and Brock (1992) test, fully developed in Hiemstra and Jones (1994), to examine nonlinear Granger causality between volume and returns. The Baek and Brock (1992) approach begins with a testable implication of the definition of Granger non-causality. Consider two strictly stationary and weakly dependent time series $\{X_t\}$ and $\{Y_t\}$, t = 1, 2,.... Denote the m-length lead vector of X_t by X_t^m and the Lx-Length and Ly length lag vectors of X_t and Y_t, respectively. For given values of m, Lx, and Ly $\geq$ 1 and for e > 0, Y does not Granger cause X if:

$$\Pr(\| X_t^m - X_s^m \| < e \,|\, \| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \| < e, \| Y_{t-ly}^{Ly} - Y_{s-Ly}^{Ly} \| < e$$
$$= \Pr(\| X_t^m - X_x^m \| < e \,|\, \| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \| < e) \qquad (4)$$

in which Pr( ) denotes probability and || || denotes the maximum norm. The probability on the left side of equation (4) is the conditional probability that two arbitrary m-length lead vectors of $\{X_t\}$ are within a distance, e, of each other, given that the corresponding Lx-length lag vectors of $\{X_t\}$ and Ly-length lag vectors of $\{Y_t\}$ are within, e, of each other.

The Granger non-causality condition in equation (4) can then be expressed as

$$\frac{C1(m+Lx,Ly,e)}{C2(Lx,Ly,e)} = \frac{C3(m+Lx,e)}{C4(Lx,e)} \qquad (5)$$

for given values of m, Lx, and Ly $\geq$1 and e>0, where C1,…,C4 are the correlation-integral estimates of the joint probabilities. Hiemstra and Jones (1994) show how to derive the joint probabilities and their corresponding correlation-integral estimators. Assuming that X_t and Y_t are strictly stationary, weakly dependent, and satisfy the mixing conditions of Denker and Keller (1983), if Y_t does not Granger cause X_t, then,

$$\sqrt{n}\ (\frac{C1(m+Lx,Ly,e,n)}{C2(Lx,Ly,e,n)} = \frac{C3(m+Lx,e,n)}{C4(Lx,e,n)}) \sim N(0,\sigma^2\ (m,Lx,Ly,e)), \qquad (6)$$

Hiemstra and Jones (1994) show that a consistent estimator of the variance is, σ^2(m, Lx, Ly, e) = $\delta(n).\Sigma(n).\delta(n)'$.[4] To test for nonlinear causality between volume and returns, we apply the test in equation (6) to residual series extracted from the VAR models. Since the VAR model accounts

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[3] In an empirical application of the Baek and Brock approach, Ciner (2001) reports nonlinear causal dynamics between oil futures prices and S&P 500 index returns, undetected by linear tests.

[4] A significantly positive value for the test statistic in (6) indicates that past values of Y help to forecast X, while a significantly negative value indicates that past values of Y confound the forecast of X. Therefore, Hiemstra and Jones (1994) argue that the test statistic should be evaluated with right-tailed critical values when testing for Granger causality.

for any linear dependencies, any remaining predictive power of one residual series for another can be considered nonlinear predictive power.

III. Data

The data set consists of daily closing values and aggregate trading volume for the S&P 600 and the NM stock indices. The S&P 600 is a value-weighted index of 600 domestic stocks of small capitalization. The data for the S&P 600 cover the period between August 16, 1995, which is the inception of the S&P 600, and April 25, 2002. Volume series is constructed by aggregating daily trading volume of each stock included in the index. We use natural logarithm of volume series throughout the study. The NM Index is the main index of Nouveau Marche (NM), which is a part of the Paris Stock Exchange. The NM is an exchange mainly for small, high-growth firms. It is an order-driven market. A dual trading mechanism, combination of continuous and call auctions, is used.[5] There are two call auction sessions (at open and close) and stocks are continuously traded by market makers posting bid and ask quotes between these calls. Volume series is the daily aggregate trading volume on the NM. The data for the NM are obtained from the Paris Stock Exchange and cover the period between January 2, 1998 and August 31, 2001.

We report summary statistics of the sample in Table 1. Returns on both indices have, on average, zero means, negative skewness and excess kurtosis. The Augmented Dickey Fuller (ADF) tests for unit root are also reported in Table 1. Unit root tests are important since the VAR approach requires that the variables are stationary. We calculate the ADF test statistics including a time trend in regressions for trading volume, since trading volume seems to grow through time on both markets. The lag lengths are determined using the Akaike's Information Criteria (AIC).

The ADF test statistics suggest that volume series for the S&P 600 can be characterized as stationary, however, volume on the NM is nonstationary. The volume for NM is, therefore, first-differenced to obtain stationary series for the empirical investigation. Finally, we calculate first-order autocorrelations for returns on both indices, which are .10 for the S&P 600 and .22 for the NM Index, significant at comfortable levels. Positive first-order autocorrelation on major US stock indices has been detected by prior studies, such as Lo and McKinlay (1988) and Boudokh, Richardson and Whitelaw (1995).[6] To consider the economic significance of these autocorrelations, notice that the r-square of a regression of returns on a constant and its first lag is the square of the slope coefficient, which is simply the first-order autocorrelation. Hence, an autocorrelation of .22, for example, implies that 4.84% of the variation in the index return is predictable using the preceding return.

IV. Empirical Findings

A. Volume and Absolute Returns

We estimate the system of equations in (1) by the GMM and report the results in Table 2. An important point to determine is whether the system is exactly identified, i.e. a unique set of estimates for the coefficients in the model exists. If the system is overidentified, there will be multiple estimates for the coefficients. We use Hansen's (1982) test to investigate

[5] Call auctions resemble classical Walrasian auctions. Buy and sell orders are collected from market participants in discrete sessions and all orders are executed at a single, market-consensus price. The clearing price is determined as the price at which trading volume is maximized.

[6] Boudokh, Richardson and Whitelaw (1995) provide an extensive discussion of the possible explanations for this evidence of predictability. They support a market-efficiency-based explanation, arguing that institutional factors are the most likely source of the autocorrelation patterns.

overidentification. The test statistics, also in Table 2, are very small in all of the cases, supporting a good fit of the model to the data.

The estimation results indicate a positive contemporaneous relationship between trading volume and absolute returns for both of the markets. This finding suggests that volume and volatility are endogenously determined and respond to the same exogenous variable, the daily flow of information to the market in the MDH context. However, there is no evidence to suggest that volume has forecasting power for future price variability. The coefficient of interest, b_2, is not statistically significant in either of the models. This finding contradicts the analysis in BEO and Suominen (2001), who argue that lagged volume contains information to forecast absolute returns.[7]

B. Volume and Returns

We first discuss the results of linear Granger causality tests between volume and returns. We estimate the VAR models by the OLS, with dummy variables for day of the week and month of the year effects, and calculate White's (1980) heteroskedasticity consistent standard errors. Volume series is regressed over a trend variable and the residuals from this regression are used as volume variable to eliminate the deterministic time trend present on both markets. We use the AIC to determine the optimal lag lengths in the VAR model, with a maximum lag length of 40.

The results of the χ^2-tests, which can be found in Table 3, indicate that volume contains predictive power for future returns on both of the markets. The null hypothesis that lagged volume coefficients jointly equal zero is safely rejected in both of the cases. This finding is markedly different from the conclusions of Gallant, Rossi and Tauchen (1992), Hiemstra and Jones (1994) and Lee and Rui (2001), who do not find any predictive power of volume for large market indices. For the S&P 600, the causality dynamics are unilateral, volume causing returns. However, there is a feedback relation between returns and volume for the NM Index.

We use Ljung-Box (LB) tests to examine the residuals from the VAR models for linear and nonlinear dependencies. The results of LB tests applied to the residuals indicate that the VAR models successfully account for linear dependencies. However, significant nonlinear dependencies remain in the residuals, evinced by the significant values of the LB tests applied to squared residuals.[8]

As mentioned before, volume and returns can also have nonlinear linkages. Empirical studies by Hiemstra and Jones (1994), Gallant, Rossi and Tauchen (1992) and Fujihara and Mougoue (1997) find that there are significant nonlinear linkages between volume and returns on the US equity and futures markets, respectively.[9] The models of Campbell, Grossman and Wang (1993) and Llorente et al. (2001) suggest nonlinear linkages between volume and returns. Significant values of the LB tests applied to squared residuals also indicate that there could be nonlinear linkages uncovered by the VAR models.

We apply to the modified Baek and Brock (1992) test to the residuals extracted from the VAR models to test for nonlinear Granger causality and report the results in Table 4. To calculate the Baek and Brock tests, the lead and lag truncation lags (m, Lx, Ly) and the scaling parameter, e, have to be determined. We follow the Monte Carlo evidence in Hiemstra and Jones (1993) to set the values of these parameters, since there is no established selection criterion. Hiemstra and Jones (1993) find that for samples sizes of 500 or more observations, a lead length

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[7] This finding also contradicts the *sequential information flow* model of Copeland (1976).

[8] The sole exception is volume series for the NM, which does not seem to contain nonlinear dependency.

[9] Ciner (2002) shows that there are nonlinear linkages between volume and returns on Japanese commodity futures markets, also.

of m=1, lag lengths of Lx=Ly=1,2,…5 and length scale of e=1.0 provide good finite-sample size and power properties. The test statistics in Table 4 indicate some evidence of nonlinear causality from volume to returns for the S&P 600, the test statistics are significant at only three lags. Also, there is strong evidence of causality from returns to volume, the test statistics are significant and much larger at all lags. Hence, the nonlinear analysis indicates that there is a feedback relation between volume and returns for the S&P 600 index, rather than a unilateral relation. However, there is no evidence of nonlinear causality in either direction for the NM Index and the conclusions from the previous analysis remains unchanged.

V. Concluding Remarks

We investigate the dynamic linkages between volume and price movements for the S&P 600 small firm index and the NM Index of the Paris Stock Exchange, which also lists small, high-growth firms. Although many studies have examined the stock price-volume dynamics for market-wide indices, the literature does not contain evidence on the information content of trading volume for small firms. Our investigation should be of interest to market participants, since trading volume is public information that could easily be incorporated into trading strategies, and to entrepreneurs, who use stock markets to take their enterprises public. This study is mainly motivated by the theoretical results in BEO and Suominen (2001), who show that trading volume conveys valuable information to the market about future stock price movements.

In our empirical analysis, we investigate the information content of volume for both the absolute value of returns and returns per se. We construct a structural model to examine the linkages between volume and absolute returns and estimate it by the GMM. We find that a positive simultaneous relation exists between volume and absolute returns, consistent with the empirical and theoretical literature on stock price-volume relations. However, we find no forecasting power for lagged volume for absolute returns, contrary to the predictions of BEO and Suominen (2001).

We investigate the information content of volume for future returns using linear and nonlinear causality tests. Linear Granger causality tests, conducted within the context of VAR models, suggest that lagged volume has predictive power for subsequent returns on both of the markets. This finding has implications against market efficiency and contradicts the results of studies, such as Gallant, Rossi and Tauchen (1992) and Lee and Rui (2002), which do not detect forecasting power for volume for the main stock indices of New York, London and Tokyo.

The predictive power of volume for small-capitalization stock indices seems to be consistent with the contention that the information conveyed by volume should be more important for small firm stocks, since these firms tend to be less widely followed by analysts and more dominated by information asymmetry problems. Our findings are also consistent with Lo and McKinlay (1990) and Chordia and Swaminathan (2000), who argue that small firms tend to underreact to new information. It is also noteworthy that the empirical findings are very similar for the two markets we examine. Future research should provide additional evidence on the stock price-volume relation of small firms to determine whether the findings of this study represent universal facts. Future research is also required to assess the economic significance of the statistical predictability detected in this paper for conclusions about market efficiency.

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Table 1

Sample Summary Statistics

	S&P 600		NM Index	
	R_t	V_t	R_t	V_t
N	1684		928	
Mean	.0004	18.074	.00002	16.728
Std Deviation	.011	.401	.024	1.139
Skewness	-.252	-.059	-.373	.150
Kurtosis	2.620	-.775	5.731	-1.100
ADF	-6.94	-5.85	-11.55	-1.87

Note- This table provides descriptive statistics for daily returns, R_t, and trading volume, V_t, for the S&P 600 small firm index and the NM Index of Nouveau Marche of the Paris Stock Exchange. N denotes the number of observations in the sample. The ADF test for unit roots is calculated with an intercept for R_t and with an intercept and a time trend for V_t. The null hypothesis of the ADF test is nonstationarity and the respective critical values are –2.86 and –3.41.The augmentation lags are 28 and 35 for S&P 600 and 30 and 8 for NM Index, for R_t and V_t, respectively.

Table 2

Volume and Absolute Value of Returns

	S&P 600	NM Index
a_o	-.035 (.02)	-.088 (.01)
a_1	4.287 (.02)	5.514 (.01)
a_2	.588 (.00)	.593 (.00)
a_3	.015 (.59)	.296 (.00)
b_o	.006 (.00)	.011 (.00)
b_1	.007 (.93)	.009 (.06)
b_2	-.002 (.97)	-.002 (.52)
b_3	.217 (.02)	.245 (.00)
Hansen	.000 (.99)	.000 (.99)

Note- This table provides GMM estimation results of equation (1). P-values for statistical significance are in parentheses. The row labeled Hansen refers to Hansen's (1982) goodness of fit test. The null hypothesis of this test is no overidentification restrictions.

Table 3

Volume and Returns: Linear Tests

Panel A: Granger Causality Tests

	S&P 600	NM Index
$V_t \rightarrow R_t$	39.69 (.02)	21.42 (.00)
$R_t \rightarrow V_t$	14.98 (.92)	23.99 (.00)

Panel B: Residual Diagnostics

	S&P 600	NM Index
Q_{Rt}	.30 (.99)	2.21 (.99)
Q_{Vt}	.80 (.99)	11.28 (.50)
Q^2_{Rt}	601.47 (.00)	322.99 (.00)
Q^2_{Rt}	46.73 (.00)	11.18 (.51)

Note- This table provides the results of testing for linear Granger causality between daily returns, R_t, and trading volume, V_t for the S&P 600 and the NM Index. The arrows indicate the direction of causality. The VAR models are estimated using 24 lags for the S&P 600 and 7 lags for the NM Index. The χ^2-tests for joint exclusion restrictions are calculated using White's (1980) heteroskedasticity consistent standard errors and p-values are in parentheses. Q and Q^2 are Ljung-Box test statistics applied to residuals and squared residuals, respectively, at 12 lags. The results of the Ljung-Box tests are, however, robust to other lag length specifications.

Table 4

Volume and Returns: Nonlinear Tests

$V_t \rightarrow R_t$

	S&P 600		NM Index	
Lx=Ly	CS	TVAL	CS	TVAL
1	.005	1.444	-.008	-1.939
2	.006	1.915	-.028	-3.798
3	.010	1.320	-.040	-3.626
4	.016	1.689	-.027	-1.706
5	.019	1.722	-.004	-.233

$R_t \rightarrow V_t$

	S&P 600		NM Index	
Lx=Ly	CS	TVAL	CS	TVAL
1	.007	2.724	-.010	-2.256
2	.016	3.477	-.027	-3.924
3	.017	3.155	-.036	-3.659
4	.016	2.973	-.047	-3.629
5	.018	3.015	-.050	-3.201

Note-This table presents the results of testing for nonlinear causality between daily returns, R_t, and trading volume, V_t for the S&P 600 and the NM Index. The modified Baek and Brock test is applied to the obtained residuals from the VAR models. The tests are applied to unconditionally standardized series, the lead length, m, is set to 1 and the length scale, e, is set to 1.0. CS and TVAL are the difference between the two conditional probabilities in equation (3) and the standardized test statistic in equation (5), respectively. The null hypothesis of the test statistic is no nonlinear Granger causality and it is asymptotically distributed N(0,1). The critical value at 5% significance level is 1.64.