The Empirical Relation between Price Changes and Trading Volumes: Further Evidence from European Stock Markets

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Abstract

Extant literature on price-volume relation of stock markets relies mainly on standard linear Granger causality tests and draws evidence mostly from individual or aggregate US stock markets and those of other major industrial economies. This paper employs linear and nonlinear Granger causality tests to examine the price-volume relation of 10 relatively small European stock markets. Because these markets present a broader range of institutional, organizational, and structural factors than the major industrial markets, their analyses will enrich the literature on price-volume relation of stock markets. The empirical results using the traditional Granger causality tests indicate, in general, a mild causal relation between stock returns and trading volumes. In contrast, the nonlinear Granger causality tests indicate a stronger causal relation between the two variables. These results demonstrate the largely untapped capacity of nonlinear techniques to unravel financial asset price dynamics that may be beyond the scope of linear analyses.

Introduction

The dynamic relation between stock prices and trading volumes has been the subject of extensive research in recent years. The nature of the price-volume relation has important implications for financial and derivative markets. Specifically, knowledge of this relationship can potentially shed light on important issues such as:

(i) market structure and information arrival,

(ii) market efficiency,

(iii) empirical distribution of asset prices,

(iv) derivative market dynamics, and

(v) alternative types of asset behavior obtainable from the joint dynamics of price and trading volume.

Most of the previous studies on price-volume relation either focus on the contemporaneous relation between asset returns and volumes (Hanna, 1978; Karpoff, 1987) or investigate causal relation using traditional linear Granger causality tests (Jain & Joh, 1988; Rogalski, 1978; Smirlock & Starks, 1988). However, although these previous investigations may be well suited for uncovering linear causal relations, they are not designed to capture nonlinear causal relations. As noted by Hsieh (1991) and Brock (1993), the recent focus in both the financial press and the academic literature on nonlinear structures in financial prices is motivated by the more informative types of asset dynamics that nonlinear models unveil. In addition, Hinich and Patterson (1985), Scheinkman and LeBaron (1989), and Brock, Hsieh, and LeBaron (1991), among others, report evidence of significant nonlinear dependence in asset returns. Hiemstra and Jones (1992) also find evidence of significant nonlinearities in aggregate trading volume.

In a more recent work, Hiemstra and Jones (1994) use both linear and nonlinear causality tests to study daily Dow Jones stock returns and percentage changes in New York Stock Exchange trading volumes[1]. Their nonlinear Granger causality test is based on nonparametric estimators of temporal relations within and

[1] Hiemstra and Jones (1994) also provide detailed explanations for the presence of causal linear and nonlinear relation between stock prices and trading volume. These include the sequential information arrival models, the tax and no-tax-related trading motives, the mixture of distributions models, the noise trader models and the models with heterogeneous agents.

across time series. Their linear models reveal a unidirectional Granger causality from stock returns to trading volume in contrast to their nonlinear tests, which provide evidence of significant nonlinear bidirectional Granger causality between stock returns and trading volumes. Their results illustrate the promising nature of a nonlinear approach for uncovering significant dynamic interrelations between economic variables.

Most of the previous research on causal relation among stock prices and trading volumes focuses on individual or aggregate stock prices from the U.S. market or its G7 counterparts. This paper employs linear and nonlinear Granger causality tests to examine the dynamic relation between daily broad market index returns and trading volumes in 10 relatively small European stock markets: Belgium, Denmark, Greece, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and Turkey. These markets exhibit a broader range of institutional, organization, structural, size, and longevity factors than the G7 markets. By extending the price-volume investigation over these European markets, this paper makes two important contributions to the literature. First, it sheds light on the impact of institutional, organizational, and structural factors on the traditional linear causal relation between price and volume. Second, it provides broader empirical evidence on the nonlinear dynamics in price-volume relation documented in Hiemstra and Jones (1994).

The empirical results indicate that traditional linear Granger causality tests detect only a mild causal relation between returns and volumes, with most of the impact running from returns to volumes. On the other hand, the nonlinear Granger causality tests confirm the existence of a strong causal relation between the two variables, with most of the impact running from volumes to returns. These results affirm the potentials for nonlinear techniques to unravel financial asset price dynamics that may be beyond the scope of linear analyses.

The rest of the paper is organized as follows: Section 2 describes the data and examines the stationarity of the stock indexes and volumes by implementing several unit root tests. Section 3 discusses the methodology and the estimation results of the linear and nonlinear causality tests. The last section sets forth the summary and conclusion.

The Data

The data consists of daily closing broad market indexes and trading volumes of varying sample periods from January 4, 1982, to February 12, 1996. The different sample periods are necessary to accommodate variations in longevity of each country's broad market index. The data source is Data Resource International. Table 1 presents each country's index, the sample space, and the number of observations.

Since the validity of regression results hinges crucially on the stationarity of the data employed, this study uses three unit root tests, namely the Augmented Dickey-Fuller, the Phillips and Perron (1988) and the Sims (1988) tests to determine whether the stock indexes and trading volumes are level-stationary or first difference-stationary. The null-hypothesis in the Augmented Dickey-Fuller and the Phillips and Perron (1988) tests is that the series contains a unit root. Because this approach has been recently criticized for lacking the power to distinguish between a unit root and weakly stationary alternatives, the Sims (1988) Bayesian posterior odds ratio test is also used. The Sims' test is especially important because Sims (1988) suggests that rejecting or failing to reject the null hypothesis should result in the consideration of some set of nearby parameter settings and that a unit root test failing to address this issue may be misleading because it is often difficult to distinguish between unit root models and those containing roots that lie near the unit circle. Appendix A provides a brief description of each of the three techniques.

The unit root test results presented in Table 2 show that all the stock indexes contain a unit root and therefore are nonstationary, implying that tests for causality should rely on the return on the series[2]. The test results, however, indicate that the volume series are stationary at the levels.

[2]The same three unit root test applied to the first differences (returns) of the index series show that the differenced series are stationary.

In light of the results in Table 2, several descriptive statistics for the return and volume series are provided in Table 3. The distributions of the daily returns on nine of the indexes display significant negative skewness while that of the 10th (Denmark) is positively skewed. In the case of the volume series, all 10 series display significant positive skewness. Additionally, the distributions of all 10 return and trading volume series have excess kurtosis relative to the normal distribution. Hall, Brorsen, and Irwin (1989) suggest that the excess kurtosis may be due to a possible time-varying variance in the evolution of the data.

Methodology and Empirical Results

Tests for Linear Granger Causality

The linear causality testing technique used in this study is from Granger (1969)[3]. Other causality methodologies reported in the literature include those proposed by Sims (1972) and Pierce and Haugh (1977). However, Granger's causality tests are employed because they are superior to Sims' (Geweke et al., 1983) and perform well for small samples (Guilkey & Salemi, 1982). The Granger tests involve the estimation of the following equations:

$$\Delta R_t = \alpha_1 + \sum_{i=1}^{m_1} \beta_{1,i}\Delta R_{t-i} + \sum_{j=1}^{m_2} \gamma_{1,j}\Delta V_{t-j} + \epsilon_1 \quad (1)$$

$$\Delta V_t = \alpha_2 + \sum_{i=1}^{m_3} \beta_{2,i}\Delta V_{t-i} + \sum_{j=1}^{m_4} \gamma_{2,j}\Delta R_{t-j} + \epsilon_2 \quad (2)$$

where ΔR is the change in the daily stock return; ΔV is the change in the daily trading volume; and α, β, and γ are the parameters to be estimated. (ϵ_1, ϵ_2) are the standard random errors assumed to have zero mean and constant variance. Finally, m_i, $i = 1 \ldots 4$ are the optimal lags chosen using Akaike's (1969, 1970) information criterion (AIC).

Equations (1) and (2) provide a convenient framework for examining linear causal relations. If the estimated lagged coefficient vector γ_1 of equation (1) is statistically significant while the estimated lagged coefficient vector γ_2 of equation (2) is not statistically significant, then trading volumes Granger cause stock returns with no feedback (i.e., a uni directional causality exists from trading volume to stock returns), implying that knowledge of past values of the volume improves the predictions of the returns while knowledge of past values of the return has no predictive power over the volumes. If, on the other hand, the estimated lagged coefficient γ_2 of equation (2) is statistically significant while the estimated coefficient vector γ_1 of equation (1) is not statistically significant, then unidirectional causality runs from stock returns to trading volumes. If both vectors of lagged coefficients are statistically significant in equations (1) and (2), then bi directional causality exists, implying that knowledge of the past values of either variable is useful in the prediction of the other. Finally, if both γ_1 and γ_2 are statistically insignificant, then no causality exists between the trading volumes and the stock returns.

This study uses partial F-statistics to test for causality in equations (1) and (2). That is, these F-statistics are used to test the two joint hypotheses;

$$H_0 : \gamma_{1,j} = 0 \, (j = 1, \ldots m_2) \text{ and}$$

$$H_0 : \gamma_{2,j} = 0 \, (j = 1, \ldots m_4)^4$$

The results of the linear causality tests are reported in Table 4, panels A-J respectively for each of the ten countries. The t-statistics for the impacts of specific lags, and aggregate impacts of each right-hand side variable on the left-hand side variable as well as the F-statistics for testing the joint significance of the lags on the right hand side variables are indicated for each equation.

The results indicate bi-directional causality between stock returns and trading volumes in two countries (Denmark and Greece) where the two variables Granger-cause each other with one lag respectively. In addition, unidirectional causality running from stock returns to trading volumes is indicated in four countries (Belgium, Norway, Spain, and Turkey) where stock returns are shown to Granger-cause trading volumes with an average of about three lags. In the

[3] Given two times X_t and Y_t, Granger causality tests involve testing whether lagged values of Xt (Yt) play a significant role in explaining variabilities in Y_t (X_t). If so, X_t (Y_t) is said to "Granger cause" Y_t (X_t).

[4] The partial F-statistic employed has the following form, $F(d_R - d_{UR}, d_{UR}) \approx \left(\frac{SSE_R - SSE_{UR}}{SSE_R}\right) \div \left(\frac{d_R - d_{UR}}{d_{UR}}\right)$ where SSE_R and SSE_{UR} are respectively sum of squared errors for the restricted and unrestricted versions of equations (1) or (2) and d is the degree of freedom.

remaining four countries (Netherlands, Norway, Portugal, and Switzerland), however, the results show that no causal relations exist between stock returns and trading volumes. The overall result from linear Granger causality tests, therefore, shows mild causal relations between stock returns and trading volumes with stock returns affecting trading volumes but rarely vice versa.

Test for Nonlinear Granger Causality

The results reported in Table 4 are based on the presumption that any causal relation between the stock returns and trading volumes is of a linear nature. However, this method is not capable of detecting nonlinear causal relationships[5]. The evidence presented in Table 3 shows that the distribution of the two series is not independent and identically distributed (iid)[6]. Moreover, this dependence is likely to be nonlinear because conditional heteroscedasticity is exhibited by all the series. Therefore, a complete investigation of the causal relation between the returns and the volumes should embody tests for both linear and nonlinear dependence.

Baek and Brock (1992) propose a nonparametric statistical technique for uncovering nonlinear causal relations. Consider the two time series of $\{R_t\}$ and $\{V_t\}$. Let the m-length lead vectors of R_t and V_t be denoted by R_t^m and V_t^m respectively and the L_{rt}-length and L_{vt}-length lag vectors of R_t and V_t, respectively, by R_{t-Lvt}^{Lvt} and V_{t-Lvt}^{Lvt}. For known values of m, L_{rt}, and $L_{vt} \geq 1$ and for $e > 0$, V_t does not strictly Granger-cause R_t if:

$$\begin{aligned} &\mathrm{prob}(\|R_t^m - R_s^m < e\|R_{t-Lrt}^{Lrt} - R_{s-Lrt}^{Lrt}\| < e, \\ &\quad \|V_{t-Lvt}^{Lvt} - V_{s-Lvt}^{Lvt}\| < e) \\ &= \mathrm{prob}(\|R_t^m - R_s^m\| < e\|R_{t-Lrt}^{Lrt} - R_{s-Lrt}^{Lrt}\| < e) \end{aligned} \quad (3)$$

where Prob(.) denotes probability and $\| \ \|$ denotes the maximum norm. The probability on the left hand side (LHS) of equation (3) is the conditional probability that two arbitrary m-length lead vectors of $\{R_t\}$ are within a distance e of each other, given that the corresponding L_{rt}-length lag vectors of $\{R_t\}$ and L_{vt}-length lag vectors of $\{V_t\}$ are within e of each other. The probability on the right hand side (RHS) of equation (3) is the conditional probability that two arbitrary m-length lead vectors of $\{R_t\}$ are within a distance e of each other, given that their corresponding L_{rt}-length lag vectors are within a distance e of each other. The strict Granger noncausality condition in equation (3) is expressed as:

$$\frac{C1(m + L_{rt}, L_{vt}, e)}{C2(L_{rt}, L_{vt}, e)} = \frac{C3(m + L_{rt}, e)}{C4(L_{rt}, e)} \quad (4)$$

where CI(.) are the correlation-integral estimators of the joint probabilities[7]. Assuming that $\{R_t\}$ and $\{V_t\}$ are strictly stationary, weakly dependent, and obey the conditions of Denker and Keller (1983), if $\{V_t\}$ does not strictly Granger cause $\{R_t\}$ then,

$$\begin{aligned} &\sqrt{n}\left(\frac{C1(m + L_{rt}, L_{vt}, e, n)}{C2(L_{rt}, L_{vt}, e, n)} - \frac{C3(m + L_{rt}, e, n)}{C4(L_{rt}, e, n)}\right) \\ &\sim N(0, \sigma^2(m, L_{rt}, L_{vy}, e)) \end{aligned} \quad (5)$$

Hiemstra and Jones (1994) show that a consistent estimator of the variance $\sigma^2(m, L_{rt}, L_{vt}, e)$ in equation (5) is, $\hat{\sigma^2}(m, L_{rt}, L_{vt}, e, n) = \hat{d}(n)\hat{\sum}(n)\hat{d}(n)$, where the correlation integrals provide a consistent estimator of d.

The test statistics given in equations (4) and (5) are applied to the two estimated residual series from the VAR model in equations (1) and (2), $\{\hat{e}_1\}$ and $\{\hat{e}_2\}$. The null-hypothesis is that $\{V_t\}$ does not nonlinearly strictly Granger-cause $\{R_t\}$, and that equation (5) holds for all m, L_{rt}, and $L_{vt} = 1$ and for all $e > 0$. By removing linear predictive power with a linear VAR model, any remaining incremental predictive power of one residual series for another can be considered nonlinear predictive power (Baek and Brock, 1992).

Values for the lead length m, the lag lengths L_{rt} and L_{vt}, and the scale parameter e must be selected in order to conduct the Baek and Brock test. However, because there is no literature on the appropriate way to

[5]See Brock , et al. (1991) for an illustration of how linear causality tests, such as the Granger test, may fail to uncover nonlinear predictive power.

[6]A formal test for nonlinear dependence, known as the BDS test, is used and the results (not reported here) strongly support the existence of nonlinearities in the Eurodollar and CD rates.

[7]See Hiemstra and Jones (1994) for the derivation of the joint probabilities and their correlation-integral estimators

specify optimal values for lag lengths and the scale parameter in nonlinear causality tests, this study relies on the Monte Carlo results found in Hiemstra and Jones (1993) by setting, for all cases, the lead length to m = 1 and $L_{rt} = L_{vt}$. Common lag lengths of 1 to 6 are also used. Additionally, for all cases, the test is applied to standardized series using a common scale parameter of $e = 1.5\sigma$, where $\sigma = 1.0$ denotes the standard deviation of the standardized time series.

The empirical results for nonlinear Granger causality tests are reported in Table 5, panels A-J respectively for each of the 10 countries. DIFF and NORM, respectively, denote the difference between the two conditional probabilities in equation (4) and the standardized test statistic in equation (5). Under the null hypothesis of nonlinear Granger noncausality, the NORM test statistic is asymptotically distributed $N(0, 1)$.

Table 5 reveals significant bi-directional nonlinear Granger causality between stock returns and trading volumes in five countries (Denmark, Netherlands, Portugal, Sweden, and Turkey). In addition, unidirectional causality, running from trading volumes to stock returns but not vice versa, is statistically significant in four countries (Belgium, Greece, Norway, and Spain). Finally, in the remaining country (Switzerland), the results show no significant nonlinear causality between the two variables. It is curious to note that Switzerland also shows no significant linear causality between returns and trading volumes and thereby remains the only country in the sample where no significant causal relation, linear or nonlinear, is detected.

Conclusion

Previous research on the price-volume relation of stock markets relies mainly on standard linear Granger causality tests and present evidence mostly from the US and other "first tier" industrial economies. This paper employs linear and nonlinear Granger causality tests to examine the price-volume relation of 10 European stock markets. These markets exhibit a broader range of institutional, organizational, and structural factors than the major industrial economies.

The empirical results show that the traditional linear Granger causality tests detect significant unidirectional or bi-directional causal relation between stock returns and trading volumes in six of the 10 countries and no significant causal relation between the two variables in the remaining four countries. In contrast, the results from nonlinear Granger causality tests demonstrate the existence of significant unidirectional or bi-directional causal relation between stock returns and trading volumes in nine countries and no significant causal relation between the two variables in only one country. It is clear that without the nonlinear analyses, significant interrelation in the evolution of the returns and volumes of the ten markets would have been missed. These results demonstrate the largely untapped capacity of nonlinear techniques to unravel financial asset price dynamics that may be beyond the scope of linear analyses.

We speculate that observed non-linearity in asset prices could arise due to asymmetric price adjustments or from interactions between informed and noise traders. This suggests the need for further research to determine whether observed market dynamics are impacted more by the actions of informed traders who attempt to drive prices back to equilibrium or by noise traders who may drive prices away from equilibrium. It is also hoped that the results presented here generate future areas of research to accurately model the role of transaction costs and institutional constraints on the non-linear dynamics of asset prices and whether identified inefficiencies can be profitably exploited in trading strategies.

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Appendix A

1. The first unit root test we use is the Augmented Dickey-Fuller (ADF) test. The ordinary Dickey-Fuller unit root test assumes that the error terms are uncorrelated. In higher order models and models where the error terms may be correlated, the ADF test is more appropriate. The ADF test is based on the regression,

   $$\Delta y_t = \alpha + \beta y_{t-l} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-j} + \epsilon_t \quad \text{(A1)}$$

   where y is the series being tested, k is the number of lagged differences included to capture any autocorrelation and is chosen such that the Ljung-Box Q-statistic fails to reject the null hypothesis of no serial correlation in the residual of equation (A1). The test is a pseudo t-statistic for the null hypothesis that $\beta = 0$.

2. The second test is the Phillips and Perron (1988) unit root test. Unlike the widely used Dickey and Fuller (1981) test, this procedure is more general and can be applied even in the presence of autocorrelated and heteroscedastic innovation sequences. To implement the Phillips-Perron test, the following regression equation is estimated:

   $$Y_t = \eta + \beta(t - T/2) + \rho Y_{t-1} + \zeta_t, \quad \text{(A2)}$$

   $$t = 1, 2, \ldots, T$$

   where Y_t denotes the series being tested, $(t - T/2)$ is a time trend, and T is the sample size.

   The null hypothesis to be tested is that the series contains a unit root with a drift and a time trend ($H_0^1 : \rho = 1$) and the statistics $Z(t_p)$ is used in testing hypothesis H_0^1. Under the null hypothesis the ten percent, five percent and one percent critical values of $Z(t_p)$ are −3.13, −3.43 and −3.99, respectively[8].

3. The last test is attributed to Sims (1988). Based on work by Leamer (1978), Sims constructs a test using the Bayesian posterior odds ratio. The resulting test statistic is:

   $$\gamma = 2\log\left(\frac{1-\alpha}{\alpha}\right) - \log\left(\sigma_p^2\right) + 2\log\left(1 - 2^{-1/s}\right) - 2\log(\Phi(\tau)) - \log(2\pi) - \tau^2 \quad \text{(A3)}$$

   where α is the prior probability assigned to the alternative hypothesis of a large but stationary autocorrelation coefficient denoted as ρ, σ_p is the standard error of the estimated autocorrelation coefficient from a univariate autoregression, s is the number of periods per year (e.g., for weekly data $s = 52$), $\tau = (1 - \hat{\rho})/\sigma_p$, and $\Phi(.)$ is the standard normal cumulative distribution function. The null hypothesis of a unit root, $\rho = 1$, is rejected if $\gamma < 0$. Sims' criterion essentially amounts to comparing τ^2 to $-\log(\sigma_p^2)$. When $\sigma_p < 1$, which is indicated as being typical, $-\log(\sigma_p^2)$ is positive and thus smaller values of σ_p will tend to favor the unit root hypothesis. The inclusion of , however, will favor the alternative hypothesis as τ gets larger.

[8] See Fuller (1976) and Dickey and Fuller (1981).

Table 1
Data Description for Stock Indexes and Trading Volumes

Country	Index	Period	No. of Observations
Belgium	DS TOTAL MARKET	1/2/86 - 2/12/96	2,487
Denmark	DS TOTAL MARKET	10/7/91 - 2/12/96	1,096
Greece	DS TOTAL MARKET	1/2/89 - 2/12/96	1,751
Netherlands	DS TOTAL MARKET	2/3/86 - 2/12/96	2,523
Norway	DS TOTAL MARKET	1/2/84 - 2/12/96	3,025
Portugal	DS TOTAL MARKET	1/2/92 - 2/12/96	834
Spain	DS TOTAL MARKET	2/5/90 - 2/12/96	1,514
Sweden	DS TOTAL MARKET	1/4/82 - 2/12/96	3,525
Switzerland	DS TOTAL MARKET	1/16/89 - 2/12/96	1,759
Turkey	DS TOTAL MARKET	1/4/88 - 2/16/96	2,024

Table 2

Augmented Dickey Fuller, Phillips Perron, and Sims Unit Root Test for Stock Returns and Volumes

	DF	PP	Sims			
			t^2	SL	SSL	α
Belgium						
P_t	– 2.200	– 2.003	4.597	13.849	7.852	.953
V_t	– 12.329[a]	– 19.980[a]	64.056	8.412	2.415	.000
Denmark						
P_t	– 1.046	–.941	1.069	12.513	6.516	.984
V_t	– 9.277[a]	– 16.104[a]	49.633	7.090	4.093	.000
Greece						
P_t	– 2.320	– 2.294	5.411	12.985	6.988	.898
V_t	– 6.307	– 17.805	48.436	7.946	1.949	.000
Netherlands						
P_t	.536	.639	.277	14.659	8.663	.966
V_t	– 5.178[a]	– 14.005[a]	– 25.247	8.949	2.952	.000
Norway						
P_t	–.867	–.882	.751	14.885	8.888	.996
V_t	– 6.391[a]	– 16.857[a]	49.465	8.978	2.981	.000
Portugal						
P_t	– 1.511	– 1.394	2.069	12.604	6.608	.975
V_t	– 11.645[a]	– 28.786[a]	162.766	5.111	–.886	.000
Spain						
P_t	– 1.177	– 1.141	1.518	12.643	6.646	.981
V_t	– 7.092[a]	– 17.506[a]	51.701	7.644	1.647	.000
Sweden						
P_t	–.049	.041	.003	15.599	9.602	.998
V_t	– 4.211[a]	– 11.242[a]	20.160	9.863	3.866	.001
Switzerland						
P_t	.281	.338	.054	14.089	8.092	.996
V_t	– 2.714	– 7.956[a]	9.060	9.197	3.200	.176
Turkey						
P_t	1.343	1.521	1.697	14.339	8.342	.991
V_t	– 3.908[a]	– 7.770[a]	16.819	9.351	3.354	.005

P_t = Stock index at t
DF = Dickey Fuller Test
t^2 = Squared t
SSL = Small Sample Limit

V_t = Volume / 1000
PP = Phillips Perron Test
SL = Schwarz Limit
α = Marginal Alpha

a Indicates significance at the 1% level.

1 These results use six lagged terms for the regression and exculde the trend. Results are similar if the trend is included or if four or twelve lags are used.

2 Squared t-statistic is used as the test statistic.

3 The Schwarz limit is the asymptotic critical value for the test statistic, while the small sample limit is the finite sample critical value.

4 The marginal α is the threshold value at which the posterior odds for and against the unit root are even. A small value of the marginal α indicates evidence against a unit root.

For all tests, the null hypothesis is that the series contain a unit root, i.e., $\rho = 1$.

Table 3

Summary Statistics for Stock Returns and Trading Volumes

	Mean	SD	t-statistic	Skewness	Kurtosis	Minimum	Maximum
Belgium							
R_t	.032	.016	1.983[b]	– 1.529[a]	27.889[a]	– 11.765	6.263
V_t	.300	.005	55.675[a]	2.099[a]	7.271[a]	.028	2.633
Denmark							
R_t	.009	.022	.403	–.065	3.641[a]	– 4.560	4.070
V_t	.634	.011	56.25[a]	1.506[a]	4.052[a]	.086	3.220
Greece							
R_t	.081	1.849	.044[c]	.317[a]	7.033[a]	– 11.131	13.981
V_t	.322	.008	41.160[a]	3.892[a]	35.034[a]	.020	5.077
Netherlands							
R_t	.031	.016	1.939[c]	– 1.367[a]	21.397[a]	– 10.813	6.109
V_t	8.734	.123	71.215[a]	2.004[a]	5.900[a]	.010	61.188
Norway							
R_t	.048	.026	1.891[c]	– 1.464[a]	27.060[a]	– 21.849	10.574
V_t	1.798	.041	44.309[a]	2.426[a]	11.323[a]	.010	28.004
Portugal							
R_t	.034	.027	1.274	–.096[a]	10.304[a]	– 5.801	3.848
V_t	1.189	.600	1.980[b]	28.406[a]	814.710[a]	.001	498.404
Spain							
R_t	.011	.025	.431	–.316[a]	5.667[a]	– 7.748	6.031
V_t	9.990	.136	73.400[a]	1.042[a]	1.825[a]	.155	42.714
Sweden							
R_t	.059	.020	3.031[a]	–.015[a]	6.858[a]	– 8.094	9.350
V_t	3.053	.091	33.676[a]	2.905[a]	18.078[a]	.023	84.058
Switzerland							
R_t	.037	.020	1.867[c]	– 1.661[a]	17.484[a]	– 9.389	4.674
V_t	.668	.017	39.356[a]	1.562[a]	2.461[a]	.013	4.488
Turkey							
R_t	.221	.061	3.629[a]	–.122[b]	1.448[a]	– 14.144	10.034
V_t	108.527	4.424	24.533[a]	2.434[a]	5.954[a]	.012	1214.740

$R_t = 100^* \log(P_t/P_{t-1})$; V_t = Volume / 1000

SD is the Standard deviation of the mean.

The t-statistics is for the null hypothesis that the mean equals zero.

[a] indicates significance at the 1% level.

[b] indicates significance at the 5% level.

[c] indicates significance at the 10% level.

Table 4
Test Results of Linear Causality between Stock Returns and Trading Volumes

PANEL A: BELGIUM

Dependent Variable	Coefficients (t-statistics) R_t		V_t		Q-Stat.	F-Stat.
R_t	$\Phi_{1,1} = .150(3.05)^a$	$\Phi_{1,14} = .001(.04)$	$\Phi_{2,1} = -.037(-.70)$		$.763^a$	0.479
	$\Phi_{1,2} = .003(.06)$	$\Phi_{1,15} = .058(2.03)^b$				
	$\Phi_{1,3} = -.000(-.01)$	$\Phi_{1,16} = .032(-.94)$				
	$\Phi_{1,4} = .025(.72)$	$\Phi_{1,17} = .005(.21)$				
	$\Phi_{1,5} = .035(.72)$	$\Phi_{1,18} = -.052(-1.51)$				
	$\Phi_{1,6} = -.055(-1.61)$	$\Phi_{1,19} = -.032(-1.21)$				
	$\Phi_{1,7} = .133(2.50)^b$	$\Phi_{1,20} = -.000(-.01)$				
	$\Phi_{1,8} = .081(1.94)^c$	$\Phi_{1,21} = .039(1.45)$				
	$\Phi_{1,9} = -.045(-.85)$	$\Phi_{1,22} = .013(.57)$				
	$\Phi_{1,10} = .054(1.75)^c$	$\Phi_{1,23} = .047(1.57)$				
	$\Phi_{1,11} = .013(.43)$	$\Phi_{1,24} = -.020(-.75)$				
	$\Phi_{1,12} = .047(1.89)^c$	$\Phi_{1,25} = -.033(-1.28)$				
	$\Phi_{1,13} = -.013(-.39)$	$\Phi_{1,26} = .037(1.34)$				
	$3\Phi_{1,i} = .457(3.521)^a$		$3\Phi_{2,i} = -.037(-.70)$			
V_t	$\Phi_{3,1} = .009(2.31)^b$		$\Phi_{4,1} = .305(6.42)^a$	$\Phi_{4,11} = .068(2.64)^a$	3.060	9.574^b
	$\Phi_{3,2} = -.001(-.21)$		$\Phi_{4,2} = .199(3.72)^a$	$\Phi_{4,12} = .023(.80)$		
	$\Phi_{3,3} = .009(2.38)^b$		$\Phi_{4,3} = .033(.82)$	$\Phi_{4,13} = .015(.56)$		
			$\Phi_{4,4} = .008(.25)$	$\Phi_{4,14} = .013(.52)$		
			$\Phi_{4,5} = .079(2.72)^c$	$\Phi_{4,15} = .035(1.03)$		
			$\Phi_{4,6} = -.025(-1.03)$	$\Phi_{4,16} = .005(.19)$		
			$\Phi_{4,7} = .023(.86)$	$\Phi_{4,17} = -.004(-.14)$		
			$\Phi_{4,8} = .025(1.04)$	$\Phi_{4,18} = -.022(-.81)$		
			$\Phi_{4,9} = .001(.02)$	$\Phi_{4,19} = .012(.38)$		
			$\Phi_{4,10} = .054(2.09)^b$	$\Phi_{4,20} = .102(2.63)^a$		
	$3\Phi_{3,i} = .0164(2.52)^b$		$3\Phi_{4,i} = .952(48.28)^a$			

[1] $R_t = 100^* \log(P_t/P_{t-1})$; V_t = Volume / 1000

[2] The t statistics are reported in parentheses next to the estimated coefficients. The coefficients show the impact of a specific lag of a given right-hand variable on the left-hand side variable. For example, $\Phi_{2,1}$ represents the impact of Volume (variable 2) on Returns (variable 1) for a given lag of one.

[3] Q-Stat. is the Q-statistic for serial independence. This statistic is based on the revised Box-Ljung Q-test for serial correlation among the regression residuals.

[4] F-Stat. is the partial F-statistic testing for the joint significance of the lags on the right-hand side variables. [a], [b], and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

[5] For a given s, the t-statistic t, is calculated as $t = s/\sigma_s$ where $s = \Sigma^n a_i$ and n = number of lags on the independent variable whose impact is being investigated. For example, if n = 3 then, $s = \Sigma a_i = a_1 + a_2 + a_3$ and

$$(6)\quad \sigma_s = \sigma_{(a_1+a_2+a_3)} = \sqrt{\sigma_{a_1}^2 + \sigma_{a_2}^2 + \sigma_{a_3}^2 + 2\sigma_{a_1a_2} + 2\sigma_{a_2a_3} + 2\sigma_{a_1a_3}}$$

PANEL B: DENMARK

Dependent Variable	Coefficients (*t*-statistics) R_t	V_t	V_t	Q-Stat.	F-Stat.
R_t	$\Phi_{1,1} = .264(7.12)^a$	$\Phi_{2,1} = .130(1.75)^c$		14.856	3.053^c
	$\Phi_{1,2} = -.097(-2.79)^a$				
	$3\Phi_{1,i} = .167(3.33)^a$	$3\Phi_{2,i} = .130(1.75)^c$			
V_t	$\Phi_{3,1} = .062(4.49)^a$	$\Phi_{4,1} = .388(9.53)^a$	$\Phi_{4,11} = -.086(-2.73)^a$	2.756	90.749^a
		$\Phi_{4,2} = .082(2.12)^b$	$\Phi_{4,12} = .018(.47)$		
		$\Phi_{4,3} = .063(1.82)^c$	$\Phi_{4,13} = .012(.36)$		
		$\Phi_{4,4} = .014(.44)$	$\Phi_{4,14} = .029(.82)$		
		$\Phi_{4,5} = .124(3.62)^a$	$\Phi_{4,15} = .035(1.02)$		
		$\Phi_{4,6} = -.054(-1.63)$	$\Phi_{4,16} = .035(1.07)$		
		$\Phi_{4,7} = -.044(-1.35)$	$\Phi_{4,17} = -.021(-.58)$		
		$\Phi_{4,8} = .089(2.53)^b$	$\Phi_{4,18} = -.038(-1.20)$		
		$\Phi_{4,9} = .086(2.08)^b$	$\Phi_{4,19} = -.036(-1.03)$		
		$\Phi_{4,10} = .061(1.72)^c$	$\Phi_{4,20} = .109(3.51)^a$		
	$3\Phi_{3,i} = .062(4.49)^a$	$3\Phi_{4,i} = .868(25.74)^a$			

PANEL C: GREECE

Dependent Variable	Coefficients (*t*-statistics) R_t	V_t	V_t	Q-Stat.	F-Stat.
R_t	$\Phi_{1,1} = .187(4.23)^a$	$\Phi_{2,1} = -.196(-1.76)^c$		15.539	3.153^c
	$\Phi_{1,2} = -.090(-2.42)^b$				
	$\Phi_{1,3} = .014(.40)$				
	$\Phi_{1,4} = .043(1.42)$				
	$\Phi_{1,5} = -.034(-1.06)$				
	$\Phi_{1,6} = .063(2.07)^b$				
	$\Phi_{1,7} = .042(1.33)$				
	$\Phi_{1,8} = .050(1.74)^c$				
	$3\Phi_{1,i} = .275(3.16)^a$	$3\Phi_{2,i} = -.196(-1.76)^c$			
V_t	$\Phi_{3,1} = .014(4.79)^a$	$\Phi_{4,1} = .300(3.59)^a$	$\Phi_{4,11} = .042(.74)$	9.096	22.971^a
		$\Phi_{4,2} = .145(2.81)^a$	$\Phi_{4,12} = -.002(-.06)$		
		$\Phi_{4,3} = .109(2.45)^b$	$\Phi_{4,13} = .005(.22)$		
		$\Phi_{4,4} = .068(1.45)$	$\Phi_{4,14} = -.023(-.80)$		
		$\Phi_{4,5} = .018(.40)$	$\Phi_{4,15} = .039(1.31)$		
		$\Phi_{4,6} = .020(.63)$	$\Phi_{4,16} = .069(1.94)^c$		
		$\Phi_{4,7} = .081(1.21)$	$\Phi_{4,17} = .016(.68)$		
		$\Phi_{4,8} = .007(.21)$	$\Phi_{4,18} = .011(.35)$		
		$\Phi_{4,9} = .001(0.04)$	$\Phi_{4,19} = .607(1.74)^c$		
		$\Phi_{4,10} = -.018(-.50)$			
	$3\Phi_{3,i} = .014(4.79)^a$	$3\Phi_{4,i} = .950(28.93)^a$			

PANEL D: NETHERLANDS

Dependent Variable	Coefficients (t-statistics) R_t		V_t		Q-Stat.	F-Stat.
R_t	$\Phi_{1,1}$ = .000(.01)	$\Phi_{1.16}$ = − .031(−.74)	$\Phi_{2,1}$ = − .000(−.14)		.371[a]	0.020
	$\Phi_{1,2}$ = .026(.49)	$\Phi_{1,17}$ = −.069(−1.60)				
	$\Phi_{1,3}$ = − .020(−.61)	$\Phi_{1,18}$ = .035(1.22)				
	$\Phi_{1,4}$ = .042(.74)	$\Phi_{1,19}$ = −.033(−1.16)				
	$\Phi_{1,5}$ = .010(.33)	$\Phi_{1,20}$ = .044(1.60)				
	$\Phi_{1,6}$ = .015(.32)	$\Phi_{1,21}$ = .002(.09)				
	$\Phi_{1,7}$ = − .007(−.25)	$\Phi_{1,22}$ = − .023(.85)				
	$\Phi_{1,8}$ = .057(1.10)	$\Phi_{1,23}$ = .022(0.79)				
	$\Phi_{1,9}$ = .084(2.46)[b]	$\Phi_{1,24}$ = − .019(−.71)				
	$\Phi_{1,10}$ = .004(0.12)	$\Phi_{1,25}$ = .008(0.33)				
	$\Phi_{1,11}$ = .056(1.73)[c]	$\Phi_{1,26}$ = .037(1.50)				
	$\Phi_{1,12}$ = − .019(−.55)	$\Phi_{1,27}$ = .029(1.27)				
	$\Phi_{1,13}$ = − .008(−.24)	$\Phi_{1,28}$ = − .050(−2.08)[b]				
	$\Phi_{1,14}$ = .018(.42)	$\Phi_{1,29}$ = .034(1.19)				
	$\Phi_{1,15}$ = − .025(−.70)					
	3$\Phi_{1,i}$ = .265(1.19)		3$\Phi_{2,i}$ = − .000(−.14)			
V_t	$\Phi_{3,1}$ = .137(1.57)		$\Phi_{4,1}$ = .391(11.19)[a]	$\Phi_{4,11}$ = − .022(−.76)	22.487[a]	2.467
			$\Phi_{4,2}$ = .054(2.10)[b]	$\Phi_{4,12}$ = .014(.47)		
			$\Phi_{4,3}$ = .061(2.39)[b]	$\Phi_{4,13}$ = .014(.53)		
			$\Phi_{4,4}$ = .093(2.01)[b]	$\Phi_{4,14}$ = .036(1.50)		
			$\Phi_{4,5}$ = .159(5.33)[a]	$\Phi_{4,15}$ = .033(1.27)		
			$\Phi_{4,6}$ = − .086(−3.16)	$\Phi_{4,16}$ = − .024(−.79)		
			$\Phi_{4,7}$ = .019(.67)	$\Phi_{4,17}$ = − .031(−1.13)		
			$\Phi_{4,8}$ = − .007(−.16)	$\Phi_{4,18}$ = .050(1.58)		
			$\Phi_{4,9}$ = .036(1.53)	$\Phi_{4,19}$ = − .007(−.23)		
			$\Phi_{4,10}$ = .072(3.15)[a]	$\Phi_{4,20}$ = .135(4.84)[a]		
	3$\Phi_{3,i}$ = .137(1.57)		3$\Phi_{4,i}$ = .988(56.86)[a]			

PANEL E: NORWAY

Dependent Variable	Coefficients (*t*-statistics) R_t		V_t	Q-Stat.	F-Stat.
R_t	$\Phi_{1,1}$ = .120(1.94)[b] $\Phi_{1,2}$ = −.053(−1.71)[c] $\Phi_{1,3}$ = − .038(−1.27) $\Phi_{1,4}$ = − .002(−.07) $\Phi_{1,5}$ = − .007(−.29) $\Phi_{1,6}$ = .013(.46) $\Phi_{1,7}$ = .070(2.53)[b] $\Phi_{1,8}$ = .006(.18) $\Phi_{1,9}$ = − .035(1.50) $\Phi_{1,10}$ = .011(.46)[c] $\Phi_{1,11}$ = .010(.37)	$\Phi_{1.12}$ = .054(2.07)[b] $\Phi_{1,13}$ = −.017(−.57) $\Phi_{1,14}$ = .050(1.21) $\Phi_{1,15}$ = .040(1.08) $\Phi_{1,16}$ = − .004(−.11) $\Phi_{1,17}$ = − .018(−.70) $\Phi_{1,18}$ = − .017(−.66) $\Phi_{1,19}$ = − .032(−1.31) $\Phi_{1,20}$ = .022(1.09) $\Phi_{1,21}$ = − .004(−2.06)[b]	$\Phi_{2,1}$ = − .002(.17)	5.143	.027
	$3\Phi_{1,i}$ = .204(1.34)		$3\Phi_{2,i}$ = − .037(−.70)		
V_t	$\Phi_{3,1}$ = .080(3.28)[a]		$\Phi_{4,1}$ = .354(6.52)[a] $\Phi_{4,2}$ = .141(3.89)[a] $\Phi_{4,3}$ = .010(.39) $\Phi_{4,4}$ = .025(.86) $\Phi_{4,5}$ = .108(2.63)[a] $\Phi_{4,6}$ = .002(.07) $\Phi_{4,7}$ = .059(2.16)[b] $\Phi_{4,8}$ = .038(1.12) $\Phi_{4,9}$ = .021(.69) $\Phi_{4,10}$ = .043(1.25) $\Phi_{4,11}$ = − .011(−.33) $\Phi_{4,12}$ = .004(.14) $\Phi_{4,13}$ = − .014(−.48) $\Phi_{4,14}$ = .052(1.69) $\Phi_{4,15}$ = .090(3.11)[b] $\Phi_{4,16}$ = − .021(−.59) $\Phi_{4,17}$ = .009(.27) $\Phi_{4,18}$ = − .005(−.14) $\Phi_{4,19}$ = 0.32(.93) $\Phi_{4,20}$ = .033(1.38)[b]	18.745[a]	10.729
	$3\Phi_{3,i}$ = .080(3.28)[a]		$3\Phi_{4,i}$ = .969(51.30)[a]		

PANEL F: PORTUGAL

Dependent Variable	Coefficients (*t*-statistics) R_t	V_t	Q-Stat.	F-Stat.
R_t	$\Phi_{1,1}$ = .260(4.73)[a] $\Phi_{1,2}$ = .080(1.50) $\Phi_{1,3}$ = − .043(−.79) $\Phi_{1,4}$ = − .007(−.14) $\Phi_{1,5}$ = .009(.22) $\Phi_{1,6}$ = − .016(−.38) $\Phi_{1,7}$ = .017(.46) $\Phi_{1,8}$ = .040(1.15) $\Phi_{1,9}$ = .009(2.38)[b]	$\Phi_{2,1}$ = .000(1.51)	10.891	2.291
	$3\Phi_{1,i}$ = .440(3.90)[a]	$3\Phi_{2,i}$ = .000(1.51)		
V_t	$\Phi_{3,1}$ = .003(.64)	$\Phi_{4,1}$ = .001(−.02)	.085	.000
	$3\Phi_{3,i}$ = .003(.64)	$3\Phi_{4,i}$ = − .001(−.02)		

PANEL G: SPAIN

Dependent Variable	Coefficients (*t*-statistics) R_t	V_t		Q-Stat.	F-Stat.
R_t	$\Phi_{1,1}$ = .127(2.96)[a]	$\Phi_{2,1}$ = .004(.75)		22.989	.567
	$3\Phi_{1,i}$ = .127(2.96)[a]	$3\Phi_{2,i}$ = .004(.75)			
V_t	$\Phi_{3,1}$ = .280(2.78)	$\Phi_{4,1}$ = .360(9.31)[a]	$\Phi_{4,11}$ = − .044(−1.35)	17.908	17.826[a]
	$\Phi_{3,2}$ = − .082(−.82)	$\Phi_{4,2}$ = .122(3.58)[a]	$\Phi_{4,12}$ = .035(1.22)		
	$\Phi_{3,3}$ = .147(1.54)	$\Phi_{4,3}$ = .044(1.39)	$\Phi_{4,13}$ = .000(.01)		
	$\Phi_{3,4}$ = .250(2.73)[b]	$\Phi_{4,4}$ = .040(1.29)	$\Phi_{4,14}$ = .037(1.36)		
		$\Phi_{4,5}$ = .090(2.99)[a]	$\Phi_{4,15}$ = .035(1.23)		
		$\Phi_{4,6}$ = − .057(−1.93)[c]	$\Phi_{4,16}$ = −.023(−.77)		
		$\Phi_{4,7}$ = .019(.67)	$\Phi_{4,17}$ = .020(.70)		
		$\Phi_{4,8}$ = .031(1.23)	$\Phi_{4,18}$ = .036(1.25)		
		$\Phi_{4,9}$ = .063(2.15)[b]	$\Phi_{4,19}$ = −.000(−.01)		
		$\Phi_{4,10}$ = .042(1.45)	$\Phi_{4,20}$ = .067(2.58)[a]		
	$3\Phi_{3,i}$ = .595(3.39)[a]	$3\Phi_{4,i}$ = .916(38.19)[a]			

PANEL H: SWEDEN

Dependent Variable	Coefficients (*t*-statistics) R_t	V_t		Q-Stat.	F-Stat.
R_t	$\Phi_{1,1}$ = .198(6.09)[a]	$\Phi_{2,1}$ = − .001(−.34)		27.167[c]	.904
	$\Phi_{1,2}$ = − .032(−1.15)				
	$\Phi_{1,3}$ = − .026(−.91)				
	$\Phi_{1,4}$ = .060(2.08)[b]				
	$\Phi_{1,5}$ = − .011(.42)				
	$\Phi_{1,6}$ = − .037(−1.36)				
	$\Phi_{1,7}$ = .048(1.60)				
	$3\Phi_{1,i}$ = .222(3.08)[a]	$3\Phi_{2,i}$ = − .001(−.34)			
V_t	$\Phi_{3,1}$ = .040(1.07)	$\Phi_{4,1}$ = .329(3.29)[a]	$\Phi_{4,11}$ = .015(.53)	21.823[a]	1.139
		$\Phi_{4,2}$ = .101(1.94)[c]	$\Phi_{4,12}$ = .052(1.13)		
		$\Phi_{4,3}$ = .078(1.89)[b]	$\Phi_{4,13}$ = −.002(−.09)		
		$\Phi_{4,4}$ = .116(3.38)[a]	$\Phi_{4,14}$ = − .022(−.61)		
		$\Phi_{4,5}$ = .103(1.59)	$\Phi_{4,15}$ = .086(2.33)[b]		
		$\Phi_{4,6}$ = − .003(−.08)	$\Phi_{4,16}$ = .030(.90)		
		$\Phi_{4,7}$ = − .019(−.74)	$\Phi_{4,17}$ = .021(.69)		
		$\Phi_{4,8}$ = − .011(−.52)	$\Phi_{4,18}$ = .004(.18)		
		$\Phi_{4,9}$ = .008(.30)	$\Phi_{4,19}$ = .007(.29)		
		$\Phi_{4,10}$ = − .057(1.36)	$\Phi_{4,20}$ = .042(1.43)		
	$3\Phi_{3,i}$ = .040(1.07)	$3\Phi_{4,i}$ = .993(76.06)[a]			

PANEL I: SWITZERLAND

Dependent Variable	Coefficients (*t*-statistics) R_t	V_t	Q-Stat.	F-Stat.
R_t	$\Phi_{1,1} = .041(.86)$	$\Phi_{2,1} = .024(.99)$	22.859	.979
	$3\Phi_{1,i} = .041(.86)$	$3\Phi_{2,i} = .024(.99)$		
V_t	$\Phi_{3,1} = .007(1.06)$	$\Phi_{4,1} = .293(5.92)^{a}$ $\Phi_{4,2} = .047(1.01)$ $\Phi_{4,3} = .112(2.69)^{b}$ $\Phi_{4,4} = .004(.09)$ $\Phi_{4,5} = .172(3.69)^{a}$ $\Phi_{4,6} = .015(.33)$ $\Phi_{4,7} = .004(.08)$ $\Phi_{4,8} = .027(.67)$ $\Phi_{4,9} = -.031(-.57)$ $\Phi_{4,10} = .038(.77)$ $\Phi_{4,11} = .057(1.06)$ $\Phi_{4,12} = .064(1.34)$ $\Phi_{4,13} = .003(.07)$ $\Phi_{4,14} = .038(.81)$ $\Phi_{4,15} = .073(1.50)$ $\Phi_{4,16} = -.020(-.41)$ $\Phi_{4,17} = .098(2.40)^{b}$	50.069^{a}	1.120
	$3\Phi_{3,i} = .007(1.06)$	$3\Phi_{4,i} = .994(58.68)^{a}$		

PANEL J: TURKEY

Dependent Variable	Coefficients (*t*-statistics) R_t	V_t	Q-Stat.	F-Stat.
R_t	$\Phi_{1,1} = .242(8.79)^{a}$ $\Phi_{1,2} = -.069(-2.53)^{b}$	$\Phi_{2,1} = -.000(-.40)$	25.897	.163
	$3\Phi_{1,i} = .174(4.85)^{a}$	$3\Phi_{2,i} = -.000(-.40)$		
V_t	$\Phi_{3,1} = 4.718(6.40)^{a}$ $\Phi_{3,2} = -2.284(-3.73)^{a}$ $\Phi_{3,3} = 1.565(2.78)^{a}$	$\Phi_{4,1} = .485(8.18)^{a}$ $\Phi_{4,2} = .052(.86)$ $\Phi_{4,3} = .157(2.92)^{a}$ $\Phi_{4,4} = -.009(-.17)$ $\Phi_{4,5} = .092(1.45)$ $\Phi_{4,6} = -.013(-.20)$ $\Phi_{4,7} = -.046(-.81)$ $\Phi_{4,8} = .077(1.20)$ $\Phi_{4,9} = .056(.90)$ $\Phi_{4,10} = -.072(1.25)$ $\Phi_{4,11} = -.055(-.91)$ $\Phi_{4,12} = .057(-.99)$ $\Phi_{4,13} = .023(.43)$ $\Phi_{4,14} = -.043(-.75)$ $\Phi_{4,15} = .047(.78)$ $\Phi_{4,16} = .013(.22)$ $\Phi_{4,17} = -.003(-.05)$ $\Phi_{4,18} = -.064(-1.20)$ $\Phi_{4,19} = .081(1.68)^{c}$	38.442^{a}	44.695^{a}
	$3\Phi_{3,i} = 3.400(4.95)^{a}$	$3\Phi_{4,i} = .982(45.51)^{a}$		

Table 5

Results of Nonlinear Granger Causality Test between Stock Returns and Trading Volumes

	H_0: Stock Returns Do Not Cause Volume						H_0: Volume Does Not Cause Stock Returns					
Lr = Lv	1	2	3	4	5	6	1	2	3	4	5	6
PANEL A: BELGIUM												
DIEF	0.0012	0.0056	0.0090	0.0127	0.0089	0.0116	0.0021	0.0107	0.0110	0.0413	0.0207	0.0207
NORM	0.296	0.780	0.903	1.059	0.617	0.713	0.635	1.840^{b}	1.472^{c}	1.456^{c}	1.736^{c}	1.432^{c}
PANEL B: DENMARK												
DIFF	0.0147	0.0185	0.0272	0.0423	0.0409	0.0028	0.0071	0.0125	0.0097	0.0073	– 0.0000	0.0498
NORM	2.809^{a}	1.946^{b}	1.785^{b}	1.679^{b}	1.047	0.035	1.475^{c}	1.590^{b}	0.733	0.323	– 0.007	0.665
PANEL C: GREECE												
DIEF	0.0021	0.0000	– 0.0062	– 0.0023	– 0.0016	– 0.0020	– 0.0018	0.0097	– 0.0153	– 0.0292	0.0409	0.0568
NORM	0.444	0.008	– 0.554	– 0.153	– 0.083	– 0.087	– 0.469	$–.288^{c}$	$– 1.406^{c}$	$– 2.037^{b}$	0.724	0.919
PANEL D: NETHERLANDS												
DIEF	0.0028	– 0.0035	– 0.0103	– 0.0065	– 0.0197	– 0.0400	– 0.0030	– 0.0111	0.0190	– 0.0192	– 0.0115	– 0.0269
NORM	0.843	– 0.5524	– 1.060	– 0.494	– 1.063	$– 1.480^{c}$	– 1.013	$– 2.112^{b}$	$– 2.492^{a}$	$– 2.141^{b}$	– 0.710	– 1.069
PANEL E: NORWAY												
DIEF	– 0.0031	0.0000	0.0020	0.0055	0.0092	0.0143	– 0.0075	– 0.0131	– 0.0186	– 0.0192	– 0.0210	– 0.0102
NORM	– 0.937	0.133	0.218	0.501	0.757	1.062	$– 2.801^{a}$	$– 2.558^{a}$	$– 2.663^{a}$	$– 2.141^{b}$	$– 1.876^{b}$	– 0.765
PANEL F: PORTUGAL												
DIEF	– 0.0013	0.0021	– 0.0041	– 0.0066	– 0.0065	0.0000	– 0.0011	– 0.0032	0.0053	– 0.0058	– 0.0080	– 0.0066
NORM	$– 1.418^{c}$	$– 1.400^{c}$	$– 1.401^{c}$	$– 1.408^{c}$	– 1.162	0.184	$– 1.434^{c}$	– 1.157	– 1.232	– 1.253	$– 1.515^{c}$	– 0.937
PANEL G: SPAIN												
DIEF	0.0025	0.0011	0.0054	0.0186	0.0132	0.0152	0.0082	0.0154	0.0190	0.0190	0.0413	0.0485
NORM	0.594	0.124	0.331	0.769	0.373	0.244	1.958^{b}	1.898^{b}	1.547^{c}	1.074	1.455^{c}	1.140
PANEL H: SWEDEN												
DIEF	0.0039	0.0062	0.0076	0.0051	0.0064	0.0051	0.0085	0.0099	0.0132	0.0292	0.0266	0.0114
NORM	1.314^{c}	1.571^{c}	1.878^{b}	1.130	0.844	0.981	1.950^{b}	2.200^{b}	2.808^{a}	2.880^{a}	3.449^{a}	2.612^{a}
PANEL I: SWITZERLAND												
DIEF	0.0040	0.0032	0.0028	0.0054	0.0146	0.0148	0.0021	0.0021	– 0.0000	0.0071	0.0103	0.0073
NORM	0.874	0.390	0.268	0.467	1.041	0.944	0.490	0.338	– 0.062	0.780	0.994	0.532
PANEL J: TURKEY												
DIEF	0.0069	0.0237	0.0265	0.0334	0.0391	0.0412	0.0032	0.0128	0.0189	0.0270	0.0287	0.0352
NORM	1.684^{b}	3.868^{a}	3.906^{a}	5.773^{a}	6.227^{a}	6.3308^{a}	0.853	1.997^{b}	2.772^{a}	3.336^{a}	3.444^{a}	3.922^{a}

The results are based on the residual series $\zeta_{R,t}$ and $\mu_{V,t}$ from equations (1) and (2). Lr = Lv designates the number of lags on the residuals series $\zeta_{R,t}$ and $\mu_{V,t}$. DIFF and NORM, respectively, denote the difference between the two conditional probabilities in equation (3) and the standardized test statistic in equation (4). Under the null hypothesis of nonlinear Granger noncausality, the test statistic is asymptotically distributed N(0,1). The tests employ the unconditionally standardized series with the lead length, m, set to unity, and the length scale, *d*. set to 1.0.[a], [b], and [c] indicate significance at the 1%, 5% and 10% levels, respectively.

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