INTERNATIONAL EVIDENCE ON THE RELATIONSHIP BETWEEN TRADING VOLUME AND SERIAL CORRELATION IN STOCK RETURNS

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ABSTRACT
This paper examines the relationship between trading volume and stock return autocorrelation in different international stock markets. The results show that the relationship is asymmetric among markets and is stronger in those less developed. The relationship is stronger in markets where informed trading based on private information is possible.

Key words: Stock Returns, Trading Volume, Serial Correlation

JEL Classification: G12, G15

I. INTRODUCTION

Morse (1980) is among the first to develop a theoretical framework for the relationship between trading volume and the serial autocorrelation in stock return. He observes significant serial autocorrelations during periods of unusually high trading volumes, which he attributes to asymmetric information. For investors with private information, there may be a divergence between their perception of the fundamental value of a stock and its actual market price. The larger the divergence, the more investors with private information will trade. As they trade, the private information is

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revealed, and the stock price adjusts to its 'correct' level. It follows that high trading volume is expected prior to a large price change in the presence of asymmetric information.

Unlike Morse, Campbell, Grossman and Wang (1993) who develop a model in which the assumption of informed trading is not required, argue that investors may trade even when they have no private information. For example, a mutual fund may trade as a result of a change in its mandate or investment strategy. An individual investor may trade at the end of a calendar year for tax reasons. Hence, an investor may trade even if there has been no change in the value of the stocks. In cases like this, we observe a period of heavy trading where prices will drop (rise) because of the need for liquidation (purchases). However, since the fundamental value of the stock has not changed, we should expect a reversal in stock price once the liquidation (purchases) is complete.

Investors will also trade when there is a change in their risk aversion level. If investors become more risk averse, they will trade their risky securities for those with less risk. Hence, we would see a price-reversal after the trading is complete as there has been no change in the fundamental value of the stocks.

In the case of Campbell, Grossman and Wang (1993), if trading volume is high, then the price change is due to preference-hedging shocks, as explained in the examples above. On the other hand, if trading volume is small, then the price change is due to the arrival of new public information. As a result, price changes accompanied by high trading volume will tend to be reversed, implying a negative serial correlation in stock returns.[2]

In line with Campbell, Grossman and Wang (1993), Wang (1994) assumes a constant aggregate asset supply curve and shows that if trading is motivated by reasons of liquidity, a price reversal will follow once the trading is complete. However, stock returns will be positively correlated in informed trading. The theory of Wang (1994) is supported empirically by Llorente, Michaely, Saar and Wang (2001). They show that information trading causes positively autocorrelated returns and liquidity trading causes negatively autocorrelated returns.

Although the above studies suggest that there is a relationship between trading volume and the serial correlation in stock returns, He and Wang (1995) argue that the strength of the relationship may not always be evident. For example, if information is private, only informed investors trade while the rest of the market does not, which supports this theory. When this happens, the relationship between trading volume and the serial correlation in stock returns may be opaque. However, if the information is

[2] This result is also confirmed by Conrad, Hameed and Niden (1994). Using weekly data, they observe large price-reversals for highly traded stocks, and positive autocorrelation in thinly traded stocks. Lee and Swaminathan (2000) and Chan, Hameed and Tong (2000) examine the relationship between trading volume and profits of momentum strategies. They find that securities with high trading volume in the past earn lower return in the future and exhibit faster price reversals than securities that are thinly traded. Their findings are consistent with Campbell, Grossman and Wang (1993).

made public, all investors trade simultaneously, in which case the information flow generates both trading volume changes and price changes almost instantaneously.

Overall, the various theoretical frameworks seem to suggest that the interaction between informed and uninformed investors (private and public information) results in the relationship between trading volume and stock return serial correlation. This paper extends the previous literature by examining the relationship between trading volume and the serial autocorrelation of stock returns in a global context. While the present literature focuses mainly on the U.S. stock market, we explore an extension of this issue internationally in the face of increased globalization. We also look into the factors that may affect this relationship. A cross-country analysis enables us to determine the factors. The rest of the paper proceeds as follows. We describe our data and methodology in Section II. We report our results in Section III and conclude in Section IV.

II. DATA AND METHODOLOGY

To ensure consistency and comparability amongst the countries and regions, we use the Datastream Total Market Indices.[3] The sample includes 23 national stock market indices and four indexes for Emerging countries, European Monetary Union, Latin American countries and Pacific countries excluding Japan, respectively, over the period 1995 to 2005.

We use the turnover ratio as a proxy for trading volume (also used in Campbell, Grossman and Wang (1993), Jain and Joh (1988) and Chordia and Swaminathan (2000)). The turnover ratio, measured in log, is equal to the total value of stocks traded, divided by the total market capitalization.

We plot the turnover ratio series for the 27 markets to see if there is any trend and consequently, any adjustment that is needed.[4] We find that the turnover ratio series has an upward trend for most of the countries. Hence, to control for the trends, we use the detrended log turnover series, calculated as follows:

$$DETRENDEDTURNOVER_t = LOGTURNOVER_t - \frac{1}{200}\sum_{s=1}^{200} LOGTURNOVER_{t-s} \qquad (1)$$

Plots of the detrended log turnover still show up non-stationarity. As a result, we use the change in total traded volume (i.e. *VOLCHANGE*) and the detrended log turnover series as alternative proxies for trading volume. Plots of the change in the traded volume series show no trends.[5]

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[3] The MSCI country index is a possible candidate; the index is calculated for each country in the same way by Morgan Stanley Capital International Inc. However, aside from the performance data, corresponding trading volume data for the index is not provided (unlike Datastream, the database we use for this study).

[4] Figures of plots are available upon request from the authors.

[5] The Augmented Dickey-Fuller tests accept the null hypothesis of unit root at the 5 percent level for the *VOLCHANGE* series.

To examine the relationship between trading volume and the serial autocorrelation in international stock market index returns, we test four models as suggested by Campbell, Grossman and Wang (1993). For ease of exposure, we present the models in the next section as we discuss the findings of the models. In the first model, current returns are regressed against first-lagged returns. The results from this model will demonstrate, in the markets examined, whether stock return autocorrelation exists. Next, we substitute the first-lagged returns by an interaction variable (*the second model*). The interaction variable is the product of a proxy for trading volume and the first-lagged return. We use the second model to examine how trading volume impacts the autocorrelation in stock returns. Next, in the second model, we control for stock volatility (*the third model*). Many empirical studies document a significant positive correlation between trading volumes and return volatility.[6] They argue that heterogeneous opinions (information asymmetry) among investors cause a positive relationship between trading volumes and return volatility. In a fourth model, we extract the coefficients on the interaction terms from the third model and compare the coefficients amongst the markets.

III.RESULTS

Examining the autocorrelation in stock returns

In Table 1, we regress the contemporary returns on the first-lagged returns as follows:

$$R_{it} = \alpha + \beta R_{i,t-1} + \varepsilon_{it} \qquad (2)$$

where $R_{i,t}$ is the return on the Datastream Total Market Index for country i at time t. In most markets, we find positive first-order autocorrelation. The adjusted R-squared of the models are relatively low. The U.S. stock market index shows highly significant first-order autocorrelation. Its adjusted R-squared statistic is high, as well, at 0.2248. While the coefficients on the first-lagged returns for most of the markets are smaller than 0.1, the coefficient for the U.S. market is 0.472. This result is consistent with the findings of others (see, for example, Campbell, Grossman and Wang (1993)) about the significant autocorrelation in U.S. stock market returns.[7]

[6] Karpoff (1987) provides a detailed survey of the findings.

[7] The difference between Campbell, Grossman and Wang (1993) results and ours is that our R-squared and the coefficient on the first-lagged return are larger. The reason, we believe, is due to the use of different market indices. We use the Datastream Total Market Index instead of the CRSP Equally-Weighted Index or CRSP Value – Weighted Index (as used in Campbell, Grossman and Wang (1993).

Table 1 The autocorrelation in stock market index return

This table provides results using two models for forecasting returns from lagged returns:

Equation 2: $R_{it} = \alpha + \beta R_{i,t-1} + \varepsilon_{it}$, where R_{it} is the return on country market *i* at time *t*.

Equation 3: $R_{it} = \alpha + \sum_{n=2}^{6} \beta (D_n \times R_{i,t-1}) + \varepsilon_{it}$, where D_n is a dummy variable for the day of the week (*n* =2 to 6). *D2* is a dummy for Monday, *D3* for Tuesday, *D4* for Wednesday, *D5* for Thursday and *D6* for Friday. *t-statistics* are corrected for heteroskedasticity. *, ** and *** indicate significance level at 10%, 5% and 1%, respectively.

		Panel A (Equation 2)			Panel B (Equation 3)	
Country	*N*	*Adj. R^2*	*β*	*t Value*	*Adj. R^2*	*Significant Interaction Terms*
Australia	2477	0.0005	0.023	1.17	0.0081	*D2, D4, D6*
Austria	2368	0.0032	0.056	2.78***	0.0091	*D2, D3, D5*
Belgium	2467	0.0286	0.168	8.52***	0.0318	*D2, D3, D4, D5, D6*
Brazil	1424	0.0154	0.122	4.71***	0.0438	*D2, D3, D5, D6*
Canada	2448	0.0056	0.076	3.86***	0.0094	*D2, D4, D5, D6*
China	2382	0.0024	0.048	2.42***	0.0166	*D2, D4, D6*
Emerging country markets	2507	0.0540	0.253	13.39***	0.0877	*D2, D3, D4, D5, D6*
EMU	2552	0.0073	0.085	4.44***	0.0059	*D2, D6*
France	2462	0.0006	0.022	1.19	0.0055	*D6*
Germany	2468	0.0040	0.058	3.16***	0.0086	*D2, D6*
Hong Kong	2373	0.0024	-0.005	-2.38**	0.0170	*D2, D3, D4, D5*
Italy	2470	0.0005	0.021	1.09	0.0168	*D2, D3, D4, D6*
Japan	2604	0.00001	0.00001	0.23	0.0025	*D5*
Latin America country markets	2541	0.0488	0.220	11.46***	0.0550	*D2, D3, D4, D5, D6*
Malaysia	2607	0.0047	0.033	3.65***	0.1124	*D2, D5, D6*
Mexico	2604	0.0001	-0.001	-0.54	0.0103	*D2, D3, D6*
Netherlands	2491	0.0004	0.019	0.99	0.0087	*D6*
Pacific countries excl. Japan	2591	0.0257	0.154	8.49***	0.0497	*D2, D5, D6*
Singapore	2423	0.0240	0.151	7.72***	0.0519	*D3, D4, D5, D6*
South Africa	2400	0.0239	0.153	7.67***	0.0313	*D2, D3, D5, D6*
South Korea	2385	0.0256	0.067	4.89***	0.0413	*D2, D3, D5, D6*
Spain	2426	0.0012	0.034	1.71*	0.0072	*D2, D5, D6*
Sweden	2431	0.0012	0.034	1.68*	0.0082	*D2*
Switzerland	2452	0.0012	0.033	1.69*	0.0090	*D6*
Taiwan	2348	0.0000	0.006	0.27	0.0051	*D2*
United Kingdom	2469	0.0010	0.032	1.60	0.0370	*D2, D6*
United States	2865	0.2248	0.472	28.84***	0.1900	*D2, D3, D4, D5, D6*

Campbell, Grossman and Wang (1993) suggest that the model *R*-squared can be improved by allowing the significant autocorrelation terms to vary with the day of the week. Hence, we create interaction terms between the day of the week and the first lagged returns and run the following model:

$$R_{it} = \alpha + \sum_{n=2}^{6} \beta(D_n \times R_{i,t-1}) + \varepsilon_{it} \quad (3)$$

where D_n is a dummy for the day of the week. Results of this regression are presented in Panel B of Table 1. The *R*-squared statistics are higher compared to those in Panel A of Table 1. For most markets, the Friday return plays a significant role in explaining the next trading day return. Since the inclusion of the day-of-the-week dummies improves the model's predictability power, we incorporate them in subsequent regressions.

Examining the relationship between the autocorrelation in stock returns and trading volumes

To examine the relationship between trading volumes and return serial correlation, we have included two alternative proxies of volume in a second model as follows:

$$R_{it} = \alpha + (\sum_{n=2}^{6} \beta_i D_n + \gamma VOLCHANGE_{i,t-1})R_{i,t-1} + \varepsilon_{it} \quad (4)$$

where D_n is the dummy variable for the day of the week, and $VOLCHANGE_{i,t-1}$ is the change in trading volume of country *i* at time *t*-1.

$$R_{it} = \alpha + (\sum_{n=2}^{6} \beta D_n + \eta DETRENDEDTURNOVER_{i,t-1})R_{i,t-1} + \varepsilon_{it} \quad (5)$$

where $DETRENDEDTURNOVER_{i,t-1}$ is the detrended turnover ratio of country *i* at time *t*-1.

Results of equations 4 and 5 are presented in Table 2. The outcomes are similar using both equations, however equation (4) has a higher *R*-squared while the coefficients from equation (5) are statistically significant at higher levels.[8] In comparison to Table 1, the adjusted *R*-squared statistics from Table 2 are higher, suggesting that volume does improve the first-order autocorrelation of stock returns.

[8] These differences may be due to the *VOLCHANGE* series being more stationary than the *DETRENDEDTURNOVER* series as mentioned earlier.

Table 2 Relationship between the autocorrelation in stock returns and trading volumes

This table provides the results of running the following 2 models:

$R_{it} = \alpha + (\sum_{n=2}^{6} \beta D_n + \gamma VOLCHANGE_{i,t-1})R_{i,t-1} + \varepsilon_{it}$, where R_{it} is the returns on country market *i* at time *t* and $VOLCHANGE_{i,t-1}$ is the change in trading volume of country *i* at time *t*.

$R_{it} = \alpha + (\sum_{n=2}^{6} \beta D_n + \eta DETRENDEDTURNOVER_{i,t-1})R_{i,t-1} + \varepsilon_{it}$, where $DETRENDEDTURNOVER_{i,t-1}$ is the detrended log turnover ratio of country *i* at time *t*. D_n is a dummy variable for the day of the week (n = 2 to 6 for Monday through Friday). *t*-statistics are corrected for heteroskedasticity. *, ** and *** indicate significance level at 10%, 5% and 1%, respectively.

	Panel A (Equation 4)				Panel B (Equation 5)			
Country	*n*	*Adj. R^2*	γ	*t Value*	*n*	*Adj. R^2*	η	*t Value*
Australia	1314	0.0033	0.084	1.37	1344	0.0024	0.055	0.83
Austria	1275	0.0025	0.010	0.25	1332	0.0019	-0.015	-0.25
Belgium	1325	0.0170	0.005	0.27	1354	0.0175	0.088	1.51
Brazil	791	0.0139	-0.055	-0.90	824	0.0172	0.155	2.10**
Canada	1332	0.0080	0.00014	0.18	1378	0.0057	-0.052	-0.58
China	1202	0.0194	0.003	2.54**	1220	0.0237	0.101	3.49***
Emerging country market	1394	0.0152	0.0007	3.08***	1394	0.0147	0.104	2.7***
EMU	1354	0.0013	0.0003	0.25	1380	0.0015	0.047	0.78
France	1304	0.0134	-0.102	-1.30	1341	0.0105	-0.014	-0.18
Germany	1295	0.0087	-0.0003	-0.03	1330	0.0090	0.005	0.08
Hong Kong	1202	0.0109	0.045	1.29	1250	0.0081	-0.0045	-0.82
Italy	1275	0.0082	0.002	0.03	1308	0.0100	0.119	1.89*
Japan	1148	0.0088	-0.000002	-0.91	1201	0.0075	-0.011	-0.81
South Korea	1170	0.0024	0.005	0.30	1238	0.0051	0.102	2.35**
Latin American country markets	1332	0.0295	0.003	2.05**	1351	0.0250	0.027	0.87
Malaysia	1154	0.0353	0.151	3.84***	1203	0.0925	0.282	9.51***
Mexico	1271	0.1090	0.0002	0.45	1311	0.0115	0.009	0.23
Netherlands	1330	0.0148	-0.083	-0.92	1359	0.0145	0.105	1.38
Pacific countries excl. Japan	1371	0.0118	0.025	1.59	1378	0.0097	-0.044	-0.50
Singapore	1194	0.0315	0.083	1.54	1239	0.0309	0.079	1.99*
South Africa	1255	0.0109	-0.047	-1.9*	1315	0.0140	-0.0143	-2.77***
Spain	1319	0.0059	-0.00006	-0.001	1357	0.0082	0.134	1.84*
Sweden	1255	0.0094	0.009	0.17	1305	0.0095	0.0023	0.04
Switzerland	1293	0.0114	-0.006	-0.3	1329	0.0114	0.042	0.71
Taiwan	1132	0.0028	-0.001	-0.32	1184	0.0115	0.220	3.21***
United Kingdom	1309	0.0094	-0.350	2.95***	1343	0.0032	0.015	0.17
United States	594	0.0529	0.505	4.38***	755	0.0251	-0.190	-1.28

Upon a closer examination of the coefficients in Table 2, we find that there exists a statistically significant relationship between the proxies for trading volumes and the autocorrelation in stock returns in Brazil, China, Emerging country market, Italy, South Korea, Latin American countries, Malaysia, Singapore, South Africa, Spain, Taiwan, the

U.K. and the U.S. There exists a positive relationship between trading volumes and the autocorrelation in stock returns in most countries except for South Africa and the U.K.

Examining the effect of the volatility in stock returns on the relationship between the autocorrelation in stock returns and trading volumes

We now examine whether the relationship between trading volume and stock return autocorrelation is still significant when we control for stock return volatility.

To extract return volatility in each market, we employ EGARCH (1, 1) and GARCH-M (1, 1) in stock market index return autoregressive models.[9] Thus, the general model for the return series is AR (*k*)-EGARCH (1,1) or AR(*k*)-GARCH-M(1,1), where *k* is the number of significant autoregressive terms. From these two models we obtain the estimates of country return volatility. In non-tabulated results, we find that the *R*-squared statistics are higher for the AR(*k*)-EGARCH(1,1) model than for the AR(*k*)-GARCH-M (1,1) model, suggesting that the former is a better fit than the latter.[10] Accordingly, the return volatility measure extracted from the AR(*k*)-GARCH(1,1) model is used in the following regressions.

Table 3 reports the results of the following two regression models:

$$R_{it} = \alpha + (\sum_{n=2}^{6} \beta_i D_n + \gamma VOLCHANGE_{i,t-1} + \nu VOLCHANGE_{i,t-1}^2 + \theta 1000\sigma_{t-1}^2) R_{i,t-1} + \varepsilon_{it} \qquad (6)$$

$$R_{it} = \alpha + \left(\sum_{n=2}^{6} \beta D_n + \gamma DT_{i,t-1} + \nu DT_{i,t-1}^2 + \theta 1000\sigma_{t-1}^2 \right) R_{i,t-1} + \varepsilon_{i,t} \qquad (7)^{11}$$

In the above two models, σ_{t-1}^2 is the conditional variance of the return series extracted from the AR(*k*)-EGARCH(1,1) model.

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[9] To identify the appropriate lagged terms for the return series, we use the BACKSTEP function in the PROC AUTOREG procedure in SAS. This function removes insignificant autoregressive parameters. The parameters are removed in order of least significance.

[10] Tables of results are available upon request from the authors.

[11] *DT=DETRENDEDTURNOVER*

Table 3 The effect of the volatility in stock returns on the relationship between the autocorrelation in stock returns and trading volumes

Panel A (Equation 6)

This table provides the results for the following model: Equation 6 $R_{it} = \alpha + (\sum_{n=2}^{6} \beta \ D_n + \gamma VOLCHANGE_{i,t-1} + \nu VOLCHANGE^2_{i,t-1} + \theta 1000\sigma^2_{t-1}) R_{i,t-1} + \varepsilon_{it}$, where R_{it} is the returns on country market *i* at time *t*, $VOLCHANGE_{i,t-1}$ is the change in trading volume of country *i* at time *t*, and D_n is the dummy variable for the day of the week (n = 2 to 6 for Monday through Friday). σ^2_t is the conditional variance of stock returns for each country market extracted from an AR(*k*)-EGARCH(1,1) model. The *t*-statistics are corrected for heteroskedasticity. *t*-statistics are presented in [ ]. *, ** and *** indicate significance level at 10%, 5% and 1%, respectively.

Country	*N*	*Adj. R^2*	γ		υ		θ	
Australia	1314	0.005	-0.003	[-0.03]	0.050	[1.37]	0.140	[0.57]
Austria	1275	0.004	0.054	[1.20]	-0.015	[-1.54]	-0.156	[-0.57]
Belgium	1325	0.017	0.007	[0.15]	-0.00008	[-0.05]	0.074	[0.95]
Brazil	791	0.028	0.118	[2.10**]	-0.130	[-2.20**]	0.199	[2.33**]
Canada	1332	0.008	-0.008	[-0.35]	0.00001	[0.37]	0.103	[0.59]
China	1202	0.021	0.0003	[2.17**]	0.00009	[0.35]	-0.03	[-1.43]
Emerging countries	1394	0.015	0.0006	[1.94*]	0.00001	[0.20]	0.157	[0.87]
EMU	1354	0.005	0.0004	[0.03]	-0.00003	[-0.01]	0.384	[2.45**]
France	1304	0.015	-0.204	[-1.98**]	0.117	[1.49]	0.089	[1.03]
Germany	1295	0.009	-0.012	[-0.37]	0.00005	[0.38]	0.110	[1.38]
Hong Kong	1202	0.013	0.132	[2.10**]	-0.024	[-1.55]	0.025	[0.21]
Italy	1275	0.011	-0.151	[-1.74*]	0.204	[1.90*]	0.0001	[0.03]
Japan	1148	0.010	-0.00007	[-1.42]	0.00004	[1.12]	0.0001	[0.31]
Latin America	1332	0.034	0.006	[0.98	-0.00001	[-0.52]	0.131	[2.47**]
Malaysia	1154	0.059	0.448	[5.34***]	-0.158	[-4.50***]	0.011	[4.50***]
Mexico	1271	0.018	0.013	[1.09]	-0.00005	[-1.03]	0.580	[2.93**]
Netherlands	1330	0.016	-0.021	[-0.19]	-0.135	[-0.85]	0.049	[0.89]
Pacific countries excl. Japan	1371	0.021	0.025	[1.95*]	-0.001	[-1.37]	0.322	[3.35***]
Singapore	1194	0.034	0.142	[1.39]	-0.050	[-0.55]	0.050	[1.31]
South Africa	1255	0.012	-0.015	[-1.70*]	0.001	[-1.00]	0.004	[0.14]
South Korea	1170	0.003	-0.02	[-0.45]	0.001	[0.55]	0.001	[0.49]
Spain	1319	0.007	-0.004	[-0.12]	0.00003	[0.12]	0.084	[0.70]
Sweden	1255	0.013	0.021	[0.25]	-0.005	[-0.15]	0.157	[2.25**]
Switzerland	1293	0.017	-0.031	[-0.51]	0.0002	[0.47]	0.195	[2.60**]
Taiwan	1132	0.008	0.143	[1.88*]	-0.0007	[-1.89*]	0.159	[1.23]
United Kingdom	1309	0.010	-0.490	[-3.03***]	0.155	[1.13]	0.085	[0.52]
United States	755	0.080	0.043	[3.30***]	0.089	[0.75]	0.001	[4.25***]

Panel B (Equation 7)

This table provides the results for the following model: Equation 7

$$R_{it} = \alpha + (\sum_{n=2}^{6} \beta D_n + \gamma DETRENDEDTURNOVER_{i,t-1} + \nu DETRENDEDTURNOVER_{i,t-1}^2 + \theta 1000\sigma_{t-1}^2) R_{i,t-1} + \varepsilon_{it},$$

where R_{it} is the returns on country market i at time t , $DETRENDEDTURNOVER_{i,t-1}$ is the detrended log turnover ratio of country i at time t, and D_n is the dummy variable for the day of the week (n = 2 to 6 for Monday through Friday). σ^2_t is the conditional variance of stock returns for each country market extracted from an AR(k)-EGARCH(1,1) model. The t-statistics are corrected for heteroskedasticity. t-statistics are presented in [ ]. *, ** and *** indicate significance level at 10%, 5% and 1%, respectively.

Country	*N*	*Adj. R²*	γ		υ		θ	
Australia	1344	0.0025	-0.070	[0.83]	-0.040	[-0.36]	0.004	[0.02]
Austria	1298	0.0230	-0.003	[-0.05]	-0.007	[-0.09]	-0.100	[-0.46]
Belgium	1364	0.0232	-0.027	[-0.35]	-0.026	[-0.28]	0.220	[2.69***]
Brazil	824	0.0222	0.071	[1.72*]	0.230	[1.78*]	-0.0001	[-0.03]
Canada	1378	0.0063	-0.083	[-0.84]	-0.112	[-0.74]	0.115	[0.70]
China	1220	0.0251	0.072	[2.15**]	0.039	[1.03]	-0.002	[-1.26]
Emerging countries	1394	0.0168	0.119	[3.00***]	0.037	[1.38]	-0.188	[-1.10]
EMU	1380	0.0040	-0.990	[-0.24]	-0.009	[-0.42]	0.269	[1.85*]
France	1341	0.0133	-0.104	[-2.10**]	0.246	[1.55]	0.070	[0.79]
Germany	1330	0.0070	-0.029	[-0.35]	-0.024	[-0.40]	0.111	[1.98*]
Hong Kong	1250	0.0083	-0.009	[-0.10]	-0.056	[-0.52]	0.001	[0.08]
Italy	1308	0.0128	-0.018	[-2.10**]	0.214	[1.92*]	-0.020	[-0.32]
Japan	1201	0.0080	0.050	[0.98]	-0.018	[-0.14]	0.00001	[0.23]
Latin America	1351	0.0300	-0.037	[0.81]	0.025	[1.58]	0.063	[1.87*]
Malaysia	1203	0.0958	0.436	[4.70***]	-0.119	[-1.95*]	0.0002	[0.97]
Mexico	1311	0.0103	0.055	[0.73]	-0.019	[-1.20]	0.003	[0.34]
Netherlands	1369	0.0160	0.072	[1.20]	0.207	[1.28]	-0.001	[-0.13]
Pacific countries excl. Japan	1378	0.0320	0.260	[3.03***]	0.540	[4.20***]	0.137	[1.39]
Singapore	1239	0.0310	0.091	[1.13]	-0.001	[-0.02]	-0.015	[-0.40]
South Africa	1315	0.0157	-0.110	[-1.95*]	-0.011	[-1.29]	0.021	[0.66]
South Korea	1238	0.0090	0.103	[1.69*]	-0.033	[-0.81]	0.0002	[1.66*]
Spain	1367	0.0090	0.133	[1.45]	-0.124	[-0.85]	0.100	[0.81]
Sweden	1306	0.0120	-0.078	[-1.00]	0.048	[0.50]	0.095	[1.63]
Switzerland	1329	0.0149	-0.057	[-0.74]	0.047	[0.56]	0.142	[1.89*]
Taiwan	1184	0.0123	0.193	[1.72*]	-0.017	[-0.12]	0.122	[1.01]
United Kingdom	1343	0.0047	0.018	[0.10]	0.092	[0.96]	0.088	[0.57]
United States	694	0.0263	-0.107	[-1.06]	-0.960	[-0.30]	0.330	[0.26]

Results in Table 3 show that after controlling for volatility, the coefficients on the trading volume interaction variables and lagged returns are statistically significant for Brazil, China, Emerging countries, France, Italy, Malaysia, Pacific countries excluding Japan, South Africa and Taiwan in both Panels A and B.

Examining why the relationship between trading volume and stock return autocorrelation varies among countries

The results show that the relationship between trading volume and serial correlation in stock market index returns differs among countries. In this section, we attempt to explain the observed variation in that relationship using market characteristics such as short-selling and stock market efficiency.

In countries where short-sale is unrestricted, we expect to find a strong relationship between trading volume and stock return autocorrelation. Short-sellers become more active if they expect a decline in stock prices. The larger the decline, the more likely a short-seller will trade. As a result, in markets where short-selling is permitted, greater trading prior to a large price change is to be expected.

Next, we expect to find a weak relationship between trading volume and stock return autocorrelation in informational-efficient stock markets. When markets are efficient, information is revealed more quickly, which in turn limits the ability of informed traders to trade beforehand. We use a country's level of economic development as proxy for its stock market efficiency. The more developed the economy; we expect a more efficient stock market.

We extract the coefficients on $VOLCHANGE \times R_{it-1}$ and $DETRENDEDTURNOVER \times R_{it-1}$ from equations (6) and (7), and compare them in Table 4. We observe that the relationship between trading volume and stock return autocorrelation is higher in countries where short-selling is not allowed (see Panel A of Table 4) and in developing countries (see Panel B of Table 4). Hence, contrary to our first hypothesis, the relationship between trading volume and stock return autocorrelation is not found to be stronger in markets where short-sales are allowed. However, consistent with our second hypothesis, we find that the relationship is stronger in developing countries.

Table 4 Comparison of the relationship between trading volume and stock return autocorrelation between groups of countries

In this table, we compare the γs and the υs obtained from the following two regressions:

Equation 6: $R_{it} = \alpha + (\sum_{n=2}^{6} \beta D_n + \gamma VOLCHANGE_{i,t-1} + \nu VOLCHANGE_{i,t-1}^2 + \theta 1000\sigma_{t-1}^2)R_{i,t-1} + \varepsilon_{it}$,

where R_{it} is the returns on country market *i* at time *t*, $VOLCHANGE_{i,t}$ is the change in trading volume of country *i* at time *t*, and D_n is a dummy variable for the day of the week (*n*=2 to 6). Equation 7:

$$R_{it} = \alpha + (\sum_{n=2}^{6} \beta D_n + \gamma DETRENDEDTURNOVER_{i,t-1} + \nu DETRENDEDTURNOVER_{i,t-1}^2 + \theta 1000\sigma_{t-1}^2)R_{i,t-1} + \varepsilon_{it},$$

where $DETRENDEDTURNOVER_{i,t-1}$ is the detrended log turnover ratio of country *i* at time *t*. σ_t^2 is the conditional variance of stock returns for each country market extracted from an AR(*k*)-EGARCH(1,1) model. *, ** and *** indicate significance level at 10%, 5% and 1%, respectively.

Panel A Comparison of countries where short-sales are possible versus those where it is not				
	Short-Sale	*No Short-Sale*	*t Value*	*Kruskal-Wallis χ^2 p values*
	(n=19)	*(n=8)*		
γ in Equation 6 (Table 3 Panel A)	-0.003	0.035	-1.98*	0.0374**
υ in Equation 6 (Table 3 Panel A)	0.009	-0.016	1.85	0.0955*
γ in Equation 7 (Table 3 Panel B)	0.012	0.045	0.58	0.1486
υ in Equation 7 (Table 3 Panel B)	0.025	0.083	0.92	0.3740

Panel B Comparison of Developed versus Developing economies				
	Developed countries	*Developing countries*	*t Value*	*Kruskal-Wallis χ^2 p values*
	(n=17)	*(n=10)*		
γ in Equation 6 (Table 3 Panel A)	-0.031	0.073	1.86*	0.0264**
υ in Equation 6 (Table 3 Panel B)	0.021	-0.029	-1.77*	0.0950
γ in Equation 7 (Table 3 Panel A)	0.002	0.055	0.24	0.3990
υ in Equation 7 (Table 3 Panel B)	0.037	0.052	0.86	0.9100

IV. CONCLUSION

In this paper, we look at the relationship between trading volume and the serial autocorrelation of stock returns in different stock markets. Our study seeks to contribute to the relatively little work conducted in the area of national markets outside the U.S. Using a similar methodology as Campbell, Grossman and Wang (1993), we find that there is great variation in the relationship between trading volume and the serial autocorrelation of stock returns across countries. We use different regressions to examine the relationship but the findings are not consistent across these regressions. We also look at the effects of market characteristics on the relationship. We find that the relationship is stronger in less developed stock markets. Such markets tend to be less informational-efficient allowing informed investors to benefit from private information. Hence, we conclude that the relationship between trading volume and the serial autocorrelation of stock returns can be useful to traders without access to private information in formulating trading strategies in less-developed stock markets.

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