The Dynamic Relationship Between Stock Returns and Trading Volume Revisited: A MODWT-VAR Approach

Suman Gupta , Debojyoti Das , Haslifah Hasim ,
Aviral Kumar Tiwari

PII: S1544-6123(17)30641-4
DOI: 10.1016/j.frl.2018.02.018
Reference: FRL 871

To appear in: *Finance Research Letters*

Received date: 9 October 2017
Revised date: 26 December 2017
Accepted date: 22 February 2018

Highlights

- The relationship between market returns and trading volume is investigated in a time-frequency domain.
- The relationship varies across different time-horizons.
- Both Chinese and Indian markets depict the artifact of efficiency in short to medium run.
- Markets become inefficient in the longest time-horizon.

The Dynamic Relationship between Stock Returns and Trading Volume Revisited: A MODWT-VAR Approach

Suman Gupta
Finance Area, Indian Institute of Management Raipur
GEC Campus, Sejbahar, Raipur- 492015, Chhattisgarh, India.
e-mail: suman.fpm2013@iimraipur.ac.in
Contact: +91-8105954805

Debojyoti Das
Finance Area, Indian Institute of Management Raipur
GEC Campus, Sejbahar, Raipur- 492015, Chhattisgarh, India.
e-mail: debojyoti.fpm2014@iimraipur.ac.in
Contact: +91-7024120125

Haslifah Hasim
Department of Mathematical Sciences, University of Essex
Wivenhoe Park, Colchester CO4 3SQ, United Kingdom
e-mail: hhashim@essex.ac.uk
Contact: +44-7907095724

Aviral Kumar Tiwari
Montpellier Business School, 2300, Avenue des Moulins 34185 Montpellier Cedex 4, France
Email: aviral.eco@gmail.com
Contact: +33-758758648

The Dynamic Relationship Between Stock Returns and Trading Volume Revisited: A MODWT-VAR Approach

ABSTRACT

This paper revisits the relationship between market returns and trading volume in a time-frequency domain using a wavelet-based vector autoregression approach. Over 15 years of almost concurrent data from two major emerging stock markets – China and India – are considered for analysis. The relationship is found to vary across different time horizons. In addition, we report that both Chinese and Indian markets depict the artifact of efficiency in the short to medium run. However, markets become inefficient in the longest time horizon studied.

Keywords: Wavelet; Trading Volume; Market Returns; Time-frequency domain.

JEL classification: C40; G10; G15

1. Introduction

Understanding the dynamic relationship between trading volume and stock returns has been a conspicuous aspect in the extant literature of financial research (Gebka and Wohar, 2013). The scholars in the past have developed several theoretical models in order to explain this intertwined relationship.[1] These theoretical models serve the basis to set testable hypotheses concerning the contemporaneous and dynamic relationships between the variables of interest. Thus, there exists considerable literature that focuses upon the returns-volume causality. Based on the direction of the returns-volume causality, two strands of literature can be broadly classified: the first strand of literature examine whether there exists any causal relationship between lagged trading volume and stock returns. In this respect, Campbell, et al. (1993) argues that high volume has negative predictive power over returns when the daily returns autocorrelation is considered. While Chordia and Subrahmanyam (2002) predict the market returns on the basis of the pressure of market order imbalance. Using lagged volume as the switching variable, McMillan (2007) reports weak evidence for return predictability by high lagged volume and strong momentum phenomena by low lagged volume. However, most of the evidences are not in favor of this hypothesis (Lee and Rui, 2002; Statman et al., 2006; Griffin et al., 2007; Chen, 2012). Trading volume does not cause returns in the three largest stock markets (Lee and Rui, 2002); there is weak evidence of trading volume predicting market returns (Chen, 2012); and there is a heterogeneous effect of volume on returns across quintiles (Chuang et al., 2009). The other strand of literature highlights that

[1] Some of the theoretical models predominantly used in this domain of research are: the mixture of distribution hypothesis (Clark, 1973), the hypothesis of sequential information arrival (Copeland, 1976), interpretation of news (Harris and Raviv, 1993; Kandel and Pearson, 1995), asymmetry in information endowment (He and Wang, 1995; Kyle, 1985; Llorente et al., 2002) and precision of information (Schneider, 2009). The readers are requested to refer the respective articles for a detailed understanding.

returns do cause trading volume in various asset markets. There are stable causal effects of market returns on trading volume across quintiles (Chuang et al., 2009); market returns have positive predictive power if regarding trading volumes (Statman et al., 2006; Griffin et al., 2007).

The theory of market microstructure suggests that shifts in trading volume and stock prices are associated with new information arrival to the market (Karpoff, 1987; Wang et al., 2017). Ideally, in congruence with the underlying assumptions of the Efficient Market Hypothesis (EMH) (Fama, 1970), the stock prices supposedly reflect all prevailing information in the market. In other words, the EMH assumes all market participants are homogenous in terms of their trading behaviour i.e. the information is interpreted and assimilated identically. However, such assumptions of normality under EMH may not hold true in the real world since market participants are heterogeneous in terms of market expectations, risk appetite and available information set. Consequentially, the Heterogeneous Market Hypothesis (HMH) emerged as an important extension to the EMH (Chin et al., 2017; Harrison and Kreps, 1978). The HMH conjectures the existence of short (such as speculators/market makers), medium and long-term investors (institutional investors/central banks etc.) (Mensi et al., 2016). Thus, according to HMH, given the same information set, the reaction time of different market participants varies considerably. Hence, testing the existing phenomenon for different time horizons becomes inevitable. Thus, motivated by HMH we adopt the wavelet decomposition framework to unravel newer insights on the traditional relationship between trading volume and stock prices. The decomposition of trading volume and stock prices series also enables us to test the hypothesis of sequential information arrival (Copeland, 1976), besides the mixture of distribution hypothesis (Clark, 1973) at different timescales.

In the existing empirical literature, the causality of returns-volume is examined mainly through the Granger causality test in linear and non-linear fashion. In vector autoregression (VAR), which comprises the Granger causality test, the direction of causality is of less concern than the causality of variables (Kirchgässner et al., 2013). Thus, VAR enables the independent testing of each variable without the knowledge of direction of causality, which is not the case in the Granger causality test. Hence, some of the prominent studies in the existing literature use VAR-based techniques to examine the returns-volume relationship (Chordia et al., 2002; Statman et al., 2006; Griffin et al., 2007; Chuang et al., 2009; Chen, 2012). One of the crucial limitations in past literature is the use of the traditional econometric approach, which does not capture the time and frequency information simultaneously. The wavelet-based methods are superior as they are immune to the limitations of many standard econometric techniques and analyze data on a time-frequency domain (Reboredo and Rivera-Castro, 2013).

This paper attempts to fill the gap in existing literature by first examining returns-volume causality in a time-frequency framework using the wavelet approach. First, the discrete wavelet multi-resolution analysis decomposes the data into different time horizons, which provides the basis for further analysis. The approach helps us to categorized market according to heterogeneous time horizons, which is controlled in empirical studies (Statman et al., 2006; Griffin et al., 2007). Second, the VAR approach is adapted on decomposed values to extend the range of the existing body of empirical evidences by emphasizing the short, medium, and long horizon returns-volume causality. This may help to devise better investment management and improved risk mitigation tools during the periods of uncertain outcome.

Third, most studies suggest the returns-volume causal relationship for developed markets (Chordia et al., 2002; Statman et al., 2006; Chen, 2012). Griffin et al. (2007) have examined the variations over time in the returns-volume relation and reports that the relation dissipates slowly in high-income countries, but persists in most developing countries. This suggests information asymmetry among countries and consistent investor behavioral biases in developing countries, e.g., 3 times more increase in turnover with 1 standard deviation shock to return. Among the emerging markets, China and India exhibit the weak form of market efficiency, which suggests a stronger returns-volume relationship (Jlassi et al., 2014), mainly due to transaction costs, poor norms for information disclosure, and inadequate accounting policies, which are common pedagogical features of emerging markets (El Hedi Arouri et al., 2010). The returns-volume relationship in developing countries varies significantly, as compared with high-income countries (Griffin et al., 2007). **Thus, in this study we consider two prominent Asian emerging economies – China and India owing to high voluminous trade and market capitalization. Understanding the returns-volume causality phenomenon in the selected countries also becomes a matter of paramount importance since: (a) China and India are the main countries contributing to global trading activities and mainly China towards Asia-Pacific region.[2] (b) India attracts the highest foreign inflows into equities in the Asia-Pacific region ex-China[3]. Besides, the other shared characteristics of India and China, which endows them global prominence are the rapid economic growth and economic development stage that served as a basis for formation of association of countries such as BRICS (Brazil, Russia, India, China, South Africa). In addition, it may also be noted that despite a relative longer history of Indian stock market than of China, the financial liberalization was enforced since 1991. The year 1991 nearly corresponds to period when Chinese markets were evolved (Chen et al., 2006). The role of financial liberalization, governance and stage of market development as channels for improving market efficiency is well established in literature (Atje and Jovanovic, 1993; Levine, 1997; Levine and Zervos, 1998; Porta et al., 1998). Thus, the shared characteristics also motivate us to examine whether there exists similar (or divergent) artifact of market efficiency.**

We report the evidence that both Chinese and Indian markets depict the artifact of efficiency in the short to medium run. However, markets become inefficient in the longest time horizon. The findings of our study are relevant to members of the global investor community who prefer to invest in these countries. The organization of paper as

[2] Market Highlights Report for the first semester of 2015, published by the World Federation of Exchanges.

[3] BSE Annual Report 2015-16.

follows: Section 2 presents the methodological approach adopted. Section 3 relates to data. The empirical results are presented in Section 4, followed by the conclusion in Section 5.

2. Estimation Methodology

2.1. Maximum Overlap Discrete Wavelet Transform (MODWT)

Wavelets are capable of multi-resolution, that is, they can separate a signal into multi-horizon components. Splitting up a signal by the wavelet transformation technique can capture the finer details of a signal at smaller time scales (Lehkonen and Heimonen, 2014). According to Ramsey (2002), any function of time, $f(t) \in L^2(R)$, can be represented as a sequence of projections by the father ϕ and mother ψ wavelets. The long-scale smooth components are represented by the father wavelets that integrate to one. On the other hand, deviations from the smooth components are represented by mother wavelets, which integrate to zero. The scaling coefficients are generated by the father wavelets, whereas the differencing coefficients are generated by the mother wavelets.

The wavelet representation of a function $f(t) \in L^2(R)$ is defined as the linear combination of wavelet functions, as shown below:

$$f(t) = \sum_k s_{J,k}\, \phi_{J,k}(t) + \sum_k d_{J,k}\, \psi_{J,k}(t) + ... + \sum_k d_{j,k}\, \psi_{j,k}(t) + ... + \sum_k d_{1,k}\, \psi_{1,k}(t). \quad (1)$$

Eq. (1) may be simplified as

$$f(t) = S_J + D_J + D_{J-1} + ... + D_j + ... + D_1, \quad (2)$$

with the orthogonal components given by $s_J = \sum_k S_{J,k}\, \phi_{J,k}(t)$ and $D_J = \sum_k d_{j,k}\, \psi_{j,k}(t)$ for $j = 1,2,....., J$.

From Eq. (2), $(S_J, D_{J-1}, ..., D_1)$ is the resulting multiscale decomposition of $f(t)$. The j^{th} level wavelet detail that corresponds to the changes in the series w_{ij} is defined by D_j. The aggregated sum of variations at each detail scale is represented by S_J, which becomes smoother with higher levels of j (Gencay et al., 2002).

The Maximum Overlap Discrete Wavelet Transform (MODWT) is applied to calculate the scale and wavelet coefficients. The decomposition of the time-series data under consideration was done using Daubechies (a family of orthogonal wavelets) least asymmetric filter of length eight (referred as LA(8), hereafter). In comparison to Haar wavelet filters, the LA(8) filters are smoother (Gencay et al., 2002). Further, betteruncorrelated coefficients across scales are exhibited by LA(8) filters than Haar filters (Cornish et al., 2006). The decomposition of the series are done to wavelet coefficients D_1 to D_6 following Bouri et al., (2017). For the resolution of the data under investigations, scales are at 2^j to 2^{j+1}. The oscillation periods of 2-4, 4-8, 8-16, 16-32, 32-64 and 64-128 days corresponds to wavelet scales $D_1,.....,D_6$, respectively (Table 1).

Table 1. Time interpretation of different frequencies

D_1	2~4 days
D_2	4~8 days
D_3	8~16 days
D_4	16~32 days
D_5	32~64 days
D_6	64~128 days

2.2. Vector autoregression (VAR)

There is no specified lag length to build precisely the decomposed VAR model. A good model has the property of lower information loss when approximating reality (Kullback and Leibler, 1951). We used the Schwarz Information Criterion (SIC)[4] which is designed as per the log-likelihood function, penalizes for the number of parameters, and handles well the large sample sizes (Lütkepohl, 1999). According to SIC, a lag length of 6 is set for the original data-series (returns-volume).

Let *r* and *V* represent the market return calculated from the adjusted closing prices of the specified country's index and the trading volume, respectively. The bivariate VAR model of lag six (*k*) is expressed as shown in Eqs. (3) and (4):

$$r_t = a + \sum_{k=1}^{k=6} \beta_k r_{t-k} + \sum_{k=1}^{k=6} \gamma_k V_{t-k} + u_t, \text{ and} \tag{3}$$

$$V_t = \mu + \sum_{k=1}^{k=6} \delta_k r_{t-k} + \sum_{k=1}^{k=6} \varphi_k V_{t-k} + u_t. \tag{4}$$

3. Data

We analyze the daily index returns and trading volume data for China and India for the period from 4 January 2002 to 18 September 2017 and 1 January 2001 to 18

[4] The SIC takes the form of $SIC = -2\Omega / T - p\left(\log(T)/T\right)$, where *p* is the number of estimated parameters included in the model; *T* is the number of observations in the model; and Ω is the value of the log-likelihood function using the *p* estimated parameters.

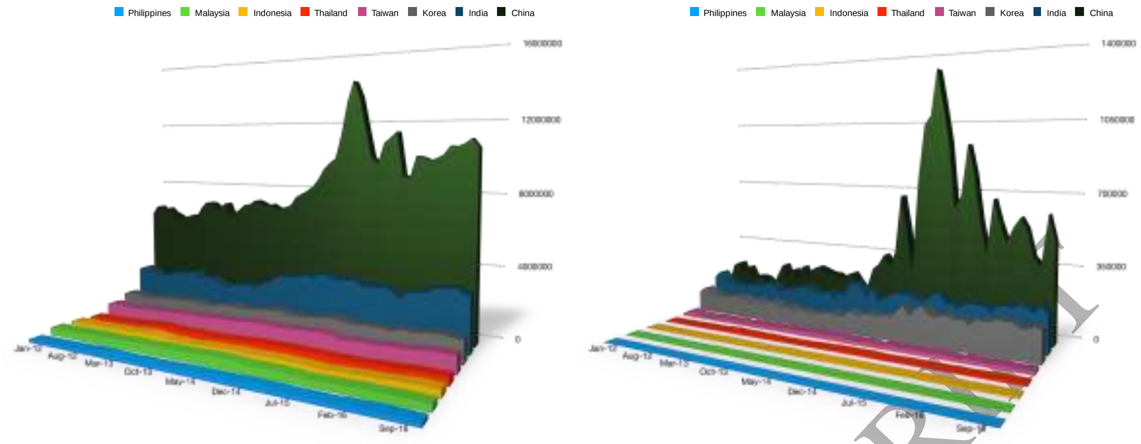
September 2017, respectively.[5] The descriptive analysis of the data set in Table 2 is presented for first logged differences of returns and trading volume and calculated as: $R_t = \ln(P_t - P_{t-1})$, where R_t represents the returns at time *t*, P_t and P_{t-1} represent the index prices at time *t* and $t-1$, respectively. The skewness coefficients are negative for all the variables except for the Chinese market's trading volume. A negative skewness signifies more frequent occurrences of negative than positive returns. In addition, all the data series under consideration are kurtosis and non-normal, as shown by the kurtosis coefficient and Jarque-Bera test results. Further, we find that the series under examination are auto-correlated since the *p*-values are significant in the Ljung-Box test. In order to test for stationarity, the augmented Dickey-Fuller and Phillips-Perron tests are used. The results show that all the time-series are stationary at the 1% level.

Table 2. Descriptive Statistics

	China		**India**	
	Returns	*Volume*	*Returns*	*Volume*
Mean	0.0002	0.0011	0.0005	-0.0003
Median	0.0007	-0.0110	0.0009	-0.0055
Minimum	-0.0926	-1.5698	-0.1181	-12.1331
Maximum	0.0903	2.1554	0.1599	12.0139
SD	0.0163	0.2226	0.0144	0.7474
Skewness	-0.4191	0.8576	-0.1401	-0.2019
Kurtosis	7.4404	9.0021	11.6678	87.3579
JB	3242.477	6187.634	13086.252	1238255.227
LB Q-stat	-60.425	-76.53	-59.862	-110.302
ADF	-60.469	-86.752	-59.705	-207.341
PP	0.0002	0.0011	0.0005	-0.0003
N	3811	3811	4176	4176

Note: The critical value of the Jarque-Bera (JB) test at 5% level is 5.99. The Ljung-Box (LB) test is performed by taking lag of 10 days. The LB Q-stat, with the corresponding *p*-values in parentheses, is reported. The *z*-statistics of ADF and PP, which stand for the Augmented Dickey-Fuller and Phillips-Perron tests for unit root, respectively, are reported.

[5] The Shanghai Composite Index (Bloomberg quote: 'SHCOMP') is considered for China, whereas BSE SENSEX (Bloomberg quote: 'Sensex') is considered for India. All data is retrieved from Bloomberg.



(a) Market Capitalization (b) Trade

Figure 1. Market capitalization and trading volume of selected Asian markets
Note: The following stock exchanges are considered China: Hong Kong Exchanges and Clearing, Shenzhen Stock Exchange, Shanghai Stock Exchange, India: Bombay Stock Exchange, National Stock Exchange, Indonesia: Indonesia Stock Exchange, Korea: Korea Exchange, Malaysia: Bursa Malaysia, Philippines: Philippine Stock Exchange, Taiwan: Taipei Exchange, Taiwan Stock Exchange, Thailand: The Stock Exchange of Thailand. The Green and denim Blue areas correspond to China and India respectively, which also represents markets with higher market capitalization and trade among all other Asian emerging markets. *Data source:* World Federation of Exchanges.

4. Empirical Results

To examine the dynamic relationship between trading volume and market returns, we first apply the MODWT process to decompose the level series. We decomposed the level series of trading volume and market returns for the Chinese and Indian markets into six orthogonal components, which range from D_1 to D_6 (i.e., from a short horizon to a long horizon; refer Table 1). Figures 2 and 3 represent the Multi-Resolution Analysis (MRA) –a method to display MODWT of order six – for the Chinese and Indian market, respectively. Second, we apply VAR on the decomposed data to get a richer picture of returns-volume causality for different time-scale horizons. We employed the VAR methodology to gauge horizon-based investor behaviour and whether it is trading volume that predicts market returns or vice versa.

The empirical results presented in Tables 3 and 4 reveal that returns and volume are not causally related in the short-time horizon (D_1, D_2) in the Indian market. In the Chinese market, there is weak evidence for return predictability through trades, but lagged trading volume is able to predict the market returns for short time horizons (2-8 days), which can be interpreted as a sign of speculative trading. The inability to predict market returns supports the Efficient Market Hypothesis (EMH), which states that stock returns cannot be predicted because the stock prices always integrate and reflect all the relevant information.

In the medium-time horizon (D_3, D_4), there is again no evidence for return predictability through lagged trading volume in Indian market, while trading volume has predictive power over market return of a moderate level. This presents evidence for the presence of hedge fund activities and involvement of market makers to provide liquidity in the market. For the Chinese market, trading volume is causing the market returns, which supports the inefficient market hypothesis. Inefficient market hypothesis mentions the deviation of asset prices from the true future discounted cash flows, and thus, creating avenues to seize excess returns. The trading volume has also been observed to cause lagged market returns in medium time horizons (8-32 days). The finding supports the overconfidence hypothesis, which is about the relationship of lagged market returns to the trading volume (Chuang and Lee, 2006; Statman et al., 2006; Griffin et al., 2007; Glaser and Weber, 2014; Liu et al., 2016).

In the long-time horizons (D_5, D_6), lagged market returns cause trading activities in both Chinese and Indian markets. On the other hand, there is moderate causality of trading on market returns in the Indian market and, moderate & strong causality of trading on returns in the Chinese market. The predictive power of trading volume over market returns again highlights the inefficient market hypothesis. The coefficients are not always positive, which suggests that the market losses also occur in long time horizons, when signals from past trades are decomposed.

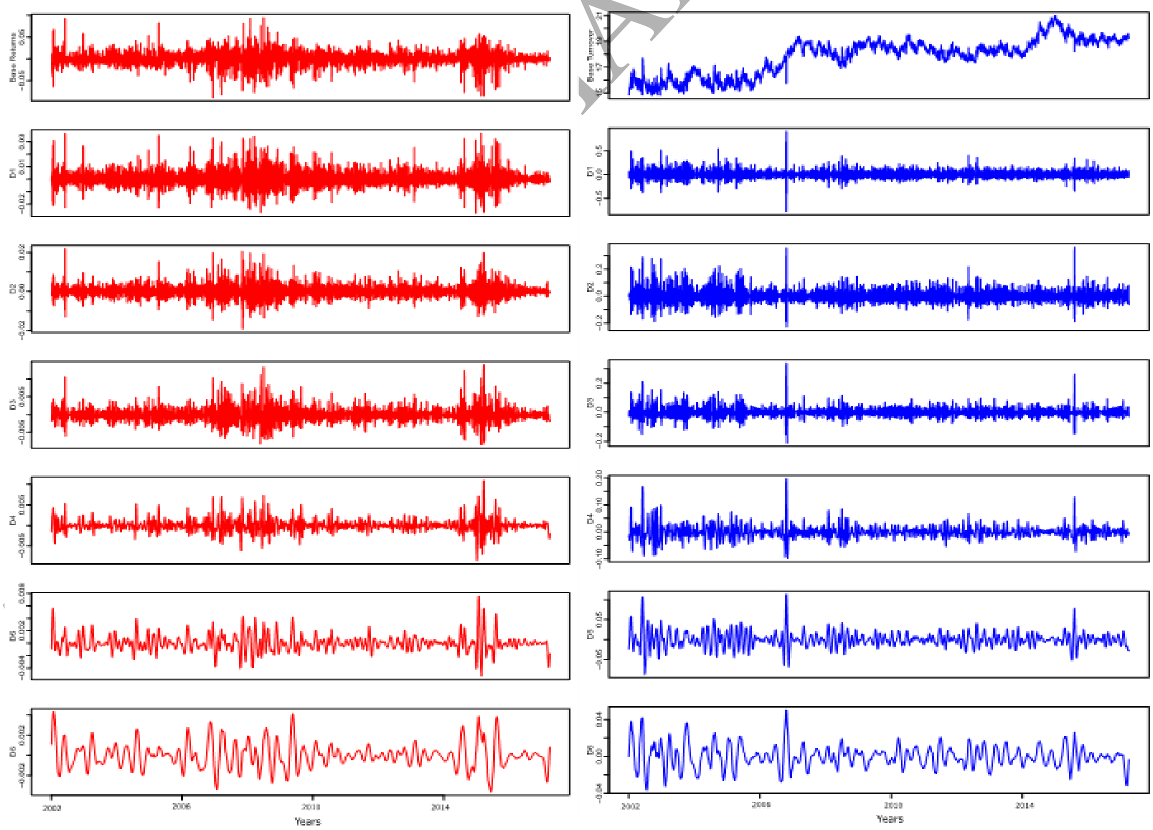


Figure 2. Plots of raw and wavelet decomposed series for returns and trading volume of China.

Note: The first row corresponds to raw series of returns and trading volume. The stock returns and trading volume are represented in red and blue color, respectively.

Table 5 presents the summary of overall results reported by MODWT-VAR based approach. From the results, it becomes apparent that the market works on EMH in the short-time horizon and reaches a stage of market inefficiency in the long run. The fact that the Chinese market is more inefficient than the Indian one may be related to the difference in the micro market structure and economies of the two countries. The results $(D_1 - D_4)$ on return predictability through trading volume is consistent with the empirical works by Campbell et al. (1993); Lee and Rui (2002); Statman et al. (2006); Chen (2012). The fact that trading activities are caused by market returns in both the Chinese and Indian markets suggest the overconfidence hypothesis, but the negative linkage suggests the involvement and operation of different types of market participants.

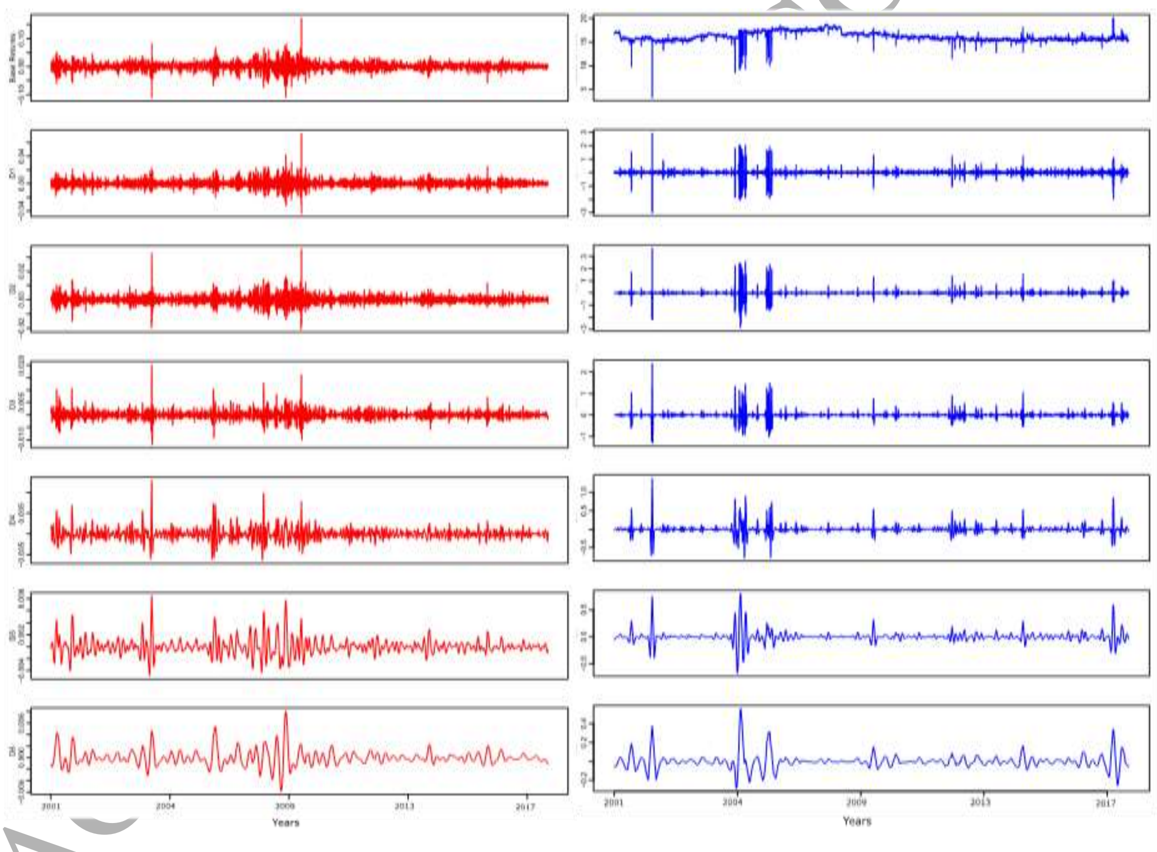


Figure 3. Plots of raw and wavelet decomposed series for returns and trading volume of India.
Note: The first row corresponds to the raw series of returns and trading volume. The stock returns and trading volume are represented in red and blue color, respectively.

Our results are consistent with Rizvi et al. (2014), which also purports that developed markets are more efficient in the short-run than long run and a similar

artifact is also depicted for the emerging markets as well. In this respect, Jennings et al. (1981) provides that the mixture of information may mislead the investors not to capture the true value of information and at later stage the true value dissipates as gradual information process which results in long-term inefficiencies. It could be the possible underlying phenomenon that governs the empirical results.

Table 3. Estimates for the wavelet decomposed-vector autoregression for China

		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$
D_1	(1)	0.0007	0.0001	-0.0007	-0.0013	-0.0025	-0.0022*
	(2)	0.9963****	1.818****	2.205****	2.551****	1.659****	0.6917***
D_2	(1)	0.001	-0.0007	0.0019	-0.0011	0.0002	-0.0002
	(2)	0.9853****	-0.9466****	1.948****	-1.276****	1.013****	-0.5037**
D_3	(1)	-0.0007	0.0008	-0.0008	-0.0008	0.0012	-0.0005
	(2)	0.9216****	-0.9610****	-0.0948	0.3684	0.2518	-0.3826**
D_4	(1)	0.0017	-0.0023	0.0056**	-0.0098****	0.0057**	-0.0003
	(2)	0.9059****	-1.412****	1.353***	-0.6673	-1.053**	1.254****
D_5	(1)	0.0001	-0.0019	0.0043	-0.0061**	0.0058**	-0.0023**
	(2)	1.187****	-1.157**	-0.7037	1.359***	-1.535***	0.965****
D_6	(1)	-0.0005	-0.0007	-0.0015	0.0029	0.0037	-0.004***
	(2)	0.756****	-1.324***	1.063**	-0.9061*	0.2967	0.1296

Note: 1. (1) denotes the equation of $r_t = a + \sum_{k=1}^{k=6} \beta_k r_{t-k} + \sum_{k=1}^{k=6} \gamma_k V_{t-k} + u_t$, and (2) denotes the equation of

$$V_t = \mu + \sum_{k=1}^{k=6} \delta_k r_{t-k} + \sum_{k=1}^{k=6} \varphi_k V_{t-k} + u_t.$$

2. **** indicates statistical significance at the 0.1% level; *** at the 1% level; ** at the 5% level; and * at the 10% level.

Table 4. Estimates for the wavelet decomposed-vector autoregression for India

		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$
D_1	(1)	0	0.0001	0.0002	-0.002	0	0.0002
	(2)	-1.441	0.4595	-0.9652	0.121	0.1933	0.1576
D_2	(1)	0	0.00002	-0.00004	-0.0001	0	-0.0001
	(2)	0.7661	1.209	-1.153	1.268	-0.2825	0.0141
D_3	(1)	0.0001	-0.0001	-0.00003	0.00007	0.00005	0.00005
	(2)	-1.471*	2.959**	-2.637**	1.771	-2.667**	1.405*
D_4	(1)	-0.0002	0.0007	-0.0008	0.00007	0.0003	-0.0002
	(2)	-2.311**	3.275*	-1.277	0.9111	-1.798	1.044
D_5	(1)	-0.0005*	0.0017**	-0.0022**	0.0013	-0.0001	-0.0001
	(2)	-1.946**	4.423***	-3.431*	2.245	-2.443	1.188
D_6	(1)	0.0005*	-0.0016**	0.002**	-0.0014	0.0004	0.00001
	(2)	-1.691*	6.259***	-8.944****	5.273**	-0.0538	-0.8442

Note: 1. (1) denotes the equation of $r_t = a + \sum_{k=1}^{k=6} \beta_k r_{t-k} + \sum_{k=1}^{k=6} \gamma_k V_{t-k} + u_t$, and (2) denotes the equation of $V_t = \mu + \sum_{k=1}^{k=6} \delta_k r_{t-k} + \sum_{k=1}^{k=6} \varphi_k V_{t-k} + u_t$.

2. **** indicates statistical significance at the 0.1% level; *** at the 1% level; ** at the 5% level; and * at the 10% level.

Table 5. Summary of results

	China		India	
	(1)	(2)	(1)	(2)
D_1	Weak	Very strong	-	-
D_2	-	Very strong	-	-
D_3	-	Very strong	-	Moderate
D_4	Strong	Very strong	-	Moderate
D_5	Moderate	Very strong	Moderate	Strong
D_6	Strong	Very strong	Moderate	Very Strong

Note: 1. (1) denotes the equation of $r_t = a + \sum_{k=1}^{k=6} \beta_k r_{t-k} + \sum_{k=1}^{k=6} \gamma_k V_{t-k} + u_t$, and (2) denotes the equation of $V_t = \mu + \sum_{k=1}^{k=6} \delta_k r_{t-k} + \sum_{k=1}^{k=6} \varphi_k V_{t-k} + u_t$.

2.**** indicates statistical significance at the 0.1% level; *** at the 1% level; ** at the 5% level; and * at the 10% level. (-) denotes non-existence of statistically significant relationship.

5. Conclusions

Our results are consistent with the mixture of distributions hypothesis where the linkage of variation in price change and volume is established presenting trading volume is the function of price change process (Clark, 1973), the variance of change in log price is the function of transaction volume, a mixing variable (Eps and Eps, 1976), and both daily price change and the trading volume are the mixture of the information variable (Karpoff, 1987; Tauchen and Pitts, 1983). Thus, the empirical research works also motivated to capture the underlying facets of price-volume dynamic relationship. Our results are inconsistent with the sequential information arrival model of Copeland (1976) in the sense of the last trader remains uninformed about the information due to gradual information process which enables first trader to revise its belief and take inputs from the information. But our results also support the finding of Jennings et al. (1981) that there may be many information arrives in the market at the same time and gradual information dissipation may happen due to mix reaction by investors who may not be able to capture the true essence of the information. The mix of optimistic and pessimistic investors (interpretation of

current information) and other variables suggests the variation between the price change and trading volume, which propounds the HMH.

References

Atje, R., Jovanovic, B., 1993. Stock markets and development. Eur. Econ. Rev. 37, 632–640.

Bouri, E., Gupta, R., Tiwari, A.K., Roubaud, D., 2017. Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Financ. Res. Lett. 1–9. doi:10.1016/j.frl.2017.02.009

Campbell, J.Y., Grossman, S.J., Wang, J., 1993. Trading Volume and Serial Correlation in Stock Returns. Q. J. Econ. 108, 905–939.

Chen, H., Lobo, B.J., Wong, W.-K., 2006. Links between the Indian, US and Chinese stock markets. Natl. Univ. Singapore, Dep. Econ. Work. Pap. 602.

Chen, S.S., 2012. Revisiting the empirical linkages between stock returns and trading volume. J. Bank. Financ. 36, 1781–1788. doi:10.1016/j.jbankfin.2012.02.003

Chin, W.C., Lee, M.C., Tan, P.P., 2017. Heterogenous market hypothesis evaluation using multipower variation volatility. Commun. Stat. Comput. 1–14.

Chordia, T., Roll, R., Subrahmanyam, A., 2002. Order imbalance, liquidity, and market returns. J. financ. econ. 65, 111–130. doi:10.1016/S0304-405X(02)00136-8

Chuang, C.-C., Kuan, C.-M., Lin, H.-Y., Cai, Z., Hong, Y., Hsu, P.-H., Mcaleer, M., Maasoumi, E., Wang, S., Zellner, A., 2009. Causality in Quantiles and Dynamic Stock Return-Volume Relations. J. Bank. Financ. 33, 1351–1360.

Chuang, W.I., Lee, B.S., 2006. An empirical evaluation of the overconfidence hypothesis. J. Bank. Financ. 30, 2489–2515. doi:10.1016/j.jbankfin.2005.08.007

Clark, P.K., 1973. A subordinated stochastic process model with finite variance for speculative prices. Econom. J. Econom. Soc. 41, 135–155.

Copeland, T.E., 1976. A model of asset trading under the assumption of sequential information arrival. J. Finance 31, 1149–1168.

Cornish, C.R., Bretherton, C.S., Percival, D.B., 2006. Maximal overlap wavelet statistical analysis with application to atmospheric turbulence. Boundary-Layer Meteorol. 119, 339–374. doi:10.1007/s10546-005-9011-y

El Hedi Arouri, M., Jawadi, F., Nguyen, D.K., 2010. The Dynamics of Emerging Stock Markets, Contributi. ed, Empirical Assessments and Implications. Springer Verlag. doi:10.1007/978-3-7908-2389-9

Eps, T.W., Eps, M.L., 1976. The stochastics dependence og security price changes and transaction volumes: Implications for the mixture of distribution hypothesis. Econometrica 44, 305–321. doi:10.2307/1912726

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. J. Finance 25, 383–417.

Gebka, B., Wohar, M.E., 2013. Causality between trading volume and returns: Evidence from quantile regressions. Int. Rev. Econ. Financ. 27, 144–159.

Gencay, R., Selcuk, F., Whitcher, B., 2002. An introduction to wavelets and other filtering methods in finance and economics, Academic Press. doi:doi:10.1201/9780203881095.fmatt

Glaser, M., Weber, M., 2014. Overconfidence and trading volume. doi:10.1007/sl07

Griffin, J.M., Nardari, F., Stulz, R.M., 2007. Do investors trade more when stocks have performed well? evidence from 46 countries. Rev. Financ. Stud. 20, 905–951. doi:10.1093/rfs/hhl019

Harris, M., Raviv, A., 1993. Differences of opinion make a horse race. Rev. Financ. Stud. 6, 473–506.

Harrison, J.M., Kreps, D.M., 1978. Speculative Investor Behavior in a Stock Market with Heterogeneous Expectations. Q. J. Econ. 92, 323. doi:10.2307/1884166

He, H., Wang, J., 1995. Differential information and dynamic behavior of stock trading volume. Rev. Financ. Stud. 8, 919–972.

Jennings, R.H., Starks, L.T., Fellingham, J.C., 1981. An Equilibrium Model of Asset Trading with Sequential Information Arrival. J. Finance 36, 143–161. doi:10.1111/j.1540-6261.1981.tb03540.x

Jlassi, M., Naoui, K., Mansour, W., 2014. Overconfidence Behavior and Dynamic Market Volatility: Evidence from International Data. Procedia Econ. Financ. 13, 128–142. doi:10.1016/S2212-

5671(14)00435-3
Kandel, E., Pearson, N.D., 1995. Differential interpretation of public signals and trade in speculative markets. J. Polit. Econ. 103, 831–872.
Karpoff, J.M., 1987. The Relation Between Price Changes and Trading Volume : A Survey. J. Financ. Quant. Anal. 22, 109–126.
Kirchgässner, G., Wolters, J., Hassler, U., 2013. Introduction to modern time series analysis. Springer.
Kullback, S., Leibler, R.A., 1951. On Information and Sufficiency. Ann. Math. Stat. doi:10.2307/2236703
Kyle, A.S., 1985. Continuous auctions and insider trading. Econom. J. Econom. Soc. 1315–1335.
Lee, B.S., Rui, O.M., 2002. The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence. J. Bank. Financ. 26, 51–78. doi:10.1016/S0378-4266(00)00173-4
Lehkonen, H., Heimonen, K., 2014. Timescale-dependent stock market comovement: BRICs vs. developed markets. J. Empir. Financ. 28, 90–103. doi:10.1016/j.jempfin.2014.06.002
Levine, R., 1997. Financial Development and Economic Growth : Views and Agenda. J. Econ. Growth XXXV, 688–726.
Levine, R., Zervos, S., 1998. Stock Markets , Banks , and Economic Growth. Am. Econ. Rev. 88, 537–558.
Liu, H.H., Chuang, W.I., Huang, J.J., Chen, Y.H., 2016. The overconfident trading behavior of individual versus institutional investors. Int. Rev. Econ. Financ. 45, 518–539. doi:10.1016/j.iref.2016.07.016
Llorente, G., Michaely, R., Saar, G., Wang, J., 2002. Dynamic volume-return relation of individual stocks. Rev. Financ. Stud. 15, 1005–1047.
Lütkepohl, H., 1999. Vector Autoregressions. Interdiscip. Res. Proj. (Discussion Pap. 4. doi:10.1257/jep.15.4.101
McMillan, D.G., 2007. Non-linear forecasting of stock returns: Does volume help? Int. J. Forecast. 23, 115–126. doi:10.1016/j.ijforecast.2006.06.002
Mensi, W., Hammoudeh, S., Tiwari, A.K., 2016. New evidence on hedges and safe havens for Gulf stock markets using the wavelet-based quantile. Emerg. Mark. Rev. 28, 155–183.
Porta, R. La, Lopez-de-Silanes, F., Shleifer, A., Vishny, R.W., 1998. Law and finance. J. Polit. Econ. 106, 1113–1155.
Ramsey, J., 2002. Wavelets in economics and finance: Past and future. Stud. Nonlinear Dyn. Econom. 6, 1–27. doi:10.2202/1558-3708.1090
Reboredo, J.C., Rivera-Castro, M.A., 2013. A wavelet decomposition approach to crude oil price and exchange rate dependence. Econ. Model. 32, 42–57. doi:10.1016/j.econmod.2012.12.028
Rizvi, S.A.R., Dewandaru, G., Bacha, O.I., Masih, M., 2014. An analysis of stock market efficiency: Developed vs Islamic stock markets using MF-DFA. Phys. A Stat. Mech. its Appl. 407, 86–99.
Schneider, J., 2009. A rational expectations equilibrium with informative trading volume. J. Finance 64, 2783–2805.
Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. Rev. Financ. Stud. 19, 1531–1565. doi:10.1093/rfs/hhj032
Tauchen, G., Pitts, M., 1983. The Price Variability-Volume Relationship on Speculative Markets. Econometrica 51, 485–505. doi:10.2307/1912002
Wang, Z., Qian, Y., Wang, S., 2017. Dynamic trading volume and stock return relation: Does it hold out of sample? Int. Rev. Financ. Anal.