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Trading volume and stock market volatility: evidence from emerging stock markets

Abstract

Based on the 'mixture of distribution' hypothesis, this paper investigates the relationship between trading volume and conditional volatility of returns by using 12 emerging stock market indices over the period between January 2000 and August 2006. The results show that when total trading volume is included in the conditional volatility equation as a proxy for information flow, a moderate level of decline in volatility persistence was observed only for two stock markets. In four stock markets the decline in conditional volatility persistence is very small. On the other hand, for the remaining markets, total trading volume is a poor proxy for information flow. The findings are consistent with the findings of prior research, which suggest that volume may be a good proxy for stock-level analysis, but not for market-level analysis. Furthermore, following Wagner and Marsh (2005) and Arago and Nieto (2005) the relationship between unexpected trading volume (surprise trading volume as an alternative proxy for information flow) and conditional volatility is analyzed. The findings illustrate that for most of the markets, the relationship between surprise volume and conditional volatility is statistically significant.

Keywords: volatility persistence, information flow, GARCH models, emerging stock markets.
JEL Classification: G14, G15.

Introduction

Two stylized facts about the empirical distribution of stock returns, conditional time varying volatility and volatility persistence have long attracted academic interest in the literature. One of the arguments used to explain conditional time varying volatility is based on the idea that returns on financial assets are generated from a mixture of distributions (MDH) in which the stochastic mixing variable is considered to be the rate of arrival of information flow into the market[1]. The MDH implies that return volatility is proportional to the rate of information arrival, thus offering an explanation for the observed heteroskedasticity in returns.

Engle's (1982) autoregressive conditional heteroskedasticity process and its extension, Bollerslev's (1986) generalized autoregressive conditional heteroskedasticity (GARCH) process have been popular models of volatility persistence. Even though these models possessed good explanatory power, they did not offer an economic explanation for this empirical phenomenon. An explanation for volatility persistence was offered later on in Lamoureux and Lastrapes (1990). They relate the observation of persistent return volatility to the mixture of distributions hypothesis and suggest that conditional volatility persistence in stock returns (the GARCH effects) may reflect serial correlation in the rate of information arrival. For a sample of US common stocks, Lamoureux and Lastrapes (1990) found that in the generalized autoregressive conditional heteroskedasticity model, GARCH effects vanished when contemporaneous volume was added to the conditional variance equation.

The idea proposed by Lamoureux and Lastrapes (1990) has been applied in the literature to both individual stocks and stock market indices. While studies that rely on individual stock data in general support Lamoureux and Lastrapes (1990) finding, reported results are much weaker for studies that use stock market indices. These findings suggest that volume may be a good proxy for stock-level analysis, but not for market-level analysis. One notable aspect of the literature is that the vast majority of studies performing a market-level analysis examined developed markets and we have limited evidence from emerging markets on this issue. Yet, as Bekaert and Harvey (2002) discuss, emerging markets research is valuable because of different institutional, legal and regulatory environments in these markets.

Based on this observation, the purpose of this paper is to provide additional evidence from emerging markets on the relation between conditional volatility and trading volume. It accordingly explores stock markets indices of 12 emerging markets over the period of 2000-2006. This will allow for a cross-sectional check of the robustness of the above finding for developed markets that trading volume seems to be a poor proxy for market-level analysis. In the analysis the attention is paid to the predictability of trading volume. While most of the studies have used total trading volume as a proxy for information flow, recent studies decompose total volume in its predictable and unpredictable components before examining its effect on conditional volatility by arguing that unexpected trading volume is a better sign of new information. To make our results comparable to those of recent studies, we report our findings with and without this decomposition.

It is found that, regarding these two issues, the evidence provided by earlier studies that examined

[1] The 'mixture of distribution' hypothesis was developed to model stock returns by Clark (1973), Epps and Epps (1976) and Tauchen and Pitts (1983).

developed markets holds in emerging markets. Specifically, trading volume seems to be a poor proxy for market-level analysis. There is some evidence that unexpected trading volume is a proxy for the arrival of new information in the context of mixture of distributions hypothesis.

The remainder of the paper is organized as follows. The next section lists existing findings in the literature. The second section introduces the data and methodology used in the study. The third section contains the empirical results. The last section provides the concluding remarks.

1. Literature

Lamoureux and Lastrapes (1990) idea has found wide application in the literature. The findings of these subsequent studies are particularly important for two reasons. First, they suggest that, while testing stock market efficiency, the heteroskedasticity of the returns must be taken into consideration (Lo and MacKinlay, 1989; Islam and Khaled, 2005). Second, they suggest that estimated return variance is one of the important factors in the option pricing model (Black and Scholes, 1972).

One of the early studies is Brailsford (1996). It tests the relationship between total trading volume and conditional volatility using the Australian stock market index over the period from 1989 to 1993. They conclude that including total trading volume in the conditional volatility model reduces the GARCH effect notably; indicating that total trading volume is a suitable proxy for information flow.

Phylaktis et al. (1996) examine the relationship between total trading volume and conditional volatility in the Athens Stock Exchange over the period from 1988 to 1993. They divide the sample period into two sub-periods with respect to size of the market to examine and compare the relationship between total trading volume and conditional volatility. They find that total trading volume is a good proxy for information flow, since the GARCH effect decline after total trading volume is included in the model. Comparing the results for the two periods, Phylaktis et al. (1996) find that, as the size of the market increases, the information content of trading volume also increases.

Sharma et al. (1996) examine the NYSE index over the period between 1986 and 1989. They find that the inclusion of volume in the conditional volatility model gives rise to a notable reduction but not to a complete disappearance of the GARCH effects. Their results are weaker than those of Lamoureux and Lastrapes (1990). Sharma et al. (1996) attribute this to volume being a poor proxy for the news arrival that contributes conditional heteroskedasticity to market-wide returns. Their argument is based on the difference between an individual stock and a market portfolio regarding the extent to which systematic and firm-specific factors affect their volume and return volatility. Both factors affect both volume and return volatility for individual stocks. While both factors affect market volume, only systematic factors affect market index volatility.

Pyun et al. (2000) provide firm-level evidence using 15 individual stocks listed in the Korean Stock Market from 1990 to 1994. Their paper analyzes the relationship between volatility spillover and information flow for firms with different sizes. The authors report that total trading volume reduces the GARCH effect and volatility spillover occurs only from large to small firms, not vice versa.

Employing the same method and sample period as Lamoureux and Lastrapes (1990), Omran and McKenzie (2000) analyze the relationship between total trading volume and volatility persistence for 50 UK stocks. Even though their results are consistent with Lamoureux and Lastrapes (1990), diagnostic tests show that their GARCH model cannot fully capture the volatility persistence in their data.

Miyakoshi (2002) investigates the effects of total trading volume on conditional volatility persistence for both individual stocks and the market index of the Tokyo Stock Exchange. The results show that trading volume reduces the GARCH effect, both for individual stocks and the market index. The results are consistent with the view that total trading volume is a good proxy for information flow.

Bohl and Henke (2003) analyze the relationship for 20 Polish stocks between January 4, 1999 and October 31, 2000. They observe a decline in conditional volatility persistence after including total trading volume in the model. They argue that their results are consistent with the previous studies done in developed stock markets.

Finally, Wang et al. (2005) examine the relationship between total trading volume and volatility for both Chinese individual stocks and the stock market index. They find that trading volume can be a proxy for information flow for individual stocks, but not for the market indices. The reason for this is asynchronous information arrivals for each firm listed in the index.

Unlike the previous studies outlined above, Wagner and Marsh (2005) and Arago and Nieto (2005) use unexpected trading volume (surprise volume) as a proxy for information flow and examine its relationship with conditional volatility for developed stock markets.

Wagner and Marsh (2005) analyze the relationship by using seven major stock market indices (those of France, Germany, Holland, Hong Kong, Japan, the UK, and US) over the period between 1988 and 1997. They find that there is a significant positive relationship between surprise trading volume and conditional volatility, and that including surprise trading volume in the model gives rise to a moderate decrease in volatility persistence. Moreover, they observe that there is an asymmetric relationship between surprise volume and conditional volatility, meaning that compared to negative surprise volume positive surprise volume has a significantly greater effect on conditional volatility.

Arago and Nieto (2005) also use unexpected trading volume as a proxy for the information flow to investigate the changes in conditional volatility persistence by using seven major stock market indices (those of France, Germany, the UK, the US, Italy, Japan, Spain, and Switzerland) between 1995 and 2000. However, Arago and Nieto's results conflict with Wagner and Marsh's. The inclusion of neither total volume nor its predictable and unpredictable components leads to a considerable reduction in volatility persistence.

The evidence regarding the adequacy of trading volume as a proxy for information arrival as reported by studies that performed a stock-level analysis can be summarized as follows. After including total trading volume in the model, in general, there is: (1) either a considerable or complete reduction in Garch effects (US, Polish and Korean stocks), (2) a considerable reduction in Garch effects (Chinese stocks), (3) a moderate reduction in Garch effects (Japanese stocks).

On the other hand, the evidence from studies that performed a market-level analysis can be summarized as follows. After including total trading volume in the model, there are: (1) considerable reduction in Garch effects (stock market index of Greece), (2) little or no reduction in Garch effects (stock market indices of: Australia, China, France, Germany, Holland, Hong Kong, Italy, Japan, Spain, Switzerland, UK, US).

As can be seen from the summary above, out of 12 markets for which a market-level analysis has been done, only two are emerging one (China and Greece). Moreover, the evidence indicates that volume may be a good proxy for stock-level analysis, but not for market-level analysis. Note that the evidence from Japan and China, the two markets for which we have both stock and market-level analyses, is in line with the conclusion above. Among other things, this summary indicates the need for more evidence from emerging markets.

2. Data and methodology

The data set for 12 emerging stock markets was gathered from Datastream. Out of these markets, four are Latin American (Colombia, Mexico, Peru and Venezuela), two Eastern European (Czech Republic, and Hungary), one African (South Africa), and five Asian (Indonesia, South Korea, Singapore, Sri Lanka, and Taiwan)[1].

The variables in the data set are Datastream's daily stock market indices and daily trading volumes for the period from January 3, 2000 to August 15, 2006. The stock market indices are adjusted for the capital increases, dividend payments and stock splits. The daily market returns, R_t, are calculated as the logarithmic first differences of the daily closing values of the stock indices. Total trading volume, V_t, is the logarithm of trading volume, as measured by the number of shares traded daily.

The unexpected trading volume is calculated as in Arago and Nieto (2005) by taking the differences between total and expected trading volumes to be used as a proxy for new information flow. In order to be able to estimate expected trading volume, $V_{t,exp}$, the following ARMA(p, q) model is used:

$$V_t = \sum_{h=1}^{p} \theta_h V_{t-h} + \sum_{i=1}^{q} {}_i\varepsilon_{t-i} + DUM_t + \varepsilon_t, \quad (1)$$

where V_t – total trading volume on day t; ε_t – residual on day t; DUM – dummy variables used to eliminate day of the week effect: $p = 1,2,\ldots,5$ and $q = 1,2,\ldots,5$.

For each index, total trading volume data during the first 120 days (approximately until 06/30/2000) are used to choose the optimal ARMA(p,q) model[2]. After choosing the optimal p and q values for each market index, expected trading volume is estimated using a rolling window which drops the first observation and adds one more observation to the sample. Thus, the data set for the expected trading volume, $V_{t,exp}$, and the unexpected trading volume, $V_{t,unexp}$, (which is the difference between total trading volume, V_t, and expected trading volume, $V_{t,exp}$) covers the period between July 1, 2000 and August 15, 2006[3]. Descriptive statistics for return, total trading volume, expected trading volume and unexpected trading volume are presented in Table 1[4].

[1] These markets are charactarized as emerging by ISI Emerging Markets.
[2] To choose the optimal model (p and q values) for each index, Akaike Information Criteria (AIC) were employed.
[3] Due to public holidays, the exact date for the beginning of the sample period was different for each market index.
[4] Stationarity of the series is tested using the Augmented Dickey-Fuller (ADF) tests and the results show that the series are stationarity.

Table 1. Descriptive statistics

		Mean	Std. dev	Skewness	Kurtosis	Jarque-Bera	Q(12)	Observation number
Latin America								
Colombia	Return	0.0012	0.0110	-0.1263	20.6777	19444.24***	108.14***	1493
	Total trading volume	22.9387	2.1339	-0.2251	2.1324	59.43***	10730.00***	
	Unexpected trading volume	0.0364	1.0818	0.2077	7.2277	1122.58***	16.24	
Mexico	Return	0.0006	0.0107	-0.1034	5.4447	388.75***	41.74***	1550
	Total trading volume	25.1106	0.5197	-1.0065	6.6786	1135.67***	1702.10***	
	Unexpected trading volume	0.0092	0.4483	-0.8510	8.8064	2364.43***	17.53	
Peru	Return	0.0005	0.0082	-1.3282	16.9521	12859.47***	29.81***	1530
	Total trading volume	21.8076	0.9054	0.4516	4.0828	126.76***	1728.90***	
	Unexpected trading volume	-0.0018	0.7750	0.7381	5.3006	476.34***	12.88	
Venezuela	Return	0.0008	0.0112	0.4790	11.4760	4398.97***	90.49***	1451
	Total trading volume	22.3691	1.2488	-0.1036	3.7280	34.64***	1846.90***	
	Unexpected trading volume	-0.0064	1.1064	0.1801	3.8565	52.19***	16.17	
Eastern Europe								
Czech Republic	Return	0.0007	0.0125	-0.2319	5.6489	464.35***	8.77	1541
	Total trading volume	21.6573	0.7406	-0.1568	3.4310	18.24***	4722.90***	
	Unexpected trading volume	0.0167	0.5369	-0.5081	4.9101	300.55***	18.70	
Hungary	Return	0.0004	0.0134	-0.1019	4.4417	135.95***	19.69*	1539
	Total trading volume	21.9561	0.5268	-0.3265	3.5201	44.69***	1860.80***	
	Unexpected trading volume	0.0087	0.4606	-0.2192	4.0980	89.63***	9.56	
Asia								
Indonesia	Return	0.0005	0.0155	-0.6435	7.9249	1608.61***	27.88***	1490
	Total trading volume	26.6029	0.7867	0.0252	2.4666	17.82***	6220.50***	
	Unexpected trading volume	0.0144	0.5134	0.1874	3.2641	13.05***	18.33	
South Korea	Return	0.0003	0.0185	-0.3736	5.9789	593.44***	13.76	1510
	Total trading volume	25.7084	0.7104	0.7195	3.0351	130.37***	10314.00***	
	Unexpected trading volume	0.0007	0.3619	0.0879	6.7417	882.78***	17.13	
Singapore	Return	0.0001	0.0101	-0.1895	5.3245	356.38***	24.34***	1542
	Total trading volume	25.9580	0.5025	-0.1850	2.7518	12.75***	7028.80***	
	Unexpected trading volume	0.0056	0.3032	0.3568	4.8161	244.61***	10.28	
Sri Lanka	Return	0.0008	0.0155	-0.1499	39.3248	80494.26***	55.55***	1464
	Total trading volume	21.3565	1.2588	-0.3308	2.9227	27.07***	5608.90***	
	Unexpected trading volume	-0.0111	0.9038	0.5411	4.1456	151.48***	17.62	
Taiwan	Return	-0.0002	0.0168	-0.0664	5.3934	362.73***	20.26*	1515
	Total trading volume	27.9025	0.4353	0.0831	2.9979	1.75	6783.50***	
	Unexpected trading volume	*-0.0007*	*0.2705*	*0.3442*	*3.8865*	*79.53****	*18.25*	

Table 1 (cont.). Descriptive statistics

		Mean	Std. dev	Skewness	Kurtosis	Jarque-Bera	Q(12)	Observation number
Africa								
South Africa	Return	0.0006	0.0105	-0.2618	5.8441	534.18***	23.74**	1533
	Total trading volume	24.9139	0.3947	-0.5549	5.8690	604.45***	1409.40***	
	Unexpected trading volume	0.0085	0.3267	-0.0599	6.4180	747.16***	13.45	

Notes: In the table, 'Return' refers to daily logarithmic return of stock market indices. 'Total trading volume' is calculated as the logarithm of the number of shares traded in a day. 'Unexpected trading volume' is calculated as the difference between total trading volume and expected trading volume. Q(12), Ljung-Box statistic up to 12 lags measures serial correlation in series. *, **, and *** refer to 10, 5, and 1 percent statistical significance levels respectively.

Table 1 shows that the mean of daily returns ranges between -0.02% (stock market index of Taiwan) and 0.12% (stock market index of Colombia), and the standard deviation between 0.82% (stock market index of Peru) and 1.85% (Korean stock market index). The Jarque-Bera (1980) normality test shows that all return distributions are non-normal. Finally, Ljung-Box statistics up to 12 lags (Q(12)) indicates that all of the total trading volume series display serial correlation. We select GARCH (p,q) (Bollerslev, 1986) type models[1], as suggested by Lamoureux and Lastrapes (1990), to investigate the relationship between trading volume and volatility. In the first model (Model I), persistence in conditional volatility is examined with the following equations:

Model I:

$$R_t = c + \varphi R_{t-1} + \lambda \sigma_t + \varepsilon_t , \quad (2)$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}^- , \quad (3)$$

where R_t – Logarithmic return on day t; σ_t – conditional standard deviation on day t; ε_t – residual term in the mean equation; I_{t-1}^- – dummy variable, equal to 1 if $\varepsilon_{t-1} < 0$, and 0 otherwise.

The mean equation contains a constant, an AR(1) term, and the contemporaneous conditional standard deviation. The AR(1) term accounts for the time dependence in return due to nonsynchronous trading (Najand and Yung, 1991; Sharma et al., 1996; and Miyakoshi, 2002). The conditional standard deviation is also included to allow time-varying risk premium (Engle et al., 1987; Gennotte and Marsh, 1993).

In the conditional volatility equation, α_i and β_j refer to the coefficients of squared residuals lagged by i period(s) and conditional variance lagged by j period(s), respectively. A special type of GARCH model developed by Glosten et al. (1993) (GARCH-GJR(p,q)) is used to allow asymmetric effects of good and bad news on conditional variance. In model I, if γ is greater than zero, then bad news increases volatility more than good news (leverage effect).

To measure the effects of total trading volume on conditional volatility persistence, the first model is modified by adding total trading volume into the conditional variance equation. Thus the second model is characterized by the following conditional variance equation:

Model II:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}^- + \quad V_t . \quad (4)$$

Finally, since some of the studies in the literature (such as Bessembinder and Seguin, 1993; and Wagner and Marsh, 2005) support the use of unexpected trading volume (surprise volume) rather than total trading volume as a proxy for new information flow, both expected trading volume ($V_{t,exp}$) and unexpected trading volume ($V_{t,unexp}$) are included into the third model (Model III) as explanatory variables. A dummy variable (D_t) is also added to the model to treat potential asymmetry (Bessembinder and Seguin, 1993; and Wagner and Marsh, 2005). This takes on the value of one when the unexpected trading volume is positive and zero otherwise. If there is an asymmetry in trading volume, the effect of positive volume shocks on the conditional volatility equation is expected to be greater than the effect of the negative ones (ϑ>0).

Model III:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 +$$

$$+ \gamma \varepsilon_{t-1}^2 I_{t-1}^- + \mu V_{t,exp} + \psi V_{t,un\,exp} + \quad D_t , \quad (5)$$

[1] For the stock market index of Singapore, the GARCH(1,1) model could not eliminate autocorrelation in the residuals. For that reason, GARCH (p,q) models with p and q values greater than 1 were used.

The models are estimated by the method of the maximum likelihood with the Marquardt optimization algorithm. It is assumed that the conditional distribution of the error term has Generalized Error Distribution (GED).

3. Results

The results for the benchmark model (Model I) are presented in Table 2. They show that volatility persistence, as measured by the sum of all GARCH coefficients ($\sum_{j=1}^{q}\beta_j + \sum_{i=1}^{p}\alpha_i$), is high for all market indices and takes values of more than 0.70 and even 1.0 for the stock markets of Colombia and Peru. A similar finding is reported in Phylaktis et al. (1996). This finding implies not only high volatility persistence but also non-stationarity in the variance of stock market index returns for Colombia and Peru.

Table 2. Results of estimating GARCH-GJR(p,q) model (Model I).

In the table, α_1, α_2, β_1, β_2 and γ represent estimated parameters of Model I:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}^-$$

	α_1	α_2	$\sum_{i=1}^{p}\alpha_i$	β_1	β_2	$\sum_{j=1}^{q}\beta_j$	$\sum_{j=1}^{q}\beta_j+\sum_{i=1}^{p}\alpha_i$	γ
Latin America								
Colombia	0.394(5.30)***		0.394	0.614(13.55)***		0.614	1.008	-0.060(0.72)
Mexico	0.007(0.42)		0.007	0.884(37.83)***		0.884	0.891	0.143(4.91)***
Peru	0.063(4.66)***		0.063	0.948(95.47)***		0.948	1.011	0.063(4.66)***
Venezuela	0.434(4.18)***		0.434	0.295(3.28)***		0.295	0.728	-0.443(4.20)***
Eastern Europe								
Czech Republic	0.036(1.62)		0.036	0.850(32.62)***		0.850	0.885	0.036(1.62)
Hungary	0.046(2.91)***		0.046	0.884(38.71)***		0.884	0.930	0.046(2.91)***
Asia								
Indonesia	0.060(2.08)**		0.060	0.759(15.21)***		0.759	0.819	0.136(3.29)***
South Korea	0.015(1.04)		0.015	0.935(62.47)***		0.935	0.950	0.076(4.40)***
Singapore	0.021(0.96)	0.069(2.25)**	0.113	0.502(4.62)***	0.238(2.10)**	0.859	0.972	0.105(4.37)***
Sri Lanka	0.409(5.16)***		0.409	0.556(10.98)***		0.556	0.965	0.023(0.22)
Taiwan	0.024(1.97)**		0.024	0.947(83.25)***		0.947	0.971	0.051(3.07)***
Africa								
South Africa	0.020(1.21)		0.020	0.874(44.14)***		0.874	0.894	0.140(5.34)***

Notes: In the conditional volatility equation, α_i and β_j refer to the coefficients of the squared residuals lagged by i period(s) and the conditional variance lagged by j period(s) respectively. I^-_{t-1} is a dummy variable, which is equal to one if ε_{t-1} is negative and zero otherwise. t-statistics are in parentheses. *, **, and *** refer to 10, 5, and 1 percent statistical significance levels respectively. For the stock market index of Singapore, since p>2 and q>2, only α_1, α_2, β_1 and β_2 coefficients are listed.

As expected, there is a leverage effect (γ>0) in eight out of the 12 market indices (Mexico, Peru, Hungary, Indonesia, South Korea, Singapore, Taiwan and South Africa). This result is consistent with Wagner et al. (2005) and Arago and Nieto (2005), which find a leverage effect in almost all of the stock market indices included in their data sets. Surprisingly, negative leverage effect is observed in the stock market index of Venezuela, which means that bad news generates less volatility than good news. There is no leverage effect in the remaining three market indices.

Table 3. Results of estimating GARCH-GJR(p,q)-Total Trading Volume Model (Model II).
In the table, α_1, α_2, β_1, β_2, γ, and φ represent estimated parameters of Model II:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}^- + \varphi V_t$$

	α_1	α_2	$\sum_{i=1}^{p}\alpha_i$	β_1	β_2	$\sum_{j=1}^{q}\beta_j$	$\sum_{j=1}^{q}\beta_j+\sum_{i=1}^{p}\alpha_i$	γ	φ
Latin America									
Colombia	0.371(5.00)***		0.371	0.573(10.69)***		0.573	0.945	0.371(5.00)***	0.011(2.35)**
Mexico	0.004(0.24)		0.004	0.893(41.93)***		0.893	0.897	0.141(5.08)***	0.030(2.93)***
Peru	0.060(3.93)***		0.060	0.937(69.17)***		0.937	0.997	0.060(3.93)***	0.007(1.80)*
Venezuela	0.187(4.18)***		0.187	0.772(16.06)***		0.772	0.959	-0.189(4.11)***	-0.008(0.59)
Eastern Europe									
Czech Republic	0.034(1.47)		0.034	0.842(30.56)***		0.842	0.876	0.034(1.47)	0.020(1.63)
Hungary	0.020(0.84)		0.020	0.731(18.39)***		0.731	0.752	0.020(0.84)	0.260(7.17)***
Asia									
Indonesia	0.060(2.05)**		0.060	0.768(14.87)***		0.768	0.827	0.130(0.00)	-0.012(0.71)
South Korea	0.003(0.27)		0.003	0.907(44.88)***		0.907	0.910	0.108(4.44)***	0.111(3.92)***
Singapore	0.010(0.35)	0.059(1.22)	0.069	0.529(0.95)	0.834(1.68)*	0.874	0.943	0.083(2.00)**	-0.001(0.45)
Sri Lanka	0.184(4.14)***		0.184	0.602(17.82)***		0.602	0.787	0.050(1.16)	0.197(163.11)***
Taiwan	0.012(1.04)		0.012	0.947(81.89)***		0.947	0.959	0.072(4.33)***	0.040(9.13)***
Africa									
South Africa	0.032(1.80)*		0.032	0.847(44.66)***		0.847	0.879	0.032(1.80)*	-0.009(21.96)***

Notes: α_i and β_j are the coefficients of the squared residuals lagged by i period(s) and the conditional variance lagged by j period(s) respectively. I^-_{t-1} is a dummy variable which is equal to one if ε_{t-1} is negative, and zero otherwise. V_t refers to total trading volume, which is the logarithm of trading volume as measured by the number of shares traded during the day. t-statistics are provided in parentheses. *, **, *** represent 10, 5, and 1 percent significance levels, respectively. For the stock market index of Singapore, since p>2 and q>2, only α_1, α_2, β_1 and β_2 coefficients are listed.

Table 3 reports the estimation results of the second model (Model II), where total trading volume is used as a proxy for information flow. They show that total trading volume has a statistically significant positive effect on the conditional volatility of seven out of 12 emerging market indices (Columbia, Mexico, Peru, Hungary, South Korea, Sri Lanka, and Taiwan). The GARCH coefficients are still statistically significant and for all the markets volatility persistence is more than 0.70. The inclusion of trading volume produces a moderate reduction in volatility persistence for Hungary and Sri Lanka. For the remaining markets the change is small.

For four stock market indices (Venezuela, Czech Republic, Indonesia, and Singapore), the coefficient estimate of total trading volume is insignificant and thus evidence from these markets does not support even the mixture of distributions hypothesis, namely the static relation between information arrival and volatility. Furthermore, surprisingly, there is a significant negative relationship between total trading volume and conditional volatility for the stock market index of South Africa. Regarding the leverage effect the results from Model II are very similar to those from Model I.

Overall, the results in Table 3 show that the inclusion of total trading volume helps in explaining conditional volatility persistence to a moderate extent for two markets and to a small extent for four markets. For the remaining markets total trading volume as a proxy for information flow cannot explain even the conditional heteroskedasticity in market returns. These findings are consistent with those in Sharma et al. (1996) and thus give support to their argument that volume may be a good proxy for stock-level analysis, but not for market-level analysis.

Table 4. Results of estimating GARCH-GJR(p,q)-Unexpected Trading Volume Model (Model III). In the table, α_1, α_2, β_1, β_2, γ, μ, ψ, and ϑ represent estimated parameters of Model III:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}^- + \mu V_{t,\exp} + \psi V_{t,un\exp} + \vartheta D_t$$

	α_1	α_2	$\sum_{i=1}^{p}\alpha_i$	β_1	β_2	$\sum_{j=1}^{q}\beta_j$	$\sum_{j=1}^{q}\beta_j+\sum_{i=1}^{p}\alpha_i$	γ	μ	ψ	θ	$\mu=\psi$
Latin America												
Colombia	0.356 (5.25)***		0.356	0.580 (11.16)***		0.580	0.936	-0.022 (0.27)	0.016 (2.95)***	-0.027 (2.05)**	0.033 (1.09)	9.949(0.00)***
Mexico	0.001 (0.06)		0.001	0.878 (38.72) ***		0.878	0.879	0.159 (5.45)*	0.010 (0.62)	0.041 (1.31)	0.036 (0.96)	0.652 (0.42)
Peru	0.043 (2.62)***		0.043	0.928 (49.34)***		0.928	0.971	-0.023 (1.26)	0.004 (0.82)	0.009 (0.46)	0.036 (1.27)	0.060 (0.81)
Venezuela	0.410 (4.02)***		0.410	0.235 (2.66)***		0.235	0.645	-0.419 (4.00)***	-0.100 (2.50)**	0.138 (2.78)***	-0.015 (0.12)	12.886 (0.00)***
Eastern Europe												
Czech Republic	0.052 (2.04)**		0.052	0.782 (22.45)***		0.782	0.834	0.148 (3.53)***	-0.043 (2.48)**	0.174 (3.22)***	0.098 (1.54)	11.822 (0.00)***
Hungary	0.014 (0.72)		0.014	0.791 (25.36)***		0.791	0.805	0.014 (0.72)	0.157 (3.56)***	0.231 (3.35)***	0.183 (2.13)**	0.738 (0.39)
Asia												
Indonesia	0.008 (0.27)		0.008	0.535 (8.85)***		0.535	0.543	0.008 (0.27)	-0.079 (1.62)	0.735 (5.39)***	0.190 (0.98)	50.391 (0.00)***
South Korea	0.015 (1.17)		0.015	0.927 (51.52)***		0.927	0.942	0.106 (4.99)***	0.090 (3.71)***	0.179 (1.04)	0.145 (1.51)	0.267 (0.61)
Singapore	0.018 (0.88)	0.078 (2.28)**	0.292	0.216 (1.69)	0.182 (1.23)	0.543	0.835	0.065 (1.64)	-0.152 (4.52)***	0.304 (3.91)***	0.126 (2.02)**	24.677 (0.00)***
Sri Lanka	0.323 (4.29)***		0.323	0.440 (8.58)***		0.440	0.763	0.142 (1.34)	0.040 (1.95)*	0.045 (1.22)	0.392 (3.95)***	0.010 (0.92)
Taiwan	0.00 6(0.47)		0.006	0.937 (69.21)***		0.937	0.943	0.096 (4.37)***	0.019 (1.02)	0.324 (2.49)***	-0.015 (0.02)	5.762 (0.01)***
Africa												
South Africa	0.019 (1.12)		0.019	0.875 (46.08)***		0.875	0.894	0.019 (1.12)	-0.037 (1.44)	0.076 (1.47)	0.000 (0.00)	3.345 (0.07)*

Notes: α_i and β_j are the coefficients of the squared residuals lagged by i period(s) and the conditional variance lagged by j period(s) respectively. Γ_{t-1} is a dummy variable, which is equal to one if ε_{t-1} is negative, and zero otherwise. $V_{t,exp}$ refers to expected trading volume. $V_{t,unexp}$ is unexpected trading volume, which is the difference between total trading volume and expected trading volume. D_t is a dummy variable, which is equal to one if unexpected trading volume is positive, and zero otherwise. Except for the last column ($\mu=\psi$), in all of the columns t-statistics are in parentheses. In the last column, Wald test results for the hypothesis of $\mu=\psi$ are presented and p-values are in parentheses. *, **, *** represent 10, 5, and 1 percent significance levels, respectively. For the stock market index of Singapore, since $p>2$ and $q>2$, only α_1, α_2, β_1 and β_2 coefficients are listed.

In the final model (Model III), conditional volatility equation includes both expected and unexpected trading volumes. As Table 4 shows, the estimated coefficient on unexpected trading volume is statistically significant for most of the stock markets in the sample (seven out of 12). Except for the Colombian Stock Market, the direction of relationship between unexpected trading volume and conditional volatility is positive in those markets. Moreover, there is some evidence regarding the existence of an asymmetric relationship between unexpected trading volume and conditional volatility. For three market indices (Hungary, Singapore, and Sri Lanka) positive unexpected trading volume generates more volatility than negative unexpected trading volume ($\vartheta>0$). However, for the remaining indices, this term is insignificant. For three of the market indices (Mexico, Peru, and South Africa), the coefficient estimate on neither expected trading volume nor unexpected trading volume is statistically significant, meaning that expected trading volume and unexpected trading volume cannot explain conditional volatility. For all of the markets (except Colombia) the coefficient on unexpected trading volume is greater than that on expected trading volume. As reported in the table, the Wald test rejects the null hypothesis of the equality of coefficients on expected and unexpected trading volume for seven stock markets. Overall, the results in Table 4 suggest that for the six markets where the coefficient on unexpected volume is significantly positive, unexpected volume indeed appears to be a proxy for new information arrival consistent with the mixture of distributions hypothesis. Since it has no serial correlation by construction, it cannot explain GARCH effects.

Finally, in order to check the robustness of our findings, a series of diagnostic tests are also carried out. The results are presented in Table 5. For the three models, the null hypothesis of no autocorrelation is tested by Ljung-Box tests on the level and squared residual series with 12 lags (Q(12) and $Q^2(12)$, respectively). These results show that except for the level residuals of the Sri Lanka stock market in Model II, the null hypothesis of no autocorrelation on the level and squared residuals cannot be rejected at the five percent significance level for all models and emerging market indices. The Lagrange multiplier test (LM(5)) is used to test for the existence of the ARCH effect. The results reveal that there is no ARCH effect in the residuals at the five percent significance level either.

Table 5. Diagnostic tests for Model I, Model II and Model III.

Q(12), $Q^2(12)$ are Ljung-box tests on the level and squared residuals series with 12 lags. They are distributed with a $\chi 2$ (12) under the null of no autocorrelation; LM(5) is the Engle's (1982) Lagrange multipliers test for the existence of ARCH effects. It is distributed with a $\chi 2$ (5) under the null of no autocorrelation. P-values are in parentheses.

$$R_t = c + \phi R_{t-1} + \lambda \sigma_t + \varepsilon_t$$

Model I: $$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}^-$$

Model II: $$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}^- + \varphi V_t$$

Model III: $$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}^- + \mu V_{t,\exp} + \psi V_{t,un\exp} + \vartheta D_t$$

	MODEL I			MODEL II			MODEL III		
	Q(12)	$Q^2(12)$	LM(5)	Q(12)	$Q^2(12)$	LM(5)	Q(12)	$Q^2(12)$	LM(5)
Latin America									
Colombia	17.917 (0.08)	6.894 (0.81)	0.786 (0.56)	15.827 (0.15)	5.279 (0.92)	0.628 (0.68)	17.020 (0.10)	5.134 (0.92)	0.659 (0.65)
Mexico	12.479 (0.33)	11.733 (0.38)	0.774 (0.57)	12.584 (0.32)	12.988 (0.29)	0.697 (0.63)	13.547 (0.26)	12.801 (0.31)	0.727 (0.6)
Peru	16.710 (0.12)	14.772 (0.19)	1.962 (0.08)	16.544 (0.12)	12.319 (0.34)	1.596 (0.16)	15.329 (0.17)	9.646 (0.56)	1.270 (0.27)
Venezuela	14.276 (0.22)	9.827 (0.55)	0.218 (0.95)	10.736 (0.47)	3.532 (0.98)	0.417 (0.84)	12.557 (0.32)	12.085 (0.36)	0.230 (0.95)
Eastern Europe									
Czech Republic	7.396 (0.77)	10.523 (0.48)	1.430 (0.21)	7.419 (0.76)	10.116 (0.52)	1.405 (0.22)	7.665 (0.74)	11.258 (0.42)	1.582 (0.16)
Hungary	13.551 (0.26)	5.826 (0.89)	0.714 (0.61)	12.995 (0.29)	18.102 (0.08)	1.067 (0.38)	12.441 (0.33)	15.993 (0.14)	1.297 (0.26)

Table 5 (cont.). Diagnostic tests for Model I, Model II and Model III

	MODEL I			MODEL II			MODEL III		
	Q(12)	$Q^2(12)$	LM(5)	Q(12)	$Q^2(12)$	LM(5)	Q(12)	$Q^2(12)$	LM(5)
Asia									
Indonesia	8.532 (0.67)	8.874 (0.63)	0.184 (0.97)	8.477 (0.67)	8.714 (0.65)	0.183 (0.97)	13.918 (0.24)	17.131 (0.10)	0.732 (0.60)
South Korea	10.851 (0.46)	10.851 (0.46)	0.541 (0.75)	12.684 (0.32)	12.448 (0.33)	0.661 (0.65)	12.051 (0.36)	11.336 (0.42)	0.623 (0.68)
Singapore	15.262 (0.17)	5.205 (0.92)	0.512 (0.77)	15.513 (0.16)	5.217 (0.92)	0.486 (0.79)	16.767 (0.12)	4.785 (0.94)	0.529 (0.75)
Sri Lanka	10.535 (0.48)	1.786 (1.00)	0.116 (0.99)	51.924 (0.00)	1.817 (1.00)	0.226 (0.95)	11.565 (0.40)	1.887 (1.00)	0.093 (0.99)
Taiwan	8.237 (0.69)	11.486 (0.40)	1.693 (0.13)	7.489 (0.76)	10.407 (0.49)	1.204 (0.30)	7.721 (0.74)	11.789 (0.38)	1.393 (0.22)
Africa									
South Africa	13.030 (0.29)	12.405 (0.33)	1.127 (0.34)	12.629 (0.32)	12.983 (0.29)	1.067 (0.38)	12.823 (0.31)	11.559 (0.40)	0.960 (0.44)

Conclusion

This study investigates the effect of trading volume on the conditional volatility persistence of 12 emerging stock market index returns between January 3, 2000 and August 15, 2006 by using Lamoureux and Lastrapes (1990) methodology. The results reveal the following:

All stock markets indices in the sample display a high degree of volatility persistence. When trading volume is included in the conditional variance equation, as a proxy for information flow, some small to moderate level reduction is observed in the volatility persistence of six stock market indices. This finding is consistent with the argument in Sharma et al. (1996) that volume may be a good proxy for stock-level analysis, but not for market-level analysis.

The use of unexpected and expected volume instead of total volume in the conditional variance equation gives some support to the argument that unexpected volume acts as a proxy for new information arrival consistent with the mixture of distributions hypothesis. Since unexpected volume has no serial correlation by construction, it cannot be expected to explain GARCH effects in index returns.

Finally, two effects documented earlier by research on developed markets, namely the leverage effect and the existence of asymmetry in the contemporaneous relation between trading volume and volatility, are confirmed in emerging markets.

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