The stock volatility-volume relationship in Canada and France.

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Abstract: - This paper investigates the stock volatility-volume relation in Canada and France for the period 1992-2002. In this study the 'total' trading volume is separated into the expected and the unexpected volume. Further, in addition to the absolute value of the returns and their squares we use the conditional volatilities from two GARCH-type models as alternative measures of stock volatility. The following observations, among other things, are noted about the volume-volatility causal relationship. First, for France there is a bidirectional feedback between volume and volatility whereas in Canada there is strong evidence of causality running only from volatility to volume. Second, we find substantial cross-country interactions and an influential role for volatility. Third, in most cases these causal relationships are positive and robust to the measures of volume and volatility used. However, the positive volume-volatility relationship is stronger for expected volume than for 'total' and unexpected volumes.

Key-words: - Bidirectional feedback, stock volatility, trading volume.

1 Introduction

This paper investigates the stock volatility-volume relation in the Canadian and French markets. In particular, we use Granger causality tests to examine the dynamic relation between daily stock price volatility and trading volume. Causality tests can provide useful information on whether knowledge of past trading volume movements improves short-run forecasts of current and future movements in stock price volatility, and vice versa (see Brooks, 1998). Although there have been numerous empirical studies that have examined the relationship between trading volume and stock volatility, these studies have focused almost exclusively on the US markets. There is a relative scarcity of literature investigating the relation in the less well-developed markets. Following Lee and Rui (2002) we examine the causal relations not only for domestic stock markets but also for cross-country markets using the data of the Canadian and French stock markets. Moreover, in this research the 'total' trading volume is separated into the expected and the unexpected volume whereas most previous research investigated 'total' volume. Further, in addition to the two most commonly used measures of stock volatility-that is the absolute value of the returns and their squares-we use the conditional volatilities from two alternative GARCH-type models. These models can mimic two stylized empirical facts of stock market volatility: (i) volatilities are highly persistent, and (ii) volatility responds to price movements asymmetrically.

This study provides strong empirical support for the argument made among others by Brooks (1998) that daily stock price volatility and trading volume are intertemporally related. Hence, instead of focusing only on the univariate dynamics of stock price volatility one should study the joint dynamics of stock price volatility and trading volume. Moreover, as Bessembinder and Seguin (1993) point out, it is important to distinguish between expected and unexpected trading volume. The following observations, among other things, are noted about the volume-volatility causal relationship. First, for the entire period from 1992 to 2002, in France there is a strong bidirectional feedback between volume and volatility whereas in Canada there is strong ev-

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idence of causality running only from volatility to volume. These causal relationships are robust to the measures of volatility used. Second, regarding the cross-country relationships the Canadian (French) volatility in three (two) out of the four cases affects French (Canadian) volume significantly. Third, although the above results are not qualitatively altered by changes in the measure of volume,' the volume-volatility relationship is weaker for unexpected volume than for expected volume. Finally, when we examine the sign of effects of a variable on the other variable common response patterns emerge from the two stock markets. That is, in most cases the causal relations are positive.

The remainder of this paper is organized as follows. Section 2 provides a summary of existing theories and empirical evidence. Section 3 outlines the data which are used in the empirical tests of this paper. Section 4 lays out our econometric model and reports and discusses our results. Section 5 contains summary remarks and conclusions.

2 Prior research

This section reviews previous research on the relation between stock price changes and trading volume. There are several explanations for the presence of a causal relation between stock price volatility and trading volume. According to various mixtures of distributions models there is a positive relation between current stock return variance and trading volume. The sequential information arrival models also suggest that lagged absolute stock returns could have predictive power for current trading volume and vice versa. Harris and Raviv (1993) assume that traders receive common information but differ in the way in which they interpret it. Their model predicts that absolute price changes and trading volume are positively correlated. Brailsford (1996) points out that a positive correlation between the trading volume, returns and variance may be inferred from the fact that the trading volume and both the level and variance of returns exhibit similar U-shaped patterns during the trading day.

In what follows we summarize several empirical studies that investigate the relationship between stock price and trading volume or between volatility and volume. In a survey paper Karpoff (1987) finds that 18 of the 19 empirical investigations that examine the relationship between absolute price change and volume report a positive correlation. Bhagat and Bhatia (1996) test for causality in both the mean and the variance and demonstrate that price changes lead volume. Brooks (1998), employing both linear and non linear Granger causality tests, provides extensive evidence of bidirectional feedback between volume and volatility. He used the square of the day's return as a measure of the Dow Jones stock returns volatility. Lee and Rui (2002) show that there exists a positive feedback relationship between trading volume and return volatility in the three largest stock markets.

Although there has been extensive research into the empirical and theoretical aspects of the stock price volatility-volume relation, most of this research has focused on the well-developed financial markets, usually the US markets. However, some studies have examined the volatility-volume relation in markets outside of the United States. In particular, Brailsford (1996) uses both the squared returns and the absolute value of the returns as measures of volatility. He provides support for a positive relationship between trading volume and volatility for the Australian stock market. Saatcioglou and Starks (1998) employ Latin America stock data and document a positive relation between volume and both the price changes and their magnitude. Chen et al. (2001) find a positive correlation between trading volume and the absolute value of the stock price change for nine major stock markets. Some recent studies have examined the price-volume relation in the Korean stock market. For example, Karanasos and Kim (2004) examine whether the financial crisis affects the dynamic interaction between volume and volatility and show that it is important to distinguish between domestic and foreign investors' trading volume.

3 Measurement issues

3.1 Data and sample periods

The data set used in this study comprises daily trading volume and closing prices of the TSX Composite Index (Canada) and CAC 40 Index (France), running from 2 January 1992 to 30 December 2002. The data were obtained from the datastream. Daily stock returns (r_t) are measured by the daily difference of the log prices (p_t) [$r_t = \log(\frac{p_t}{p_{t-1}}) \times 100$].

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3.2 Volume

The measures of trading volume used in this paper are the daily total French (in Euro) and Canadian (in Canadian dollars) value of shares traded. The value of shares is used as the measure of trading volume in this study because the number of shares does not take into account the relative market value of the individual shares. Brailsford (1996) employs three different measures of trading volume (number of transactions, number of shares traded and value of shares traded) and argues that the number of shares traded is the least preferred measure of trading volume and should be avoided in future research. Stationarity in the trading volume series is induced by detrending the series by dividing by a 100-day moving average of the value of shares traded and then taking the natural logarithm (see Brooks, 1998).

Moreover, as Lee and Rui (2002) point out, an important distinction in investigating the volatility-volume relationship may be to distinguish between expected and unexpected trading volume. For example, Bessembinder and Seguin (1993) find that the effect of changes in expected volume on stock volatility is much lower than the impact of an unanticipated volume shock. Accordingly, to assess whether the volume-volatility relation differs for forecastable versus surprise components of volume we decompose each volume series into two components. To compute expected and unexpected trading volume, we use autoregressive models with 13 and 15 lags for Canada and France respectively. We use the regression residuals as unexpected volume and the rest as expected volume.

3.3 Volatility

In what follows, we use three different measures of stock volatility. The most commonly used measure is the squared return series (see Brooks, 1998, and the references therein). Second, we use the absolute value of the return series (see Saatcioglou and Starks, 1998). Brailsford (1996) uses both the absolute value of the returns and their squares as a measure of volatility. Lee and Rui (2002) point out that the results from their causality tests between trading volume and volatility measured by a GARCH(1,1) model were very similar to those with squared returns. Hence, as a third measure we use the estimated volatility from two alternative GARCH-type models. These are the fractional integrated asymmetric power ARCH (FIAPARCH) model proposed by Tse (1998) and the fractionally integrated exponential GARCH (FIEGARCH) model defined in Bollerslev and Mikkelsen (1996).

Next, we define the mean equation of stock returns (r_t) as

$$r_t = c + \varepsilon_t + \theta\varepsilon_{t-1}.$$

That is stock returns follow an MA(1) specification. We also assume that ε_t is conditionally normal with mean zero and variance h_t. Put differently, $\varepsilon_t|\Omega_{t-1} \sim N(0, h_t)$, where Ω_{t-1} is the information set up to time $t-1$. First, we use the FIEGARCH(1,1) model, proposed by Bollerslev and Mikkelsen (1996)

$$\ln(h_t) = \omega + \frac{(1+\alpha L)}{(1-\beta L)(1-L^d)}[\gamma e_t + \eta(|e_t| - \mathsf{E}|e_t|)],$$

where $\omega > 0$, and $e_t \equiv \varepsilon_t/\sqrt{h_t}$. Second, we use the FIAPARCH(1,1) model introduced by Tse (1998)

$$h_t^{\delta} = \omega + \left[1 - \frac{(1-\alpha L)}{(1-\beta L)(1-L)^d}\right](|\varepsilon_t| + \gamma\varepsilon_t)^{\delta},$$

where $\delta, \omega > 0$, and $|\gamma| < 1$.

We estimate the various GARCH models using quasi maximum likelihood estimation (QMLE). Estimates of the GARCH parameters are shown in Table 1. Several findings emerge from this table. For the four fractionally integrated models the estimated long memory parameter is in the range $0.351 < \widehat{d} < 0.781$. In the FIEGARCH models the estimates for the fractional differencing parameters ($\widehat{d}$) are relatively large and are statistically significant. Further, negative shocks predict higher volatility than positive shocks, since in all four cases the estimated asymmetry coefficient ($\widehat{\gamma}$) is significant and negative. For France the value of the power coefficient ($\widehat{\delta}$) is less than but not significantly different from two. That is, the conditional variance is a linear function of lagged squared residuals. In sharp contrast, for Canada the power term is not significantly different from unity. Thus, it seems that the conditional standard deviation is a linear function of lagged absolute residuals. Generally speaking, the parameter estimates support the idea that long memory effects are present in stock volatility. The results also show strong evidence of asymmetry in the conditional variance.

Table 1: Two alternative GARCH models.

	FIEGARCH		FIAPARCH	
	FR	CAN	FR	CAN
$\hat{c}$	0.02 [0.01]	0.09 [0.01]	0.01 [0.01]	0.04 [0.15]
$\hat{\theta}$	0.03 [0.02]	0.17 [0.02]	0.03 [0.02]	0.16 [0.34]
$\hat{\omega}$	−1.19 [0.29]	−1.06 [0.28]	0.02 [0.01]	0.07 [0.04]
$\hat{\alpha}$		1.62 [0.75]	0.26 [0.07]	0.19 [0.12]
$\hat{\beta}$	0.38 [0.18]	−0.46 [0.29]	0.57 [0.13]	0.60 [0.21]
$\hat{\gamma}$	−0.06 [0.02]	−0.08 [0.03]	−0.46 [0.15]	−0.53 [0.30]
$\hat{\eta}$	0.16 [0.05]	0.16 [0.04]		
$\hat{d}$	0.78 [0.06]	0.72 [0.05]	0.35 [0.10]	0.48 [0.19]
$\hat{\delta}$			1.65 [0.30]	1.25 [0.38]

Notes: This table reports QMLE parameter estimates for two alternative GARCH(1,1) models. Standard errors are given in brackets.

3.4 Unit root tests

We also test for the stationarity properties of our data using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The results of these tests (not reported), imply that we can treat the various stock volatility series and detrended trading volume series as stationary processes.

4 Granger causality tests

The following bivariate autoregression is used to test for causality between the trading volume and stock return volatility

$$x_t = \sum_{i=1}^{5} a_i x_{t-i} + \sum_{i=1}^{5} b_i y_{t-i} + e_t,$$
$$y_t = \sum_{i=1}^{5} c_i x_{t-i} + \sum_{i=1}^{5} d_i y_{t-i} + v_t,$$

where e_t and v_t are i.i.d processes with zero mean and constant variance. The optimal lag length (5) of the system is determined by utilizing the Akaike (AIC) and Schwarz (SIC) information criteria. The test of whether $y(x)$ strictly Granger causes $x(y)$ is simply a test of the joint restriction that all the $b_i(c_i)$, $i = 1, \ldots, 5$, are zero. In each case, the null hypothesis of no Granger causality is rejected if the exclusion restriction is rejected. Bidirectional feedback exists if all the elements b_i, c_i, $i = 1, \ldots, 5$, are jointly significantly different from zero.

Next we report the results of Granger causality tests to provide some statistical evidence on the nature of the relationship between trading volume and stock volatility. We first perform Wald tests and in Table 2 we report the F statistics of Granger causality tests using five lags, as well as the sign of the effect in case of statistical significance.[1] Panel A considers Granger causality from trading volume to stock volatility. Panel B reports the results of the causality tests where causality runs from the stock volatility to the trading volume.

For France, there is strong evidence of a bidirectional feedback between volume and volatility. This causal relationship is robust to the measure of volatility used. However, we find that the trading volume does not Granger-cause 'FIAPARCH' volatility and that it is independent of changes in squared returns. Moreover, in Canada there is strong evidence of causality running only from volatility to volume. This confirms the difficulty of improving the predictability of volatility by adding public information about trading volume. These results are not qualitatively altered by changes in the measure of volatility. However, when we use the absolute returns as a measure of stock volatility we find that volume has a weak impact on stock volatility.

Next, we investigate causal relations among trading volume and volatility across the Canadian and French stock markets. Overall, we find substantial cross-country interactions and an influential role for volatility. In particular, the Canadian (French) volatility in three (two) out of the four cases has a mild impact on French (Canadian) volume. There is a lack of a causal effect only of 'FIAPARCH' Canadian (French) volatility to French (Canadian) volume. This finding has an important implication. For example, the evidence of causality running from the Canadian volatility to the French volume suggests that it may be possible to use lagged values of Canadian volatility to predict French volume. In sharp contrast, the French (Canadian) volatility in almost all the cases is independent of changes in Canadian (French) volume. However, the French volume affects the Canadian absolute returns weakly.

[1] Figures showing dynamic effects based on impulse responses are available upon request.

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Table 2: Granger causality tests between trading volume and stock volatility.

	$\lvert r_t\rvert$	r_t^2	AP	EXP
Panel A				
(H_0:$VLM_{CA} \nrightarrow VLT_{it}$)				
i =CA	2.09 *(+)	0.86	1.59	0.94
i =FR	0.48	0.37	0.51	0.43
(H_0: $VLM_{FR} \nrightarrow VLT_{it}$)				
i =FR	2.55 **(+)	2.82 **(−)	1.51	2.80 **(+)
i =CA	2.11 *(+)	1.01	0.77	1.24
Panel B				
(H_0:$VLT_{CA} \nrightarrow VLM_{it}$)				
i =CA	2.20 **(+)	1.61 (+)	2.02 *(+)	2.66 **(+)
i =FR	2.82 **(+)	1.65 (+)	1.31	2.81 **(+)
(H_0:$VLT_{FR} \nrightarrow VLM_{it}$)				
i = FR	1.74 (+)	1.18	2.93 **(+)	3.20 ***(+)
i = CA	2.47 **(−)	1.80 *(+)	1.19	1.54

Notes: $VLM_{it} \nrightarrow VLT_{it}$: Trading volume does not Granger-cause stock volatility. $VLT_{it} \nrightarrow VLM_{it}$: Stock volatility does not Granger-cause trading volume. VLM_{it} is the detrending trading volume. VLT_t is the stock volatility as measured by either the absolute value of returns ($|r_t|$), or their squares (r_t^2) or the estimated conditional variance from one of the two alternative GARCH type models (AP and EXP denote the 'FIAPARCH' and 'FIEGARCH' volatilities respectively). ***,**,* and ⁻ denote significance at the 0.01, 0.05,0.10 and 0.15 levels, respectively. A +(-) indicates that the dynamic effect based on impulse responses is positive (negative).

The above results are not qualitatively altered by changes in the measure of volume. Table 3 reports the causal relations between stock volatility and expected trading volume. For France we find a feedback relation between expected volume and volatility whereas in Canada there is strong evidence of causality running only from volatility to expected volume. In addition, the Canadian volatility affects the French expected volume strongly. These causal relationships are robust to the measure of volatility used. Moreover, the French volatility in two out of the four cases has a significant impact on the Canadian expected volume. We should also mention that the volume-volatility relationship is weaker for 'total' volume than for expected volume.

Furthermore, Table 4 presents the causal relations between stock volatility and unexpected trading volume. In most of the cases the results from the causality tests between volatility and unexpected volume are very similar to those between volatility and expected volume. However, in France the unexpected volume is independent of changes in both absolute and squared returns and it does not Granger-cause the 'FIAPARCH' volatility. In addition, in Canada there is a lack of a causal effect of squared returns to unexpected volume. In sum, the volume-volatility relationship is stronger for expected volume than for unexpected volume.

Finally, as Lee and Rui (2002) point out, once we establish causal relations it is natural to examine the sign of effects of a variable on the other variable. In particular, we examine the response of volatility (volume) to a one-standard deviation shock in volume (volatility). Some common response patterns emerge from the two stock markets. In most cases the causal relations are positive. In sharp contrast, for France the expected trading volume has a negative impact on volatility. In sum, there is strong evidence of a positive volume-volatility relationship.

Table 3. Granger causality tests between expected trading volume and volatilility.

	$\lvert r_t\rvert$	r_t^2	AP	EXP
Panel A				
(H_0:$VLM_{CA} \nrightarrow VLT_{it}$)				
i =CA	1.56	0.55	0.93	1.64 (+)
i =FR	1.24	1.55	1.37	1.46
(H_0: $VLM_{FR} \nrightarrow VLT_{it}$)				
i =FR	2.76 **(−)	3.13 ***(−)	1.81 *(−)	2.50 **(−)
i =CA	1.37	0.43	0.78	0.65
Panel B				
(H_0:$VLT_{CA} \nrightarrow VLM_{it}$)				
i =CA	13.80 ***(+)	7.56 ***(+)	2.41 **(−)	6.20 ***(−)
i =FR	2.88 **(+)	1.81 *(+)	2.17 **(+)	3.96 ***(+)
(H_0:$VLT_{FR} \nrightarrow VLM_{it}$)				
i =FR	11.40 ***(+)	4.94 ***(+)	7.05 ***(+)	9.12 ***(+)
i =CA	2.36 **(+)	1.47	1.76 (+)	1.53

Table 4: Granger causality tests between unexpected trading volume and volatility.

	$\|r_t\|$	r_t^2	AP	EXP
Panel A				
(H_0:$VLM_{CA} \nrightarrow VLT_{it}$)				
i =CA	1.94 *(+)	0.68	1.68 (+)	0.87
i =FR	0.33	0.48	0.46	0.48
(H_0: $VLM_{FR} \nrightarrow VLT_{it}$)				
i =FR	1.81 *(+)	1.88 *(−)	1.12	2.46 **(+)
i =CA	2.56 **(+)	1.12	0.56	1.15
Panel B				
(H_0:$VLT_{CA} \nrightarrow VLM_{it}$)				
i =CA	1.77 (+)	1.39	1.79 (−)	2.71 **(+)
i =FR	3.09 ***(+)	1.93 *(+)	1.38	2.93 **(+)
(H_0:$VLT_{FR} \nrightarrow VLM_{it}$)				
i =FR	1.41	0.78	2.36 **(+)	2.76 **(+)
i =CA	2.28 **(−)	1.71 (+)	1.02	1.32

5 Conclusions

In this paper, we have examined the dynamic causal relations between stock volatility and trading volume for the Canadian and French markets. For the overall period from 1992 to 2002 we found that in France there is a bidirectional feedback between volume and volatility while in Canada there is strong evidence of causality running only from volatility to volume. These causal relationships are robust to the measure of volatility used. In addition we found substantial cross-country interactions and an influential role for volatility. In particular, the Canadian (French) volatility in three (two) out of the four cases has a mild impact on French (Canadian) volume. These results are not qualitatively altered by changes in the measures of volume. However, the volume-volatility relationship is stronger for expected volume than for unexpected volume. Further, we have examined the response of volatility (volume) to a one-standard deviation shock in volume (volatility). Some common response patterns emerge from the two stock markets. In most cases the causal relations are positive.

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