THE EMPIRICAL RELATIONSHIP BETWEEN STOCK RETURNS, RETURN VOLATILITY AND TRADING VOLUME ON THE AUSTRIAN STOCK MARKET

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- - -   November 2003   - - -

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Abstract

This study investigates the empirical relationship between stock returns, return volatility and trading volume using data from the Austrian stock market. We find only weak support for a contemporaneous as well as dynamic relationship between stock returns and trading volume, implying that forecasts of one of these variables cannot be improved by knowledge of the other. On the other hand, our results indicate that there is a strong contemporaneous relationship between return volatility and trading volume. Additionally we find that return volatility contains information about upcoming trading volume by applying Granger's test for causality.

JEL-Classification: C32; G14

Keywords: Stock returns; Return Volatility; Trading Volume; GARCH cum volume; Granger causality

1 INTRODUCTION

Empirical investigations on stock markets traditionally focus primarily on stock prices and their behaviour over time. Based on the available set of information about a company, its stock price reflects investors' expectations on the future performance of that firm. The arrival of new information causes investors to adapt their expectations and is the main source for price movements.

However, since investors are heterogeneous in their interpretations of new information, prices may remain unchanged even though new information is revealed to the market. This will be the case if some investors interpret it as good news whereas others find it to be bad news. Changes in prices therefore reflect the average reaction of investors to news.

On the other hand, stock prices may only change if there is positive trading volume. As with prices, trading volume and volume changes mainly reflect the available set of relevant information on the market. Unlike stock prices, however, a revision in investors' expectations always leads to an increase in trading volume which therefore reflects the sum of investors' reactions to news. Studying the joint dynamics of stock prices and trading volume therefore improves the understanding of the microstructure of stock markets.

Based on the above, a body of literature has examined the empirical relationship between trading volume and stock returns. Karpoff (1987), Hiemstra/Jones (1994), Brailsford (1996) and Lee/Rui (2002) investigated the relationship between trading volume and price changes per se, mainly using index prices. The results of these studies are different, although a positive relationship is mainly reported.

The association between stock return volatility and trading volume was analyzed by Karpoff (1987), Brock/LeBaron (1996), and Lee/Rui (2002). Recently, stochastic time series models of conditional heteroscedasticity have been applied to explore this relationship (see Lamoureux/Lastrapes (1990), Andersen (1996), Brailsford (1996), Gallo/Pacini (2000) and Omran/McKenzie (2000)). The studies mostly conclude that there is evidence for a strong relationship (contemporaneous as well as dynamic) between return volatility and trading volume. However, Darrat/Rahman/Zhong (2003) using intraday data from DJIA stocks reported evidence of only significant lead/lag relations but not of contemporaneous correlation between return volatility and trading volume.

Our study is the first to analyze the relation between stock returns, return volatility and trading volume for the Austrian stock market. Unlike most other studies on that issue, we use individual stock data instead of index data. In addition, our investigations cover not only contemporaneous but also dynamic (causal) relationships. Our results indicate that on average there is only a weak association in either direction between stock returns and trading volume on the Austrian stock market. This implies, i.a., that knowledge of trading volume cannot improve short-run return forecasts. On the other hand, we find strong support for the hypothesis of a positive relationship between return volatility and trading volume. Most interestingly, return volatility precedes trading volume in many cases.

The paper is organized as follows: In section 2 we present our data and section 3 discusses some basic statistics and preliminary results. In section 4 we investigate the contemporaneous relationship between stock returns, return volatility and trading volume and section 5 extends our analysis by examining dynamic (causal) relationship. Section 6 (finally) concludes the paper.

2 DATA

Our data set comprises daily market price and trading volume series for 31 companies listed on the Austrian stock market. The investigation covers the period 06/2000 - 04/2003. The companies were selected due to their membership of the ATX Prime on April 30th, 2003. The ATX Prime is a market-capitalization weighted stock index that tracks the total return performance of all securities traded in the prime market segment of the Vienna Stock Exchange and serves as a benchmark for institutional investors.

We included all those companies that have been quoted in the ATX Prime for at least 100 trading days over the period under study. All data are derived from the Vienna Stock Exchange and from Bloomberg. Continuously compounded stock returns are calculated from daily stock prices at close, adjusted for dividend payouts and stock splits.

To measure stock trading volume we compute the daily turnover ratio which is defined as the daily number of shares traded divided by the total number of shares outstanding. Since this ratio is very small ($< 10^{-3}$) in the majority of cases we multiplied each realization by 1,000.

3 Basic Statistics and Preliminary Results

3.1 Descriptive Statistics

We started our investigation with some basic descriptive analysis of the time series of stock returns and trading volume. The mean daily stock return across the whole sample equals –0.025% with a standard deviation of 1.9%. The 'fat-tailed and highly-peaked' stylized fact that is often reported for return series is mostly present in our data. The mean (median) excess kurtosis is 7.23 (4.32) and ranges from 27.38 (RHI AG) to 0.85 (Immofinanz AG). Return skewness is highest for Wolford AG (1.44) and lowest for Do&Co AG (–1.40) with an average of 0.06 across the whole sample. Applying Jarque-Bera test for normality we additionally find strong support for the hypothesis that return time series do not come from a normal distribution. When looking at the autocorrelation function we find about 60% of the return series to exhibit no significant serial correlation. The remaining series show significant low-order autocorrelation.

Unlike stock returns, return volatility as well as trading volume commonly feature strong persistence in their times series. By means of Ljung-Box test statistics for first to twelfth-order autocorrelation we found strong support for the hypothesis that trading volume is serially correlated. In accordance with the stylized facts of volume series listed by Andersen (1996) our volume data show high non- normality (positive excess kurtosis and skewed to the right). In addition, we find that log-values of trading volume can be assumed to follow a normal distribution.

To proxy return volatility we use squared values of daily stock returns. These time series display the usual time dependency of stock returns in the second order moment (volatility persistence) implying, i.a., that returns cannot be assumed to be i.i.d. We take this fact into account in our further analysis.

3.2 Cross-Correlation Analysis

As a first step to investigate the relationship between stock return and volume data we simply calculate cross-correlation coefficients *Corr* for all companies:

$$Corr\,[R_t, V_t] = Cov\,[R_t, V_t]/(SD[R_t] \cdot SD[V_t]), \qquad (3.1)$$

where R_t (V_t) stands for stock return (trading volume) on day t, *Cov* denotes covariance and *SD* abbreviates standard deviation. From Panel A of Table 1 we find that there is only a weak contemporaneous correlation between stock return levels and trading volume. Note that the correlation is also weak if one computes *Corr* between stock returns and lagged (lead) trading volume.

Table 1. Cross-correlation coefficients between stock returns, return volatility and trading volume

Panel A: $Corr\,(R_t, V_{t-j})$					
	$j = -2$	$j = -1$	$j = 0$	$j = 1$	$j = 2$
Min	–0,13	–0,14	–0,13	–0,04	–0,12
1. Quartil	–0,05	0,00	0,04	0,02	–0,01
Median	0,01	0,02	0,07	0,06	0,03
3. Quartil	0,06	0,05	0,13	0,08	0,04
Max	0,15	0,32	0,55	0,31	0,12

Panel B: $Corr\,(R_t^2, V_{t-j})$					
	$j = -2$	$j = -1$	$j = 0$	$j = 1$	$j = 2$
Min	–0,03	–0,05	0,00	–0,03	–0,05
1. Quartil	0,06	0,11	0,27	0,08	0,04
Median	0,10	0,19	0,36	0,13	0,08
3. Quartil	0,15	0,24	0,40	0,16	0,10
Max	0,33	0,64	0,56	0,37	0,31

On the other hand, Panel B of Table 1 indicates that there is a positive contemporaneous relationship between trading volume and return volatility, the latter being proxied by squared returns. Of additional interest, we find an asymmetry in that cross-correlation around lag 0. This is in accordance with the findings by Brock/LeBaron (1996).

Taken together, the results from table 1 can be seen as a first indication that higher trading volume is typically accompanied with an increase in return volatility but is uncorrelated with the direction of price changes. Additionally we find that volatility might precede trading volume. These findings will be further evaluated in sections 4 and 5.

3.3 TESTING FOR UNIT ROOT

To test for the contemporaneous as well as causal relation between trading volume, stock returns and return volatility, we use a Vector Autoregressive (VAR) model that can be sensitive to non-stationarities. Therefore we check the hypothesis whether the time series of stock returns and trading volume can be assumed to be stationary by using augmented Dickey-Fuller (ADF) test. This test is based on the regression:

$$\Delta y_t = \mu + \gamma \cdot y_{t-1} + \sum_{i=1}^{p} \delta_i \cdot \Delta y_{t-i} + \varepsilon_t \, , \tag{3.2}$$

where y stands for stock return and trading volume, respectively, μ, γ and δ are model parameters and ε_t is a white noise variable.

The unit root test is carried out by testing the null hypothesis $\gamma = 0$ against the one-sided alternative $\gamma < 0$. Unfortunately the *t*-Student-statistic of the estimated parameter γ does not have a conventional *t*-distribution under the null hypothesis of a unit root. Instead we use the critical values recommended by Charemza/Deadman (1997). If the ADF *t*-statistic for γ lies to the left of these values, the null hypothesis can be rejected.

Conducting ADF tests for each company's time series of stock returns and trading volume we find the parameter γ to be negative and statistically significant at the sensible levels. Hence we come to the conclusion that both time series can be assumed to be invariant with respect to time.

4 CONTEMPORANEOUS RELATIONSHIP

4.1 STOCK RETURNS AND TRADING VOLUME

The empirical procedure in this section further tests the contemporaneous relationship between stock returns and trading volume. We apply the multivariate model proposed by Lee/Rui (2002) which is defined by the two equations:

$$R_t = \alpha_0 + \alpha_1 \cdot V_t + \alpha_2 \cdot V_{t-1} + \alpha_3 \cdot R_{t-1} + \varepsilon_t \, ; \tag{4.1}$$

$$V_t = \beta_0 + \beta_1 \cdot R_t + \beta_2 \cdot V_{t-1} + \beta_3 \cdot V_{t-2} + \xi_t \, . \tag{4.2}$$

α_i and β_i (i = 0, …,3) are the model parameters and ε_t and ξ_t, respectively, denote white noise variables. To estimate the model parameters we apply the two-stage least square method (2SLS).

Our findings corroborate our early inferences that there is almost no evidence of a contemporaneous relationship between stock returns and trading volume. The parameters α_1 and α_2 in equation (4.1) are essentially insignificant at the 5% level and there is no clear trend whether the signs of these parameters are positive or negative. The same is true for parameter β_1 in equation (4.2), although this parameter is found to be significant in 9 out of 31 cases.

Since the majority of our return series exhibit no serial correlation we find parameter α_3 in equation (4.1) to be significant in only 12 cases. In contrast, the strong time dependency of trading volume time series is documented by highly significant parameters β_2 and β_3 (equation (4.2)).

Although we find stock return levels and trading volume to be mostly uncorrelated that does not mean that there is no relationship between that market data at all. It is often reported that price fluctuations tend to increase if there is high trading volume, especially in times of bullish markets. That is, there might be a relation between higher order moments of stock returns and trading volume.

We investigated this by extending a model proposed by Brailsford (1996) which relates trading volume to squared stock returns by the following regression[1]:

$$V_t = \alpha_0 + \phi_1 \cdot V_{t-1} + \phi_2 \cdot V_{t-2} + \alpha_1 \cdot R_t^2 + \alpha_2 \cdot D_t \cdot R_t^2 + \varepsilon_t \ . \qquad (4.3)$$

D_t denotes a dummy variable that equals 1 if the corresponding return R_t is negative and 0 otherwise. Note that the estimate of parameter α_1 measures the relationship between return volatility and trading volume irrespective of the direction of the price change. The estimate of α_2, however, measures the degree of asymmetry in that relationship. Applying ML-method to estimate equation (4.3) we find parameter α_1 to be positive and significant over the whole sample. Parameter α_2 has a negative sign in 24 cases, where 17 estimates are significantly different from 0. These findings strongly support our earlier hypothesis that higher trading volume is associated with an increase in stock return volatility and that this relationship is more pronounced when stock prices increase. Good news (increasing prices) therefore induces more trading volume than bad news (declining prices), which is also consistent with the conjectures from behavioral finance (see e.g. Ritter (2003)).

4.2 Conditional Volatility and Trading Volume

The finding of a contemporaneous relationship between trading volume and squared stock returns raises the question whether trading activity can be identified as one potential source for the observed serial dependence (persistence) in return volatility. This is motivated by the theoretical works on the *Mixture of Distribution Hypothesis (MDH)* (Clark (1973); Epps/Epps (1976); Tauchen/Pitts (1983); Lamoureux/Lastrapes (1990); Andersen (1996)). This states that stock returns are

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[1] To avoid the problem of serially correlated residuals documented in Brailsford (1996) we include lagged values of V up to lag 2. After this, we find ε_t in equation (4.3) to be largely uncorrelated. We re-run regression (4.3) with absolute stock returns instead of squared returns. The use of this alternative measure of return volatility, however, resulted in very similar inferences.

generated by a mixture of distributions in which the number of information arrivals into the market represents the stochastic mixing variable. Return data can be viewed as a stochastic process, conditional on the information flow, with a changing second order moment reflecting the intensity of information arrivals. Under the assumptions of the MDH model, innovations to the information process lead to momentum in stock return volatility.

Since the information flow into the market is widely unobservable, we use trading volume as a proxy. Systematic variations in trading volume are assumed to be caused solely by the arrival of new information. As is documented in chapter 3, trading volume typically exhibit the assumed time dependence.

We specify the stochastic process of stock returns as a simple GARCH (1,1) process with an autoregressive term in the mean equation and trading volume as an additional predetermined regressor in the conditional variance equation:

$$R_t = \mu + \phi \cdot R_{t-1} + \varepsilon_t \,; \tag{4.4}$$

$$\varepsilon_t \mid I_{t-1} \sim \mathrm{N}(0,\sigma_t^2) \,; \tag{4.5}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}^2 + \beta_1 \cdot \sigma_t^2 + \gamma_1 \cdot V_t \,, \tag{4.6}$$

where I_{t-1} denotes the set of information available at $t-1$ and σ_t^2 stands for the variance of ε_t. The parameters of equations (4.4) and (4.6) are estimated by means of ML-method. Note that in (4.6) the sum of parameters α_1 and β_1 is a measure of the persistence in the variance of the unexpected return ε_t taking values between 0 and 1. The more this sum tends to unity the greater the persistence of shocks to volatility (volatility clustering).

We first estimated the parameters of equation (4.6) under the assumption that γ is equal to 0 (restricted variance equation). From this we found parameter α_1 to be significant in all but 2 cases, whereas β_1 is significant over the whole sample. In 20 cases the observed sum (α_1+β_1) lies within the range [0,9 - 1], indicating high persistence in conditional volatility.

In the next step we were interested in the unrestricted conditional variance equation. We found the estimated parameter γ_1 to be positive and highly significant in all but 2 cases. Most interestingly, our data showed a decrease in the persistence of volatility when including trading volume in equation (4.6). Table 2 reports the sum $(\alpha_1+\beta_1)$ for the restricted and the unrestricted equation for all stocks.

Table 2. Persistence in volatility of unexpected stock returns for all stocks in the sample

ISIN[a]	$(\alpha_1+\beta_1)$[b]	$(\alpha_1+\beta_1)'$[c]	ISIN	$(\alpha_1+\beta_1)$	$(\alpha_1+\beta_1)'$
AT0^{4}603709	0,956	0,105	AT0^{4}809058	0,906	0,929
AT0^{4}730007	0,625	0,587	AT0^{4}705355	0,918	0,396
AT0^{4}620158	0,834	0,505	AT0^{4}938204	0,941	0,627
AT0^{4}930409	0,998	0,933	AT0^{4}743059	0,678	0,189
AT0^{4}910997	0,407	0,486	AT0^{4}758305	0,750	0,491
AT0^{4}767553	0,970	0,701	AT0^{4}676903	0,999	0,672
AT0^{4}903851	0,971	0,615	AT0^{4}922554	0,897	0,592
AT0^{4}925904	0,989	0,852	AT0^{4}785555	0,918	0,616
AT0^{4}737705	0,975	0,356	AT0^{4}720008	0,987	0,618
AT0^{4}943402	0,781	0,788	AT0^{4}821103	0,991	0,988
AT0^{4}943352	0,822	0,717	AT0^{4}816301	0,999	0,447
AT0^{4}818802	0,545	0,802	AT0^{4}937453	0,973	0,157
AT0^{4}652011	0,975	0,182	AT0^{4}746409	0,940	0,704
AT0^{4}741053	0,905	0,119	AT0^{4}831706	0,921	0,689
AT0^{4}911805	0,787	0,160	AT0^{4}834007	0,600	0,785
NL0^{4}238301	0,988	0,731			

[a]...International Securities Identification Number

[b]...restricted version of equation (4.6) (i.e. $\gamma_1 = 0$)

[c]...unrestricted version of equation (4.6)

To some extent our results for the Austrian stock market supports the MDH model. Trading volume as a proxy for the flow of information at least partly rids the ARCH effect in stock returns. Therefore, our results to some extent support the MDH model.

On the other hand, we found the parameters α_1 and β_1 to remain significant in almost 75% of all cases after including trading volume in equation (4.6). This can be seen as a signal that either trading volume might only be a crude proxy for the flow of information, or that the assumption of the MDH that information flows simultaneously into the market might be (at least partly) incorrect.

5 CAUSAL RELATIONSHIP

Up to now we have mainly concentrated on the contemporaneous relationship between stock returns, return volatility and trading volume. In this section we extended our analysis by examining the dynamic (causal) relationship. Testing for causality is important since this can help to better understand the microstructure of stock markets and can also have implications for other markets (e.g. options markets).

In section 3.2 we reported that the correlation between stock returns and lagged/lead trading volume is mostly negligible, whereas squared returns and non-contemporaneous volume exhibit positive correlation. From this we get a first impression that causality might be present in the relation between return volatility and trading volume. We further investigated this hypothesis by means of Granger's test for causality (Granger (1969)). A variable *y* is said to not Granger-cause a variable *x* if the distribution of *x*, conditional on past values of *x* alone, equals the distribution of *x*, conditional on the past of both *x* and *y*. On the other hand, if this equality does not hold, *y* is said to Granger-cause *x*, denoted by $y \overset{G.c.}{\rightarrow} x$. However, this does not mean that *y* causes *x* in the more common sense of the term but only indicates that *y* precedes *x*.

To test for Granger causality we use a bivariate VAR model of order *p* of the form:

$$R_t = \mu_R + \sum_{i=1}^{p} \alpha_i \cdot R_{t-i} + \sum_{i=1}^{p} \beta_i \cdot V_{t-i} + \varepsilon_t \,, \tag{5.1}$$

$$V_t = \mu_V + \sum_{i=1}^{p} \alpha_i \cdot V_{t-i} + \sum_{i=1}^{p} \beta_i \cdot R_{t-i} + \xi_t \,. \tag{5.2}$$

The null hypothesis of *R* (*V*) not to Granger-cause *V* (*R*) implies that β_i ($i = 1, \dots, p$) are all equal to 0. To test the null we calculate the *F*-statistic:

$$F = \frac{SSE_0 - SSE}{SSE} \cdot \frac{N - 2p - 1}{p} \,, \tag{5.3}$$

where SSE_0 stands for the sum of squared residuals of the restricted regression (i.e. $\beta_1 = \dots = \beta_p = 0$), *SSE* is the sum of squared residuals of the unrestricted equation, and *N* denotes the number of observations. The statistic in (5.3) is asymptotic *F* distributed under the null hypothesis with p d.f. in the numerator and (N – $2p$ –1) d.f. in the denominator. The parameters α_i and β_i in equation (5.1) and (5.2), respectively, are estimated by use of OLS. To decide upon the appropriate order p of the VARs we used the corrected R^2 and the Akaike information criterion (AIC). These are measures of goodness of fit that correct for the loss of d.f. resulting from adding additional lags to the model. The bivariate regressions in (5.1) and (5.2) are re-run with squared values of stock returns instead of return levels.

Table 3 reports our results of Granger testing for unidirectional causality between returns and trading volume, and squared returns and trading volume, respectively.

Table 3. Number of rejected null hypothesis based on Granger causality test

Level of significance	$R \overset{G.c.}{\rightarrow} V$	$V \overset{G.c.}{\rightarrow} R$	$R^2 \overset{G.c.}{\rightarrow} V$	$V \overset{G.c.}{\rightarrow} R^2$
1%	5	8	13	8
5%	13	10	17	9

Order p in regressions (5.1) and (5.2) is maximal 5.

In line with our expectations, we found only weak evidence of a causal relationship between stock returns and trading volume in either direction. That means that short-run forecasts of current or future stock returns in most cases cannot be improved by knowledge of recent trading volume data et vice versa. In addition, table 3 illustrates that trading volume does not Granger-cause return volatility in the majority of cases.

On the other hand, the data show that return volatility precedes trading volume in about 55% of all cases. This result corroborates our earlier finding that stock price changes in any direction have information content for upcoming trading activities. Preceding return volatility can be seen as some evidence that new information arrival might follow a sequential rather than a simultaneous process. This implies that the strong form of market efficiency does not hold since some private information exists that is not reflected in stock prices. In addition, our finding would have to be heeded when modelling investors' behaviour.

6 CONCLUSION

In this study the empirical relationship between stock returns, return volatility and trading volume was examined by use of data from the Austrian stock market. We found evidence of a relationship (contemporaneous as well as causal) between return volatility and trading volume. The persistence of variance over time partly declines if one includes trading volume as a proxy for information arrivals in the equation of conditional volatility. In addition our results indicate that return volatility precedes trading volume in about half of all cases, implying that information might flow sequentially rather than simultaneously into the market.

The relationship between stock returns and trading volume is mostly negligible. Knowledge of one of these variables cannot improve short-run forecasts of the other. Our results can help to better understand the microstructure of stock markets. However, since the Austrian stock market is only very small compared to other markets (even in Europe), comparable investigations of other markets would be desirable.

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