Joint Dynamics of Prices and Trading Volume on the Polish Stock Market

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This paper concerns the relationship between stock returns and trading volume. We use daily stock data of the Polish companies included in the WIG20 segment (the twenty most liquid companies quoted on the primary market of the Warsaw Stock Exchange). The sample covers the period from January 1995 to April 2005. We find that there is no empirical support for a relationship between stock return levels and trading volume. On the other hand, our calculations provide evidence for a significant contemporaneous interaction between return volatility and trading volume. Our investigations reveal empirical evidence for the importance of volume data as an indicator of the flow of information into the market. These results are in line with suggestions from the *Mixture of Distribution Hypothesis.* By means of the Granger causality test, we establish causality from both stock returns and return volatility to trading volume. Our results indicate that series on trading activities have little additional explanatory power for subsequent price changes over that already contained in the price series.

Key Words: abnormal stock returns, return volatility, abnormal trading volume, GARCH-cum-volume, causal relations
JEL *Classification:* C32, G14

1 Introduction

Most empirical research about stock markets focuses on stock price movements over time. The stock price of a company reflects investors' expectations about the future prospects of the firm. New information

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causes investors to change their expectations and is the main reason for stock price changes.

However, the release of new information does not necessarily induce stock prices to move. One can imagine that investors may evaluate the news heterogeneously (as either good or bad). Think of a company that announces an increase in dividend payout. Investors may interpret this as a positive signal about the future performance of the company and raise their demand prices. On the other hand, investors interested in capital gains might wish to sell the stock on the basis of this information, rather than receive dividend payouts (e. g. due to tax reasons). On average, despite its importance to individual investors, such information does not noticeably affect prices. Another situation in which new information might leave stock prices unaltered can arise if investors interpret the news homogeneously but start with different prior expectations (e. g. due to asymmetrically distributed information). One can conclude that stock prices do not mirror the information content of news in all cases.

On the other hand, a necessary condition for price movement is positive trading volume. Trading volume can be treated as descriptive statistics, but may also be considered as an important source of information in the context of the future price and price volatility process. Prices and trading volume build a market information aggregate out of each new piece of information. Unlike stock price behaviour, which reflects the average change in investors' beliefs due to the arrival of new information, trading volume reflects the sum of investors' reactions. Differences in the price reactions of investors are usually lost by averaging of prices, but they are preserved in trading volume. In this sense, the observation of trading volume is an important supplement of stock price behaviour.

In 1989 Poland, and thereupon other Eastern European countries, started the transition process from a centrally planned economy to a market economy. There was no pre-existing economic theory of such a process to rely on. The early 1990s were extremely difficult for these countries. Stock quotations on the WSE were launched on April 16, 1991. This was the day of the re-establishment of the WSE as the exclusive place of trading on the Polish stock market after a break of more than 50 years. Continuous trading started in 1996, but only the most liquid stocks were included in this system. Hence, an interesting question arises as to whether the initial difficulties of the Polish stock market have now been overcome, and whether the same mechanisms on the Polish stock market as in developed capital markets can be identified.

To answer this question, we concentrate on the role of trading volume in the process that generates stock returns and return volatilities on the Polish stock market. Unlike most other studies on this issue, we use individual stock data instead of index data. Our investigation covers not only contemporaneous but also dynamic (causal) relationships because we are mainly interested in whether trading volume can be regarded as a prognosis of stock return levels and/or return volatilities. One important difference distinguishing this study from contributions in the existing literature is methodological. We do not use simple return and volume data but replace these two variables with abnormal stock returns and abnormal trading volume. To obtain these variables, we first calculate normal (expected) returns and trading volume and then compute abnormal realizations as the difference between the actual ex-post observations and those expected from the model. Note that such a variable can be regarded as a measure of the unexpected part of a given realization.

Our computations show that, on average, there is almost no relationship between abnormal stock returns and excess trading volume in either direction. It follows that knowledge of trading volume cannot improve short-run return forecasts and vice versa. On the other hand, our data support the hypothesis of a positive contemporaneous as well as causal relationship between return volatility and trading volume. We find that these results are mostly independent of the direction of stock price changes. Finally, our models show that return volatility in many cases precedes trading volume.

The rest of the paper is organized as follows. Section 2 contains a brief overview of the existing literature on the relationship between stock prices and trading volume. Section 3 describes our data, reports preliminary results, and also gives a detailed description of the applied methodology to obtain abnormal return and excess volume outcomes. Section 4 is dedicated to the tests used to check the contemporaneous relationship between stock returns, return volatility and trading volume. Section 5 extends our analysis to the examination of dynamic (causal) relationships. Section 6 concludes and provides suggestions for further research.

2 Existing Literature

An early work dedicated to the role of trading volume in the price generating process is that by Clark (1973). He developed the well known *Mixture of Distribution Hypothesis* (MDH). This hypothesis argue that stock returns are generated by a mixture of distributions. Clark states that stock returns and trading volume are related due to the common dependence on a latent information flow variable. According to Clark, the more information arrives on the market within a given time interval, the more strongly stock prices tend to change. The author advises the use of volume data as a proxy for the stochastic (information) process. From the MDH assumption it follows that there are strong positive contemporaneous but no causal linkages between trading volume and return volatility data. Under the assumptions of the MDH model, innovations in the information process lead to momentum in stock return volatility. At the same time, return levels and volume data exhibit no common patterns. The theoretical framework developed by Clark has been generalized among others by Epps and Epps (1976), Tauchen and Pitts (1983), Lamoureux and Lastrapes (1990), and Andersen (1996).

An important model explaining the arrival of information on a market is the sequential information flow model introduced by Copeland (1976). It implies that news is revealed to investors sequentially rather than simultaneously. This causes a sequence of transitional price equilibrium which is accompanied by a persistently high trading volume. The most important conclusion from this model is that there exist positive contemporaneous and causal relationships between price volatility and trading activities.

In a framework which assumes stochastic fluctuations of stock prices, recent studies, e. g. by Blume et al. (1994) and Suominen (2001) state that data concerning trading volume deliver unique information to market participants; information which is not available from prices. Blume et al. argues that informed traders transmit their private information to the market through their trading activities. Uninformed traders can draw conclusions about the reliability of informational signals from volume data. Therefore, return volatility and trading volume show time persistence even in a case where the arrival of information does not show it. As do Blume et al., Suominen (2001) applies a market microstructure model in which trading volume is used as a signal to the market by uninformed traders and can help to reduce information asymmetries. These two studies argue that trading volume describes market behaviour and influences market participants' decisions. Both authors suggest strong relationships, not only contemporaneous but also causal, between volume and return volatility.

These theoretical contributions have been accompanied by a number of empirical studies which deal with volume-price relationships on capital markets. The most important findings are those by Karpoff (1987), Hiemstra and Jones (1994), Brailsford (1996) and Lee and Rui (2002). The cited authors mainly use index data. Although these studies differ significantly with respect to sample data and applied methodologies, they convey empirical evidence of the existence of a positive volume-to-price relationship.

The interdependencies between stock return volatility and trading volume have been the subject of investigation by Karpoff (1987), Bessembinder and Seguin (1993), Brock and LeBaron (1996), Avouyi-Dovi and Jondeau (2000), and Lee and Rui (2002). All these studies give evidence of a strong relationship (contemporaneous as well as dynamic) between return volatility and trading volume. In contrast to these authors, Darrat et al. (2003), using intraday data from DJIA stocks find evidence of significant lead and lag relations only. They do not report a contemporaneous correlation between return volatility and trading volume.

Lamoureux and Lastrapes (1990) were the first to apply stochastic time series models of conditional heteroscedasticity (GARCH-type) in the context of price-volume investigations. They analyzed the contemporaneous relationship between volatility and volume. They found that the persistence of stock return variance vanishes when trading volume is included in the conditional variance equation. Considering that trading volume is a proxy for the flow of information into the market, this result supports the MDH. A paper by Lamoureux and Lastrapes (1990) gives general proof of the fact that trading volume and return volatility are driven by the same factors. They do not, however, answer the question on the identity of these factors. Lamoureux and Lastrapes (1994), Andersen (1996), Brailsford (1996), and Omran and McKenzie (2000) expanded this GARCH-cum-volume approach.

3 The Data and Preliminary Results

Our data set consists of daily stock price and trading volume series for all companies listed in the WIG20 on April 29, 2005. The WIG20 reflects the performance of the twenty most liquid Polish companies in terms of free float market capitalization. Our time series are derived from the database of PARKIET. The investigation covers the period from January 1995 to April 2005. An appendix at the end of the paper contains a list of all companies included in the sample as well as their period of quotation. We use continuously compounded stock returns calculated from daily stock prices at close, adjusted for dividend payouts and stock splits.

As a proxy for return volatility we employ the squared values of daily stock returns. We repeated all computations using absolute instead of squared stock returns and find that the use of this alternative measure for stock return volatility delivers almost the same results. To measure trading volume the daily number of shares traded is being used.

DESCRIPTIVE STATISTICS

We start with some basic descriptive analysis of the time series of stock returns and trading volume. As can be seen from panel A of table 1, the average daily stock return over the period under study ranges from –0.28% (Netia) to 0.12% (BRE) with a median of –0.05%. Standard deviation is the lowest for PKN (1.85%) and the highest for Netia (4.45%).

The commonly reported fact of fat-tailed and highly-peaked return distributions is being supported by most of our series. The median of stock return kurtosis is 6.88 and ranges from 34.98 (SFC) to 3.9 (PKN). Return skewness is the highest for Netia (0.92) and the lowest for SFC (–1.8) with a median of 0.19. By applying Jarque-Bera and chi-square goodness-of-fit tests for normality, we additionally find strong support for the hypothesis that our return series do not come from a normal distribution. Concerning autocorrelation properties, the Ljung-Box Q-test statistics for the 15th order autocorrelation provide evidence of significant low-order autocorrelation in about 50% of all cases.

Unlike stock returns, both return volatility and trading volume commonly display strong persistence in their time series. By means of Ljung-Box Q (15)-statistics we find strong support for the hypothesis that trading volume exhibits serial autocorrelation. Consistent with the stylized facts of volume series listed by Andersen (1996), our volume data exhibit a high degree of non-normality, expressed by their considerable kurtosis and their being skewed to the right (see panel C of table 1).

As a proxy for return volatility we use the 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, among other things, that returns cannot be assumed to be i. i. d. As for trading volume, the null hypothesis of squared returns coming from a normal distribution is strongly rejected (panel B in table 1).

ABNORMAL RETURNS AND ABNORMAL TRADING VOLUME

One point that is essential in distinguishing our study from other contributions is that we focus on interactions between abnormal stock returns

TABLE 1 Aggregated summary statistics for stock market data of WIG20 companies

	Mean · 10^3	Std. dev. · 10^3	Skewness	Kurtosis
Panel A: Daily stock returns				
Min	–2.81	18.50	–1.80	3.90
1st Quartile	0.10	24.85	–0.07	6.50
Median	0.52	26.33	0.19	6.88
3rd Quartile	0.73	32.00	0.27	8.78
Max	1.15	44.49	0.92	34.98
Panel B: Daily squared stock returns				
Min	0.34	0.59	3.89	22.83
1st Quartile	0.62	1.47	5.83	49.55
Median	0.69	1.93	7.18	77.15
3rd Quartile	1.03	2.69	8.53	120.20
Max	1.99	7.83	35.35	1 435.61
Panel C: Daily trading volume				
Min	9.80	16.42	1.66	7.82
1st Quartile	28.57	41.03	2.98	17.24
Median	70.10	73.98	4.11	29.22
3rd Quartile	231.53	314.82	7.40	119.33
Max	1337.54	1286.82	34.97	1359.58

and abnormal trading volume, instead of simple return and volume data. Since we concentrate on individual companies, instead of index data, our goal is to establish unique firm-specific relationships, i. e. we filter out systematic price and volume effects. For each trading day t we compute the abnormal return $AR_{i,t}$ for company i as the difference between the actual ex-post return and the security's normal (expected) return. Formally we have

$$AR_{i,t} = R_{i,t} - E\left[R_{i,t}|I_{i,t-1}\right] \tag{1}$$

where $R_{i,t}$ stands for the actual return of firm i on day t and $E[R_{i,t}|I_{t-1}]$ stands for the predicted (normal) return conditional on the information set I_{t-1}.

To model risk-adjusted expected returns $E[R_{i,t}|I_{t-1}]$ we use the Market Model approach, which relates a security's return to the return of the market. The latter is approximated in our study by the log-returns of the WIG, which comprises the majority of firms listed on the primary market of the Warsaw Stock Exchange. For each day the relevant model parameters are estimated by means of an OLS method. The estimation window comprises 100 trading days prior to that date. Since our analysis starts on January 2, 1995, this implies that the first realisation of abnormal stock returns for each company can be observed for the 101st trading day in 1995.

Abnormal trading volume is computed in a similar way. To isolate information-related trading activity, we follow Tkac (1999) who found that market-wide trading is also an important component of the trading activity of individual firms, and that it should be taken into account when modeling volume time series. However, the application of a 'Volume Market Model' proposed in Ajinkya and Jain (1989) generates many statistical problems. We find that the resulting abnormal volume series mostly depart from the underlying model assumptions. This leads to biased inferences. Taking this into account, we follow, among others, Beneish and Whaley (1996) by using firm-specific average volume data as a benchmark for normal trading volume. As was the case with the estimation window for the return parameters in the Market Model, the estimation window for the mean firm-specific volume also covers 100 trading days.

TESTING FOR UNIT ROOT

Testing for causal relationships between trading volume and stock price data can be sensitive to non-stationarities. Therefore, we check whether the time series of stock returns and trading volume can be assumed to be stationary by using the augmented Dickey-Fuller (ADF) test. This is necessary to avoid model misspecifications and biased inferences. The ADF test is based on the regression:

$$\Delta y_t = \mu + \gamma y_{t-1} + \sum_{i=1}^{p} \delta \Delta y_{t-i} + \varepsilon_t, \tag{2}$$

where y_t stands for stock return or trading volume on day t, μ, γ and δ are model parameters, and ε_t represents a white noise variable. The unit root test is carried out by testing the null hypothesis of a unit root in the stochastic process generating $y_t(\gamma = 0)$ against the one-sided alternative $\gamma < 0$.

We conduct ADF tests for each company's time series of stock returns. We find the parameter γ to be negative and statistically significant at reasonable levels in all cases. The same is true for the time series of trading

TABLE 2 Cross-correlation coefficients between abnormal stock returns (AR), abnormal return volatility (AR^2) and abnormal trading volume (AV)

	$j = -2$	$j = -1$	$j = 0$	$j = 1$	$j = 2$
Panel A: $Corr(AR_t, AV_{t-j})$					
Min	–0.02	–0.01	0.04	–0.03	–0.02
1st Quartile	0.03	0.08	0.09	–0.01	–0.01
Median	0.04	0.10	0.12	0.00	0.00
3rd Quartile	0.07	0.13	0.13	0.03	0.02
Max	0.13	0.18	0.16	0.05	0.04
Panel B: $Corr(AR_t^2, AV_{t-j})$					
Min	–0.10	–0.06	–0.07	–0.08	–0.13
1st Quartile	0.05	0.08	0.09	0.03	0.01
Median	0.08	0.15	0.17	0.07	0.04
3rd Quartile	0.11	0.20	0.20	0.10	0.07
Max	0.17	0.30	0.32	0.14	0.13

volume. Hence we come to the conclusion that both time series of stock returns and trading volume can be assumed to be invariant with respect to time.

CROSS-CORRELATION ANALYSIS

At the beginning of our investigation of interactions between abnormal stock return and abnormal trading volume data we calculate simple cross-correlation coefficients *Corr* for all companies:

$$Corr[AR_t, AV_t] = \frac{Cov[AR_t, AV_t]}{SD[AR_t] \cdot SD[AV_t]}, \tag{3}$$

where AR_t (AV_t) denotes abnormal stock return (abnormal trading volume) on day t, *Cov* stands for covariance and *SD* is standard deviation. From panel A of table 2 we see that there is no direct contemporaneous correlation between abnormal stock return levels and excess trading volume. The same results are obtained when one computes *Corr* between AR and lagged (leading) data of AV.

On the other hand, panel B of table 2 shows a positive contemporaneous correlation between abnormal trading volume and abnormal return volatility. From this observation it follows that, due to its impact on return volatility, trading volume might indirectly contain information about stock price behaviour.

We also find an asymmetry in the cross correlation between squared AR and AV around zero. In all cases, $Corr[AR_t^2, AV_{t-j}]$ is greater for $j = -1$ than for $j = 1$. This fact is in line with the widespread expectation that trading volume is, at least partly, induced by heavy price fluctuations.

4 Contemporaneous Relationship

STOCK RETURNS AND TRADING VOLUME

In this section we test the contemporaneous relationship between abnormal stock returns and excess trading volume. We use a multivariate simultaneous equation model proposed by Lee and Rui (2002), which is defined by the two equations:

$$
\begin{aligned}
AR_t &= \alpha_0 + \alpha_1 AV_t + \alpha_2 AR_{t-1} + \varepsilon_{1,t};\\
AV_t &= \beta_0 + \beta_1 AR_t + \beta_2 AV_{t-1} + \beta_3 AV_{t-2} + \varepsilon_{2,t}.
\end{aligned} \tag{4}
$$

We assume ε_t to be white noise. One has to take into account that the jointly determined endogenous variables in each equation are not independent of the disturbances. This is important in respect to the estimation process. To take this possible dependence into account, we apply Full-Information Maximum Likelihood (FIML) methodology. FIML generates asymptotically efficient estimators. An additional advantage is that the cross-equation correlations of the error terms are taken into account (see e. g. Davidson and MacKinnon 2003). The significance of all coefficients in models (4), (5) and (6) (see below), is proved by means of the t-Student test (t-ratio coefficients).

The findings are in line with our expectations of almost no essential contemporaneous relationship between abnormal stock returns and excess trading volume. Across the whole sample, the parameters α_1 and β_1 in (4) turn out to be statistically significant in only 4 cases. Since the majority of our abnormal return series exhibit no serial correlation, we find parameter α_2 to be significant in only 6 cases.

Time dependence in the trading volume time series is supported by the highly significant values found for parameters β_2 (16 cases) and β_3 (11 cases). As one would expect, the sign of these coefficients is positive in all but two cases, implying positive autocorrelation in volume data.

Even though we find abnormal stock return levels and trading volume to be mutually independent, this does not mean that no relationships can be found in these market data at all. Several authors report that price fluctuations tend to increase in face of high trading volume. Therefore, a relation might exist between higher order moments of excess stock returns and trading volume.

In addition, we check whether this volatility-volume relationship is the same irrespective of the direction of the price change, or whether trading volume is predominantly accompanied by either a large rise or a large fall in stock prices. We test this by using a bivariate regression model, given by the following equation:

$$AV_t = \alpha_0 + \phi_1 AV_{t-1} + \phi_2 AV_{t-2} + \alpha_1 AR_t^2 + \alpha_2 D_t AR_t^2 + \varepsilon_t. \quad (5)$$

In model (5), D_t denotes a dummy variable that equals 1 if the corresponding abnormal return AR_t is negative, and 0 otherwise. The estimator of parameter α_1 measures the relation between abnormal return volatility and excess trading volume, irrespective of the direction of the price change. The estimator of α_2, however, reflects the degree of asymmetry in this relationship. To avoid the problem of serially correlated residuals, we include lagged values of AV up to lag 2. After this, we find the error term ε_t in equation (5) to be largely serially uncorrelated.

By means of the ML method we estimate equation (5). According to our computations, the estimate of parameter ϕ_1 is significant in 17 cases and the estimate of parameter ϕ_2 is significant in 15 cases. We also establish that parameter α_1 is positive and significant for all but 2 companies. This is in line with our earlier hypothesis of a strong contemporaneous relationship between squared AR and AV. The estimate of parameter α_2 is significant in 13 cases and negative in all of these. We find that for our sample of the Warsaw Stock Exchange, strong price changes are always accompanied by an increase in trading volume, irrespective of the direction of price fluctuations.

TRADING VOLUME AND VOLATILITY

The stochastic process of stock returns is given by means of an augmented Market Model with an autoregressive term of order 1 in the conditional mean equation below. The conditional variance is captured by an adapted GJR-GARCH(1,1) model (Glosten et al. 1993). In this version, trading volume is included as an additional predetermined regressor. The GJR model captures the asymmetric (leverage) effect discovered by Black (1976), which states that bad information, reflected in an unexpected decrease in prices, causes volatility to increase more than good news. Engle and Ng (1993) supplied a theoretical and empirical support and stated that, among alternative models of time-varying volatility, the GJR model is the best at efficiently capturing this effect.

The model is represented by the following two equations:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 R_{m,t} + \varepsilon_t,\ \varepsilon_t \sim (0, \sigma_t^2);$$
$$\sigma_t^2 = h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \beta_3 S_{t-1}^- \varepsilon_{t-1}^2 + \gamma V_t. \tag{6}$$

Here ε_t is assumed to be distributed as t-Student with ν degrees of freedom conditional on the set of information available at $t-1$; σ_t^2 represents the conditional variance of ε_t; and S_{t-1}^- is a dummy variable, which takes the value of 1 in the case of the innovation ε_{t-1} being positive and 0 otherwise. Model (6) rests upon the assumption that trading volume is a proxy for the flow of information into the market: if return volatility is in fact mostly influenced by the information flow, the effect of volatility clustering should decrease if one incorporates trading volume in the conditional variance equation. In (6) the sum of parameters β_1 and β_2 reflects the persistence in the variance of the unexpected return ε_t, taking values between 0 and 1. The closer this sum is to unity, the greater the persistence of shocks to volatility (volatility clustering). The estimate of parameter β_3 accounts for potential asymmetries in the relationship between return innovation and volatility.

We apply a t-Student distribution for the return innovations ε_t because we find this to fit our turnover ratio series best. Thus, we use the conditional t-Student distribution for which the normal is a special case ($\nu > 30$). For model (6), a likelihood function L is defined as:

$$L = T\left\{\ln\Gamma\left(\frac{\nu+1}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\ln[\pi(\nu-2)]\right\}$$
$$-\frac{1}{2}\sum_{t=1}^{t}\left[\ln(\sigma_t^2) + (1+\nu)\ln\left(1 + \frac{1}{\nu-2}\frac{\varepsilon_t}{\sigma_t^2}\right)\right], \tag{7}$$

where T denotes the sample size and $\Gamma(.)$ denotes the gamma function.

The model parameters are estimated by means of the ML method. As a first step, we estimate the parameters of model (6) assuming that γ is equal to 0 (restricted variance equation, see table 3). We find that the estimate of parameter β_1 as well as the estimate of parameter β_2 is significant in nearly all cases. For 14 companies, the observed sum $(\beta_1 + \beta_2)$ lies within the range $[0.9 - 1]$. The average is 0.93, which indicates high persistence in conditional volatility. In most cases, β_3 is positive, but turns out to be statistically significant for one company only. This indicates that the asymmetric reaction of conditional variance to return innovations is rather modest in our data. In the next step we are interested in the unrestricted equation for conditional variance. We find parameter γ

TABLE 3 Persistence in conditional stock return volatility [restricted versus unrestricted version of model (6)]

Symbol	$(\beta_1+\beta_2)^a$	$(\beta_1+\beta_2)^b$	Symbol	$(\beta_1+\beta_2)^a$	$(\beta_1+\beta_2)^b$
AGO	0.93	0.08	KTY	1.00	0.03
BPH	0.98	0.97	NET	1.00	0.88
BRE	0.95	0.13	ORB	0.97	0.21
BZW	0.81	0.90	PEO	0.87	0.91
CPL	0.99	0.08	PKM	0.96	0.06
CST	0.75	0.41	PKN	0.96	0.89
DBC	0.70	0.11	SFT	0.91	0.04
FSC	0.96	0.37	STX	0.96	0.89
KGH	0.98	0.89	TPS	0.98	0.83
			Average	0.93	0.48

to be positive and highly significant across the whole sample. Our data show a considerable decrease in the persistence of volatility when trading volume is included in (6). The sum of parameters β_1 and β_2 declines for almost all companies. The mean falls from 0.93 to 0.48. The estimate of parameter β_2 shows a significant drop. In the unrestricted form it becomes, for the most part, insignificant. Table 3 gives the degree of persistence in variance, measured by the sum $(\beta_1+\beta_2)$ for the restricted and unrestricted form of (6). Results are shown for all stocks under consideration.

It cannot be derived from our data that trading volume is the true source of persistence in volatility. Empirical results support the conjecture that trading volume might itself be partly determined by return volatility, causing a simultaneity bias in the coefficient estimates. To solve this simultaneity problem we re-run model (6) substituting V_{t-1} for V_t. In line with Gallo and Pacini (2000), we find that volatility persistence under this approach remains almost the same as in the restricted version of (6). It can be concluded that contemporaneous trading volume is a sufficient statistic for the history of return volatility. Despite this, our results can only partly be interpreted as an indication that the MDH holds true.

5 Dynamic Relationship

Up to this point, our investigations focused exclusively on contemporaneous relationships between trading volume and stock returns, and trading volume and return volatility. The following part of the paper studies dynamic (causal) interactions between these variables. Testing for causality is important because it permits a better understanding of the dynamics of stock markets, and may also have implications for other markets.

From section 3 we get a hint that it is probable that causality is present in the relationship between return volatility and trading volume. This hypothesis can be proved by means of the Granger causality test (Granger 1969). A variable Y is said not to Granger-cause a variable X if the distribution of X, conditional on past values of X alone, equals the distribution of X, conditional on past realizations of both X and Y. If this equality does not hold, Y is said to Granger-cause X. This is denoted by $Y \overset{G.c.}{\rightarrow} X$. Granger causality does not mean that Y causes X in the more common sense of the term, but only indicates that Y precedes X. In the case of the feedback relationship (i. e. X Granger-causes Y and vice versa) this relation is written as $Y \overset{G.c.}{\leftrightarrow} X$.

As a test of Granger causality, we apply a bivariate vector autoregression (VAR) of the form:

$$AR_t = \mu_1 + \sum_{i=1}^{p} \alpha_{1,i} AR_{t-i} + \sum_{i=1}^{p} \beta_{1,i} AV_{t-i} + \varepsilon_{1,t};$$

$$AV_t = \mu_2 + \sum_{i=1}^{p} \alpha_{2,i} AV_{t-i} + \sum_{i=1}^{p} \beta_{2,i} AR_{t-i} + \varepsilon_{2,t}. \tag{8}$$

Model (8) is estimated using an OLS method. In order to choose an appropriate autoregressive lag length p of the VAR, we apply the Akaike information criterion (AIC). Based on this measure of goodness-of-fit, we establish the proper lag length p to be equal to 2 for all companies.

In terms of the Granger causality concept, it is said that AR (AV) does not Granger-cause AV (AR) if the coefficients β_i ($i = 1, \ldots, p$) in (8), respectively, are not significant, i. e. the null hypothesis H_0: $\beta_1 = \beta_2 = \ldots = \beta_p = 0$ cannot be rejected.

To test the null, we calculate the F-statistic:

$$F = \frac{SSE_0 - SSE}{SSE} \cdot \frac{N - 2p - 1}{p}. \tag{9}$$

In (9) SSE_0 denotes the sum of squared residuals of the regression model constrained by $\beta_i = 0$ ($i = 1, \ldots, p$), SSE is the sum of squared residuals of the unrestricted equation, and N stands for the number of observations. The statistic (9) is asymptotically F distributed under the

TABLE 4 Number of rejected null hypotheses based on the Granger causality test

Panel A: Causality between excess trading volume and abnormal stock returns			
	$AR \overset{G.c.}{\rightarrow} AV$	$AV \overset{G.c.}{\rightarrow} AR$	$AR \overset{G.c.}{\leftrightarrow} AV$
Sample size: 18 companies	11	0	1
Panel B: Causality between excess trading volume and squared abnormal stock returns			
	$AR^2 \overset{G.c.}{\rightarrow} AV$	$AV \overset{G.c.}{\rightarrow} AR^2$	$AR^2 \overset{G.c.}{\leftrightarrow} AV$
Sample size: 18 companies	8	1	3

Level of significance is 5%. Order p in (8) is equal to 2.

non-causality assumption, with p degrees of freedom in the numerator and $(N - 2p - 1)$ degrees of freedom in the denominator.

Concentrating on the rejection of the null hypothesis of Granger non-causality, panel A of table 4 demonstrates that abnormal returns (excess trading volume) precede excess trading volume (abnormal returns) in 11 (0) cases. Both numbers reflect exclusively unidirectional causalities. Only in one case a two-way causality (feedback relation) is detected. To conclude, short-run forecasts of current or future stock returns in general cannot be improved by the knowledge of recent trading volume data. The observation that stock returns precede trading volume in approximately half of all cases is in line with similar findings by Glaser and Weber (2004) and confirms predictions from overconfidence models. To summarize, we find only weak evidence of causality between abnormal stock returns and excess trading volume, especially causality running from trading volume to stock returns. This is in line with our expectations.

To evaluate dynamic relationships between stock return volatility and trading volume, we substitute the abnormal return level for the squared values of abnormal stock returns, and re-estimate the model (8). Panel B of table 4 confirms the existence of causal relationships from AR^2 to AV. In 10 cases, AR^2 precedes AV, whereas in only 1 case does Granger causality run from AV to AR^2. This result is again in line with our earlier finding that stock price changes in any direction have information content for upcoming trading activities. The preceding return volatility can also be seen as some evidence that the arrival of new information might follow a sequential rather than a simultaneous process.

Our results indicate that data on trading activity have only little additional explanatory power for subsequent price changes that is independent of the price series. In this sense, our empirical results for the Polish stock market does not overall corroborate theoretical suggestions made by Blume et al. (1994) and more recently by Suominen (2001).

6 Conclusions

Our paper presents a joint dynamics study of daily trading volume and stock returns for Polish companies listed in the WIG20. We test whether volume data provide only a description of trading activities or whether they convey unique information that can be exploited for modeling stock returns or return volatilities. These relationships are investigated by the use of abnormal stock return and excess trading volume data. Our results give no evidence of a contemporaneous relationship between market adjusted stock returns and mean adjusted trading volume. The linear Granger causality test of dynamic relationships between these data does not indicate substantial causality. We can conclude that short-run forecasts of current or future stock returns cannot be improved by the knowledge of recent volume data and vice versa. This finding is in line with the efficient capital market hypothesis. However, the Polish data show extensive interactions between trading volume and stock price fluc-

APPENDIX A Companies included in the sample, symbol legend and period of quotation*

PLPKN0000018	20 April 1999 – 29 April 1999
PLPEKAO00016	7 February 1995 – 29 April 2005
PLTLKPL00017	2 January 1995 – 29 April 2005
PLKGHM000017	2 January 1995 – 29 April 2005
PLBPH0000019	27 October 1995 – 29 April 2005
PLAGORA00067	25 May 1998 – 29 April 2005
PLBZ00000044	2 January 1995 – 29 April 2005
PLPROKM00013	22 April 1997 – 17 February 2005
PLNETIA00014	10 July 1997 – 29 April 2005
PLBRE0000012	30 January 1996 – 29 April 2005
PLSTLEX00019	11 July 2000 – 29 April 2005
PLKETY000011	20 November 1997 – 29 April 2005
PLORBIS00014	30 June 1998 – 29 April 2005
PLSOFTB00016	10 February 1998 – 29 April 2005
PLCMPLD00016	26 November 1999 – 29 April 2005
PLCRSNT00011	2 June 1998 – 29 April 2005
PLCELZA00018	2 January 1995 – 29 April 2005
PLDEBCA00016	18 November 1998 – 29 April 2005

* In the case of two firms included in the WIG20, data series have been too short.

tuations. We find that squared abnormal stock returns and excess trading volume are contemporaneously related. This implies that both time series might be driven by the same underlying process. In contrast to Brailsford (1996), our findings provide evidence that for the Polish stock market this volatility-volume relationship is independent of the direction of the observed price change. We apply our investigations to a conditional asymmetric volatility framework in which trading volume serves as a proxy for the rate of information arrival on the market. The results to some extent support suggestions of the Mixture of Distribution Hypothesis, i. e. that ARCH is a manifestation of daily time dependence in the rate of new information arrival. We also detect dynamic relationships between return volatility and trading volume data.

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