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# Stock returns, volume and stock price volatility : An empirical firm-level analysis

Jurgen Schraepen

## Abstract :

*This paper examines the relation between stock returns and stock market volatility in an autoregressive conditional heteroskedasticity model framework. Using a GARCH-M model, we examine the relation between stock returns, volume and stock price volatility. Using daily returns from January 1990 until December 1999 for a sample of 20 firms listed on the Tokyo Stock Exchange, first of all, we examine if there exists a risk premium for stock return volatility. Second, using daily volume and a new measure of daily stock price volatility as a proxy for the amount of daily arrival of information, we try to find out how contemporaneous and lagged trading volume and volatility explain conditional volatility.*

*As a result we find that (1) stock returns are positively related to the conditional variance but the correlation is not always significant. Only when introducing contemporaneous volume in the variance equation, the GARCH parameter in the mean equation becomes significant; (2) contemporaneous trading volume is positively correlated to the conditional variance and highly statistically significant, while lagged trading volume has a mixed impact on the conditional variance; (3) we find evidence that our new measure of stock price volatility using the daily high, low and closing price can catch information in return volatility. Both contemporaneous and lagged stock price volatility are positively related with the conditional variance and are highly significant. Volatility models for daily returns are therefore improved by*

*including information such as the daily high and low price. Together with volume our measure of stock price volatility can be very useful in explaining volatility clustering in daily returns; (4) introducing stock price volatility and volume in the GARCH variance equation reduces the persistence and significance of variance considerably but does not turn them insignificant. After controlling for the rate of information flow using volume and volatility, lagged squared residuals still contribute additional information about the variance of the stock return process. This is in contrast with the research of Lamoureux and Lastrapes (1990) who found empirical evidence that the ARCH effects vanish when volume is included as an explanatory variable in the conditional variance equation.*

## 1. Introduction

Volatility clustering is a well known characteristic of financial data series. Many economic time series do not have a constant mean and exhibit phases of tranquility and high volatility (Schwert, Seguin, 1990). Different kinds of financial data series, from exchange rates, stock returns to bond rates seem to show such heteroskedastic volatility. Also, volatility in financial data series seems to be asymmetric. Large downward movements in the market are followed by higher volatility and upward movements by lower volatility.

Statistic models that can capture this heteroskedasticity in variance were developed by Engle (1982), Bollerslev (1986), Nelson (1991) and Zakoian (1994). Up until then, moving averages of standard deviations, implied volatilities or time-series models were widely used to predict volatility. With the introduction of the ARCH models, a whole new

literature and a new approach towards modeling volatility arose. ARCH models are designed to model and forecast the conditional variance or volatility of time series. In these models the variance of the dependent variable is modeled as a function of past values of the variance of the dependent variable. The idea is that if large changes in financial markets tend to be followed by more large changes, then volatility must be predictable more after large changes. By modeling volatility in the ARCH approach, we can put more weights on recent information and it is possible to model volatility to capture asymmetric properties of news shocks.

The implications for such volatility modeling are important. Models of time-varying risk premiums, time-varying hedge ratios, time-varying beta's and option pricing can be constructed using this technique. The ARCH-M model that allows the mean of a sequence to depend on its own conditional variance, developed by Engle, Lilien and Robins (1987), was introduced to capture this time-varying risk premium. This model is often used in financial applications where the expected return on an asset is related to the expected asset risk. However, the reported findings on the correlation between the conditional variance and the risk premium are conflicting. Campbell and Hentschel (1992) and French, Schwert and Stambaugh (1987) and Chou (1988) find evidence that the expected market risk premium is positively related to the predictable volatility of stock returns. In contrast, Fama and Schwert (1977), Campbell (1987), Pagan and Hong (1991), Glosten and Jagannathan (1989), Turner, Startz and Nelson (1989) and Nelson (1991) find a negative relation between excess returns and the conditional variance. Other studies find a positive but not significant relationship (Poon, Taylor, 1992). Next to a linear approach, Pagan and Hong (1991) and Harvey (1991) use nonparametric

techniques to study the risk premium.

Motivated by recent volatile events in the stock market, research on return volatility has become more ambitious. Multivariate models and the introduction of other economic variables like trading volume are now widely used (see Tauchen and Pitts (1983), Karpoff (1987), Gallant, Rossi and Tauchen (1992) for a review). The use of volume to explain the dynamics of stock price changes is considered to be an important step in developing models of returns data behaviour. An important motivation behind this is the attempt to capture and interpret the factors that are the source of ARCH effects in returns. From a market microstructure perspective, price movements are caused primarily by the arrival of new information and the process that incorporates this new information into market prices. Theory suggests that variables such as trading volume, the number of transactions, the bid-ask spread or market liquidity are related to the return volatility process<sup>1)</sup>. Empirical work has found evidence of a positive correlation between stock price changes and contemporaneous volume. In their research on stock prices and volume, Lamoureux and Lastrapes (1990) introduce volume directly into the GARCH variance equation and demonstrate that contemporaneous volume is strongly positive and significant. Schwert (1989) uses monthly aggregates as daily data and finds a positive relationship between estimated volatility and lagged volume growth rates.

In this paper we undertake an empirical investigation of the daily return-volatility relationship for a sample of 20 common stocks on the Japanese stock market. We empirically examine the relationship between

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1) Andersen, T. G., "Return volatility and trading volume: An information flow interpretation of stochastic volatility", *Journal of Finance*, 51 (1996) Page 170

stock price movements (returns), volatility, and volume. In order to do that, we estimate a more general specification of the GARCH-M model. (1) We incorporate a dummy variable in the GARCH variance equation for Mondays to capture the non-trading effect during the weekend, (2) We incorporate contemporaneous and lagged trading volume in the GARCH variance equation, and (3) We introduce a new measure of stock price volatility and introduce this contemporaneous and lagged variable in the GARCH variance equation.

Our research has three objectives, (1) We look for evidence on the relationship between stock returns and the conditional variance. We examine if there exists a risk premium for stock return volatility; (2) We try to find out how contemporaneous trading volume and lagged trading volume interact with the conditional volatility. (3) We examine if stock price volatility can help to explain the conditional volatility.

The structure of the paper is as follows. Section 2 describes the data, gives the summary statistics and the unit root tests. In section 3, we introduce the different GARCH-M models used for estimation. Section 4 gives the results and section 5 concludes.

## **2. Data, summary statistics and Unit Root Tests**

We will perform a firm-level analysis using a sample of 20 Japanese common stocks listed on the Tokyo Stock Exchange. We use daily returns for a period of ten years from 04-jan-1990 to 31-dec-1999 as our sample period. The firms in the sample are chosen to be mainly large, economically important firms with a large trading volume. The raw data which we use to calculate the returns consist of the daily closing prices, taken from the TOYO KEIZAI-KABUKA CD-ROM. The continuous

compounded daily returns are calculated as

$$r_t = \text{Log} \left( \frac{S_t}{S_{t-1}} \right) \quad (2-1)$$

where  $S$  are the data series. There are in total 2465 daily stock returns observations for every firm in the sample. There are two caveats to point out concerning the returns. First of all, the returns are not expressed as returns in excess of the return on a risk-free asset. Using raw returns instead of excess returns will not change the function of the risk premium, but it will change the magnitude of the premium. Second, the measure of return we use is the daily capital gain on the individual common stocks, excluding dividends. Since on daily basis the capital gain component dominates the dividend one, we believe results are still robust without making these adjustments.

**Table 1 Summary statistics of the stock returns**

	Mean %	Stand. Dev.	Skewness	Kurtosis	Jarque-Bera
Sekisui	-0.0402	1.826	0.420	3.814	1558.62***
Kirin Beer	-0.0240	1.912	0.368	2.688	793.51***
Nisshin Foods	-0.0206	2.081	0.049	8.431	7267.38***
Shinetsu Chem.	0.0385	2.036	0.511	3.623	1448.28***
Takeda Chem.	0.0316	1.958	0.236	2.083	465.52***
Shiseido	-9.8E-03	1.756	0.169	3.655	1376.48***
Bridgestone	0.0116	1.989	0.132	6.949	4943.26***
Rinnai	-0.0098	2.005	0.025	3.018	930.66***
Hitachi Seisakusho	5.1E-03	1.963	0.524	2.433	717.24***
NEC	0.0107	2.020	0.523	2.771	896.46***
TDK	0.0367	2.191	0.418	3.827	1567.88***
Kyocera	0.0645	2.045	0.704	4.530	2300.69***
Honda	0.0296	2.130	0.030	4.408	1985.96***
Toyota	0.0349	1.788	0.389	4.475	2108.29***
Nikon	0.0281	2.548	0.262	1.470	248.38***

Nintendo	0.0169	2.396	-0.300	8.647	7680.12***
Sanrio	-0.0291	3.368	0.076	4.020	1653.29***
Shimamura	0.0849	2.269	0.134	6.702	4598.96***
Itoyokado	0.0353	2.020	0.912	6.991	5337.25***
Nihon Terebi	0.0480	2.119	0.304	2.288	572.46***

Table 1 presents summary statistics for the daily returns of the firms in our sample for the 1990–1999 period. The average daily returns are shown in the first column. The daily return standard deviation is presented in column two and ranges from 1.7 to 3.4 %. Looking at the distribution of returns, column 3 shows the daily returns are slightly positively skewed, while the fourth column shows the returns of some firms are highly leptokurtic. The Jarque-Bera test in the last column rejects the null hypothesis of normality. This fat tail or leptokurtic behaviour of the daily stock returns is a widely observed feature among financial data.

The first five auto-correlations for the daily returns are reported in table 2. The auto-correlations indicate significant time dependence up to five lags. The Box-Ljung portmanteau test rejects the null hypothesis of no serial dependence up to the fifth moment.

**Table 2 Auto-correlations of the daily stock returns for all the firms in the sample**

	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$	Box-Ljung $Q\chi^2(5)$
Sekisui	-0.028	-0.072	-0.077	0.01	-0.037	18.493***
Kirin	-0.134	-0.022	-0.04	0.009	-0.041	53.975***
Nisshin	-0.023	-0.064	-0.017	-0.046	-0.004	17.427***
Shinetsu Chem.	-0.027	-0.044	-0.054	0.014	-0.016	14.942**
Takeda Chem.	-0.06	-0.047	-0.044	-0.037	-0.032	24.707***
Shiseido	-0.053	-0.086	-0.029	-0.037	-0.027	32.687***
Bridgestone	-0.053	-0.074	-0.023	-0.009	-0.061	30.798***
Rinnai	-0.053	0.019	-0.012	0.000	-0.026	9.977*



Hitachi Seisakusho	0.034	-0.051	-0.039	-0.055	-0.006	20.728***
NEC	0.102	-0.008	-0.058	-0.021	-0.029	37.442***
TDK	0.112	-0.056	-0.093	-0.025	-0.063	71.622***
Kyocera	0.119	-0.006	0.028	0.032	-0.013	40.159***
Honda	-0.028	-0.031	-0.032	-0.014	-0.05	13.477**
Toyota	0.005	-0.093	0.001	-0.028	-0.069	35.26***
Nikon	0.001	-0.056	-0.009	-0.015	-0.027	10.33*
Nintendo	0.06	-0.072	-0.065	-0.033	-0.006	34.635***
Sanrio	0.12	0.006	0.004	-0.028	0.004	37.52***
Shimamura	0.046	0.011	-0.001	-0.04	0.005	9.575*
Itoyokado	-0.015	-0.099	-0.04	-0.016	-0.022	28.023***
Nihon Terebi	0.021	-0.043	-0.006	-0.017	-0.036	9.658*

\*, \*\*, \*\*\* indicates the parameter is significant at the 10%, 5% and 1% significance level

Next we perform a unit root test to check if our logged returns are stationary. Stationarity is necessary for main standard inference procedures to apply.

**Table 3 Unit root tests on the stock returns**

	case 1 <sup>3)</sup>		case 2 <sup>4)</sup>		case 3 <sup>5)</sup>	
	ADF <sup>1)</sup>	PP <sup>2)</sup>	ADF	PP	ADF	PP
Sekisui	-23.928***	-51.372***	-23.958***	-51.401***	-23.963***	-51.404***
Kirin Beer	-24.822***	-57.854***	-24.832***	-57.864***	-24.839***	-57.871***
Nisshin Foods	-24.213***	-51.265***	-24.216***	-51.263***	-24.226***	-51.266***
Shinetsu Chem.	-23.681***	-51.360***	-23.704***	-51.376***	-23.748***	-51.417***
Takeda Chem.	-25.298***	-53.531***	-25.319***	-53.549***	-25.497***	-53.758***
Shiseido	-25.539***	-53.522***	-25.536***	-53.513***	-25.548***	-53.524***
Bridgestone	-25.34***	-53.308***	-25.339***	-53.299***	-25.34***	-53.304***
Rinnai	-22.979***	-52.364***	-22.977***	-52.355***	-22.973***	-52.344***
Hitachi Seisakusho	-23.963***	-48.061***	-23.958***	-48.050***	-24.037***	-48.110***
NEC	-23.305***	-44.586***	-23.301***	-44.577***	-23.393***	-44.633***
TDK	-25.174***	-44.109***	-25.188***	-44.113***	-25.241***	-44.142***
Kyocera	-20.173***	-43.843***	-20.753***	-43.863***	-20.868***	-43.908***
Honda	-24.564***	-51.356***	-24.575***	-51.361***	-24.584***	-51.363***

Toyota	-25.189***	-49.773***	-25.217***	-49.793***	-25.294***	-49.862***
Nikon	-23.753***	-49.673***	-23.756***	-49.671***	-23.855***	-49.741***
Nintendo	-24.133***	-46.805***	-24.131***	-46.797***	-24.155***	-46.807***
Sanrio	-21.859***	-43.897***	-21.859***	-43.890***	-21.972***	-43.945***
Shimamura	-22.344***	-47.304***	-22.422***	-47.351***	-22.452***	-47.361***
Itoyokado	-24.799***	-51.218***	-24.825***	-51.238***	-24.860***	-51.277***
Nihon Terebi	-23.581***	-48.587***	-23.69***	-48.607***	-23.843***	-48.779***

1) ADF is the augmented Dickey-Fuller test.

2) PP is the Phillips-Perron test.

3) Unit root test regression run without constant or time trend.

4) Unit root test regression run with constant but without time trend

5) Unit root test regression run with constant and time trend

\*\*\* Null hypothesis of the existence of a unit root rejected at the 1% significance level.

The Augmented Dickey-Fuller (DF) test and the Phillips-Perron (PP) test are used to check the return data for unit roots. The tests are performed using four lagged differences in the regression, including a constant, a constant and a linear time trend, or neither a constant nor a linear time trend.

The unit root tests show overwhelming evidence the data series are stationary. For all three cases, using either the Dickey-Fuller or the Phillips-Perron test, the null hypothesis of a unit root is rejected at the 1% significance level.

Next we will turn to our measure of stock price volatility. Using only the daily high, low and closing price of the individual firm, we calculate stock price volatility as follows,

$$\text{Stock Price Volatility}_i = \frac{\text{HIGH price}_i - \text{LOW price}_i}{\text{CLOSING price}_i} \quad (2-2)$$

Dividing the high minus the low price by the closing price of the day we try to capture the stock price volatility of that day. We believe it might be a measure that is able to capture some important aspects of daily volatility. It is easy to understand that a combination of the spread in the

nominator and the closing price in the denominator will determine the level of stock price volatility. A lower spread in the nominator and a higher closing price in the denominator will lower the level of stock price volatility, while a higher spread and a lower closing price will turn the level of stock price volatility in the opposite direction.

For lack of space we do not show the volatility summary statistics, or the summary statistics for the volume data series. We checked the volume series of the firms in the sample for unit roots and found that the null hypothesis of a unit root is largely rejected. Since the logged volume series contain no unit roots we do not have to de-trend them.

### 3. The GARCH-M models

Many economic time series do not have a constant mean and exhibit mostly phases of tranquility and high volatility. Autoregressive Conditional Heteroskedasticity (ARCH) models try to deal with this type of time-series behaviour. ARCH models are designed to model and forecast the conditional variance or volatility of time series. In these models the variance of the dependent variable is modeled as a function of past values of the variance of the dependent variables.

The GARCH ( $p, q$ ) model of Bollerslev (1986), which is an extension of Engle's ARCH (1982) can be specified as

$$r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t \quad (3-1)$$

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

where (3-1) is the mean equation written as a function of exogenous variables and an error term, and  $\sigma_t^2$  in (3-2) is the conditional variance or

one-period ahead forecast variance, based on the conditional variance or the past variance information.  $\omega$  is the intercept,  $\varepsilon_{t-i}^2$  are the lagged squared residuals, or the so-called ARCH terms, and  $\sigma_{t-i}^2$  is the last period's conditional variance. GARCH therefore models variance as a combination of a weighted average of a long term average (the intercept term), news about volatility from the previous period, measured as the lag of the square residuals (the ARCH term) and the last period's forecast variance, measured by the GARCH term. In the GARCH model  $p$  refers to the ARCH term and  $q$  refers to the GARCH term.

Further developing the GARCH model to capture the risk-return relationship, we get the ARCH-M model. The ARCH-in-Mean or ARCH-M model, developed by Engle, Lilien and Robins (1987) allows the mean of a sequence to depend on its own conditional variance. The model can be specified as

$$r_t = \gamma x_t + \widetilde{\Omega} \sigma_t^2 + \varepsilon_t \quad (3-3)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 \quad (3-4)$$

with a mean equation and a variance equation. The left-hand side of the mean equation contains the returns, and the right hand side contains the regressors and the estimated conditional variance from (3-4). In other words, the forecasts of variance in (3-4) can be used to predict expected returns. The parameter of interest is therefore  $\widetilde{\Omega}$ . This parameter will be positive for a risk averse investor. While the  $\gamma$  parameter in (3-3) can be compared to the risk free return in the CAPM, the  $\widetilde{\Omega}$  parameter represents the market risk premium for expected volatility. This model is thought to be particularly suited to the study of asset markets. The theory behind this simple model is that risk-averse agents will require

compensation for holding a risky asset. If the risk of an asset can be measured by its conditional variance, the risk premium will be an increasing function of the conditional variance. The estimated coefficient on the expected risk is therefore a measure of the risk-return tradeoff.

We will extend the simple GARCH model to include both contemporaneous and lagged stock price volatility, as well as contemporaneous and lagged volume in the variance equation.

Lamoureux and Lastrapes (1990) argue that volume is important in the ARCH variance equation since they believe it can catch important properties of conditional heteroskedasticity. They claim that daily returns are generated by a mixture of distributions, in which the rate of daily information arrival is the stochastic mixing variable that is responsible for the ARCH effects. In other words, in the mixture model the variance of daily price movements is heteroskedastic or positively related to the rate of daily information arrival. Using daily trading volume as a proxy for the mixing variable, they give empirical evidence that the ARCH effects vanish when volume is included as an explanatory variable in the conditional variance equation. They argue that the high degree of volatility persistence in GARCH models might be due to misspecification of the variance equation. Stating that the ARCH effect is a manifestation of clustering in trading volumes and introducing contemporaneous volume in the variance equation, they find that ARCH persistence dramatically drops and becomes statistically insignificant. Considering the fact volume is likely to contain information about the disequilibrium dynamics of asset markets, we will pick up volume as one of the variables of interest to specify our variance equation.

We will use stock price volatility, as measured in Section 2, as our second variable in the GARCH variance equation. Just like volume, we

believe that this variable can catch important properties of conditional heteroskedasticity. Using daily stock price volatility as a proxy for the rate of daily information arrival we look at how well it helps explaining conditional volatility. Although the daily squared return is an unbiased estimator of the realized daily volatility, it is also a very noisy one. If on a trading day the return was zero, but the within the day prices fluctuate heavily, the lagged squared return is misleading information. Other measures are then needed to capture the “real” volatility information. This explains the reason for using the daily high and low price to calculate stock price volatility.

The use of daily high and low stock prices when measuring volatility, although not always in GARCH form, can also be found in previous research. In Parkinson (1980) the moments of the high/low price ratio (range statistics) are used as a function of the underlying variance of the process. He suggests an estimator of variance, based on the realized interperiod highs and lows. Other research using daily high and low prices can be found in Parkinson, 1980; Garman and Klass, 1980; Beckers, 1983 and Taylor, 1987.

As in the above studies, models are extended by including additional intraday information like the high and low price. We will use the high/low price difference divided by the closing price to capture the underlying variance of the process. We expect that a combination of the spread in the nominator and the closing price in the denominator will help determine the level of stock price volatility. A lower spread in the nominator and a higher closing price in the denominator will lower the level of stock price volatility, while a higher spread and a lower closing price will turn the level of stock price volatility in the opposite direction. For this we believe this variable is likely to contain information about the

amount of daily information flow into the market.

In our empirical research we will use daily volume (contemporaneous and lagged) and stock price volatility (contemporaneous and lagged) as a proxy for the amount of daily arrival of information (mixing variable). We also will include a dummy variable for Mondays in the ARCH variance equation to capture the non-trading effect during the weekend, since it is found that the variance of returns tends to be higher on days following closure of the market (see French and Roll, 1986). French, Schwert, Stambaugh (1987), Nelson (1989, 1991) and Connolly (1989) find that a failure to take proper account of such deterministic influences like the weekend effect might lead to a spurious ARCH effect.

We will estimate the following GARCH (1,1) models extended with other daily information.

GARCH-M model 1 :

$$\text{Mean equation } r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t + \theta_{t-1} + \tilde{\Omega} \sigma_t^2 \quad (k=1)$$

$$\text{Variance equation } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \phi MON_t$$

GARCH-M model 2 :

$$\text{Mean equation } r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t + \theta_{t-1} + \tilde{\Omega} \sigma_t^2 \quad (k=1)$$

$$\text{Variance equation } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \phi MON_t + \gamma Vol_{t-1}$$

GARCH-M model 3 :

$$\text{Mean equation } r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t + \theta_{t-1} + \tilde{\Omega} \sigma_t^2 \quad (k=1)$$

$$\text{Variance equation } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \phi MON_t + \gamma Vol_{t-1} + \delta Volat_{t-1}$$

GARCH-M model 4 :

$$\text{Mean equation } r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t + \theta_{t-1} + \widetilde{\Omega} \sigma_t^2 \quad (k=1)$$

$$\text{Variance equation } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \phi MON_t + \gamma Vol_t$$

GARCH-M model 5 :

$$\text{Mean equation } r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t + \theta_{t-1} + \widetilde{\Omega} \sigma_t^2 \quad (k=1)$$

$$\text{Variance equation } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \phi MON_t + \gamma Vol_t + \delta Volat_t$$

Model 1 is a normal GARCH (1,1) model with an AR(1) and MA(1) specification and with the conditional variance in the mean equation. The variance equation contains the ARCH ( $\varepsilon_{t-1}^2$ ), GARCH ( $\sigma_{t-1}^2$ ) variables together with the Monday dummy variable ( $MON$ ) to capture the non-trading effect during the weekend. We restrict our attention to a GARCH (1,1) specification since it has been shown to be a representation of conditional variance that fits many time series (Bollerslev, 1987). All the models ahead have the same mean equation as GARCH model 1. Model 2 is a GARCH (1,1) model with lagged volume ( $Vol_{t-1}$ ) added as an extra regressor in the variance regression. Model 3 is a GARCH (1,1) model with the variables of lagged stock price volatility ( $Volat_{t-1}$ ) and lagged volume added in the variance regression. Model 4 is a GARCH (1,1) model with contemporaneous volume ( $Vol_t$ ) in the variance equation, while model 5 is a GARCH (1,1) model with both contemporaneous volume and stock price volatility in the variance regression.

We will fit these five GARCH-M models to the returns of the 20 individual common stocks in our sample.



## 4. Empirical Results

**Table 4 Empirical results of the GARCH-M Model 1**

$$\text{Mean equation } r_i = \pi_0 + \sum_{i=1}^k \pi_i y_{i-i} + \varepsilon_i + \theta_{i-1} + \widetilde{\Omega} \sigma_i^2 \quad (k=1)$$

$$\text{Variance equation } \sigma_i^2 = \omega + \alpha \varepsilon_{i-1}^2 + \beta \sigma_{i-1}^2 + \phi MON_i$$

	$\pi_0$	$\pi_1$	$\theta$	$\widetilde{\Omega}$	$\omega$	$\alpha$	$\beta$	$\phi$	$\alpha+\beta$
Sekisui	-0.001**	0.667***	-0.735***	2.605**	3.4E-06	0.093***	0.877***	3.4E-05*	0.97
Kirin Beer	-0.001***	0.492***	-0.645***	4.271***	3.2E-05***	0.131***	0.783***	8.92E-07	0.91
Nisshin Foods	-0.0003	0.694***	-0.752***	0.950	1.27E-05	0.152***	0.822***	1.2E-05	0.97
Shinetsu Chem.	-0.0002	0.847***	-0.873***	0.728	5.1E-06	0.085***	0.908***	-5.12E-06	0.99
Takeda Chem.	-0.001**	0.652***	-0.745***	3.278**	1.56E-05*	0.08***	0.885***	-1.2E-05	0.96
Shiseido	-5E-04*	0.539***	-0.664***	1.987	4.1E-07	0.066***	0.926***	1.24E-05	0.99
Bridgestone	3.56E-05	0.765***	-0.822***	0.219	9.52E-06*	0.087***	0.902***	-2.23E-05	0.98
Rinnai	-0.001	-0.524**	0.465*	2.633	1.42E-05**	0.124***	0.845***	4.1E-06	0.96
Hitachi Seisakusho	-3E-04	-0.369	0.403	1.155	4.02E-06	0.075***	0.909***	1.36E-05	0.98
NEC	-0.001	-0.057	0.141	2.551	1.5E-05	0.084***	0.871***	2.1E-05	0.95
TDK	0.001	-0.068	0.205	-0.104	6.4E-06	0.101***	0.881***	2.1E-05	0.98
Kyocera	-4E-04	-0.098	0.210	3.611**	8.39E-06*	0.099***	0.891***	-1.32E-05	0.99
Honda	-4E-04	0.754***	-0.788***	1.051	3.8E-05***	0.142***	0.787***	-2.54E-05	0.93
Toyota	0.001	-0.452	0.471	0.853	5.66E-06	0.133***	0.841***	2.54E-05	0.97
Nikon	-0.001	-0.991***	0.989***	4.20***	1.22E-05	0.088***	0.888***	2.29E-05	0.98
Nintendo	-0.001	-0.142	0.205	3.539**	8.3E-07	0.046***	0.945***	2.64E-05	0.99
Sanrio	-0.002	0.223	-0.171	1.711*	3.34E-05	0.134***	0.822***	0.0001	0.95
Shimamura	5.47E-05	0.513*	-0.471	0.552	1.4E-05*	0.063***	0.922***	-3.12E-05	0.98
Itoyokado	0.001	-0.578	0.586	0.092	1.04E-05	0.134***	0.814***	6.24E-05	0.95
Nihon Terebi	-0.001	0.637***	-0.655***	2.730*	2.2E-05**	0.078***	0.881***	-1.39E-05	0.96
Average z-statistic	-0.915	-4.488	3.00	1.394	1.556	5.643	44.71	0.261	

z-statistics calculated using the Woolridge-Bollerslev robust standard errors.

\*, \*\*, \*\*\* indicates the parameter is significant at the 10%, 5% and 1% significance level

In Garch-M model 1 we estimate the simple GARCH model with no other specification in the variance equation than the Monday dummy variable. We can verify from the average z-statistics that the  $\widetilde{\Omega}$  or

conditional variance parameter in the mean equation is positive but not statistically significant on average. The ARCH ( $\varepsilon_{t-1}^2$ ) and GARCH ( $\sigma_{t-1}^2$ ) parameters in the variance equation are positive and highly significant. Combining these two variables we are able to check the persistence of variance. We can confirm by looking at the sum of the ARCH and GARCH parameters ( $\alpha+\beta$ ) that variance persistence is very high (0.94).

**Table 5 Empirical results of the GARCH-M Model 2**

$$\text{Mean equation } r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t + \theta_{t-1} + \widetilde{\Omega} \sigma_t^2 \quad (k=1)$$

$$\text{Variance equation } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \phi MON_t + \gamma Vol_{t-1}$$

	$\pi_0$	$\pi_1$	$\theta$	$\widetilde{\Omega}$	$\omega$	$\alpha$	$\beta$	$\phi$	$\gamma$	$\alpha+\beta$
Sekisui	0.001	0.047	-0.099	-4.467	1.2E-04*	0.106***	0.856***	4.1E-05*	-8.3E-06*	0.96
Kirin Beer	-0.002***	0.449***	-0.604***	5.327***	-3.4E-04**	0.155***	0.658***	1.74E-05	2.9E-05***	0.81
Nissshin Foods	-0.0003	0.220	-0.271	0.606	-4.1E-06	0.190***	0.761***	2.02E-05	2.11E-06	0.95
Shinetsu Chem.	0.001	0.203	-0.209	-1.39	6.2E-05	0.111***	0.881***	-1.4E-05	-4.1E-06	0.99
Takeda Chem.	-0.004***	0.251	-0.351*	11.743***	6.2E-05	0.085***	0.866***	-2.0E-05	-2.9E-06	0.95
Shiseido	-0.002***	0.386***	-0.517***	7.067***	3.4E-05*	0.081***	0.905***	2.07E-05	-2.6E-06*	0.98
Bridgestone	-5.9E-04	0.137	-0.189	3.356*	3.67E-05	0.103***	0.877***	-1.5E-05	-1.9E-06	0.98
Rinnai	-0.001*	-0.511**	0.456*	4.260**	9.3E-05**	0.136***	0.822***	-6.5E-06	-6.9E-06**	0.96
Hitachi Seisakusho	2.9E-04	-0.207	0.244	-1.180	-9.7E-05	0.103***	0.853***	2.4E-05	7.31E-06	0.95
NEC	-0.002	-0.118**	0.197	8.007***	6.15E-05	0.084***	0.864***	2.06E-05	-3.0E-06	0.95
TDK	0.003***	-0.125	0.260	-8.503***	7.41E-05**	0.101***	0.871***	4.01E-05	-5.5E-06**	0.97
Kyocera	-8.6E-04	-0.151	0.264	5.696***	2.58E-05	0.113***	0.873***	-4.2E-06	-1.4E-06	0.98
Honda	-7.5E-04*	0.641***	-0.675***	2.093*	1.21E-04	0.144***	0.788***	-2.0E-05	-6.2E-06	0.93
Toyota	-6.1E-05	-0.355	0.376	3.788*	-5.7E-06	0.141***	0.822***	2.39E-05	1.01E-06	0.96
Nikon	-0.003**	-0.715	0.714	6.628***	3.97E-05	0.084***	0.891***	3.01E-05	-2.1E-06	0.97
Nintendo	-0.001	-0.179	0.230	2.827	4.4E-04*	0.177***	0.609***	2.22E-05	-3.6E-05*	0.78
Sanrio	-0.002	0.181*	-0.127	2.201**	-1.1E-04	0.137***	0.804***	1.2E-04	1.3E-05	0.94
Shimamura	-2.8E-04	0.120	-0.079	2.624**	3.64E-05	0.082***	0.903***	-2.9E-05	-2.3E-06	0.98
Itoyokado	0.001**	-0.110	0.123	-3.959***	-2.6E-05	0.159***	0.774***	6.86E-05	3.27E-06	0.93
Nihon Terebi	-0.001*	0.609**	-0.624**	2.881*	8.52E-05	0.101***	0.842***	-1.2E-05	-6.1E-06	0.94
Average z-statistic	-0.904	0.465	-0.612	1.347	0.755	5.739	35.099	0.370	-0.517	

z-statistics calculated using the Woolridge-Bollerslev robust standard errors.

\*, \*\*, \*\*\* means the parameter is significant at the 10%, 5% and 1% significance level

The sign for the dummy variable for Mondays is not statistically significant with the sign being neither positive nor negative.

GARCH-M model 2 further specifies the variance equation of model 1 with lagged volume. Again, the conditional variance parameter in the mean equation is positive but not statistically significant on average. Also, The ARCH ( $\varepsilon_{t-1}^2$ ) and GARCH ( $\sigma_{t-1}^2$ ) parameters in the variance equation are still positive and highly significant. The sign of lagged volume is negative but not statistically significant. More important, introducing lagged volume in the variance equation does not change the persistency of variance. It is still very high, with an average of 0.94. As in model 1, the dummy variable to control for the Monday effect is not statistically significant.

Table 6 Empirical results of the GARCH-M Model 3

Mean equation  $r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t + \theta_{t-1} + \widetilde{\Omega} \sigma_t^2 \quad (k=1)$

Variance equation  $\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \phi MON_t + \gamma Vol_{t-1} + \delta Volat_{t-1}$

	$\pi_0$	$\pi_1$	$\theta$	$\widetilde{\Omega}$	$\omega$	$\alpha$	$\beta$	$\phi$	$\gamma$	$\delta$	$\alpha + \beta$
Sekisui	5.9E-04	0.046	-0.082	-4.565	9.14E-05	0.078***	0.709***	4.3E-05*	-9.4E-06	0.004***	0.78
Kirin Beer	-0.002***	0.455***	-0.585***	5.326***	-3E-04**	0.041*	0.626***	-2.2E-07	2.1E-05**	0.006***	0.66
Nissshin Foods	4.7E-04	0.060	-0.099	0.444	-3.0E-05	0.140***	0.632***	1.62E-05	1.33E-06	0.005***	0.77
Shinetsu Chem.	5.4E-04	0.172	-0.154	-1.258	2E-04***	0.032	0.641***	-4E-05***	-2E-05***	0.008***	0.67
Takeda Chem.	-0.001**	0.623***	-0.712***	3.129**	-4.6E-05	0.055**	0.645***	1.9E-06	6.2E-07	0.006***	0.70
Shiseido	-0.002***	0.427***	-0.543***	6.188***	1.4E-05	0.096***	0.765***	1.22E-05	-2.4E-06	0.003***	0.86
Bridgestone	-7.5E-04	0.174	-0.214	3.418*	8.4E-05	0.072***	0.839***	-2.6E-05	-7E-06*	0.002***	0.91
Rinnai	-0.001**	-0.565**	0.521*	4.438**	2E-04***	0.109***	0.757***	-3.7E-05	-2E-05***	0.003***	0.86
Hitachi Seisakusho	-4.1E-04	0.035	0.005	-1.269	2.7E-04	0.15	0.60***	-1E-04	-1.7E-05	0.003	0.75
NEC	-0.003***	-0.021	0.114	8.012***	5.2E-06	0.043**	0.763***	1.82E-05	-1.2E-06	0.004***	0.81
TDK	0.001*	-0.054	0.203	-2.485	3E-04***	0.075***	0.754***	-1.2E-05	-3E-05***	0.005***	0.83
Kyocera	-0.001**	-0.059	0.189	6.024***	2E-04***	0.079***	0.662***	-9.7E-06	-2E-05***	0.006***	0.74
Honda	-7.1E-04	0.107	-0.089	2.402	7.2E-05	0.079***	0.710***	-2.2E-05	-6.3E-06	0.005***	0.79
Toyota	-2.7E-04	-0.390	0.414	3.772	-1.1E-05	0.058**	0.697***	1.0E-05	-1.5E-06	0.005***	0.75

Nikon	-0.002**	-0.690	0.694	5.172***	3.05E-05	0.048***	0.828***	2.47E-05	-4.7E-06	0.004***	0.87
Nintendo	-0.001	-0.149	0.202	3.649	4.2E-04*	0.131***	0.608***	1.42E-05	-4E-05*	0.003	0.74
Sanrio	-0.002*	0.258	-0.181	2.085*	1.4E-05	0.078***	0.781***	1.1E-04	-3.4E-06	0.005***	0.86
Shimamura	-3.3E-04	0.20	-0.147	2.631	9.2E-05*	0.067***	0.827***	-9.5E-06	-9E-06*	0.003***	0.89
Itoyokado	-3.9E-04	-0.596*	0.618	2.617	9.1E-05	0.144***	0.463***	1.8E-05	-8.2E-06	0.008***	0.61
Nihon Terebi	-0.002**	0.316	-0.298	4.932**	2E-04	0.093***	0.667***	-1.8E-05	-2.0E-05	0.005***	0.76
Average z-statistic	-1.269	0.501	-0.570	1.426	1.016	3.015	15.636	-0.169	-1.203	4.013	

z-statistics calculated using the Woolridge-Bollerslev robust standard errors.

\*, \*\*, \*\*\* means the parameter is significant at the 10%, 5% and 1% significance level

GARCH-M model 3 further introduces lagged volatility as an additional variable into the variance equation. Specifying the variance with lagged volume and lagged volatility makes the conditional variance in the mean equation almost statistically significant at the 10% level (average z-statistic of 1.43). While the sign of lagged volume is not statistically significant, lagged volatility in the variance regression is positive and highly statistically significant (average z-stat of 4.013). Although the ARCH and GARCH parameters are still positive, their significance level drops significantly with the introduction of lagged volatility. Volatility persistence also takes a drop to an average of 0.78 (average statistic not reported).

**Table 7 Empirical results of the GARCH-M Model 4**

$$\text{Mean equation } r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t + \theta_{t-1} + \tilde{\Omega} \sigma_t^2 \quad (k=1)$$

$$\text{Variance equation } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \phi MON_t + \gamma Vol_t$$

	$\pi_0$	$\pi_1$	$\theta$	$\tilde{\Omega}$	$\omega$	$\alpha$	$\beta$	$\phi$	$\gamma$	$\alpha + \beta$
Sekisui	2.9E-4	0.543***	-0.623***	-2.168	-7E-04***	0.195***	0.524***	4.1E-05*	5.7E-05***	0.72
Kirin Beer	-0.004***	0.385***	-0.571***	11.343***	-0.003***	0.193***	0.0616	4.59E-05**	1.4E-04***	0.25
Nissin Foods	-3.8E-04	-0.023	0.005	0.350	-1.2E-04***	0.152***	0.601***	-5E-05***	1.8E-05***	0.75
Shinetsu Chem.	7.1E-04	0.328	-0.343	-0.989	-1.1E-05	0.105***	0.884***	-2.3E-05	1.7E-06	0.99
Takeda Chem.	-0.004***	0.448***	-0.579***	12.034***	-0.001***	0.131***	0.168	2.4E-05	1.2E-04***	0.30
Shiseido	-0.002***	0.509***	-0.665***	5.605***	-7E-04***	0.259***	0.227***	5.6E-05**	6.7E-05***	0.48

Bridgestone	-0.001**	0.593***	-0.673***	2.568**	-1.8E-04***	0.125***	0.828***	-2E-05	1.5E-05***	0.95
Rinnai	-0.001	-0.518**	0.462*	4.31**	3.9E-05	0.125***	0.840***	-1.56E-06	-2.2E-06	0.96
Hitachi Seisakusho	-0.004***	-0.322	0.324	9.303***	-0.002***	0.174***	-0.04	1.7E-06	1.7E-04***	0.13
NEC	-0.006***	-0.318**	0.355**	18.278***	-0.002***	0.050*	-0.330***	3.7E-05**	2E-04***	-0.28
TDK	0.003***	-0.12***	0.258	-8.79	2.7E-05	0.095***	0.877***	3.3E-05	-1.6E-06	0.97
Kyocera	-0.001	-0.194	0.301*	6.048***	-0.002***	0.171***	0.766***	1.7E-07	1.7E-05***	0.94
Honda	-0.001**	0.718***	-0.780***	1.342*	-0.002***	0.272***	-0.021	4.5E-05*	1.4E-04***	0.25
Toyota	-2.2E-04	-0.264	0.273	3.839*	-1.5E-04***	0.149***	0.789***	2.64E-05	1.2E-05***	0.94
Nikon	-0.007***	-0.632**	0.619**	11.711***	-0.002***	0.182***	0.031	8.06E-05***	2.1E-04***	0.21
Nintendo	-0.002*	-0.159	0.228	5.492***	4.23E-05	0.056***	0.914***	4.2E-05	-4E-06	0.97
Sanrio	-0.003***	0.117	0.003	3.546***	-4.1E-04***	0.154***	0.602***	1E-04	5.1E-05***	0.75
Shimamura	-2.9E-04	0.147	-0.106	2.687*	2E-04	0.083***	0.898***	-1.4E-05	-8E-07	0.98
Itoyokado	0.001**	-0.459	0.473	-3.563*	-1.2E-04	0.14***	0.781***	8.04E-05*	1.04E-05	0.92
Nihon Terebi	-0.002***	0.328	-0.335	6.816***	-7.8E-06	0.087***	0.856***	1.2E-05	3.3E-06	0.94
Average z-statistic	-2.152	1.355	-1.899	2.247	-6.093	5.385	16.583	0.764	8.689	

z-statistics calculated using the Woolridge-Bollerslev robust standard errors.

\*, \*\*, \*\*\* means the parameter is significant at the 10%, 5% and 1% significance level

GARCH model 4 introduces contemporaneous volume ( $Vol_t$ ) as an additional variable into the variance equation. Specifying the variance equation with contemporaneous volume makes the conditional variance in the mean equation statistically significant (average z-statistic of 2.247), which is in contrast with model 2 where we introduced lagged volume in the variance regression. Although the ARCH and GARCH parameters are still positive, the significance level of the GARCH parameter drops significantly with the introduction of contemporaneous volume. Volatility persistence also drops to an average of 0.656 (average statistic not reported).

**Table 8 Empirical results of the GARCH-M Model 5**

$$\text{Mean equation } r_t = \pi_0 + \sum_{i=1}^k \pi_i y_{t-i} + \varepsilon_t + \theta_{t-1} + \tilde{\Omega} \sigma_t^2 \quad (k=1)$$

$$\text{Variance equation } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \phi MON_t + \gamma Vol_t + \delta Volat_t$$

	$\pi_0$	$\pi_1$	$\theta$	$\tilde{\Omega}$	$\omega$	$\alpha$	$\beta$	$\phi$	$\gamma$	$\delta$	$\alpha+\beta$
Sekisui	2.7E-04	-0.026	0.005	-5.032*	-1.3E-04**	0.149***	0.60***	4.1E-05***	6.2E-06	0.005***	0.75
Kirin Beer	-0.002***	-0.139	0.005	5.286***	-1.7E-04**	0.146***	0.60***	4.1E-06	8.3E-06	0.007***	0.74
Nissin Foods	-5.3E-04	-0.023	0.005	0.350	1E-04***	0.150***	0.60***	-7E-05***	-9E-05***	0.005***	0.75
Shinetsu Chem.	0.001	-0.023	0.006	-1.916	-1.2E-04**	0.153***	0.60***	-4E-05**	9.4E-06*	0.003***	0.75
Takeda Chem.	-0.003***	0.146	-0.219	12.074***	-1.7E-04*	0.047***	0.488***	1.7E-05	6.8E-06	0.009***	0.535
Shiseido	-0.002***	-0.057	0.005	7.541***	2.1E-05	0.150***	0.60***	-6.7E-06	-3.6E-06*	0.004***	0.75
Bridgestone	-8.8E-04*	-0.055	0.005	3.565*	-1.2E-04	0.146***	0.597***	2.6E-06	6.2E-06	0.006***	0.74
Rinnai	-0.001	-0.054	0.005	4.472	1.7E-04	0.149***	0.60***	-6.5E-06	-1.8E-05	0.005***	0.75
Hitachi Seisakusho	1E-04	0.035	0.005	-1.269	3E-04***	0.156***	0.60***	-1.2E-05	-2E-05***	0.007***	0.75
NEC	-0.002***	0.091	0.002	8.308***	-7.5E-05	0.131***	0.585***	2.4E-05	-2.5E-07	0.008***	0.71
TDK	0.003***	0.117	0.007	-11.046***	2.4E-04***	0.144***	0.60***	-1E-05***	-2E-05***	0.007***	0.74
Kyocera	-0.001***	0.100	0.005	6.044***	5.4E-05	0.150***	0.60***	-5.3E-06	-7.1E-06*	0.005***	0.75
Honda	-7.4E-04	-0.028	0.005	2.141	-1.5E-04	0.145***	0.60***	1.5E-05	6.4E-06	0.007***	0.74
Toyota	-3.3E-04	-6.4E-04	0.005	3.870**	8.2E-05***	0.149***	0.60***	-5.1E-06	-8E-05***	0.005***	0.75
Nikon	-0.003***	-0.007	0.005	7.470***	2.8E-05	0.147***	0.60***	-3E-05**	-6.1E-06	0.006***	0.75
Nintendo	-0.003*	0.065	0.005	5.727**	3.4E-04*	0.144***	0.599***	-2.7E-06	-3.6E-05*	0.004**	0.74
Sanrio	-0.003**	0.117	0.004	3.546**	2.1E-04***	0.149***	0.598***	4.4E-05	-3E-04***	0.011***	0.75
Shimamura	-5.5E-04	0.044	0.005	2.779*	2.1E-04***	0.150***	0.599***	-5E-04***	-2E-05***	0.005***	0.75
Itoyokado	5.8E-04	-0.003	0.005	-4.04*	1E-04*	0.150***	0.600***	-3E-05***	-1E-05**	0.006***	0.75
Nihon Terebi	-0.002***	0.013	0.005	8.867***	1.4E-04**	0.149***	0.599***	-2.7E-05	-2E-04***	0.006***	0.75
Average z-statistic	-1.344	0.113	-0.043	1.277	3.902	6.381	16.96	-0.958	-13.192	8.09	

z-statistics calculated using the Woolridge-Bollerslev robust standard errors.

\*, \*\*, \*\*\* means the parameter is significant at the 10%, 5% and 1% significance level

GARCH model 5 introduces contemporaneous volume ( $Vol_t$ ) and contemporaneous volatility ( $Volat_t$ ) as additional variables into the variance equation. Specifying the variance with both contemporaneous volume and volatility turns the conditional variance in the mean regression insignificant (average z-statistic of 1.277). Also, when putting contemporaneous stock price volatility and volume together in the

variance regression, the sign of trading volume becomes negative and significant. Although the ARCH and GARCH parameters are still positive, the significance level of the GARCH parameter drops with the introduction of contemporaneous volume and volatility. Volatility persistence also drops to an average of 0.73 (average statistic not reported).

## 5. Conclusion

Motivated by volatile events in the stock market, research on return volatility has become more ambitious. Multivariate models and the introduction of other economic variables like trading volume are now widely used. The use of volume to explain the dynamics of stock price changes is considered to be an important step in developing models of returns data behaviour. An important motivation behind this is the attempt to capture and interpret the factors that are the source of ARCH effects in returns. From a market microstructure perspective, price movements are caused primarily by the arrival of new information and the process that incorporates this new information into market prices. Theory suggests that variables such as trading volume, the number of transactions, the bid-ask spread or market liquidity are related to the return volatility process.

In this paper we have undertaken an empirical investigation of the daily return-volatility relationship for a sample of 20 common stocks on the Japanese stock market. We empirically examined the relationship between stock price movements (returns), volatility and volume, using a more general specification of the GARCH-M model. Modeling our research after Lamoureux and Lastrapes (1990), we tried to incorporate

contemporaneous and lagged trading volume in the GARCH variance equation, as well as a contemporaneous and lagged volatility, calculated from the daily high, low and closing price. Volume and stock price volatility were used as a proxy for the amount of daily arrival of information, hoping it can catch important properties of conditional heteroskedasticity.

From the empirical evidence we find that (1) Stock returns are positively related to the conditional variance but the correlation is not always significant. Only when introducing contemporaneous volume in the variance equation, the GARCH parameter in the mean equation becomes significant; (2) Contemporaneous trading volume is positively correlated to the conditional variance and highly statistically significant, while lagged trading volume has a mixed impact on the conditional variance; (3) Our new measure of stock price volatility can catch information in return volatility. Both contemporaneous and lagged stock price volatility are positively related with the conditional variance and highly significant. Together with volume, our measure of stock price volatility can be very useful in explaining volatility clustering in daily returns; (4) Introducing stock price volatility and volume in the GARCH variance equation also reduces the persistence and significance of variance considerably, but does not turn it insignificant as in Lamoureux and Lastrapes.

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