UNIVERSITY of PIRAEUS
Department of Banking and Financial Management
Postgraduate Program

Master Thesis:

"Trading activity and stock price volatility: Evidence from the Greek stock market"

by

Mpoumpoukioti Eftichia
MXRH/0417

Members of Committee: **Dr. Ch. Christou (Supervisor)**
Dr. D. Maliaropoulos
Dr. N. Kourogenis

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Abstract

In this dissertation the relationship between trading volume and stock return volatility is examined for the FTSE-20 Greek stocks. By using different measures of return volatility and trading activity, this study investigates the contemporaneous and the causal trading activity-volatility relation as well. The main purpose of this paper is to explore not only if any relation between these two variables exists but also if this relation is affected by the different measures of volatility and trading activity used. Our calculations provide evidence for a positive contemporaneous interaction and a feedback causal relationship between the two variables. Furthermore, it is tested if volatility persistence tends to disappear when the trading activity proxy is included in the conditional variance equation. In accordance with the findings from the US stock market our empirical results show that in the majority of cases GARCH effects tend to disappear when trading activity is included in the variance equation.

KEY WORDS: Trading activity, stock return volatility, volatility persistence, GARCH models, VAR, Granger-causality, FTSE-20 Greek stocks.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΑ

1. Introduction

In recent years, there has been a renewed interest in the relation between trading volume and the volatility of share prices. Part of this interest has been fueled by several episodes of high price volatility coupled with heavy trading volume in equity markets. Another source of this interest has been the emergence of a theoretical literature that examines the interactions of market makers and speculative, informed traders.

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

Indeed, a necessary condition for price movement is positive trading volume. Trading volume can be treated as descriptive statistics, but may also be consider 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 behavior, 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 behavior.

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.

Earlier works are motivated in part by the events on the stock market, which suggest that more can be learned about the market – and, in particular, about volatility – by studying prices in conjunction with volume, instead of prices alone. It is also motivated by an objective of providing a full set of stylized facts that theoretical work will ultimately have to comfort. Because of the limitations of existing theory, the empirical work is not organized around the specification and testing of a particular model or class of models. Instead, the empirical effort is mainly data-based.

Knowledge of the dynamic relationship between volatility and volume is essential for understanding the information assimilation process, market efficiency and liquidity. There are at least four reasons why the price-volume relation is important. First, it provides insight into the structure of financial markets. The empirical models predict various price-volume relations that depend on the rate of information flow to the market, how the information is disseminated, the extent to which market prices convey the information, the size of the market and the existence of short sales constraints. Empirical relations between prices and volume can help discriminate between differing hypotheses about market structure. Second, the price – volume relation is important for event studies that use a combination of price and volume data from which to draw inferences. If price changes and volume are jointly determined, incorporating the price volume relation will increase the power of these tests. In other tests, price changes are interpreted as the market evaluation of new information, while the corresponding volume is considered an indication of the extent to which investors disagree about the meaning of the information. The construction of tests and validity of the inferences drawn depend on the joint distribution of price changes and volume. Third, the price-volume relation is critical to the debate over the empirical distribution of speculative prices. Knowledge of the price-volume relationship can be used in event studies to measure changes in the variance of the price process from non-event to event time. And fourth, price-volume relations have significant implications for research into future markets. Price variability affects the volume of trade in future contracts. The price-volume relation can also indicate the importance of private versus public information in determining investors' demands.

The objective of this study is very specific. We concentrate on the role of trading activity in the process that generates stock return volatilities on the Greek 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 interested in whether trading activity can be regarded as a prognosis of stock return volatilities. One important difference distinguishing this study from contributions in the existing literature is the variety of proxies used to approach trading activity and return volatility.

The remainder of the paper is organized as follows. Section 2 contains a brief overview of the existing literature on the relationship between stock return prices/volatilities and trading activity. The section after explains why is important to model volatility and how it can be modeled or measured. The fourth section describes the data set and reports some preliminary results. In section 5 the models used in this study are specified. Section 6 presents the empirical results on the volatility-trading activity relation for several alternative measures of return volatility and activity and provides a discussion of the findings and their implications. Concluding remarks are contained in Section 7.

2. *Existing Literature*

2.1. *Empirical Evidence*

It is an old Wall Street adage that "It takes volume to make prices move". Although one can question the asserted causality, numerous empirical findings support what would be could here a "positive volume-absolute price change correlation".

Academic treatment of a price-volume relation can be traced to **Osborne (1959)**, who attempted to model the stock price change as a diffusion process with variance dependent on the number of transactions. This could imply a positive correlation between volume (V) and volatility ($|\Delta p|$), as later developed by Clark (1973) and **Tauchen and Pitts (1983)**. However, by assuming transactions are uniformly distributed in time, Osborne was able to reexpress the price process in terms of time intervals, and did not directly address the volume – price issue.

An early empirical examination of the volume – price relation was conducted by **Granger and Morgenstern (1963)**. Using spectral analysis of weekly data from 1939-1961, they could discern no relation between movements in a Securities and Exchange Commission composite price index and the aggregate level of volume on the New York Stock Exchange. Data from two individual stocks also displayed no price-volume relation. In **1964, Godfrey, Granger and Morgenstern** presented new evidence from several data series, including daily and transaction data for individual stocks. But once again they could find no correlation between prices or the absolute values of price differences and volume.

Another finding by Godfrey, Granger and Morgenstern is that daily volume correlates positively with the difference between the daily high and the daily low. This is supported by their later finding that daily volume correlates with the squared difference between the daily open and close. The authors attribute this correlation to institutional factors such as stop-loss and buy-above-market orders that increase volume as the price diverges from its current mean.

The failure of Godfrey et al. to uncover price-volume relation motivated the empirical test of **Ying (1966)**. Ying applied a series of chi-squared tests, analyses of variance, and cross-spectral methods to six-year (1957 to 1962), daily series of price and volume. Prices were measured by the Standard and Poor's 500 composite index adjusted for dividend payouts, and volume by the proportion of outstanding NYSE shares traded. The following list is a subset of his findings:

- A small volume is usually accompanied by a fall in price.
- A large volume is usually accompanied by a rise in price.
- A large increase in volume is usually accompanied by either a large rise in price or a large fall in price.
- A large volume is usually followed by a rise in price.
- If the volume has been decreasing consecutively for a period of five trading days, then there will be a tendency for the price to fall over the next four trading days.
- If the volume has been increasing consecutively for a period of five trading days, then there will be a tendency for the price to rise over the next four trading days.

Ying's empirical methods are easily criticized. One problem arises because the price series (S & P's 500 index) and volume series (NYSE percentage volume) he used are not necessarily comparable. A second problem arises from his adjustments to the data for dividends and total NYSE shares outstanding. Ying's daily price series was adjusted by quarterly dividend data, and the daily volume series was adjusted by monthly data on the number of outstanding shares, each using linear interpolations. Also, several of Ying's findings are inconsistent with weak form market efficiency. However, items (1) and (2) suggest V and Δp are positively correlated, and item (3) is consistent with a correlation between V and $|\Delta p|$. Thus, Ying was the first to document both price-volume correlations in the same data set.

2.2. Theoretical Explanations

It is true that there is little evidence in this area. A major limitation has been the lack of substantial theory linking trading activity directly to stock returns. There are two theoretical explanations for the observed volume-volatility relations of stocks.

An early work dedicated to the role or trading volume in the price generating process is that by Clark (1973). He developed the well known *Mixture of Distribution Hypothesis* (MDH). 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. Clark advises the use of volume data as a proxy for the stochastic (information) process. Under the MDH the daily stock return r_t and the daily trading volume V_t is the sum of a random number of individual price increments and volumes. This random number depends on the rate of information arrival during the day. Each time that information arrives to the market, traders adjust the equilibrium price and there is above average trading activity in the market as it adjusts to the new equilibrium. Assuming each intraday return is identically and independently distributed (i.i.d.) with mean zero and variance σ^2, the joint distribution of daily returns and trading volume is a bivariate normal conditional on the daily number of information arrivals, I_t,

$$r_t \mid I_t \sim N\left(0, \sigma^2 I_t\right) \tag{2.1}$$

$$V_t \mid I_t \sim N\left(bI_t, cI_t\right) \tag{2.2}$$

It follows from the above equations that the dynamics of the volatility process of returns are dependent on the time series behavior of I_t which also affects the dynamics of trading volume.

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)**, **Andersen (1996)** and **Lamoureoux and Lastrapes (1990)**.

In a first form of the MDH, that of **Clark (1973)**, and **Tauchen and Pitts (1983)** the daily price change Δp is the sum of a variable number m of independent with-in day price changes. Thus, the variance of the daily price change is a random variable with a mean proportional to the mean number of daily transactions. For a given m, the Central Limit Theorem implies that Δp is approximately normal with variance proportional to m. For a variable m however, the Central Limit Theorem is applicable and the distribution of Δp is subordinate to the distribution of m[1] (finite-variance subordination model). It is intuitively attractive to interpret m as the number of within-day information arrivals, so the conditional variance of Δp is considered to be an increasing function of the rate at which new information enters the market. The V, |Δp| correlation results because volume is also an increasing function of the number of within-day price changes. Clark argues that the trading volume is related positively to the number of within-day transactions, and so the trading volume is related positively to the variability of the price change.

The central proposition of the models by Clark, and Tauchen and Pitts is that transaction time intervals are variable. There is also some empirical support for this

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[1] See Clark (1973) for discussions of subordinated process. Loosely, the distribution of the daily change is “subordinate” to that of m because its parameters are functions of m.

contention. Clark's tests use daily data from the cotton futures markets and volume as a proxy variable for the number of transactions variable m, and show that the leptokurtosis in the empirical distribution of daily price changes largely disappears when the changes are grouped by volume classes.

The hypothesis that transactions time differs from calendar time provides insights into several related market phenomena. The **Tauchen and Pitts (1983)** model implies that the volume-volatility correlation increases with the variance of the daily rate of information flow, and that, as the traders' number increases, the volume of trade increases and price variability decreases. The reason for this is that the market price change during a single market clearing is the average of the changes in the traders' reservation prices. More terms in the average tend to wash out the effects of inter-trader differences. This latter prediction is consistent with evidence from the 90-day Treasury bill futures market daily data.

In a second form of the MDH, **Epps and Epps (1976)** derive a model, which implies stochastic dependence between transaction volume and the change in the logarithm of security price from one transaction to the next since the variance of the price change on a single transaction is conditional upon the volume of that transaction. The change in the logarithm of price can therefore be viewed as following a mixture of distributions, with transaction volume as the mixing variable. For common stocks these distributions (of which the distribution of $\Delta\log(p)$ is a mixture) appear to have a pronounced excess of frequency near the mean and a deficiency of outliers, relative to the normal. These findings are consistent with the hypothesis that stock price changes over fixed intervals of time follow mixtures of finite-variance distributions. While their results support Clark's view that the variance of the change in log price depends on volume, it is worth pointing out that their findings do not by themselves rule out the possibility that the change in log price over fixed intervals of time (Y) has infinite variance.

The Epps and Epps model is similar to the sequential information arrival model, which is discussed below, in that it places a particular structure on the way investors receive and respond to information. Epps and Epps provide empirical support for their contention that a volume-volatility correlation occurs at the transaction level by using transactions data from 20 N.Y.S.E. common stocks.

The Clark and Epps and Epps models are complementary and they give considerable insight into the behavior of speculative markets. Yet, even when taken together, the two models provide a description of speculative markets that is incomplete and can be extended in two directions. First, both models work with the conditional distribution of the square of the price change over a short interval of time, ΔP^2, given the volume of trading, V, for the same interval of time. Application of either model requires the investigator to specify in advance or discover by nonlinear regression the functional form of the conditional expectation, $E[\Delta P^2 \mid V]$. On the contrary, the Tauchen and Pitts model eliminates the need for this. The theory gives an explicit expression for the joint probability distribution of the price change and the trading volume over any interval of time. The joint distribution contains all relevant information about the price variability-volume relationship. Specifically, it determines the conditional distribution of the price change given the volume and the conditional absolute moments of all orders. Second, neither model considers growth in the size of speculative markets such as that experienced by many of the new financial futures markets. Trading on a new market is initially very thin. If the market is viable, then the trading volume increases secularly as more traders become aware of the market's possibilities. Eventually a steady state is reached. The empirical results of other studies suggest that price variability should increase with the growth in the trading volume. This seems unlikely. In fact, one might conjecture that more traders would tend to stabilize prices.

A major difference between the Tauchen and Pitts model and that of Epps and Epps is the way in which they connect the price change to the trading volume. Epps and Epps's key assumption gives them a nearly exact positive relationship between the absolute value of the change in the market price and the trading volume on each within –day market clearing. Tauchen and Pitts do not invoke their assumption. Instead, they use a variance-components scheme to model the within-day revisions of traders' reservation prices. This allows them to derive the joint probability distribution of the price change and the trading volume for each within-day market clearing. Adding the random number of within-day price changes and volumes gives the daily values of each variable. The result is a bivariate normal mixture model with a likelihood function that depends only on a few easily interpreted parameters.

It should be noted that, while the **Epps and Epps (1976)** model requires all investors to receive information simultaneously, the Clark, and Tauchen and Pitts models can be mutually consistent with sequential information arrival. While these models imply simultaneous dispersion of an information bit, they do not require it. The successive equilibria presumed by these models can result from a gradual dissemination of a single bit of information, as in the sequential information arrival model (SIAM), which is discussed below, or from a process in which investors receive information simultaneously. These models are also more general than the SIAM, for two reasons. First, they are consistent with either simultaneous or gradual information dissemination, while Copeland's model implies a negative V, $|\Delta p|$ correlation when simultaneous information arrival is supposed. And second, they explain greater number of phenomena. The MDH is consistent with the empirical distribution of price changes and the difference in the V, $|\Delta p|$ correlation over different frequencies.

Later, **Andersen (1996)** developed a model of the daily return-volume relationship by integrating the market microstructure setting of **Glosten and Milgrom (1985)** [2] with the stochastic volatility, information flow perspective of the MDH. At first, the joint distribution is derived via weak conditions on the information arrival process. Subsequently, the model is expanded into a full dynamic representation by providing a specific stochastic volatility process for the information arrivals. Both representations are estimated and tested for five major individual common stocks on the New York Stock Exchange over the period 1973-1991. The main contributions of his article are as follows. First, he developes modifications to the standard MDH that arise naturally from the microstructure setting, in which informational asymmetries and liquidity needs motivate trade in response to the arrival of new information. The specification is generally consistent with the "Mixture of Distributions Hypothesis" for asset returns, although the volume equation differs from standard specifications. This is due to an accommodation of microstructure features as well as a Poisson, rather normal, approximation to the limiting distribution of the binomial process that drives the trading volume. Second, he reinforces the recent empirical findings by resoundingly rejecting the restrictions that the standard MDH imposes on contemporaneous return-volume observations, while controlling for the trend in

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[2] Glosten and Milgrom (1985) develop a sequential trading model with informed and uninformed investors and find that market makers and uninformed investors experience adverse selection when trading with informed investors. By assumption, each investor is allowed to transact one unit of stock per unit of time, so price changes are completely independent of trade size.

volume and using a long sample. In contrast his alternative version of the MDH provides an overall acceptable characterization of these features of the data, so the general framework of the MDH may yet provide a useful basis for structural modeling of the interaction of market variables in response to information flows and, ultimately, the sources of return volatility. Third, he demonstrates that a stochastic volatility representation of the information arrival process that generalized the popular GARCH(1,1) results in a dynamic specification of the joint system that is consistent with the main contemporaneous as well as dynamic features of the data. Fourth, he documents that, in spite of the overall satisfactory fit, the simultaneous incorporation of returns and volume data results in a significant reduction in the estimated volatility persistence relative to the usual results obtained from univariate returns series.

Easley and O'Hara (1987), also, extends Glosten and Milgrom model to allow traders to transact at varying trade sizes and introduced uncertainty in the information arrival process of the informed trader. When investors act competitively, Easley and O'Hara find that larger-sized traders tend to be executed by better informed investors, so that larger trades exhibit a greater adverse selection effect. In particular, they showed that an adverse selection problem arises because, given that they wish to trade, informed traders prefer to trade larger amounts at any given price. Since uninformed traders do not share this quantity bias, the larger the trade size, the more likely it is that the market maker is trading with an informed trader. This information effect dictates that the market maker's optimal pricing strategy also depends on quantity, with large trade prices reflecting this increased probability of information-based trading. In their model, trade size affects security prices because it changes perceptions of the value of the underlying asset. Thus, there is a positive relation between trade size and price volatility.

In critically evaluating the Easley and O'Hara model, theorists have observed that traders are not allowed to act strategically, which could result in large blocks being broken up into a number of smaller trades. If informed investors are allowed to strategically breakup orders as in **Admati and Pfleiderer (1988)**, then the effect of trade size on price volatility is attenuated and its impact may be shifted to the number of trades. Supporting this view, **Barclay and Warner (1993)** report empirical evidence from the NYSE consistent with informed investors breaking up large trades so as to better hide their information – motivated trading activity. Their evidence is based on how influential trades of various sizes are on price changes. Indeed, they found that most of the sample securities' preannouncement cumulative stock-price change occurs on medium-size trades. This evidence is consistent with the hypothesis that informed trades are concentrated in medium sizes and that price movements are due mainly to informed traders' private information. These results appear more general because they also apply to a nonevent period long before the sample securities experience systematic unusual behavior, and to a sample of all NYSE securities.

Based on Admati and Pfleiderer model, **Foster and Viswanathan (1995)** present a model of speculative trading that predicts conditional heteroskedasticity in trading volume and the variance of price changes and positive autocorrelation in trading volume. They use speculative trading model in which a lognormal latent variable is used to mix conditionally normal parameters, thereby generating persistence in trading volume and squared price changes. Using moment conditions from the model, they estimate its parameters for IBM in 1988. Although, they reject the model, we learn several things. It appears that many informed traders pay little to receive relatively imprecise information and that the bulk of trading comes due to intense competition between these information traders. Hence it may be the case that the material information about IBM is revealed through public disclosure and there is much less private information for IBM that is revealed through trading. Moreover, it appears that the model is unable to explain the relation between current trading and lags of trading volume and squared volume's relation to squared price changes. After scaling these values by their standard errors it is less clear that these moment conditions are responsible for the model's demise.

An important model explaining the arrival of information on a market is the *sequential information arrival model* introduced by **Copeland (1976)**. It implies that news is revealed to investors sequentially (information is disseminated only to one trader at a time) 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.

Copeland (1976) presented a new technique for demand analysis under the key assumption that individuals shift their demand curves sequentially as new information is revealed to them. The information causes a one time-upward shift in each "optimist's" demand curve by a fixed amount δ and a downward shift of δ in each "pessimist's" demand curve. Trading occurs after each trader receives the information, but uninformed traders do not infer the content of the information from informed traders' actions. Also, short sales are prohibited. With N traders, there will in general be k optimists, r pessimists, and N-k-r uninformed investors at any point in time before all investors become informed. The values of k and r depend on the order in which investors become informed. Because of the short sales prohibition, volume generated by a pessimist is generally less than that generated by an optimist (i.e., the pessimist cannot sell short upon receiving the information). So the price change and the trading volume when the next trader becomes informed depend upon both (i) the previous pattern of who has been informed and (ii) whether the next trader is an optimist or pessimist. Likewise, the total volume after all traders become informed depends on the path by which the final equilibrium is reached. The expected volume for each possible sequence between the initial and final equilibria is weighted by its probability, and then the probabilistically weighted paths are summed in order to derive the expected number of trades given N, the total number of trades, S, the number of shares outstanding, δ, the strength of new information, and j*, the number of optimists among N traders. It was theoretically demonstrated that the expected number of trades is a logarithmically increasing function of the number of trades and of the strength of new information. It is a concave function of changes in the number of shares outstanding, and a "U-shaped" function of the percent of optimists. By assuming that the percentage of optimists was symmetrically distributed with mean 0.5 it was possible to show that the sequential information model predicted a positive correlation between the absolute value of price changes and volume, positive skewness in the distribution of volume, and increasing positive skewness as a function of the strength of new information. Simulation tests indicate that volume (V) is highest when investors are all optimists or all pessimists. Also the absolute value of price changes ($|\Delta p|$) is lowest at the same percentage of optimists at which volume is lowest, and rises with volume. This supports a positive correlation of volume and volatility.

This model is open to at least two criticisms. First, is the assumption that prohibits traders from learning from the market price as other traders become informed. Second is the implication that volume is greatest when all investors agree on the meaning of the information. This is contrary to the inference drawn from high measures of volume. Copeland attributes this to the short sales constraint, but that is only part of the story. Also important is rather peculiar interpretation of disagreement among traders, who are forced into a binary response to new information.

In an extension of Copeland's model (SIAM) to incorporate real world margin constraints and short selling, **Jennings, Starks, and Fellingham (1981)** provide an alternate theory consistent with the correlation between V and $|\Delta p|$. In previous informational studies using equilibrium analysis, all market participants are assumed to become informed simultaneously. The *sequential information arrival model* assumes that only one trader observes the information initially. This trader interprets the news, revises his beliefs, and trades to arrive to a new optimal position. The outcome of this series of events is the generation of transaction volume and a new equilibrium price. After the market arrives at this new equilibrium, the next investor becomes informed and, after a similar sequence of events, a second temporary equilibrium is achieved. This process continues until all traders are informed and results in a series of momentary equilibria. When the last trader receives the information, the market reaches a final equilibrium. The sequential process allows one to observe the path of trades, prices, and volume. In addition it provides a more realistic model for most information events. The key innovation in their model is that short positions are possible but are more costly than long positions, which implies that the quantity demanded of an investor with a short position is less responsive to price changes than the quantity demanded of an investor with a long holding. They showed that, for many cases, the volume that results when a previously uninformed trader interprets the news pessimistically is less than when the trader is an optimist. Since price decreases with a pessimist (who sells) and increases with an optimist (who buys), it is argued that volume is relatively high when the price increases and low when the price decreases. While is inconsistent with the empirical correlation between V and Δp, this model is subject to the same criticisms as Copeland's.

In a framework which assumes stochastic fluctuations of stock prices, recent studies, e.g. by **Blume, Easley and O'Hara (1994)** and **Suominen (2001)** state that data concerning trading volume deliver unique information to market participants; information that is not available from prices. **Blume et al.** in their investigation over the informational role of volume develop a new equilibrium model in which aggregate supply is fixed and traders receive signals with differing quality. They argue 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 that cannot be deduced from the price statistic. They also show that traders who use information contained in market statistics do better than traders who do not. Thus, it can be inferred that volume plays a role beyond simply being a descriptive parameter of the trading process. 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. It explains why trading volume contains useful information for predicting volatility and can help to reduce information asymmetries. Specifically, his paper studies an asset market where the availability of private information is stochastically changing over time due to changes in the source of uncertainty in the asset returns. In equilibrium, liquidity traders and speculators use past periods' trading volume to estimate the availability of private information. As the public estimate on the availability of private information increases, liquidity traders become wary and start posting more conservative limit orders. Initially, the number of informed traders increases but, in response to more conservative trading by liquidity traders, it may subsequently decrease. Because the trading by informed traders reveals private information, there is a positive correlation between price variability and trading volume. He shows that the conditional variance is autocorrelated and mean reverting and that it may be either positively or negatively correlated with the expected trading volume and that price changes are not sufficient statistics to characterize the evolution of conditional variance, but that information on trading volume is also needed. In many ways his paper is a theoretical extension of the MDH model. These two studies argue that trading volume describes market behavior and influences market participant's decisions. Both authors suggest strong relationships, but not only contemporaneous but also causal, between volume and return volatility. These two papers also develop models in which traders use previous periods' trading volume to make inferences about the quality of informed traders' signals, which is important for estimating the payoff to the security.

2.3. Summary of theoretical explanations

The two theoretical explanations for the observed volume-volatility relations of stocks are the sequential information arrival hypothesis (SIAH) of **Copeland (1976), Jennings et al. (1981)**; and the Mixture of Distribution Hypothesis (MDH) advanced by **Clark (1973), Tauchen and Pitts (1983),** and **Andersen (1996)**.

SIAH assumes that traders receive new information in a sequential, random fashion. From an initial position of equilibrium where all traders possess the same set of information, new information arrives in the market and traders revise their expectations accordingly. However, traders do not receive the information signals simultaneously. Reactions of different traders to information are parts of a series of incomplete equilibria. Once all traders have reacted to the information signal, a final equilibrium is reached. The sequential reaction to information in the SIAH suggests that lagged values of volatility may have the ability to predict current trading volume, and vice versa.

On the other hand, the MDH implies an alternative volatility-volume nexus, in which the relation is critically dependent upon the rate of information flow into the market. The model assumes that the joint distribution of volume and volatility is bivariate normal conditional upon the arrival of information. All traders simultaneously receive the new price signals. As such, the shift to a new equilibrium is immediate and there will be no intermediate partial equilibrium. This is contrary to the SIAH, which assumes that there are immediate equilibria en route to the final equilibrium. Thus, under the MDH, there should be no information content in past volatility data that can be used to forecast volume or vice versa since these variables contemporaneously change in response to the arrival of new information. While having some success in characterizing the empirical behavior of volatility and volume, the MDH model has its limitations. For example, the model does not allow for serial dependence in return volatility and volume, conditional on the underlying information flow. Furthermore, the model does not account for the effect of time duration between trades.

2.4. ***Recent Empirical Studies***

These theoretical contributions have been accompanied by a number of empirical studies which deal with volume-price relationships on capital markets. **Karpoff (1987)** concludes from a review of prior empirical literature that volume and changes in absolute returns are positively associated, but that this association weakens as the measurement interval shortens.

More recent support for this relation is found **in Jain and Joh (1988), Hiemstra and Jones (1994), Lee and Rui (2002), Gallant, Rossi and Tauchen (1992), Lamoureoux and Lastrapes (1990), Foster and Vishwanathan (1995)** and **Andersen (1996). Jain and Joh (1988)** analyze hourly trading volume on the New York Stock Exchange and hourly returns on the Standard and Poor's 500 index for the years 1979 to 1983 in order to investigate the joint generating process for hourly common stock trading volume and returns. The results showed a strong positive contemporaneous trading volume and absolute value of returns and are consistent with the MDH (Mixture of Distribution Hypothesis). The results also show that the average trading volumes across six trading hours of the day and across days of the week differ significantly. Specifically, average volume is highest during the first hour, declines monotonically until the fourth hour, but increases again on the fifth and the sixth hours, while average daily trading volume is lowest on Monday, increases monotonically from Monday to Wednesday, and then declines monotonically on Thursday and Friday. Moreover, common stocks returns differ across trading hours of the day. On average, largest stock returns occur during the first (except on Monday) and the last trading hours.

In their article **Hiemstra and Jones (1994)** use linear and nonlinear Granger causality tests to examine the dynamic relation between aggregate daily stock prices and trading volume. They apply the tests to daily Dow Jones stock returns and percentage changes in NYSE trading volume over the 1915 to 1946 and 1947 to 1990 periods. Their tests provide evidence of significant bidirectional nonlinear Granger causality between stock returns and trading volume in both sample periods. They also examine whether the nonlinear causality from volume to stock returns detected by their test could be due to volume serving as a proxy for daily information flow in the stochastic process generating stock return variance. After controlling for simple volatility effects, the test continues to provide evidence of significant nonlinear Granger causality from trading volume to stock returns. Their results contribute to the empirical literature on the stock price-volume relation by indicating the presence of bidirectional nonlinear Granger causality between aggregate daily stock prices and trading volume.

Using daily data, **Lee and Rui (2002)** examine causal relations not only between stock market trading volume and price changes but also between volume and volatility of returns both in domestic and international markets and investigate dynamic effects among these variables of the three largest stock markets: New York, Tokyo, and London. They include volatility in their analysis as well as return and volume in part because it is possible that the dynamic relation between return and volume may be affected by volatility effects associated with information flow and in part because volatility is a key ingredient of the risk-return tradeoff that permeates modern financial theories. The following bivariate vector autoregression (VAR) model[3] is used to test for causality between the two variables among trading volume, stock returns and volatility of stock returns:

$$\chi_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i \chi_{t-i} + \sum_{i=1}^{n} \beta_i y_{t-i} + \varepsilon_t \qquad (2.3)$$

$$y_t = \gamma_0 + \sum_{i=1}^{m} \gamma_i \chi_{t-i} + \sum_{i=1}^{n} \delta_i y_{t-1} + \eta_t \qquad (2.4)$$

Lee and Rui's evidence shows that trading volume does not Granger-cause stock market returns on each of the markets since trading volume does not add significant predictive power for future returns in the presence of current and past returns. However, volume helps predict return volatility and vise versa. Taken together, trading volume helps predict the volatility of returns but not the level of returns.

Gallant, Rossi and Tauchen (1992) use a different approach to investigate the price and volume co-movement. They use nonparametric methods. The main reason for doing this is to avoid bias due to a specification error. They utilize daily data on the S&P composite index and total NYSE trading volume from 1928 to 1987 and found that the daily trading volume is positively and nonlinearly related to the magnitude of the daily price change. This association is a characteristic of both the unconditional distribution of price changes and volume and the conditional distribution given past price changes and volume constant. Their finding means that the volume-volatility association is still observable after taking account of non-normalities, stochastic volatility and other forms of conditional heterogeneity. Using daily individual security data (1981-1983), **Lamoureoux and Lastrapes (1990)** find a positive conditional volume volatility relationship in models with Gaussian errors and Garch-type volatility specifications. However, these earlier studies typically do not consider competing measures of trading activity, nor do they examine the number of trades as a measure of trading activity, as Jones, Kaul and Lipson do.

Findings that are quite contrary to the old Wall Street adage that "it takes volume to make prices move" are these of **Jones, Kaul and Lipson (1994)**. Their investigation can be viewed as a direct test of the Mixture of Distribution Hypothesis (MDH), which asserts that volatility and volume are positively correlated only because both are positively related to the number of daily information arrival (the mixing variable). With a fixed number of traders who all trade a fixed number of times in response to new information; the number of daily transactions will be proportional to the number of information arrivals [see **Clark (1973), and Tauchen and Pitts (1983)**]. Therefore, the volatility-volume relation should be rendered statistically insignificant when volatility is conditioned on the number of transactions as well.

Jones, Kaul and Lipson (1994) report a startling result concerning stock price volatility. After decomposing trading volume into two components, the number of trades and the average trade size, which they use as regressors in their model, they find that the first (trade frequency) is much more important than the latter in affecting stock price volatility. Their evidence is based on an examination of a large sample of Nasdaq stocks using daily data over the 1986-1991 period and they use average trade size (total number of shares traded divided by number of daily transactions) as the measure of volume. Their results, however, are insensitive to the choice of the empirical measure of volume, since alternative measures like dollar volume, number of shares traded, or turnover (number of shares traded divided by total number of

[3] Methodology developed by Sims (1972, 1980)

shares outstanding) yield virtually identical inferences. They also measure daily volatility using the absolute residuals of the following model:

$$R_{it} = \sum_{k=1}^{5} \hat{\alpha}_{ik} D_{kt} + \sum_{j=1}^{12} \hat{\beta}_j R_{it-j} + \hat{\varepsilon}_{it}, \qquad (2.5)$$

where R_{it} is the return of security i on day t, D_{kt}'s are the five day of the week dummies used to capture differences in mean returns. The 12 lagged returns are used as regressors to estimate short-term movements in conditional expected returns.
To gauge the relative importance of number of transactions versus volume of trade, they estimate the following three sets of regressions for each security:

$$\left|\hat{\varepsilon}_{it}\right| = \alpha_i + \alpha_{im} \mathrm{M}_t + \beta_i \mathrm{A}V_{it} + \sum_{j=1}^{12} \rho_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \eta_{it}, \qquad (2.6a)$$

$$\left|\hat{\varepsilon}_{it}\right| = \alpha_i + \alpha_{im} \mathrm{M}_t + \gamma_i \mathrm{N}_{it} + \sum_{j=1}^{12} \rho_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \eta_{it}, \qquad (2.6b)$$

and

$$\left|\hat{\varepsilon}_{it}\right| = \alpha_i + \alpha_{im} \mathrm{M}_t + \beta_i \mathrm{A}V_{it} + \gamma_i \mathrm{N}_{it} + \sum_{j=1}^{12} \rho_{ij} \left|\hat{\varepsilon}_{it-j}\right| + \eta_{it}, \qquad (2.6c)$$

where $\left|\hat{\varepsilon}_{it}\right|$ is the absolute residual from (2.5), M_t is a trading-gap dummy variable that is equal to 1 for Mondays and 0 otherwise, AV_{it} is the average trade size (total number of shares traded divided by the number of transactions for security i or day t), N_{it} is the number of transactions for security i on day t, and the coefficients ρ_{ij}'s measure the persistence in the volatility of security i.

Jones, Kaul, and Lipson's (JKL) evidence shows that the volatility-volume relation typically disappears when they control for the relation between volatility and number of transactions. Specifically, daily volatility is significantly positively related to both average daily trade size and number of daily transactions. However, in regressions of volatility on average trade size and number of transactions, the volatility-volume relation is rendered statistically insignificant while the relation between volatility and number of transactions remains virtually unaltered. Average size of trades has a statistically significant positive relation with volatility only for small firms, but on average even this statistical relation seems to be of little economic significance. Thus, their evidence strongly suggests that the occurrence of transactions per se contains all the information pertinent to the pricing of securities. In a summary, Jones, Kaul, and Lipson showed that the positive volatility-volume relation documented by numerous researchers simply reflects the positive relation between volatility and number of transactions. The most notable implication of this finding is that on average the size of trades has virtually no incremental information content; any information in the trading behavior of agents is almost entirely contained in the frequency of trades during a particular interval. This evidence appears to run counter to the dominant market microstructure theories of stock price determination, which emphasize the role of trade size as a means of detecting likely informed trading and adverse selection.

Huang and Masulis (2003) assess the generality of the JKL conclusions by studying this relation in another major competing dealer market, the London Stock Exchange (LSE). To examine the question of how trading activity impacts price volatility, they analyze daytime and hourly price changes and trading activity for the 100 larger stocks, based on equity capitalization, in the London market for the year 1995. They also explore two extensions of the basic JKL experiment. First, they consider whether time aggregation of individual trades into daily sums and averages strongly smoothes the underlying variability of the trade size variable, thereby lowering its information content and significance. Second, they consider the fundamental question of whether trades of all sizes have the same effect on price volatility. If information traders break up large trades to gain better price execution, then any remaining large trades are likely to be liquidity-driven, with little impact on price volatility. **Barclay and Warner (1993)** as mentioned above, presented evidence consistent with information traders intentionally breaking up large orders, thus making large trades less frequent and medium-size trades more informative. This is referred to as the stealth trading hypothesis. Further attenuation of the empirical relation between trade size and price volatility can result from an infrequency of large trades relative to small trades, potential front running prior to the completion of large trades, reporting of some contemporaneous small trades as a single large trade and delayed reporting of large trades. Therefore, in analyzing the trading activity-price volatility relation, they also investigate the empirical relevance of trade size categories and of trade reporting rules.

Huang and Masulis (2003) use as price volatility measure the absolute value of the closing price minus the opening price, which represents daytime volatility rather than daily volatility. Average trade size is defined as share volume divided by number of trades, where trades are for buy transactions. They use JKL's linear specification in their statistical model:

$$V_{it} = \alpha + \beta \mathrm{A}_{it} + \gamma \mathrm{N}_{it} + \varepsilon_{it}, \tag{2.7}$$

where V_{it} represents price volatility, A_{it} represents average trade size and N_{it} represents the number of trades, in each case for stock i over the interval t. They estimate this equation using Hansen's (1982) generalized method of moments (GMM)[4]. For their overall sample, price volatility on the London Stock Exchange is directly related to trade frequency and more weakly, but positively related to trade size. In this regard, they support the general conclusion of Jones, Kaul and Lipson. They also conclude that small trades are the only ones that consistently have a significant impact on price volatility. Furthermore, for small trades, they find significant impact on price volatility from both trade size and trade frequency, particularly when we move from daytime to hourly data. In examining whether this relation varies across stocks categorized by equity capitalization or trading volume, they find no evidence of significant differences, which indicates that the trade size is not acting as a proxy for equity capitalization or stock liquidity.

[4] The GMM estimation method imposes weak distribution assumptions on the observable variables and endogenously adjusts the estimates to account for general forms of conditional heteroskedasticity and/or serial correlation that may be present in the error structure. Serial correlation in stock price volatility is a particular concern, given the widely documented strong positive serial correlation found in squared stock returns. In contrast, JKL use a two-step estimation procedure and measure price volatility by the absolutes residuals from daily returns regressed against five day of the week dummies and 12 lagged returns to handle the serial correlation in the residuals.

Besides **Huang and Masulis (2003), Ané and Ureche-Rangau** have also tried to find out to which extent the temporal dependence of volatility and volume of speculative assets is compatible with a MDH model through a systematic analysis of the long memory properties of power transformations of both series by using data from 50 London Stock Exchange "blue chips" quoted between January 1990 and May 2001. Returns are calculated as differences of price logarithms and the trading volume is also used in logarithms. They use a semiparametric framework to test for the MDH model adequacy. Although, this type of approach necessarily results in an efficiency loss compared to parametric methods (like MLE or GMM), it allows avoiding problems resulting from model misspecifications in the parametric case. The results suggest that volatility and volume may share common short-term movements but that their long-run behavior is fundamentally different.

A relevant research concerning return volatilities and trading activities took place in an emerging Asian market as well. It has been documented in the U.S. stock market that return variance in the active trading hours of the stock market (open-to-close) is bigger than in the non-trading hours (close-to-open) due to the existence of noise traders in the market. **Ho, Cheung, Draper and Pope (1992)** show that this relationship between the volatility pattern and the opening hours of stock exchange is also valid under different market microstructures. The Hong Kong stock market, one of the most important emerging Asian markets, is different from the U.S. market in two major aspects as far as the trading hours are concerned. First, when the stock exchange is officially closed, i.e., close-to-open, 27 of the major Hong Kong stocks continue to trade actively on the London exchange. Second, during the trading hours (open-to-close) in the U.S. market, there is continuous trading in the U.S. market throughout the whole trading day but there is a full two hours in Hong Kong from 12:30 p.m. to 2:30 p.m. when the market is closed for people to have lunch. Contrary to the findings in the U.S., their results show that the open-to-close return variance is not different from the close-to-open return variance. Thus, even when the market is officially closed, the return can stay volatile if trading can continue in other places. Thus, volatility is caused by trading activity but not by the hours when the exchange is officially open. This point is further confirmed by the fact that the return variance during the lunch break (the duration when there is no trading at all for Hong Kong stock either in Hong Kong or in other places) is smaller than that when there is active trading. The noon time (during the lunch break) return variance is also found to be statistically smaller than that for the close-to-open period when the Hong Kong market is officially closed but trading continues in the London market. Thus, these results confirm the notion that volatility is caused by active trading.

An important paper is that titled "International transmission and volume effects in G5 stock market returns and volatility" (by **Avouyi-Dovi and Jondeau**[5]). This paper analyzes the links between stock market return, volatility and trading volume. This framework is used to study the daily returns of the reference stock market indices of the G5 countries over the period 1988-1998. The data used in their paper are leading G5 stock market indices (Dow Jones in New York, DAX in Frankfurt, CAC 40 in Paris, FTSE 100 in London and Nikkei in Tokyo), trading volumes for each market, and the 10-year benchmark interest rates. The model is composed of three equations (for volume, return and volatility). Their findings show that, for all stock markets, a negative shock (bad news) has a larger effect on the

[5] Research Department, Bank of France. The views expressed in this paper are those of the authors and do not necessarily represent those of the bank of France.

volatility than the positive shock (good news) and that trading volume has a strong positive impact on all indices. In the return equation, this influence is more pronounced for the DAX, the FTSE 100 and the Nikkei. Moreover, all volatilities are strongly influenced by volume effects. Unexpected volume appears to have asymmetric effects on return as well as on volatility. A positive shock on volume effects German, UK and Japanese returns more strongly than a negative shock does. Similarly, a positive shock on volume affects US, German and Japanese volatility more strongly than a negative shock does.

In their recent research **Xu, Chen and Wu (2005)** examine volume and volatility dynamics by accounting for market activity measured by the time duration between two consecutive transactions. A time- consistent vector autoregressive (VAR) model is employed to test the dynamic relationship between return volatility and trades using intraday irregularly spaced transaction data of Dow Jones 30 stocks over the period April 1 to June 30, 1995. The model is used to identify the informed and uninformed components of return volatility and to estimate the speed of price adjustment to new information. Their model accounts for the effect of time duration in measuring the information content of trades and examining its impacts on volatility and trading costs. In addition, serial dependence in volatility and volume is accommodated. It is found that volatility and volume are persistent and highly correlated with past volatility and volume. The time duration between trades has a negative effect on the volatility response to trades and correlation between current and past trading volume. **Xu, Chen and Wu (2005)** paper contributes to literature in several ways. First, their model generalizes the traditional MDH model, which imposes a restriction that volatility and trading volume are only contemporaneously correlated. Second, their model accounts for the effect of time duration or market activity on return volatility and the price adjustment to new information. Third, it provides a convenient framework to decompose return volatility into informed and uninformed components.

In **2005, Gurgul, Majdosz and Mestel** published their paper, which concerns the relationship between stock returns (and stock returns volatility) and trading volume. They 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. They tested 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 stock returns volatilities. Their investigation covers not only contemporaneous but also dynamic (causal) relationships because they are mainly interested in whether trading volume can be regarded as a prognosis of stock return levels and/or return volatilities. These relationships are investigated by the use of abnormal stock return and excess trading volume data. Their 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. They 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 fluctuations. Gurgul, Majdosz and Mestel 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. Furthermore, their findings provide evidence that for the Polish stock market this volatility-volume relationship is independent of the direction of the observed price change. They apply their 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. They also detect dynamic relationships between return volatility and trading volume data.

Before the above research **Gurgul, Majdosz and Mestel (2003)** and **Gurgul and Mestel** had already investigated the empirical relationship between stock returns, return volatility and trading volume using data from the Austrian and the German Stock Market, respectively. In their research, they use abnormal stock returns and excess trading volume data as they do later in the Polish case. As proxies of volatility they use the absolute returns and the squared returns and conclude that the use of these alternative measures of volatility leads to identical results. Their results from the Austrian and from the German Stock Market as well are identical with those found in the Polish case. Specifically, their findings indicate that there is neither a contemporaneous nor a causal relation between market adjusted stock returns and mean adjusted trading volume, which means that short-run forecasts of current or future stock returns cannot be improved by knowledge of recent volume data and vice versa. This is in keeping with the efficient capital market hypothesis. On the other hand, they find evidence of a contemporaneous and a causal relation as well 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 their results indicate that return volatility precedes trading volume, implying that information might flow sequentially rather than simultaneously into the market.

The empirical study by **Wang, Wang and Liu (2005)** investigates the dynamic relationship between stock return volatility and trading volume for individual stocks listed on the Chinese stock market as well as market portfolios of these stocks. The data set used consists of the bivariate daily return and trading volume series for 22 actively traded stocks listed on the Chinese Stock Exchange and four market portfolios, proxied by four market indices. They find that the inclusion of trading volume, which is used as a proxy of information arrival, in the GARCH specification reduces the persistence of the conditional variance dramatically, and the volume effect is positive and statistically significant in all the cases for individual stocks. Consistent with their analysis of the institutional and ownership structure of listed Chinese companies, trading volume is found to play a role of proxies of information arrivals only for two of the four portfolios. Thus their findings confirm the relevancy and the validity of the MDH for individual stocks but fall short of supporting half of the cases for the market portfolios when return volatility and trading volume are concerned. The findings indicate that, while return volatility and trading volume are driven by the same underlying information flow variable in individual stocks, information arrivals represented by trading volume tend to be company specific and the timing of market activity of individuals companies appears to be asynchronous. These findings also imply and explain the incapability of trading volume to play a role in reducing return volatility for market portfolios, since trading volume here, unlike in the case of individual stocks where it measures and detects the timing of information arrivals effectively, is a blurred aggregate of individual asynchronous information arrivals with no clear association with return volatility. Their results also suggest that, while trading volume absorbs persistence to a great extent in the individual stock cases, it does not account for all the sources of conditional heteroscedasticity in stock returns in the Chinese stock market.

In his paper **Brailsford (1994)** tests the relationship between any function of price change and trading volume in the Australian market both for the aggregate market and for individual stocks. His methodology involves testing the relationship between different measures of price change and trading volume. This initially conducted using standard OLS regressions which test the following relationships:

$$V_t = \alpha_0 + \gamma_1 |r_t| + \gamma_2 D_t |r_t| + \mu_t \qquad (2.8)$$

$$V_t = \alpha_1 + \gamma_3 r_t^2 + \gamma_4 D_t r_t^2 + \mu_t \qquad (2.9)$$

where V_t is the daily measure of volume; r_t is the daily return; D_t=1 if r_t<0, and D_t=0 if $r_t \geq 0$. The second test in Brailsford paper examines the effect of trading volume on conditional volatility. This is examined through modification of the GARCH model so that it includes trading volume as an explanatory variable following the methodology of **Lamoureux and Lastrapes (1990)**. The basic GARCH model is modified:

$$r_t = \gamma_0 + \gamma_1 r_{t-1} + \varepsilon_t \quad \text{where } \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t) \qquad (2.10)$$

$$h_t = \omega + \beta_1 h_{t-1} + \alpha_1 \varepsilon_{t-1}^2 + \lambda_1 V_t \qquad (2.11)$$

where Ω_{t-1} is the information set available at period t-1.

The GARCH (1,1) model is used for comparison with **Lamoureux and Lastrapes (1990)**. The significance of the coefficient estimate (λ_1) indicates the influence of trading volume. His sample consists of daily All Ordinaries Index (AOI) values and covers the period 24 April 1989 to 31 December 1993.

Through his research evidence is found which supports an asymmetric model. The relationship between price changes and volume, irrespective of the direction of the price change, was significant for the aggregate market and for individual stocks as well. Further more, evidence was found supporting the hypothesis that the volume – price changes slope for negative returns is less steep than the slope for positive returns, thereby supporting the asymmetric relationship. As far as the effect of trading volume on the conditional volatility concerns the findings of his research show a reduction in the significance and magnitude of the GARCH coefficients, and a reduction in the persistence of variance when trading volume is added as an exogenous variable to the conditional variance. Hence, there is evidence that if trading volume proxies for the rate of information arrival, then ARCH effects and much of the persistent in variance can be explained.

In their paper **Darrat, Rahman and Zhing (2003)** examine the contemporaneous correlation under the Mixture of Distribution Hypothesis (MDH) as well as the lead-lag relation (causal) under the sequential information arrival hypothesis (SIAH) between trading volume and return volatility in all stocks comparing the Dow Jones industrial average (DJIA).

In their study they test both alternative explanations (SIAH-MDH) of the volume-volatility relation and by this way they contribute to the literature in several respects. First, they use 5-minute intraday data to investigate the volume – volatility relation. Intraday observations seem particularly suitable for examining the above relation. Since stock markets display high speeds of adjustment, empirical results reported in prior studies using longer time frequencies, such as daily or weekly observations, might fail to capture valuable information contained in intraday market movements. Second, they utilize the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model to measure return volatility. The proposed EGARCH model accounts for the time-varying volatility process with asymmetric responses to both positive and negative price changes. Third, they avoid the "large sample problem" in their intraday data by appropriately adjusting the critical values in the test using a Bayesian approach.

Their sample consists of transaction prices and trading volumes from April 1, 1998 to June 30, 1998 on the 30 stocks of the DJIA, which are very actively traded and typically experience the most frequent flow of information into the market. From the data, they compute 5-minute interval return and trading volumes and they generate 5-minute return series for each stock by taking the log of the ratio of transaction prices in successive intervals, excluding overnight returns as well as the first two 5-minute returns from the series. Disregarding the first two 5-minute return observations each day can mitigate the effects of stale price information.

Following **Nelson (1991)**, they use the exponential version of GARCH (EGARCH) to measure return volatility. They allow the squared root of the conditional variance to enter the mean return equation, leading to an EGARCH-in-mean model (EGARCH-M). To allow for sufficient flexibility in the estimation, they use up to 12 autoregressive lags in the mean equation and specify the conditional variance as an EGARCH-M(1,1) process to obtain parsimonious estimators. The model can be written as

$$R_t = \psi + \sum_{i=1}^{12} \alpha_i R_{t-i} + \sqrt{h_t^2} + \varepsilon_t \text{, where } \varepsilon_t \sim \mathrm{GED}(0, \mathrm{h}_t^2) \qquad (2.12)$$

$$h_t^2 = \exp\left\{ \phi \ln\left(h_{t-1}^2\right) + \varphi \left[\gamma \left(\left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| - \mathrm{E}\left(\left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| \right) \right) + o\left(\left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| \right) \right] \right\} \qquad (2.13)$$

where R_t denotes stock returns; the ε_t's are innovations distributed as a GED (generalized error distribution) with zero mean and conditional variance, h_t^2; and the coefficients $\psi, \alpha, \phi, \varphi, \gamma$, and o are the estimated parameters. Eq. (2.12) represents dynamic changes in the first moment of returns (mean), while Eq. (2.13) describes time variations in the conditional second moment (variance). They estimate the EGARCH-M system of Eq. (2.12) and (2.13) jointly using the predicted values of h_t^2 from Eq. (2.13) to represent the conditional variance. Then they apply the EGARCH-M (1,1) model for each of the 30 DJIA stock return series, and then extact the associated conditional variance to represent return volatility.

Their results suggest that contemporaneous correlations are positive and statistically significant in only three of the 30 DJIA stocks. However, all remaining stocks of the DJIA (27) exhibit no significant positive correlation between trading volume and return volatility. Such weak evidence of contemporaneous correlations contradicts the prediction of the MDH in intraday data. The results support instead the SIAH since trading volume and return volatility are found to follow a clear lead-lag pattern in a large number of the DJIA stocks.

Later on, **Darrat, Zhong and Cheng** re-examine the intraday lead-lag relation of volume and volatility in two perspectives: with and without identifiable public news. Separating the periods with and without public news and employing Bayesian adjustments to avoid large sample biases, they find consistent evidence that trading volume Granger-causes return volatility even during the periods without public news. These results provide support to the overconfidence hypothesis over the SIAH and suggest that investors trade according to their private signals and appear reluctant to close their positions afterwards. They examine the intraday causal dynamics of trading volume and return volatility in a vector autoregression model (VAR):

$$\sigma_t^2 = \gamma_1 + \sum_{k=1}^{L} \alpha_k \sigma_{t-k}^2 + \sum_{k=1}^{L} b_k v_{t-k} + \varepsilon_{1t} \qquad (2.14)$$

$$v_t = \gamma_2 + \sum_{k=1}^{L} c_k v_{t-k} + \sum_{k=1}^{L} d_k \sigma_{t-k}^2 + \varepsilon_{2t} \qquad (2.15)$$

where σ_t^2 is the conditional volatility of intraday stock returns, v_t is the natural log of trading volume during time interval t, ε_{it} is the disturbance reflecting variation of the left-hand-side variable that cannot be accounted for by the right-hand-side variables, and a,b,c, and d are the group lagged coefficients in the Granger-causality testing equations.

3. *Measures of volatility*

There are several reasons to model and forecast volatility. First, volatility is an important factor in options trading, where volatility means the conditional variance of the underlying asset return. Second, it is important in risk management, since volatility modeling provides a simple approach to calculating value at risk of a financial position. Finally, modeling the volatility of a time series can improve the efficiency in parameter estimation and the accuracy in interval forecast.

Although volatility is not directly observable, it has some characteristics that are commonly seen in asset returns. First, there exist volatility clusters (i.e., volatility may be high for certain time periods and low for other periods). Second, volatility evolves over time in a continuous manner-that is, volatility jumps are rare. Third, volatility does not diverge to infinity-that is, volatility varies within some fixed range. Statistically speaking, this means that volatility is often stationary. Fourth, volatility seems to react differently to a big price increase or a big price drop. These properties play an important role in the development of volatility models. Some volatility models were proposed specifically to correct the weaknesses of the existing ones for their inability to capture the characteristics mentioned earlier. For example, the EGARCH model was developed to capture the asymmetry in volatility induced by big "positive" and "negative" asset returns.

The basic idea behind volatility study is that the series $\{r_t\}$, where r_t is the log return of an asset at time index t, is either serially uncorrelated or with minor lower order serial correlations, but it is dependent. Volatility models attempt to capture such dependence in the return series.

To put the volatility models in a proper perspective, it is informative to consider the conditional mean and conditional variance of r_t given F_{t-1}-that is,

$$\mu_t = E(r_t|F_{t-1}),\ \sigma_t^2 = Var(r_t|F_{t-1}) = E[(r_t - \mu_t)^2|F_{t-1}], \quad (3.1)$$

where F_{t-1} denotes the information set available at time t-1. Typically, F_{t-1} consists of all linear functions of the past returns. Empirical examples show that serial dependence of a stock return series r_t is weak if it exists at all. Therefore, the equation for μ_t in (3.2) should be simple, and we assume that μ_t follows a simple time series model such as a stationary ARMA(p, q) model. In other words, we entertain the model

$$r_t = \mu_t + \alpha_t, \qquad \mu_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i} - \sum_{i=1}^{q} \theta_i \alpha_{t-1} \quad (3.2)$$

where p and q are non-negative integers. The model for μ_t in Eq. (3.2) is referred to as the *mean* equation for r_t and the model for σ_t^2 is the *volatility* equation for μ_t. Therefore, modelling conditional heteroscedasticity amounts to augmenting a dynamic equation to a time series model to govern the time evolution of the conditional variance of the shock.

Many methods have been proposed for modeling and forecasting financial market volatility. The most widespread procedure used is through several econometric models that are available in the literature for modeling the volatility of an asset return. These models are referred to as conditional heteroscedastic models. The conditional heteroscedastic models are concerned with the evolution of σ_t^2. The manner under which σ_t^2 evolves over time distinguishes one volatility model from another.

Conditional heteroscedastic models can be classified into two general categories. Those in the first category use an exact function to govern the evolution of σ_t^2, whereas those in the second category use a stochastic equation to describe σ_t^2. The GARCH model belongs to the first category, and the stochastic volatility model is in the second category.

3.1. Conditional Heteroscedastic Models

3.1.1. The ARCH Model

The first model that provides a systematic framework for volatility modeling is the ARCH model of **Engle (1982)**. The basic idea of ARCH models is that (a) the mean corrected asset return α_t is serially uncorrelated, but dependent, and (b) the dependence of α_t can be described by a simple quadratic function of its lagged values.

Specifically, an ARCH(*m*) model assumes that:

$$\alpha_t = \sigma_t \varepsilon_t, \qquad \sigma_t^2 = \alpha_0 + \alpha_1 \alpha_{t-1}^2 + \ldots + \alpha_m \alpha_{t-m}^2, \quad (3.3)$$

where $\{\varepsilon_t\}$ is a sequence of independent and identically distributed (iid) random variables with mean zero and variance 1, $\alpha_0 > 0$, and $\alpha_i \geq 0$ for $i > 0$. The coefficients α_i must satisfy some regularity conditions to ensure that the unconditional variance of α_t is finite. In practice, $\{\varepsilon_t\}$ is often assumed to follow the standard normal or a standardized Student-*t* distribution.

From the structure of the model, it is seen that large past squared shocks $\{\alpha_{t-i}^2\}_{i=1}^m$ imply a large conditional variance σ_t^2 for the mean-corrected return α_t. Consequently, α_t tends to assume a large value (in modulus). This means that, under the ARCH framework, large shocks tend to be followed by another large shock. This feature is similar to the volatility clusterings observed in asset returns.

The simplest model of this class is ARCH(1) model:

$$\alpha_t = \sigma_t \varepsilon_t, \qquad \sigma_t^2 = \alpha_0 + \alpha_1 \alpha_{t-1}^2,$$

where $\alpha_0 > 0$, and $\alpha_i \geq 0$ for $i > 0$.

First, the unconditional mean of α_t remains zero because $E(\alpha_t) = E[E\alpha_t(\mid F_{t-1})] = E[\sigma_t E(\varepsilon_t)] = 0$.

Second, the unconditional variance of α_t can be obtained as:

$$\text{Var}(a_t) = E(a_t^2) = E[E(a_t^2 \mid F_{t-1})] = E(\alpha_0 + \alpha_1 a_{t-1}^2) = \alpha_0 + \alpha_1 E(a_{t-1}^2).$$

Because α_t is a stationary process with $E(\alpha_t)=0$, $\text{Var}(\alpha_t)=\text{Var}(\alpha_{t-1})=E(\alpha_{t-1}^2)$. Therefore, we have $\text{Var}(\alpha_t)=\alpha_0+\alpha_1\text{Var}(\alpha_t)$ and $\text{Var}(\alpha_t)=\alpha_0/(1-\alpha_1)$. Because the variance of α_t must be positive, we need $0 \leq \alpha_1 < 1$. Third, in some applications, we need higher order moments of α_t to exist and, hence, α_1 must also satisfy some additional constraints. For instance, to study its tail behaviour, we require that the fourth moment of α_t is finite. Under the normality assumption of ε_t in Eq. (3.3), we have $E(\alpha_t^4|F_{t-1}) = 3[E(\alpha_t^2|F_{t-1})]^2 = 3(\alpha_0+\alpha_0 a_{t-1}^2)^2$. Therefore,

$$E(a_t^4) = E[E(a_t^4 \mid F_{t-1})] = 3E(\alpha_0 + \alpha_1 a_{t-1}^2)^2 = 3E[\alpha_0^2 + 2\alpha_0\alpha_1 a_{t-1}^2 + \alpha_1^2 a_{t-1}^4]$$

If α_t is fourth-order stationary with $m_4 = \text{E}(\alpha_t^4)$, then we have

$$\begin{aligned} m_4 &= 3[\alpha_0^2 + 2\alpha_0\alpha_1 \text{Var}(a_t) + \alpha_1^2 m_4] \\ &= 3\alpha_0^2\left(1 + 2\frac{\alpha_1}{1-\alpha_1}\right) + 3\alpha_1^2 m_4. \end{aligned}$$

Consequently,

$$m_4 = \frac{3\alpha_0^2(1+\alpha_1)}{(1-\alpha_1)(1-3\alpha_1^2)}.$$

This result has two important implications: (a) since the fourth moment of α_t is positive, we see that α_1 must also satisfy the condition $1\text{-}3\alpha_1^2 > 0$; that is, $0 \leq \alpha_1^2 < 1/3$; and (b) the unconditional kurtosis of α_t is

$$\frac{E(a_t^4)}{[\text{Var}(a_t)]^2} = 3\frac{\alpha_0^2(1+\alpha_1)}{(1-\alpha_1)(1-3\alpha_1^2)} \times \frac{(1-\alpha_1)^2}{\alpha_0^2} = 3\frac{1-\alpha_1^2}{1-3\alpha_1^2} > 3.$$

Thus, the excess kurtosis of α_t is positive and the tail distribution of α_t is heavier than that of a normal distribution. In other words, the shock α_t of a conditional Gaussian ARCH(1) model is more likely than a Gaussian white noise series to produce "outliers." This is in agreement with the empirical finding that "outliers" appear more often in asset returns than that implied by an iid sequence of normal random variables. These properties continue to hold for general ARCH models, but the formulas become more complicated for higher order ARCH models.

Weaknesses of ARCH Models

Apart from the advantages of ARCH models, which discussed above the model also has some weaknesses:

- The model assumes that positive and negative shocks have the same effects on volatility because it depends on the square of the previous shocks. In practice, it is well known that price of a financial asset responds differently to positive and negative shocks.
- The ARCH model is rather restrictive. For instance, α_1^2 of an ARCH(1) model must be in the interval $\left[0, \tfrac{1}{3}\right]$ if the series is to have a finite fourth moment. The constraint becomes complicated for higher order ARCH models.
- The ARCH model does not provide any new insight for understanding the source of variations of a financial time series. They only provide a mechanical way to describe the behaviour of the conditional variance. It gives no indication about what causes such behaviour to occur.
- ARCH models are likely to overpredict the volatility because they respond slowly to large isolated shocks to the return series.

3.1.2. The GARCH Model

Although the ARCH model is simple, it often requires many parameters to adequately describe the volatility process of an asset return. **Bollerslev (1986)** proposed a useful extension known as the generalized ARCH (GARCH) model. For a log return series r_t, we assume that the mean equation of the process can be adequately described by an ARMA model. Let $\alpha_t = r_t - \mu_t$ be the mean-corrected log return. Then α_t follows a GARCH(*m, s*) model if

$$a_t = \sigma_t \epsilon_t, \qquad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2,$$

where again $\{\varepsilon_t\}$ is a sequence of iid random variables with mean 0 and variance 1.0, $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, and $\sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i) < 1$. Here it is understood that $\alpha_i = 0$ for i>m and β_j =0 for j > s. The latter constraint on $\alpha_i + \beta_i$ implies that the unconditional variance of α_t is finite, whereas its conditional variance σ_t^2 evolves over time. As before, ε_t is often assumed to be a standard normal or standardized Student-*t* distribution.

The strengths and weaknesses of GARCH models can easily be seen by focusing on the simplest GARCH(1,1) model with

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \quad 0 \leq \alpha_1, \beta_1 \leq 1, (\alpha_1 + \beta_1) < 1.$$

First, a large α_{t-1}^2 or σ_{t-1}^2 gives rise to a large σ_t^2. This means that a large α_{t-1}^2 tends to be followed by another large α_t^2, generating, again, the well-known behaviour of volatility clustering in financial time series. Second, it can be shown that if 1-2α_1^2-
$(\alpha_1 + \beta_1)^2 > 0$, then

$$\frac{E(a_t^4)}{[E(a_t^2)]^2} = \frac{3[1 - (\alpha_1 + \beta_1)^2]}{1 - (\alpha_1 + \beta_1)^2 - 2\alpha_1^2} > 3.$$

Consequently, similar to ARCH models, the tail distribution of a GARCH(1,1) process is heavier than that of a normal distribution. Third, the model provides a simple parametric function that can be used to describe the volatility evolution.

The model encounters the same weaknesses as the ARCH model. For instance, it responds equally to positive and negative shocks. In addition, recent empirical studies of high frequency financial time series indicate that the tail behaviour of GARCH models remains too short even with standardized Student-*t* innovations.

3.1.3. The Integrated GARCH Model

IGARCH models are unit-root GARCH models. Similar to ARIMA models, a key feature of IGARCH models is that the impact of past squared shocks $\eta_{t-i} = \alpha_{t-i}^2 - \sigma_{t-i}^2$ for i>0 on α_t^2 is persistent.
An IGARCH(1,1) model can be written as

$$a_t = \sigma_t \epsilon_t, \quad \sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + (1 - \beta_1) a_{t-1}^2,$$

where $\{\varepsilon_t\}$ is defined as before and 1>β_1>0.
From a theoretical point of view, the IGARCH phenomenon might be caused by occasional level shifts in volatility.

3.1.4. The GARCH-M Model

In finance, the return of a security may depend on its volatility. To model such a phenomenon, one may consider the GARCH-M model, where "M" stands for GARCH *in mean*. A simple GARCH(1,1)-M model can be written as

$$r_t = \mu + c\sigma_t^2 + a_t, \quad a_t = \sigma_t \epsilon_t,$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

where μ and c are constant. The parameter c is called the risk premium parameter. A positive c indicates that the return is positively related to its past volatility. Other specifications of risk premium have also been used in the literature, including $r_t = \mu + c\sigma_t + \alpha_t$.

The formulation of the GARCH-M model implies that there are serial correlations in the return series r_t. These serial correlations are introduced by those in the volatility process $\{\sigma_t^2\}$. The existence of risk premium is, therefore, another reason that some historical stock returns have serial correlations.

3.1.5. The Exponential GARCH Model

To overcome some weaknesses of the GARCH model in handling financial time series, **Nelson (1991)** proposed the exponential GARCH (EGARCH) model. In particular, to allow for asymmetric effects between positive and negative asset returns, he considered the weighted innovation

$$g(\epsilon_t) = \theta\epsilon_t + \gamma[|\epsilon_t| - E(|\epsilon_t|)],$$

where θ and γ are real constants. Both ε_t and $|\varepsilon_t| - E(|\varepsilon_t|)$ are zero-mean iid sequences with continuous distributions. Therefore, $E[g(\varepsilon_t)] = 0$. The asymmetry of $g(\varepsilon_t)$ can easily be seen by rewriting it as

$$g(\epsilon_t) = \begin{cases} (\theta + \gamma)\epsilon_t - \gamma E(|\epsilon_t|) & \text{if } \epsilon_t \geq 0, \\ (\theta - \gamma)\epsilon_t - \gamma E(|\epsilon_t|) & \text{if } \epsilon_t < 0. \end{cases}$$

Based on this representation, some properties of the EGARCH model can be obtained in a similar manner as those of the GARCH model. For instance, the unconditional mean of $\ln(\sigma_t^2)$ is α_0. However, the model differs from the GARCH model in several ways. First, it uses logged conditional variance to relax the positiveness constraint of model coefficients. Second, the use of $g(\varepsilon_t)$ enables the model to respond asymmetrically to positive and negative lagged values of α_t. The EGARCH model also allows for a general probability density function, which nests the normal distribution along with several other possible densities.

3.1.6. The Stochastic Volatility Model

An alternative approach to describe the volatility evolution of a financial time series is to introduce an innovation to the conditional variance equation of α_t[6]. The resulting model is referred to as a stochastic volatility (SV) model. Similar to EGARCH models, to ensure positiveness of the conditional variance, SV models use $\ln(\sigma_t^2)$ instead of σ_t^2. A SV model is defined as

$$a_t = \sigma_t\epsilon_t, \qquad (1 - \alpha_1 B - \cdots - \alpha_m B^m)\ln(\sigma_t^2) = \alpha_0 + v_t,$$

[6] See Melino and Turnbull (1990), Harvey, Ruiz, and Shephard (1994) and Jacquier, Polson and Rossi (1994).

where ε_t s are iid $\mathrm{N}(0,1)$, u_t s are iid $\mathrm{N}\left(0,\sigma_u^2\right)$, $\{\varepsilon_t\}$ and $\{u_t\}$ are independent, α_0 is a constant, and all zeros of the polynomial $1\text{-}\sum_{i=1}^{m}\alpha_i \mathrm{B}^i$ are greater 1 in modulus. Introducing the innovation u_t substantially increases the flexibility of the model in describing the evolution of σ_t^2, but it also increases the difficulty in parameter estimation. To estimate a SV model, we need a quasi-likelihood method via Kalman filtering or a Monte Carlo method. Jacquier, Polson, and Rossi (1994) provide some comparison of estimation results between quasi-likelihood and Monte Carlo Markov Chain (MCMC) methods. The difficulty in estimating a SV model is understandable because for each shock α_t the model uses two innovations ε_t and u_t. Limited experience shows that SV models often provided improvements in model fitting, but their contributions to out-of-sample volatility forecasts received mixed results.

3.1.7. The Long-Memory Stochastic Volatility Model

More recently, the SV model is further extended to allow for long memory in volatility, using the idea of fractional difference. A time series is a long-memory process if its autocorrelation function decays at a hyperbolic, instead of an exponential, rate as the lag increases. The extension to long-memory models in volatility study is motivated by the fact that autocorrelation function of the squared or absolute-valued series of an asset return often decays slowly, even though the return series has no serial correlation[7].
A simple long-memory stochastic volatility (LMSV) model can be written as

$$a_t = \sigma_t \epsilon_t, \qquad \sigma_t = \sigma \exp(u_t/2), \qquad (1-B)^d u_t = \eta_t,$$

where σ>0, ε_t s are iid N(0,1), η_t s are iid $\mathrm{N}\left(0,\sigma_\eta^2\right)$ and independent of ε_t, and 0<d<0.5. The feature of long memory stems from the fractional difference (1-B)d, which implies that the ACF of u_t decays slowly at a hyperbolic, instead of an exponential, rate as the lag increases. For model (3.35), we have

$$\begin{aligned}\ln(a_t^2) &= \ln(\sigma^2) + u_t + \ln(\epsilon_t^2)\\ &= [\ln(\sigma^2) + E(\ln \epsilon_t^2)] + u_t + [\ln(\epsilon_t^2) - E(\ln \epsilon_t^2)]\\ &\equiv \mu + u_t + e_t.\end{aligned}$$

Thus, the $\ln\left(\alpha_t^2\right)$ series is a Gaussian long-memory signal plus a non-Gaussian white noise[8]. Estimation of the long-memory stochastic volatility model is complicated, but the fractional difference parameter d can be estimated by using either a quasi-maximum likelihood method or a regression method.

All these econometric models have in common that the resulting volatility measures are only valid under the specific assumptions of the models used and it is generally uncertain which or whether any of these specifications provide a good description of actual volatility. Furthermore, the focus on volatility modelling continues to be decidedly low-dimensional, if not universally univariate. Many

[7] See Ding, Granger, and Engle (1993)
[8] See Breidt, Crato, and de Lima (1998)

multivariate ARCH and stochastic volatility models for time-varying return volatilities and conditional distributions have been proposed, but those models generally suffer from a course-of-dimensioanality problem that severely constrains their practical application. Consequently, it is rare to see practical applications of such procedures dealing with more than a few assets simultaneously.

3.2. Realized Volatility

3.2.1. Intraday returns

A model-free measure of volatility is the sample variance of returns. Recent work (**e.g.Andersen, Bollerslev, Diebold and Ebens(2001)**) suggests that intraday returns can be used to construct estimates of daily return volatility that are more precise than those constructed using daily returns. If we calculate the daily volatility from the sample variance of intraday returns, we then have the 'realized' volatility. In a way realized volatility becomes observable. Realized variances are free of the assumptions necessary when the statistical or economic approaches are employed and, as we have an (almost) continuous record of returns for each day, we can calculate the interdaily variances with little or perhaps negligible error.

Using daily data, for instance, it may be freely estimated using returns spanning over any number of days and, as such, one can construct a time series of model-free variance estimates. When one chooses the observation frequency of this series, an important trade-off has to be made, however. When the variances are calculated using a large number of observations (e.g the returns over an entire year), many interesting properties of volatility tend to disappear (the volatility clustering and leverage effect, for instance). On the other hand, if only very few observations are used, the measures are subject to great error. However, using the five-minute frequency avoids market microstructure problems such as the bid-ask bounce. At the extreme, only one return observation is used for each daily variance estimate.

Let $p_{n,t}$ denote the time n $\geq$ 0 logarithmic price at day t. The discretely observed time series of continuously compounded returns with *N* observations per day is then defined by:

$$r_{n,t} = p_{n,t} - p_{n-1,t}$$

where $n = 1, \ldots, N$ and $t = 1, \ldots, T$. If $N = 1$, for any series we ignore the first subscript n and thus r_t denotes the time series of daily return.

We shall assume that:

A.1: $E[r_{n,t}] = 0$

A.2: $E[r_{n,t}\ r_{m,s}] = 0$ $\forall$ n,m,s,t but not n=m and s=t

A.3: $E[r_{n,t}^2 r_{m,s}^2] < \infty$ $\forall$ n,m,s,t

Hence, returns are assumed to have mean zero and to be uncorrelated and it is assumed that the variance and covariances of squared returns exist and are finite.

The continuously compounded daily squared returns may be decomposed as:

$$r_t^2 = \left(\sum_{n=1}^{N} r_{n,t}\right)^2 = \sum_{n=1}^{N} r_{n,t}^2 + \sum_{\substack{n=1 \\ n \neq m}}^{N} \sum_{m=1}^{N} r_{n,t}\, r_{m,t} = \sum_{n=1}^{N} r_{n,t}^2 + 2\sum_{n=1}^{N} \sum_{m=n+1}^{N} r_{n,t}\, r_{m-n,t}$$

Assuming that A.1 holds, the squared daily return is therefore the sum of two components: the sample variance (at the daily unit) and twice the sum of $N-1$ sample autocovariances (at the 1/Nth day interval unit). In this decomposition it is the sample variance that is of interest – the sample autocovariances are measurement error and induce noise in the daily squared return measure.

It therefore follows that an unbiased estimator of the daily return volatility is the sum of intraday squared returns, the realized volatility:

$$s_t^2 = \sum_{i=1}^{N} r_{n,t}^2$$

as:

$$E\left[s_t^2\right] = \sigma_t^2$$

where σ_t^2 is daily population variance.

Under conditions of serial correlation, the realized variance will unambiguously overestimate actual volatility. To mitigate the problem of bias we can take five-minute returns to obtain daily variance estimates. These are constructed from the logarithmic difference between the prices recorded at or immediately before the five-minute marks.

3.2.2. Squared Returns-Absolute Returns

Common choices for estimating the realized volatility is the daily squared return, the daily absolute return and some form of the daily high-low price range. Although unbiased, the daily squared return is a noisy estimate of true realized volatility.

If the absolute returns rather than the variance specification are used as a measure of volatility, the loss of efficiency is much smaller for the absolute return regression model when the error term deviates from the normal distribution.

4. Data and Preliminary results

4.1. Data description

The data set consists of daily stock price and trading activity data for all companies listed in the FTSE-20 on March 27, 2006. The FTSE-20 is composed of the 20 largest Greek stocks based on equity capitalization. Studying this sample of stocks is attractive, since they are much more likely to have significant numbers of trades of varying sizes and a sufficiently large number of information arrivals per day than small capitalization stocks. Our time series are derived from the Effect Finance database. The investigation covers the period from January 1995 to January 2006. Table 1 lists the sample stocks, the number of observations and the range of data used to generate the reported results.

Table 1
Companies included in the sample and period of quotation

Companies	T	Period
alpha	2754	1/02/1995-1/10/2006
ate	1241	1/19/2001-1/10/2006
bioxalko	2198	3/27/1997-1/10/2006
germanos	1476	2/14/2000-1/10/2006
deh	1014	12/13/2001-1/10/2006
coca cola	2754	1/02/1995-1/10/2006
elpe	1886	6/30/1998-1/10/2006
emporiki	2754	1/02/1995-1/10/2006
ete	2754	1/02/1995-1/10/2007
eurobank	1687	4/14/1999-1/10/2006
hyatt	1573	9/27/1999-1/10/2006
intracom	2754	1/02/1992-1/10/2006
kae	1948	3/30/1998-1/10/2006
cosmote	1308	10/12/2000-1/10/2006
motoroil	1105	8/06/2001-1/10/2006
opap	1176	4/25/2001-1/10/2006
ote	2431	4/19/1996-1/10/2006
peiraiws	2158	5/27/1997-1/10/2006
titan	2263	12/18/1996-1/10/2006
foli foli	2050	10/29/1997-1/10/2006

Stocks returns are calculated from daily stock prices at close, adjusted for dividend payouts and stock splits as: $R_t = (P_t - P_{t-1})/P_{t-1}$, where P_t and P_{t-1} are the adjusted closing price for day t and t-1 respectively.

To measure return volatility the absolute (|R|) and the squared value (R^2) of closing price minus lagged closing price (close to close), the conditional variance estimated by a GARCH(1,1) model, and the daytime volatility measured as the absolute value of adjusted closing price minus opening price (open to close) are being used. As a proxy for information arrival and trading activity measure the daily number of shares traded (volume), the daily number of trades (trades), the daily value of trades (value) and the daily average trade size (ats) are being used. Average trade size is defined as share volume divided by number of trades. Volume and value are expressed in billions, while trades and average trade size are expressed in millions. Using weekly or lower frequency data was deemed unnecessary because it would reduce the sample size without any corresponding gains.

4.2. Descriptive statistics

We start with some basic descriptive analysis of the time series of stock returns. Table 2 demonstrates the average daily stock return over the period under study ranges from 0.02% (Ate) to 0.18% (Foli Foli). The sample mean of returns (0.0008) is small and not significantly different from zero. Standard deviation is the lowest for Deh (0.0137) and the highest for Hyatt (0.0390). The sample standard deviation seems to be fairly stable across stocks.

The commonly reported fact of fat-tailed and highly-peaked return distributions is being supported by most of the series. The mean of stock return skewness is 1.5275 and all of the skewness statistics are significant and positive, with all cases being tilted to the right, indicating that the data are not symmetric. Moreover, all returns are characterized by statistically significant kurtosis (the kurtosis is substantially larger than 3 in all stocks), suggesting that the underlying data are leptokurtic, that is, all series have a thicker tail and a higher peak than a normal distribution. So it is not surprising that the Jarque-Bera test suggests that all returns distributions are non-normal.

Table 2

Preliminary analysis of daily returns

Companies	Mean	Max	Min	Std.Dev.	skewness	kurtosis	Jarque-Bera	
							Statistic	Prob.
alpha	0.0010	0.1180	-0.0879	0.0216	0.3942	5.7666	949.64	0.0000
ate	0.0002	0.2632	-0.1424	0.0214	2.2415	30.9707	41493.80	0.0000
bioxalko	0.0012	0.1163	-0.1161	0.0276	0.3114	4.2177	171.32	0.0000
germanos	0.0003	0.4102	-0.1217	0.0210	4.6652	103.90	631497.1	0.0000
deh	0.0005	0.0595	-0.0553	0.0137	0.1623	4.2508	70.55	0.0000
coca cola	0.0006	0.0875	-0.0915	0.0212	0.2146	5.9195	999.17	0.0000
elpe	0.0007	0.3087	-0.0998	0.0245	1.3990	17.4946	17125.14	0.0000
emporiki	0.0009	0.1158	-0.1026	0.0244	0.2875	5.5123	762.23	0.0000
ete	0.0012	0.1170	-0.0937	0.0219	0.4480	5.6295	885.54	0.0000
eurobank	0.0000	0.1202	-0.0799	0.0190	0.5550	6.8003	1101.81	0.0000
hyatt	0.0011	0.9883	-0.1165	0.0390	13.3053	310.41	6240261	0.0000
intracom	0.0006	0.1098	-0.1612	0.0280	0.3191	4.5314	315.85	0.0000
kae	0.0008	0.1466	-0.1192	0.0288	0.1978	5.1493	387.63	0.0000
cosmote	0.0007	0.0805	-0.0646	0.0154	0.2084	4.8247	190.93	0.0000
motoroil	0.0007	0.1293	-0.0797	0.0157	0.9087	12.29	4124.64	0.0000
opap	0.0016	0.0977	-0.0693	0.0175	0.5856	6.4755	659.11	0.0000
ote	0.0004	0.0874	-0.0995	0.0204	0.2458	5.3969	606.41	0.0000
peiraiws	0.0011	0.1000	-0.1077	0.0244	0.5322	5.5181	672.02	0.0000
titan	0.0011	0.1023	-0.0802	0.0216	0.3418	5.7786	772.03	0.0000
foli foli	0.0018	0.5138	-0.1177	0.0280	3.2261	58.573	267350.6	0.0000
Mean	0.0008	0.2036	-0.1003	0.0228	1.5275	30.4706		

**Jarque-Bera statistic tests for normality and under the null, is distributed as χ^2 (2).Five percent critical value is 5.99.*

4.3. Testing for unit root

The vector autoregression model we use to test for causal relationships between the various trading activity and stock return volatility measures assumes that the variables in the system are stationary. As such, we check whether stock return volatility and trading activity time series can be assumed to be stationary. This is necessary to avoid model misspecifications and biased inferences.

There are two ways to achieve stationarity. Some series need to be detrended (called the trend-stationary process), and others need to be defferenced (called the difference-stationary process or unit root process).

To test for a unit root, we employ both the augmented Dickey-Fuller (ADF) test and the Phillip and Perron (P-P) test:

- Augmented Dickey-Fuller regression

$$\Delta\chi_t = \rho_0 + \rho\chi_{t-1} + \sum_{i=1}^{n}\delta_i\Delta\chi_{t-i} \tag{4.1}$$

- Phillips_perron regression

$$\chi_t = \alpha_0 + \alpha \chi_{t-1} + u_t \qquad (4.2)$$

The difference between the two unit root tests lies in their treatment of any "nuisance" serial correlation. The P-P test tends to be more robust to a wide range of serial correlation and time-dependent heteroskedasticity. In these tests, the null hypothesis is that a series is nonstationary (a unit root exists): ρ=0 and α=0.

We conduct ADF and P-P tests for each company's time series of stock return volatility and trading activity. We find the parameters ρ and α statistically significant at 5% in all cases, since the null hypothesis that a unit root exists is rejected in all tests. Hence, we come to the conclusion that time series of stock return volatility and trading activity can be assumed to be invariant with respect to time. The detailed test results are available at the appendix A.

5. *Methodology*

5.1. Contemporaneous Relationship

As mentioned above, the contemporaneous relationship between stock return volatility and trading activity has been extensively studied from a variety of perspectives (Karpoff, 1987). We investigate this relationship using two different approaches.

5.1.1. The heteroskedastic Mixture Model and Arch

The MDH model suggested by Clark (1973) provides theoretical explanation for the use of GARCH models in order to study the trading activity-volatility relation. The model estimated in our empirical study is based on the GARCH model suggested by Bollerslev (1986). We first specify the variance of return on the stocks only explained by the lags in conditional and unconditional variance using the specification included in the equations:

$$R_t = \alpha_0 + \alpha_1 \sum_{i=1}^{k} R_{t-i} + \varepsilon_t, \quad \varepsilon_t \mid (\varepsilon_{t-1}, \ldots) \sim (0, h_t^2) \qquad (5.1)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} \qquad (5.2)$$

Here ε_t is assumed to be distributed as t-Student with n degrees of freedom conditional on the set of information available at t-1 and h_t^2 represents the conditional variance of ε_t. As Eq. (5.2) shows, in order to model the conditional variance of return, a GARCH (1,1) process for each stock has been used where: β_0 is the parameter including the constant term of the conditional variance; β_1, β_2 are the parameters of the squared residuals and of conditional variance, respectively, lagged by one period[9]. The model parameters are estimated by means of the Maximum Likelihood (ML) method.

We apply the GARCH (1,1) model for each of the FTSE-20 stock return series, and then extract the associated conditional variance h_t^2 from Eq. (5.2) to represent return volatility. These series are going to be used later in both other methods in order to test for the trading activity-volatility relation's presence.

Our first task is to investigate whether any contemporaneous relation between the estimated conditional variance of returns and the various measures of trading activity exists. Considering that the number of trades, the value of trades and the number of shares traded reflect the flow of new information into the market, since they are likely to contain information about the disequilibrium dynamics of asset markets, they are going to be used as trading activity measures in this model. Under the assumption that the trading activity variables are weakly exogenous, they can be incorporated into the GARCH (1,1) model, which is shown as below:

$$R_t = \alpha_0 + \alpha_1 \sum_{i=1}^{k} R_{t-i} + \varepsilon_t, \quad \varepsilon_t \mid (\varepsilon_{t-1}, \ldots) \sim \left(0, h_t^2\right) \tag{5.3}$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 T_t, \tag{5.4}$$

where ε_t is assumed to be distributed as t-Student with n degrees of freedom conditional on the set of information available at t-1; h_t^2 represents the conditional variance of ε_t and T represents the trading activity measure. If β_3 coefficient proved to be positive and statistically significant, then a positive relation between volatility return and trading activity will exist. If the model is correctly specified, the residuals should be i.i.d. random variables with mean zero and variance one(and follow the assumed t-Student distribution with the estimated scale parameter or degrees of freedom). The standardized residuals generated by each model are checked with Ljung-Box Q-statistics, Arch LM test and normality tests.

Furthermore, following the methodology of Lamoureax and Lastrapes (1990) we study the persistence of return volatility of the FSTE-20 stocks with the use of GARCH models in which the trading activity is included as an explanatory variable of conditional variance. A succinct measure of the persistence of variance of the unexpected return ε_t as measured by a GARCH (1,1) model without including trading activity as an explanatory variable, is the sum of coefficients $\beta_1 + \beta_2$. The greater is the sum, the greater is the persistence of shocks to volatility (volatility clustering). If return volatility is in fact mostly influenced by the information flow, the effect of volatility clustering should decrease if one incorporates trading activity variables in the conditional variance equation. In other words, if the trading activity is incorporated into the model, it is expected that $\beta_3 > 0$ and the persistence of volatility as measured by $\beta_1 + \beta_2$ becomes negligible. If the MDH is relevant in explaining the GARCH effects of stock returns, then the inclusion of trading activity series in the conditional variance should absorb volatility persistence in the conditional variance process of the GARCH(1,1). Since this information flow explains the variance persistence presented and approximated by the GARCH effect, it is predicted that $\beta_3 > 0$, and β_1 and β_2 should become smaller and insignificant due to this inclusion.

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[9] Other GARCH models (p, q) for p = 1, 2 and q = 1, 2, have been estimated. Nevertheless, the results obtained through several selection criteria did not provide satisfactory results.

5.1.2. GMM estimation

Besides GARCH specification, a GMM estimated model is applied to test the contemporaneous trading activity-volatility relation. We follow Huang and Masulis (2003) procedure, which is based on the JKL (1994) model.

To explore the relation between trading activity and return volatility, we begin by decomposing trading activity into two components, the number of trades and the average trade size. We then use these two variables as regressors in our model of stock price volatility.[10] The reason we choose these two variables is because of an extremely interesting characteristic they have. As JKL and Huang and Masulis observed, these two trading activity measures have the attractive properties of being weakly correlated with each other, while being strongly, positively correlated with share volume. *Table 3*, which follows seems to confirm this property in the Greek stocks in a different approach. According to Greek data that trading activity measure cannot be decomposed into these two components. While ats and trades are weakly correlated with each other, they are not highly correlated with any other trading activity measure, as the results of Table 3 confirm. Indeed, as Table 3 shows, volume (value) is positively and strongly correlated with only the average trade size, with a correlation of 0.7476 (0.5918), while the number of trades and average trade size have low negative correlation of -0.0045. Instead, the correlation between volume (value) and trades is 0.1973 (0.2562). The correlation between ats and trades indicates that, they seem to contain different information about trading activity because they are not strongly correlated with each other. This is why ats and trades are concerned to be two components of trading activity and not two components of volume or value, as it was assumed by JKL and Huang and Masulis.

According to the above analysis, the estimated model is:

$$V_{it} = \alpha + \beta \mathrm{A}_{it} + \gamma \mathrm{N}_{it} + \varepsilon_{it}, \qquad (5.5)$$

where V_{it} represents price volatility, A_{it} represents average trade size and N_{it} represents the number of trades, in each case for stock i over the day t. The equation is estimated from time series of absolute return, squared return, conditional variance and daytime volatility for each of the FTSE-20 stocks. We estimate this equation using Hansen's (1982) generalized method of moments (GMM). The GMM estimation method imposes weak distribution assumptions on the observable variables and endogeneously adjusts the estimates to account for general forms of conditional heteroskedasticity and/or serial correlation that may be present in the error structure. Serial correlation in stock price volatility is a particular concern, given the widely documented strong positive serial correlation found in squared stock returns.

Furthermore, we develop JKL's methodology following a similar approach. Looking carefully the average correlations between the various trading activity measures in Table 3 one concludes that trades and volume (value) are not strongly correlated with each other, with a correlation of 0.1973 (0.2562). The two low correlation coefficients reveal that these two combinations contain different

[10] In section 6, we examine a variety of return volatility and trading activity measures including: the absolute and squared value of closing price minus lagged closing price, the absolute value of closing price minus opening price and the estimated conditional variance as far as the volatility concerns and the number of trades, the value of trades, the number of shares traded and the average trade size as far as the trading activity concerns.

information about trading activity. It can be inferred that either trades and value or trades and volume compose trading activity.

Table 3
Correlations coefficients between trading activity measures

	ats-trades	ats-value	ats-volume	trades-value	trades-volume	value-volume
alpha	-0.0244	0.5283	0.8066	0.0708	0.0474	0.8061
ate	0.0587	0.3311	0.2625	0.8656	0.8310	0.9300
bioxalko	-0.0104	0.7168	0.8135	0.0455	0.0299	0.8500
germanos	-0.0284	0.3748	0.6015	0.7954	0.5595	0.9119
deh	0.0667	0.9065	0.8985	0.3863	0.3373	0.9801
coca cola	-0.0189	0.7213	0.9117	0.0422	0.0160	0.8918
elpe	0.0101	0.8315	0.8793	0.2148	0.2270	0.9622
emporiki	-0.0265	0.5534	0.7942	0.1451	0.0888	0.8448
ete	0.0206	0.7321	0.8628	0.1634	0.1038	0.8552
eurobank	-0.0516	0.8751	0.7698	0.2535	0.1201	0.8955
hyatt	-0.0355	0.3637	0.7810	0.8128	0.2965	0.6604
intracom	-0.0270	0.1540	0.6080	0.0672	0.0755	0.4696
kae	0.0035	0.6626	0.8754	0.1460	0.1161	0.9166
cosmote	0.0719	0.8151	0.8134	0.4198	0.4259	0.9814
motoroil	0.0041	0.1659	0.3069	0.3105	0.3112	0.9864
opap	0.0445	0.6788	0.9139	0.2815	0.2407	0.8821
ote	-0.0167	0.9634	0.9670	0.0010	0.0025	0.9899
peiraiws	-0.0367	0.3683	0.7520	0.0483	0.0337	0.8359
titan	-0.0507	0.4307	0.6509	0.0332	0.0442	0.7985
foli foli	-0.0433	0.6620	0.6828	0.0218	0.0389	0.9420
mean	**-0.0045**	**0.5918**	**0.7476**	**0.2562**	**0.1973**	**0.8695**

This is why trades and value, and trades and volume separately are used as regressors in the following models, which are estimated also by using the generalized method of moments, in order to study the return volatility and trading activity relationship.

$$V_{it} = \alpha + \beta N_{it} + \gamma VO_{it} + \varepsilon_{it}, \qquad (5.6)$$

$$V_{it} = \alpha + \beta N_{it} + \gamma VA_{it} + \varepsilon_{it}, \qquad (5.7)$$

where V_{it} represents price volatility, N_{it} represents the number of trades, VO_{it} represents the number of shares traded and VA_{it} represents the value of trades in each case for stock i over the day t.

Moreover, we are interesting in exploring if each measure of trading activity alone is contemporaneously related with the different measures of return volatility. To success this, the estimation of the model

$$V_{it} = \alpha + \beta T_{it} + \varepsilon_{it}, \qquad (5.8)$$

is necessary, where V_{it} represents price volatility and T_{it} represents the different measures of trading activity in each case for stock i over the day t.

When all models are estimated we check whether the coefficients of the explanatory variables are statistically significant in order to find out if any contemporaneous relation between return volatility and trading activity exists. In case that such a relation exists we are interested in the type of it. This is why we pay attention in the sign of the estimated coefficients also. From their sign we can conclude if return volatility relates with trading activity positively or negatively and if the different measures are used for each variable affect this relation.

5.2. Dynamic relationship

Up to this point, we are focused exclusively on testing the presence and type of contemporaneous relation between return volatility and trading activity. In this part we study dynamic (causal) interactions between these variables. Testing for causality is important because it permits a better understanding of the dynamics of stock markets. Significant causal relations running in either direction between trading activity and return volatility suggests that the information arrival follows a sequential rather than a simultaneous process. A sequential process means that trading activity precedes stock return volatility and/or vice versa.

This is the notion behind causality testing in Granger (1969), and it is based on the premise that the future cannot cause the present or the past. 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 $Y \xrightarrow{G.C.} X$. Granger causality does not mean that Y causes X in the most common sense of the term, but only indicates that Y proceeds X.

The following bivariate vector autoregression (VAR) is used to test for causality between the two variables of trading activity and stock return volatility.

$$\sigma_t^2 = \gamma_1 + \sum_{k=1}^{L} \alpha_k \sigma_{t-k}^2 + \sum_{k=1}^{L} b_k T_{t-k} + \varepsilon_{1t}$$

$$T_t = \gamma_2 + \sum_{k=1}^{L} c_k T_{t-k} + \sum_{k=1}^{L} d_k \sigma_{t-k}^2 + \varepsilon_{2t} \qquad (5.9)$$

where σ_t^2 is the estimated volatility of stock returns, T_t is the trading activity measure during time interval t, ε_{it} is the disturbance reflecting variation of the left-hand-side variable that cannot be accounted for the right-hand-side variables, and a, b, c, and d are the group lagged coefficients in the Granger-causality testing equations.

Model (5.9) is estimated using an OLS method. In order to choose an appropriate autoregressive lag length L of the VAR, we apply the Akaike information criterion (AIC). If the coefficients b_k are statistically significant, inclusion of past values of trading activity, in addition to past history of return volatility, yields a better forecast of future volatility, and we say trading activity causes volatility. If a standard F-test does not reject the hypothesis that b_k=0 for all *k*, then trading activity does not cause volatility. Similarly, in the second equation if causality runs from volatility to trading activity, the d_k coefficients will jointly be different from zero. If both b_k and d_k are different from zero, there is a feedback relation between return volatility and trading activity.

6. Empirical Results

6.1. Contemporaneous Relationship

6.1.1. The heteroskedastic Mixture Model and Arch

We first estimate the simple GARCH (1,1) model without any trading activity measure being included in the variance equation and obtain the conditional return variances (volatilities) of the 20 stocks. The number of lags in mean equation varies on each stock accordingly with the type of autocorrelation that characterizes the returns. Table 4, which follows, reports the estimated coefficients, the asymptotic t-statistics, the p-values concerning each coefficient, and the p-values for each stock's Arch test. The estimated method used in the estimation of the GARCH models is the Maximum Likelihood, under the assumption that the innovations are t-Student distributed. Under this assumption, from Table 4 it is clear that all of the arch and garch terms are positive and statistically significant. The coefficient estimates and p-values provide strong evidence that daily stock returns can be characterized by volatility clustering in all cases. The averages values of coefficients indicate that the average coefficient for the previous shock, β_1, is 0.1509 and the coefficient for the lagged variance, β_2, is 0.83, which means that the lagged variance affects the conditional variance more than the lagged shock. The sum of these two coefficients is 0.9809. The results suggest that the persistence of volatility, measured as the absolute value of the sum $|\beta_1+\beta_2|$, is very high, being over 0.94 for all cases except for deh and cosmote stocks for which it is 0.8823 and 0.8433, respectively. The sum of the coefficients is very close to one for many stocks and above one for four stocks, which indicates that the GARCH (1,1) model is integrated. These results are similar to the ones obtained by Lamoureax and Lastrapes (1990), among others. From the Arch tests results we conclude that the GARCH (1,1) model is adequate for all but one case, the coca cola stock, which reveals that a GARCH (1,1) model suffices to remove ARCH effects.

We then estimate a GARCH (1,1) model for each stock having incorporated trading activity measured as the number of trades in the variance equation. The results are reported in Table 5. According to Lamoureax and Lastrapes (1990), if serial correlation in the trading activity measure does exist, its inclusion as an exogenous variable in the variance equation produces a reduction in the persistence of conditional volatility reflected in an important reduction in the coefficients β_1, β_2 and the loss of their significance. In contrast with this argument, the results from FTSE-20 stocks analyzed agree that the inclusion of trades does not seem to eliminate GARCH effects. Even though the coefficient associated with the number of trades is positive and highly significant in all cases, which reveals a positive and significant relation between return volatility and trading activity measured as the number of trades for the FTSE-20 stocks, only the β_2 coefficients seems to lose their significance for six stocks. That means that the volatility clustering still exists. Although the coefficients β_1 remain at very similar levels to the ones estimated in the restricted model, in fact they have increased a little, the average β_2 is reduced from 0.83 to 0.2006. This reduction induces a significant fall in the persistence from 0.9809 to 0.4281 (the average reduction is 56.36%). Indeed, the persistence in volatility is reduced in 13 out of the 20 stocks. Our results imply that when number of trades is included in the

Table 4
Maximum Likelihood estimation of the GARCH(1,1) without trading activity

$$R_t = \alpha_0 + \alpha_1 \sum_{i=1}^{k} R_{t-i} + \varepsilon_t, \varepsilon_t \mid (\varepsilon_{t-1},...) \sim t - Student, \; h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$$, R_t *is the daily return.*

In case that the conditional stock return is not t-Student distributed, then the estimated standard error for that stock may be biased.

Companies	β_1			β_2			$\lvert\beta_1+\beta_2\rvert$	Arch Test
	Coefficient	t-stat.	Prob.	Coefficient	t-stat.	Prob.	persistence	Prob.
alpha	0.1697*	8.1343	0.0000	0.8161*	44.1279	0.0000	0.9858	0.6584
ate	0.4202*	4.1048	0.0000	0.7803*	64.5721	0.0000	1.2005	0.9938
bioxalko	0.1551*	6.4172	0.0000	0.7911*	26.4233	0.0000	0.9462	0.3262
germanos	0.1719*	4.5074	0.0000	0.8339*	34.2543	0.0000	1.0058	0.6151
deh	0.1033*	2.7510	0.0059	0.7790*	9.4389	0.0000	0.8823	0.4821
coca cola	0.0506*	6.2410	0.0000	0.9495*	127.5792	0.0000	1.0000	0.0000
elpe	0.1302*	6.0442	0.0000	0.8276*	34.5092	0.0000	0.9578	0.7582
emporiki	0.1529*	7.1613	0.0000	0.8279*	41.7812	0.0000	0.9808	0.8255
ete	0.1088*	6.3243	0.0000	0.8474*	36.8398	0.0000	0.9562	0.6080
eurobank	0.1407*	5.2091	0.0000	0.8044*	25.7592	0.0000	0.9451	0.2686
hyatt	0.0875*	5.2510	0.0000	0.9093*	65.2620	0.0000	0.9968	0.4973
intracom	0.1586*	7.1660	0.0000	0.8125*	36.7482	0.0000	0.9711	0.8113
kae	0.2023*	6.9072	0.0000	0.8168*	42.3694	0.0000	1.0191	0.8922
cosmote	0.1458*	3.9686	0.0001	0.6975*	10.1721	0.0000	0.8433	0.5406
motoroil	0.1299*	3.4910	0.0005	0.8531*	27.1656	0.0000	0.9831	0.7325
opap	0.1183*	4.1271	0.0000	0.8277*	22.5182	0.0000	0.9460	0.8590
ote	0.0849*	6.0215	0.0000	0.9109*	71.4031	0.0000	0.9958	0.2726
peiraiws	0.1840*	7.1112	0.0000	0.8027*	37.3448	0.0000	0.9867	0.9959
titan	0.1468*	6.9272	0.0000	0.8530*	50.2666	0.0000	0.9998	0.4964
foli foli	0.1567*	2.9495	0.0032	0.8585*	50.0431	0.0000	1.0152	0.9349
Mean	0.1509			0.8300			0.9809	

* *Statistically significant at 5% assuming that returns are following t-Student distribution. The Arch LM test tests for remaining Arch effects in the standardized residuals of the model.*

Table 5
Maximum Likelihood estimation of the GARCH(1,1) with trades

$R_t = \alpha_0 + \alpha_1 \sum_{i=1}^{k} R_{t-i} + \varepsilon_t , \varepsilon_t \mid (\varepsilon_{t-1},...) \sim t - Student \, , h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 N_t$, *where* R_t *is the daily return and* N_t *is the daily number of trades. In those cases that the conditional stock return is not t-Student distributed, the estimated standard error may be biased.*

Companies	β1			β2			β3			|β1+β2|	Arch Test
	Coefficient	t-stat.	Prob.	Coefficient	t-stat.	Prob.	Coefficient	t-stat.	Prob.	persistence	Prob.
alpha	0.2182*	6.0772	0.0000	0.0327	1.1300	0.2563	0.3217*	13.0892	0.0000	0.2509	0.8213
ate	0.8252*	3.3698	0.0008	0.7151*	42.1950	0.0000	0.0012*	10.2721	0.0000	1.5403	0.1730
bioxalko	0.1752*	6.3319	0.0000	0.7427*	21.4067	0.0000	0.1215*	2.3104	0.0209	0.9179	0.5375
germanos	0.4076*	4.8783	0.0000	0.2702*	6.9791	0.0000	0.6999*	7.9272	0.0000	0.6778	0.3036
deh	0.0300	1.2522	0.2105	-0.2810*	-4.8427	0.0000	0.2481*	9.4792	0.0000	0.2510	0.2501
coca cola	0.3040*	6.8459	0.0000	0.0330	1.7316	0.0833	0.8107*	11.7316	0.0000	0.3370	0.7897
elpe	0.0571*	2.6509	0.0080	-0.2393*	-4.9073	0.0000	0.8356*	14.1053	0.0000	0.1822	0.0003
emporiki	0.1718*	5.8268	0.0000	0.0184	1.0121	0.3115	0.8226*	13.6632	0.0000	0.1902	0.7257
ete	0.2384*	5.8207	0.0000	0.0556	1.1576	0.2470	0.2212*	8.0714	0.0000	0.2940	0.6377
eurobank	0.1307*	3.2951	0.0010	0.0913*	2.6225	0.0087	0.2581*	9.3413	0.0000	0.2220	0.8424
hyatt	0.2718*	5.1427	0.0000	0.1756*	3.6058	0.0003	1.1709*	11.3887	0.0000	0.4475	0.2593
intracom	0.2917*	6.7246	0.0000	0.0681	1.6267	0.1038	0.8919*	9.9662	0.0000	0.3597	0.1936
kae	0.2189*	6.7997	0.0000	0.7823*	33.0286	0.0000	0.1372*	2.7803	0.0054	1.0012	0.9135
cosmote	0.0674*	3.7915	0.0001	-0.2256*	-3.6973	0.0002	0.4158*	10.5577	0.0000	0.1582	0.0165
motoroil	0.0605*	1.9612	0.0499	-0.1895*	-2.5576	0.0105	1.4882*	7.0051	0.0000	0.1290	0.7355
opap	0.2127*	3.6812	0.0002	0.0692	0.8167	0.4141	0.1759*	5.3002	0.0000	0.2820	0.9763
ote	0.0834*	3.0076	0.0026	0.0426*	3.8855	0.0001	0.2552*	18.0087	0.0000	0.1260	0.1930
peiraiws	0.3709*	6.0533	0.0000	0.2737*	5.0346	0.0000	0.1909*	6.4082	0.0000	0.6447	0.0361
titan	0.1901*	6.9889	0.0000	0.7800*	34.6791	0.0000	0.0796*	3.2340	0.0012	0.9701	0.9653
foli foli	0.2241*	6.3386	0.0000	0.7971*	37.5142	0.0000	0.0693*	2.2765	0.0228	1.0212	0.5859
Mean	0.2275			0.2006			0.4608			0.4281	

** Statistically significant at 5% assuming that returns are following t-Student distribution. The Arch LM test tests for remaining Arch effects in the standardized residuals of the model.*

variance equation, the degree of persistence is reduced, or absorbed by the trades series to some extent.

Table 6 presents the results from the estimated GARCH (1,1) model for each FTSE-20 stock when the value of trades is included as exogenous variable in the variance equation. Looking at the column with value coefficient estimations we observe that in all but three cases the coefficient β_3 is positive, which implies a positive volatility-trading activity (measured as the value of trades) relation once again. This relation seems to be statistically significant too, since the β_3 coefficient is statistically significant above the 5% level in the majority of Greek stocks (14 out of 20 cases). The positive value and statistical significance of β_3 coefficient in most of the cases neither makes β_1, β_2 coefficients insignificant nor decreases the average β_1 coefficient. On the contrary, a reduction of average β_2 coefficient from 0.83 to 0.4851 exists, that makes the persistence in volatility to fall from 0.9809 to 0.6950, with the GARCH effect still being significant. The average reduction in persistence when the value of trades is included as exogenous variable in the variance equation is 29.15%, which is clearly smaller than the reduction when the number of trades is included in the model. This can be explained by the fact that the sum of the two β_1, β_2 coefficients in the unrestricted model is lower than that of the restricted model only in 8 stocks. From our results one could infer that when the value of trades is included in the model, the degree of persistence is reduced, but in a lower percentage and in fewer stocks than in the former case.

Table 7 shows the results of the estimation of the GARCH (1,1) models when the daily number of shares traded (volume) is included in the variance equation. The results in Table 7 seem to be similar with those in *Table 6*. The coefficient for volume, β_3, is positive (17 out of 20) and statistically significant (14 out of 20) above the 5% level for most of the cases, which implies a positive and significant relation between return volatility and trading volume. Furthermore, in all cases the GARCH effect remains significant, since both estimated parameters β_1, β_2 are statistically significant in almost all cases, while the persistence of the conditional volatility is reduced only in 6 stocks, with the presence of trading volume series in the model. The average sum of β_1, β_2 coefficients is 0.7549 compared with 0.9809 when the trading volume is excluded from the variance equation (the average reduction is 23.04%). The results prove that the presence of trading volume in the model induces a small reduction in the volatility persistence, but this does not seem efficient to vanish the GARCH effect in total.

In the light of the evidence presented above, our conclusion is that, the inclusion of the trading activity variable, represented by trades, value or volume, which is used as a proxy of information arrival in the GARCH specification, reduces the persistence of the conditional variance, suggesting that the information based effect helps in explaining the GARCH effect to some extent. However, GARCH does not completely vanish as a result of this inclusion. When the trading activity is measured as the daily number of trades, a greater reduction in the persistence, both in percentage and in number of stocks, is observed. Moreover, when trades are included in the variance equation, the β_3 coefficient is positive and statistically significant in all cases. This makes trades to be the most appropriate measure of trading activity in the Greek market. Finally, as far as the FTSE-20 domestic stocks concerns, the results prove that the return volatility and trading activity relationship is always positive and statistically significant regardless of which of the three aforementioned measures of trading activity is used as a proxy of information arrival in individual companies. The results are presented concisely in Table 8.

Table 6
Maximum Likelihood estimation of the GARCH(1,1) with value

$R_t = \alpha_0 + \alpha_1 \sum_{i=1}^{k} R_{t-i} + \varepsilon_t , \varepsilon_t \mid (\varepsilon_{t-1},...) \sim t - Student , h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 VA_t$, *where* R_t *is the daily return and* VA_t *is the daily value of trades. In those cases that the conditional stock return is not t-Student distributed, the estimated standard error may be biased.*

Companies	β1			β2			β3			|β1+β2|	Arch Test
	Coefficient	t-stat.	Prob.	Coefficient	t-stat.	Prob.	Coefficient	t-stat.	Prob.	persistence	Prob.
alpha	0.2970*	6.5789	0.0000	0.1497*	3.2228	0.0012	0.0254*	9.4220	0.0000	0.4467	0.2861
ate	0.6155*	3.4011	0.0007	0.7350*	46.4617	0.0000	0.0003*	4.8225	0.0000	1.3505	0.0922
bioxalko	0.1514*	6.3464	0.0000	0.7926*	26.8573	0.0000	0.0066*	2.1448	0.0320	0.9440	0.4332
germanos	0.1885*	4.6739	0.0000	0.8073*	30.2626	0.0000	0.0045*	2.3562	0.0185	0.9958	0.6706
deh	0.0450	1.3664	0.1718	-0.0913*	-2.3291	0.0199	0.0164*	7.6102	0.0000	0.0464	0.5676
coca cola	0.3613*	6.9079	0.0000	0.0778*	2.1624	0.0306	0.0816*	9.0578	0.0000	0.4391	0.1786
elpe	0.1890*	4.7425	0.0000	-0.0039*	-2.3193	0.0204	0.1390*	10.1189	0.0000	0.1851	0.6458
emporiki	0.2250*	5.8477	0.0000	0.0359	0.9887	0.3228	0.0882*	9.0470	0.0000	0.2609	0.4383
ete	0.2017*	6.4283	0.0000	0.6918*	18.4156	0.0000	0.0019*	3.4533	0.0006	0.8935	0.2819
eurobank	0.1596*	5.3181	0.0000	0.7695*	21.9662	0.0000	0.0009	1.4655	0.1428	0.9291	0.3772
hyatt	0.0865*	5.2532	0.0000	0.9109*	66.3085	0.0000	-0.0008	-0.6885	0.4911	0.9974	0.5013
intracom	0.2108*	6.7081	0.0000	-0.0679*	-2.7324	0.0063	0.2286*	11.9268	0.0000	0.1428	0.9201
kae	0.2031*	6.9011	0.0000	0.8090*	39.2733	0.0000	0.0047	1.6188	0.1055	1.0122	0.9393
cosmote	0.1694*	4.1412	0.0000	0.6289*	8.4741	0.0000	0.0014	1.7712	0.0765	0.7983	0.3051
motoroil	0.2191*	2.8402	0.0045	0.1460	1.7652	0.0775	0.1103*	3.8542	0.0001	0.3651	0.3244
opap	0.1114*	4.0895	0.0000	0.8417*	24.4214	0.0000	-0.0001	-0.8353	0.4036	0.9530	0.7448
ote	0.1397*	4.0544	0.0001	0.0024	0.0858	0.9317	0.0254*	11.6070	0.0000	0.1421	0.6439
peiraiws	0.2706*	6.7045	0.0000	0.6476*	17.3388	0.0000	0.0060*	3.9722	0.0001	0.9182	0.1896
titan	0.1765*	6.8535	0.0000	0.7971*	35.7487	0.0000	0.0075*	3.2929	0.0010	0.9736	0.8240
foli foli	0.1766*	6.1969	0.0000	0.8395*	45.3379	0.0000	0.0037	1.6503	0.0989	1.0161	0.9780
Mean	0.2099			0.4851			0.0376			0.6950	

** Statistically significant at 5% assuming that returns are following t-Student distribution. The Arch LM test tests for remaining Arch effects in the standardized residuals of the model.*

Table 7
Maximum Likelihood estimation of the GARCH(1,1) with volume

$R_t = \alpha_0 + \alpha_1 \sum_{i=1}^{k} R_{t-i} + \varepsilon_t, \varepsilon_t \mid (\varepsilon_{t-1},...) \sim t-Student, h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 VO_t$, *where* R_t *is the daily return and* VO_t *is the daily volume of trades. In those cases that the conditional stock return is not t-Student distributed, the estimated standard error may be biased.*

Companies	β1			β2			β3			|β1+β2|	Arch Test
	Coefficient	t-stat.	Prob.	Coefficient	t-stat.	Prob.	Coefficient	t-stat.	Prob.	persistence	Prob.
alpha	0.2367*	7.9788	0.0000	0.7034*	25.6321	0.0000	0.0907*	4.4474	0.0000	0.9401	0.6433
ate	0.8393*	2.8094	0.0050	0.7431*	42.0975	0.0000	0.0197*	3.9329	0.0001	1.5824	0.2474
bioxalko	0.1527*	6.4229	0.0000	0.7960*	27.2930	0.0000	0.0286	1.0256	0.3051	0.9487	0.3174
germanos	0.1837*	4.7069	0.0000	0.8148*	31.8615	0.0000	0.0816*	2.2648	0.0235	0.9985	0.6261
deh	0.0457	1.4881	0.1367	-0.0563*	-1.9864	0.0470	0.3258*	8.3113	0.0000	0.0106	0.5487
coca cola	0.3980*	6.9693	0.0000	0.0629	1.8543	0.0637	1.5225*	8.5047	0.0000	0.4609	0.1419
elpe	0.1688*	4.4483	0.0000	-0.0043*	-2.4999	0.0124	1.4778*	11.4662	0.0000	0.1645	0.6819
emporiki	0.1858*	5.7713	0.0000	-0.0245	-1.8350	0.0665	4.8878*	12.8827	0.0000	0.1614	0.7525
ete	0.1396*	6.3717	0.0000	0.8206*	35.7022	0.0000	-0.0143*	-3.3652	0.0008	0.9603	0.9155
eurobank	0.1485*	5.2724	0.0000	0.7924*	24.3823	0.0000	0.0067	0.6137	0.5394	0.9409	0.3001
hyatt	0.1676*	6.0657	0.0000	0.8270*	40.8069	0.0000	-0.0033	-0.1489	0.8816	0.9946	0.7586
intracom	0.2419*	7.0242	0.0000	0.6628*	19.3132	0.0000	0.3161*	4.9734	0.0000	0.9047	0.1869
kae	0.2064*	6.9439	0.0000	0.8061*	38.9759	0.0000	0.0784	1.7120	0.0869	1.0125	0.9486
cosmote	0.1880*	4.1664	0.0000	0.5523*	6.4414	0.0000	0.0349*	2.1235	0.0337	0.7404	0.2291
motoroil	0.1521*	2.3717	0.0177	-0.0131*	-3.0747	0.0021	2.0507*	5.8099	0.0000	0.1390	0.4805
opap	0.0967*	4.0629	0.0000	0.8684*	29.5914	0.0000	-0.0034	-1.6113	0.1071	0.9651	0.5346
ote	0.1917*	4.8569	0.0000	0.0092	0.2783	0.7808	0.3742*	10.2742	0.0000	0.2009	0.9953
peiraiws	0.2177*	7.0690	0.0000	0.7571*	29.4846	0.0000	0.0321*	2.1493	0.0316	0.9747	0.6300
titan	0.1473*	6.9270	0.0000	0.8522*	50.1663	0.0000	0.0215	0.6067	0.5440	0.9995	0.5138
foli foli	0.2051*	6.2722	0.0000	0.8137*	40.4341	0.0000	0.1438*	2.2426	0.0249	1.0188	0.7880
Mean	0.2157			0.5392			0.5736			0.7549	

** Statistically significant at 5% assuming that returns are following t-Student distribution. The Arch LM test tests for remaining Arch effects in the standardized residuals of the model.*

Table 8
Persistence in conditional stock return's volatility

Companies	no trading activity	trades	value	volume
alpha	0.9858	0.2509	0.4467	0.9401
ate	1.2005	1.5403	1.3505	1.5824
bioxalko	0.9462	0.9179	0.9440	0.9487
germanos	1.0058	0.6778	0.9958	0.9985
deh	0.8823	0.2510	0.1363	0.0106
coca cola	1.0000	0.3370	0.4391	0.4609
elpe	0.9578	0.1822	0.1851	0.1645
emporiki	0.9808	0.1902	0.2609	0.1614
ete	0.9562	0.2940	0.8935	0.9603
eurobank	0.9451	0.2220	0.9291	0.9409
hyatt	0.9968	0.4475	0.9974	0.9946
intracom	0.9711	0.3597	0.1428	0.9047
kae	1.0191	1.0012	1.0122	1.0125
cosmote	0.8433	0.1582	0.7983	0.7404
motoroil	0.9831	0.1290	0.3651	0.1390
opap	0.9460	0.2820	0.9530	0.9651
ote	0.9958	0.1260	0.1421	0.2009
peiraiws	0.9867	0.6447	0.9182	0.9747
titan	0.9998	0.9701	0.9736	0.9995
foli foli	1.0152	1.0212	1.0161	1.0188
Mean	**0.9809**	**0.4281**	**0.6950**	**0.7549**
Reduction(%)		**56.36%**	**29.15%**	**23.04%**

6.1.2. GMM-Estimation

Firstly, we test if there is any relation between the various measures of trading activity, as they were already analyzed, and the various return volatility measures. Table 9 presents GMM estimates of the relation between the daily return volatility measured as the absolute value of closing price minus the lagged closing price (|R|) and each trading activity measure separately for the FTSE-20 individual stocks. Looking at Table 9, we observe that the coefficients of the average trade size are negative and statistically insignificant in most cases (only for three stocks are significant), while the coefficients of the trade frequency, value of trades and trading volume are positive in all cases and statistically significant in the majority of stocks. The same result holds for the various alternative measures of return variability: the squared value of closing price minus the lagged closing price (R^2), the conditional variance estimated by a GARCH (1,1) model under the assumption that the innovations are t-Student distributed and the absolute value of closing price minus the opening price (daytime volatility). Tables 10, 11, 12 report very similar results, which confirm this inference. We conclude that trades and value are related to each volatility measure positively (in all cases) and their relation is statistically significant in most cases, while the average trade size with negative and insignificant coefficients is unrelated with each volatility measure. On the contrary, the trading volume-volatility relation is positive but not always statistically significant. Specifically, when volatility is measured as the squared value of the daily return or as the estimated conditional variance, volume seems to be unrelated with volatility.

Table 9

Regressions of |R| and various trading activity measures

Companies	ats			trades			value			volume		
	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.
alpha	-0.0157	-0.9121	0.3618	0.1304	1.5548	0.1201	0.4429*	4.4762	0.0000	5.3723*	2.2816	0.0226
ate	0.0625	0.5226	0.6013	12.9984*	7.9496	0.0000	1.7270*	5.1998	0.0000	7.2806*	11.2188	0.0000
bioxalko	-0.1115	-1.2655	0.2058	1.3482	1.4015	0.1612	0.2770	1.4343	0.1516	1.6479	1.2728	0.2032
germanos	-1.0920*	-2.2375	0.0254	11.6432*	2.2560	0.0242	1.7114*	2.1670	0.0304	34.9740	1.4800	0.1391
deh	0.0886	0.3996	0.6896	6.2690*	4.2138	0.0000	0.0602	1.4660	0.1430	0.8396	1.4845	0.1380
coca cola	-0.3867	-1.3258	0.1850	0.1756	1.9302	0.0537	0.7653*	2.0781	0.0378	3.1309	1.0985	0.2721
elpe	0.0277	0.2186	0.8270	9.1932*	5.5116	0.0000	0.9652*	2.2672	0.0235	1.2317*	2.0925	0.0365
emporiki	1.1271	0.4867	0.6265	0.9935	1.5444	0.1226	0.4833*	2.4594	0.0140	16.8598	1.8044	0.0713
ete	-1.2082*	-2.8018	0.0051	0.5938	1.2685	0.2047	0.1010*	2.4514	0.0143	0.7132	1.0695	0.2850
eurobank	-0.5341	-1.8217	0.0687	5.3731*	4.1581	0.0000	0.1100	1.5459	0.1223	0.8267	0.9731	0.3307
hyatt	-4.8887	-1.6103	0.1075	27.8903*	4.4749	0.0000	1.9297*	2.5354	0.0113	9.9620	0.9815	0.3265
intracom	0.4666	0.2266	0.8208	0.5868*	2.6479	0.0081	0.9586*	3.3041	0.0010	15.0432*	5.7722	0.0000
kae	0.0703	0.4892	0.6248	35.5703*	11.2829	0.0000	0.2223*	5.0232	0.0000	2.6096	1.9355	0.0531
cosmote	-0.1642	-0.9552	0.3397	9.8232*	7.2982	0.0000	0.0660*	2.4153	0.0159	0.7276*	2.1738	0.0299
motoroil	0.0126	0.6410	0.5217	34.3115*	8.8615	0.0000	0.1303*	2.2546	0.0244	2.4734*	2.1694	0.0303
opap	0.0652	1.3889	0.1651	5.9121*	5.5344	0.0000	0.0123	1.1817	0.2376	0.2367*	2.0973	0.0362
ote	0.0162	0.0682	0.9456	0.0308*	3.9613	0.0001	0.0192	1.3498	0.1772	0.3832	1.4224	0.1550
peiraiws	-2.0958	-1.6318	0.1029	0.1218*	4.5385	0.0000	0.7087*	5.8679	0.0000	7.4033*	2.5592	0.0106
titan	-5.8739*	-4.1080	0.0000	0.2668*	1.9631	0.0498	1.7999*	8.4142	0.0000	36.3180*	3.8451	0.0001
foli foli	0.3973	0.2378	0.8121	1.3240*	3.4802	0.0005	1.9749*	3.8008	0.0001	51.9472*	3.4815	0.0005

*An * indicates statistical significance at 5%.*
The following equation is estimated by GMM for each individual stock of FTSE-20 over the whole research period,
$V_{it} = \alpha + \beta T_{it} + \varepsilon_{it}$, *where* V_{it} *is the volatility measure for stock i at day t and* T_{it} *is the trading activity measure for stock i at day t.*
Volatility is measured by the absolute value of closing price minus lagged closing price, while trading activity is measured by the average trade size (ats), the number of trades (trades), the value of trades (value), and the number of shares traded during the day t (volume).

Table 10

Regressions of R^2 and various trading activity measures

Companies	ats			trades			value			volume		
	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.
alpha	-0.0014	-1.3647	0.1725	0.0070	1.4056	0.1600	0.0282*	3.8139	0.0001	0.3071*	1.9885	0.0469
ate	0.0055	0.5324	0.5945	1.0309*	3.9365	0.0001	0.1386*	2.7259	0.0065	0.6661*	4.7934	0.0000
bioxalko	-0.0081	-1.3935	0.1636	0.1142	1.4458	0.1484	0.0285	1.5314	0.1258	0.1602	1.3221	0.1863
germanos	-0.0953	-1.5659	0.1176	4.1634	1.7221	0.0853	0.6143	1.6446	0.1003	12.1020	1.1814	0.2376
deh	0.0073	0.5757	0.5649	0.2457*	4.1164	0.0000	0.0028	1.4015	0.1614	0.0417	1.4455	0.1486
coca cola	-0.0202	-1.5524	0.1207	0.0081	1.5162	0.1296	0.0499*	2.0034	0.0452	0.2055	1.0538	0.2921
elpe	0.0053	0.5186	0.6041	1.1010*	2.2517	0.0245	0.0108*	1.9995	0.0457	0.1507	1.6453	0.1001
emporiki	-0.0569	-0.8386	0.4018	0.0472	1.5561	0.1198	0.0237*	2.3656	0.0181	0.6729	1.6799	0.0931
ete	-0.0659*	-2.3324	0.0198	0.0331	1.1876	0.2351	0.0066*	2.4917	0.0128	0.0433	1.1585	0.2468
eurobank	-0.0328*	-1.9682	0.0492	0.3426*	3.7208	0.0002	0.0069	1.5248	0.1275	0.0477	1.0085	0.3134
hyatt	-0.5699	-1.3461	0.1785	9.5001	1.8576	0.0634	0.8716	1.7226	0.0851	3.1479	0.7592	0.4479
intracom	0.0248	0.1407	0.8881	0.0430*	2.3878	0.0170	0.0734*	3.1099	0.0019	1.1208*	3.2110	0.0013
kae	0.0094	0.7460	0.4558	0.5589*	10.3011	0.0000	0.0193*	5.6267	0.0000	0.2374*	2.1927	0.0284
cosmote	-0.0046	-0.8024	0.4225	0.4660*	5.7289	0.0000	0.0031*	2.3698	0.0179	0.0357*	2.2306	0.0259
motoroil	-0.0000375	-0.0471	0.9625	1.9763*	5.0253	0.0000	0.0054	1.9401	0.0526	0.1097	1.8181	0.0693
opap	0.0101*	2.1107	0.0350	0.3436*	3.4828	0.0005	0.0005	0.9897	0.3225	0.0103	1.5097	0.1314
ote	0.0070	0.4745	0.6352	0.0018*	2.9855	0.0029	0.0013	1.5591	0.1191	0.0251	1.6133	0.1068
peiraiws	-0.1494	-1.8000	0.0720	0.0100*	5.1740	0.0000	0.0495*	5.2985	0.0000	0.4822*	2.4021	0.0164
titan	-0.2518*	-3.1980	0.0014	0.0144	1.4435	0.1490	0.1094*	6.6711	0.0000	2.1229*	3.4019	0.0007
foli foli	-0.0463	-0.2130	0.8314	0.1489*	2.2091	0.0273	0.1911*	2.7984	0.0052	6.9921	1.8347	0.0667

*An * indicates statistical significance at 5%.*
The following equation is estimated by GMM for each individual stock of FTSE-20 over the whole research period,
$V_{it} = \alpha + \beta T_{it} + \varepsilon_{it}$, *where* V_{it} *is the volatility measure for stock i at day t and* T_{it} *is the trading activity measure for stock i at day t. Volatility is measured by the squared value of closing price minus lagged closing price, while trading activity is measured by the average trade size (ats), the number of trades (trades), the value of trades (value), and the number of shares traded during the day t (volume).*

Table 11

Regressions of conditional variance and various trading activity measures

Companies	**ats**			**trades**			**value**			**volume**		
	Coeff.	**t-stat.**	**prob.**	**Coeff.**	**t-stat.**	**prob.**	**Coeff.**	**t-stat.**	**prob.**	**Coeff.**	**t-stat.**	**prob.**
alpha	-0.0017*	-2.1834	0.0291	0.0051	1.8465	0.0649	0.0128*	3.4854	0.0005	0.0552	1.4020	0.1610
ate	0.0110	1.1250	0.2608	1.4599*	4.2301	0.0000	0.1224*	3.9916	0.0001	0.5044*	2.9544	0.0032
bioxalko	-0.0086*	-4.2255	0.0000	0.0837*	2.8269	0.0047	0.0083	1.1863	0.2356	-0.0038	-0.1075	0.9144
germanos	-0.0586*	-2.5999	0.0094	0.2204*	3.6573	0.0003	0.0163	1.6287	0.1036	0.1103	0.7633	0.4454
deh	0.0063*	4.2731	0.0000	0.0311*	6.3724	0.0000	0.0007*	3.8570	0.0001	0.0104*	5.9643	0.0000
coca cola	-0.0276	-1.4179	0.1563	0.0060*	2.4406	0.0147	0.0110	1.7113	0.0871	0.0196	0.6857	0.4930
elpe	0.0015	0.6650	0.5061	0.3869*	7.8756	0.0000	0.0035*	2.3677	0.0180	0.0408*	2.1177	0.0343
emporiki	-0.0884	-1.5847	0.1131	0.0483*	2.2436	0.0249	0.0184*	2.7280	0.0064	0.4504*	2.0436	0.0411
ete	-0.0383	-1.3950	0.1631	0.1630	1.6521	0.0986	0.0023*	2.8888	0.0039	0.0054	0.9500	0.3422
eurobank	-0.0141	-0.7644	0.4447	0.1682*	4.8625	0.0000	0.0024*	2.4432	0.0147	0.0162*	3.7853	0.0002
hyatt	-0.4527	-1.7363	0.0827	1.7943*	6.8024	0.0000	0.1104*	2.5155	0.0120	0.2940	0.9605	0.3370
intracom	-0.2233*	-2.5466	0.0109	0.0350*	5.3885	0.0000	0.0315*	3.4788	0.0005	0.1798	1.5781	0.1147
kae	0.0038	0.6906	0.4899	2.0512*	8.0584	0.0000	0.0102*	5.0697	0.0000	0.1170*	2.2761	0.0229
cosmote	-0.0012	-0.3156	0.7524	0.0819*	5.1441	0.0000	0.0004	0.9830	0.3258	0.0071	1.5196	0.1289
motoroil	-0.0003	-0.6598	0.5095	0.7783*	6.9840	0.0000	0.0041*	3.7128	0.0002	0.0676*	4.3062	0.0000
opap	0.0086	1.6464	0.0999	0.0401*	2.2405	0.0252	0.0004	1.4530	0.1465	0.0107*	2.1905	0.0287
ote	-0.0082	-1.6885	0.0915	0.0004	1.3545	0.1757	0.0002	1.6180	0.1058	0.0019	1.0608	0.2889
peiraiws	-0.1855	-1.6637	0.0963	0.0066*	2.0960	0.0362	0.0248*	4.5655	0.0000	0.1186	1.8016	0.0718
titan	-0.3048*	-5.7536	0.0000	0.0107*	3.1952	0.0014	0.0590*	5.8051	0.0000	0.3478	1.0714	0.2841
foli foli	-0.1682*	-2.2962	0.0218	0.0936*	4.9530	0.0000	0.0096	0.5912	0.5544	0.0103	0.0298	0.9762

*An * indicates statistical significance at 5%.*
The following equation is estimated by GMM for each individual stock of FTSE-20 over the whole research period,
$V_{it} = \alpha + \beta T_{it} + \varepsilon_{it}$, *where* V_{it} *is the volatility measure for stock i at day t and* T_{it} *is the trading activity measure for stock i at day t. Volatility is measured by the conditional variance estimated by a GARCH(1,1) model, while trading activity is measured by the average trade size (ats), the number of trades (trades), the value of trades (value), and the number of shares traded during the day t (volume).*

Table 12

Regressions of daytime volatility and various trading activity measures

Companies	ats			trades			value			volume		
	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.
alpha	-0.1480	-0.5758	0.5650	128.5353*	7.4644	0.0000	3.5264	1.7400	0.0823	51.5067	1.4665	0.1430
ate	-3.8663	-0.7708	0.4411	-324.6474*	-8.9663	0.0000	-48.6112*	-6.2718	0.0000	-156.7956*	-2.9734	0.0031
bioxalko	0.0607	0.1141	0.9092	215.0556*	5.2692	0.0000	1.2357*	26.6435	0.0000	6.9617	1.4869	0.1375
germanos	-1.0177	-0.2547	0.7991	135.5524*	3.9789	0.0001	2.0978*	3.3971	0.0007	38.0044*	2.0093	0.0449
deh	8.8711*	4.7566	0.0000	8.6015	0.8354	0.4038	0.6650*	4.9497	0.0000	11.1244*	5.0222	0.0000
coca cola	31.1879*	10.3507	0.0000	21.6377	0.1173	0.9066	5.1428	1.1331	0.2576	69.4611*	8.3068	0.0000
elpe	2.0240*	6.5871	0.0000	154.0021*	10.7713	0.0000	0.7585	1.8043	0.0716	4.6896*	2.2398	0.0254
emporiki	0.6433	0.0155	0.9876	320.1872*	8.4165	0.0000	4.2268	0.8747	0.3820	118.3988	0.9007	0.3681
ete	-1.5884	-0.3301	0.7414	116.0045*	7.6611	0.0000	0.6318	1.6321	0.1031	8.3172	1.2349	0.2173
eurobank	-8.6181	-1.6048	0.1090	116.9264*	6.2232	0.0000	0.9290	0.8108	0.4178	3.0276	0.3619	0.7176
hyatt	12.7838*	2.1091	0.0353	186.0704*	6.3643	0.0000	2.8755*	3.0478	0.0024	25.3219*	3.1190	0.0019
intracom	-165.9137	-0.7952	0.4268	834.4844*	5.3593	0.0000	221.0728*	4.8924	0.0000	773.0864*	3.2259	0.0013
kae	-0.4979*	-11.6983	0.0000	397.3889*	4.6879	0.0000	-0.2401	-0.5238	0.6006	-3.4760	-1.4992	0.1343
cosmote	8.6637*	2.1410	0.0326	119.4287*	6.0953	0.0000	1.4591*	4.1698	0.0000	16.9886*	4.3292	0.0000
motoroil	4.9873	0.9683	0.3332	528.7208*	11.2067	0.0000	1.8569*	2.4482	0.0146	32.4982*	2.4722	0.0137
opap	-2.5977	-1.5711	0.1166	179.9383*	7.7745	0.0000	0.3734	1.4583	0.1452	4.2964	1.4548	0.1462
ote	-0.5214	-0.3609	0.7183	88.4258*	11.6017	0.0000	0.3566	0.9338	0.3507	7.6697	0.9911	0.3220
peiraiws	7.9766*	4.2676	0.0000	81.5616*	5.1711	0.0000	4.6034*	3.1174	0.0019	43.2559*	2.1005	0.0361
titan	28.3795	0.5688	0.5696	433.9787*	6.3435	0.0000	14.1481*	2.3143	0.0209	415.7406*	2.7589	0.0060
foli foli	-19.9387	-0.5215	0.6022	366.8959*	5.0908	0.0000	26.7498*	2.2605	0.0241	551.3485*	2.4048	0.0165

*An * indicates statistical significance at 5%.*

The following equation is estimated by GMM for each individual stock of FTSE-20 over the whole research period,

$V_{it} = \alpha + \beta T_{it} + \varepsilon_{it}$, *where* V_{it} *is the volatility measure for stock i at day t and* T_{it} *is the trading activity measure for stock i at day t. Volatility is measured by the absolute value of closing price minus opening price, while trading activity is measured by the average trade size (ats), the number of trades (trades), the value of trades (value), and the number of shares traded during the day t (volume).*

We then study the trading activity-volatility relation according to JKL specification. Having observed from Table 3 that trades is weakly correlated with ats, value and volume, we decompose trading activity in three different combinations of two components: ats-trades, trades-value and trades-volume. The reason for doing this is that we assume that the low correlation between the two measures of trading activity implies that these two variables explain a different part of trading activity.

Table 13 presents GMM estimates of the return volatility (measured as the absolute value of closing price minus the lagged closing price (|R|)) relation with average trade size and trades, with trades and value, and with trades and volume. The most notable aspect of the evidence in Table 13 is that average trade size has virtually no marginal explanatory power when volatility measured as the absolute value of daily return is conditioned on the number of transactions. Indeed, average trade size coefficients are negative and statistically insignificant in most FTSE-20 stocks, as it was observed when average trade size was the only regressor in the volatility equation. On the other hand, there is strong evidence that the absolute value of daily return is primarily determined by the number of transactions, rather than their size. Number of trades seems to have positive (for all cases) and significant relation with |R| for most stocks. Moreover, inclusion of average trade size has virtually no effect on the coefficients of trades that the latter variable has when being the sole regressor. As far as the other two decompositions of trading activity concerns, the trade frequency has a very similar view when is regressed with either the value of trades or the volume of shares. It is always positive and statistically significant for the majority of stocks. When value with trades are regressed, value seems to be positive and marginally statistically significant for most of the cases, as it is when it is the only regressor in the volatility equation. On the contrary, volume becomes insignificant when it is regressed with trades frequency, while it remains positively related with the absolute value of return.

Tables 14, 15, 16 present GMM estimates of the return volatility relation with the three combinations of the trading activity measures, where volatility is measured as the squared value of closing price minus the lagged closing price (R^2), the conditional variance estimated by a GARCH (1,1) model under the assumption that the innovations are t-Student distributed and the absolute value of closing price minus the opening price (daytime volatility). The results as far as the ats-trades combination concerns are the same for all volatility measures. That means that the number of trades coefficients are always positive and statistically significant, while the ats' are consistently negative and statistically insignificant independently of the volatility measure used. When dependent variable is the conditional volatility or the daytime volatility and the number and value of trades are used as regressors, we note that value still has positive coefficients, but it becomes marginally unrelated with these two volatility measures. Finally, the volatility measure used seems to affect the coefficients of volume too, when the number of trades is the second regressor. Contrary to the results when volume was the only regressor, as Tables 13,14,15 and 16 present volume coefficients are positive but insignificant when volatility is measured as the absolute or squared value of the daily return or as the conditional variance, while they are negative and statistically significant when volatility is measured as the daytime volatility.

In summary, the evidence presented appears to generally support that trade frequency has a more dominant effect on price volatility. The number of trades is

Table 13

Regressions of |R| and various trading activity measures combinations

Companies	ats-trades						trades-value						trades-volume					
	ats			trades			trades			value			trades			volume		
	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.
alpha	-0.015	-0.882	0.378	0.129	1.507	0.132	0.081	1.738	0.082	0.439*	4.459	0.000	0.115	1.599	0.110	5.285*	2.285	0.022
ate	-0.059	-1.479	0.140	13.020*	7.957	0.000	16.475*	4.207	0.000	-0.677	-0.915	0.360	11.246*	2.895	0.004	1.340	0.485	0.628
bioxalko	-0.108	-1.224	0.221	1.358	1.815	0.070	1.285	1.418	0.156	0.266	1.418	0.156	1.322	1.409	0.159	1.577	1.244	0.214
germanos	-0.760	-1.890	0.059	11.622*	2.250	0.025	9.310	1.562	0.118	0.486	1.149	0.251	10.890*	2.027	0.043	6.331	1.232	0.218
deh	-0.084	-0.546	0.585	6.283*	4.217	0.000	6.346*	4.389	0.000	-0.005	-0.258	0.797	6.273*	4.369	0.000	-0.004	-0.012	0.991
coca cola	-0.375	-1.329	0.184	0.174	1.823	0.068	0.138*	1.985	0.047	0.760*	2.074	0.038	0.169*	1.975	0.048	3.110	1.098	0.272
elpe	-0.005	-0.045	0.964	9.193*	5.512	0.000	9.089*	5.421	0.000	0.019	0.716	0.474	9.069*	5.456	0.000	0.258	0.923	0.356
emporiki	1.384	0.586	0.558	0.998	1.862	0.063	0.691	1.569	0.117	0.461*	2.391	0.017	0.862	1.565	0.118	16.033	1.773	0.076
ete	-1.289*	-2.819	0.005	0.598	1.395	0.163	0.473	1.245	0.213	0.091*	2.293	0.022	0.578	1.257	0.209	0.512	0.857	0.391
eurobank	-0.190	-0.868	0.386	5.365*	4.158	0.000	5.293*	3.917	0.000	0.021	0.649	0.517	5.368*	4.096	0.000	0.054	0.133	0.894
hyatt	-3.699*	-2.918	0.004	27.782*	4.443	0.000	22.061*	2.352	0.019	0.551	0.639	0.523	28.018*	4.365	0.000	-0.545	-0.297	0.766
intracom	0.642	0.318	0.751	0.574*	2.990	0.003	0.494*	3.031	0.003	0.936*	3.277	0.001	0.504*	3.142	0.002	14.540*	5.746	0.000
kae	0.066	0.506	0.613	35.667*	11.306	0.000	34.285*	10.929	0.000	0.142*	4.365	0.000	34.864*	10.981	0.000	1.567	1.509	0.132
cosmote	-0.339*	-2.029	0.043	9.923*	7.459	0.000	10.583*	8.924	0.000	-0.045	-1.214	0.225	10.574*	9.545	0.000	-0.468	-1.369	0.171
motoroil	0.009	1.094	0.274	34.310*	8.859	0.000	35.142*	8.438	0.000	-0.042*	-2.091	0.037	34.832*	8.437	0.000	-0.451	-1.441	0.150
opap	0.005	0.091	0.927	5.911*	5.528	0.000	6.140*	5.583	0.000	-0.011*	-2.634	0.009	5.988*	5.575	0.000	-0.066	-1.065	0.287
ote	0.026	0.111	0.912	0.031*	5.310	0.000	0.031*	4.019	0.000	0.019	1.350	0.177	0.031*	3.995	0.000	0.382	1.422	0.155
peiraiws	-1.970	-1.624	0.105	0.120*	5.729	0.000	0.102*	5.844	0.000	0.700*	5.838	0.000	0.114*	5.023	0.000	7.280*	2.555	0.011
titan	-5.647*	-4.027	0.000	0.252	1.790	0.074	0.225	1.805	0.071	1.789*	8.358	0.000	0.241	1.821	0.069	35.663*	3.789	0.000
foli foli	0.732	0.440	0.660	1.334*	4.477	0.000	1.280*	3.859	0.000	1.948*	3.788	0.000	1.234*	4.304	0.000	50.887*	8.036	0.000

*An * indicates statistical significance at 5%.*

The following equations are estimated by GMM for each individual stock of FTSE-20 over the whole research period, $V_{it} = \alpha + \beta A_{it} + N_{it} + \varepsilon_{it}$, $V_{it} = \alpha + \beta N_{it} + VA_{it} + \varepsilon_{it}$ *and* $V_{it} = \alpha + \beta N_{it} + VO_{it} + \varepsilon_{it}$. V_{it} *is the volatility measured by the absolute value of closing price minus lagged closing price,* A_{it} *is the average trade size (ats),* N_{it} *is the number of trades (trades) ,* VA_{it} *is the value of trades (value), and* VO_{it} *is the number of shares traded during the day t (volume), for stock i at day t.*

Table 14

Regressions of R^2 and various trading activity measures combinations

Companies	ats-trades						trades-value						trades-volume					
	ats			trades			trades			value			trades			volume		
	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.
alpha	-0.001	-1.347	0.178	0.007	1.332	0.183	0.004	1.502	0.133	0.028*	3.799	0.000	0.006	1.434	0.152	0.303*	1.987	0.047
ate	-0.004	-1.069	0.285	1.032*	3.941	0.000	1.274	1.852	0.064	-0.047	-0.362	0.718	0.517	0.780	0.435	0.393	0.821	0.412
bioxalko	-0.008	-1.342	0.180	0.115	1.813	0.070	0.108	1.483	0.138	0.028	1.525	0.128	0.112	1.462	0.144	0.154	1.303	0.193
germanos	0.023	0.648	0.517	4.164	1.722	0.085	3.299	1.288	0.198	0.180	0.990	0.323	3.964	1.609	0.108	1.676	0.859	0.390
deh	0.001	0.064	0.949	0.246*	4.145	0.000	0.241*	4.353	0.000	0.000	0.236	0.814	0.237*	4.277	0.000	0.010	0.431	0.666
coca cola	-0.020	-1.561	0.119	0.008	1.521	0.128	0.006	1.477	0.140	0.050*	2.000	0.046	0.008	1.547	0.122	0.205	1.053	0.292
elpe	0.001	0.197	0.844	1.101*	2.252	0.025	1.093*	2.214	0.027	0.002	0.667	0.505	1.085*	2.240	0.025	0.034	1.258	0.209
emporiki	-0.045	-0.653	0.514	0.047	1.852	0.064	0.032	1.552	0.121	0.023*	2.303	0.021	0.042	1.570	0.117	0.633	1.644	0.100
ete	-0.070*	-2.367	0.018	0.033	1.301	0.193	0.025	1.146	0.252	0.006*	2.366	0.018	0.032	1.176	0.240	0.032	0.957	0.339
eurobank	-0.011	-1.006	0.315	0.342*	3.721	0.000	0.338*	3.545	0.000	0.001	0.611	0.541	0.343*	3.676	0.000	-0.002	-0.083	0.934
hyatt	-0.163	-0.400	0.689	9.495	1.856	0.064	0.837	0.122	0.903	0.819	1.019	0.309	9.607	1.875	0.061	-0.455	-0.677	0.498
intracom	0.038	0.219	0.827	0.043*	2.806	0.005	0.036*	2.649	0.008	0.072*	3.090	0.002	0.037*	2.777	0.006	1.084*	3.169	0.002
kae	0.009	0.781	0.435	2.569*	10.346	0.000	2.436*	9.912	0.000	0.014*	5.482	0.000	2.485*	9.974	0.000	0.163	1.897	0.058
cosmote	-0.013*	-2.155	0.031	0.470*	5.784	0.000	0.502*	6.068	0.000	-0.002	-1.310	0.190	0.499*	6.138	0.000	-0.021	-1.405	0.160
motoroil	0.000	-0.329	0.742	1.976*	5.026	0.000	2.069*	4.872	0.000	-0.005*	-2.010	0.045	2.048*	4.883	0.000	-0.062*	-2.145	0.032
opap	-0.004	-1.283	0.200	0.344*	3.489	0.001	0.362*	3.501	0.001	-0.001*	-2.208	0.027	0.352*	3.504	0.001	-0.008*	-2.057	0.040
ote	0.008	0.514	0.608	0.002*	3.867	0.000	0.002*	3.020	0.003	0.001	1.560	0.119	0.002*	3.001	0.003	0.025	1.613	0.107
peiraiws	-0.139	-1.805	0.071	0.010*	6.021	0.000	0.009*	5.404	0.000	0.049*	5.257	0.000	0.010*	5.479	0.000	0.472*	2.394	0.017
titan	-0.239*	-3.082	0.002	0.014	1.365	0.172	0.012	1.270	0.204	0.109*	6.628	0.000	0.013	1.315	0.189	2.088*	3.352	0.001
foli foli	-0.009	-0.042	0.967	0.149*	2.612	0.009	0.145*	2.323	0.020	0.188*	2.792	0.005	0.137*	2.448	0.014	6.875	1.819	0.069

*An * indicates statistical significance at 5%.*

The following equations are estimated by GMM for each individual stock of FTSE-20 over the whole research period, $V_{it} = \alpha + \beta A_{it} + N_{it} + \varepsilon_{it}$ *,* $V_{it} = \alpha + \beta N_{it} + VA_{it} + \varepsilon_{it}$ *and* $V_{it} = \alpha + \beta N_{it} + VO_{it} + \varepsilon_{it}$ *.* V_{it} *is the volatility measured by the squared value of closing price minus lagged closing price,* A_{it} *is the average trade size (ats),* N_{it} *is the number of trades (trades) ,* VA_{it} *is the value of trades (value), and* VO_{it} *is the number of shares traded during the day t (volume), for stock i at day t.*

Table 15

Regressions of conditional variance and various trading activity measures combinations

Companies	ats-trades						trades-value						trades-volume					
	ats			trades			trades			value			trades			volume		
	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.	Coeff.	t-stat	Prob.
alpha	-0.002*	-2.182	0.029	0.005	1.781	0.075	0.004	1.770	0.077	0.013*	3.461	0.001	0.005	1.860	0.063	0.051	1.363	0.173
ate	-0.003	-0.323	0.747	1.461*	4.221	0.000	3.288*	3.060	0.002	-0.356*	-2.109	0.035	2.596*	3.114	0.002	-0.862	-1.892	0.059
bioxalko	-0.008*	-4.097	0.000	0.084*	3.284	0.001	0.082*	2.930	0.003	0.008	1.143	0.253	0.084*	2.838	0.005	-0.008	-0.247	0.805
germanos	-0.054*	-2.545	0.011	0.218*	3.662	0.000	0.248*	3.474	0.001	-0.007	-1.252	0.211	0.244*	3.702	0.000	-0.224*	-2.221	0.027
deh	0.006*	4.280	0.000	0.030*	6.354	0.000	0.026*	5.297	0.000	0.000*	3.425	0.001	0.026*	5.356	0.000	0.007*	5.005	0.000
coca cola	-0.027	-1.421	0.155	0.006*	2.352	0.019	0.005*	2.573	0.010	0.011	1.701	0.089	0.006*	2.459	0.014	0.019	0.674	0.500
elpe	0.000	0.125	0.901	0.387*	7.875	0.000	0.385*	7.917	0.000	0.000	0.982	0.326	0.386*	7.870	0.000	0.001	0.332	0.740
emporiki	-0.076	-1.486	0.137	0.048*	2.695	0.007	0.037*	2.727	0.006	0.017*	2.666	0.008	0.045*	2.357	0.019	0.407*	2.012	0.044
ete	-0.040	-1.438	0.151	0.016	1.801	0.072	0.014	1.734	0.083	0.002*	2.744	0.006	0.016	1.637	0.102	0.000	-0.036	0.971
eurobank	-0.004	-0.299	0.765	0.168*	4.868	0.000	0.169*	4.685	0.000	0.000	-0.297	0.767	0.169*	4.796	0.000	-0.007	-0.416	0.677
hyatt	-0.386*	-2.748	0.006	1.783*	6.894	0.000	1.814*	8.015	0.000	-0.002	-0.130	0.897	1.870*	6.871	0.000	-0.317	-1.750	0.080
intracom	-0.213*	-2.509	0.012	0.034*	4.544	0.000	0.032*	6.152	0.000	0.030*	3.439	0.001	0.034*	5.801	0.000	0.146	1.337	0.181
kae	0.004	0.743	0.457	2.059*	8.065	0.000	2.000*	7.914	0.000	0.006*	4.257	0.000	2.025*	7.980	0.000	0.058	1.561	0.119
cosmote	-0.003	-0.593	0.553	0.083*	5.191	0.000	0.090*	4.765	0.000	-0.001	-1.285	0.199	0.086*	4.535	0.000	-0.003	-0.661	0.509
motoroil	0.000	-1.291	0.197	0.778*	6.981	0.000	0.773*	6.584	0.000	0.000	0.461	0.645	0.775*	6.619	0.000	0.002	0.223	0.824
opap	0.008	1.595	0.111	0.038*	2.224	0.026	0.034*	2.032	0.042	0.000	1.200	0.230	0.029	1.852	0.064	0.009	1.897	0.058
ote	-0.008	-1.678	0.094	0.000	1.519	0.129	0.000	1.351	0.177	0.000	1.620	0.106	0.000	1.353	0.176	0.002	1.057	0.291
peiraiws	-0.179	-1.666	0.097	0.006*	2.051	0.040	0.006*	6.010	0.000	0.024*	14.154	0.000	0.006*	2.084	0.037	0.112	1.757	0.079
titan	-0.296*	-5.756	0.000	0.010*	3.216	0.001	0.009*	2.708	0.007	0.059*	5.761	0.000	0.010*	3.888	0.000	0.319	1.930	0.054
foli foli	-0.145*	-2.127	0.034	0.093*	5.171	0.000	0.093*	4.937	0.000	0.008	0.476	0.634	0.094*	4.945	0.000	-0.069	-0.200	0.841

*An * indicates statistical significance at 5%.*

The following equations are estimated by GMM for each individual stock of FTSE-20 over the whole research period, $V_{it} = \alpha + \beta A_{it} + N_{it} + \varepsilon_{it}$, $V_{it} = \alpha + \beta N_{it} + VA_{it} + \varepsilon_{it}$ *and* $V_{it} = \alpha + \beta N_{it} + VO_{it} + \varepsilon_{it}$. V_{it} *is the volatility measured by conditional variance estimated by a GARCH(1,1) model,* A_{it} *is the average trade size (ats),* N_{it} *is the number of trades (trades),* VA_{it} *is the value of trades (value), and* VO_{it} *is the number of shares traded during the day t (volume), for stock i at day t.*

Table 16

Regressions of daytime volatility and various trading activity measures combinations

Companies	ats-trades						trades-value						trades-volume					
	ats			trades			trades			value			trades			volume		
	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.	Coeff.	t-stat.	prob.
alpha	-0.088	-0.603	0.547	128.420*	7.464	0.000	128.624*	6.853	0.000	-0.009	-0.027	0.979	128.947*	7.184	0.000	-1.007	-0.168	0.866
ate	-1.583	-0.887	0.375	-324.157*	-8.962	0.000	-312.901*	-5.944	0.000	-2.269	-0.235	0.815	-364.948*	-6.832	0.000	29.965	0.978	0.329
bioxalko	0.078	0.151	0.880	215.064*	5.270	0.000	214.023*	5.157	0.000	0.216	0.315	0.753	214.454*	5.180	0.000	0.739	0.183	0.855
germanos	0.196	0.053	0.958	135.663*	3.971	0.000	128.158*	3.494	0.001	0.926	0.768	0.443	0.244*	3.702	0.000	-0.224*	-2.221	0.027
deh	8.866*	4.734	0.000	8.575	0.830	0.407	0.888	0.079	0.937	0.656*	5.059	0.000	1.892	0.166	0.869	10.811*	4.363	0.000
coca cola	31.158*	10.527	0.000	15.897	0.086	0.931	-40.583	-0.210	0.834	5.571	1.269	0.205	-22.605	-0.123	0.903	70.202*	11.813	0.000
elpe	1.068*	5.477	0.000	153.679*	10.794	0.000	152.853*	10.701	0.000	0.180*	6.778	0.000	153.094*	10.724	0.000	1.432*	7.491	0.000
emporiki	-85.037*	-5.394	0.000	329.867*	8.476	0.000	342.557*	8.499	0.000	-2.584*	-5.017	0.000	343.498*	8.487	0.000	-68.376*	-5.059	0.000
ete	-10.377*	-3.848	0.000	116.875*	7.713	0.000	117.517*	7.644	0.000	-0.101	-0.895	0.371	119.217*	7.715	0.000	-5.360*	-5.357	0.000
eurobank	-15.114*	-3.000	0.003	118.650*	-0.354	0.000	120.297*	6.168	0.000	-0.268	-0.563	0.574	121.371*	6.412	0.000	-7.792*	-3.244	0.001
hyatt	1.364	0.258	0.797	185.139*	5.870	0.000	179.310*	5.479	0.000	0.620*	2.202	0.028	179.661*	5.460	0.000	5.280*	1.976	0.049
intracom	-478.479*	-2.381	0.018	879.230*	5.363	0.000	-112.648	-0.207	0.836	244.178	1.678	0.094	1141.070*	4.494	0.000	-452.694*	-1.987	0.047
kae	-0.479*	-10.269	0.000	397.163*	4.685	0.000	401.475*	4.733	0.000	-0.658*	-5.339	0.000	399.432*	4.711	0.000	-5.363*	-7.910	0.000
cosmote	6.185	1.752	0.080	117.512*	6.288	0.000	106.930*	5.796	0.000	0.739*	4.948	0.000	108.940*	5.962	0.000	8.522*	4.975	0.000
motoroil	-3.144	-1.579	0.115	531.818*	11.104	0.000	542.792*	10.755	0.000	-0.561*	-3.403	0.001	541.961*	10.717	0.000	-9.289*	-3.482	0.001
opap	-2.912	-1.950	0.052	180.030*	7.834	0.000	182.410*	7.901	0.000	-0.108*	-3.261	0.001	183.713*	7.879	0.000	-3.638*	-2.988	0.003
ote	-2.429*	-2.269	0.024	88.572*	11.585	0.000	88.897*	11.396	0.000	-0.042	-0.670	0.503	89.946*	11.545	0.000	-1.658*	-3.579	0.000
peiraiws	7.942*	4.111	0.000	81.555*	5.175	0.000	73.645*	4.662	0.000	1.071	1.744	0.082	75.919*	4.906	0.000	11.402*	2.822	0.005
titan	36.015	0.667	0.505	436.187*	6.405	0.000	473.757*	5.541	0.000	-5.271	-0.866	0.387	483.767*	5.571	0.000	-168.286	-1.068	0.286
foli foli	-29.834	-0.816	0.415	368.253*	5.109	0.000	321.049*	4.139	0.000	6.628	0.570	0.569	366.646*	5.325	0.000	0.757	0.003	0.997

*An * indicates statistical significance at 5%.*

The following equations are estimated by GMM for each individual stock of FTSE-20 over the whole research period, $V_{it} = \alpha + \beta A_{it} + N_{it} + \varepsilon_{it}$, $V_{it} = \alpha + \beta N_{it} + VA_{it} + \varepsilon_{it}$ *and* $V_{it} = \alpha + \beta N_{it} + VO_{it} + \varepsilon_{it}$. V_{it} *is the volatility measured by the absolute value of closing price minus opening price,* A_{it} *is the average trade size (ats),* N_{it} *is the number of trades (trades),* VA_{it} *is the value of trades (value), and* VO_{it} *is the number of shares traded during the day t (volume), for stock i at day t.*

always positively related with return volatility independently the way volatility is measured, even if it is not the only regressor in the volatility equation. This evidence confirms the aforementioned GARCH result, which reveals a positive and significant relation between trades and conditional variance. On the contrary, value-volatility and volume-volatility relations are both influenced by the volatility measure and the number of regressors used in the equation. Furthermore, we observe that daytime volatility is that measure of volatility that affects more than the others the trading activity-return volatility relationship. Daytime volatility appears to affect not only the sign of regressors' coefficients, but also their statistical significance.

6.2. Dynamic relation

To evaluate dynamic relationships between stock return volatility and trading activity, we estimate the following bivariate vector autoregression (VAR) for the various volatility and trading activity measures.

$$\sigma_t^2 = \gamma_1 + \sum_{k=1}^{L} \alpha_k \sigma_{t-k}^2 + \sum_{k=1}^{L} b_k T_{t-k} + \varepsilon_{1t}$$

$$T_t = \gamma_2 + \sum_{k=1}^{L} c_k T_{t-k} + \sum_{k=1}^{L} d_k \sigma_{t-k}^2 + \varepsilon_{2t}$$

where σ_t^2 is the estimated volatility of stock returns, T_t is the trading activity measure during time interval t, ε_{it} is the disturbance reflecting variation of the left-hand-side variable that cannot be accounted for the right-hand-side variables, and a, b, c, and d are the group lagged coefficients in the Granger-causality testing equations.

Concentrating on the rejection of the null hypothesis of Granger non-causality, Table 17 presents the results of the causal relationship tests between the various measures of trading activity and volatility. As we observe, when trading activity is expressed as the number of trades a strong two-way causality (feedback relation) is detected in most stocks for the three volatility measures (13,17,13 stocks), contrary to the other two trading activity measures. This feedback relation is even stronger between trade frequency and conditional variance, while it appears to weakens when value or volume is used as activity measure. That means that the number of trades helps predict return volatility and vice versa. In this sense, trades contains information about returns indirectly through its predictability of return volatility. This finding seems consistent with Clark's (1973) latent common-factor model in that trading activity (volume is used as measure of trading activity) may serve as a proxy for daily information flow in the stochastic process generating stock return variance. Moreover, this finding supports our inference that a strong, positive contemporaneous relation exists between trades and all the volatility measures.

Looking at the second column of *Table 17*, we note that there is a strong causality from trading activity to return volatility only when the first is measured as the number of trades. Marginal causality exists when volatility is measured as the conditional variance and activity as the value of trades (12 stocks) or volume (11 stocks). In all other cases we cannot infer that trading activity Granger-causes return volatility. This implies that, besides the strong positive contemporaneous relation between trades and return volatility, trading activity adds significant predictive power for future price changes in the presence of current and past volatility. This finding is consistent with Copeland's (1976) theoretical model that implies information content of volume for future returns (sequential information arrival model), but at odds with Clark's (1973) mixture model that predicts no causal relation from trading activity measured as the share volume to return volatility. However, *Table 17* demonstrates that when volatility is measured as the conditional variance, a causality from trading activity to volatility exists in more cases than when other volatility measures are used.

Table 17

Number of rejected null hypotheses based on the Granger causality test

Causality between number of trades (N) and absolute daily return (|R|)			
	$N \xrightarrow{G.C.} \|R\|$	$\|R\| \xrightarrow{G.C.} N$	$N \xleftrightarrow{G.C.} \|R\|$
Sample size: 20 companies	**15**	**17**	**13**
Causality between number of trades (N) and conditional variance(C.V.)			
	$N \xrightarrow{G.C.} C.V.$	$C.V. \xrightarrow{G.C.} N$	$N \xleftrightarrow{G.C.} C.V.$
Sample size: 20 companies	**20**	**17**	**17**
Causality between number of trades (N) and squared daily return (R^2)			
	$N \xrightarrow{G.C.} R^2$	$R^2 \xrightarrow{G.C.} N$	$N \xleftrightarrow{G.C.} R^2$
Sample size: 20 companies	**15**	**17**	**13**
Causality between value of trades (VA) and absolute daily return (|R|)			
	$VA \xrightarrow{G.C.} \|R\|$	$\|R\| \xrightarrow{G.C.} VA$	$VA \xleftrightarrow{G.C.} \|R\|$
Sample size: 20 companies	**8**	**17**	**6**
Causality between value of trades (VA) and conditional variance(C.V.)			
	$VA \xrightarrow{G.C.} C.V.$	$C.V. \xrightarrow{G.C.} VA$	$VA \xleftrightarrow{G.C.} C.V.$
Sample size: 20 companies	**12**	**6**	**2**
Causality between value of trades (VA) and squared daily return (R^2)			
	$VA \xrightarrow{G.C.} R^2$	$R^2 \xrightarrow{G.C.} VA$	$VA \xleftrightarrow{G.C.} R^2$
Sample size: 20 companies	**8**	**15**	**7**
Causality between volume of shares (VO) and absolute daily return (|R|)			
	$VO \xrightarrow{G.C.} \|R\|$	$\|R\| \xrightarrow{G.C.} VO$	$VO \xleftrightarrow{G.C.} \|R\|$
Sample size: 20 companies	**6**	**14**	**5**
Causality between volume of shares (VO) and conditional variance(C.V.)			
	$VO \xrightarrow{G.C.} C.V.$	$C.V. \xrightarrow{G.C.} VO$	$VO \xleftrightarrow{G.C.} C.V.$
Sample size: 20 companies	**11**	**7**	**4**
Causality between volume of shares (VO) and squared daily return (R^2)			
	$VO \xrightarrow{G.C.} R^2$	$R^2 \xrightarrow{G.C.} VO$	$VO \xleftrightarrow{G.C.} R^2$
Sample size: 20 companies	**6**	**14**	**5**

Level of significance is 5%.

From *Table 17* also concludes that a strong Granger causality runs from volatility to trading activity in all cases but that of value or volume being the activity measure and conditional variance being the volatility measure. This result implies 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. Tables, which report analytically the results of causality tests (the χ^2 statistics, the p-values and the degrees of freedom) when different measures of volatility and trading activity are used, are available at the appendix B. The tests are based on the VAR estimation for each of the 20 stocks.

7. Summary and conclusions

In this study, the relationship between daily trading activity and stock return volatility for Greek companies listed in the FTSE-20 is investigated. By using various volatility and trading activity measures we examine if any contemporaneous or any lead-lag relation exists between them.

Our results give evidence of a positive contemporaneous relation between trading activity and volatility, with the number of trades to have a more dominant effect on price volatility. This implies that both time series might be driven by the same underlying process. This result is confirmed by both approaches used to test for this kind of relation: a GARCH(1,1) specification with trading activity being an exogenous variable in the variance equation and a GMM estimation of the volatility equation with the various trading activity measures and their combinations being the regressors. The GARCH estimation results show that the value-volatility and the volume-volatility relation is positive and significant as well for the majority of the FTSE-20 Greek stocks but the inclusion of value or volume in the variance equation does not induce such an important reduction in volatility persistence as in the trades case. We conclude that the inclusion of the trading activity measure, which is used as a proxy for information arrival in the GARCH specification, reduces the persistence of the conditional variance for the majority of stocks. Our conclusion is that the information-based effect helps in explaining the GARCH effect to some extent.

The GMM estimation evidence generally supports the GARCH specification that trade frequency has a more dominant effect on price volatility than the other trading activity measures. It is always positive and statistically significant. On the contrary, the average trade size does not appear to affect the return volatility. Thus, it is the occurrence of transactions and not their size that generates volatility which means that trade size has no information beyond that contained in the frequency of trades. Instead, the value-volatility and volume-volatility relation while being marginally significant it seems to be affected by the way volatility is measured and by the number of regressors used in the equation. Specifically, daytime volatility is that volatility measure that appears to affect not only the sign of regressors' coefficients, but also their statistical significance.

The linear causality tests of dynamic relationships between these data indicates substantial two way causality only in the case that trading activity is measured as the daily number of trades. This evidence is accordance with the presence of a contemporaneous relation between the two variables. We also conclude that short-run forecasts of current or future price changes could be improved by the knowledge of recent trading activity data and vice versa.

Appendix A

In this Appendix, all the necessary tests to check if the various time series used in this study are stationary are presented.

Table 18a					
Unit root tests for trading activity measured as the ats					
Companies	Test Critical Values	ADF*		P-P	
		t-stat	Prob.	t-stat	Prob.
alpha	test stat	-2.4443	0.0141	-54.5703	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ate	test stat	-34.4810	0.0000	-34.5963	0.0000
	1%level	-2.5668		-2.5668	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
bioxalko	test stat	-43.5029	0.0001	-46.6630	0.0001
	1%level	-2.5660		-2.5660	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
germanos	test stat	-4.5630	0.0000	-30.9942	0.0000
	1%level	-2.5665		-2.5665	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
deh	test stat	-8.3640	0.0000	-32.8893	0.0000
	1%level	-2.5673		-2.5672	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
coca cola	test stat	-9.0615	0.0000	-63.9613	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
elpe	test stat	-42.0278	0.0000	-43.0359	0.0001
	1%level	-2.5662		-2.5662	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
emporiki	test stat	-4.1187	0.0000	-63.4813	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ete	test stat	-5.0704	0.0000	-67.2136	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
eurobank	test stat	-39.5579	0.0000	-40.4070	0.0000
	1%level	-3.4340		-3.4340	
	5%level	-2.8630		-2.8630	
	10%level	-2.5676		-2.5676	

* *Schwarz information criterion is being used.*

Table 18b					
Unit root tests for trading activity measured as the ats					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
hyatt	**test stat**	-38.1701	0.0000	-38.4326	0.0000
	1%level	-3.9639		-3.9639	
	5%level	-3.4127		-3.4127	
	10%level	-3.1283		-3.1283	
intracom	**test stat**	-9.1567	0.0000	-59.2035	0.0000
	1%level	-3.9615		-3.9614	
	5%level	-3.4115		-3.4115	
	10%level	-3.1276		-3.1276	
kae	**test stat**	-43.0503	0.0001	-43.0826	0.0001
	1%level	-2.5662		-2.5662	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
cosmote	**test stat**	-6.6581	0.0000	-38.7697	0.0000
	1%level	-2.5667		-2.5667	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
motoroil	**test stat**	-33.0143	0.0000	-33.0181	0.0000
	1%level	-2.5671		-2.5671	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
opap	**test stat**	-11.1465	0.0000	-34.1912	0.0000
	1%level	-2.5669		-2.5669	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
ote	**test stat**	-9.9982	0.0000	-58.1984	0.0001
	1%level	-2.5659		-2.5659	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
peiraiws	**test stat**	-2.2355	0.0245	-54.4723	0.0001
	1%level	-2.5661		-2.5660	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
titan	**test stat**	-12.8392	0.0000	-45.7589	0.0000
	1%level	-3.9622		-3.9621	
	5%level	-3.4118		-3.4118	
	10%level	-3.1278		-3.1278	
foli foli	**test stat**	-25.2447	0.0000	-41.9164	0.0000
	1%level	-3.9626		-3.9626	
	5%level	-3.4120		-3.4120	
	10%level	-3.1279		-3.1279	

* *Schwarz information criterion is being used.*

Table 19a					
Unit root test for trading activity measured as the number of trades					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
alpha	**test stat**	-7.5972	0.0000	-66.4124	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ate	**test stat**	-10.1431	0.0000	-12.3830	0.0000
	1%level	-3.9656		-3.9655	
	5%level	-3.4135		-3.4134	
	10%level	-3.1288		-3.1288	
bioxalko	**test stat**	-6.7733	0.0000	-56.2533	0.0001
	1%level	-2.5660		-2.5660	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
germanos	**test stat**	-9.3580	0.0000	-32.7651	0.0000
	1%level	-2.5665		-2.5665	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
deh	**test stat**	-12.6694	0.0000	-21.6068	0.0000
	1%level	-3.9672		-3.9671	
	5%level	-3.4143		-3.4143	
	10%level	-3.1292		-3.1292	
coca cola	**test stat**	-11.0411	0.0000	-48.8055	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
elpe	**test stat**	-9.0010	0.0000	-14.5034	0.0000
	1%level	-3.9629		-3.9629	
	5%level	-3.4122		-3.4122	
	10%level	-3.1280		-3.1280	
emporiki	**test stat**	-8.6328	0.0000	-59.7079	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ete	**test stat**	-7.1516	0.0000	-69.3901	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
eurobank	**test stat**	-8.0703	0.0000	-20.8429	0.0000
	1%level	-3.9635		-3.9635	
	5%level	-3.4125		-3.4125	
	10%level	-3.1282		-3.1282	

* *Schwarz information criterion is being used.*

Table 19b					
Unit root test for trading activity measured as the number of trades					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
hyatt	**test stat**	-8.7869	0.0000	-10.0059	0.0000
	1%level	-2.5664		-2.5664	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
intracom	**test stat**	-7.2583	0.0000	-65.3371	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
kae	**test stat**	-7.5519	0.0000	-27.1479	0.0000
	1%level	-3.9628		-3.9628	
	5%level	-3.4121		-3.4121	
	10%level	-3.1280		-3.1280	
cosmote	**test stat**	-9.3843	0.0000	-27.3999	0.0000
	1%level	-3.9651		-3.9651	
	5%level	-3.4133		-3.4133	
	10%level	-3.1287		-3.1286	
motoroil	**test stat**	-5.4777	0.0000	-23.3886	0.0000
	1%level	-3.9664		-3.9664	
	5%level	-3.4139		-3.4139	
	10%level	-3.1290		-3.1290	
opap	**test stat**	-11.9613	0.0000	-25.2041	0.0000
	1%level	-3.9659		-3.9659	
	5%level	-3.4136		-3.4136	
	10%level	-3.1289		-3.1289	
ote	**test stat**	-8.8064	0.0000	-59.7173	0.0001
	1%level	-2.5659		-2.5659	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
peiraiws	**test stat**	-9.2805	0.0000	-52.6557	0.0001
	1%level	-2.5660		-2.5660	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
titan	**test stat**	-9.4458	0.0000	-47.7287	0.0001
	1%level	-2.5660		-2.5660	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
foli foli	**test stat**	-18.8552	0.0000	-54.3031	0.0001
	1%level	-2.5661		-2.5661	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	

* *Schwarz information criterion is being used.*

Table 20a					
Unit root test for trading activity measured as the value of trades					
Companies	Test Critical Values	ADF*		P-P	
		t-stat	Prob.	t-stat	Prob.
alpha	test stat	-3.9726	0.0001	-48.8974	0.0001
	1%level	-2.5658		-3.4325	
	5%level	-1.9409		-2.8624	
	10%level	-1.6166		-2.5673	
ate	test stat	-17.5865	0.0000	-133.0633	0.0001
	1%level	-3.9655		-3.9655	
	5%level	-3.4135		-3.4134	
	10%level	-3.1288		-3.1288	
bioxalko	test stat	-10.0611	0.0000	-50.7269	0.0001
	1%level	-2.5660		-2.5660	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
germanos	test stat	-8.2460	0.0000	-34.1448	0.0000
	1%level	-2.5665		-2.5665	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
deh	test stat	-13.0058	0.0000	-27.4042	0.0000
	1%level	-2.5673		-2.5672	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
coca cola	test stat	-6.2902	0.0000	-58.0410	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
elpe	test stat	-15.0317	0.0000	-45.2891	0.0001
	1%level	-2.5662		-2.5662	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
emporiki	test stat	-5.8435	0.0000	-54.7211	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ete	test stat	-5.3314	0.0000	-60.9607	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
eurobank	test stat	-6.2152	0.0000	-43.9489	0.0001
	1%level	-2.5663		-2.5663	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	

* *Schwarz information criterion is being used.*

Table 20b					
Unit root test for trading activity measured as the value of trades					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
hyatt	**test stat**	-12.5399	0.0000	-26.7371	0.0000
	1%level	-2.5664		-2.5664	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
intracom	**test stat**	-3.2652	0.0166	-57.3714	0.0001
	1%level	-3.4326		-3.4325	
	5%level	-2.8624		-2.8624	
	10%level	-2.5673		-2.5673	
kae	**test stat**	-20.9793	0.0000	-38.3638	0.0000
	1%level	-2.5662		-2.5662	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
cosmote	**test stat**	-8.0471	0.0000	-36.4842	0.0000
	1%level	-2.5667		-2.5667	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
motoroil	**test stat**	-30.5812	0.0000	-32.4506	0.0000
	1%level	-2.5671		-2.5671	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
opap	**test stat**	-18.8514	0.0000	-30.4992	0.0000
	1%level	-2.5669		-2.5669	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
ote	**test stat**	-15.6755	0.0000	-52.8701	0.0001
	1%level	-2.5659		-2.5659	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
peiraiws	**test stat**	-7.9611	0.0000	-39.9804	0.0000
	1%level	-3.9623		-3.9623	
	5%level	-3.4119		-3.4119	
	10%level	-3.1278		-3.1278	
titan	**test stat**	-8.7179	0.0000	-40.7497	0.0000
	1%level	-3.9621		-3.9621	
	5%level	-3.4118		-3.4118	
	10%level	-3.1278		-3.1278	
foli foli	**test stat**	-19.8128	0.0000	-38.9604	0.0000
	1%level	-3.9625		-3.9625	
	5%level	-3.4120		-3.4120	
	10%level	-3.1279		-3.1279	

* *Schwarz information criterion is being used.*

Table 21a					
Unit root test for trading activity measured as the share volume					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
alpha	**test stat**	-3.9175	0.0001	-55.8674	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ate	**test stat**	-17.0321	0.0000	-145.1513	0.0001
	1%level	-2.5668		-2.5668	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
bioxalko	**test stat**	-10.1845	0.0000	-50.4996	0.0001
	1%level	-2.5660		-2.5660	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
germanos	**test stat**	-5.2177	0.0000	-35.3792	0.0000
	1%level	-2.5665		-2.5665	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
deh	**test stat**	-26.3514	0.0000	-28.2390	0.0000
	1%level	-2.5672		-2.5672	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
coca cola	**test stat**	-10.2900	0.0000	-60.2488	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
elpe	**test stat**	-15.5308	0.0000	-44.5990	0.0001
	1%level	-2.5662		-2.5662	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
emporiki	**test stat**	-6.4967	0.0000	-63.0296	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ete	**test stat**	-6.7077	0.0000	-63.3561	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
eurobank	**test stat**	-9.0237	0.0000	-43.4943	0.0001
	1%level	-2.5663		-2.5663	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	

* *Schwarz information criterion is being used.*

Table 21b					
Unit root test for trading activity measured as the share volume					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
hyatt	**test stat**	-11.5627	0.0000	-40.9631	0.0000
	1%level	-2.5664		-2.5664	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
intracom	**test stat**	-17.2785	0.0000	-44.0322	0.0000
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
kae	**test stat**	-40.6769	0.0000	-41.7139	0.0000
	1%level	-2.5662		-2.5662	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
cosmote	**test stat**	-12.4377	0.0000	-37.5607	0.0000
	1%level	-2.5667		-2.5667	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
motoroil	**test stat**	-30.6286	0.0000	-32.4705	0.0000
	1%level	-2.5671		-2.5671	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
opap	**test stat**	-19.1053	0.0000	-28.5907	0.0000
	1%level	-2.5669		-2.5669	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
ote	**test stat**	-13.5938	0.0000	-54.0614	0.0001
	1%level	-2.5659		-2.5659	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
peiraiws	**test stat**	-11.2392	0.0000	-48.0459	0.0000
	1%level	-3.9623		-3.9623	
	5%level	-3.4119		-3.4119	
	10%level	-3.1278		-3.1278	
titan	**test stat**	-9.7987	0.0000	-46.0311	0.0000
	1%level	-3.9621		-3.9621	
	5%level	-3.4118		-3.4118	
	10%level	-3.1278		-3.1278	
foli foli	**test stat**	-20.6814	0.0000	-37.4849	0.0000
	1%level	-3.9625		-3.9625	
	5%level	-3.4120		-3.4120	
	10%level	-3.1279		-3.1279	

* *Schwarz information criterion is being used.*

Table 22a					
Unit root test for volatility measured as the absr					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
alpha	**test stat**	-3.4290	0.0006	-45.9148	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ate	**test stat**	-4.8262	0.0000	-30.0927	0.0000
	1%level	-2.5668		-2.5668	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
bioxalko	**test stat**	-3.3825	0.0007	-36.3010	0.0000
	1%level	-2.5660		-2.5660	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
germanos	**test stat**	-4.5920	0.0000	-41.8828	0.0000
	1%level	-2.5665		-2.5665	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
deh	**test stat**	-1.9628	0.0476	-25.1926	0.0000
	1%level	-2.5673		-2.5672	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
coca cola	**test stat**	-16.9027	0.0000	-49.0840	0.0000
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
elpe	**test stat**	-3.2117	0.0013	-38.9797	0.0000
	1%level	-2.5662		-2.5662	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
emporiki	**test stat**	-15.8059	0.0000	-52.0440	0.0000
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
ete	**test stat**	-4.1840	0.0000	-50.0144	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
eurobank	**test stat**	-16.9755	0.0000	-37.7894	0.0000
	1%level	-3.4340		-3.4340	
	5%level	-2.8631		-2.8631	
	10%level	-2.5676		-2.5676	

* *Schwarz information criterion is being used.*
Absr is the absolute value of closing price minus lagged closing price.

Table 22b					
Unit root test for volatility measured as the absr					
Companies	Test Critical Values	ADF*		P-P	
		t-stat	Prob.	t-stat	Prob.
hyatt	test stat	-5.2848	0.0000	-32.3721	0.0000
	1%level	-2.5664		-2.5664	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
intracom	test stat	-13.3580	0.0000	-53.9308	0.0001
	1%level	-3.4325		-3.4325	
	5%level	-2.8624		-2.8624	
	10%level	-2.5673		-2.5673	
kae	test stat	-17.2841	0.0000	-37.7058	0.0000
	1%level	-3.9628		-3.9628	
	5%level	-3.4121		-3.4121	
	10%level	-3.1280		-3.1280	
cosmote	test stat	-21.5225	0.0000	-33.1370	0.0000
	1%level	-3.9651		-3.9651	
	5%level	-3.4133		-3.4133	
	10%level	-3.1287		-3.1286	
motoroil	test stat	-4.0392	0.0001	-29.3458	0.0000
	1%level	-2.5671		-2.5671	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
opap	test stat	-28.4849	0.0000	-30.4711	0.0000
	1%level	-3.9659		-3.9659	
	5%level	-3.4136		-3.4136	
	10%level	-3.1289		-3.1289	
ote	test stat	-16.4011	0.0000	-50.1593	0.0001
	1%level	-3.4329		-3.4328	
	5%level	-2.8625		-2.8625	
	10%level	-2.5673		-2.5673	
peiraiws	test stat	-14.1910	0.0000	-42.1799	0.0000
	1%level	-3.9623		-3.9623	
	5%level	-3.4119		-3.4119	
	10%level	-3.1278		-3.1278	
titan	test stat	-15.5258	0.0000	-45.5345	0.0000
	1%level	-3.9621		-3.9621	
	5%level	-3.4118		-3.4118	
	10%level	-3.1278		-3.1278	
foli foli	test stat	-12.2623	0.0000	-45.5561	0.0001
	1%level	-3.4334		-3.4333	
	5%level	-2.8628		-2.8627	
	10%level	-2.5675		-2.5675	

** Schwarz information criterion is being used.*
Absr is the absolute value of closing price minus lagged closing price.

Table 23a					
Unit root test for volatility measured as the rr					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
alpha	**test stat**	-8.8718	0.0000	-53.4913	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ate	**test stat**	-9.7277	0.0000	-37.1763	0.0000
	1%level	-2.5668		-2.5668	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
bioxalko	**test stat**	-8.7688	0.0000	-45.8734	0.0001
	1%level	-2.5660		-2.5660	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
germanos	**test stat**	-8.1233	0.0000	-73.5047	0.0001
	1%level	-2.5665		-2.5665	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
deh	**test stat**	-7.1516	0.0000	-32.1605	0.0000
	1%level	-2.5673		-2.5672	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
coca cola	**test stat**	-17.5034	0.0000	-46.9587	0.0000
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
elpe	**test stat**	-9.2027	0.0000	-54.5151	0.0001
	1%level	-2.5662		-2.5662	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
emporiki	**test stat**	-18.0673	0.0000	-49.7408	0.0000
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
ete	**test stat**	-7.2073	0.0000	-56.9856	0.0001
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
eurobank	**test stat**	-6.6615	0.0000	-36.4416	0.0000
	1%level	-2.5663		-2.5663	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	

** Schwarz information criterion is being used.*
rr is the squared value of closing price minus lagged closing price.

Table 23b					
Unit root test for volatility measured as the rr					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
hyatt	**test stat**	-9.0505	0.0000	-218.0795	0.0001
	1%level	-2.5664		-2.5664	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
intracom	**test stat**	-19.0102	0.0000	-52.8437	0.0000
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
kae	**test stat**	-11.7545	0.0000	-40.4866	0.0000
	1%level	-3.4335		-3.4335	
	5%level	-2.8628		-2.8628	
	10%level	-2.5675		-2.5675	
cosmote	**test stat**	-6.5823	0.0000	-39.4236	0.0000
	1%level	-2.5667		-2.5667	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
motoroil	**test stat**	-7.0450	0.0000	-35.8709	0.0000
	1%level	-2.5671		-2.5671	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
opap	**test stat**	-27.9156	0.0000	-28.9695	0.0000
	1%level	-3.9659		-3.9659	
	5%level	-3.4136		-3.4136	
	10%level	-3.1289		-3.1289	
ote	**test stat**	-8.0535	0.0000	-57.2091	0.0001
	1%level	-2.5659		-2.5659	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	
peiraiws	**test stat**	-12.2820	0.0000	-44.9337	0.0001
	1%level	-3.4332		-3.4332	
	5%level	-2.8627		-2.8627	
	10%level	-2.5674		-2.5674	
titan	**test stat**	-15.9089	0.0000	-45.5473	0.0000
	1%level	-3.9621		-3.9621	
	5%level	-3.4118		-3.4118	
	10%level	-3.1278		-3.1278	
foli foli	**test stat**	-6.1011	0.0000	-71.0233	0.0001
	1%level	-2.5661		-2.5661	
	5%level	-1.9410		-1.9410	
	10%level	-1.6166		-1.6166	

* *Schwarz information criterion is being used.*
rr is the squared value of closing price minus lagged closing price.

Table 24a					
Unit root test for volatility measured as the conditional variance					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
alpha	**test stat**	-6.8300	0.0000	-5.3898	0.0000
	1%level	-2.5658		-2.5658	
	5%level	-1.9409		-1.9409	
	10%level	-1.6166		-1.6166	
ate	**test stat**	-6.5039	0.0000	-8.0563	0.0000
	1%level	-2.5668		-2.5668	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
bioxalko	**test stat**	-9.8535	0.0000	-9.7936	0.0000
	1%level	-3.4331		-3.4331	
	5%level	-2.8627		-2.8627	
	10%level	-2.5674		-2.5674	
germanos	**test stat**	-6.8957	0.0000	-7.5917	0.0000
	1%level	-3.9643		-3.9643	
	5%level	-3.4129		-3.4129	
	10%level	-3.1284		-3.1284	
deh	**test stat**	-9.7100	0.0000	-9.7229	0.0000
	1%level	-3.9672		-3.9672	
	5%level	-3.4143		-3.4143	
	10%level	-3.1292		-3.1292	
coca cola	**test stat**	-4.5264	0.0013	-4.5282	0.0013
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
elpe	**test stat**	-9.1071	0.0000	-8.6669	0.0000
	1%level	-3.9629		-3.9629	
	5%level	-3.4122		-3.4122	
	10%level	-3.1280		-3.1280	
emporiki	**test stat**	-9.3500	0.0000	-9.5944	0.0000
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
ete	**test stat**	-8.8477	0.0000	-8.8580	0.0000
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
eurobank	**test stat**	-10.0116	0.0000	-8.5395	0.0000
	1%level	-3.9635		-3.9635	
	5%level	-3.4125		-3.4125	
	10%level	-3.1282		-3.1282	

* *Schwarz information criterion is being used.*
Conditional variance is estimated by a GARCH(1,1) model, where innovations are t-Student distributed.

Table 24b					
Unit root test for volatility measured as the conditional variance					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
hyatt	**test stat**	-9.8460	0.0000	-10.4904	0.0000
	1%level	-3.9639		-3.9639	
	5%level	-3.4127		-3.4127	
	10%level	-3.1283		-3.1283	
intracom	**test stat**	-10.6392	0.0000	-10.8343	0.0000
	1%level	-3.9614		-3.9614	
	5%level	-3.4114		-3.4114	
	10%level	-3.1276		-3.1276	
kae	**test stat**	-10.9003	0.0000	-10.5067	0.0000
	1%level	-3.9628		-3.9628	
	5%level	-3.4121		-3.4121	
	10%level	-3.1280		-3.1280	
cosmote	**test stat**	-11.2882	0.0000	-11.2331	0.0000
	1%level	-3.9651		-3.9651	
	5%level	-3.4133		-3.4133	
	10%level	-3.1286		-3.1286	
motoroil	**test stat**	-5.2463	0.0000	-4.8988	0.0000
	1%level	-2.5671		-2.5671	
	5%level	-1.9411		-1.9411	
	10%level	-1.6165		-1.6165	
opap	**test stat**	-7.9585	0.0000	-7.3783	0.0000
	1%level	-3.4357		-3.4357	
	5%level	-2.8638		-2.8638	
	10%level	-2.5680		-2.5680	
ote	**test stat**	-6.9241	0.0000	-7.1261	0.0000
	1%level	-3.9618		-3.9618	
	5%level	-3.4117		-3.4117	
	10%level	-3.1277		-3.1277	
peiraiws	**test stat**	-8.6710	0.0000	-9.0462	0.0000
	1%level	-3.9623		-3.9623	
	5%level	-3.4119		-3.4119	
	10%level	-3.1278		-3.1278	
titan	**test stat**	-8.6872	0.0000	-9.0747	0.0000
	1%level	-3.9621		-3.9621	
	5%level	-3.4118		-3.4118	
	10%level	-3.1278		-3.1278	
foli foli	**test stat**	-9.9407	0.0000	-8.2318	0.0000
	1%level	-3.9625		-3.9625	
	5%level	-3.4120		-3.4120	
	10%level	-3.1279		-3.1279	

** Schwarz information criterion is being used.*
Conditional variance is estimated by a GARCH(1,1) model, where innovations are t-Student distributed.

Table 25a					
Unit root test for volatility measured as the daytime volatility					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
alpha	**test stat**	-25.9162	0.0000	-19.6575	0.0000
	1%level	-3.9717		-2.5684	
	5%level	-3.4165		-1.9413	
	10%level	-3.1306		-1.6164	
ate	**test stat**	-3.8253	0.0158	-6.6613	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
bioxalko	**test stat**	-15.9578	0.0000	-24.6785	0.0000
	1%level	-3.4398		-3.4398	
	5%level	-2.8656		-2.8656	
	10%level	-2.5690		-2.5690	
germanos	**test stat**	-22.8136	0.0000	-23.1123	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
deh	**test stat**	-23.7628	0.0000	-23.8760	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
coca cola	**test stat**	-17.1468	0.0000	-5.1749	0.0000
	1%level	-3.9718		-3.4398	
	5%level	-3.4165		-2.8656	
	10%level	-3.1306		-2.5690	
elpe	**test stat**	-6.7691	0.0000	-26.9947	0.0000
	1%level	-3.4399		-3.4398	
	5%level	-2.8656		-2.8656	
	10%level	-2.5690		-2.5690	
emporiki	**test stat**	-22.5183	0.0000	-23.0098	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
ete	**test stat**	-25.5459	0.0000	-25.7986	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
eurobank	**test stat**	-22.5449	0.0000	-22.9739	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	

** Schwarz information criterion is being used.*
Daytime volatility is the absolute value of closing price minus opening price.

Table 25b					
Unit root test for volatility measured as the daytime volatility					
Companies	**Test Critical Values**	**ADF***		**P-P**	
		t-stat	**Prob.**	**t-stat**	**Prob.**
hyatt	**test stat**	-24.4716	0.0000	-24.5299	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
intracom	**test stat**	-30.7067	0.0000	-30.7201	0.0000
	1%level	-2.5684		-2.5684	
	5%level	-1.9413		-1.9413	
	10%level	-1.6164		-1.6164	
kae	**test stat**	-23.5030	0.0000	-23.9643	0.0000
	1%level	-3.4398		-3.4398	
	5%level	-2.8656		-2.8656	
	10%level	-2.5690		-2.5690	
cosmote	**test stat**	-24.0911	0.0000	-24.5155	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
motoroil	**test stat**	-4.9182	0.0003	-25.0658	0.0000
	1%level	-3.9718		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
opap	**test stat**	-22.8877	0.0000	-23.6217	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
ote	**test stat**	-23.4672	0.0000	-23.4672	0.0000
	1%level	-3.4398		-3.4398	
	5%level	-2.8656		-2.8656	
	10%level	-2.5690		-2.5690	
peiraiws	**test stat**	-14.8222	0.0000	-23.5357	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
titan	**test stat**	-14.6074	0.0000	-24.8409	0.0000
	1%level	-3.9717		-3.9717	
	5%level	-3.4165		-3.4165	
	10%level	-3.1306		-3.1306	
foli foli	**test stat**	-24.0911	0.0000	-24.1894	0.0000
	1%level	-3.4399		-3.4399	
	5%level	-2.8656		-2.8656	
	10%level	-2.5690		-2.5690	

** Schwarz information criterion is being used.*
Daytime volatility is the absolute value of closing price minus opening price.

Appendix B

In this appendix tables with all the causality tests in details are presented. These tables report the χ^2-statistic, the p-value and the degrees of freedom used to test for causality for each stock. They also demonstrate if the causality between the two tested variables exists.

Table 26

Granger-causality test between return volatility and trading activity in the FTSE-20 stocks

Null Hypothesis: N does not G.C. |R|					Null Hypothesis: |R| does not G.C. N				
Companies	**Chi-sq**	**Prob.**	**df**	**Causality**	**Companies**	**Chi-sq**	**Prob.**	**df**	**Causality**
alpha	33.7796*	0.0037	15	yes	**alpha**	25.5013*	0.0436	15	yes
ate	37.1339*	0.0012	15	yes	**ate**	97.3557*	0.0000	15	yes
bioxalko	55.4657*	0.0002	23	yes	**bioxalko**	51.0885*	0.0007	23	yes
germanos	28.8484*	0.0024	11	yes	**germanos**	57.6933*	0.0000	11	yes
deh	3.9836	0.5518	5	no	**deh**	7.4146	0.1916	5	no
coca cola	61.4409*	0.0070	37	yes	**coca cola**	58.4303*	0.0139	37	yes
elpe	46.1286*	0.0000	13	yes	**elpe**	66.7413*	0.0000	13	yes
emporiki	27.1273*	0.0185	14	yes	**emporiki**	64.4994*	0.0000	14	yes
ete	22.1614	0.0754	14	no	**ete**	85.1944*	0.0000	14	yes
eurobank	34.4132*	0.0003	11	yes	**eurobank**	66.2854*	0.0000	11	yes
hyatt	26.5418*	0.0327	15	yes	**hyatt**	52.8673*	0.0000	15	yes
intracom	39.5106*	0.0241	24	yes	**intracom**	71.3447*	0.0000	24	yes
kae	24.5157*	0.0397	14	yes	**kae**	32.4775*	0.0034	14	yes
cosmote	9.4799	0.4872	10	no	**cosmote**	19.2992*	0.0366	10	yes
motoroil	26.8385	0.0605	17	no	**motoroil**	32.5913*	0.0127	17	yes
opap	13.4199	0.4938	14	no	**opap**	38.6734*	0.0004	14	yes
ote	43.0017*	0.0000	8	yes	**ote**	8.5770	0.3792	8	no
peiraiws	35.9700*	0.0003	12	yes	**peiraiws**	33.2434*	0.0009	12	yes
titan	47.4343*	0.0001	16	yes	**titan**	16.5344	0.4163	16	no
foli foli	47.2298*	0.0000	15	yes	**foli foli**	41.7497*	0.0002	15	yes

*An * indicates statistical significance at 5%.*

Volatility is measured by the absolute value of closing price minus lagged closing price, while trading activity is measured by the number of trades (N).

Table 27

Granger-causality test between return volatility and trading activity in the FTSE-20 stocks

Null Hypothesis: VA does not G.C. |R|					Null Hypothesis: |R| does not G.C. VA				
Companies	**Chi-sq**	**Prob.**	**df**	**Causality**	**Companies**	**Chi-sq**	**Prob.**	**df**	**Causality**
alpha	29.9437*	0.0048	13	yes	**alpha**	75.0528*	0.0000	13	yes
ate	45.1111*	0.0215	28	yes	**ate**	228.3960*	0.0000	28	yes
bioxalko	17.7593*	0.0381	9	yes	**bioxalko**	9.9141	0.3575	9	no
germanos	18.6472*	0.0284	9	yes	**germanos**	13.9721	0.2345	11	no
deh	2.1078	0.5503	3	no	**deh**	33.9530*	0.0000	3	yes
coca cola	28.6875*	0.0261	16	yes	**coca cola**	48.8153*	0.0000	16	yes
elpe	24.8189	0.1666	19	no	**elpe**	43.6232*	0.0011	19	yes
emporiki	22.1542	0.0755	14	no	**emporiki**	58.6959*	0.0000	14	yes
ete	13.2831	0.5044	14	no	**ete**	27.3999*	0.0171	14	yes
eurobank	10.7905	0.4610	11	no	**eurobank**	40.6207*	0.0000	11	yes
hyatt	8.3680	0.3013	7	no	**hyatt**	37.3731*	0.0000	7	yes
intracom	33.7041*	0.0060	16	yes	**intracom**	59.1477*	0.0000	16	yes
kae	34.1529*	0.0020	14	yes	**kae**	47.6052*	0.0000	14	yes
cosmote	12.7302*	0.0053	3	yes	**cosmote**	7.4420	0.0591	3	no
motoroil	16.0418	0.0984	10	no	**motoroil**	60.4337*	0.0000	10	yes
opap	2.6434	0.4499	3	no	**opap**	36.2079*	0.0000	3	yes
ote	2.3435*	0.9384	7	no	**ote**	10.8299	0.1462	7	no
peiraiws	18.5864	0.0458	10	yes	**peiraiws**	29.6949*	0.0010	10	yes
titan	10.4260	0.4039	10	no	**titan**	37.1994*	0.0001	10	yes
foli foli	21.1997	0.1306	15	no	**foli foli**	31.3799	0.0078	15	yes

*An * indicates statistical significance at 5%.*

Volatility is measured by the absolute value of closing price minus lagged closing price, while trading activity is measured by the value of trades (VA).

Table 28

Granger-causality test between return volatility and trading activity in the FTSE-20 stocks

Null Hypothesis: VO does not G.C. |R|					Null Hypothesis: |R| does not G.C. VO				
Companies	**Chi-sq**	**Prob.**	**df**	**Causality**	**Companies**	**Chi-sq**	**Prob.**	**df**	**Causality**
alpha	7.6647	0.8647	13	no	alpha	45.0488*	0.0000	13	yes
ate	42.5245*	0.0158	25	yes	ate	383.4697*	0.0000	25	yes
bioxalko	5.9482	0.6530	8	no	bioxalko	7.5540	0.4782	8	no
germanos	13.9721	0.2345	11	no	germanos	18.2952	0.0750	11	no
deh	2.8518	0.4150	3	no	deh	38.3060*	0.0000	3	yes
coca cola	32.4077*	0.0088	16	yes	coca cola	17.5206	0.3527	16	no
elpe	13.0432	0.2468	13	no	elpe	38.5455*	0.0002	13	yes
emporiki	7.2029	0.7062	10	no	emporiki	45.0602*	0.0000	10	yes
ete	7.8119	0.8556	13	no	ete	17.4260	0.1806	13	no
eurobank	11.1618	0.4298	11	no	eurobank	38.5855*	0.0001	11	yes
hyatt	1.7970	0.9702	7	no	hyatt	10.9611	0.1403	7	no
intracom	28.5197*	0.0121	14	yes	intracom	48.9062*	0.0000	14	yes
kae	29.3982*	0.0143	15	yes	kae	49.7766*	0.0000	15	yes
cosmote	10.8049*	0.0128	3	yes	cosmote	9.6813*	0.0215	3	yes
motoroil	14.8173	0.1389	10	no	motoroil	59.0360*	0.0000	10	yes
opap	2.5428	0.4676	3	no	opap	64.6875*	0.0000	3	yes
ote	1.2181	0.9431	5	no	ote	2.0775	0.8383	5	no
peiraiws	6.1107	0.8059	10	no	peiraiws	18.6224*	0.0453	10	yes
titan	7.0096	0.7245	10	no	titan	27.7380*	0.0020	10	yes
foli foli	38.2008*	0.0036	18	yes	foli foli	40.0059*	0.0021	18	yes

*An * indicates statistical significance at 5%.*
Volatility is measured by the absolute value of closing price minus lagged closing price, while trading activity is measured by the volume of shares traded (VO).

Table 29

Granger-causality test between return volatility and trading activity in the FTSE-20 stocks

Null Hypothesis: N does not G.C. C.V.					Null Hypothesis: C.V. does not G.C. N				
Companies	**Chi-sq**	**Prob.**	**df**	**Causality**	**Companies**	**Chi-sq**	**Prob.**	**df**	**Causality**
alpha	30.6400*	0.0007	10	yes	**alpha**	10.1362	0.4286	10	no
ate	89.5533*	0.0000	15	yes	**ate**	107.1982*	0.0000	15	yes
bioxalko	43.3987*	0.0004	17	yes	**bioxalko**	36.5802*	0.0038	17	yes
germanos	94.7967*	0.0000	11	yes	**germanos**	29.1714*	0.0021	11	yes
deh	200.6105*	0.0000	6	yes	**deh**	14.1064*	0.0285	6	yes
coca cola	70.2090*	0.0008	37	yes	**coca cola**	54.0010*	0.0351	37	yes
elpe	311.5362*	0.0000	12	yes	**elpe**	58.2231*	0.0000	12	yes
emporiki	11.8022*	0.0027	2	yes	**emporiki**	19.8233*	0.0000	2	yes
ete	29.2787*	0.0096	14	yes	**ete**	30.7874*	0.0059	14	yes
eurobank	233.3315*	0.0000	16	yes	**eurobank**	43.2226*	0.0003	16	yes
hyatt	121.0844*	0.0000	15	yes	**hyatt**	40.2708*	0.0004	15	yes
intracom	61.1891*	0.0000	22	yes	**intracom**	41.8030*	0.0066	22	yes
kae	72.0179*	0.0000	7	yes	**kae**	21.3846*	0.0032	7	yes
cosmote	165.2791*	0.0000	9	yes	**cosmote**	6.2229	0.7174	9	no
motoroil	247.5037*	0.0000	10	yes	**motoroil**	15.3483	0.1199	10	no
opap	285.7379*	0.0000	14	yes	**opap**	45.9808*	0.0000	14	yes
ote	26.1404*	0.0000	4	yes	**ote**	11.7887*	0.0190	4	yes
peiraiws	92.9883*	0.0000	15	yes	**peiraiws**	35.0210*	0.0024	15	yes
titan	57.2629*	0.0000	15	yes	**titan**	28.4174*	0.0191	15	yes
foli foli	86.5644*	0.0000	10	yes	**foli foli**	38.6232*	0.0000	10	yes

*An * indicates statistical significance at 5%.*
Volatility is measured by the conditional variance of a GARCH(1,!) model, while trading activity is measured by the number of trades (N).

Table 30
Granger-causality test between return volatility and trading activity in the FTSE-20 stocks

Null Hypothesis: VA does not G.C. C.V.					Null Hypothesis: C.V. does not G.C. VA				
Companies	**Chi-sq**	**Prob.**	**df**	**Causality**	**Companies**	**Chi-sq**	**Prob.**	**df**	**Causality**
alpha	161.8864*	0.0000	13	yes	**alpha**	0.0016	1.0000	13	no
ate	36.7846	0.0605	25	no	**ate**	576.1512*	0.0000	25	yes
bioxalko	20.6028*	0.0083	8	yes	**bioxalko**	4.2819	0.8308	8	no
germanos	5.3188	0.3782	5	no	**germanos**	1.4163	0.9225	5	no
deh	6.8594	0.0765	3	no	**deh**	71.7035*	0.0000	3	yes
coca cola	123.9415*	0.0000	12	yes	**coca cola**	11.5669	0.4811	12	no
elpe	45.3864*	0.0001	16	yes	**elpe**	19.0196	0.2676	16	no
emporiki	77.9895*	0.0000	11	yes	**emporiki**	11.6675	0.3892	11	no
ete	32.0727	0.0063	15	yes	**ete**	15.1197	0.4428	15	no
eurobank	12.8159	0.6862	16	no	**eurobank**	22.8043	0.1191	16	no
hyatt	15.2928	0.3584	14	no	**hyatt**	15.7035	0.3318	14	no
intracom	129.9900*	0.0000	13	yes	**intracom**	24.4290*	0.0274	13	yes
kae	31.9144*	0.0410	14	yes	**kae**	43.6731*	0.0001	14	yes
cosmote	4.7342	0.0938	2	no	**cosmote**	3.6957	0.1576	2	no
motoroil	7.7486	0.6534	10	no	**motoroil**	50.2510*	0.0000	10	yes
opap	1.6791	0.4319	2	no	**opap**	55.8473*	0.0000	2	yes
ote	13.3218*	0.0003	1	yes	**ote**	3.5193	0.0607	1	no
peiraiws	118.9088*	0.0000	10	yes	**peiraiws**	14.3178	0.1590	10	no
titan	10.6388*	0.0000	15	yes	**titan**	11.9935	0.6795	15	no
foli foli	104.1853*	0.0000	12	yes	**foli foli**	17.3695	0.1362	12	no

*An * indicates statistical significance at 5%.*
Volatility is measured by the conditional variance of a GARCH(1,!) model, while trading activity is measured by the value of trades (VA).

Table 31

Granger-causality test between return volatility and trading activity in the FTSE-20 stocks

Null Hypothesis: VO does not G.C. C.V.					Null Hypothesis: C.V. does not G.C. VO				
Companies	**Chi-sq**	**Prob.**	**df**	**Causality**	**Companies**	**Chi-sq**	**Prob.**	**df**	**Causality**
alpha	57.5734*	0.0000	13	yes	**alpha**	9.9168	0.7007	13	no
ate	61.7041*	0.0000	16	yes	**ate**	117.6040*	0.0000	16	yes
bioxalko	10.4803	0.2329	8	no	**bioxalko**	4.9493	0.7630	8	no
germanos	6.7322	0.2413	5	no	**germanos**	2.3531	0.7984	5	no
deh	4.8879	0.0868	2	no	**deh**	86.0597*	0.0000	2	yes
coca cola	79.7921*	0.0000	11	yes	**coca cola**	2.3096	0.9971	11	no
elpe	39.6835*	0.0002	13	yes	**elpe**	17.2080	0.1900	13	no
emporiki	46.5671*	0.0000	5	yes	**emporiki**	11.9845*	0.0350	5	yes
ete	7.7113	0.8073	12	no	**ete**	12.0753	0.4397	12	no
eurobank	6.3409	0.9572	14	no	**eurobank**	6.9739	0.9357	14	no
hyatt	4.8244	0.1851	3	no	**hyatt**	4.9115	0.1784	3	no
intracom	232.7546*	0.0000	13	yes	**intracom**	32.7277*	0.0019	13	yes
kae	32.5787*	0.0084	16	yes	**kae**	43.7873*	0.0002	16	yes
cosmote	3.7734	0.1516	2	no	**cosmote**	2.1884	0.3348	2	no
motoroil	8.4993	0.5802	10	no	**motoroil**	47.4339*	0.0000	10	yes
opap	5.9646	0.6512	8	no	**opap**	151.3277*	0.0000	8	yes
ote	15.6314*	0.0001	1	yes	**ote**	0.5862	0.4439	1	no
peiraiws	57.7439*	0.0000	10	yes	**peiraiws**	7.0525	0.7205	10	no
titan	55.9983*	0.0000	17	yes	**titan**	10.2336	0.8935	17	no
foli foli	134.4352*	0.0000	15	yes	**foli foli**	22.4867	0.0957	15	no

*An * indicates statistical significance at 5%.*
Volatility is measured by the conditional variance of a GARCH(1,!) model, while trading activity is measured by the volume of shares traded (VO).

Table 32
Granger-causality test between return volatility and trading activity in the FTSE-20 stocks

Null Hypothesis: N does not G.C. R^2					Null Hypothesis: R^2 does not G.C. N				
Companies	**Chi-sq**	**Prob.**	**df**	**Causality**	**Companies**	**Chi-sq**	**Prob.**	**df**	**Causality**
alpha	26.9820*	0.0289	15	yes	**alpha**	17.2222	0.3058	15	no
ate	24.5549*	0.0264	13	yes	**ate**	95.1338*	0.0000	13	yes
bioxalko	39.2648*	0.0001	12	yes	**bioxalko**	40.5783*	0.0001	12	yes
germanos	27.6467*	0.0021	10	yes	**germanos**	53.2067*	0.0000	10	yes
deh	3.6367	0.6028	5	no	**deh**	17.4779*	0.0037	5	yes
coca cola	68.6680*	0.0012	37	yes	**coca cola**	71.5496*	0.0006	37	yes
elpe	72.6274*	0.0000	13	yes	**elpe**	125.7135*	0.0000	13	yes
emporiki	27.9270*	0.0458	17	yes	**emporiki**	69.2556*	0.0000	17	yes
ete	19.2938	0.1540	14	no	**ete**	98.3950*	0.0000	14	yes
eurobank	21.5495*	0.0281	11	yes	**eurobank**	81.1954*	0.0000	11	yes
hyatt	35.2892*	0.0022	15	yes	**hyatt**	76.2794*	0.0000	15	yes
intracom	36.2133*	0.0145	20	yes	**intracom**	85.8753*	0.0000	20	yes
kae	31.9070*	0.0041	14	yes	**kae**	37.8592*	0.0005	14	yes
cosmote	22.7767	0.4144	22	no	**cosmote**	35.2228*	0.0367	22	yes
motoroil	9.1112	0.5216	10	no	**motoroil**	16.6269	0.0830	10	no
opap	10.9470	0.6902	14	no	**opap**	47.5277*	0.0000	14	yes
ote	31.9986*	0.0000	5	yes	**ote**	13.0664*	0.0228	5	yes
peiraiws	68.0349*	0.0000	15	yes	**peiraiws**	60.6050*	0.0000	15	yes
titan	54.3098*	0.0000	17	yes	**titan**	17.0993	0.4477	17	no
foli foli	60.7951*	0.0000	15	yes	**foli foli**	41.0326*	0.0003	15	yes

*An * indicates statistical significance at 5%.*
Volatility is measured by the squared value of closing price minus lagged closing price, while trading activity is measured by the number of trades (N).

Table 33

Granger-causality test between return volatility and trading activity in the FTSE-20 stocks

Null Hypothesis: VA does not G.C. R^2					Null Hypothesis: R^2 does not G.C. VA				
Companies	**Chi-sq**	**Prob.**	**df**	**Causality**	**Companies**	**Chi-sq**	**Prob.**	**df**	**Causality**
alpha	32.3006*	0.0022	13	yes	**alpha**	85.6142*	0.0000	13	yes
ate	10.6913	0.9685	21	no	**ate**	450.4345*	0.0000	21	yes
bioxalko	14.3465	0.1105	9	no	**bioxalko**	10.2058	0.3341	9	no
germanos	7.2545	0.6106	9	no	**germanos**	14.1992	0.1154	9	no
deh	0.2164	0.8974	2	no	**deh**	73.7244*	0.0000	2	yes
coca cola	46.5509*	0.0001	17	yes	**coca cola**	42.4692*	0.0006	17	yes
elpe	37.2599*	0.0019	16	yes	**elpe**	41.8017*	0.0004	16	yes
emporiki	22.8659*	0.0185	11	yes	**emporiki**	101.2380*	0.0000	11	yes
ete	11.2812	0.6638	14	no	**ete**	22.9879	0.0605	14	no
eurobank	5.6344	0.8966	11	no	**eurobank**	63.9762*	0.0000	11	yes
hyatt	12.5709	0.0833	7	no	**hyatt**	65.8094*	0.0000	7	yes
intracom	51.4435*	0.0000	17	yes	**intracom**	66.8795*	0.0000	17	yes
kae	35.0402*	0.0015	14	yes	**kae**	56.1533*	0.0000	14	yes
cosmote	17.3247*	0.0002	2	yes	**cosmote**	5.7562	0.0562	2	no
motoroil	6.3566	0.7845	10	no	**motoroil**	50.3830*	0.0000	10	yes
opap	2.8410	0.7245	5	no	**opap**	62.2271*	0.0000	5	yes
ote	0.3474	0.8406	2	no	**ote**	1.9851	0.3706	2	no
peiraiws	28.4843	0.0745	19	no	**peiraiws**	55.2928*	0.0000	19	yes
titan	36.6135*	0.0357	23	yes	**titan**	56.5934*	0.0001	23	yes
foli foli	41.1889*	0.0014	18	yes	**foli foli**	36.3764*	0.0063	18	yes

*An * indicates statistical significance at 5%.*
Volatility is measured by the squared value of closing price minus lagged closing price, while trading activity is measured by the value of trades (VA).

Table 34
Granger-causality test between return volatility and trading activity in the FTSE-20 stocks

Null Hypothesis: VO does not G.C. R^2					Null Hypothesis: R^2 does not G.C. VO				
Companies	**Chi-sq**	**Prob.**	**df**	**Causality**	**Companies**	**Chi-sq**	**Prob.**	**df**	**Causality**
alpha	6.1001	0.8068	10	no	**alpha**	37.0274*	0.0001	10	yes
ate	9.8138	0.9574	19	no	**ate**	1356.0750*	0.0000	19	yes
bioxalko	4.3170	0.8275	8	no	**bioxalko**	4.3170	0.8275	8	no
germanos	3.9935	0.9118	9	no	**germanos**	8.0137	0.5328	9	no
deh	0.4283	0.8072	2	no	**deh**	96.6985*	0.0000	2	yes
coca cola	58.3011*	0.0000	10	yes	**coca cola**	9.4085	0.4938	10	no
elpe	30.8518*	0.0035	13	yes	**elpe**	31.0478*	0.0033	13	yes
emporiki	6.3255	0.3877	6	no	**emporiki**	78.3603*	0.0000	6	yes
ete	4.6256	0.9825	13	no	**ete**	9.0778	0.7670	13	no
eurobank	6.3042	0.8523	11	no	**eurobank**	53.5036*	0.0000	11	yes
hyatt	0.4151	0.9997	7	no	**hyatt**	7.4893	0.3798	7	no
intracom	37.6589*	0.0006	14	yes	**intracom**	64.9326*	0.0000	14	yes
kae	32.9185*	0.0048	15	yes	**kae**	50.5683*	0.0000	15	yes
cosmote	14.8338*	0.0006	2	yes	**cosmote**	8.6179*	0.0134	2	yes
motoroil	5.9740	0.8174	10	no	**motoroil**	47.5325*	0.0000	10	yes
opap	4.6420	0.4611	5	no	**opap**	1146.5258*	0.0000	5	yes
ote	0.4509	0.7982	2	no	**ote**	1.2625	0.5319	2	no
peiraiws	5.8503	0.8277	10	no	**peiraiws**	23.3037*	0.0097	10	yes
titan	8.7908	0.7886	13	no	**titan**	40.3465*	0.0001	13	yes
foli foli	52.4251*	0.0000	18	yes	**foli foli**	42.7367*	0.0009	18	yes

*An * indicates statistical significance at 5%.*
Volatility is measured by the squared value of closing price minus lagged closing price, while trading activity is measured by the volume of shares traded (VO).

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