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Intraday Risk – Return Relationship and Price Patterns in the Athens Stock Exchange

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Abstract

This study presents an empirical analysis of the risk - return relationship and the existence or not of intraday patterns during the trading session in the Athens Stock Exchange. The most interesting findings are (1) the negative intraday relationship between risk and return, possibly because of inventory restructure by liquidity traders in a market with narrow trading activity and (2) the existence of intraday patterns which are characterized by statistical significant positive returns in the first and the last quarter of the session.

Keywords: Risk – return relationship, patterns, intraday analysis, market microstructure, market efficiency
JEL Classification Codes: G10, G14, G15

I. Introduction

The relationship between risk and return in the stock markets has been one of the most investigated topics in financial economics. Although the risk-return relationship is of fundamental importance in economy, the empirical asset pricing literature has not yet reached an agreement on the existence of such a positive risk-return trade off for stock market indices.

The relationship between return and risk, as it is often defined by the variance or standard deviation, is a widely examined relationship in the literature of finance. According to the portfolio theory (Markowitz, 1952), investors require a higher return from the market portfolio than from risk free return investments. This market portfolio return depends on risk indicating a positive relationship. Merton (1973) shows that the conditional expected excess return on the aggregate stock market is a linear function of its conditional variance with a positive slope. French et al. (1987), Campbell (1987), Chou (1988), Chan et al. (1992), Chou, et al. (1992), Glosten et al. (1993), Harvey (1989, 2001), Bollerslev and Zhou (2005) and Ludvigson and Ng (2007) used daily data in order to examine the risk - return relationship with most of these studies to support the expected positive relationship.

This paper differs from previous researches as our purpose is to examine the risk - return relationship during the trading session, an approach that is not elaborated in the literature. Bali and Peng (2006) investigate S&P 500 in the New York Stock Exchange and they find a positive and significant relation during the trading session. Additionally, in our paper, we use high frequency data from the Athens Stock Exchange (ASE), in order to examine intraday characteristics and price patterns of a stock exchange that is in transition from emerging into developed European stock markets.

There are a lot of researches investigating intraday patterns in stock markets. One of the most interesting findings is that return, volume and volatility follow a U-shaped pattern during the trading session. Wood et al. (1985) first report high positive returns at the beginning and at the end of the session. Especially at the end of the session, many researchers have mentioned this behaviour too [Harris (1986), McInish and Wood (1990), Lockwood and Linn (1990), Foster and Viswanathan (1993), Jang and Lee (1993), Brooks and Chiou (1995), Copeland and Jones (2000), Darrat et al. (2003)], and, for the Greek stock market, Alexakis and Xanthakis (2003) and Niarchos and Alexakis (2003)].

The rest of the paper is organized as follows. Sections II and III provide the empirical analysis (section II: data, methodology, section III: descriptive statistics and results) and in Section IV the conclusions of the paper are reported.

II. Data and Methodology

Data

The raw data consists of tick by tick disclosure of the examined index's price (30 second frequency) during the trading session (11:00 h to 16:00 h) for the period 1st of June 2002 to 30th of September 2004, a period with no peculiar price characteristics like stock price rallies or sharp declines. Data collected from an official vendor of the ASE.

The period is divided into fifteen minutes intervals arbitrary as this interval is big enough for new information to be incorporated in prices of stocks in markets like the Greek one which is not characterized by liquidity for all stocks. Additionally, fifteen minute intervals have been used in a lot of studies and thus we have a basis for comparison.

In all cases we used the logarithmic transformation of the price series and we calculated the returns as the difference of the logarithmic prices. The price of each fifteen minute interval is the weighted average of the index's prices during the examined interval. That is:

$$P_t = \frac{\sum_{i=1}^{n} (P_{it})}{T_{it}}$$

where P_i and T_i is the price and the number of the disclosed index's prices in the fifteen minute interval respectively. Each one of the time series consists of 11.640 observations (582 trading days, 20 15-minute intervals per day).

From each session, twenty fifteen minutes intervals have been created and all of them have been used in the analysis. The first observation of the session could be subtracted because it incorporates information that has not been derived during the session, but during the period the stock market was closed. Despite this argument, the time series have remained uncut as the goal of this study is to investigate the characteristics of the trading session which are connected with the way that information is incorporated into prices in every time.

The sample used in this study consists of 4 indices of the ASE. ASE, based on the capitalization of the firms, has created a general index (ATHEX General) and FTSE indices. The ATHEX General index is a large capitalization index which includes the 60 largest companies listed on ASE. The FTSE/ASE 20 index is a large capitalization index which includes the 20 largest companies listed on ASE (blue chips). The FTSE/ASE Mid 40 Index focuses on companies of middle capitalization and comprises 40 such companies, ranked by capitalisation. The next 80 largest companies by capitalization are included in FTSE Small Cap Index. Shares that have been rejected from the FTSE/ASE Mid 40 are candidates for participation in the FTSE/ASE Small Cap 80.

Methodology

In order to examine the intraday relationship between returns and conditional volatility during the trading session in ASE, we use a variant of the GARCH (Generalized Autoregressive Conditional Heteroscedasticity, Bollerslev, 1986) framework known as GARCH(p,q)-M or GARCH in mean (Engle et al., 1987), which allows for mean returns to be specified as a linear function of time – varying conditional second moments. Returns depend jointly on a common underlying directing variable, the rate of information flow to the market. The intraday price change is the sum of the price changes, which depends on the number of information events, m, occurring in any interval and assumed random. That is, the price change is subordinate to the stochastic change of information arrival and the conditional variance of the price change is considered to be an increasing function of the rate at which new information enters the market.

The general GARCH(p,q)-M model for stock returns at time t, may be represented by the following system of equations:

$$r_t = \gamma_0 c + \gamma_i \sum_{i=0}^{\infty} r_{t-i} + \lambda h_t + e_t \tag{1}$$

$$h_t^2 = \alpha_0 + \alpha_i \sum_{i=1}^{p} e_{t-i}^2 + \beta_j \sum_{j=1}^{q} h_{t-1}^2 \tag{2}$$

where r_t is the return on time t, r_{t-i} is the return conditional on past information, c is the constant term, e_t is a zero mean, serially uncorrelated random error term with a normal distribution conditional on past information $e_t \rightarrow (0,h_t^2)$, ht is the standard deviation of the error term, $\alpha_0 > 0$, $\alpha_i,\beta_j > 0$ to ensure $h_t > 0$. The sum of the coefficients α_i and β_j denote the degree of persistence in the conditional variance given a shock to the system and as it tends to 1, the higher is the instability in variance and shocks tend to persist instead of dying out.

The GARCH(p,q)-M allows for stock returns to be determined by past information and by the own conditional variance h_t^2 with a general parameterization of heteroskedasticity which encompasses simpler specifications as special cases. The conditional variance h_t^2 may vary over time as a result of linear dependence on the behavior of past squared innovations e_{t-i}^2 (with volatility clustering effects up to q periods indicated by a non zero α_i parameters) and as a result of own temporal persistence (with serial correlation up to p periods indicated by non zero coefficients). The squared innovation terms imply that volatility shocks are likely to continue to be large, and therefore capture the observed tendency for volatility to cluster in time.

The term h_t links return to volatility and based on portfolio theory, a positive and statistically significant parameter λ is expected to indicate that investors are rewarded with higher returns for bearing risk during the examined period.

By using the sequence of past returns, we may test the weak form Efficient Market Hypothesis (EMH). According to Fama (1970), a stock market is efficient if prices rationally, fully, and instantaneously reflect all relevant available information. In an efficient market, past information is of no use in predicting profitably future stock returns, since it has already been reflected on stock prices by a number of competing, profit maximizing investors. EMH is thus typically associated with the absence of serial correlation for the time series of returns, the absence of patterns.

Finally, we examine the possibility that intraday stock returns are time dependent and the possibility that stock return patterns exist by using the following model:

$$r_t = \gamma_0 c + \gamma_i \sum_{i=1}^{20} r_{t-i} + \pi_i D_i + e_t \tag{3}$$

where D_i is the dummy variable for each of the 20 quarters of the trading session in ASE for the examined period (e.g. the D_5 dummy variable, takes the value of 1 if the observation falls on the 5^{th} quarter and zero in all other cases). If there is informational efficiency, π_i coefficients should equal to zero. If there exist statistically significant returns in specific time periods of the session, then there is evidence for trading patterns. On these trading patterns, trading rules can be formed, rules that rational investors can follow in order to achieve abnormal returns.

III. Empirical Analysis and Discussion

Descriptive Statistics

Table 1 summarizes the descriptive statistics on the four indices. The absolute values of returns and volatility are higher the higher the level of capitalization is. From the statistics of skewness, kurtosis and normality, we conclude that the time series are not normally distributed and are characterized by leptokurtosis. The correlation coefficients are large enough and significant in order to reject the null hypothesis of white noise in all cases. The Augmented Dickey-Fuller Tests (Table 1, ADF) in levels and first differences show stationarity in returns. The above characteristics are consistent with the volatility clustering often seen in financial returns data, where large changes in returns are likely to be followed by further large changes, increasing the estimate of the variance for the next period.

These characteristics are not surprising for high frequency data. Many researchers have reported deviations from theoretical models like Fama (1965, 1976) who supported that daily and monthly return series are not normally distributed, but characterized by volatility clustering and leptokurtosis. Until then, the econometric analysis has been injected by new tests and procedures to correct these deviations.

The average absolute returns are smaller for big capitalization stocks in relation to medium caps, and for medium caps in relation to small capitalization stocks. In all cases, the first's quarter return is the highest, followed by negative ones. From equality tests for the mean returns across all quarters we conclude the rejection of the hypothesis that mean returns among the intervals of the session are equal (Table 1, ANOVA F-Stat).

Historical volatility is high at the beginning of the session (Table 2), becomes lower as time passes and is increasing at the end of the session. In general, volatility is higher for small capitalization stocks compared to medium and big capitalization ones. The shape of volatility diagram tends to U for all indices. Levene (1960) and Bartlet (1946) tests of equal variances show that intraday risk is not distributed equally across the 15-minute intervals of the trading session.

Estimation Results and Discussion

The AR(i)-GARCH(p,q) models were estimated for each stock using the quasi maximum likelihood method. Box-Jenkins (1976) methods based on sample autocorrelations suggested the specification of the order of the autoregressive process for the intraday returns, which was the first step of the process. The second step consisted in examining the residuals for the presence of GARCH effects by using a specification search method based on a general-to-specific modeling strategy. This involved re-estimating jointly the AR(i)-GARCH(p,q) model by Marquardt (1963) optimization algorithm, starting from GARCH(4,4) specification and eliminating insignificant terms, in order of least significance and high values of the information criteria of Schwarz and Akaike. We followed White's (1980) heteroskedasticity consistent covariance matrix estimator and finally, no leverage effect detected for all indices.

The results presented in table 3 show that serial correlation in return time series has been investigated. The measure of volatility persistence given by the sum of the $\alpha+\beta$ coefficients is considerably less than unity, implying that the effect of shocks to volatility tends to decay within a few quarters. These findings imply a departure form the EMH, suggesting that relevant market information was only gradually reflected in price changes.

The hypothesis that volatility is a significant determinant of stock pricing is confirmed for all indices. An interesting finding is that the estimated parameter λ capturing the volatility on stock returns is negative and statistically significant in all cases. The estimates do not confirm the positive relation between risk and return which is supported by portfolio theory (Markovitz, 1952).

The results for price patterns during the trading session are summarized in Graphs 1 and not in tables due to format difficulties. In addition, the graphs with the statistical significant results are clearer in examining the investigated patterns. From the summarized results we observe that every index has a strong positive statistical significant return at the beginning of the session. After the first quarter and until fifteen minutes before the end of the session, all indices present statistical significant negative returns. As we examine indices with smaller capitalization than FTSE 20, we observe that the number of statistical significant negative intervals is bigger. Especially FTSE 80, which is the small capitalization index, has the biggest positive return from all indices in the first quarter and the most statistical significant negative intervals during the session. Big capitalization stocks, which in general are the most liquid stocks, present the least negative intervals. Finally, during the last quarter of the session, a price reversal is detected for FTSE 20 and FTSE 80.

From the statistical and econometric analysis we conclude that stock returns are at the highest level in the first quarter. After the first 15 minutes, stocks present a negative performance. These findings indicate that the positive performance is not a result only of new information. It could be a result of overreaction of investors to new information, overreaction that is corrected in the next quarters. In addition, it could be a result of specific market microstructure characteristics like the pre-opening session or due to specific transaction restrictions.

The pre-opening procedure targets a representative opening price formation. Possibly, the pre-opening procedure does not lead to an efficient opening price because of its structure, or because it is easily manipulated. Investors maybe realize this inefficiency after the first quarter and there trading activity adjusts prices to efficient levels.

Another explanation for this behavior may be the type of investors and their transaction restrictions. Institutional investors need liquidity in order to execute big transaction orders and intraday and liquidity traders need liquidity too in order to take their positions. Liquidity in the beginning of the session is higher, so these investors' movements can boost prices higher.

For all indices, a negative performance has been detected during the last hour of the session, which tends to a reversal except for FTSE 40 (non statistical significant positive coefficient). The significant positive closing return is in line with other studies which produced evidence of the so called "end of the day" anomaly. Possible explanations for this behavior are a) investor's replacements considering next session's positive performance; b) the position's closing up by short sellers; c) a closing price manipulation which is connected with the closing price computation.

As far it is concerned the risk - return relationship, there are a lot of papers that report a non positive risk - return relationship but only for data based on daily observations. Harvey (1989) supports that the sign of the risk's coefficient depends on the market trend. Chou et al. (1992), Whitelaw (1994), Lettau and Ludvigson (2004) show that the risk-return relationship may be time-varying and they suggest a risk specification problem. LeBaron (1989) refers that a negative risk - return relationship can be a result of non synchronous trading where the market is characterized by illiquidity. Bali and Peng (2006) use high frequency data and support a positive relationship.

A possible explanation for the negative risk-return relationship that has been extracted from the analysis could be based on trading activity. During the first quarter, the positive return and volatility have high values. After the first quarter, the statistical significant intervals have a negative sign, especially for the small capitalization index. In the middle of the session, the information flow is lower and this is a reason for lower trading activity. During this interval, liquidity traders want to make transactions. Their desire to transact, especially in a market with narrow trading activity, possibly makes them not to ask for risk premium. Given the level of volatility during the session, we conclude that this negative risk – return relationship could take place for inventory reasons, as liquidity traders, in a low liquidity market, sell stocks and push prices lower.

IV. Conclusions

The paper investigates the risk - return relationship and the existence or not of trading patterns during the trading session. The most interesting findings are (1) the negative intraday relationship between returns and risk and (2) the existence of intraday patterns which are characterized by statistical significant positive returns in the first and the last quarter of the session.

We believe that these results contribute to the current literature as it is one of the first studies that examine the risk – return relationship during the trading session. In addition, connecting the negative risk – return relationship, which has been extracted from the analysis, with the trading patterns that we observed during the session in the ASE, we conclude that market microstructure changes should take place in order to make information incorporated into prices easier and faster.

Future research along these lines holds the promise of delivering a deeper understanding of the risk – return relationship and of the effect of trading rules on price formation.

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Appendix

Table 1: Descriptive statistics
Average returns

	ASE General	FTSE 20	FTSE 40	FTSE 80
11:00-11:15	0.156%	0.155%	0.248%	0.413%
11:15-11:30	-0.016%	-0.032%	-0.003%	-0.014%
11:30-11:45	-0.035%	-0.036%	-0.058%	-0.085%
11:45-12:00	-0.008%	-0.006%	-0.022%	-0.045%
12:00-12:15	0.005%	0.006%	-0.003%	-0.014%
12:15-12:30	-0.004%	-0.005%	-0.012%	-0.013%
12:30-12:45	-0.001%	0.003%	-0.011%	-0.020%
12:45-13:00	-0.016%	-0.016%	-0.028%	-0.037%
13:00-13:15	-0.003%	0.003%	-0.016%	-0.028%
13:15-13:30	-0.007%	-0.007%	-0.017%	-0.025%
13:30-13:45	-0.013%	-0.013%	-0.012%	-0.029%
13:45-14:00	-0.007%	-0.004%	-0.015%	-0.026%
14:00-14:15	-0.003%	-0.001%	-0.007%	-0.019%
14:15-14:30	-0.006%	-0.006%	-0.012%	-0.021%
14:30-14:45	0.001%	0.002%	-0.007%	-0.011%
14:45-15:00	-0.008%	-0.008%	-0.015%	-0.025%
15:00-15:15	-0.006%	-0.006%	-0.018%	-0.038%
15:15-15:30	-0.013%	-0.013%	-0.028%	-0.035%
15:30-15:45	-0.010%	-0.007%	-0.026%	-0.040%
15:45-16:00	-0.002%	-0.002%	0.010%	0.027%
Mean	0.000%	0.000%	-0.003%	-0.004%
Median	-0.005%	-0.004%	-0.012%	-0.020%
Max	2.586%	2.888%	4.981%	4.042%
Min	-2.974%	-2.682%	-4.323%	-4.928%
Standard dev.	0.213%	0.233%	0.239%	0.295%
Skewness	0.60	0.72	1.09	0.92
Kurtosis	22.80	21.37	43.69	28.34
Jarque-Bera	190,757	164,640	805,197	313,048
ACF	0.19**	0.16**	0.19**	0.26**
ADF (levels)	0.03	0.12	-0.99	-1.29
ADF (returns)	-45.86**	-45.43**	-45.83**	-45.17**
Anova F-stat.	18.62**	15.83**	39.46**	75.17**

* indicate statistical significance at 5% level, ** at 1% level of the t-statistics values
ACF = Auto-correlation function
ADF (levels) = Augmented Dickey Fuller statistic in levels, Dickey and Fuller (1979,1981)
ADF (returns) = Augmented Dickey Fuller statistic in first difference, Dickey and Fuller (1979,1981)

Table 2: Descriptive statistics
Standard deviation

	ASE General	FTSE 20	FTSE 40	FTSE 80
11:00-11:15	0.602%	0.664%	0.620%	0.716%
11:15-11:30	0.299%	0.323%	0.377%	0.380%
11:30-11:45	0.235%	0.255%	0.264%	0.328%
11:45-12:00	0.192%	0.209%	0.217%	0.289%
12:00-12:15	0.175%	0.186%	0.196%	0.253%
12:15-12:30	0.165%	0.180%	0.182%	0.245%
12:30-12:45	0.154%	0.168%	0.170%	0.214%
12:45-13:00	0.185%	0.189%	0.202%	0.249%
13:00-13:15	0.146%	0.164%	0.158%	0.201%
13:15-13:30	0.133%	0.143%	0.154%	0.195%
13:30-13:45	0.123%	0.135%	0.143%	0.182%
13:45-14:00	0.124%	0.135%	0.148%	0.188%
14:00-14:15	0.124%	0.137%	0.146%	0.176%
14:15-14:30	0.126%	0.138%	0.149%	0.178%
14:30-14:45	0.123%	0.134%	0.143%	0.187%
14:45-15:00	0.126%	0.138%	0.139%	0.201%
15:00-15:15	0.128%	0.143%	0.145%	0.185%
15:15-15:30	0.135%	0.146%	0.150%	0.195%
15:30-15:45	0.167%	0.185%	0.185%	0.229%
15:45-16:00	0.169%	0.193%	0.199%	0.257%
Bartlett stat.	2188.91**	2112.46**	2989.59**	4118.71**
Levene	84.34**	65.09**	68.79**	139.30**

* indicates statistical significance at 5% level, ** at 1% level of the t-statistics values
Bartlett stat. = Statistic from the test of equal variances of Bartlet
Bartlett stat. = F-statistic from the test of equal variances of Levene

Table 3: Econometric analysis
AR(i) - GARCH(p,q) models

$$r_t = \gamma_0 c + \gamma_i \sum_{i=0}^{\infty} r_{t-i} + \lambda h_t + e_t$$

$$h_t^2 = \alpha_0 + \alpha_i \sum_{i=1}^{p} e_{t-i}^2 + \beta_j \sum_{j=1}^{q} h_{t-1}^2$$

	ASE General	**FTSE 20**	**FTSE 40**	**FTSE 80**
λ	-0.375 *(-3.48)***	-0.209 *(-3.25)***	-0.149 *(-2.07)**	-0.167 *(-2.69)***
γ_0	0.001 *(3.53)***	0.001 *(3.439)***	0.000 *(1.63)*	0.000 *(2.01)**
γ_1	0.275 *(20.31)***	0.254 *(16.04)***	0.333 *(20.23)***	0.416 *(23.98)***
γ_2	-0.101 *(-8.43)***	-0.082 *(-6.30)***	-0.111 *(-8.03)***	-0.131 *(-7.98)***
γ_3	0.034 *(3.08)***	0.031 *(2.90)***	0.042 *(3.40)***	0.049 *(3.62)***
α_0	0.000 *(7.91)***	0.000 *(9.30)***	0.000 *(6.55)***	0.000 *(5.94)***
α_1	0.149 *(5.65)***	0.280 *(6.65)***	0.281 *(5.52)***	0.315 *(7.27)***
β_1	0.162 *(2.37)**	0.216 *(3.75)***	0.248 *(3.44)***	0.312 *(4.45)***
GARCH term sum	0.31	0.50	0.53	0.63
Log Likelihood R^2 Schwarz Akaike	55480 3.51% -9.529 -9.535	54508 2.61% -9.363 -9.367	54644 2.22% -9.386 -9.391	52265 6.69% -8.977 -8.982
arch test ACF	0.693 1.239	1.671 0.168	0.640 0.838	1.110 1.577

* indicates statistical significance at 5% level, ** at 1% level of the t-statistics values

Graphs 1: Statistical significant intervals during the trading session