Efficiency and Volatility on the Istanbul Stock Exchange

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DECLARATION

This thesis may be made available by the University librarian to allow single copies to made for study purposes.

ABSTRACT

This thesis investigates characteristics of the prices of shares traded on the Istanbul Stock Exchange (ISE), an important and fast-growing market. We look at five issues:

- the shape of the distribution of daily returns
- the predictability of these returns
- the presence of day-of-the-week effects in the mean and variance of returns
- the behaviour of the mean and variance of returns around stock split and dividend dates and
- the predictability of variances, and in particular the performance of adaptive models relative to the GARCH models.

Our main findings can be summarised as follows. First, the hypothesis of normality is rejected, mainly due to excess kurtosis. To explain excess kurtosis, we used an autoregressive conditional heteroskedastic (ARCH) model, and a GARCH(1,1) model is found to fit the ISE index data well. A significant further finding, based on a t-GARCH-M model is that in the early years of the exchange, mean returns were significantly influenced by the returns variance.

Second, standard tests for serial correlation, and for runs of same-sign returns, show that the hypothesis of a random walk can be rejected, with index returns showing significant first and second order serial correlation. Again, these effects are stronger in the early years of the exchange.

Third, using a GARCH model, we find no strong evidence of the day of the week effect in mean returns on the index or on the 20 actively traded companies. But there is evidence to suggest that the market is more volatile on Mondays and after holidays. Again, these effects are not stable over time.

Taken together, these results point to the market becoming progressively more efficient and more integrated with the international capital market over the period of the study.

Fourth, the results from the EV-GARCH model, a GARCH model with event-dependent intercept terms, a technical novelty, show that there is no effect on mean returns from stock dividends. Surprisingly, cash dividends do cause returns to rise/fall after their payment. On the other hand, stock dividends do significantly increase the variance of returns around the event day, and for several weeks thereafter.

Finally, although we have characterised the daily returns series by an autoregressive model with a GARCH process for volatility, it turns out that the GARCH model does not unambiguously dominate alternatives in forecasting and trading applications. In 5- to 20-day ahead forecasts, the GARCH model is slightly more accurate than four alternatives, including exponential smoothing models (RiskMetrics) and historic volatility. However, it is (inevitably) less accurate than a model which pools forecasts from all models.

In a simulated options market – another technical innovation of the thesis - we find that traders using a GARCH model would on balance lose money to traders using other methods, in spite of the apparently greater accuracy of the GARCH forecasts. This confirms for volatility forecasts an important result which is already know to hold for mean forecasts – that in forecasting financial markets, there is little correlation between mean-square accuracy and trading profitability.

CHAPTER ONE:

INTRODUCTION

This thesis analyses characteristic of the prices of shares traded on the Istanbul Stock Exchange (ISE). The ISE is an important and fast-growing market. It has a long history, but in its present form has been active since the mid-1980s. Towards the end of the 1980s, the market was given a considerable fillip by a number of major privatisation issues by the Turkish Government. In the 1990s, it has also benefited from liberalisation, and the internationalisation of portfolios by developed country investors. The history and operations of the ISE are described in Chapter 2.

In the following Chapters, we look at four issues. The first is the shape of the distribution of daily returns. The second is the predictability of these returns, which we examine by looking at serial correlation and runs tests. The third is the presence of day-of-the-week effects in the mean and variance of returns. The fourth is the behaviour of the mean and variance of returns around the (very frequent) stock split and dividend dates. And we concluded some work on predictability of variance and forecasting power of GARCH model.

Chapter 3 tests the normality of daily returns on the ISE index, and on 20 leading stocks. In common with most stock markets, and certainly with most emerging markets, the hypothesis that all returns are generated by a single normal distribution is rejected. The main reason for rejection is excess kurtosis - the presence of more extreme market rises and falls than would be likely under a normal distribution. The reasons for excess kurtosis in financial markets are not completely understood, but one plausible explanation - which is maintained throughout this thesis - is that returns are more-or-less normally distributed, but with a variance that changes over time.

This proposition is investigated more fully in Chapter 6, where we estimate autoregressive conditional heteroskedastic models of the ISE returns. These ARCH-family models allow the variance to change from day to day depending on past shocks to returns. A GARCH(1,1) model is found to fit the ISE index data well, and also provides a good description of the individual stock returns variance. However, further testing shows that the underlying returns distribution is still non-normal even after these GARCH effects are removed, and is better modelled by the more leptokurtic t-distribution. A significant further finding, based on a t-GARCH-M model is that in the early years of the exchange, mean returns were significantly influenced by the returns variance. However, in more recent years this effect has vanished. This is consistent with the idea that the ISE was originally a market dominated by Turkish-based investors, but over time has become more dominated by investors with internationally diversified portfolios.

The predictability of returns in general is investigated in Chapter 5, where we conduct standard tests for serial correlation, and for runs of same-sign returns. The runs tests are based on a three-category classification, by which returns can be positive, negative, or (effectively) zero. These tests show that the hypothesis of a random walk can be rejected, with index returns showing significant first and second order serial correlation. These effects have become a little less significant over time, which is again consistent with the increasing openness of the market, and the increased volume of well-informed trading.

Chapter 7 looks more closely at one of the frequently investigated market anomalies in finance literature, the day of the week effect. The finding in developed markets is that stock returns are negative and lower on Monday than on any other days of the week, while stock returns are higher than average on the last trading day of the week. We investigate this proposition, and the associated proposition that daily returns variances differ, using a GARCH model. The model includes dummies for days of the week, weekends and holidays, in both the mean and variance equations. We find no strong evidence of the day of the week effect in mean returns on the index or on the 20 actively traded companies. But there is evidence to suggest that the market is more volatile on Mondays and after holidays, an effect that may simply reflect the continuing arrival of information during periods when the market is closed.

Chapter 8 investigates the impact of stock dividends (stock splits) on returns and return volatility. Stock splits are a very regular occurrence on the ISE as companies try to maintain stable nominal share values in the face of steady annual inflation rates of 80-100%. Such stock splits simply change the number of shares per shareholder, without changing the percentage ownership of any shareholder, or the assets or earnings of the company. This implies that stock splits should have no effect on the value of the firm. However, many researchers in the US, following the pioneering work of Fama, Fisher, Jensen, and Roll (1969) find that companies that in practice firms that announce a stock split experience an increase in returns after the announcement, and an increase in variance after the split.

In the case of the ISE, analysis is complicated by the fact that stock dividends are paid simultaneously with cash dividends. We construct a novel event study methodology to separate the effects of stock and cash dividends. The technique also allows for GARCH effects, and for step changes in the mean and variance of returns through the event window. From an analysis of 110 dividend payment events, we find that there is no effect on mean returns from stock dividends, though (surprisingly) cash dividends do cause returns to rise/fall after their payment. On the other hand, stock dividends do significantly increase the variance of returns around the event day, and - through the GARCH mechanism - for several weeks thereafter.

In Chapter 9, we have conducted some work on forecasting volatility. We have used five volatility forecasting systems – a GARCH model, an optimised exponential smoothing model (SES), a non-optimised "RiskMetrics" smoothing model (RM), a long term historic volatility model based on all previous daily returns (HMAX), and a short term historic volatility model based on the past 20 days of daily returns (H20). The volatility forecasts has calculated across four horizons – 1-day, 5-day, 10-day and 20-days ahead.

The GARCH model does not clearly take over alternatives in forecasting and trading applications. In 5- to 20-day ahead forecasts, the GARCH model is slightly more accurate than others, including exponential smoothing models and historic volatility. However, it is less accurate than a model that pools forecasts from all models.

In the second part of this chapter we imagine a market in options on the ISE index, with five different types of participant, each using one of the five forecasting methods to gauge the fair price of the option. The market price is set at the price implied by the median volatility forecast, and the other players take long or short positions in at-the-money straddles according as their forecasts are higher or lower than the median volatility.

The best volatility forecasting method depends on the behaviour of the market. And it depends on the use to which the forecasts are to be put. A method may work well one year, and not the next. A method may be very relevant to value-at-risk calculations, which depends on accurate estimates of the variance, but not to options trading, which relies more on accurate directional signals.

In Chapter 10, We draw some conclusions from the study. One is that the ISE has become significantly more efficient and more closely integrated with the international capital markets over the years 1988-98. This trend is likely to continue, and any models of the market will have to recognise the ongoing structural changes.

Another conclusion is that there are strong but complex patterns in volatility on the ISE. Volatility modelling and forecasting is likely to become more important as more institutions hold Turkish shares, and apply Value-at-Risk measures to this part of their portfolio. The ISE is also introducing a futures contract, and may in time introduce traded options. The efficient pricing of options will of course require efficient volatility forecasting.

We also note that the main technical innovations in the thesis – the EV-GARCH model, and the synthetic options market – have potential applications to other problems and other markets, beyond their immediate application to ISE data.

CHAPTER TWO:

AN OVERVIEW OF THE ISTANBUL STOCK EXCHANGE

2.1 INTRODUCTION

A properly functioning capital market is beneficial for economic development in an increasingly industrialised country such as Turkey. The existence of capital markets allows direct financing through financial instruments as opposed to indirect financing through bank credit. Capital markets provide liquidity for outstanding securities. As both seller and buyers can trade quickly in such markets, investors are provided with the desired flexibility. Capital markets provide the possibility of increased asset diversification, thus leading to encouragement of saving. The liquidity of the capital markets also permits long term investments to be financed by short-term funds. Finally properly functioning capital markets may lead to increased share ownership, closer monitoring of companies, and improved business performance.

In this chapter we provide an overview of the development of the capital market in Turkey and discuss some of the background to the data which we used later of this study.

2.2 BRIEF OVERVIEW OF CAPITAL MARKETS IN TURKEY.

Although the Istanbul Stock Exchange (ISE) formally came into existence in December 1985, the history of stock exchange in Turkey dates back to 1866. Turkey's first stock exchange was established in Istanbul in order to regulate trading on bonds and bills that had been issued by the Ottoman Empire to finance the Crimean War (1853-1856) in 1866. It was a highly active and speculative market. Dersaadet Securities Exchange also facilitated foreign investment in debt securities issued by The Ottoman Empire. After the foundation of the Republic in 1923, a new law was enacted in 1929 aimed at reorganising the secondary market under the name of the "Istanbul Securities and Foreign Exchange Bourse", Foreign exchange transactions ceased soon after the opening of the Bourse. The name was not changed until 1985. The Stock Exchange was not active during the early years of The Republic. A number of factors contributed to this failure. The main obstacles to the development of capital markets have been the lack of supply and demand in primary markets due to the nature of the economic policy. The economic structure based on agriculture development policy also caused delay capital market and Stock Exchange establishment. Finally a, new capital tax was implemented during the Second World War that caused economic depression and an outflow of funs from country. Other factors inhibiting the development of capital markets in Turkey were the 1929 Great Depression, the economic disruption of World War 2 and the move of the Bourse between 1938-1941 to the commercially inactive capital city of Ankara.

However, over the counter markets, particularly in corporate bonds, were active by the late 1970's and early 1980's. This unregulated market came to a rapid end with the failure, one after another, of almost all of the brokerage houses in 1981-1982. This is known as the Kastelli Case in Turkish financial history. A market existed without any investor security, providing a fertile ground for misdeeds and mismanagement.

In 1981, the Capital Market Law (CML) was enacted and this long awaited legal development was hoped to aim at addressing the basic issues of emerging capital markets. It was prepared more with the remnants of 1981 in mind. But it was a development in the right direction and it was perceived as such by the economy. The CML included several provisions concerning primary markets, new issues etc. It did not make any provision concerning the operations of secondary markets, and the law left the void to be filled with regulations to be prepared and issued by the Cabinet and as soon as the necessary regulations were prepared The Istanbul Stock Exchange (ISE) itself was inaugurated at the end of 1985.

2.3 DEVELOPMENT CONCERNING THE ISTANBUL STOCK EXCHANGE.

Since its establishment in late December 1985, and its inauguration in January 1986, The Istanbul Stock Exchange and its related institutions have shown significant growth and have began to play an effective role as a part of the financial system of Turkey, competing for funds with the banking system and also in co-operation with them as a part of the total financial system.

The number of listed companies on the ISE has increased from 42 in beginning of 1986 to over 277 in 1998. The average daily trading volume was less than US$ 1 million before 1988 and it was grown to more than US$ 284 millions in 1998. Institutional investors started becoming main participants in the market place. The Rapid development of daily trading volume encouraged many family-owned companies to go public and to finance long term projects by recourse to capital markets. The market value of shares traded on the exchange rich from $ 13 million in 1986 to $70,396 million by 1998. The number of stock traded on the ISE increased from 3 million 1986 to 2,242,531 million in 1998 number of contracts increased from 112,000 (1988) to 21,571,000.

The privatisation of many state economic enterprises through public flotation has helped to boost supply side, and set examples for the private sector to follow. Since 1985 a total of 163 government owned companies have been taken into privatisation portfolio and sales value of the companies was about $3.4 billion. Yem Sanayii (Animal feed Production), Sut Endustrisi Kurumu (milk and diary products), cement plants, and public banks were privatised. Public shares in Netas (telecommunication) and Tofas (automobile) were offered to foreign investors through the offering in international markets that helped ISE's integration with foreign stock exchanges. The government plans to privatise public companies in 1999 with a value of about $4 billion.

Restrictions on trading by foreign investors were completely lifted in 1989 and this was one of the most important reasons for the increased daily trading volume thereafter. International Stock Exchange(ISE IM) division was activated in the first quarter of 1997. The market operates as free trade zone where prices and transactions are conducted in dollars and transactions and income earned will be tax free. The objective of the ISE International Market is to encourage the flow of international capital to the ISE. Shares are traded at the ISE IM Equities Market, and debt instruments are traded at The ISE IM International Bonds and Bills Market. A Depository Receipts Market where the depository receipts representing stocks issued globally will be opened, The Foreign Mutual Funds Market intended to provide a fair and organised market for the trading of open ended foreign mutual funds, started operations within the ISE IM in June 1997.

The Bonds and Bills Market was established on June 1991 and Repo/Reverse Repo transactions began on February 1993, The Real Estate Certificates Market was introduced on June 1996 within the ISE Bonds and Bills Market. The purpose of The Bonds and Bills Market is to provide a transparent, liquid, competitive and efficient environment for secondary market trading of fixed income securities comprising Government bonds, Treasury bills, revenue-sharing certificates, bonds issued by the Privatisation Administration and corporate bonds listed on the ISE.

The ISE Bonds and Bills Market has introduced Price and Performance Indices from January 1996. These indices follow changes in prices and yields of fixed income securities. The aim of the ISE Government Debt Securities Indices is to provide the basis for comparison with other markets and a foundation for technical studies. The "Price Index" is an indicator reflecting price fluctuations of Treasury bills or Government bonds as a result of changes in interest rates accepted in the market, not only due to current interest rate fluctuations but also as the time to maturity diminishes. Therefore, the Performance Index is an indicator of yield gained by an investor within a certain period. The Performance Index is computed and announced for each bond/bill with the characteristic maturity.

A Derivatives Market is under construction. The early stage of derivatives market is to introduce index-based contracts with maturates of up to three months, and then gradually open up to other instruments. The ISE will launch the trading of index futures in the near future.

The computerised trading system of the ISE was completed and replaced its manual trading of stocks in November 1994. The system enables the ISE members to trade in stocks and rights coupons. In May 1995 The Istanbul Stock Exchange moved to a new modern complex in Istanbul. There are 800 workstations in the three dealing rooms. This has dramatically improved the speed of execution, and also has increased the daily trading capacity to 150 000 trades per hour. Prices are determined on a "multiple price-continuous auction" method, utilising a computerised system that automatically matches buy and sell orders on a price and time priority basis. The buyers and sellers enter the orders into the computer system through their workstations located at the ISE. All information regarding dealing, except standing order IDs, are displayed in the trading system during the sessions.

Future projects involve plans to enable members to trade directly from their offices in the Stock Exchange headquarters, links between the ISE and the Internet, and the expansion expanding the system throughout the country and world-wide. Wide Area Network (WAN) system analysis, design and implementation stages will be introduced. It will be beginning with Istanbul, Ankara and Izmir.

A new Settlement and Custody service has been introduced in July 1991. It has a 70 million certificate storage capacity, and clients have direct telephone access to their securities. The settlement system is designed increasingly to facilitate transactions by foreign investors. The Stock Exchange transfers trade details to the computer network of the Settlement and Custody Company. The company was transformed into an investment bank, called Takasbank-ISE Settlement and Custody Bank began its banking operations on 2 January 1996. The Takasbank is owned by the ISE and 105 of its members, ISE has 21.38 % of share other member can hold a share maximum 5 %, and its total paid in capital was TL1.05 trillion (US$12.7 million) at July 1996. Takasbank is a member of international institutions.

Trade contracts are processed at the end of each trading day by the ISE's fully automated system. Each ISE member has a settlement account at Takasbank, the members are able to access this report by network connection. On the settlement date, the securities are transferred from customer accounts to the pool account so that can debit this account to their own account. The cash transactions are accomplished by equity settlement account and for the bonds and bills market by means of bond settlement account. Payments may be made by EFT (Electronic Fund Transfer) or transfers from the CBT (Central Bank of Turkey) accounts, hold by ISE members.

Stock Market Settlement of transactions accrues on day T+2 (two working days following the transaction date). Settlement in the Wholesale Market was be in settlement accounts with Takasbank or outside Takasbank, subject to the agreement of both parties. Bonds and Bills Market Settlement and Repo and Reverse Repo Market Settlement date are transactions are carried out on the same day T+0. Real estate certificates are settled on T+2 (two workdays following the transaction) at Takasbank. Takasbank will be responsible for the settlement and custody operations conducted in the ISE International Market.

The risks in the settlement and custody activities are controlled by rules and regulations. Those risks are the credit risk, liquidity risk, settlement failure risk, fraud, forgery, fire, theft, physical damage, fraud risks in communication and EDP errors. These risks are covered by Delivery versus Payment method, and Collateral paid in advance. Three types of collateral was used in the ISE. Fixed Collateral that an amount each ISE member should deposit with the ISE; Proportional Collateral, 5% of the daily average volume of transactions calculated quarterly, each member should deposit with the ISE; and Additional Collateral, 10 % of the total amount of defaults that occurred within the last quarter. If this amount is greater than the proportional collateral, the difference is deposited as additional collateral. If no further shortcoming occur in the next quarter, the additional collateral will be refunded. For the Bonds and Bills market, members should deposit 1/20 of the trade limit. Also some security and safety system set up against the risk we mentioned above.

The long turn strategy of new ISE is to build on its strategic geographical location between Europe and Asia. In terms of internationalisation of Turkish Capital markets, the most important potential direction of development is to become the financial centre for the region and especially for Previously Russian, New Central Asian Republics. The funding requirements of investment projects to exploit natural resources of these countries are huge, and Turkey has the potential of becoming the meeting place between the providers of funds and users of funds. Turkey's historical ties with these countries, and the rapid development and global of financial services in Turkey, may enable Turkey to meet some of the demands of these countries and provide the security that the world financial community needs.

The Istanbul Stock Exchange is a full member of "Federation Internationale des Bourses de Valeurs" (FIBV), the "International Society of Securities Administration" (ISSA), the "International Securities Market Association" (ISMA), the "European Capital Markets Institute" (ECMI), The ISE has been designated as an "Offshore Securities Market" by US Securities and Exchange Commission (SEC). World Economic Forum (WEF) and "Swiss Commodities, Futures and Options Association" (SCFOA)

An Internet WEB site of the ISE has established in English and Turkish (www.ise.org).

Although these developments have taken place there are several issues which have not been addressed fully up to this date. There have been difficulties with the establishment of rating agencies and this remains one of the most important institutional shortcomings for investor security. Another major obstacle to smooth operation of the market is relatively minor importance of institutional investor base within the total investor portfolio.

2.4. DATA, THE PERIOD COVERED AND LIMITATION OF THE RESEARCH.

The intention has been to use in this study as long period of data as possible. In this study the period between the beginning of 1988 and the end August 1998 will be covered. The choice of period is dictated by the opening of ISE to trading in January 1986. A capital market existed in an unofficial forum before 1986, almost all brokerage houses failed during the 1981-1982, and we are unable to obtain reliable data for that period. The data of the first year of the ISE are also fragile, so we choose the starting point at the beginning of the 1988.

There is now an accessible established stock price data base consisting of all the companies listed in The Istanbul Stock Exchange. International databases such as Institutional Brokers Estimate System (I/B/E/S), Reuters, Datastream and some publish price data of Turkish Companies.

There was 42 companies listed at the ISE in 1988, we have chosen to analyse 20 of these biggest companies were traded in the relatively active continuously traded at the next ten years, as the in 2263 daily sample, and the overall ISE index (See appendix table 2.1). One of the companies Koc Yatirim merged with parent company Koc Holding in September 1997.

Our data come from The ISE, Datastream, Bogazici University and brokerage firms. The collected daily return data has been pre-adjusted for stock splits and dividend payments for the entire study period. Data obtained from multiple sources were compared with each other, and database construction stage included several visits to The Istanbul Stock Exchange and Capital Market Board. The international market indices were extracted from Datasream database.

A characteristic of the Turkish equity market is frequent stock splits, rights offerings and preference of stock dividends over the cash dividends by listed companies. These necessitate many adjustments in the price series in addition of the regular besides cash dividend adjustments. The frequency of the stock splits is due to inflationary adjustments in total asset values. Inflationary factors to be used in making accounting adjustment are announced by the government, and the incremental inflationary adjustment in the equity is distributed to the shareholder. The natures of these splits on stock returns are explained in Chapter 8.

The adjustments are performed after each event by calculating an adjustment ratio and multiplying the pre adjustment prices by the adjustment rate. The price series used to calculate the returns are all closing prices, and logarithmic returns are used in return calculations.

The table 2.2 shows daily returns on the ISE-Index. The returns exhibit volatility clustering, that large changes in prices tending to be followed by large changes of either sign. This pattern is investigated in more detail in chapter 5.

2.5 CONCLUSION

This Chapter has reviewed the history of the development of the Istanbul Stock Exchange. From the perspective of this study, four features of the market are noteworthy.

First, the number of stocks traded had grown steadily, and volume of trading has expanded considerably through the period covered by this study. The market has become increasingly deregulated. Both of these features suggest that the efficiency of the market might have increased over time, and this is an important hypothesis tested in the study.

Second, the market has grown almost in spite of an unstable economic environment. While real economic growth in Turkey has been rapid, inflation – and hence nominal interest rates – has been exceptionally high and volatile. The ability of the market to distinguish real from nominal shocks is assesses in Chapter 8, where we look at price movements around stock splits.

Third, perhaps because of the economic environment, the volatility of returns on the ISE has also been exceptionally high. The determinants of volatility are examined in some detail in Chapters 6 and 7 below.

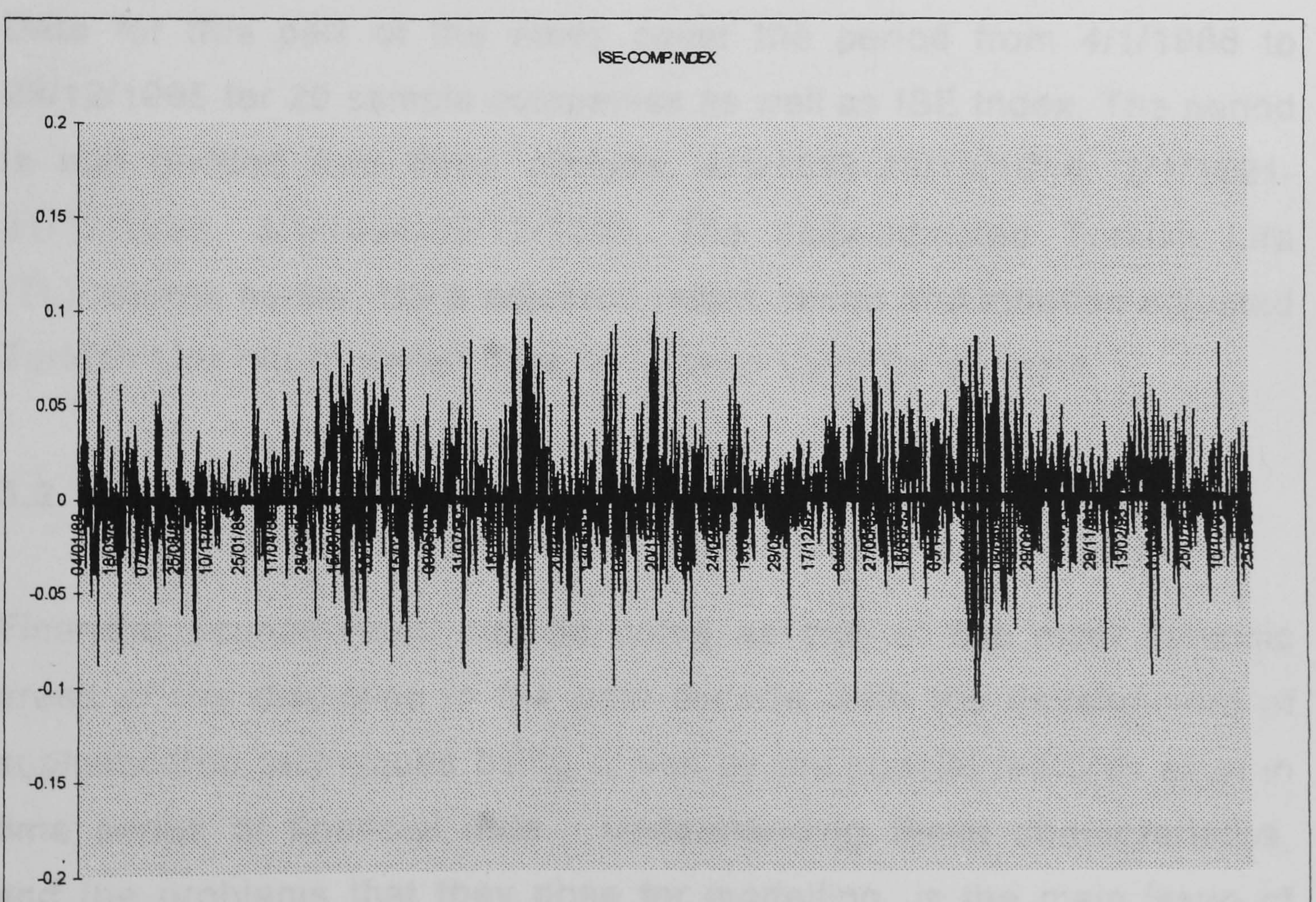
Fourth, while the market has developed fast, the process is far from complete. While the exchange has plans to introduce Index futures and options, these have still not come to fruition. Chapter 9 below anticipates these developments by assessing the predictability of the volatility observed on the ISE, and comparing the value of alternative volatility forecasting models.

APPENDICES 2

TABLE 2.1 SAMPLE 20 COMPANIES

	Code	Name of The Company	Sector
1	ARC	ARCELIK	CONSUMER DURABLES
2	BAG	BAGFAS	FERTILISERS
3	CEL	CELIK HALAT	METALS
4	CIMS	CIMSA	CEMENT
5	CUK	CUKUROVA ELEKTRIK	UTILITIES
6	DOK	DOKTAS	AUTOMOTIVE
7	ECZ	ECZACIBASI YATIRIM	HOLDING
8	EGE	EGE BIRACILIK	FOOD AND BEVERAGES
9	ERE	EREGLI DEMIR CELIK	IRON AND STEEL
10	GOOD	GOOD-YEAR	AUTOMOTIVE
11	GUN	GUNEY BIRACILIK	FOOD AND BEVERAGES
12	KAR	KARTONSAN	PAPER PRODUCTS
13	KOCH	KOC HOLDING	HOLDING
14	KOCY	KOC YATIRIM	BANKING AND FINANCE
15	OTO	OTOSAN	AUTOMOTIVE
16	SAR	SARKUYSAN	METALS
17	TIB	T. IS BANKASI (B)	BANKING AND FINANCE
18	TSI	T. SIEMENS	TELE-COMMUNICATIONS
19	TUDD	T. DEMIR DOKUM	CONSUMER DURABLES
20	YAS	YASAS	CHEMICALS

TABLE 2.2 DAILY RETURN OF THE ISE INDEX



CHAPTER THREE:

DISTRIBUTIONAL CHARACTERISTICS OF THE STOCK RETURNS ON THE ISTANBUL STOCK EXCHANGE.

3.1 INTRODUCTION.

The purpose of this chapter is to assess the statistical characteristics of the daily return series of the sample stocks and ISE index. It is useful to begin by considering what type of models one might adopt for the ISE series. To characterise the distributions of the return series we analyse mean, variance, skewness and kurtosis of the sample returns, and conduct Jarque-Bera normality tests. All our tests suggest that the hypothesis that refers to returns follows a normal distribution should be rejected. Non normality may reflect the fact that returns follow an ARCH process, and this is investigated in the Chapter 6.

Data for this part of the study cover the period from 4/1/1988 to 29/12/1995 for 20 sample companies as well as ISE Index. The period is sub divided into three periods, 4/1/1988-28/12/1990, 2/1/1991-31/12/1993, 3/1/1994-29/12/1995. The daily-adjusted Turkish Lira (TL) returns series, US $ adjusted return series and inflation adjusted Turkish Lira return series data have been used for all tests.

3.2 THE DISTRIBUTION OF THE RETURN SERIES

Financial econometrics has be come as one of the most dynamic areas of the discipline in the past decade, with the development of sophisticated techniques being driven by the special features seen in time series of financial data. Understanding these characteristics, and the problems that they pose for modelling, is the main issue of the financial econometrics. In the econometrics of the fifties and sixties, it would have been common to assume that any time series being investigated could be regarded as stationary, independently, identically and normally distributed. Such a perspective has been slowly discarded by those dealing with financial series. Fama (1965) observed that daily return series follow leptokurtic distributions indicating some deviation from normality. Non-stationarity, a lack of serial independence, and non-normality have become the characteristics of the standard model.

Statistics on skewness and the kurtosis are often used for normality tests. Skewness measures the symmetry of the distribution, kurtosis measures peakness or flatness of the distribution. Since the normal distribution is symmetric and bell shaped, it has well defined skewness and kurtosis measures. Any deviations from these measures indicate a deviation from normality. Although skewness and kurtosis individually can be used to identify deviations from normality, a more powerful test was utilised to test the null hypothesis, the Jarque-Bera normality test (Jarque and Bera 1987,1980). The test can be obtained by using the Lagrange Multiplier principle and is based on the joint statistics for skewness and kurtosis.

In order to be able to analyse the distributional characteristics of return series, measures of location (mean), dispersion (variance, and standard deviation), skewness and kurtosis were calculated. The null hypothesis tested is that the sample daily return series are normally distributed. The test results show that assumption of normality for return series is not safe assumption.

The extreme non-normality of this return need to be explained and, one possible explanation that variance of returns follows some ARCH process. The ARCH process needs leads to this kind fat tailed distribution, where extreme highs and lows are observed more than in the normal distribution.

3.3 EMPIRICAL RESULTS

Tables 3.1-3.12 summarise statistical characteristic of the daily return series of sample stocks and ISE index. We conduct normality tests firstly on returns on Turkish Lira data, secondly US $ return data and thirdly inflation adjusted Turkish lira return data. The table shows the Jarque-Bera normality test statistic, mean return, Std deviation, skewness, and kurtosis tests. The tests are conduct for whole period 1988-1995, and sub periods for 1988-1990, 1991-1993, and 1994-1995.

Using daily data for the whole period 1988-1995, the mean return on the ISE-Index is 0.2%, with $ base return is zero and inflation adjusted TL data is -0.02% for the same period. The average of the 20 sample companies returns on the same period is 0.26%, $ base return 0.05%, and inflation adjusted return -0.1% (see table 3.A). The differences between the real return and nominal return indicates that inflation was a highly significant after on nominal returns.

TABLE 3.A

Normality Test for period 1988-1995

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX TL	0.0020	0.0298	-0.0616	1.29	134.35
ISE-INDEX $	0.0000	0.0334	-0.4497	4.45	2347.80
ISE-INDEX inf	-0.0002	0.0298	-0.0560	1.29	134.04
Avg 20-Com TL	0.0026	0.0445	0.1125	0.84	81.94
Avg 20-Com $	0.0005	0.0464	-0.0889	2.10	518.23
Avg 20-Com Inf	-0.0010	0.0425	0.1126	0.84	81.37

The standard deviation of the daily returns of ISE-Index is 3% and standard deviation of the daily returns of 20-companies is 4.5%. This figure is same as for the standard deviation of daily inflation adjusted returns. The standard deviation of the US$ adjusted daily returns of ISE-Index 3.3% and standard deviation of the US$ adjusted daily returns of 20-companies is 4.6%. This indicates wide fluctuations in the daily returns, especially the US$ base returns.

The daily returns of ISE-Index, the daily inflation adjusted returns of ISE-Index and the daily US$ adjusted returns of ISE-Index are negatively skewed. The daily returns of 20-companies, the daily inflation adjusted returns of 20-companies are positively skewed and again the daily US$ adjusted returns of 20-companies is negatively skewed.

Kurtosis figures are also different from zero their expected value under normality for all ISE-Index sample. They are larger than zero and show the expected leptokurtic distribution. The results for skewness and kurtosis imply deviations from normal distribution. Kurtosis figures are different than zero for average of sample 20-companies.

Under the null of normality, the Jarque-Bera statistic is asymptotically distributed as χ^2 (2). The critical value at 5% for 2002 observations is 5.99. If Jarque-Bera statistics (JB) is smaller than 5.99, the hypothesis will be accepted. If JB value is greater than 5.99, the hypothesis will be rejected. Table 3A shows JB statistics values. In whole period we clearly reject the hypothesis of normal distribution for daily returns, inflation adjusted daily returns, and US$ adjusted daily returns.

In the sub periods; the daily mean return of the ISE-Index is 0.21% for period 1988-1990, 0.25% for period 1991-1993, and 0.13% for period 1994-1995. The daily inflation adjusted mean returns of ISE-Index are 0%, 0.04%, and -0.1% for period 1988-1990, 1991-1993, and 1994-1995 respectively. The daily US$ adjusted mean returns of ISE-Index are 0.06%, 0.03%, and -0.14% for periods 1988-1990, 1991-1993, and 1994-1995 respectively.

TABLE 3B

Normality Test For Sub Terms

ISE TL

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
1988-1990	0.0021	0.0301	-0.1119	1.19	52.07
1991-1993	0.0025	0.0285	0.2113	1.67	87.61
1994-1995	0.0013	0.0314	-0.2846	0.95	18.69
1988-1995	0.0020	0.0298	-0.0616	1.29	134.35

ISE TL INF ADJ

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
1988-1990	0.0000	0.0301	-0.1065	1.18	51.52
1991-1993	0.0004	0.0285	0.2118	1.67	87.39
1994-1995	-0.0014	0.0314	-0.2678	0.95	18.40
1988-1995	-0.0002	0.0298	-0.0560	1.29	134.04

ISE $ ADJ

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
1988-1990	0.0006	0.0313	-0.1050	1.35	113.47
1991-1993	0.0003	0.0316	-0.0243	3.21	316.40
1994-1995	-0.0015	0.0387	-1.0167	6.57	1338.09
1988-1995	0.0000	0.0334	-0.4497	4.45	2347.80

The standard deviation of the daily returns of ISE-Index in sub period 3%, 2.8%, and 3.1% for sub period one two and three respectively The standard deviation of the daily inflation adjusted returns of ISE-Index in sub period 3%, 2.8%, and 3.1% for sub period one two and three respectively. The standard deviation of the daily US$ adjusted returns of ISE-Index in sub period 3.1%, 3.1%, and 3.8% for sub period one two and three respectively. Table 3B.

In the sub period; The average of the 20-Companies daily mean returns is 0.27%, 0.32%, and 0.15% for sub period one, two, and three respectively. The average of the 20-Companies daily inflation adjusted mean returns is 0.07%, 0.012%, and -0.013% for sub period one two and three respectively. The average of the 20-Companies daily US$ adjusted mean returns is 0.013%, 0.01%, and -0.013% for sub period one two and three respectively (see table 3B).

Average standard deviation of the daily returns of 20-companies is 4.2%, 4.2%, and 5% for sub period one two and three respectively. Average standard deviation of the daily inflation adjusted returns of 20-companies is 4.2%, 4.2%, and 5% for sub period one two and three respectively. Average standard deviation of the daily US$ adjusted returns of 20-companies is 4.4%, 4.4%, and 5.5% for sub period one two and three respectively. Curiously, these figures indicate that in a sense risk and return move in opposite directions. In years when the standard deviation of returns is higher the mean return is lower.

When we look at the sub periods and test for normality; using skewness, Kurtosis, and the Jarque-Bera Tests, there is no change from the overall results. Normality is still strongly rejected. Jarque-Bera normality tests for individual companies are strongly rejected for TL, US $ and inflation adjusted return data for whole period (1988-95). In sub periods, a few companies show normality, but disappear in one other sub periods.

Adjusting for $ and inflation causes returns to become close to zero, so most of the rising index is inflation related. It tells us what the overall real increase was on period. $ Returns are more variable than Turkish lira return due to exchange rate volatility. They are also more leptokurtic, which might have something to do with exchange rate volatility rather than stock exchange volatility. The typical company share is more volatile then market, referring the benefits of diversification. For all indexes, normality is strongly rejected by the Jarque-Bera normality test.

3.4 CONCLUSION

This Chapter has looked formally at the statistical characteristics of daily returns to the ISE index, and the leading individual shares traded on the market.

While the local currency value of the index grew exponentially through the years 1988-95, when it is adjusted for inflation (or, almost equivalently, converted to US dollars), most of this growth vanishes. In real terms, there was effectively no growth in the market.

Adjustment for inflation does not, however, reduce the volatility of the underlying returns series. If anything, the US dollar series is more volatile and less "normal" than the local currency series.

Excess kurtosis and negative skewness is a common feature of high frequency returns in many stock markets, both developed and developing. A consensus has grown in recent years that this is due to time variation in the distribution of daily returns, and in particular to the alternation of periods of high and low volatility. Even if daily returns are always normally distributed, but with time-varying variance, the distribution of a mixture of low-variance and high variance days will have the empirical characteristics of Table 3B. Chapter 6 tests whether daily returns on the ISE exhibit time-varying volatility , and whether once this is taken into account there remains any intrinsic non-normality in the way shock impact on the market.

APPENDICES 3

TABLE 3.1

Normality Test for daily returns of ISE 1988-1990

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	0.0021	0.0301	-0.1119	1.19	52.07
ARC	0.0032	0.0417	-0.0439	0.43	7.67
BAG	0.0023	0.0435	-0.0796	0.10	*0.26
CEL	0.0020	0.0400	0.0508	0.56	11.34
CIMS	0.0016	0.0467	0.0746	0.12	*3.40
CUK	0.0029	0.0395	0.1213	1.05	35.75
DOK	0.0015	0.0454	0.0389	-0.01	*0.52
ECZ	0.0060	0.0439	0.0113	0.49	9.51
EGE	0.0048	0.0426	-0.0461	0.33	*4.64
ERE	0.0037	0.0415	0.0306	0.70	28.00
GOOD	0.0003	0.0462	0.0038	0.05	*0.67
GUN	0.0031	0.0444	-0.0903	0.42	9.26
KAR	0.0018	0.0376	0.0342	0.72	16.56
KOCH	0.0038	0.0432	-0.0130	0.21	*2.52
KOCY	0.0032	0.0412	-0.0020	0.93	27.65
OTO	0.0022	0.0447	0.0079	-0.01	*0.63
SAR	0.0029	0.0399	-0.0424	0.62	14.73
TIB	0.0034	0.0444	0.1097	0.42	11.97
TSI	0.0011	0.0459	-0.1104	0.95	33.74
TUDD	0.0014	0.0415	-0.0307	0.63	20.49
YAS	0.0029	0.0427	0.2065	0.31	8.14
Avg 20-Com	0.0027	0.0428	0.0116	0.45	18.06

Note. Critical value at 5% significant. for 754 observations is 5.46 for Jarque-Bera Normality test.
Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.2

Normality Test for daily returns of ISE 1991-1993

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	0.0025	0.0285	0.2113	1.67	87.61
ARC	0.0037	0.0358	0.4351	0.91	45.51
BAG	0.0021	0.0436	0.1527	0.49	9.51
CEL	0.0026	0.0429	0.3516	0.47	19.28
CIMS	0.0034	0.0410	0.1623	0.81	22.89
CUK	0.0026	0.0403	0.3585	1.03	47.35
DOK	0.0038	0.0425	0.2047	0.31	6.90
ECZ	0.0019	0.0430	0.1944	0.34	7.50
EGE	0.0044	0.0384	0.1027	0.87	25.00
ERE	0.0024	0.0430	0.2460	0.49	12.51
GOOD	0.0045	0.0423	0.2575	0.47	14.73
GUN	0.0039	0.0421	0.0221	0.48	9.25
KAR	0.0031	0.0413	0.3532	1.03	45.84
KOCH	0.0030	0.0384	0.3614	0.61	25.26
KOCY	0.0035	0.0399	0.2093	0.45	7.05
OTO	0.0046	0.0436	0.0847	0.26	*2.48
SAR	0.0030	0.0372	0.2949	0.83	24.86
TIB	0.0023	0.0478	0.1426	0.11	*1.24
TSI	0.0031	0.0444	0.1778	0.72	19.47
TUDD	0.0035	0.0417	0.2814	0.83	30.63
YAS	0.0036	0.0489	0.2108	-0.04	*4.50
Avg 20-Com	0.0032	0.0419	0.2302	0.57	21.97

Note. Critical value at 5% significant. for 744 observations is 5.46 for Jarque-Bera Normality test.
Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.3

Normality Test for daily returns of ISE 1994-1995

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	0.0013	0.0314	-0.2846	0.95	18.69
ARC	0.0005	0.0471	-0.2281	1.09	37.64
BAG	0.0013	0.0520	0.0350	0.49	6.66
CEL	0.0015	0.0678	0.1716	1.20	29.31
CIMS	0.0019	0.0459	0.7197	3.10	228.27
CUK	0.0016	0.0610	0.2574	1.31	40.45
DOK	-0.0003	0.0504	0.1481	1.03	24.30
ECZ	0.0008	0.0534	0.2005	0.70	14.83
EGE	0.0027	0.0445	0.2643	1.13	33.84
ERE	0.0011	0.0501	-0.0014	0.34	*3.32
GOOD	0.0017	0.0396	0.0220	1.95	75.52
GUN	0.0022	0.0486	-0.0486	0.76	20.97
KAR	0.0031	0.0455	0.1795	0.52	8.51
KOCH	0.0008	0.0457	0.2845	0.94	18.93
KOCY	0.0005	0.0463	0.0628	0.66	10.98
OTO	0.0003	0.0504	0.0721	2.41	129.48
SAR	0.0022	0.0438	0.0068	0.72	11.54
TIB	0.0041	0.0591	0.4239	0.56	13.64
TSI	0.0021	0.0496	-0.0313	1.19	27.27
TUDD	0.0004	0.0503	0.0114	0.65	7.58
YAS	0.0010	0.0501	0.0103	0.18	*0.58
Avg 20-Com	0.0015	0.0501	0.1280	1.05	41.09

Note. Critical value at 5% significant. for 504 observations is 5.46 for Jarque-Bera Normality test.
Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.4

Normality Test for daily returns of ISE1988-1995

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	0.0020	0.0298	-0.0616	1.29	134.35
ARC	0.0027	0.0411	-0.0159	1.00	88.30
BAG	0.0020	0.0458	0.0317	0.46	21.81
CEL	0.0021	0.0494	0.1961	2.03	337.64
CIMS	0.0023	0.0444	0.2717	1.18	128.86
CUK	0.0025	0.0461	0.2524	1.98	325.95
DOK	0.0019	0.0457	0.1114	0.51	28.53
ECZ	0.0032	0.0462	0.1238	0.65	50.64
EGE	0.0041	0.0416	0.0889	0.76	54.26
ERE	0.0026	0.0444	0.0819	0.57	37.84
GOOD	0.0022	0.0432	0.0873	0.59	34.75
GUN	0.0032	0.0446	-0.0470	0.59	44.02
KAR	0.0026	0.0411	0.2102	0.84	72.78
KOCH	0.0028	0.0422	0.1817	0.60	36.56
KOCY	0.0026	0.0421	0.0757	0.74	44.30
OTO	0.0026	0.0458	0.0416	0.99	93.36
SAR	0.0028	0.0399	0.0716	0.77	52.00
TIB	0.0032	0.0497	0.2610	0.60	40.33
TSI	0.0021	0.0463	0.0068	0.98	82.14
TUDD	0.0019	0.0440	0.0733	0.82	55.13
YAS	0.0027	0.0470	0.1467	0.18	9.67
Avg 20-Com	0.0026	0.0445	0.1125	0.84	81.94

Note. Critical value at 5% significant for 2002 observations is 5.99 for Jarque-Bera Normality test.
Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.5

Normality Test for daily *US$ adjusted* returns of ISE 1988-1990

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	0.0006	0.0313	-0.1050	1.35	113.47
ARC	0.0017	0.0428	-0.0063	0.58	16.03
BAG	0.0008	0.0447	-0.0295	0.31	*4.27
CEL	0.0006	0.0413	0.1238	1.05	43.30
CIMS	0.0001	0.0473	0.0397	0.05	*2.01
CUK	0.0015	0.0400	0.0547	1.08	36.54
DOK	0.0000	0.0464	0.0959	0.21	7.84
ECZ	0.0046	0.0450	-0.0142	0.52	10.69
EGE	0.0034	0.0432	-0.0756	0.33	*5.35
ERE	0.0023	0.0426	0.0510	0.77	37.28
GOOD	-0.0012	0.0470	-0.0148	0.05	*0.76
GUN	0.0017	0.0454	-0.0950	0.44	9.93
KAR	0.0003	0.0388	0.0825	0.90	27.40
KOCH	0.0024	0.0437	-0.0383	0.18	*1.84
KOCY	0.0018	0.0424	0.0969	1.29	66.71
OTO	0.0007	0.0459	0.0438	0.06	*1.33
SAR	0.0015	0.0409	-0.0239	0.73	24.12
TIB	0.0020	0.0450	0.1205	0.33	8.86
TSI	-0.0003	0.0465	-0.0757	0.83	26.18
TUDD	-0.0001	0.0426	-0.0767	0.64	26.78
YAS	0.0015	0.0431	0.1581	0.39	7.25
Avg 20-Com	0.0013	0.0437	0.0208	0.54	24.92

Note. Critical value at 5% significant. for 754 observations is 5.46 for Jarque-Bera Normality test.
Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.6

Normality Test for daily *US$ adjusted* returns of ISE 1991-1993

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	0.0003	0.0316	-0.0243	3.21	316.40
ARC	0.0015	0.0381	0.3638	1.39	74.83
BAG	0.0000	0.0451	0.0754	0.81	21.17
CEL	0.0004	0.0452	0.1844	0.98	34.05
CIMS	0.0012	0.0432	0.0610	1.40	57.73
CUK	0.0004	0.0426	0.2523	1.26	60.11
DOK	0.0016	0.0449	0.1182	0.69	15.69
ECZ	-0.0003	0.0452	0.0862	0.64	18.53
EGE	0.0022	0.0410	0.0322	1.41	50.87
ERE	0.0003	0.0455	0.1850	0.75	29.58
GOOD	0.0002	0.0492	0.0605	0.16	*1.57
GUN	0.0017	0.0440	-0.0484	0.71	17.97
KAR	0.0009	0.0441	0.0118	3.33	266.04
KOCH	0.0008	0.0409	0.1860	1.24	46.76
KOCY	0.0014	0.0421	0.0548	0.85	22.89
OTO	0.0025	0.0456	0.0359	0.44	7.29
SAR	0.0008	0.0394	0.1574	1.33	69.13
TIB	0.0005	0.0499	0.1858	0.67	20.74
TSI	0.0009	0.0467	0.0342	1.06	30.70
TUDD	0.0014	0.0439	0.0557	1.36	51.07
YAS	0.0014	0.0513	0.1114	0.27	*4.03
Avg 20-Com	0.0010	0.0444	0.1102	1.04	49.73

Note. Critical value at 5% significant. for 744 observations is 5.46 for Jarque-Bera Normality test.
Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.7

Normality Test for daily *US$ adjusted* returns of ISE 1994-1995

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	-0.0015	0.0387	-1.0167	6.57	1338.09
ARC	-0.0023	0.0528	-0.5547	3.82	349.26
BAG	-0.0015	0.0561	-0.1397	1.15	34.47
CEL	-0.0013	0.0720	0.0251	1.76	67.98
CIMS	-0.0009	0.0521	-0.0097	5.31	581.91
CUK	-0.0012	0.0645	-0.0914	1.71	70.14
DOK	-0.0031	0.0553	-0.3120	2.96	245.38
ECZ	-0.0020	0.0575	-0.0354	1.59	54.57
EGE	-0.0001	0.0491	0.0178	2.95	192.04
ERE	-0.0017	0.0542	-0.2031	1.43	41.32
GOOD	-0.0011	0.0462	-1.1448	8.85	1993.04
GUN	-0.0006	0.0529	-0.1422	2.24	114.43
KAR	0.0003	0.0503	-0.1919	2.26	109.57
KOCH	-0.0019	0.0504	0.0215	2.27	106.34
KOCY	-0.0023	0.0499	-0.1038	2.19	112.42
OTO	-0.0025	0.0559	-0.4421	3.55	301.47
SAR	-0.0006	0.0502	-0.3894	2.89	213.68
TIB	0.0013	0.0639	0.1171	1.21	30.09
TSI	-0.0007	0.0547	-0.3030	2.68	148.12
TUDD	-0.0024	0.0561	-0.9907	7.73	1453.46
YAS	-0.0018	0.0552	-0.3325	2.02	93.01
Avg 20-Com	-0.0013	0.0550	-0.2602	3.03	315.64

Note. Critical value at 5% significant. for 504 observations is 5.46 for Jarque-Bera Normality test. Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.8

Normality Test for daily *US$ adjusted* returns of ISE1988-1995

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	0.0000	0.0334	-0.4497	4.45	2347.80
ARC	0.0006	0.0440	-0.1845	2.75	661.31
BAG	-0.0001	0.0479	-0.0531	1.00	99.64
CEL	0.0000	0.0520	0.0606	2.82	670.47
CIMS	0.0003	0.0471	0.0214	2.43	534.27
CUK	0.0004	0.0482	-0.0069	2.49	514.74
DOK	-0.0001	0.0483	-0.0704	1.66	282.87
ECZ	0.0011	0.0486	-0.0196	1.26	155.38
EGE	0.0021	0.0440	-0.0219	1.71	264.50
ERE	0.0006	0.0468	-0.0207	1.22	156.98
GOOD	0.0002	0.0459	-0.1816	2.66	689.65
GUN	0.0011	0.0469	-0.1084	1.33	166.48
KAR	0.0005	0.0439	-0.0468	2.56	534.10
KOCH	0.0007	0.0445	0.0330	1.40	184.47
KOCY	0.0006	0.0443	-0.0053	1.62	237.93
OTO	0.0006	0.0485	-0.1656	1.85	322.01
SAR	0.0007	0.0429	-0.1301	2.08	410.91
TIB	0.0011	0.0518	0.1022	1.09	107.11
TSI	0.0001	0.0487	-0.1249	1.72	254.83
TUDD	-0.0001	0.0468	-0.4524	4.80	2175.89
YAS	0.0006	0.0494	-0.0428	1.12	111.42
Avg 20-Com	0.0005	0.0464	-0.0889	2.10	518.23

Note. Critical value at 5% significant for 2002 observations is 5.99 for Jarque-Bera Normality test. Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.9

Normality Test for daily *inflation adjusted* returns of ISE 1988-1990

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	0.0000	0.0301	-0.1065	1.18	51.52
ARC	0.0011	0.0417	-0.0414	0.43	7.52
BAG	0.0002	0.0435	-0.0777	0.10	*0.25
CEL	0.0000	0.0400	0.0519	0.57	11.39
CIMS	-0.0005	0.0467	0.0753	0.12	*3.39
CUK	0.0009	0.0395	0.1239	1.05	35.83
DOK	-0.0005	0.0454	0.0405	0.01	*0.53
ECZ	0.0040	0.0439	0.0160	0.49	9.26
EGE	0.0028	0.0426	-0.0436	0.32	*4.43
ERE	0.0017	0.0415	0.0334	0.70	27.43
GOOD	-0.0017	0.0462	0.0061	0.05	*0.70
GUN	0.0011	0.0444	-0.0874	0.42	9.02
KAR	-0.0003	0.0376	0.0382	0.72	16.35
KOCH	0.0018	0.0432	-0.0099	0.21	*2.40
KOCY	0.0012	0.0412	0.0016	0.93	27.63
OTO	0.0002	0.0447	0.0101	0.01	*0.60
SAR	0.0009	0.0399	-0.0397	0.62	14.54
TIB	0.0014	0.0444	0.1145	0.42	11.88
TSI	-0.0009	0.0459	-0.1088	0.95	33.85
TUDD	-0.0007	0.0415	-0.0269	0.62	20.25
YAS	0.0009	0.0427	0.2106	0.31	8.32
Avg 20-Com	0.0007	0.0428	0.0143	0.45	17.94

Note. Critical value at 5% significant. for 754 observations is 5.46 for Jarque-Bera Normality test. Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.10

Normality Test for daily *inflation adjusted* returns of ISE 1991-1993

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	0.0004	0.0285	0.2118	1.67	87.39
ARC	0.0016	0.0358	0.4364	0.91	46.64
BAG	0.0001	0.0436	0.1533	0.49	9.53
CEL	0.0005	0.0429	0.3517	0.47	19.38
CIMS	0.0014	0.0410	0.1639	0.80	22.86
CUK	0.0006	0.0403	0.3597	1.03	47.40
DOK	0.0018	0.0425	0.2062	0.31	7.00
ECZ	-0.0002	0.0430	0.1950	0.34	7.48
EGE	0.0023	0.0385	0.1036	0.87	24.72
ERE	0.0004	0.0430	0.2466	0.49	12.50
GOOD	0.0024	0.0423	0.2573	0.47	14.65
GUN	0.0018	0.0421	0.0235	0.48	9.01
KAR	0.0010	0.0413	0.3548	1.03	46.14
KOCH	0.0009	0.0384	0.3627	0.61	25.55
KOCY	0.0015	0.0399	0.2109	0.45	7.22
OTO	0.0026	0.0436	0.0856	0.26	*2.48
SAR	0.0010	0.0372	0.2963	0.83	24.89
TIB	0.0003	0.0478	0.1433	0.11	1.25
TSI	0.0011	0.0444	0.1788	0.72	19.47
TUDD	0.0015	0.0418	0.2816	0.83	30.69
YAS	0.0015	0.0489	0.2102	-0.04	4.51
Avg 20-Com	0.0012	0.0419	0.2311	0.57	20.05

Note. Critical value at 5% significant. for 744 observations is 5.46 for Jarque-Bera Normality test. Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.11

Normality Test for daily *inflation adjusted* returns of ISE 1994-1995

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	-0.0014	0.0314	-0.2678	0.95	18.40
ARC	-0.0022	0.0471	-0.2205	1.09	37.47
BAG	-0.0015	0.0519	0.0401	0.49	6.65
CEL	-0.0013	0.0678	0.1719	1.20	29.31
CIMS	-0.0008	0.0459	0.7302	3.11	231.44
CUK	-0.0011	0.0610	0.2644	1.31	40.55
DOK	-0.0030	0.0504	0.1530	1.03	24.39
ECZ	-0.0019	0.0534	0.2067	0.71	15.18
EGE	0.0000	0.0445	0.2690	1.13	33.84
ERE	-0.0016	0.0501	0.0030	0.34	*3.39
GOOD	-0.0010	0.0396	0.0280	1.93	74.42
GUN	-0.0005	0.0485	-0.0431	0.76	20.51
KAR	0.0003	0.0455	0.1852	0.52	8.63
KOCH	-0.0019	0.0457	0.2896	0.93	18.87
KOCY	-0.0022	0.0462	0.0696	0.66	11.25
OTO	-0.0025	0.0504	0.0773	2.40	128.78
SAR	-0.0006	0.0438	0.0190	0.72	11.66
TIB	0.0013	0.0590	0.4311	0.56	14.21
TSI	-0.0006	0.0495	-0.0265	1.18	27.06
TUDD	-0.0023	0.0503	0.0151	0.65	7.43
YAS	-0.0017	0.0500	0.0161	0.18	*0.60
Avg 20-Com	-0.0013	0.0500	0.1340	1.04	41.20

Note. Critical value at 5% significant. for 504 observations is 5.46 for Jarque-Bera Normality test.
Companies for which the null hypothesis of normality is not rejected are indicated by * .

TABLE 3.12

Normality Test for daily *inflation adjusted* returns of ISE 1988-1995

	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera
ISE-INDEX	-0.0002	0.0298	-0.0560	1.29	134.04
ARC	0.0005	0.0411	-0.0156	1.00	88.55
BAG	-0.0002	0.0458	0.0309	0.46	21.40
CEL	-0.0001	0.0494	0.1869	2.02	335.73
CIMS	0.0001	0.0444	0.2744	1.17	128.07
CUK	0.0003	0.0461	0.2485	1.98	324.38
DOK	-0.0003	0.0457	0.1115	0.51	28.34
ECZ	0.0010	0.0462	0.1240	0.64	49.78
EGE	0.0019	0.0416	0.0897	0.75	53.00
ERE	0.0004	0.0444	0.0813	0.57	37.36
GOOD	-0.0271	0.0019	0.0914	0.59	34.47
GUN	0.0010	0.0446	-0.0459	0.59	43.00
KAR	0.0004	0.0411	0.2109	0.84	72.50
KOCH	0.0005	0.0422	0.1826	0.60	36.01
KOCY	0.0004	0.0421	0.0770	0.74	44.34
OTO	0.0004	0.0459	0.0419	0.99	92.32
SAR	0.0005	0.0400	0.0744	0.77	51.72
TIB	0.0010	0.0497	0.2610	0.59	40.07
TSI	-0.0001	0.0463	0.0075	0.98	81.81
TUDD	-0.0003	0.0440	0.0721	0.81	54.71
YAS	0.0005	0.0470	0.1479	0.18	9.76
Avg 20-Com	-0.0010	0.0425	0.1126	0.84	81.37

Note. Critical value at 5% significant for 2002 observations is 5.99 for Jarque-Bera Normality test.
Companies for which the null hypothesis of normality is not rejected are indicated by * .

CHAPTER FOUR:

LITERATURE REVIEW OF EFFICIENT MARKET HYPOTHESIS

4.1 INTRODUCTION

The efficient market hypothesis is that all current information is efficiently incorporated in the current stock prices, so that returns should not be predictable. In this thesis we are going to perform various test for whether returns behave predictable manner on the Istanbul Stock Exchange. This chapter surveys academic literature review of the efficient market hypothesis.

There have been many tests of this hypothesis. Fama (1991) classifies these as return predictability tests, event study tests and tests for private information. If market returns pass these tests, then - broadly - we can say that the market is respectively either weak, semi-strong, or strong-form efficient, in term of the earlier Fama (1970) classification of degrees of market efficiency.

In this chapter we survey previous work in the US and Turkey. We ask in particular whether returns are predictable, whether the volatility of return is predictable, and whether markets react rationally to publicly announced events.

4.2 LITERATURE REVIEW

4.2.1 Introduction

In short, the efficient market hypothesis is that security prices fully reflect all available information. Abstracting from the small daily drift in prices necessary to produce the requited annual return on any share, this implies that daily price changes should be unpredictable, and follow a random walk.

The costly information and joint-hypothesis problems have been given much attention to evaluate EMH. Extreme versions of EMH assume that information and trading cost are always zero (Grossman and Stiglitz 1980). A more reasonable version of the EMH says, "prices reflect information to point where the marginal benefits of acting on information (the point to be made) do not exceed the marginal cost" Jensen (1978).

The joint-hypothesis problem is a serious obstacle to inferences about market efficiency. To test for market efficiency we compare actual returns against a benchmark, an asset pricing model, for example the CAPM developed by Sharp(1964), Linter (1965), and Black (1972) (hereafter the SLB model). However, if the asset pricing model we use is not valid, then we are liable to conclude that the market is inefficient even if it is really efficient. Fore example, many stock market anomalies have been found in recent years. Unfortunately there is always the possibility there are benchmark for market efficiency is wrong. So we can never be certain that these anomalies represent opportunities for earning abnormal risk-adjusted returns.

4.2.2 Return Predictability

Return predictability is the ability to forecast stock returns using historical data. In the 1970 definition of weak-form efficiency, Fama allowed for usage of historical prices only. If the market was efficient in the sense of weak form, one then could not expect to earn abnormal returns on the predictions based on past prices. The Fama (1991) definition of predictability allowed for the use of historical information other than prices. Variables, which in practice help predict stock returns are the dividend yield, company, size, price/earnings ratio and various term-structure variables. In the next section we discuss the evidence of predictability using historical data. The following section presents the performance of cross-sectional models.

4.2.2.1 Time-Varying Expected Returns:

The pre-1970 literature on market efficiency tests often found suggestive evidence that daily, weekly, and monthly returns are predictable from past returns. [See Fama (1965), and Fisher (1966).] But the statistical power of these tests was very low, and the amount of variance of return explained by variation in expected return was very small. Efficient markets with constant expected return were accepted as a good model for stock price behaviour.

Subsequently, Lo and MacKinlay (1988) and Conrad and Kaul (1988) found that there is a positive autocorrelation between weekly returns on portfolio and size (stock prices times shares outstanding). The autocorrelation is stronger for portfolios of small stocks. However returns are more predictable for small-stock portfolios because of portfolios have lower variance due to diversification.

French and Roll (1986) find that stock prices are more variable when the market is open rather than overnight non-trading hours and weekend non-trading hours. They related this noise to trading by uninformed investors, and the pricing errors due to noise trading are eventually reversed. This reversion process causes daily stock returns to be negatively autocorrelated. Roll (1984) concluded that noise trading results in substantial market inefficiency.

Considering the above evidence on short-term stock returns we reject the hypothesis of an efficient market and conclude that it is possible to predict stock returns based on past prices. However, the predictable component of daily and weekly expected return is only a small part of variance in returns, and it is therefore difficult or impossible to make abnormal returns from trading on short-term forecasts. The predictable component of stock returns does, however, seem to increase with the time horizon.

The autocorrelation in daily and weekly returns is important evidence against the joint hypothesis of market efficiency and constant expected returns Fama (1991). Shiller (1984) and Summers (1986) argue that if prices follows first order autoregressive (AR1) processes, then returns will look like random walks for short time horizons. With such a relationship, short-horizon price changes will appear to be permanent, and deviations away from the fundamental value are temporary. Stambaugh (1986) points out that the long swings away from the fundamental value, such as Shiller-Summers found imply strong negative autocorrelation for long horizon returns. Fama and French (1988a) find that, although there exist a strong negative autocorrelation in long-horizon returns it turns out to have a low explanatory power. They also point out that the deviations away from fundamental values can be caused by either irrational bubbles or time-varying expected returns.

DeBondt and Thaler (1985,1987) found that NYSE shares with extremely low returns over a 3 to 5 year period tend to have greater returns in the following periods, especially in January of following years. Similarly, winner shares have low returns relative to the market in following periods. They argue that this relationship is due to overreaction to extremely good or bad news about companies. However, Chan (1988), Ball and Kothari (1989) and Zarrowin (1989) argue that the winner-loser results are due to failure to risk-adjust returns.

The univariate prediction models of Fama and French (1988a) and Poterba and Summers (1988) have low statistical power. An autocorrelation is the slope in a regression of the current return on a past return. Since variation over time in expected returns is a small part of the variation in actual returns, tests based on autocorrelation models will lack power. One can increase the power of the tests by identifying less noisy proxies for expected returns than past returns.

Bodie (1976), Nelson (1976), Fama and Schwert (1977) found that inflation and interest rates could predict stock returns. However, the short horizon explanatory powers of these tests were small. More recent evidence show that other variables can be used to predict returns for longer horizons Rozeff (1984), Shiller (1984), and Fama and French (1988b) use dividend yield to predict stock returns, and Campbell and Shiller (1988b) use earnings/price ratios to predict returns. One very interesting discovery made in this research is that the power of the test increase as the horizon is increased.

Fama (1991) argues that predictability of stock returns from dividend yields or earning ratio is not in itself evidence for or against market efficiency. Some other information is needed to judge whether the forecast power the dividend yields is the result of rational variation in expected returns, or of irrational bubbles. Fama and French (1988b) find that low dividend yields imply low expected returns, but there is no evidence that its bursting bubbles, that is negative expected returns. Moreover, Fama and French (1989) found systematic patterns in the returns predictions across securities, indicating higher returns for risky securities, that is rational. The links between time varying expected returns and business conditions and prediction of asset pricing models is taking important part of the implications of return predictability for market efficiency.

LeRoy and Porter (1981) and Shiller (1979,1981) pioneered research in the area of volatility tests of market efficiency. The early tests assumed that expected returns are constant and the variations in stock prices are driven solely by shocks to expected dividends. Expected stock returns and bond returns can be predicted with expected inflation rates, interest rates, and other term-structure variables. Fama (1991), concludes that the volatility tests are not informative about market efficiency, but they are useful in showing that returns vary though time.

One "anomaly" that has attracted many researchers' attention in the last decade is return seasonality. French (1980) found that returns are lower on Mondays than on the other days of the week, and Harris (1986) provides evidence that most of the daily return of shares is earned at the beginning and end of the day. The strongest and bestdocumented seasonality is the January effect (Keim 1983). Stock returns, especially on small stocks, are on average higher in January than in any other months. Fama (1991) points out that these seasonal effects are not much of an embarrassment for the efficient market hypothesis. The tests above are of statistical significance, but when adjusted for trading costs and bid-ask spreads there seem to be few opportunities for investors to make abnormal profits. For instance, smaller stocks seem to offer better returns in January than their larger counterpart. However, the bid-ask spreads for these stocks are also much larger.

4.2.2.2. Cross-Sectional Return Predictability

Market efficiency needs to be tested conditional on an asset-pricing model, or asset-pricing models are tested conditional on efficiency. Cross-sectional return predictability testing, an asset-pricing model and an anomaly jointly. The tests presented earlier analyse returns on individual stocks only. Cross-sectional studies consider a set of stocks simultaneously.

The early 1970s extensive testing of the Sharpe-Lintner-Black (SLB) Capital Asset Pricing Model gives support to the validity of the model Black, Jensen, and Scholes (1972), Blume and Friend (1973), Fama and MacBeth (1973). These early researches agree that: 1. Expected returns are a positive linear function of beta (the measure of market risk), and 2. Beta is the only risk measure needed to explain the cross-section of expected return. However, low beta stocks tended to have higher return than predicted by the model, and high beta stocks showed lower returns than predicted by the SLB model. Following this research, Roll (1977) attacked the model and the tests on theoretical grounds. The proxies for the market used in the tests contain far fewer assets than called for by the model, therefore we will never be sure that the proxy used is mean-variance efficient (Markowitz 1959) when compared with all the asset in the universe. The usage of a mean-variance efficient market is a central assumption of the CAPM.

In addition to beta, other variables can explain stock returns. Earnings/price ratio, size, book-to-market value and leverage can explain returns that beta is not able to explain (Basu 1977,1983, Banz 1981, Bhandari 1988, and Fama and French 1992). Since most of these extra-market factors are effected by price, they are somewhat interlinked. Book-to-market value seems to be the most important SLB anomaly, followed by size (Fama and French 1992). Not only have new pricing factors entered the picture, but also beta seems to have lost much of the explanatory power found in the early research. Indeed, Fama and French (1992) find the explanatory power of beta to be very low.

The discovery of the extra-beta pricing factors is not a sign of market inefficiency, rather is indicates misspecification in the SLB capital asset pricing model. But, again, we face the problem of the joint hypothesis. We cannot say whether the existence of "anomalies" is due to model specifications or persistent mispricing of securities.

When an anomaly persists over longer time periods ones is tempted to conclude that the pricing model is misspecified (Fama 1991).

The SLB model is only allows for one factor compeer to the cross-section of expected returns on securities and portfolios, namely the market portfolios. The multifactor model of Merton (1973) and Ross (1976), allow for any number of returns generating factors. One approach based on the assumption of no arbitrage opportunities is Ross' (1976) Arbitrage Pricing Theory (APT). This method first extracts a set of factors using factor analysis, these factors are thentested to determinate whether they can explain security returns. An alternative approach used by Chen, Roll and Ross (1986) are to look for economic variables that are correlated with stock returns and then test whether they can describe cross-sectional returns. They found the most powerful variables to be the growth rate of industrial production and the corporate bond spread. Important, but of less power are unexpected inflation and term spread on government bonds. When adding beta to the four factors above the power of the model does not increase significantly. Hence, we might conclude that the multifactor model is superior to the SLB model.

Although the approach by Chen, Roll, and Ross, (1986) is promising for explaining returns it might be sensitive to the sample used. Fama (1991) points out that the above model has not been tested extensively, and the factors identified can therefore be of a temporary character. Not until we have seen further testing of the model can be fairly certain that we have found the "right " model.

One other model to test asset-pricing is the consumption based asset-pricing models of Rubinstein (1976), Lucas (1978), and Breeden (1979) that is the most elegant of the available intertemporal asset-pricing models. Breeden's (1979) version of model finds a positive linear relationship between the expected returns of securities and their consumption betas. A consumption beta is defined as the slope in the regression of its return on the growth rate of per capita consumption. The model needs strong assumptions about taste, that is the time-additive utility for consumption and constant relative risk aversion. Breeden, Gibbons, and Litzenberger (1989) find that the relationship between the consumption beta and returns is linear and positive. These results have also been supported by Wheatley (1988a,b). Fama (1991) compares the above evidence to the evidence of the CAPM in the early 1970s in the sense that it has not been thoroughly confronted with anomalies and other competing asset pricing models. Mankiw and Shàpiro (1986) found that the consumption beta has no explanatory power when added to the SLB beta, and Chen, Roll, and Ross (1986) found the consumption beta added little power to their multifactor model.

The majority of evidence is therefore against the consumption based CAPM. Chen, Roll and Ross (1986) and Mankiw and Shapiro (1986) find that the consumption beta has low explanatory power when included in other models. The multifactor model has better performance. Chen, Roll and Ross (1986) show that such a model outperforms both the SLB and Consumption CAPM. It helps to explain the size anomaly of the SLB However, these results may be sensitive to the sample used in estimating the multifactor model.

4.2.3 Event Studies

Over the last two decades we have been overwhelmed with empirical research on the impact of events and announcement on stock prices. Miller and Scholes (1978) find that dividend policy is irrelevant or dividends are taxed at higher rate than capital gains however dividends are bed news. Jensen (1986) explained why dividend increases are good news for stock prices. Asquith and Mullins (1986), Masulin and Korwar (1986) found that new issues of common stock are bed news for stock prices. But others find that stock issues are good news because they signal that firm's doing very well, managers issue stock when it is overvalued (Myers and Mailuf 1984). Some other researches are look as share redemption through tenders and open-market repurchase (Dann 1981 and Vermaelen 1981), stock splits (Fama, Fisher, Jensen, and Roll 1969), and financing decisions (Smith 1986).

Event studies do not suffer from the problem of the joint hypothesis. Since testing is concentrated on a few days around an announcement, errors in the calculation of expected returns will have little impact on inferences. For example, if expected annual return is 10%, with 250 trading days this will give a 0.04% daily return. When compared to an abnormal return of 15% in the three days around announcement of a bid for a take-over, small miscalculations in expected return will not change the conclusion that the returns are higher around the announcement day (Brown and Warner 1985).

4.2.4 Tests for Private Information.

The strong form of market efficiency assumes that available information, public and private, is incorporated in security prices. Fama (1991) looks at three types of private information: 1. Insider trading, 2. Security analysis, and 3. Professional portfolio management.

In the early study Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973) thought SLB model good to be used in tests for market efficiency instead of informal models like the market model and the constant expected returns model. Jaffe (1974) find that stock market is not efficient, in the sense that insiders have information that is not reflected in stock prices. A later study by Seyhun (1986) confirms insider profit from their trades, but he does not confirm that outsiders can profit by acting on insider trading, because Jaffe used SLB model for expected return to explain finding of outsider profits.

The Value Line Investment Survey's ability to rank (ex ante) performance of shares has attracted the attention of research. Shares ranked into top category have on average higher risk and size-adjusted returns (Black (1973), and Copeland and Mayers (1982)). Stickel (1985) find that Value Line has information not reflected in prices, also he argues the information in Value Line ratings is strongest for small stocks. Information on small stocks leads to large change in prices, including public information announcements like Value Line rank changes. Lloyds-Davies and Canes (1978), and LIU, Smith, and Syed (1990) find that The WallStreet Journal's "Heard on the Street" column cause prices to change on the announcement day, rather like Value Line rank changes. On the other hand, Hulbert (1990) reports that Value Line Centurion Fund, which is based on the top ranked group, had a lower return than the Wilshire 5000 Index over the period 1984 to mid-1990. This is, evidence that the market is strongly efficient, even though it might be possible to make profits on paper (e.g. through computer simulation) it is not possible to carry it out in practice.

Fama considered professional portfolio management in the third group of tests for private information. Jensen (1968, 1969) found that mutual funds were not able to beat the performance of a passive fund. Hence, Jensen conclude that the fund managers considered did not have inside information. These findings have been supported by later research by Elton, Gruber, Das, and Hklarka (1991). But Henriksson (1984) finds that fun managers have private information to cover the expenses and management fees they charge investors. It has been accused to SLB used that has systematic problems explaining expected returns that can affect estimate of abnormal returns. e.g. size, leverage, earning ratio, and book-to-market equity effects.

4.2.5 Efficiency Test on the Emerging Capital Markets.

In contrast to the number of studies on developed stock exchange, a small amount of work has been done on the emerging capital markets. Internationally increasing demand for investment on the emerging capital markets and understanding importance of stock exchange by less developed countries has led to the more research on emerging capital markets.

Errunza and Rosenberg (1982) find that a number of emerging capital markets are reasonably well-developed and their risk-return trade-off is lower in emerging markets than developed markets. Dickinson and Muragu (1994) studied the Nairobi stock exchange and found no strong evidence against the weak form EMH.

A few empirical tests about efficiency have been done specifically on the Istanbul Stock Exchange.

Alpaslan (1989) finds some weak-form inefficiency on ISE. Cadirci (1990) finds that ISE is inefficient at semi-strong level. Her findings are that the adjustment process is slow, and positive cumulative average abnormal returns are observed after stock splits, right issues, and dividend payment events.

Ozmen (1992) worked on anomalies on ISE. He found that Thursday shows the lowest return on stocks, Fridays the highest. But those works cover only 3-4 years right after the ISE foundation date, which is a very fragile time period. Therefore the results obtained in the above works might not be robust. Aybar (1992) also tested the day of the week effect on ISE. His sample covers the period from 2/1/1988 to 31/12/1991. He finds that ISE index returns do'not show significant negative returns on Mondays.

Kiymaz (1997) analyse initial and long-run returns for the performance of Turkish IPOs. For 138 firms listed and traded on the Istanbul Stock during the period of 1990 - 1995, he find that similar to previous international evidence, the Turkish IPOs are under-priced on initial trading day on average by 13.6%. The investigation of factors influencing the initial performance reveals that the size of issuer, the rising market between the fixing of the offer price and the first trading day, the post- listing standard deviation of market adjusted returns during the first ten trading days, and the self-issued offerings are highly significant determinants of underpricing. Furthermore, the fraction of shares offered to public is found to be a factor weakly influencing the initial underpricing. In contrast to many other studies of IPOs, the long-run average abnormal returns are found to be 44.1% at the end of 36 months. This results show that initial underpricing continues to exist even in the long-run. The factors influencing these returns include the size of issuer, post-listing return variation, self-issuance and privatisation variables.

Ozer (1997) provided evidence for the presence and reasons of abnormal returns in the IPO market in Istanbul Stock Exchange (ISE), She analysed 89 IPOs of common stocks that have been offered to public between November 1989 and April 1994. There are significant excess returns for the first three days of trading and the average market adjusted returns of IPOs on the first day is 12.24%. Relationship between the market and the IPOs establish after the third day of trading, while there appears to be no excess returns beyond this date. She concluded that reasons of abnormal returns in developed markets and characteristics of developing markets, information asymmetry is suggested as a critical reason for the presence of abnormal returns. IPOs in which the underwriter and the issuer are within the same group of companies represent cases where there can be no information asymmetry, thus no expectation of underpricing. Contrary to expectations, significantly higher excess returns in IPOs offered by related underwriters and inability to differentiate between IPOs of related and independent underwriters on other variables that can influence initial returns might suggest intentional underpricing in IPOs offered by related underwriters, where there can be no information asymmetry but possibility of strategic alliance between the underwriter and issuer. In fact, the presence of a relationship between the underwriter and the issuer seems to be the most significant factor in explaining abnormal returns in the IPO market in ISE.

Metin, Muradoglu, and Argac, (1997) test the efficiency of an emerging market (ISE) through time with respect to monetary variables by using the cointegration technique. The database is set-up at daily frequency of variables that are customarily used by the financial media as the determinants of stock investments and the cointegration technique enables us to consider changes in long-run steady-state properties of the equilibrium relationship between the non-stationary stock prices and monetary variables. The findings of this study indicate that overall results should not be used in formulating investment strategies because they can be misleading in the sense that they may indicate that a market is efficient when in fact it is not. Also, investors should be aware that the variables that explain stock prices might change through time. In the case of ISE, as the market became more mature, the influence of monetary expansion and interest rates disappeared and foreign currency prices regained their expected significance.

Annaert, Jan and Konuralp (1997) have research on the day-of-the-week effect on the Istanbul stock exchange. They use cross-sectional covariation test for fourteen liquid individual stocks and ISE index term 1990-96. They find evidence for a day-of-the-week effect in the Istanbul stock market, both for the ISE Index and fourteen individual stocks. They find that the lowest returns appeared on Tuesday and the highest on Friday for the ISE index. For the individual stocks the effect is less clear. Although for nine stocks out of fourteen the pattern was similar, the remaining five stocks experienced their lowest returns on Monday and highest on Wednesday.

When the period is divided into two subperiods, both univariate and multivariate test procedures indicate that the day-of-the-week effect is significant in the first subperiod, but that it disappears in the later subperiod.

Guner, and Onder (1997) They find that stock prices are more volatile during trading hours than non-trading hours. They examined the volatility in stock returns during trading and non-trading hours using returns on more than 200 stocks listed on the ISE-National Market. For each stock, the daily opening and closing prices are obtained for the period from January 1995 to February 1997. Open-to-close, close-to-open, open-to-open and close-to-close returns and the volatility of these returns are calculated. During their sample period, the ISE operates two trading sessions with a two-hour break between the sessions. The preliminary analysis shows that the open-to-close per hour volatility is 13 times higher than the close-to-open per hour volatility when volatility during the break is assumed to be same as the volatility during trading hours. This ratio increases to 17 when the volatility during the break is assumed to be the same as the volatility during the non-trading hours. The volatility of returns during trading and non-trading hours in size quintiles and volume quintiles are also examined. The higher volatility during trading hours is explained with information-related trade or noise using autocorrelation of returns. However, incorporation of information into prices might take longer, resulting in lower volatility during trading hours. On the other hand, because of low capitalisation of the market and the existence of large institutional investors, it might be easier to manipulate prices, causing higher volatility during trading hours.

4.3 CONCLUSION

Over the last three decades an extensive amount of empirical research has been undertaken to investigate stock market behaviour in developed and developing countries. Not surprisingly, the evidence shows that markets are more inefficient in developing countries.

In this Chapter we have reviewed some key studies, and looked at the empirical evidence relating specifically to the Turkish market.

There is only weak evidence of predictable variation in daily returns in developed markets. Some researchers do, however, claim to have uncovered serial correlation in high frequency returns and a number of "calendar" anomalies, in particular "day-of-the-week" effects. There is conflicting evidence on whether these effects are present in the Turkish market, and what evidence exists comes from the early years of the market when trading volumes were low and the market was insulated from international investors. It is clearly worth revisiting this hypothesis using more recent data, and this is done in Chapters 5 and 7 below.

In developed markets there is evidence of anomalous returns behaviour around major events affecting share values – stock splits, dividend announcements, IPOs. These studies have been replicated by other researchers on the Turkish market, and all conventional anomalies appear to be present in the ISE data. We extend this research in Chapter 9 below, where we look at a rather different and uniquely Turkish event – the market reaction to stock splits triggered by the effects of inflation on company balance sheets.

CHAPTER FIVE:

TESTING RETURN PREDICTABILITY ON THE ISTANBUL STOCK EXCHANGE.

5.1. INTRODUCTION

The purpose of this Chapter is to analyse serial dependencies in the return series. The serial dependence test is informative for the random walk behaviour of the stock returns and market structure. Evidence of serial correlation in security returns might be evidence of market inefficiency. The rejection of random walk hypothesis is not sufficient to reject the EMH, but it indicates the existence of patterns in price adjustment process.

Random walk theory involves separate hypotheses that the successive price changes are independent, and price changes conform to some probability distribution. Independence of the returns implies lack of any detectable cycle or any other pattern. Fama (1965) points out that random walk can not be an accurate description of reality, since it is almost impossible to find a time series that is characterised by a perfect dependence. He suggests that for practical purposes independence is acceptable as long as dependence in the series does not exceed some minimum acceptable level, which would depend on the problem at hand. From market efficiency point of view this acceptable dependency is considered to be the level which cannot be exploited to derive excess returns over a simple buy and hold strategy.

The random walk hypothesis and the market efficiency are linked through the independence hypothesis. Any deviation from independence implies exploitable cycles or patterns and absence of market mechanisms producing independent price changes therefore informationally inefficient markets.

5.2. THE SERIAL CORRELATION TEST.

The serial correlation test measures the correlation coefficient between a series, and lagged values of the same series. A significant positive serial correlation indicates the presence of trends and slow adjustment to new information. The presence of negative serial correlation documents the existence of more reversals than might occur randomly. Series that are truly random (walks) will have zero serial correlation.

Data for this part of the study covers the period from 4/1/1988 to 29/12/95. The period is sub divided into three periods, 4/1/1988-28/12/1990, 2/1/1991-31/12/1993, and 3/1/1994-29/12/1995. The daily adjusted return series, US $ adjusted return series and inflation adjusted return series data have been used for 20 sample companies as well as for the ISE Index. The autocorrelation coefficients of each series are calculated by using Box-Jenkins procedure in the TSP software.

The hypotheses tested are that the correlation coefficients of successive daily price returns on the ISE at lag k (k = 1, ... 30) are zero. To test the hypotheses the sample serial correlation coefficients, r_k, were computed for each company across 30 lags. The standard error of the sample serial correlation coefficient, r_k, may be computed as

$$\sigma(r_k) = 1/\sqrt{(N - k)}$$

where N is the sample size (Fama 1965, Cooper 1982).

The individual coefficients are then tested by examining whether their values r_k are significantly different from zero by comparing r_k with the two-tailed 95% critical values $|\sigma|$ times ±1.96 . If $|r_k| \leq |1.96*\sigma|$, then r_k is not significantly different from zero. If $|r_k| > |1.96*\sigma|$, then it is significantly different from zero, which means that there exists a linear dependence between the return.

The computed r_k is (1.96*0.0364=0.071), (1.96*0.0367=0.072), (1.96*0.0446=0.087), and (1.96*0.0224=0.044) for period 88-90, 91-93, 94-95, and 88-95 respectively.

5.2.1. Empirical Results.

The overall results for the serial correlation coefficients at lag 1 for daily returns and the number of significant coefficient at the five per cent level for overall period 1988-95 is presented in Tables 5.1-5.12.

Results show that AR(1) correlation coefficient for daily returns for whole term and sub period are statistically significantly different from zero at a five percent level for ISE index. This holds for $ base data and inflation adjusted data, except $ data for 91-93, due to exchange rate volatility. The serial correlation coefficients are positive. Agreement in signs among the coefficients for index may indicate that there is a constant pattern of dependence. The positiveness of serial correlation coefficients indicates the presence of trends and slow adjustment to new information.

First order serial correlation coefficient for the 20 sample companies are also statistically significantly different from zero for 88-95 period. This again true for $ adjusted data and inflation adjusted data for same period. In one sub period, some companies shows independence but it disappears in the other sub periods.

The result at lag 1 may suggest serial independence or dependence, but it is obviously desirable to extend our investigation to lags other than one. We have extended the serial coefficients to 30 lags, consistent with Cooper (1982).

The Q-statistic has been used for testing dependency of the series whether serially correlated or not. Under the null hypothesis that all serial coefficients are zero (H_0: $p_1 = p_2 = ... = p_k = 0$), the Q-statistic ($Q_k$) is given by

$$Q_k = N\sum_{j=1}^{k} r_j^2$$

where N is the number of coefficients and r_j is the sample serial correlation coefficient at lag j. The Q-statistic is distributed as Chi-square $\chi^2(k)$. The null hypothesis of independence is rejected if Q is greater than χ^2 with k degrees of freedom at the corresponding significance level (Taylor 1986).

The Q-statistics computed for 5 lags, 15 lags and 30 lags for sample companies and ISE index. The Q-statistics is simply computing jointly all of the autocorrelation up to these points. The coefficient is statistically significantly different from zero at a five percent level If $Q_5>11.1$, $Q_{15}>25$, and $Q_{30} > 43.77$.

We find that the Q-statistics for the ISE-Index are statistically significant at all 5 lags, 15 lags and 30 lags for overall period and sub period. Only the 91-93 period for $ adjusted data shows independence. Its again due to extreme exchange rate volatility. The Q-statistics for the sample of 20 companies statistically significant for lags 5, lags 15 and for lags 30 for period 88-95 for Turkish lira returns, $ adjusted returns and inflation adjusted returns data. In sub periods a few companies show independence but disappear one other term. Most of the companies in the 91-93 period with $ base data show statistically insignificant Q-statistics at all 5 lags, 15 lags and

30. It can be explained by the fact that the Turkish monetary authorities followed under--devaluated foreign currency policy in this sub term.

The empirical results of the study suggest that the majority of the sample returns exhibit significant least first order serial dependence. This leads to rejection of the random walk model and thus rejection of weak form efficient market hypothesis for the ISE.

5.3. RUNS TEST

The correlation coefficient may be influenced by a few extreme observations. In order to correct this possible bias we use a non-parametric runs test. The test was conducted to provide evidence on the randomness of price series. The hypothesis is that the successive price returns of company's shares on the ISE were random. It was tested by examining the relationship between the numbers of runs observed in the series and the expected runs.

If the assumption holds that the sample proportion of positive and negative changes are good estimators of the population proportions, and the independence hypothesis applies to the sequence of price changes, the total expected number of runs, m, is given by:

$$m = \left\{ N(N+1) - \sum_{i=1}^{3} n_i^2 \right\} \Big/ N$$

where the N is the total number of price changes and n_i(i= 1,2,3) are the numbers of price changes of each kind (positive, negative, and no-change). The standard error of m is

$$\sigma_m = \left\{ \frac{\sum_{i=1}^{3} n_i^2 \left[\sum_{i=1}^{3} n_i^2 + N(N+1) \right] - 2N \sum_{i=1}^{3} n_i^3 - N^3}{N^2(N-1)} \right\}^{1/2}$$

For large N the sampling distribution of m is approximately normal, and the standardised variable k can then be calculated from the formula:

$$k = \frac{r + \frac{1}{2} - m}{\sigma_m}$$

where r is the actual number of runs, and continuity adjustment requires the addition of 1/2 to r. The computed value of k is significant at the five per cent level if it lies beyond its critical values of ± 1.96. Wherever k ≥ |1.96|, then the sign movements series are not randomly distributed and a tendency exists for a movement in the direction to be succeeded by a further movement in the same direction. In such cases, the random walk hypothesis is rejected, otherwise, it is accepted (Wong and Kwong 1984).

5.3.1. Empirical Results.

We carried out run tests for daily returns calculated in the basis of TL, US dollars and adjusted for inflation rate. Table 5.13-5.16 presents the results for daily Turkish Lira returns. The results show that the expected numbers of runs exceeds than the actual numbers of runs in all the 20 companies and the ISE index studied for 1988-95 as well as subperiods. All 20 companies and the ISE index produce a negative k (the standardised variable) value. Since all k values are greater than its critical value of |1.96| except three companies in 1994-95, we reject the hypothesis of randomness.

When the returns are expressed in US Dollars or inflation adjusted TL data, one gets the same result for the sample period as well as the subperiods we consider. This finding of serial correlation in the signs of price changes is consistent with the results obtained for the return series themselves in the previous section.

5.4. CONCLUSION

In this chapter we tested weak form efficiency using serial correlation and nonparametric runs tests. The serial dependence test is instructive for the random walk behaviour of the stock returns. Proof of serial correlation in security returns might be evidence of market inefficiency.

The tests all suggest that daily returns on the ISE do not follow a random walk. This is true of both Turkish Lira and US Dollar based indexes. This is in line with results obtained using data from the early years of the Turkish market by Aybar (1992) and Alpaslan (1989).

However, careful reading of the Tables suggests also that the degree of inefficiency in the market is decreasing. For example, the k-statistic testing for the absence of unusual runs is –9.54 for the years 1988-90, but rises to 3.09 in the years 1994-5. While still well below the 95% critical value of –1.96, this does imply a significant lessening in the number of predictable sequences of market falls and rises.

We have repeated these experiments on returns for the 20 leading stocks as well as the overall index. While none passed the runs tests for the years 1988-193, four of the individual share returns did appear random in the years 1994-5. This again suggests a progressive increase in the efficiency of the market.

The evolution of mean returns on the index cannot be explained by a single time series model over the whole period 1988-95, and in subsequent Chapters we investigate in more depth how the process driving returns has changed over time.

We have looked also in this Chapter at serial correlation in absolute returns. Here the evidence is strong and in line with all international findings – volatility persists in the Turkish market in the sense that large movements in the price one day are typically followed by large movements (up or down) on the following and subsequent days. This rationalises our use in Chapters 6, 8 and 9 of the ARCH model to describe volatility on the ISE.

APPENDICES 5 TABLE 5.1

AR(1) Correlatiom Coefficient for Daily Returns of ISE. 1988-1990

$cor[R_t, R_{t-s}]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.319	82.10	96.80	106.00
1 ARC	0.121	18.60	23.90	31.10
2 BAG	0.187	28.70	35.10	46.40
3 CEL	0.056	12.10	20.00	35.40
4 CIMS	0.178	36.50	44.80	54.10
5 CUK	0.119	11.80	19.40	27.70
6 DOK	0.163	24.10	30.30	56.70
7 ECZ	0.229	55.80	65.80	87.30
8 EGE	0.129	22.30	44.10	63.50
9 ERE	0.213	40.40	51.40	61.90
10 GOOD	0.181	29.90	39.30	51.60
11 GUN	0.093	11.70	18.60	30.50
12 KAR	0.038	6.07	22.50	30.00
13 KOCH	0.207	33.90	50.00	60.10
14 KOCY	0.122	12.90	23.40	43.60
15 OTO	0.134	17.70	27.20	38.50
16 SAR	0.134	30.70	42.10	52.20
17 TIB	0.140	20.40	33.30	50.60
18 TSI	0.148	22.30	31.50	47.40
19 TUDD	0.172	24.90	42.00	55.90
20 YAS	0.070	8.79	23.40	41.20
No of significant	18	19	15	13

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.071 for the critical value of the serial correlation of lag one

$cor[|R_t|, |R_{t-s}|]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.362	314	408	507
1 ARC	0.302	233	362	404
2 BAG	0.316	222	280	285
3 CEL	0.296	196	251	269
4 CIMS	0.318	187	241	264
5 CUK	0.301	165	193	213
6 DOK	0.320	208	313	385
7 ECZ	0.310	203	437	583
8 EGE	0.317	279	444	508
9 ERE	0.324	186	221	235
10 GOOD	0.306	309	452	475
11 GUN	0.330	281	392	435
12 KAR	0.396	346	572	697
13 KOCH	0.345	242	317	343
14 KOCY	0.345	331	484	656
15 OTO	0.280	206	270	313
16 SAR	0.280	144	203	226
17 TIB	0.386	389	553	900
18 TSI	0.288	191	279	358
19 TUDD	0.345	277	360	424
20 YAS	0.225	141	281	403
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.071 for the critical value of the serial correlation of lag one

TABLE 5.2

AR(1) Correlatiom Coefficient for Daily Retums of ISE. 1991-1993

$cor[R_t, R_{t-s}]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.119	18.00	31.90	38.20
1 ARC	0.013	2.20	15.20	25.40
2 BAG	0.041	6.14	25.50	42.80
3 CEL	0.070	8.01	17.40	36.80
4 CIMS	0.043	12.80	22.30	31.70
5 CUK	0.106	10.80	12.90	28.70
6 DOK	0.071	5.57	11.30	19.00
7 ECZ	0.146	18.20	32.00	39.90
8 EGE	0.030	4.05	21.20	30.30
9 ERE	0.140	21.60	31.90	57.90
10 GOOD	0.013	2.29	16.40	25.00
11 GUN	0.094	13.20	21.30	38.60
12 KAR	0.009	10.10	20.90	42.00
13 KOCH	0.044	3.90	12.30	19.00
14 KOCY	0.101	9.93	14.20	21.70
15 OTO	0.090	6.07	26.80	32.60
16 SAR	0.142	20.70	29.20	40.90
17 TIB	0.161	23.90	32.90	47.20
18 TSI	0.005	9.35	24.10	34.60
19 TUDD	0.013	7.06	18.80	29.30
20 YAS	0.082	18.00	31.50	36.70
No of significant	10	8	8	2

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.072 for the critical value of the serial correlation of lag one

$cor[|R_t|, |R_{t-s}|]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.164	64	92.9	126
1 ARC	0.261	133	215	249
2 BAG	0.159	36	54.2	60.7
3 CEL	0.192	66.4	81.2	96.7
4 CIMS	0.219	77.3	137	164
5 CUK	0.175	70.4	127	143
6 DOK	0.223	79.3	87.4	107
7 ECZ	0.187	94.5	141	150
8 EGE	0.194	50.6	65.9	78.9
9 ERE	0.272	132	195	287
10 GOOD	0.215	93.3	115	129
11 GUN	0.165	40.5	56.3	82.5
12 KAR	0.237	101	118	130
13 KOCH	0.201	67.7	123	141
14 KOCY	0.269	113	191	254
15 OTO	0.245	146	202	241
16 SAR	0.291	124	155	193
17 TIB	0.222	118	153	165
18 TSI	0.142	46	56.5	63.1
19 TUDD	0.153	58.8	87.9	101
20 YAS	0.190	52.2	65.8	91.6
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.072 for the critical value of the serial correlation of lag one

TABLE 5.3

AR(1) Correlatiom Coefficient for Daily Retums of ISE. 1994-1995

$cor[R_t, R_{t-s}]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.280	40.10	58.10	68.90
1 ARC	0.121	9.06	26.60	56.50
2 BAG	0.064	2.76	10.60	22.50
3 CEL	0.116	11.30	22.80	33.50
4 CIMS	0.027	4.63	19.80	40.60
5 CUK	0.218	28.90	50.80	64.60
6 DOK	0.117	8.89	28.10	42.80
7 ECZ	0.064	5.12	17.90	47.00
8 EGE	0.152	21.90	45.60	55.40
9 ERE	0.170	22.80	32.00	47.90
10 GOOD	0.066	7.52	16.50	52.20
11 GUN	0.132	24.10	47.60	56.10
12 KAR	0.017	11.90	20.70	39.00
13 KOCH	0.139	15.60	30.10	64.00
14 KOCY	0.166	23.20	64.50	91.70
15 OTO	0.153	13.00	26.10	38.20
16 SAR	0.196	23.30	39.20	59.70
17 TIB	0.163	16.10	35.80	48.20
18 TSI	0.143	13.20	23.60	27.80
19 TUDD	0.048	2.13	12.40	36.50
20 YAS	0.069	5.09	25.00	35.20
No of significant	14	13	12	11

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.087 for the critical value of the serial correlation of lag one

$cor[|R_t|, |R_{t-s}|]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.308	246	676	1060
1 ARC	0.235	85.8	193	273
2 BAG	0.264	117	226	355
3 CEL	0.285	82.5	142	159
4 CIMS	0.315	153	171	292
5 CUK	0.340	135	167	201
6 DOK	0.219	56.5	88.4	160
7 ECZ	0.244	185	449	692
8 EGE	0.294	171	337	565
9 ERE	0.311	230	525	829
10 GOOD	0.214	37.8	71.8	87.4
11 GUN	0.311	118	273	420
12 KAR	0.255	157	335	464
13 KOCH	0.260	151	468	807
14 KOCY	0.289	224	557	836
15 OTO	0.203	56.8	97.1	139
16 SAR	0.398	260	770	1120
17 TIB	0.270	87.2	142	188
18 TSI	0.262	141	351	568
19 TUDD	0.173	23	41.8	70.9
20 YAS	0.199	124	344	587
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.087 for the critical value of the serial correlation of lag one

TABLE 5.4

AR(1) Correlatiom Coefficient for Daily Retums of ISE. 1988-1995

$cor[R_t, R_{t-s}]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.240	124.00	142.00	156.00
1 ARC	0.091	22.30	33.10	55.70
2 BAG	0.098	21.70	35.20	49.20
3 CEL	0.088	23.50	35.40	47.60
4 CIMS	0.095	26.30	41.20	50.30
5 CUK	0.159	56.30	69.60	91.60
6 DOK	0.120	31.50	43.70	62.60
7 ECZ	0.147	56.50	83.00	95.30
8 EGE	0.101	21.10	43.90	60.00
9 ERE	0.174	68.20	76.90	103.00
10 GOOD	0.098	23.90	32.60	52.20
11 GUN	0.104	29.30	37.90	51.30
12 KAR	0.021	13.70	26.90	39.30
13 KOCH	0.139	44.20	55.90	77.40
14 KOCY	0.131	38.30	58.20	80.00
15 OTO	0.123	31.20	47.70	56.70
16 SAR	0.156	53.50	74.10	86.40
17 TIB	0.156	55.10	82.30	93.10
18 TSI	0.098	24.30	37.40	46.90
19 TUDD	0.081	13.60	24.40	50.60
20 YAS	0.075	23.30	44.00	55.20
No of significant	20	21	20	20

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.044 for the critical value of the serial correlation of lag one

$cor[|R_t|, |R_{t-s}|]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.282	594	1040	1460
1 ARC	0.276	478	860	1030
2 BAG	0.251	358	543	660
3 CEL	0.307	514	882	1130
4 CIMS	0.289	433	554	707
5 CUK	0.311	509	724	887
6 DOK	0.257	325	455	620
7 ECZ	0.261	536	1140	1620
8 EGE	0.276	491	833	1080
9 ERE	0.307	575	891	1210
10 GOOD	0.259	547	621	635
11 GUN	0.274	411	670	848
12 KAR	0.301	576	891	1110
13 KOCH	0.279	462	893	1200
14 KOCY	0.306	659	1230	1760
15 OTO	0.244	379	545	664
16 SAR	0.321	528	991	1290
17 TIB	0.306	578	856	1160
18 TSI	0.234	370	611	814
19 TUDD	0.230	278	410	521
20 YAS	0.211	309	619	908
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.044 for the critical value of the serial correlation of lag one

TABLE 5.5

AR(1) Correlatiom Coefficient for Daily *US$* Adjusted Returns of ISE. 1988-1990

$\boxed{cor\left[R_t, R_{t-s}\right]}$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.303	72.90	88.30	98.30
1 ARC	0.112	14.00	20.20	29.70
2 BAG	0.177	25.70	32.00	41.30
3 CEL	0.056	9.12	17.60	34.40
4 CIMS	0.179	33.80	42.90	50.50
5 CUK	0.116	10.60	18.30	27.40
6 DOK	0.165	23.20	29.10	54.50
7 ECZ	0.220	51.50	62.40	84.90
8 EGE	0.135	23.90	47.20	70.60
9 ERE	0.203	35.50	48.60	62.40
10 GOOD	0.173	28.10	37.80	50.40
11 GUN	0.089	12.30	19.70	31.60
12 KAR	0.044	6.11	24.20	35.20
13 KOCH	0.216	36.80	54.70	65.10
14 KOCY	0.119	12.90	23.70	48.00
15 OTO	0.138	17.70	27.60	40.10
16 SAR	0.139	31.10	42.70	56.20
17 TIB	0.144	21.60	34.90	51.90
18 TSI	0.143	21.10	29.80	42.50
19 TUDD	0.170	24.10	41.70	59.80
20 YAS	0.061	5.68	20.20	36.60
No of significant	18	17	15	12

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.071 for the critical value of the serial correlation of lag one

$\boxed{cor\left[\left|R_t\right|, \left|R_{t-s}\right|\right]}$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.351	274	330	386
1 ARC	0.277	199	312	360
2 BAG	0.308	204	253	257
3 CEL	0.284	171	207	222
4 CIMS	0.320	183	233	252
5 CUK	0.297	155	178	195
6 DOK	0.307	204	283	352
7 ECZ	0.283	163	332	434
8 EGE	0.320	268	418	486
9 ERE	0.308	155	179	196
10 GOOD	0.317	313	446	474
11 GUN	0.284	227	295	335
12 KAR	0.388	322	500	579
13 KOCH	0.328	230	299	321
14 KOCY	0.316	275	390	511
15 OTO	0.269	179	228	274
16 SAR	0.272	130	163	182
17 TIB	0.357	335	460	725
18 TSI	0.275	171	250	318
19 TUDD	0.353	270	333	384
20 YAS	0.221	140	264	374
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.071 for the critical value of the serial correlation of lag one

TABLE 5.6

AR(1) Correlatiom Coefficient for Daily *US$* Adjusted Retums of ISE. 1991-1993

$cor\left[R_t, R_{t-s}\right]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.002	4.60	18.40	27.90
1 ARC	-0.041	4.27	19.50	31.90
2 BAG	0.006	3.87	22.10	43.20
3 CEL	0.011	4.73	14.30	36.20
4 CIMS	-0.014	8.35	16.70	26.60
5 CUK	0.048	4.14	8.37	23.60
6 DOK	-0.001	3.10	9.99	15.70
7 ECZ	0.088	9.19	27.00	39.50
8 EGE	-0.051	2.02	18.30	29.10
9 ERE	0.082	11.80	20.60	44.60
10 GOOD	-0.044	3.80	15.00	21.10
11 GUN	0.036	5.12	18.20	32.30
12 KAR	-0.061	8.47	21.90	44.00
13 KOCH	-0.021	1.95	13.50	22.60
14 KOCY	0.038	2.84	7.70	15.70
15 OTO	0.046	2.25	22.50	27.90
16 SAR	0.081	9.56	19.10	28.00
17 TIB	0.121	13.70	24.20	40.50
18 TSI	-0.035	11.30	31.70	44.40
19 TUDD	-0.044	9.42	22.30	32.20
20 YAS	0.022	12.50	25.30	34.30
No of significant	3	4	3	4

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.072 for the critical value of the serial correlation of lag one

$cor\left[\left|R_t\right|, \left|R_{t-s}\right|\right]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.209	66.6	84.6	134
1 ARC	0.242	111	147	188
2 BAG	0.171	41.9	59.4	75.6
3 CEL	0.191	64.8	69.6	98.9
4 CIMS	0.250	96.2	127	200
5 CUK	0.186	67.7	97.6	112
6 DOK	0.224	81.1	97.1	131
7 ECZ	0.177	77.4	103	122
8 EGE	0.238	66.6	88.5	111
9 ERE	0.279	126	153	209
10 GOOD	0.237	109	131	160
11 GUN	0.147	40.3	57.8	92
12 KAR	0.283	117	124	145
13 KOCH	0.218	69.1	96.1	120
14 KOCY	0.260	99.6	145	225
15 OTO	0.265	125	164	221
16 SAR	0.292	124	150	224
17 TIB	0.219	109	137	157
18 TSI	0.171	52.9	60.8	72.8
19 TUDD	0.165	53.5	66.1	104
20 YAS	0.201	49.7	61.9	75.1
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.072 for the critical value of the serial correlation of lag one

TABLE 5.7

AR(1) 'Correlatiom Coefficient for Daily *US$* Adjusted Retums of ISE. 1994-1995

$$cor\left[R_t, R_{t-s}\right]$$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.253	56.60	77.90	128.00
1 ARC	0.110	14.90	40.40	70.10
2 BAG	0.109	11.30	23.60	49.30
3 CEL	0.147	23.80	36.20	48.90
4 CIMS	0.031	2.07	14.30	39.30
5 CUK	0.215	28.40	48.10	60.80
6 DOK	0.153	12.70	25.50	49.70
7 ECZ	0.146	32.80	45.60	98.20
8 EGE	0.113	7.91	21.70	35.10
9 ERE	0.191	25.90	41.50	69.10
10 GOOD	0.102	17.10	41.30	84.10
11 GUN	0.101	6.75	14.80	29.90
12 KAR	0.011	9.55	19.30	44.80
13 KOCH	0.155	18.00	33.20	69.50
14 KOCY	0.125	10.50	31.40	62.30
15 OTO	0.170	18.10	23.80	45.20
16 SAR	0.220	29.60	62.90	106.00
17 TIB	0.182	19.20	31.70	51.00
18 TSI	0.194	25.50	40.50	59.70
19 TUDD	0.082	5.81	16.50	58.00
20 YAS	0.131	14.90	34.90	57.20
No of significant	18	15	14	18

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.087 for the critical value of the serial correlation of lag one

$$cor\left[\left|R_t\right|, \left|R_{t-s}\right|\right]$$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.402	245	581	920
1 ARC	0.264	103	234	329
2 BAG	0.281	136	286	478
3 CEL	0.311	116	194	236
4 CIMS	0.309	123	147	216
5 CUK	0.336	131	169	220
6 DOK	0.272	79.9	122	256
7 ECZ	0.263	217	466	704
8 EGE	0.333	193	362	617
9 ERE	0.359	261	582	943
10 GOOD	0.296	67.1	119	156
11 GUN	0.355	137	325	500
12 KAR	0.271	162	335	478
13 KOCH	0.273	157	514	934
14 KOCY	0.365	226	541	785
15 OTO	0.230	67.4	112	158
16 SAR	0.403	262	771	1140
17 TIB	0.303	90.9	157	215
18 TSI	0.302	190	461	696
19 TUDD	0.197	38.6	78.7	110
20 YAS	0.217	142	394	653
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.087 for the critical value of the serial correlation of lag one

TABLE 5.8

AR(1) Correlatiom Coefficient for Daily US$ Adjusted Returns of ISE. 1988-1995

$cor[R_t, R_{t-s}]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.186	91.80	116.00	145.00
1 ARC	0.069	22.50	39.20	66.30
2 BAG	0.097	26.70	39.20	64.30
3 CEL	0.087	31.10	43.50	52.10
4 CIMS	0.073	20.90	30.50	40.70
5 CUK	0.142	45.30	55.50	74.70
6 DOK	0.109	28.90	38.80	56.90
7 ECZ	0.153	68.80	92.40	120.00
8 EGE	0.066	11.50	29.90	41.60
9 ERE	0.157	61.60	72.20	103.00
10 GOOD	0.080	17.90	27.00	50.90
11 GUN	0.076	13.30	21.80	32.60
12 KAR	-0.006	14.60	26.70	45.20
13 KOCH	0.125	37.40	58.80	75.50
14 KOCY	0.097	19.40	33.50	51.00
15 OTO	0.117	29.70	43.90	55.10
16 SAR	0.149	58.40	89.00	109.00
17 TIB	0.151	48.60	74.10	90.70
18 TSI	0.099	32.60	46.90	55.60
19 TUDD	0.071	11.20	24.80	53.00
20 YAS	0.069	24.40	42.20	52.70
No of significant	20	21	19	18

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.044 for the critical value of the serial correlation of lag one

$cor[|R_t|, |R_{t-s}|]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.326	594	955	1350
1 ARC	0.271	455	800	1010
2 BAG	0.262	398	619	807
3 CEL	0.318	573	953	1310
4 CIMS	0.297	416	519	659
5 CUK	0.315	511	735	945
6 DOK	0.271	358	474	721
7 ECZ	0.255	521	1020	1450
8 EGE	0.302	525	875	1180
9 ERE	0.323	597	909	1260
10 GOOD	0.287	431	611	676
11 GUN	0.269	393	643	863
12 KAR	0.318	583	831	1050
13 KOCH	0.279	460	892	1260
14 KOCY	0.318	614	1090	1540
15 OTO	0.256	352	494	637
16 SAR	0.329	562	1050	1450
17 TIB	0.311	546	826	1150
18 TSI	0.253	422	689	941
19 TUDD	0.243	299	427	567
20 YAS	0.223	346	723	1030
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.044 for the critical value of the serial correlation of lag one

TABLE 5.9

Correlatiom Coefficient for Daily *Inflation* Adjusted Retums of ISE. 1988-1990

$\boxed{cor[R_t, R_{t-s}]}$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.320	82.60	97.80	107.00
1 ARC	0.122	18.60	23.80	31.20
2 BAG	0.188	28.90	35.20	46.50
3 CEL	0.056	12.10	20.10	35.30
4 CIMS	0.179	36.60	45.00	54.10
5 CUK	0.120	11.90	19.50	27.70
6 DOK	0.164	24.30	30.30	56.80
7 ECZ	0.230	56.50	66.70	88.40
8 EGE	0.129	22.30	44.10	63.50
9 ERE	0.213	40.40	51.50	62.00
10 GOOD	0.181	30.10	39.40	51.70
11 GUN	0.093	11.70	18.60	30.40
12 KAR	0.039	6.12	22.60	30.20
13 KOCH	0.208	34.20	50.70	60.80
14 KOCY	0.123	13.00	23.50	43.80
15 OTO	0.134	17.70	27.20	38.60
16 SAR	0.134	30.60	42.20	52.30
17 TIB	0.140	20.50	33.50	50.70
18 TSI	0.148	22.30	31.70	47.50
19 TUDD	0.173	25.00	42.20	56.10
20 YAS	0.070	8.77	23.50	41.30
No of significant	19	19	15	15

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.071 for the critical value of the serial correlation of lag one

$\boxed{cor[|R_t|, |R_{t-s}|]}$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.358	309	397	488
1 ARC	0.301	235	361	398
2 BAG	0.316	218	272	277
3 CEL	0.298	198	254	275
4 CIMS	0.310	180	231	251
5 CUK	0.297	163	189	209
6 DOK	0.317	209	311	382
7 ECZ	0.302	194	417	552
8 EGE	0.320	285	447	508
9 ERE	0.318	181	213	228
10 GOOD	0.305	307	450	472
11 GUN	0.321	270	368	405
12 KAR	0.395	345	564	681
13 KOCH	0.344	236	308	333
14 KOCY	0.346	331	487	659
15 OTO	0.272	201	263	306
16 SAR	0.278	143	196	218
17 TIB	0.378	381	535	859
18 TSI	0.282	184	264	338
19 TUDD	0.341	273	351	409
20 YAS	0.226	147	287	410
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.071 for the critical value of the serial correlation of lag one

TABLE 5.10

Correlatiom Coefficient for Daily *Inflation* Adjusted Retums of ISE. 1991-1993

$cor\left[R_t, R_{t-s}\right]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.120	18.20	32.20	38.50
1 ARC	0.013	2.26	15.40	25.60
2 BAG	0.041	6.12	25.60	43.00
3 CEL	0.071	8.11	17.50	36.80
4 CIMS	0.043	12.70	22.30	31.70
5 CUK	0.107	10.80	13.00	28.70
6 DOK	0.072	5.64	11.50	19.10
7 ECZ	0.147	18.30	32.20	40.00
8 EGE	0.031	4.04	21.10	30.30
9 ERE	0.140	21.70	32.00	57.90
10 GOOD	0.013	2.29	16.40	25.00
11 GUN	0.094	13.20	21.40	38.80
12 KAR	0.009	10.10	20.90	42.00
13 KOCH	0.044	3.96	12.40	19.00
14 KOCY	0.101	9.97	14.30	21.70
15 OTO	0.091	6.14	27.10	33.00
16 SAR	0.143	20.80	29.60	41.30
17 TIB	0.159	24.70	32.60	49.50
18 TSI	0.005	9.31	24.10	34.60
19 TUDD	0.014	7.10	19.00	29.40
20 YAS	0.083	18.10	31.60	36.80
No of significant	11	9	9	2

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.072 for the critical value of the serial correlation of lag one

$cor\left[\left|R_t\right|, \left|R_{t-s}\right|\right]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.162	66.4	93.6	125
1 ARC	0.262	136	212	247
2 BAG	0.152	34.2	51.8	57.8
3 CEL	0.187	64.8	78.3	94
4 CIMS	0.216	77.3	136	163
5 CUK	0.179	72.5	130	146
6 DOK	0.216	78.4	85.7	104
7 ECZ	0.180	91.7	134	142
8 EGE	0.196	51	66.5	78.8
9 ERE	0.266	127	183	270
10 GOOD	0.215	96.3	120	134
11 GUN	0.160	40.7	56.6	82.4
12 KAR	0.236	101	115	127
13 KOCH	0.193	67.7	122	140
14 KOCY	0.255	107	181	243
15 OTO	0.234	141	194	234
16 SAR	0.286	122	151	187
17 TIB	0.202	114	151	165
18 TSI	0.139	45	54.4	60.6
19 TUDD	0.150	58	85.2	98.7
20 YAS	0.186	52.6	67.4	93.3
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.072 for the critical value of the serial correlation of lag one

TABLE 5.11

Correlatiom Coefficient for Daily *Inflation* Adjusted Retums of ISE. 1994-1995

$cor[R_t, R_{t-s}]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.278	39.60	58.20	69.10
1 ARC	0.121	9.02	26.70	56.70
2 BAG	0.062	2.61	10.30	22.20
3 CEL	0.116	11.30	22.70	33.50
4 CIMS	0.027	4.62	19.80	40.60
5 CUK	0.218	28.90	50.80	64.60
6 DOK	0.116	8.76	28.50	43.10
7 ECZ	0.063	4.96	17.60	46.70
8 EGE	0.151	21.90	45.50	55.30
9 ERE	0.169	22.40	31.90	48.40
10 GOOD	0.065	7.46	16.40	51.50
11 GUN	0.131	23.90	47.60	56.10
12 KAR	0.016	11.80	20.60	39.00
13 KOCH	0.138	15.40	30.30	64.30
14 KOCY	0.166	23.10	64.50	91.70
15 OTO	0.152	13.00	26.10	38.30
16 SAR	0.196	23.20	39.10	60.00
17 TIB	0.163	15.90	35.60	48.10
18 TSI	0.142	13.20	23.80	28.00
19 TUDD	0.048	2.13	12.50	36.70
20 YAS	0.067	4.93	24.40	34.30
No of significant	14	13	13	11

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.087 for the critical value of the serial correlation of lag one

$cor[|R_t|, |R_{t-s}|]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.318	258	700	1080
1 ARC	0.226	83.3	191	271
2 BAG	0.269	123	236	369
3 CEL	0.281	82.6	140	158
4 CIMS	0.320	159	178	298
5 CUK	0.329	129	163	197
6 DOK	0.206	52.7	80.9	145
7 ECZ	0.249	186	452	691
8 EGE	0.287	169	335	559
9 ERE	0.314	239	546	848
10 GOOD	0.217	39.1	73.2	89.5
11 GUN	0.305	110	265	406
12 KAR	0.256	159	338	470
13 KOCH	0.260	154	473	816
14 KOCY	0.286	221	544	814
15 OTO	0.200	55.9	96.8	137
16 SAR	0.399	271	805	1170
17 TIB	0.275	91.1	147	193
18 TSI	0.261	139	344	555
19 TUDD	0.162	21.5	39.8	70.1
20 YAS	0.202	127	352	594
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.087 for the critical value of the serial correlation of lag one

TABLE 5.12

Correlatiom Coefficient for Daily *Inflation* Adjusted Retums of ISE. 1988-1995

$cor[R_t, R_{t-s}]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.240	124.00	143.00	157.00
1 ARC	0.091	22.50	33.20	55.80
2 BAG	0.098	21.70	35.20	49.20
3 CEL	0.088	23.50	35.40	47.40
4 CIMS	0.095	26.40	41.20	50.40
5 CUK	0.160	56.40	69.80	91.50
6 DOK	0.120	31.80	43.80	62.80
7 ECZ	0.148	57.00	83.80	96.00
8 EGE	0.101	21.30	43.70	59.60
9 ERE	0.174	68.20	76.90	103.00
10 GOOD	0.098	23.90	32.50	52.20
11 GUN	0.104	29.40	37.80	51.10
12 KAR	0.021	13.70	27.00	39.40
13 KOCH	0.140	44.70	56.60	77.90
14 KOCY	0.132	38.80	57.80	79.50
15 OTO	0.123	31.40	48.30	57.20
16 SAR	0.156	53.60	74.40	86.50
17 TIB	0.156	55.00	82.20	93.10
18 TSI	0.098	24.30	37.40	46.80
19 TUDD	0.081	13.70	24.60	50.50
20 YAS	0.075	23.40	44.20	55.30
No of significant	20	21	20	20

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.044 for the critical value of the serial correlation of lag one

$cor[|R_t|, |R_{t-s}|]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.282	605	1050	1460
1 ARC	0.273	481	862	1030
2 BAG	0.250	360	544	656
3 CEL	0.306	524	897	1150
4 CIMS	0.287	433	552	697
5 CUK	0.308	507	733	902
6 DOK	0.251	321	445	603
7 ECZ	0.258	527	1120	1580
8 EGE	0.276	496	838	1080
9 ERE	0.304	575	892	1200
10 GOOD	0.259	417	598	648
11 GUN	0.268	395	642	806
12 KAR	0.301	577	885	1100
13 KOCH	0.277	463	890	1190
14 KOCY	0.302	654	1220	1740
15 OTO	0.237	369	529	647
16 SAR	0.319	536	1000	1300
17 TIB	0.304	576	852	1150
18 TSI	0.231	361	588	780
19 TUDD	0.226	274	401	515
20 YAS	0.210	318	636	924
No of significant	21	21	21	21

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.044 for the critical value of the serial correlation of lag one

TABLE 5.13
Runs Test for Daily Returns of ISE. 1988-1990

TL 88-90	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	424	635.79	22.15	-9.54
ARC	492	610.10	21.64	-5.43
BAG	504	604.81	21.53	-4.66
CEL	485	611.08	21.66	-5.80
CIMS	483	616.68	21.79	-6.11
CUK	479	614.20	21.72	-6.20
DOK	481	616.81	21.79	-6.21
ECZ	500	619.66	21.90	-5.44
EGE	490	612.42	21.70	-5.62
ERE	453	631.17	22.07	-8.05
GOOD	493	606.11	21.55	-5.23
GUN	481	629.36	22.08	-6.70
KAR	496	614.99	21.77	-5.44
KOCH	493	608.37	21.60	-5.32
KOCY	497	605.31	21.54	-5.01
OTO	508	598.31	21.38	-4.20
SAR	500	608.93	21.63	-5.01
TIB	514	606.94	21.61	-4.28
TSI	482	620.37	21.87	-6.30
TUDD	475	614.95	21.74	-6.42
YAS	507	602.92	21.49	-4.44

TABLE 5.14
Runs Test for Daily Returns of ISE. 1991-1993

TL 91-93	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	468	597.81	23.09	-5.60
ARC	518	583.15	22.81	-2.84
BAG	518	592.42	23.03	-3.21
CEL	516	586.75	22.89	-3.07
CIMS	507	591.96	23.00	-3.67
CUK	494	595.77	23.07	-4.39
DOK	496	593.35	23.01	-4.21
ECZ	480	601.69	23.18	-5.23
EGE	500	602.65	23.24	-4.40
ERE	495	595.70	23.07	-4.34
GOOD	488	599.51	23.14	-4.80
GUN	478	606.24	23.28	-5.49
KAR	494	608.21	23.35	-4.87
KOCH	503	593.98	23.04	-3.93
KOCY	488	604.41	23.25	-4.98
OTO	507	590.29	22.96	-3.61
SAR	501	591.31	22.97	-3.91
TIB	494	594.05	23.03	-4.32
TSI	499	590.26	22.95	-3.96
TUDD	490	596.58	23.08	-4.60
YAS	486	604.04	23.24	-5.06

TABLE 5.15
Runs Test for Daily Returns of ISE. 1994-1995

TL 94-95	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	333	394.99	19.87	-3.09
ARC	339	401.55	20.05	-3.10
BAG	339	398.63	19.97	-2.96
CEL	329	403.80	20.09	-3.70
CIMS	359	391.91	19.82	-1.64
CUK	335	402.38	20.06	-3.33
DOK	338	407.09	20.19	-3.40
ECZ	326	408.60	20.21	-4.06
EGE	342	397.88	19.95	-2.78
ERE	339	399.82	20.00	-3.02
GOOD	341	405.72	20.16	-3.19
GUN	353	395.34	19.90	-2.10
KAR	339	397.42	19.94	-2.90
KOCH	353	392.42	19.82	-1.96
KOCY	348	400.79	20.05	-2.61
OTO	348	400.80	20.05	-2.61
SAR	344	402.25	20.08	-2.88
TIB	332	402.54	20.06	-3.49
TSI	342	398.47	19.97	-2.80
TUDD	355	393.45	19.86	-1.91
YAS	358	386.58	19.67	-1.43

TABLE 5.16
Runs Test for Daily Returns of ISE. 1988-1995

TL 88-95	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	1229	1625.77	37.73	-10.50
ARC	1353	1591.15	37.33	-6.37
BAG	1363	1593.13	37.37	-6.14
CEL	1332	1598.80	37.42	-7.12
CIMS	1350	1598.60	37.43	-6.63
CUK	1310	1609.26	37.55	-7.96
DOK	1319	1613.14	37.61	-7.81
ECZ	1308	1627.92	37.80	-8.45
EGE	1337	1608.44	37.56	-7.21
ERE	1291	1623.29	37.72	-8.80
GOOD	1324	1608.93	37.56	-7.57
GUN	1315	1628.81	37.82	-8.28
KAR	1331	1618.50	37.70	-7.61
KOCH	1352	1591.22	37.33	-6.39
KOCY	1337	1606.28	37.53	-7.16
OTO	1368	1584.34	37.25	-5.79
SAR	1347	1599.42	37.44	-6.73
TIB	1344	1599.67	37.44	-6.81
TSI	1327	1605.38	37.51	-7.41
TUDD	1322	1602.29	37.46	-7.47
YAS	1355	1589.87	37.31	-6.28

TABLE 5.17

Runs Test for Daily *US$ Adjusted* Returns of ISE. 1988-1990

$ 88-90	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	434	630.10	23.67	-8.26
ARC	492	605.58	23.21	-4.87
BAG	512	594.54	22.98	-3.57
CEL	500	598.71	23.06	-4.26
CIMS	485	609.95	23.30	-5.34
CUK	479	610.77	23.31	-5.63
DOK	485	609.37	23.28	-5.32
ECZ	519	604.32	23.23	-3.65
EGE	498	602.95	23.16	-4.51
ERE	464	623.20	23.55	-6.74
GOOD	495	598.88	23.06	-4.48
GUN	503	610.20	23.33	-4.57
KAR	506	601.88	23.14	-4.12
KOCH	503	597.98	23.05	-4.10
KOCY	508	594.14	22.97	-3.73
OTO	491	602.05	23.13	-4.78
SAR	495	605.40	23.21	-4.74
TIB	520	594.02	22.98	-3.20
TSI	507	598.37	23.06	-3.94
TUDD	469	615.74	23.41	-6.25
YAS	523	588.51	22.85	-2.84

TABLE 5.18

Runs Test for Daily *US$ Adjusted* Returns of ISE. 1991-1993

$ 91-93	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	466	599.06	24.82	-5.34
ARC	505	573.61	24.31	-2.80
BAG	486	586.92	24.59	-4.08
CEL	511	569.51	24.23	-2.39
CIMS	485	586.92	24.59	-4.12
CUK	476	592.73	24.70	-4.71
DOK	502	575.64	24.36	-3.00
ECZ	480	590.16	24.65	-4.45
EGE	486	586.92	24.59	-4.08
ERE	481	590.16	24.65	-4.41
GOOD	482	589.51	24.64	-4.34
GUN	495	580.33	24.45	-3.47
KAR	481	590.16	24.65	-4.41
KOCH	492	582.32	24.49	-3.67
KOCY	473	595.28	24.75	-4.92
OTO	474	594.64	24.74	-4.86
SAR	478	591.45	24.68	-4.58
TIB	476	592.73	24.70	-4.71
TSI	484	587.57	24.60	-4.19
TUDD	500	576.99	24.39	-3.14
YAS	479	590.81	24.66	-4.51

TABLE 5.19
Runs Test for Daily US$ *Adjusted* Returns of ISE. 1994-1995

$ 94-95	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	314	407.19	20.05	-4.62
ARC	324	402.13	19.93	-3.90
BAG	325	400.21	19.88	-3.76
CEL	316	405.94	20.02	-4.47
CIMS	340	390.99	19.65	-2.57
CUK	319	404.05	19.97	-4.23
DOK	321	403.41	19.96	-4.10
ECZ	303	413.92	20.20	-5.47
EGE	346	386.23	19.52	-2.04
ERE	327	398.92	19.85	-3.60
GOOD	310	410.27	20.12	-4.96
GUN	331	396.96	19.80	-3.31
KAR	331	396.31	19.78	-3.28
KOCH	346	387.59	19.56	-2.10
KOCY	331	396.31	19.78	-3.28
OTO	327	399.57	19.86	-3.63
SAR	320	404.04	19.97	-4.18
TIB	314	407.19	20.05	-4.62
TSI	338	392.33	19.68	-2.73
TUDD	321	402.78	19.94	-4.08
YAS	340	390.32	19.63	-2.54

TABLE 5.20
Runs Test for Daily *US$ Adjusted* Returns of ISE. 1988-1995

$ 88-95	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	1218	1632.49	39.78	-10.41
ARC	1324	1578.12	39.13	-6.48
BAG	1325	1578.72	39.13	-6.47
CEL	1329	1571.67	39.04	-6.20
CIMS	1311	1585.92	39.22	-7.00
CUK	1276	1604.52	39.45	-8.32
DOK	1312	1584.65	39.21	-6.94
ECZ	1304	1607.28	39.49	-7.67
EGE	1335	1571.56	39.04	-6.05
ERE	1276	1608.81	39.50	-8.41
GOOD	1288	1596.29	39.35	-7.82
GUN	1332	1585.30	39.22	-6.45
KAR	1320	1585.71	39.22	-6.76
KOCH	1344	1564.35	38.95	-5.64
KOCY	1316	1581.43	39.17	-6.76
OTO	1295	1592.44	39.30	-7.56
SAR	1295	1598.02	39.37	-7.68
TIB	1314	1590.19	39.28	-7.02
TSI	1331	1575.45	39.09	-6.24
TUDD	1292	1593.11	39.31	-7.65
YAS	1346	1565.59	38.97	-5.62

TABLE 5.21
Runs Test for Daily *Inflation Adjusted* Returns of ISE. 1988-1990

INF 88-90	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	424	635.79	22.26	-9.49
ARC	493	609.48	21.74	-5.33
BAG	508	602.84	21.61	-4.37
CEL	484	611.13	21.77	-5.82
CIMS	483	616.68	21.90	-6.08
CUK	479	614.20	21.84	-6.17
DOK	479	616.95	21.90	-6.28
ECZ	506	617.00	21.96	-5.03
EGE	490	611.88	21.80	-5.57
ERE	452	631.23	22.18	-8.06
GOOD	495	605.42	21.65	-5.08
GUN	484	627.63	22.16	-6.46
KAR	499	613.67	21.86	-5.22
KOCH	494	607.73	21.70	-5.22
KOCY	495	605.42	21.65	-5.08
OTO	509	597.67	21.48	-4.10
SAR	498	609.64	21.76	-5.11
TIB	515	606.31	21.71	-4.18
TSI	486	618.99	21.96	-6.03
TUDD	477	614.30	21.84	-6.26
YAS	508	602.29	21.59	-4.34

TABLE 5.22
Runs Test for Daily *Inflation Adjusted* Returns of ISE. 1991-1993

INF 91-93	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	468	597.81	23.13	-5.59
ARC	514	584.02	22.86	-3.04
BAG	516	592.67	23.07	-3.30
CEL	516	586.18	22.91	-3.04
CIMS	507	591.96	23.03	-3.67
CUK	493	595.83	23.10	-4.43
DOK	495	593.41	23.05	-4.25
ECZ	480	601.69	23.22	-5.22
EGE	501	601.54	23.25	-4.30
ERE	494	595.77	23.10	-4.38
GOOD	488	599.51	23.18	-4.79
GUN	480	605.56	23.30	-5.37
KAR	495	607.61	23.38	-4.80
KOCH	502	593.51	23.06	-3.95
KOCY	485	605.19	23.30	-5.14
OTO	507	589.17	22.97	-3.56
SAR	501	591.31	23.01	-3.90
TIB	494	593.47	23.05	-4.29
TSI	498	590.31	22.98	-4.00
TUDD	492	595.89	23.10	-4.48
YAS	486	603.50	23.26	-5.03

TABLE 5.23
Runs Test for Daily *Inflation Adjusted* Returns of ISE. 1994-1995

INF 94-95	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	333	394.99	19.91	-3.09
ARC	339	401.55	20.08	-3.09
BAG	339	398.63	20.01	-2.96
CEL	329	403.80	20.13	-3.69
CIMS	361	391.14	19.84	-1.49
CUK	335	402.38	20.10	-3.33
DOK	338	407.09	20.23	-3.39
ECZ	326	408.60	20.25	-4.06
EGE	341	397.93	19.99	-2.82
ERE	339	399.23	20.02	-2.98
GOOD	341	405.21	20.19	-3.16
GUN	354	393.54	19.89	-1.96
KAR	339	397.42	19.98	-2.90
KOCH	354	391.76	19.84	-1.88
KOCY	348	400.79	20.08	-2.60
OTO	348	400.26	20.07	-2.58
SAR	344	402.25	20.11	-2.87
TIB	329	403.25	20.12	-3.67
TSI	342	398.47	20.01	-2.80
TUDD	355	393.45	19.89	-1.91
YAS	356	387.30	19.72	-1.56

TABLE 5.24
Runs Test for Daily *Inflation Adjusted* Returns of ISE. 1988-1995

INF 88-95	Actual No.of Runs	Expected No. of Runs	Standard Error	k-Value
ISE-INDEX	1229	1625.77	37.84	-10.47
ARC	1350	1591.36	37.44	-6.43
BAG	1365	1591.31	37.45	-6.03
CEL	1331	1598.28	37.52	-7.11
CIMS	1352	1597.87	37.53	-6.54
CUK	1309	1609.32	37.66	-7.96
DOK	1316	1613.36	37.72	-7.87
ECZ	1314	1625.30	37.88	-8.20
EGE	1337	1606.82	37.65	-7.15
ERE	1289	1622.85	37.82	-8.81
GOOD	1325	1607.75	37.65	-7.50
GUN	1321	1624.64	37.88	-8.00
KAR	1335	1616.55	37.78	-7.44
KOCH	1353	1589.44	37.42	-6.31
KOCY	1332	1607.22	37.65	-7.30
OTO	1369	1582.00	37.32	-5.69
SAR	1345	1600.13	37.56	-6.78
TIB	1342	1599.27	37.54	-6.84
TSI	1330	1604.05	37.60	-7.28
TUDD	1326	1600.91	37.55	-7.31
YAS	1354	1589.37	37.41	-6.28

CHAPTER SIX:

TESTING ARCH EFFECTS ON THE ISTANBUL STOCK EXCHANGE.

6.1 INTRODUCTION.

From the various tests for skewness, kurtosis, variances and normality in the previous Chapter, we conclude the hypothesis that log-returns on the ISE follow a normal distribution can be rejected.

The main non-normal features of the series are the fat tails. There are several possible reasons for this. For example, the returns may follow a single non-normal distribution, such as a t-distribution or a stable Paretian distribution, which are more leptokurtic than the normal. An alternative possibility which has been much discussed in the finance literature in recent years, is that the returns follow a mixture of normal distributions, at some times with high variance and at other times with lower variance.

Specifically, returns in many financial markets appear to follow autoregressive conditional heteroskedastic (ARCH) processes, with volatility changing conditional on past shocks to the returns series. The aim of this chapter is to test whether there are ARCH effects present in the ISE returns series, to test the hypothesis of ARCH against the alternative of a constant-variance non-normal (t-) distribution, and to estimate ARCH-type models for both the ISE index and returns on leading shares.

These exercises show that the returns variance on the ISE is well described by a GARCH model. But there has been some structural change in the processes driving both mean returns and the variance of returns over the period of our study. These changes are consistent with increasing market efficiency. There is less serial correlation in mean returns in recent years, so they can be described by a lower order AR model. And the level of returns is less affected by the own-variance of returns in recent years, consistent with an increasing integration of the ISE into the international capital market.

6.2 METHODOLOGY

The AutoRegresive Conditional Heteroscedasticity (ARCH) model was introduced by Robert Engle (1982) and generalised to GARCH by Tim Bollerslev in (1986). These models have aroused enormous academic and practical interest, since then many papers have been published in literature. Recent surveys include Bollerslev, Chou, and Kroner (1992), Bera and Higgins (1993), and Pagan (1996).

The ARCH models are found to be more appropriate than standard statistical models, because error terms from regressions involving stock return are almost certainly not normally distributed, but rather leptokurtic, the tails of distribution have too many extreme observations to fit the normal distribution, negatively skewed large stock returns are more common than large positive ones and heteroskedastic. Hence the test statistics based on nonrobust standard error estimates cannot be interpreted in the usual way. Ordinary regression analysis cannot cope with non-linearity and heteroscedasticity problems in time series.

Volatility clustering mean that large changes in stock markets tend to be followed by large changes of either sign, in the price of many financial instruments. For this reason, the concept of Autoregressive conditional heteroscedasticity (ARCH) is particularly useful for modelling volatility. The "autoregressive conditional" heteroscedasticity means that a large past variance induces a large current variance for the error term. Therefore the ISE time series data in which turbulent periods are interspersed with more tranquil spells may be suited for this type of analysis.

Prior to the introduction of ARCH, researchers were very much aware of changes in variance, but used only informal procedures to take account of this. Among these models recursive estimates of the variance over time and moving variance estimates can be mentioned. Engle's (1982) ARCH model was the first formal model, which seemed to capture the stylised facts mentioned above.

Volatility measures the variability in returns. In finance, attention has typically focused on variance - σ^2 - as a measure of volatility. There are several ways of predicting volatility. Some traders measure standard deviations over various periods and use what they judge to be the most appropriate moving average to predict volatility. Some adjust standard deviations to reflect recent events, recognising that these may contain useful information in forecasting volatility. In order to incorporate past information, conditional variances that are defined as the variance of a random variable when some other random variables are known has to be used.

An ARCH process is usually defined in terms of the distributions of the errors of a dynamic linear regression model. Consider, without loss of generality, the following *p*th order autoregressive model for returns y_t:

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_p y_{t-p} + u_t \qquad (6.1)$$

The classical regression assumption is that $u_t \sim N(0, h^2)$, where h^2 is a constant variance, and $Cov(u_t, u_{t-k}) = 0$ and $Cov(u_t, y_{t-k}) = 0 \ \forall \ k$.

The simple ARCH model generalises this by making the variance time-varying, and conditional on past squared shocks to the mean equation (6.1). Thus an ARCH(q) model assumes:

$$u_t \sim N(0, h_t^2) \tag{6.2}$$

$$h_t^2 = b_0 + b_1 u_{t-1}^2 + b_2 u_{t-2}^2 + \dots + b_q u_{t-q}^2 \tag{6.3}$$

This means that is there is a large shock to returns, positive or negative, the returns variance is raised on the following day, and for q days thereafter. The higher variance will of course be reflected in higher price volatility. So the ARCH model assumes that any large shock will cause a period of sustained high volatility. The size and persistence of the ARCH effects will depend on the parameters b_0, b_1, ..., b_q.

The model (6.1) - (6.3) is highly parameterised, and although in principle it can be estimated by maximum likelihood, in practice this may be difficult if the order q of the ARCH process is high. To circumvent this problem, Bollerslev (1986) suggested adding lagged variance terms to (6.3), to yield what he termed the generalised ARCH (GARCH) model. A GARCH (q, r) model would be:

$$h_t^2 = b_0 + b_1 u_{t-1}^2 + b_2 u_{t-2}^2 + \dots + b_q u_{t-q}^2$$

$$+ c_1 h_{t-1}^2 + c_2 h_{t-2}^2 + \dots + c_r h_{t-r}^2 \tag{6.4}$$

The value of this is that even if the effects of a shock are very long-lived, this can be described with a small number of parameters. For example, a GARCH(1,1) model has been found to provide a good description of most developed country stock market returns. In this case, the initial impact of any shock persists indefinitely, but with an exponentially declining effect.

For the GARCH model, the long-run unconditional variance h, say, can be determined by setting $h_{t-i} = u_{t-i} = h \ \forall$ I. This yields:

$$h = b_0 / [1 - (b_1 + b_2 + \ldots + b_q + c_1 + c_2 + \ldots c_r)] \qquad (6.5)$$

This shows that in (6.4), in order for the unconditional variance to be finite, we require $(b_1 + b_2 + \ldots + b_q + c_1 + c_2 + \ldots c_r) < 1$.

We also, of course, require both conditional and unconditional variances to be positive. This is hard to impose on (6.4), but one possibility is to use $\log(h_t^2)$ rather than h_t^2 as the dependent variable. A further popular generalisation of the ARCH model which ensures non-negativity and also has the interesting feature that negative shocks may affect the variance differently from positive shocks, is the exponential GARCH (E-GARCH) model due to Nelson (1991);

$$\ln(h_t^2) = b_0 + b^*_1(u_{t-1}/h_{t-1}) + b^*_2(u_{t-2}/h_{t-2}) + \ldots + b^*_q(u_{t-q}/h_{t-q})$$

$$+ b_1 \left| (u_{t-1}/h_{t-1}) - \mu \right| + b_2 \left| (u_{t-2}/h_{t-2}) - \mu \right| + \ldots + b_q \left| (u_{t-q}/h_{t-q}) - \mu \right|$$

$$+ c_1 h_{t-1}^2 + c_2 h_{t-2}^2 + \ldots + c_r h_{t-r}^2 \qquad (6.6)$$

where μ is the average value of the ratios (u_{t-i}/h_{t-i}). If the b^*_i are significantly nonzero, this indicates that the sign of the shock is important for its impact on the variance, and that some asymmetry is present.

Finally, note that the assumption (6.2) that the error distribution is normal is not necessary. For our purposes, we consider the alternative

that

$$u_t \sim t_k\,(0,\ h_t^2) \qquad (6.7)$$

That is, the error distribution may follow a Student t-distribution with k degrees of freedom. The smaller is k, the more centrally peaked and the more fat the tails of the error distribution. By freely estimating the degrees of freedom parameter k, we can test whether the leptokurtosis observed in the ISE returns is due to ARCH effects, or to an underlying non-normal distribution, or indeed to a combination of both factors.

According to the CAPM, the risk premium on the whole stock market depends on the risk aversion of market participants, and on the variance of returns themselves. When the whole market is expected to be volatile, it should yield higher expected returns. It is therefore interesting to consider whether the variance h_t^2 is significant in the mean equation (6.1), as:

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_p y_{t-p} + d\,h_t^2 + u_t \qquad (6.8)$$

With the variance described by one of the ARCH models, this is an ARCH-in-mean model (ARCH-M).

Whether this is in principle credible as a description of the Istanbul stock exchange depends on how closed the market has been to international investors. If the market is mainly driven by investors with a "home-country bias", the ISE may well capture the whole set of risky assets, and the ARCH-M model may work in the sense that the parameter d will be significant. If the ISE is part of a larger international market, it will not represent the market portfolio for the typical investor, and there should be no variance-related risk premium. Testing the significance of the parameter d provides a natural test of the degree of integration of the ISE into the global capital market.

6.3 EMPIRICAL RESULTS.

Data for this part of the study cover the period from 4/1/1988 to 29/12/1995 for ISE index, and for our 20 sample companies. First, we estimate a variety of standard AR and ARCH models on the ISE index. Then we look briefly at the properties of GARCH(1,1) models for US$ and Inflation-adjusted series, and for the individual company returns.

Table 6.1 summarises results for the TL index returns. The first column shows that returns follow an AR(2) model (figures in parentheses are standard errors). However, analysis of the regression residuals reveals a high degree of nonnormality, an correlation between the squared errors and the regressors, both strongly indicative of ARCH effects.

The second column shows and ARCH(5) model, in which the current variance depends directly on the squared residuals from the past 5 trading days. The ARCH effects are still strongly significant after 5 days, and suggest that more lagged terms need to be added to the ARCH model, or some GARCH alternative needs to be estimated.

To help choose between nonnested models we have computed the Schwartz Bayesian Criterion, an increasing function of the model log-likelihood, but a decreasing function of the number of model parameters. A high (less negative) value for this criterion indicates an improvement in fit achieved without an undue increase in model complexity.

The GARCH(1,1) model in the third column of the Table has well-defined parameters, and improves the SBC substantially relative to the ARCH(5) model. A unit shock to the model will initially increase the variance by about 1/4 (0.2466) of the shock. This will die away over the following days, with a half-life of 1/(1-0.6890) = 3.2 days. The variance will eventual converge on its unconditional value of 0.6725/(1-.2466-.6890) = 10.4425 (s.d. = 3.23% per day).

Testing for asymmetry in the effects of positive and negative shocks does not prove productive. The E-GARCH has a slightly better SBC than the GARCH model, but the coefficient b^*_1 on the signed shock is not statistically significant.

Characterisation of returns by a t-distribution is helpful, however. The degrees of freedom is estimated at around 9-10, which leads to a slightly fatter-tailed distribution than normal. This helps fit extreme observations in the returns series, increases the log-likelihood significantly, and increases the SBC.

The t-GARCH-in-mean model shows that the variance is marginally significant (at 10%, but not at 5%) in the model for mean returns. There is therefore some slight evidence that more volatile periods in the ISE are periods of higher average returns.

The ARCH-M model can be used to test an interesting proposition about the integration of the ISE into the international capital market. As we have seen in Chapter 2, the ISE became progressively more open to international investment over the period of our study. If this is reflected in the risk premium on the ISE, we should expect to see larger effects on expected returns from the own-variance of the ISE early in the sample period, and smaller effects later, when the ISE is more integrated with the international capital market, and the typical investor can diversify away risks specific to the Turkish market.

In Table 6.2, we report estimates of the t-GARCH-M model estimated over the sub-periods 1988-90, 1991-92, and 1993-95. The results are consistent with the initial presence of a risk premium related to risk within the ISE market, which progressively vanishes as international integration proceeds. The coefficient d is significant in the 1988-90 period. It is positive but barely significant in 1991-92. But by 1993-95, the estimated coefficient is very close to zero, slightly negative, and wholly insignificant.

Apart from this insight into the effects of integration, the sub-period models also reveal some structural changes in the process driving returns. In the mean equation, for example, the negative second order effect (a_2) becomes progressively smaller over time. Early in the period, there were clearly many instances when the market rose or fell sharply on a particular day, only to have this move reversed in two or three days time. In recent years, there has been less of this mean-reverting noise in the series, perhaps reflecting a greater degree of market efficiency.

The other interesting structural change is the progressive fall in the impact coefficient b_1 in the GARCH model, and corresponding rise in the coefficient on the lagged variance c_1. This means that large market moves have a smaller effect on the returns variance now than in earlier years, but the effects of these shocks now last longer.

We also tested AR(1)+GARCH(1,1) for sample 20 companies for the sample period 1988-1995. The table 6.3.1-6.8.2 shows that the daily adjusted return series (in terms of TL), US$ adjusted return series and inflation adjusted return series have strong ARCH effects. As a causal inspection, the plotted residuals show that the ARCH effect is present in these figures. Another but a more precise way to look at the correlation coefficient of the error term with absolute and squared error terms they also confirm the result. The finding of the serial correlation of return on lag 1, and Q statistics of the lag 5, lag 15 and lag 30 reported at table 6.3.2-6.5.2. Tables reveal that Q statistics are significant in many cases. The most formal way of testing the ARCH effects is to test the coefficients of conditional variance equation. Precisely it is the coefficient b_1. The hypothesis is that it is nonzero. The t-statistics, written below coefficients (in bold), show that all cases are significantly different than zero. In other words, there is significant ARCH effect. In Table 6.3.1. (Daily returns, 1988-1995) values of b_1 range from 0.1 to 0.22; therefore they are nonexplosive, e.i., $b_1<1$. When the same idea is applied to the GARCH effects, Table 6.3.1 reporting significant coefficient of c_1 indicates the GARCH effects.

In explaining the ARCH effects we carried out two more estimations, namely AR(1)+GARCH(1,1) for daily US$ adjusted returns of the sample company shares and daily inflation adjusted returns of the sample company stocks. Comparing the results reported in Table 6.3.1 with Table 6.4.1 and Table 6.5.1 one can say that neither volatility in exchange rate nor volatility in inflation explain the volatility in daily share returns of ISE. Indeed, the US$ adjusted results affected the results at some degree. Unconditional (long--run) variance values increased for the US$ adjusted daily returns. Long run variances (and standard deviation) reported in Table 6.3.1-6.5.1 are calculated as in equation (6.5).,

The 20 Companies' volatility varies from 4% to 5.5% for the same period. In US$ terms standard deviations of the 20 companies vary from 4.3% to 5.7% and Inflation adjusted term standard deviations range from 4.3% to 5.5% for same period. The determinants of the volatility in daily share returns could be clustering of trade volumes, nominal interest rates, dividend yields, money supply, oil price index, etc. This investigation is beyond this study but worth pursuing.

The table 6.6-6.8 shows the period for test on AR(1)+ARCH(5) for the returns of the sample 20 companies. The test is applied for the daily adjusted return series, US $ adjusted return series and inflation adjusted return When number of the alpha increase number of significance fall, however still indicates strong ARCH effect. Also, it is worth noting that values of coefficient decline as p increases. This implies that the system is not explosive.

6.4. CONCLUSION

In Chapter 3 we found that daily returns to the ISE index, and its main components, were significantly non-normal, and in particular exhibited excess kurtosis. We speculated that this might be due either to time-variation in volatility, or to the presence of non-normal shocks.

In this Chapter, we have tried to unravel these features of the returns series. We reach five main conclusions.

First, the variance of daily returns to the ISE index are time-varying, and can be well explained by a simple GARCH(1,1) process.

Second, the GARCH effects observed in the index are also observed in the main constituents of the index.

Third, the structure of the GARCH process changes over time, with the coefficient measuring persistence (c_1) rising from .57 to .88 between 1988-90 and 1993-5. This implies that changes in the varuance of returns are more long-lived nowadays than they were in the early days of the market.

Fourth, even allowing for time variation in variances, the shocks affecting daily returns are better characterised by a t-distribution with low degrees of freedom, than by the normal distribution. In other words, this is a market which is hit by an unusually large number of large shocks, good and bad.

Finally, and importantly, there is some evidence that in the early years of the market, investors priced volatility. That is, they required a higher return on the market at times when market volatility was high.

The Capital Asset Pricing Model suggests this should only happen in a market which is isolated from the international capital market, so that investors cannot diversify away the specific risk of the Turkish market by spreading their investments internationally. We interpret the vanishing of the GARCH-in-mean effect after 1990 as empirical evidence of the increased integration of the ISE into the global capital market, and a measure of the benefit which investors in the market obtained from the relaxation of capital controls.

APPENDICES 6.

Table 6.1 ARCH Models of ISE Index Returns

Coeff:	AR(2)	ARCH(5)	GARCH	E-GARCH	t-GARCH	t-GARCH-M
a_0	0.1677	0.1203	0.1137	0.0956	0.1233	0.0053
	(0.06)	(0.05)	(0.05)	(0.02)	(0.05)	(0.08)
a_1	0.2615	0.2450	0.2449	0.2535	0.2360	0.2340
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
a_2	-0.0905	-0.0567	-0.0587	-0.0625	-0.0608	-0.0626
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
d						0.0197
						(0.01)
b_0		2.5867	0.6725	0.1853	0.5342	0.5669
		(0.25)	(0.15)	(0.03)	(0.15)	(0.16)
b_1		0.2600	0.2466	0.4139	0.2612	0.2684
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
b_2		0.2179				
		(0.04)				
b_3		0.0877				
		(0.03)				
b_4		0.1216				
		(0.03)				
b_5		0.0630				
		(0.02)				
c_1			0.6890	0.9088	0.7004	0.6901
			(0.04)	(0.02)	(0.04)	(0.04)
b^*_1				-0.0036		
				(0.02)		
k					9.60	9.73
					(1.86)	(1.85)
SBC	-4968.3	-4805.0	-4794.4	-4792.9	-4778.5	-4781.0

Table 6.2 t-GARCH-M Models of ISE Index Returns

Coeff:	1988-95	1988-90	1991-2	1993-95
a_0	0.0053	-0.0347	-0.2198	0.3595
	(0.08)	(0.09)	(0.20)	(0.21)
a_1	0.2340	0.3563	0.1274	0.1574
	(0.02)	(0.04)	(0.05)	(0.04)
a_2	-0.0626	-0.1214	-0.1042	-0.0165
	(0.02)	(0.04)	(0.05)	(0.04)
d	0.0197	0.0225	0.0222	-0.0076
	(0.01)	(0.01)	(0.03)	(0.03)
b_0	0.5669	0.4304	0.9295	0.2304
	(0.16)	(0.15)	(0.56)	(0.14)
b_1	0.2684	0.4641	0.2534	0.0862
	(0.04)	(0.07)	(0.10)	(0.03)
c_1	0.6901	0.5692	0.6589	0.8888
	(0.04)	(0.05)	(0.13)	(0.04)
k	9.73	10.63	6.23	9.75
	(1.85)	(3.89)	(1.94)	(3.15)

Figures in parenthesis show standard errors.

TABLE 6.3.1

AR(1)+GARCH(1,1) for Daily Returns of ISE. 1988-1995

Code	a0	a1	b0	b1	c1	LR sd
ISE-INDEX	0.0011	0.2301	0.0001	0.2464	0.6941	0.0328
	2.10	**10.02**	**6.93**	**9.93**	**27.89**	
1 ARC	0.0015	0.0721	0.0001	0.1668	0.7921	0.0448
	1.94	**2.97**	**6.62**	**8.89**	**41.18**	
2 BAG	0.0019	0.0546	0.0003	0.1654	0.6958	0.0457
	1.99	**2.34**	**5.15**	**6.84**	**16.28**	
3 CEL	0.0016	0.0640	0.0001	0.1414	0.8245	0.0525
	1.60	**2.71**	**6.19**	**8.90**	**52.92**	
4 CIMS	0.0013	0.0307	0.0002	0.1733	0.7556	0.0462
	1.62	**1.28**	**7.00**	**8.79**	**35.16**	
5 CUK	0.0018	0.1197	0.0000	0.1006	0.8801	0.0496
	2.02	**5.39**	**5.46**	**14.76**	**149.49**	
6 DOK	0.0010	0.0898	0.0002	0.1518	0.7676	0.0465
	1.07	**3.86**	**5.14**	**8.02**	**29.07**	
7 ECZ	0.0015	0.1177	0.0001	0.1065	0.8562	0.0459
	1.67	**4.99**	**4.58**	**6.76**	**42.46**	
8 EGEB	0.0026	0.0690	0.0001	0.1496	0.8083	0.0436
	3.23	**2.89**	**5.26**	**8.78**	**43.01**	
9 ERE	0.0010	0.1294	0.0002	0.2228	0.6785	0.0460
	1.19	**5.28**	**6.86**	**8.05**	**21.22**	
10 GOOD	0.0015	0.0709	0.0002	0.1803	0.7088	0.0433
	1.67	**2.95**	**6.63**	**7.68**	**23.39**	
11 GUN	0.0018	0.0776	0.0001	0.1396	0.7938	0.0449
	2.05	**3.23**	**5.68**	**7.54**	**31.35**	
12 KAR	0.0018	-0.0116	0.0001	0.1794	0.7568	0.0429
	2.23	**-0.48**	**6.78**	**8.75**	**33.04**	
13 KOCH	0.0012	0.0909	0.0001	0.1394	0.8078	0.0426
	1.39	**3.88**	**5.44**	**7.78**	**36.73**	
14 KOCY	0.0012	0.0636	0.0001	0.1683	0.7920	0.0450
	1.55	**2.69**	**7.69**	**8.96**	**41.73**	
15 OTO	0.0013	0.0844	0.0001	0.1296	0.8154	0.0466
	1.39	**3.60**	**5.82**	**7.90**	**39.97**	
16 SAR	0.0014	0.1112	0.0002	0.2013	0.7009	0.0403
	1.73	**4.57**	**6.41**	**7.61**	**20.56**	
17 TIB	0.0018	0.1022	0.0001	0.2070	0.7445	0.0552
	1.94	**4.24**	**5.86**	**8.69**	**29.59**	
18 TSI	0.0015	0.0540	0.0003	0.1295	0.7320	0.0464
	1.53	**2.21**	**6.14**	**6.28**	**19.26**	
19 TUDD	0.0008	0.0611	0.0002	0.1611	0.7617	0.0462
	0.83	**2.57**	**8.13**	**8.63**	**36.40**	
20 YAS	0.0024	0.0487	0.0001	0.0975	0.8695	0.0471
	2.45	**2.10**	**4.03**	**7.73**	**54.40**	
No of significant		**19**	**21**	**21**	**21**	

Figures in bold show t-statistics

TABLE 6.3.2

AR(1)+GARCH(1,1) for Daily Returns of ISE. 1988-1995

$\boxed{cor\left[\varepsilon_t, \varepsilon_{t-s}\right]}$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.0305	23.2	38	49.9
1 ARC	0.0208	7.21	16.8	36.2
2 BAG	0.0447	6.96	20.7	34.5
3 CEL	0.0267	10.1	21.8	32.2
4 CIMS	0.0653	17.2	32.1	41.4
5 CUK	0.0483	16.1	29	52.4
6 DOK	0.0306	4.78	16.9	39.7
7 ECZ	0.0290	10.4	37.6	51
8 EGE	0.0324	3.15	24.8	40.8
9 ERE	0.0463	9.5	15.6	37
10 GOOD	0.0282	5.52	14.4	35.5
11 GUN	0.0236	7.71	15.3	28.2
12 KAR	0.0317	14.6	27.7	40.1
13 KOCH	0.0484	8.52	20.4	44.1
14 KOCY	0.0675	12	29.6	48.9
15 OTO	0.0410	5.14	21.1	29.4
16 SAR	0.0486	10.2	27.4	38.3
17 TIB	0.0534	9.97	37.5	47.7
18 TSI	0.0449	8.74	22.6	31.6
19 TUDD	0.0196	1.34	11.6	36.2
20 YAS	0.0275	14	33.2	44.1
No of significant	9	6	9	7

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.0439 for the critical value of the serial correlation of lag one

TABLE 6.4.1

AR(1)+GARCH(1,1) for Daily *US$* Adjusted Returns of ISE. 1988-1995

Code	a0	a1	b0	b1	c1	LR sd
ISE-INDEX	-0.0001	0.1794	0.0000	0.2119	0.7600	0.0414
	-0.21	**7.96**	**6.56**	**13.34**	**50.40**	
1 ARC	0.0001	0.0506	0.0001	0.1523	0.8195	0.0500
	0.07	**2.19**	**9.43**	**11.06**	**80.24**	
2 BAG	0.0003	0.0481	0.0003	0.1599	0.7220	0.0479
	0.28	**2.05**	**5.55**	**7.53**	**20.84**	
3 CEL	0.0000	0.0475	0.0001	0.1471	0.8160	0.0548
	0.04	**2.00**	**6.51**	**9.99**	**53.58**	
4 CIMS	-0.0007	0.0180	0.0002	0.2166	0.7033	0.0514
	-0.84	**0.74**	**7.51**	**12.41**	**31.39**	
5 CUK	0.0000	0.0973	0.0002	0.1955	0.7307	0.0508
	0.02	**4.03**	**8.77**	**10.17**	**31.60**	
6 DOK	-0.0007	0.0729	0.0002	0.1763	0.7552	0.0507
	-0.72	**3.05**	**5.15**	**9.94**	**30.06**	
7 ECZ	0.0000	0.1111	0.0001	0.1067	0.8575	0.0482
	0.03	**4.69**	**4.78**	**7.84**	**48.65**	
8 EGEB	0.0010	0.0501	0.0001	0.1765	0.7873	0.0486
	1.25	**2.14**	**5.65**	**10.18**	**43.87**	
9 ERE	-0.0006	0.1046	0.0002	0.2148	0.6898	0.0481
	-0.61	**4.31**	**7.41**	**9.12**	**26.61**	
10 GOOD	-0.0004	0.0459	0.0002	0.1600	0.7549	0.0464
	-0.42	**1.94**	**8.03**	**10.87**	**38.68**	
11 GUN	0.0004	0.0509	0.0001	0.1144	0.8469	0.0475
	0.41	**2.19**	**5.30**	**7.66**	**47.74**	
12 KAR	-0.0001	-0.0201	0.0001	0.2064	0.7456	0.0489
	-0.07	**-0.82**	**6.43**	**9.99**	**34.43**	
13 KOCH	-0.0004	0.0798	0.0001	0.1355	0.8244	0.0457
	-0.43	**3.47**	**5.36**	**9.18**	**47.87**	
14 KOCY	-0.0004	0.0346	0.0001	0.1583	0.8152	0.0499
	-0.49	**1.52**	**6.78**	**10.34**	**54.44**	
15 OTO	-0.0004	0.0781	0.0001	0.0788	0.8955	0.0492
	-0.44	**3.60**	**6.59**	**12.95**	**184.79**	
16 SAR	-0.0002	0.0930	0.0002	0.2075	0.7058	0.0435
	-0.31	**3.87**	**6.90**	**8.96**	**24.36**	
17 TIB	0.0004	0.0842	0.0001	0.1930	0.7619	0.0574
	0.41	**3.61**	**5.84**	**8.91**	**33.64**	
18 TSI	-0.0002	0.0408	0.0003	0.1367	0.7375	0.0486
	-0.24	**1.67**	**6.62**	**7.12**	**22.07**	
19 TUDD	-0.0010	0.0347	0.0001	0.1738	0.7758	0.0526
	-1.06	**1.53**	**6.90**	**12.81**	**44.96**	
20 YAS	0.0009	0.0334	0.0001	0.1036	0.8688	0.0506
	0.87	**1.42**	**3.92**	**9.03**	**58.97**	
No of significant		**14**	**21**	**21**	**21**	

Figures in bold show t-statistics

TABLE 6.4.2

AR(1)+GARCH(1,1) for Daily *US$* Adjusted Returns of ISE. 1988-1995

$$\boxed{cor\left[\varepsilon_t, \varepsilon_{t-s}\right]}$$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.0236	31.3	50	79.9
1 ARC	0.0212	13.9	29.6	55
2 BAG	0.0506	13.2	25.4	49
3 CEL	0.0418	19.9	31.7	40
4 CIMS	0.0559	16.6	26.2	36.3
5 CUK	0.0516	14.6	23.5	43.7
6 DOK	0.0358	8.05	18.2	37.2
7 ECZ	0.0442	22.6	47.1	73.2
8 EGE	0.0165	3.45	21	34.3
9 ERE	0.0571	18.6	27.5	56.3
10 GOOD	0.0353	7.14	16.3	41.3
11 GUN	0.0248	3.23	12.1	22.9
12 KAR	0.0127	14.8	27.1	45.6
13 KOCH	0.0458	9.51	30.2	47.7
14 KOCY	0.0628	8.54	22.2	38.8
15 OTO	0.0416	6.28	19.3	29.5
16 SAR	0.0613	23.1	50.7	70.5
17 TIB	0.0679	11.1	36.7	52.4
18 TSI	0.0593	20	34.8	43.7
19 TUDD	0.0364	3.8	17.1	44.3
20 YAS	0.0357	17.8	34.3	44.4
No of significant	10	13	13	13

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.0439 for the critical value of the serial correlation of lag one

TABLE 6.5.1

AR(1)+GARCH(1,1) for Daily *Inflation* Adjusted Returns of ISE. 1988-1995

Code	a0	a1	b0	b1	c1	LR sd
ISE-INDEX	-0.0006	0.2298	0.0001	0.2459	0.6951	0.0328
	-1.18	**10.01**	**6.90**	**9.94**	**28.02**	
1 ARC	-0.0005	0.0735	0.0001	0.1659	0.7931	0.0448
	-0.64	**3.03**	**6.59**	**8.85**	**41.18**	
2 BAG	-0.0002	0.0546	0.0003	0.1657	0.6949	0.0457
	-0.24	**2.34**	**5.14**	**6.83**	**16.17**	
3 CEL	-0.0004	0.0639	0.0001	0.1416	0.8241	0.0524
	-0.42	**2.71**	**6.18**	**8.87**	**52.56**	
4 CIMS	-0.0008	0.0312	0.0002	0.1736	0.7550	0.0462
	-1.02	**1.30**	**7.01**	**8.79**	**35.07**	
5 CUK	-0.0001	0.1204	0.0000	0.0996	0.8820	0.0498
	-0.12	**5.44**	**5.41**	**14.65**	**152.26**	
6 DOK	-0.0010	0.0905	0.0002	0.1515	0.7687	0.0465
	-1.05	**3.90**	**5.13**	**8.04**	**29.35**	
7 ECZ	-0.0004	0.1180	0.0001	0.1066	0.8559	0.0459
	-0.47	**5.00**	**4.58**	**6.75**	**42.33**	
8 EGEB	0.0006	0.0697	0.0001	0.1493	0.8087	0.0436
	0.68	**2.93**	**5.25**	**8.76**	**43.00**	
9 ERE	-0.0009	0.1289	0.0002	0.2232	0.6778	0.0460
	-1.01	**5.25**	**6.87**	**8.05**	**21.16**	
10 GOOD	-0.0006	0.0709	0.0002	0.1802	0.7091	0.0433
	-0.70	**2.96**	**6.62**	**7.66**	**23.39**	
11 GUN	-0.0003	0.0783	0.0001	0.1385	0.7954	0.0449
	-0.28	**3.26**	**5.65**	**7.54**	**31.61**	
12 KAR	-0.0004	-0.0109	0.0001	0.1783	0.7582	0.0429
	-0.49	**-0.45**	**6.76**	**8.77**	**33.35**	
13 KOCH	-0.0009	0.0914	0.0001	0.1400	0.8069	0.0426
	-1.04	**3.90**	**5.44**	**7.77**	**36.51**	
14 KOCY	-0.0008	0.0645	0.0001	0.1676	0.7925	0.0449
	-1.05	**2.73**	**7.67**	**8.93**	**41.74**	
15 OTO	-0.0008	0.0853	0.0001	0.1293	0.8158	0.0466
	-0.82	**3.64**	**5.80**	**7.91**	**40.10**	
16 SAR	-0.0006	0.1118	0.0002	0.2008	0.7014	0.0403
	-0.75	**4.59**	**6.40**	**7.60**	**20.57**	
17 TIB	-0.0002	0.1018	0.0001	0.2077	0.7435	0.0552
	-0.20	**4.23**	**5.86**	**8.67**	**29.39**	
18 TSI	-0.0006	0.0540	0.0003	0.1298	0.7330	0.0463
	-0.60	**2.21**	**6.18**	**6.31**	**19.47**	
19 TUDD	-0.0013	0.0617	0.0002	0.1609	0.7621	0.0462
	-1.44	**2.60**	**8.11**	**8.63**	**36.44**	
20 YAS	0.0002	0.0489	0.0001	0.0978	0.8689	0.0471
	0.24	**2.11**	**4.02**	**7.73**	**54.07**	
No of significant		**19**	**21**	**21**	**21**	

Figures in bold show t-statistics

TABLE 6.5.2

AR(1)+GARCH(1,1) for Daily *Inflation* Adjusted Returns of ISE. 1988-1995

$$\boxed{cor\left[\varepsilon_t, \varepsilon_{t-s}\right]}$$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.0311	23.2	38.1	49.9
1 ARC	0.0201	7.1	16.6	36
2 BAG	0.0447	6.96	20.7	34.4
3 CEL	0.0270	10.1	21.8	32
4 CIMS	0.0651	17.1	31.9	41.3
5 CUK	0.0480	15.9	28.9	52.1
6 DOK	0.0304	4.82	16.7	39.7
7 ECZ	0.0290	10.5	38	51.3
8 EGE	0.0320	3.08	24.4	40.3
9 ERE	0.0468	9.59	15.7	37.1
10 GOOD	0.0281	5.51	14.4	35.5
11 GUN	0.0230	7.65	15.1	27.9
12 KAR	0.0310	14.6	27.8	40.1
13 KOCH	0.0484	8.64	20.6	44.2
14 KOCY	0.0671	12	28.9	48.1
15 OTO	0.0406	4.98	21.3	29.5
16 SAR	0.0485	10.1	27.4	38.2
17 TIB	0.0536	10	37.5	47.8
18 TSI	0.0449	8.71	22.6	31.5
19 TUDD	0.0195	1.32	11.7	35.9
20 YAS	0.0275	14	33.3	44.2
No of significant	9	6	10	7

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.0439 for the critical value of the serial correlation of lag one

TABLE 6.6.1

AR(1)+ARCH(5) for Daily Returns of ISE. 1988-1995

Code	a0	a1	b0	b1	b2	b3	b4	b5
ISE-INDEX	0.0012	0.2308	0.0003	0.2590	0.2167	0.0914	0.1266	0.0655
	2.26	**10.20**	**13.70**	**7.73**	**5.99**	**3.59**	**4.77**	**2.88**
1 ARC	0.0004	0.0466	0.0007	0.2597	0.1113	0.0901	0.1110	0.1487
	0.55	**1.87**	**16.15**	**8.64**	**4.17**	**3.45**	**4.74**	**8.59**
2 BAG	0.0001	0.0451	0.0011	0.1787	0.1471	0.0636	0.0773	0.0476
	0.16	**1.90**	**18.52**	**5.67**	**5.24**	**2.82**	**3.16**	**2.26**
3 CEL	0.0017	0.0509	0.0009	0.2128	0.0919	0.1368	0.0953	0.1340
	1.82	**2.10**	**16.60**	**6.16**	**3.67**	**5.20**	**4.74**	**5.08**
4 CIMS	0.0013	0.0264	0.0009	0.2228	0.1209	0.1124	0.0867	0.0302
	1.51	**1.04**	**18.08**	**6.30**	**4.50**	**5.03**	**3.67**	**1.54**
5 CUK	-0.0001	0.1022	0.0008	0.2749	0.1962	0.0907	0.0891	0.0497
	-0.16	**4.06**	**26.40**	**10.31**	**7.53**	**4.04**	**3.96**	**2.38**
6 DOK	0.0008	0.0865	0.0009	0.2069	0.0997	0.0934	0.0396	0.1350
	0.87	**3.61**	**17.24**	**5.51**	**3.59**	**3.57**	**1.88**	**4.67**
7 ECZ	0.0004	0.1137	0.0010	0.1316	0.1414	0.1208	0.0424	0.1084
	0.41	**4.80**	**19.34**	**4.54**	**4.49**	**4.82**	**1.83**	**4.09**
8 EGEB	0.0028	0.0651	0.0007	0.1951	0.1511	0.0802	0.1103	0.0652
	3.36	**2.66**	**20.49**	**5.77**	**5.06**	**4.10**	**4.55**	**3.02**
9 ERE	-0.0006	0.1044	0.0008	0.2524	0.1093	0.1574	0.0707	0.0489
	-0.70	**4.30**	**16.81**	**7.27**	**3.66**	**5.32**	**2.66**	**2.57**
10 GOOD	-0.0004	0.0612	0.0010	0.2680	0.0768	0.0670	0.0574	0.0928
	-0.40	**2.35**	**21.27**	**9.45**	**2.70**	**2.44**	**2.48**	**4.22**
11 GUN	0.0018	0.0718	0.0009	0.2152	0.1127	0.0917	0.0600	0.0819
	2.01	**2.78**	**18.25**	**6.07**	**3.99**	**3.80**	**2.48**	**3.51**
12 KAR	0.0019	-0.0162	0.0006	0.2403	0.0827	0.1124	0.1612	0.0795
	2.41	**-0.65**	**17.36**	**6.44**	**3.28**	**4.38**	**5.93**	**3.45**
13 KOCH	0.0015	0.0983	0.0007	0.1693	0.1586	0.0881	0.1251	0.0729
	1.76	**4.10**	**14.60**	**5.32**	**5.03**	**3.35**	**4.63**	**3.21**
14 KOCY	0.0014	0.0706	0.0006	0.1981	0.1924	0.1521	0.1085	0.0436
	1.76	**2.97**	**18.70**	**5.61**	**5.93**	**5.06**	**3.87**	**1.98**
15 OTO	0.0014	0.0890	0.0010	0.1438	0.1455	0.1350	0.0501	0.0584
	1.52	**3.79**	**19.05**	**4.68**	**5.12**	**4.89**	**2.11**	**2.59**
16 SAR	0.0014	0.1095	0.0006	0.2472	0.1402	0.1278	0.0625	0.0592
	1.76	**4.37**	**16.87**	**6.40**	**4.63**	**4.72**	**2.65**	**2.84**
17 TIB	0.0003	0.0778	0.0009	0.2435	0.1807	0.1447	0.0761	0.0825
	0.28	**3.25**	**14.60**	**6.98**	**6.18**	**5.17**	**3.87**	**3.24**
18 TSI	0.0017	0.0625	0.0012	0.1304	0.0913	0.0457	0.1108	0.0878
	1.80	**2.61**	**28.53**	**4.43**	**3.47**	**2.10**	**3.87**	**3.60**
19 TUDD	0.0011	0.0598	0.0009	0.2047	0.1192	0.0415	0.0850	0.1367
	1.23	**2.51**	**16.77**	**6.01**	**4.48**	**1.82**	**3.70**	**5.33**
20 YAS	0.0025	0.0510	0.0010	0.1322	0.1239	0.0874	0.1376	0.0467
	2.57	**2.15**	**16.78**	**3.94**	**3.77**	**3.53**	**4.68**	**1.82**
No of significant		20	21	21	21	17	16	19

Figures in bold show t-statistics

TABLE 6.6.2

AR(1)+ARCH(5) for Daily Returns of ISE. 1988-1995

$$\boxed{cor\left[\varepsilon_t, \varepsilon_{t-s}\right]}$$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDEX	0.0299	23.2	37.9	49.9
1 ARC	0.0333	19.9	28.9	43
2 BAG	0.0335	4.8	19.4	32.4
3 CEL	0.0392	11.7	23.4	34.1
4 CIMS	0.0694	18.3	33.2	42.5
5 CUK	0.0461	17.5	28.5	50.2
6 DOK	0.0339	5.19	17.3	40
7 ECZ	0.0363	12.7	35.4	46.1
8 EGE	0.0362	3.66	25.4	41.3
9 ERE	0.043	9.52	15.3	37.8
10 GOOD	0.013	4.17	12.5	32.7
11 GUN	0.0296	8.42	16.1	29
12 KAR	0.0359	15.1	28.2	40.6
13 KOCH	0.0409	7.1	19	43
14 KOCY	0.0604	10.1	27.4	46.5
15 OTO	0.0365	4.5	20.5	28.7
16 SAR	0.0503	10.5	27.7	38.7
17 TIB	0.0544	9.85	37.1	47.4
18 TSI	0.0366	7.33	21.3	30.2
19 TUDD	0.0209	1.45	11.7	36.3
20 YAS	0.0253	13.8	32.9	43.8
No of significant	5	8	12	6

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.0439 for the critical value of the serial correlation of lag one

TABLE 6.7.1

AR(1)+ARCH(5) for Daily *US$* Adjusted Returns of ISE. 1988-1995

Code	a0	a1	b0	b1	b2	b3	b4	b5
ISE-INDEX	0.0000	0.1796	0.0003	0.3295	0.1835	0.0881	0.0819	0.0746
	-0.07	**7.63**	**20.73**	**11.15**	**5.45**	**3.83**	**3.45**	**4.15**
1 ARC	0.0004	0.0466	0.0007	0.2597	0.1113	0.0901	0.1110	0.1487
	0.55	**1.87**	**16.15**	**8.64**	**4.17**	**3.45**	**4.74**	**8.59**
2 BAG	0.0001	0.0451	0.0011	0.1787	0.1471	0.0636	0.0773	0.0476
	0.16	**1.90**	**18.52**	**5.67**	**5.24**	**2.82**	**3.16**	**2.26**
3 CEL	0.0000	0.0376	0.0010	0.2255	0.0800	0.1347	0.1115	0.1188
	0.02	**1.51**	**17.54**	**6.64**	**3.36**	**5.56**	**5.33**	**4.76**
4 CIMS	-0.0006	0.0119	0.0010	0.2763	0.1257	0.1228	0.0754	0.0079
	-0.66	**0.47**	**18.68**	**10.19**	**5.23**	**4.95**	**3.50**	**0.44**
5 CUK	-0.0001	0.1022	0.0008	0.2749	0.1962	0.0907	0.0891	0.0497
	-0.16	**4.06**	**26.40**	**10.31**	**7.53**	**4.04**	**3.96**	**2.38**
6 DOK	-0.0009	0.0605	0.0009	0.2482	0.0958	0.1119	0.0293	0.1765
	-0.96	**2.52**	**15.59**	**7.28**	**3.42**	**4.48**	**1.41**	**6.29**
7 ECZ	0.0004	0.1137	0.0010	0.1316	0.1414	0.1208	0.0424	0.1084
	0.41	**4.80**	**19.34**	**4.54**	**4.49**	**4.82**	**1.83**	**4.09**
8 EGEB	0.0013	0.0474	0.0007	0.2796	0.1855	0.0468	0.1081	0.0661
	1.57	**1.96**	**15.10**	**8.42**	**5.98**	**1.93**	**4.61**	**2.86**
9 ERE	-0.0006	0.1044	0.0008	0.2524	0.1093	0.1574	0.0707	0.0489
	-0.70	**4.30**	**16.81**	**7.27**	**3.66**	**5.32**	**2.66**	**2.57**
10 GOOD	-0.0004	0.0612	0.0010	0.2680	0.0768	0.0670	0.0574	0.0928
	-0.40	**2.35**	**21.27**	**9.45**	**2.70**	**2.44**	**2.48**	**4.22**
11 GUN	0.0002	0.0359	0.0010	0.2135	0.1513	0.0955	0.0346	0.0722
	0.26	**1.39**	**17.07**	**7.22**	**5.31**	**3.91**	**1.58**	**3.47**
12 KAR	0.0001	-0.0171	0.0006	0.2374	0.1209	0.1540	0.1612	0.0752
	0.19	**-0.70**	**16.07**	**6.61**	**5.10**	**5.46**	**5.79**	**3.51**
13 KOCH	-0.0002	0.0884	0.0007	0.2080	0.1604	0.0844	0.1021	0.0916
	-0.20	**3.66**	**15.48**	**6.99**	**5.43**	**3.35**	**3.75**	**4.15**
14 KOCY	-0.0004	0.0380	0.0007	0.2355	0.1731	0.1470	0.0822	0.0714
	-0.53	**1.58**	**18.50**	**7.24**	**5.67**	**5.14**	**3.22**	**3.25**
15 OTO	-0.0002	0.0851	0.0012	0.1636	0.1373	0.1190	0.0496	0.0382
	-0.24	**3.47**	**27.13**	**5.50**	**4.85**	**5.32**	**2.46**	**1.92**
16 SAR	-0.0003	0.0837	0.0006	0.2780	0.1455	0.1342	0.0457	0.0700
	-0.42	**3.39**	**18.02**	**7.66**	**5.04**	**5.02**	**2.01**	**3.41**
17 TIB	0.0003	0.0778	0.0009	0.2435	0.1807	0.1447	0.0761	0.0825
	0.28	**3.25**	**14.60**	**6.98**	**6.18**	**5.17**	**3.87**	**3.24**
18 TSI	0.0001	0.0459	0.0012	0.1573	0.0767	0.0773	0.0955	0.0941
	0.12	**1.87**	**26.79**	**5.23**	**3.04**	**3.60**	**3.51**	**3.86**
19 TUDD	-0.0006	0.0379	0.0009	0.2480	0.0932	0.0522	0.0832	0.1907
	-0.72	**1.62**	**16.77**	**7.66**	**3.84**	**2.36**	**3.79**	**7.18**
20 YAS	0.0009	0.0358	0.0010	0.1435	0.1273	0.1128	0.1284	0.0680
	0.91	**1.47**	**17.17**	**5.03**	**4.35**	**4.40**	**4.56**	**2.67**
No of significant		12	21	21	21	20	18	20

Figures in bold show t-statistics

TABLE 6.7.2

AR(1)+ARCH(5) for Daily *US$* Adjusted Returns of ISE. 1988-1995

$$\boxed{cor\left[\varepsilon_t, \varepsilon_{t-s}\right]}$$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDE	0.0234	31.3	50	79.9
1 ARC	0.0250	14.3	30	55.6
2 BAG	0.0535	13.8	26	49.7
3 CEL	0.0513	21.6	33.5	41.9
4 CIMS	0.0618	18	27.6	37.7
5 CUK	0.0470	13.9	22.8	43
6 DOK	0.0482	10.1	20.2	39
7 ECZ	0.0417	22.1	46.7	72.7
8 EGE	0.0191	3.63	21.2	34.5
9 ERE	0.0573	18.6	27.5	56.4
10 GOOD	0.0203	5.39	14.6	40
11 GUN	0.0398	5.12	13.9	24.6
12 KAR	0.0099	14.7	26.9	45.5
13 KOCH	0.0371	8.04	28.6	46.3
14 KOCY	0.0594	7.7	21.3	37.8
15 OTO	0.0348	5.3	18.2	28.4
16 SAR	0.0702	25.3	53.2	73
17 TIB	0.0744	13	38.5	54.3
18 TSI	0.0543	18.8	33.7	42.7
19 TUDD	0.0332	3.36	16.6	43.8
20 YAS	0.0333	17.5	33.9	44
No of significan	10	13	14	11

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.0439 for the critical value of the serial correlation of lag one

TABLE 6.8.1

AR(1)+ARCH(5) for Daily *Inflation* Adjusted Returns of ISE. 1988-1995

Code	a0	a1	b0	b1	b2	b3	b4	b5
ISE-INDEX	-0.0005	0.2306	0.0003	0.2585	0.2157	0.0917	0.1269	0.0657
	-0.99	**10.19**	**13.74**	**7.71**	**5.98**	**3.60**	**4.78**	**2.89**
1 ARC	-0.0005	0.0739	0.0006	0.2056	0.1185	0.1189	0.0910	0.1316
	-0.64	**3.01**	**17.09**	**5.86**	**4.18**	**4.51**	**3.67**	**6.64**
2 BAG	-0.0003	0.0578	0.0011	0.1552	0.1630	0.0671	0.0588	0.0450
	-0.33	**2.47**	**17.53**	**4.13**	**5.60**	**2.67**	**2.33**	**1.99**
3 CEL	-0.0003	0.0516	0.0009	0.2112	0.0913	0.1390	0.0947	0.1343
	-0.32	**2.13**	**16.61**	**6.12**	**3.65**	**5.27**	**4.71**	**5.07**
4 CIMS	-0.0009	0.0270	0.0009	0.2232	0.1210	0.1123	0.0860	0.0304
	-1.06	**1.07**	**18.05**	**6.31**	**4.50**	**5.03**	**3.64**	**1.56**
5 CUK	-0.0003	0.1306	0.0008	0.1785	0.2238	0.0742	0.0860	0.0648
	-0.28	**5.37**	**28.00**	**5.51**	**7.83**	**3.02**	**3.65**	**3.09**
6 DOK	-0.0012	0.0872	0.0009	0.2074	0.0995	0.0930	0.0398	0.1349
	-1.26	**3.64**	**17.26**	**5.52**	**3.58**	**3.55**	**1.90**	**4.67**
7 ECZ	0.0000	0.1252	0.0009	0.1090	0.1369	0.1409	0.0638	0.1074
	-0.03	**5.51**	**17.97**	**3.29**	**4.26**	**6.13**	**2.54**	**4.46**
8 EGEB	0.0007	0.0659	0.0007	0.1941	0.1510	0.0808	0.1109	0.0651
	0.87	**2.69**	**20.41**	**5.73**	**5.06**	**4.10**	**4.55**	**3.00**
9 ERE	-0.0010	0.1316	0.0007	0.2349	0.1111	0.1507	0.0971	0.0588
	-1.13	**5.38**	**15.98**	**6.34**	**3.92**	**5.29**	**3.49**	**2.96**
10 GOOD	-0.0006	0.0769	0.0008	0.2222	0.1007	0.0898	0.0588	0.1027
	-0.72	**3.12**	**16.04**	**6.07**	**3.40**	**3.15**	**2.52**	**4.73**
11 GUN	-0.0003	0.0725	0.0009	0.2155	0.1124	0.0902	0.0605	0.0811
	-0.31	**2.81**	**18.24**	**6.07**	**3.98**	**3.76**	**2.49**	**3.47**
12 KAR	-0.0003	-0.0157	0.0006	0.2404	0.0810	0.1131	0.1607	0.0794
	-0.39	**-0.63**	**17.39**	**6.42**	**3.22**	**4.39**	**5.92**	**3.45**
13 KOCH	-0.0005	0.0989	0.0007	0.1694	0.1583	0.0886	0.1241	0.0735
	-0.64	**4.12**	**14.59**	**5.32**	**5.02**	**3.37**	**4.59**	**3.22**
14 KOCY	-0.0007	0.0711	0.0006	0.1966	0.1919	0.1530	0.1074	0.0448
	-0.87	**2.99**	**18.68**	**5.59**	**5.91**	**5.07**	**3.82**	**2.03**
15 OTO	-0.0006	0.0900	0.0010	0.1431	0.1456	0.1347	0.0498	0.0584
	-0.62	**3.84**	**19.08**	**4.66**	**5.14**	**4.88**	**2.10**	**2.59**
16 SAR	-0.0006	0.1099	0.0006	0.2473	0.1395	0.1278	0.0626	0.0592
	-0.72	**4.39**	**16.91**	**6.40**	**4.60**	**4.71**	**2.65**	**2.84**
17 TIB	-0.0002	0.1013	0.0008	0.2322	0.1960	0.1486	0.0991	0.0647
	-0.19	**4.22**	**14.49**	**5.92**	**6.88**	**4.80**	**4.54**	**2.51**
18 TSI	-0.0003	0.0625	0.0012	0.1299	0.0908	0.0459	0.1107	0.0885
	-0.36	**2.61**	**28.51**	**4.41**	**3.46**	**2.11**	**3.88**	**3.61**
19 TUDD	-0.0010	0.0603	0.0009	0.2044	0.1197	0.0410	0.0858	0.1369
	-1.07	**2.53**	**16.74**	**6.01**	**4.49**	**1.80**	**3.73**	**5.32**
20 YAS	0.0004	0.0508	0.0010	0.1332	0.1240	0.0869	0.1365	0.0473
	0.39	**2.14**	**16.75**	**3.96**	**3.77**	**3.53**	**4.66**	**1.84**
No of significant		19	21	21	21	21	20	19

Figures in bold show t-statistics

TABLE 6.8.2

AR(1)+ARCH(5) for Daily *Inflation* Adjusted Returns of ISE. 1988-1995

$cor\left[\varepsilon_t, \varepsilon_{t-s}\right]$

Companies	r_1	Q_5	Q_{15}	Q_{30}
ISE-INDE	0.0303	23.2	38.1	49.9
1 ARC	0.0198	7.08	16.6	35.9
2 BAG	0.0415	6.45	20.2	33.9
3 CEL	0.0387	11.6	23.3	33.8
4 CIMS	0.0692	18.2	33	42.3
5 CUK	0.0384	14.9	27.9	51.3
6 DOK	0.0337	5.23	17.1	39.9
7 ECZ	0.0217	9.58	37.2	50.6
8 EGE	0.0358	3.58	25	40.8
9 ERE	0.0440	9.07	15.2	36.5
10 GOOD	0.0222	4.87	13.8	35
11 GUN	0.0290	8.35	15.9	28.7
12 KAR	0.0356	15.1	28.2	40.6
13 KOCH	0.0408	7.2	19.2	43
14 KOCY	0.0604	10.2	26.9	45.8
15 OTO	0.0360	4.33	20.6	28.8
16 SAR	0.0502	10.4	27.7	38.6
17 TIB	0.0541	10.1	37.6	47.9
18 TSI	0.0366	7.29	21.3	30.2
19 TUDD	0.0209	1.44	11.8	36.1
20 YAS	0.0256	13.8	33	44
No of significan	5	6	9	6

The critical values of the Q statistic are 11.1, 25, and 43.77 for lag of 5, 15, and 30 respectively.
The ±1.96*standard error is 0.0439 for the critical value of the serial correlation of lag one

CHAPTER SEVEN:

DAY OF THE WEEK EFFECT AND VOLATILITY ON THE ISTANBUL STOCK EXCHANGE.

7.1 INTRODUCTION

Since mid-1970 there has been an explosion of empirical studies documenting anomalous regularities in security rates of return. One of the most frequently investigated market anomalies in finance literature is the day of the week effect. According to the day of the week effect, stock returns are negative and lower on Monday than on any other day of the week. The stock returns are also higher than average on the last trading day of the week.

In this Chapter we investigate two aspects of the day-of-the-week effect, First, we examine whether the hypothesis that mean returns differ systematically across trading days can be replicated for the ISE. Second, we extend the test to determine whether there are also systematic variations across days in the volatility of returns. In the spirit of the earlier Chapters, we use a GARCH model, with day-of-the-week dummies, to capture possible weekly volatility cycles.

There has been some previous research along these lines. For example, Connolly (1989) analyses stock returns using a GARCH model, but with daily dummies in the mean equation only. This allows for volatility persistence after shocks, but no systematic movements in the unconditional variance related to the day of the week. Alexander and Riyait (1992) do investigate the effect of the day of the week on volatility, but do not use a GARCH model. We believe our study is also original in that no previous research has been published on the day of the week effect on volatility on Istanbul Stock Exchange.

7.2 LITERATURE REVIEW

The day of the week anomaly was originally observed by French (1980), who found evidence of low and negative returns to US stocks on Mondays, using the Standard and Poor's 500 index from 1953 to 1977. This feature can also be found in work carried out by Connolly (1989), Keim and Stambaugh (1984). The day of the week effect also apparently exists in the markets for US Treasury bills (Gibbons and Hess 1981), Treasury bonds (Johnson, Kracaw and McConnell.1991), foreign exchange (McFarland, Petit, and Sung 1982) and major non-US stock markets (Jaffe and Westerfield 1985).

According to Chang, Pinegar, and Ravichandran (1993) this phenomenon can be explained by the following factors - market settlement procedures (Gibbons and Hess 1981), measurement errors in stock prices (Keim, and Stambaugh 1984), a tendency for firms to release adverse information after trading closes for the weekend (Damadoran 1989), and robustness effect (Connolly 1989 and Chang, Pinegar, and Ravichandran 1993).

French (1980) also examined that whether the return generation process operates continuously in calendar time or only during active trading time. If returns are generated continuously in calendar time, the distribution of mean returns for Mondays will naturally be different than any other day of the week, because it will incorporate news from the non-trading days Saturday and Sunday. On the other hand, if the return generation process operates only during active trading time, mean returns should be the same for all five days.

The same considerations apply to returns on days following market closes for holidays. French (1980) noted that "if the negative returns reflect some 'closed-market' effect, the expected return will be lower following holidays as well as weekends." He argued that existence of weekend effect should support by negative expected return on day after holidays as well as high return on other days of the week.

Gibbons and Hess (1981) extended the day of the week effect anomalies by comparing stock returns with US Treasury Bill yields. Their hypothesis is that the Friday/ Monday anomaly in the stock market night be due to the settlement procedure in the stock market, which means that Friday price quotes effectively have two days of interest rolled into them, whereas T-bill quotes do not. However, the same day-of-the week effect is observed in the T-bill market, which suggests that settlement procedures are not the cause of the effect.

Jaffe and Westerfield (1985) examined the weekend effect for US, UK, Japan, Canada and Australia. They find weekend effects for the US, UK and Canada with negative return on Mondays. But Japan and Australia exhibit negative return on Tuesday. This is explained by the time zone differences, because of the correlation of daily return of different countries are highly correlated.

The day of the week anomaly on returns has been tested by Aybar (1992) using daily index returns data obtained from the Istanbul Stock Exchange. The sample is covering the period from 2 January 1988 through to 31 December 1991. His test results suggest that there is no identifiable day of the week anomaly in the ISE index return series for the period analysed. He has tested both calendar time and trading time hypotheses. He has applied a parametric test that was suggested by Gibbons and Hess (1991) and non-parametric Kruskall-Wallis test with Wilcoxon-Rank test. The ISE Index returns do not exhibit significant negative returns on Mondays over the sample period. In fact, he has observed negative but insignificant returns on Thursdays. Monday, Tuesday, and Wednesday returns were found to be positive but insignificant at the 5% level of significance. The Friday return on the ISE exhibited significant average positive daily return. This result is consistent with the evidence found in our tests below.

Alexander and Riyait (1992) analyse day of the week effect using a GARCH model with daily dummies in the mean equation and variance equation. This model has applied to London daily closing rates for sterling, the Swiss franc, yen and the Deutschmark all against US dollar, from 27 February 1987 to 27 February 1992. They find that volatility of all currencies tends to increase on days following bank holidays. Also they find the sterling, the Deutschmark and the Swiss franc are most volatile on Fridays and the yen is most volatile on Mondays.

7.3 METHODOLOGY

The AutoRegressive Conditional Heteroscedasticity (ARCH) model was introduced by Robert Engle in 1982, Bollerslev (1986) extends the ARCH process is to allow past conditional variance to enter equation and allows for a more flexible lag structure the so called generalised ARCH (GARCH) model. A GARCH (1,1) specification might be:

$$y_t = a_0 + a_1x_{1t} + a_2x_{2t} + \dots + a_px_{pt} + u_t \tag{7.1}$$

$$u_t \sim N(0, h_t^2) \tag{7.2}$$

$$h_t^2 = d_0 + b_1u_{t-1}^2 + c_1h_{t-1}^2 \tag{7.3}$$

where as before y_t is the daily return, the x_i are determinants of the conditional mean return, and h_t^2 the conditional daily variance. The unconditional daily variance is $d_0 / (1 - b_1 - c_1)$.

For the purposes of this exercise, we take the x_i to be the five day-of-the week dummies Mon_t, Tue_t, Wed_t, Thu_t, Fri_t, and a sixth dummy Hol_t which takes the value 1 if the previous day was a market close for a public holiday. We also, define a variable $Days_t$ which measures the number of days since the last market opening. For most days of the week, $Days_t$ is 0. However, for most Mondays, $Days_t = 2$, since the market is closed for two previous days. On the Tuesday following a Monday public holiday, $Days_t$ will be 3, and for any day following a midweek holiday, $Days_t = 1$.

With GARCH(1, 1) model for the error variance, and these dummies included as determinants of the daily variances as well as the mean returns, our model becomes:

$$\begin{aligned} y_t &= a_0 + a_2 Tue_t + a_3 Wed_t + a_4 Thu_t + a_5 Fri_t \\ &\quad + a_7 Hol_t + a_8 Days_t + u_t \end{aligned} \tag{7.4}$$

$$\begin{aligned} h_t^2 &= d_0 + d_2 Tue_t + d_3 Wed_t + d_4 Thu_t + d_5 Fri_t \\ &\quad + b_6 Hol_t + d_7 Days_t + b_1 u_{t-1}^2 + c_1 h_{t-1}^2 \end{aligned} \tag{7.5}$$

Coefficients of a_2 - a_5 measure the excess mean returns on each day of the week, over that experience on Mondays (a_0), and a_6 measures any excess returns on the day following a holiday. Similarly, d_2 - d_5 measure the impact of the day of the week on the variance of returns, relative to the Monday variance, and d_7 the net effect of any holiday. They raise or lower the numerator of the unconditional variance. The coefficients a_7 and d_7 measure any additional effects on mean and variance of information arrival during market closes (for weekends or holidays).

7.4 EMPIRICAL RESULTS

As before, our data has been obtained from Datastream and the Istanbul Stock Exchange. The stock price data has been adjusted for dividend payments, stock splits and for rights issues. Daily closing prices are used for log returns calculations.

We estimate the above model first on the ISE index, and then on the 20 most actively traded stocks individually. Our sample period begins in 6/9/1990 and ends in 20/4/1994, giving 900 daily observations.

Table 7.1 estimates the model for the ISE index without the market close $Days_t$ variable. In the mean equation, the coefficients a_2 - a_5 on the day-of-the-week dummies are all not significantly different from zero. This suggests that there is no difference between returns on Monday, as measured by the constant term a_1, and returns on other days. There does appear to be a weak tendency for returns to be lower following holidays, as evidenced by the weakly (10% level, not 5%) significant negative coefficient a_7 on the Hol_t dummy.

In the variance equation there are the expected strong GARCH effects. In addition, variance is clearly higher for Friday-to-Monday returns, and for returns on days following holidays, as evidenced by the significantly negative coefficients on the Tuesday-Friday dummy variables.

This points to the possibility that what is happening is that returns depend on news, and news is continuing to flow during the weekend and during public holidays. To establish whether this is the source of the systematic weekly changes in variance, or whether there is some more anomalous reason for the high Monday volatility, we have added the $Days_t$ variable into the equation. the result for this complete model are shown on table 7.2.

The mean equation again shows no significant coefficients on any of the dummy variables, and in particular there is no tendency for mean returns to be higher or lower after the market reopens following a weekend or holiday.

The variance equation has changed in character, however. The number of days the market is closed does affect the size of the price move from the day before the close to the day after the close. the coefficient d_7 on $Days_t$ is significantly positive. This implies that news about ISE shares continues to flow during these non-trading periods.

This explains most of the differences observed in Table 7.1 between the Monday return volatility, and the volatility observed on other days of the week. The Friday-to-Monday volatility is higher simply because of the information arriving during the weekend. However, a new anomaly appears on Table 7.2, a "Tuesday effect". The volatility of the Monday-Tuesday return is significantly lower than between any other pair of days, once allowance is made for the effect of the weekend on the Monday return. We have no rational explanation for this anomaly. Perhaps it represents some calm returning to the market after the excitement of the volatile Monday trading.

Table 7.3 reports results for the mean and variance components of the GARCH model for the 20 individual companies. As with the index, there is little sign of any day-of-the-week effect in mean returns. The variance equations all show strong GARCH effects. in most cases there are positive coefficients on the $Days_t$ variable, suggesting that company-specific information does continue to flow at weekends and over holidays. But the effects are weaker than in the case of the index, and only for 6 companies is the coefficient d_7 statistically significant. Much of the information flow during market closes must therefore be of a general economic nature, affecting the index as a whole rather than individual companies.

There is stronger evidence of the "Tuesday effect", however, with significant negative coefficients on the Tuesday dummy in the variance equation for 17 out of the 20 companies.

7.5 CONCLUSIONS

We have used a general GARCH model to investigate anomalies in daily returns to ISE shares.

There is no strong evidence of day of the week effect in mean return on the ISE index, or in returns to 20 actively traded companies listed in the ISE. There is, however, evidence to suggest that the market is more volatile on Mondays and after holidays.

Specific Monday and holiday effects vanish when a variable measuring the number of days the market is closed is added to the model. This suggests that the Monday and holiday volatility reflects continuing news flow through days when no trading occurs, with the news incorporated into market prices through large price changes when the market subsequently opens. Controlling for this effect, there seems little unusual about Friday-to-Monday volatility. However, there is a "Tuesday effect", with Monday-to-Tuesday volatility significantly lower than average.

Some of the news which arrives during weekends and holidays is company-specific, and similar effects are found for some individual companies. But most of the news flow during market closes appears to be general - relating to the whole economy, rather than individual companies - with the result that its effects are more pronounced in the index volatility than in the volatility of individual share prices.

APPENDICES 7

TABLE 7.1 GARCH Model of Day-of-the-Week Effect: ISE Index - No Market Close Effects

Variable	Parameter	Estimate	t-statistic
Constant (Mon)	a_0	2.83E-04	0.13
Tue	a_2	-2.21E-03	-0.81
Wed	a_3	3.32E-03	1.20
Thu	a_4	4.14E-04	0.14
Fri	a_5	3.62E-03	1.31
Hol	a_6	-0.0101	-1.91
Constant (Mon)	d_0	5.27E-04	5.18
Tue	d_2	-8.36E-04	-4.81
Wed	d_3	-5.47E-04	-4.67
Thu	d_4	-3.95E-04	-3.26
Fri	d_5	-6.10E-04	-4.71
Hol	d_6	4.76E-04	3.13
Lagged Shock	b_1	0.171752	5.32
Lagged Variance	c_1	0.769255	19.77

TABLE 7.2 GARCH Model of Day-of-the-Week Effect: ISE Index - Market Close Effects

Variable	Parameter	Estimate	t-statistic
Constant (Mon)	a_0	0.0111	1.11
Tue	a_2	-8.89E-03	-1.30
Wed	a_3	-3.60E-03	-0.51
Thu	a_4	-6.59E-03	-0.93
Fri	a_5	-3.74E-03	-0.53
Hol	a_6	7.35E-05	8.04E-03
Days	a_7	-3.75E-03	-1.13
Constant (Mon)	d_0	5.22E-05	0.25
Tue	d_2	-4.69E-04	-2.27
Wed	d_3	-2.36E-04	-1.48
Thu	d_4	-6.84E-05	-0.42
Fri	d_5	-2.68E-04	-1.57
Hol	d_6	3.65E-05	0.20
Days	d_7	1.38E-04	2.00
Lagged Shock	b_1	0.1461	4.93
Lagged Variance	c_1	0.8077	22.11

TABLE 7.3 GARCH Model of Day-of-the-Week Effect: Mean Equation: individual companies

Co.	a0	a2	a3	a4	a5	a6	a7
ARC	0.0211	-0.0224	-0.0069	-0.0121	-0.0101	0.0001	-0.0052
	1.44	**-2.21**	**-0.67**	**-1.17**	**-0.97**	**0.01**	**-1.08**
BAG	0.0000	-0.0071	0.0064	-0.0012	-0.0010	-0.0178	0.0013
	0.01	**-1.15**	**1.03**	**-0.20**	**-0.16**	**-1.94**	**0.63**
CEL	0.0214	-0.0165	-0.0099	-0.0199	-0.0116	0.0061	-0.0061
	1.16	**-1.29**	**-0.76**	**-1.52**	**-0.90**	**0.31**	**-1.02**
CIMS	0.0133	-0.0113	-0.0072	-0.0067	-0.0026	0.0010	-0.0042
	1.08	**-1.28**	**-0.82**	**-0.75**	**-0.29**	**0.08**	**-1.03**
CUK	0.0068	-0.0073	-0.0009	-0.0036	-0.0017	-0.0054	-0.0015
	0.43	**-0.66**	**-0.08**	**-0.32**	**-0.15**	**-0.25**	**-0.29**
DOK	0.0155	-0.0105	-0.0083	-0.0107	-0.0055	-0.0021	-0.0053
	1.44	**-1.37**	**-1.04**	**-1.35**	**-0.69**	**-0.13**	**-1.57**
ECZ	0.0195	-0.0207	-0.0120	-0.0125	-0.0140	-0.0021	-0.0052
	1.21	**-1.87**	**-1.08**	**-1.09**	**-1.25**	**-0.15**	**-0.97**
EGEB	0.0123	-0.0110	-0.0045	-0.0030	-0.0026	0.0081	-0.0037
	1.08	**-1.35**	**-0.55**	**-0.36**	**-0.32**	**0.57**	**-0.98**
ERE	-0.0168	0.0074	0.0130	0.0132	0.0176	-0.0031	0.0044
	-1.38	**0.91**	**1.51**	**1.53**	**2.01**	**-0.30**	**1.07**
GOOD	0.0102	-0.0070	-0.0017	-0.0111	-0.0007	-0.0091	-0.0017
	0.55	**-0.55**	**-0.13**	**-0.85**	**-0.05**	**-0.60**	**-0.27**
GUN	0.0039	-0.0042	0.0023	0.0037	0.0015	-0.0074	-0.0008
	0.40	**-0.55**	**0.31**	**0.49**	**0.19**	**-0.53**	**-0.26**
KAR	0.0036	-0.0076	-0.0034	-0.0028	0.0030	-0.0005	0.0010
	0.28	**-0.82**	**-0.38**	**-0.31**	**0.32**	**-0.03**	**0.24**
KOCH	0.0140	-0.0168	-0.0051	-0.0088	-0.0044	-0.0006	-0.0040
	0.69	**-1.23**	**-0.37**	**-0.63**	**-0.31**	**-0.03**	**-0.58**
KOCY	-0.0084	0.0034	0.0082	0.0084	0.0030	-0.0063	0.0026
	-1.13	**0.59**	**1.44**	**1.44**	**0.51**	**-0.64**	**1.09**
OTO	0.0309	-0.0185	-0.0173	-0.0237	-0.0160	0.0168	-0.0103
	2.64	**-2.16**	**-2.07**	**-2.76**	**-1.87**	**1.14**	**-2.67**
SAR	0.0222	-0.0181	-0.0146	-0.0134	-0.0133	0.0103	-0.0067
	1.72	**-2.01**	**-1.62**	**-1.47**	**-1.47**	**0.75**	**-1.59**
TIB	0.0002	0.0006	0.0009	-0.0008	0.0063	-0.0109	-0.0007
	0.01	**0.07**	**0.10**	**-0.09**	**0.67**	**-0.82**	**-0.16**
TSI	0.0075	-0.0082	-0.0076	-0.0033	0.0023	0.0061	-0.0016
	0.53	**-0.83**	**-0.74**	**-0.32**	**0.22**	**0.52**	**-0.35**
TUDD	0.0114	-0.0123	-0.0064	-0.0066	-0.0048	-0.0038	-0.0017
	0.69	**-1.07**	**-0.57**	**-0.57**	**-0.41**	**-0.20**	**-0.31**
YAS	-0.0008	-0.0052	0.0067	0.0049	0.0056	-0.0207	0.0000
	-0.21	**-1.00**	**1.26**	**0.97**	**1.10**	**-1.89**	**-1.35**
No of (+) significant		-	-	-	1	-	-
No of (-) significant		4	2	1	1	2	3
Average Coefficient		-0.0097	-0.0034	-0.0055	-0.0025	-0.0021	-0.0025

Note: Absolute value ot t-statistics is reported in bold below the coefficient estimates.

TABLE 7.3 GARCH Model of Day-of-the-Week Effect: Variance Equation: individual companies

	b0	ALPHA1	BETA1	b2	b3	b4	b5	b6	b7
ARC	0.0015	0.1051	0.5369	-0.0013	-0.0009	-0.0008	-0.0010	0.0007	-0.0001
	5.57	**3.66**	**4.55**	**-4.11**	**-4.27**	**-3.21**	**-3.87**	**1.14**	**-2.40**
BAG	0.0008	0.1384	0.7641	-0.0013	-0.0003	-0.0010	-0.0009	-0.0004	0.0001
	2.01	**3.77**	**12.94**	**-2.49**	**-0.70**	**-2.78**	**-2.27**	**-1.22**	**0.58**
CEL	0.0000	0.1323	0.8017	-0.0006	-0.0002	-0.0001	-0.0001	0.0001	0.0002
	0.00	**4.66**	**20.87**	**-2.18**	**-0.83**	**-0.72**	**-0.54**	**0.16**	**2.91**
CIMS	0.0000	0.1294	0.8297	-0.0005	-0.0001	-0.0002	-0.0003	-0.0001	0.0002
	0.00	**4.61**	**25.92**	**-2.60**	**-0.65**	**-1.52**	**-2.07**	**-0.44**	**3.51**
CUK	0.0000	0.0912	0.8834	-0.0007	-0.0002	-0.0001	-0.0001	-0.0003	0.0002
	0.00	**6.23**	**51.34**	**-3.67**	**-1.09**	**-0.62**	**-0.93**	**-1.43**	**3.71**
DOK	0.0018	0.2001	0.6532	-0.0022	-0.0013	-0.0014	-0.0015	0.0008	-0.0002
	3.45	**4.49**	**10.12**	**-3.93**	**-3.09**	**-3.07**	**-3.29**	**1.23**	**-1.29**
ECZ	0.0004	0.1336	0.8455	-0.0014	-0.0008	0.0000	-0.0014	0.0003	0.0002
	0.79	**5.51**	**35.14**	**-2.48**	**-1.87**	**0.10**	**-2.96**	**0.70**	**1.23**
EGEB	0.0006	0.1733	0.7637	-0.0007	-0.0005	-0.0002	-0.0007	0.0004	-0.0001
	1.24	**5.34**	**19.79**	**-1.50**	**-1.41**	**-0.52**	**-1.68**	**0.83**	**-0.42**
ERE	0.0000	0.1873	0.7445	-0.0009	-0.0001	-0.0002	-0.0004	-0.0005	0.0003
	0.00	**5.43**	**16.50**	**-3.81**	**-0.69**	**-1.43**	**-2.19**	**-2.26**	**4.19**
GOOD	0.0020	0.0748	0.2962	-0.0009	-0.0008	-0.0007	-0.0010	0.0000	-0.0001
	4.11	**2.71**	**1.24**	**-2.30**	**-2.61**	**-2.20**	**-3.01**	**0.05**	**-1.91**
GUN	0.0014	0.1800	0.6058	-0.0014	-0.0012	-0.0006	-0.0014	0.0009	0.0000
	1.68	**4.00**	**6.74**	**-1.99**	**-1.96**	**-1.04**	**-2.27**	**1.14**	**-0.07**
KAR	0.0006	0.2080	0.6716	-0.0011	-0.0006	-0.0004	-0.0001	0.0003	0.0000
	1.15	**5.17**	**11.94**	**-2.43**	**-1.61**	**-0.97**	**-0.25**	**0.47**	**0.20**
KOCH	0.0019	0.1729	0.5203	-0.0016	-0.0016	-0.0010	-0.0013	0.0013	-0.0002
	5.64	**4.01**	**5.08**	**-4.15**	**-5.71**	**-3.22**	**-3.94**	**1.97**	**-3.35**
KOCY	0.0000	0.1355	0.8585	-0.0004	-0.0003	0.0001	-0.0004	0.0002	0.0001
	0.00	**5.78**	**47.47**	**-1.16**	**-1.29**	**0.43**	**-1.44**	**0.65**	**1.46**
OTO	0.0000	0.1541	0.7633	-0.0003	-0.0005	0.0000	-0.0005	0.0000	0.0003
	0.00	**4.27**	**16.05**	**-1.20**	**-2.21**	**-0.10**	**-2.60**	**-0.09**	**3.83**
SAR	0.0006	0.2409	0.6798	-0.0012	-0.0006	-0.0006	-0.0007	0.0002	0.0001
	1.11	**5.53**	**14.49**	**-2.64**	**-1.49**	**-1.68**	**-1.78**	**0.52**	**0.80**
TIB	0.0009	0.2262	0.6176	-0.0017	-0.0004	-0.0006	-0.0010	-0.0007	0.0002
	1.93	**4.83**	**8.81**	**-3.82**	**-1.03**	**-1.65**	**-2.48**	**-1.41**	**1.25**
TSI	0.0000	0.1418	0.7293	-0.0011	-0.0007	0.0002	-0.0006	-0.0009	0.0005
	0.00	**3.91**	**12.99**	**-1.88**	**-1.34**	**0.47**	**-1.06**	**-2.68**	**2.18**
TUDD	0.0023	0.1315	0.2219	-0.0012	-0.0011	-0.0009	-0.0012	0.0003	-0.0002
	5.35	**3.06**	**1.32**	**-3.07**	**-3.65**	**-2.75**	**-3.53**	**0.25**	**-1.54**
YAS	0.0013	0.1228	0.7988	-0.0018	-0.0014	-0.0012	-0.0013	0.0004	0.0000
	3.39	**3.72**	**15.56**	**-2.66**	**-3.00**	**-2.83**	**-2.58**	**0.94**	**0.58**
No of (+) significant		20	18	-	-	-	-	-	6
No of (-) significant		-	-	17	10	9	14	3	3
Average Coefficient		0.1540	0.6793	-0.0011	-0.0007	-0.0005	-0.0008	0.0001	0.0001

Note: Absolute value ot t-statistics is reported in bold below the coefficient estimates.

CHAPTER EIGHT:

VOLATILITY AROUND STOCK DIVIDEND PAYMENTS: AN EV-GARCH MODEL FOR THE ISTANBUL STOCK EXCHANGE

8.1. INTRODUCTION

This Chapter examines the behaviour of the prices of leading shares traded on the Istanbul Stock Exchange (ISE) in the weeks before and after the payment of stock dividends. We apply an event study methodology using pooled cross-sectional and time series data, with the novel twist that price movements through the event window are assumed to follow a mixture of GARCH processes. This allows us to measure and test the significance of stock dividends for both the level and volatility of share prices, and to control for the effects of the simultaneous payment of cash dividends.

In the United States stock splits and stock dividends are rare events, affecting in any year only about 5-15% of all traded stocks. These events tend to be triggered by particular firm characteristics - a sustained rise in price relative to the market, in the cases of stock splits, and a low dividend yield in the case of stock dividends (Lakonishok and Lev, 1988). Stock dividends ("scrip issues") and stock splits simply increase the number of shares in a company and so should reduce their value pro-rata, since the dividend or split does not in itself add value to the company. However, the prices of shares in US companies which announce a stock split typically rise in advance of the split (Fama et al, 1969; Grinblatt, Masulis and Titman, 1984; Lakonishok and Lev, 1987), and become more volatile afterwards (Ohlson and Penman, 1987). Increased volatility is also found in the studies of implied variances in the prices of options on splitting stocks by French and Dubovsky (1986) and Sheikh (1989). The rationale for the pre-split run-up in price is that investors interpret the split as a signal that the managers of the company expect its relative price rise to be permanent. In support of this idea, Fama et. al. (1969) show that pre-split price rises are sustained only if the company subsequently pays an improved dividend. No good rationale has been offered for the post-split increase in volatility, and Ohlson and Penman (1987) term it "an empirical aberration".

In Turkey, almost all major listed companies, regardless of performance, split their stock each year by means of stock dividends, which are typically paid alongside cash dividends and often accompany a rights issue. This has little to do with signaling, and everything to do with how high inflation impacts on the balance sheets of Turkish companies (see Aydogan and Muradoglu, 1998). Companies are obliged to revalue fixed assets each year by a factor close to the overall inflation rate, and this increase in value may be converted in whole or part to paid-in capital by means of the issue of stock dividends. In order to keep their debt: equity ratio below the regulatory limit, most companies choose to make this conversion.

The frequency of stock dividends makes the ISE a convenient laboratory to test propositions about their effects on share values. Even though the source of the dividends should be well understood, there is scope for firms to exploit "money illusion" on the part of stockholders, by persuading them that stock dividends are a substitute for lower cash dividends, or represent a discount on the price of rights issues. Note, however, that we are forced to look only at price behaviour only around the split itself, rather than – as is normal with US studies - the earlier announcement date. This is because of difficulties in identifying the precise announcement dates for many of the companies in our sample.

Section 2 of the chapter introduces our data on stock prices and stock dividend events on the ISE. In Section 3 we develop a GARCH model for pooled cross-sectional and time series data. This allows for time-varying event-induced residual variances, and uses an array of dummy variables to test the statistical significance of changes in the mean and variance of daily returns around event dates, and to discriminate between the effects of cash and stock dividend payments. Section 4 draws some conclusions.

We find no significant effects on returns from stock dividends either before or after their payment, but very large price volatility on the ex dividend day, presumably reflecting investor confusion as to the proper post-split value of the share. This spills over into the immediate post-dividend period, in a way well described by the GARCH model, and fully explains the apparently anomalous behaviour of volatility documented by Ohlson and Penman (1987). Real increases and decreases in cash dividends do cause returns to rise and fall after the dividend payment date rather than after the earlier announcement date, and we find evidence that firms and investors treat cash and stock dividends as substitutes. This suggests some degree of money illusion and irrationality in market reactions to dividend payments on the ISE.

8.2. STOCK PRICES AND STOCK DIVIDENDS

The Istanbul Stock Exchange started trading in its present form at the end of 1985, with around 80 listed shares. The market grew slowly until 1990, when as a result of the massive Turkish privatisation program and the lifting of restrictions on inward investment there was a jump to over 100 in the number of listed companies, and trading volume increased from under 1 million per day (valued at around US$3 million) to over 6 million per day (valued at US$24 million). This growth has continued through the 1990s, and at end-1995 over 200 shares were listed and daily trades on the ISE averaged over US$200 million.

The raw data for this study are daily closing prices in the five-year period January 1990 - December 1994 of the 20 most important shares by market capitalization at the start of 1990. The data were obtained directly from the Istanbul Stock Exchange. The companies, and their end-1994 market values, are listed on Table 8.1. All have annual dividend cycles, and almost all took the opportunity to make rights issues and distribute share dividends alongside their cash dividend payments in the period studied. A few companies also distributed stock dividends outside this cycle. Apart from any effects on company value, stock dividends and rights issues change the nominal prices of shares, and all of our price series are adjusted in proportion to the new share issues to compensate for these effects.

8.2.1. Stock Prices

Daily percentage log-return for each price series i are defined as $R_{it} = 100.\ln(P_{it}/P_{it-1})$, and P_{it} and P_{it-1} are the (adjusted) closing prices of share i on days t and t-1 respectively. Table 8.1 shows alongside each company the average daily log-return, and the standard deviation of daily log-returns, in the years 1990-94. Average daily returns are high by the standards of developed markets, but this mainly reflects the high rate of inflation in Turkey. The annual inflation rates of 50-100 per cent per annum encountered in the early 1990s translate into a daily percentage log-return of 0.2218 per cent. Comparing this with the stock returns, it is evident that the value of many of the shares listed, and the ISE index itself (log-return 0.2029), actually fell in real terms over the sample period.

To assess the effects of cash and stock dividends on share values, it is important to clean prices of any effects which might be expected to occur as a result of general market movements, and work with the residual "abnormal" or "excess" returns series. Because of the importance of inflation in driving prices, we tentatively propose a two-factor model for ISE stock returns:

$$R_{it} = R_{ft} + \beta_i \{R_{mt} - R_{ft}\} + \delta_i \pi_t + r_{it} \qquad (1)$$

where R_{it} is nominal return, R_{ft} is the nominally riskless return, R_{mt} is the market return, π_t is the expected rate of inflation, and the residual r_{it} measures abnormal returns. It is difficult to obtain a consistent series of interest rates for a nominally riskless asset in Turkey. We assume that the riskless rate consists of a real rate (which may itself depend on expected inflation) and a premium for expected inflation (which is related to past inflation p_t), so that $R_{ft} = \lambda_{1i} + \lambda_{2i}p_t$. Substituting in (1) the model becomes

$$R_{it} = \alpha_i + \beta_i . R_{mt} + \gamma_i . p_t + r_{it} \tag{2}$$

where $\alpha_i = (1 - \beta_i).\lambda_{1i}$ and $\gamma_i = \{(1 - \beta_i).\lambda_{2i} + \delta_i\}$. Equation (2) can be estimated by OLS on the daily log-returns series, and the resulting parameter estimates are shown in Table 8.1.

In practice, there is little evidence of a significant inflation premium in any of the shares studied. Co-movement with the market is important, however, and systematic risk accounts for some 35-55% of the variance of daily returns, so the variance of abnormal returns is about 45-65% of the variance of total returns. As might be expected, the betas of the shares in our sample of major companies do not deviate markedly from 1. However, shares which underperform the index (e.g. Bagfas) do not necessarily have betas below 1, and outperforming shares (e.g. Ege Biracilik) do not necessarily have betas above 1. This implies that there are important company-specific effects in returns which are not captured by the market model, but absorbed into the constant (α, price trend) terms in the regressions.

8.2.2. Stock Dividends

Table 8.2. lists the companies in our sample along with the number and type of "dividend events" with which they were associated during the years 1990-4. In total there are 20 companies x 5 cash dividend payments = 100 cash dividend events, + 11 additional stock dividend distributions, making 111 relevant events in our sample. However, in one case the adjusted price after the stock dividend distribution implied a huge 35% rise in company value on the dividend date, and we have dropped this outlier from the sample. Its inclusion would strengthen the findings artificially. All results below are based on data from the remaining 110 events.

The dividend events themselves are classified into five groups - (real) cash dividend increases, cash dividend decreases, cash dividend increases combined with a stock dividend, cash dividend decreases combined with a stock dividend, and pure stock dividend distributions. The Table also shows the frequency of rights issues by each company. These generally coincide with cash and stock dividend payments.

The size of cash and stock dividends are usually publicly announced well in advance of their payment. We have not been able to establish announcement dates for all the dividend payments early in our sample, and this means that our experiments below relate only to market reactions to the actual payments of the dividends. However, for the years 1993-4, cash dividends are typically declared about 4-5 weeks before payment, while stock dividends and rights issues are announced much earlier, often 3-6 months before the event. There are some exceptional cases - for example, the Eczacibasi cash dividend in May 1994 was declared only 2 days before the ex-dividend date. In a few cases we found that the size of dividends actually paid, cash and stock, are changed after their first announcement.

There is no obvious association in Table 8.2. of stock dividend payments with share price outperformance. Some companies which paid annual stock dividends were relatively fast-growing - Arcelik, Eczacibasi, Koc. Others like Doktas and Demir Dokum were rather slow-growing. Similarly, there is no correlation between relative price performance and the number of rights issues.

Table 8.3. which aggregates events across companies and adds information on the average level of dividend payments, does provide some explanation for the incidence of stock dividends. Three points are apparent. First, when firms paid increased cash dividends, quite often (38/ 63 times, or 60%) they also paid a stock dividend. In contrast, when firms paid a reduced cash dividend, they less often paid a stock dividend (17/ 37 times, or 46%). This might indicate some signalling rationale for the stock dividend.

Second, there is a very strong association between rights issues and stock dividends. In our sample there are 54 rights issues, 49 of which were accompanied by stock dividends. This strongly suggests that stock dividends are used by companies in hope of reducing the apparent price to shareholder of the new stock. Indeed the stock dividends are termed bedelsiz artirim, meaning bonus- or free-shares.

Rights issues are heavily concentrated on firms and years when cash dividends are increasing. Of the 50 rights issues which were made simultaneously with dividend payments, 36 (72%) coincided with an increased cash dividend. This explains better than any signalling argument why stock dividends correlate with improved cash dividends - both are associated with rights issues.

Third, regardless of whether the cash dividend is increased or reduced, or a rights issue made, the amount of the cash dividend is on average significantly lower if it is paid alongside a stock dividend. In the case of increased cash dividends, the average dividend paid was 232% if only the cash dividend was paid, but 102% if a stock dividend was also paid. It is approximately true that when a stock dividend is paid together with a cash dividend, the stock dividend is of equal apparent value, and reduces the cash dividend one-for-one. On average the 102% improved cash dividend was paid alongside a 96% stock dividend. Where the cash dividend was reduced, on average a 46% cash dividend was paid alongside a 53% stock dividend. This strongly suggests that firms hope shareholders will regard cash and stock dividends not only as partial substitutes, but as almost perfect substitutes.

8.3. THE EFFECTS OF STOCK DIVIDENDS

We use an event study methodology to assess the impact of these cash and stock dividend payments on the prices of the underlying stocks. This involves extracting, for all companies and years, strips of abnormal return data for some window around the event dates of interest, and pooling the resulting time-series/ cross-section data to identify patterns which repeatedly occur before, at, or after the event date. The methodology has the disadvantage that information in the sample which falls outside the chosen data windows is not used. Care must also be taken to test for the validity of pooling from a heterogeneous collection of firms and years. The advantage of the methodology is that we do not have to control for the many other influences which impacted on excess returns throughout the sample. Implicitly, we assume that the dividend payments are the only significant factors affecting all prices in the weeks around the events.

The "event" which we examine is the actual payment of the dividend, and the event day is the ex-dividend date for the share. Our results are therefore not directly comparable to the many US event studies, which tend to focus on the signaling hypothesis, and look at market reactions after the dividend announcement date. However, as we have seen, there is no signaling rationale for stock dividends on the ISE. And our use of the dividend payment date gives us a very strong null hypothesis in the sense that the lags between dividend announcement and dividend payment mean that it will be very surprising if there are any systematic patterns in returns around the payment date.

We look at returns in a window which runs from 30 trading days before the event date, to 30 days after. This is much shorter than the periods considered in parallel US studies, which typically look at the behaviour of returns over periods of a year or more around the event dates. The smaller event window reflects the much greater frequency of stock dividend payments on the ISE.

Figures 8.1. and 8.2. show for each event type the behaviour of average cumulative abnormal returns through this event window, where cumulative abnormal returns are defined as:

$$c_{ik} = \sum_{s=-30}^{t} r_{is} \qquad (3)$$

for day t relative to the event day 0. For straight cash dividend payments, cumulative returns rise for 10-15 days after the announcement of an improved dividend, and fall for 10-15 days after a dividend cut. For straight stock dividend events, cumulative returns start to rise about 10-15 days before the event date, and slowly fall thereafter. This mirrors closely the behaviour of returns on US stocks around split announcement dates.

This pattern is also observed for compound cash and stock dividend events. In all these cases the price rises relative to the market (strictly, cumulative excess returns increase) in advance of the dividend date. If a stock dividend is paid and the cash dividend is increased, the higher price is sustained. If a stock dividend is paid and the cash dividend is cut, the price slowly drifts down, but does not actually fall as in the case of a pure cash dividend cut. This suggests that to some degree firms are indeed able to offset the impact of a lower cash dividend by offering a stock dividend. So firm behaviour in sweetening low cash dividends with stock dividends is rational, even if investor reactions are not.

Table 8.4. shows mean returns and the standard deviation of returns in five windows around the event date - 30-11 days before, 10-1 days before, the event day itself, 1-10 days after, and 11-30 days after. The breaks 10 days before and after the event date were chosen because they are roughly the points at which local trends emerge and reverse in Figures 8.1. and 8.2. The mean returns in Table 8.4. therefore simply reflect the patterns in the Figures discussed above. But the standard deviations do contain additional interesting information.

The volatilities of excess returns for all types of events are similar prior to the event day. On the event day, the volatility of returns in the case of a pure stock dividend is much greater than in cases where cash dividends are also being paid. The volatility of returns continues to be high after the stock dividend date. There is therefore some evidence that the increased volatility observed after stock splits in US markets is also present on the ISE. The volatility of shares with high/ low returns following an improved/ worsened cash dividend also increases after the dividend date.

8.3.1. Regression with Event Dummies

We need some more formal way of testing the significance of these patterns in the mean and variance of returns. The issue is complicated by the fact that for many observations in our sample, more than one factor is affecting returns - for example a cash dividend and a stock dividend. The effects of a stock dividend could be estimated by considering only those cases where a stock dividend was paid, but no cash dividend. However, that would not use the sample data efficiently.

To identify the separate effects of cash and stock dividends we have started by regressing returns on sets of dummy variables which take the values 1 or 0 depending on whether a cash dividend or stock dividend is present, and whether the returns come from the windows before, at, or after the event date. Specifically, we define

> S_{it} = 1 if there is a stock dividend paid by company i at the event date related to t, and 0 otherwise;
> U_{it} = 1 if an increased cash dividend is paid, and 0 otherwise;
> D_{it} = 1 if a decreased cash dividend is paid, and 0 otherwise;
> T_{jt} = 1 if observation t is in the j-th window, (j = 1, 2, ..5), around the event date, and 0 otherwise. The five windows are those of Table 4, i.e.: 30-11 days before, 10-1 days before, the event day 0, 1-10 days after, and 11-30 days after.

Excess returns r_{it} can then be described as:

$$r_{it} = \sum_{j=1}^{5} a_{1j}.T_{jt}.S_{it} + \sum_{j=1}^{5} a_{2j}.T_{jt}.U_{it} + \sum_{j=1}^{5} a_{3j}.T_{jt}.D_{it} + \sum_{j=1}^{5} a_{4j}.T_{jt}.S_{it}.U_{it} + \sum_{j=1}^{5} a_{5j}.T_{jt}.S_{it}.D_{it} + v_{it} \qquad (4)$$

where we provisionally assume the residual v_{it} has constant variance h, say, so $v_{it} \sim N(0, h)$.

The coefficients on T.S measure the impact of a stock dividend (S) on abnormal returns in the window 11-30 days before the event (T_1), 1-10 days before the event (T_2), on the event day itself (T_3), 1-10 days after (T_4) and 11-30 days after. Similarly the coefficients on T.U and T.D are estimates of the effects of pure cash dividends rising and falling. The coefficients on T.S.U and T.S.D measure interaction effects which occur when a stock dividend coincides with, respectively, a cash dividend rise or fall. The full effect on excess returns of a stock dividend combined with a reduced cash dividend would in event window j be the sum of the coefficients on T.S, T.D and T.S.D = ($a_{1j} + a_{3j} + a_{5j}$).

Under the assumption that the error terms are independent, normally distributed and homoscedastic, equation (4) can be estimated by ordinary least squares. This will recover as coefficients the mean effects shown in Table 4. For example, the coefficient a_{12} on $T_{2t}S_{it}$, measuring the abnormal return during the period 1-10 days before a stock dividend, will be +0.7827. The coefficient a_{42} on $T_{2t}S_{it}U_{it}$, measuring the interaction effect of a stock dividend and an increased cash dividend in the 10 days before a dividend date, will from Table 4 be 0.2294 (joint effect) - 0.7827 (stock dividend effect) - 0.1274 (cash dividend effect) = -0.6807. The benefit of the regression framework is not that estimates are obtained of the mean effects themselves, but that estimates are also obtained of the standard errors of the coefficients, and these may let us test the significance of the observed effects.

When (4) is estimated by OLS, none of the coefficients on events in the outer windows T1 and T5 is statistically significant. Since (4) is already highly parameterised, we simplify the model by constraining these coefficients to be equal to a constant a_0. The model then simplifies to:

$$r_{it} = a_0 + \sum_{j=2}^{4} a_{1j}.T_{jt}.S_{it} + \sum_{j=2}^{4} a_{2j}.T_{jt}.U_{it} + \sum_{j=2}^{4} a_{3j}.T_{jt}.D_{it} + \sum_{j=2}^{4} a_{4j}.T_{jt}.S_{it}.U_{it} + \sum_{j=2}^{4} a_{5j}.T_{jt}.S_{it}.D_{it} + v_{it} \quad (5)$$

The resulting parameter estimates are shown in full on Table 8.5. To illustrate the workings of the model, Figure 8.3 shows the pattern implied for mean excess returns to a share experiencing a stock dividend and a reduced cash dividend, which is now (a_{0j} + a_{1j} + a_{3j} + a_{5j}). For this kind of event, excess returns rise a little ahead of the dividend date, rise sharply on the event day, and fall immediately afterwards.

The estimated rise in returns in the 10 days before a pure stock dividend payment, measured by the coefficient a_{12}, is a little higher than previously estimated (0.8089 rather than 0.7827) as a result of the constraints. It is statistically significant at the 5% level. The coefficient a_{24} measuring the rise in returns in the 10 days after a cash dividend increase is also significant. However, the fall in returns after a decreased cash dividend does not appear to be statistically significant, and no other significant effects on expected returns - including those on Figure 8.3 - are found from the regression.

8.3.2. A GARCH Model for Event Data

Unfortunately, the assumptions which would support OLS-based inference from Equation (5) are unlikely to be observed in most event study samples. The main problem is that the residuals in (5) do not have constant variance. There are three sources of heteroscedasticity, the first two well recognized in the event study literature, the third also very familiar in empirical finance but relatively neglected in event study applications.

First, the model pools data from a number of different companies and time periods. The event study methodology means we necessarily constrain the effects of, say, stock dividends on mean returns to be equal across companies. But there is no reason why the variance of returns should be constant across companies, and we have seen in Table (8.1) that there are sizable differences in the variance of excess returns to companies in our sample. This type of heteroscedasticity can be easily handled in a traditional regression framework, by normalizing the data - that is, by dividing all the observations on each company or event by the standard deviation of observations across that company or event, prior to estimation by OLS.

Second, there is no reason why the variance of returns should be constant throughout each event window. Indeed, the US research discussed above finds that the variance of returns may differ for each stock dividend event between the pre- and post-event periods, so this is an important hypothesis for investigation. This could also in principle be handled by a data normalization - for example, by dividing each observation not by the whole-event sample standard deviation, but by the standard deviation within the relevant inside-event window to which the observation belongs. This approach is suggested by Boehmer et. al. (1991). Heteroscedasticity of this kind we term event-related conditional heteroscedasticity.

Third, the generalized autoregressive heteroscedasticity (GARCH) model of Bollerslev (1986) has been found to provide a good description of the variance of daily stock returns - see, for example, Akgiray (1989) and de Santis and Imrohoroglu (1997). In this model, any large shock to a share price which causes an exceptionally high or low abnormal return on a particular day, also causes the variance of returns to be high on the following day, and to decay only slowly back to its long run average "unconditional" value. So if a dividend event causes a large mispricing on the ex-dividend day, say, prices are likely to be volatile for many days thereafter. Although there is much discussion of "event-induced variance" in the event study literature (e.g. Brown and Warner, 1985), few studies take the step of characterizing the variance of returns as a GARCH process, perhaps because of the computational problems discussed below.

In our context, the simplest GARCH(1,1) model for the variance of excess returns for event i is:

$$v_{it} \sim N(0, h_{it}) \tag{6}$$

$$h_{it} = b_{it} + c_{1i}.v_{it-1}^{2} + c_{2i}.h_{it-1} \tag{7}$$

where v_{it} is the "shock" to returns on day t of event i, and h_{it} is the time-varying variance of returns. The GARCH equation (6) makes the variance on day t be conditional on the variance of the previous day (h_{it-1}) and the most recent squared shock v_{it-1}^2. In a steady state, with the squared shock set to its expected value h_{it-1}, and variance constant over time so that $h_{it-1} = h_{it} = h_i$, the unconditional variance of event i is

$$h_i = \frac{b_{it}}{1 - c_{1i} - c_{2i}} \tag{8}$$

In the GARCH model, a large shock to returns will raise the variance of returns on the day following the shock, by an amount which depends on the size of coefficient c_{1i}. On subsequent days, provided no further shocks occur, the variance will gradually return to the long run level described by (8). Any one-off shock to returns will therefore have a persistent effect, raising variance for a number of days afterwards. The degree of persistence depends on the size of coefficient c_{2i}.

A general model would allow the variance to differ across companies and events (subscript i) and also across days within each event window (subscript t), the first two sources of heteroscedasticity described above. This is the full event-related GARCH model. By analogy with (5), we set

$$b_{it} = b_{0i} + \sum_{j=2}^{4} b_{1j}.T_{jt}.S_{it} + \sum_{j=2}^{4} b_{2j}.T_{jt}.U_{it} + \sum_{j=2}^{4} b_{3j}.T_{jt}.D_{it} \tag{9}$$
$$+ \sum_{j=2}^{4} b_{4j}.T_{jt}.S_{it}.U_{it} + \sum_{j=2}^{4} b_{5j}.T_{jt}.S_{it}.D_{it}$$

Here, the coefficient b_{22}, say, measures any increase in variance 1-10 days before ($T_{2t} = 1$) a cash dividend increase ($U_{it} = 1$). As in (5) we assume that the variances in the outer windows, 11-30 days before and after the events are equal, and are captured in the terms b_{0i}. Since it is reasonable to assume that the unconditional variance stays constant for each company over time, we write:

$$b_{0i} = \sum_{k=1}^{20} b_k E_{ik} \tag{10}$$

where the E_{ik} are dummies taking the value 1 if event i relates to company k, and zero otherwise.

Thus for each company the unconditional variance is still described by (8) with $b_{it} = b_{0i}$, since the event and time dummies are zero outside the event window. However, within the event windows j = 2, 3, 4 immediately before, during and after the event, the event-related conditional variance may temporarily be higher or lower than this long run level. For example, for a company paying an increased cash dividend (U_{it} = 1) the event-related variance in the period j = 2 immediately before the dividend payment would be $(b_{0i} + b_{22}) / (1 - c_{1i} - c_{2i})$. If b_{22} were significantly positive, this would be greater than the long run unconditional variance $b_{0i} / (1 - c_{1i} - c_{2i})$. The overall conditional variance will then depend through the GARCH model (6) - (10) on the company concerned, the type of event, the relationship of day t to the event date, and (the autoregressive component) on the size of recent shocks to returns.

To illustrate the workings of the model, and anticipating some of the estimation results below, Figure 8.4. shows the behavior of the unconditional, event-related conditional, and overall conditional variance for firms that paid an increased cash dividend and no stock dividend. The event-related conditional variance rises before the dividend date, falls sharply on the dividend date itself, rises even more sharply immediately afterwards, and finally falls back to its long run level. The overlaid GARCH process causes the overall conditional (actual, observed) variance to smoothly transit from one level of the unconditional variance towards the next. The conditional variance therefore starts rising in advance of the dividend date, falls only slightly on the dividend day, rises further after the increased dividend is paid, and falls very gradually back to its long run level.

The parameters of the system (5)-(7), (9)-(10), must be estimated by maximum likelihood. The system is highly parameterised, and it proved impossible, even after a lengthy search using a combination of simplex and Berndt-Hall-Hall-Hausman (1974) algorithms, to obtain a solution without further constraints on the system. We have chosen to impose the restriction that the GARCH parameters c_{1i} and c_{2i} are equal across companies, equal to c_1 and c_2 respectively. This is less restrictive than it might appear. For example, the J. P. Morgan RiskMetrics system assumes return variances can be described by an exponential smoothing model similar to (6) with common parameters across all asset classes and all markets, and Guldimann (1995) adduces evidence to show that this approximation is acceptable.

The parameter estimates for the constrained model are shown on Table 6. We have not shown the company-specific constant terms in the variance equation in full, but simply the average across companies, and the range. As might be expected, the unconditional variances by company for the event subsamples resemble the whole-sample residual variances implied by the market model standard errors in Table 8.1. We have however, set out all the event effects on the variances - the parameters of (9) - and indicated where these are significant.

The GARCH model has changed the estimates of the mean equation (5) in two ways. The run-up in returns prior to a stock dividend no longer appears significant. On the other hand, the fall in returns after a reduced dividend does now appear significant. The rise in returns after an improved cash dividend remains significant.

The estimated coefficients in the variance equation are also interesting. The model shows very strong GARCH effects, with highly significant coefficients c_1 and c_2. The value of 0.79 for c_2 implies a high degree of persistence, so that any shock to returns will raise variance for many days thereafter.

The coefficient b_{12} is not significantly different from zero, so there is no event-related increase in the variance in the 10 days before a stock dividend. The presence of a stock dividend does not in itself shift the variance upwards before the event. However, there is a marked increase in variance on the day of the stock dividend distribution, as shown by the significance of coefficient b_{13}. Stock dividend distributions therefore typically cause a large unexpected jump up or down in price on the day of their payment. These jumps raise the variance of returns after the event day through the GARCH effect. However, the coefficient b_{14} is significantly negative, meaning that the event-related conditional variance actually falls immediately after a pure stock dividend.

In this case and others, the net effects implied for pre- and post-dividend event variances are hard to judge from the model coefficients alone. We have already seen in Figure 8.4. the implications of the model for the variance of returns on shares paying increased cash dividends. On Figure 8.5. we simulate the behavior of the conditional variance for all types of event. In all cases, there is some increase in post-event variance. The large event day price movement associated with the pure stock dividend leads to a particularly large increase in variance on the dividend day. However, the post-dividend fall in the event-related conditional variance causes the overall conditional variance to fall very rapidly thereafter, and the Figure shows that the variance returns to its long run level within the next 10 days.

This contrasts the case of a pure cash dividend increase examined earlier. Because in Table 6 the coefficients b_{22} and b_{24} are significantly positive, the event-related conditional variance of returns increases in advance of the improved dividend payment, and stays high after the dividend date. When combined with the GARCH persistence effect, the result is a steady rise and a very gradual fall in volatility, with the variance still higher than its long run level 30 days after the dividend date.

When the stock dividend is paid alongside a cash dividend, there are also some weak interaction effects. A stock dividend combined with an increased or decreased cash dividend results in the same kind of event-day jump in variance as the pure stock dividend, but of a smaller magnitude. However, the variance remains higher for longer after the dividend date, due to the rise in event-related variance associated with an improved cash dividend, and the roughly constant event-related conditional variance following a reduced cash dividend.

8.4. CONCLUSION

This paper set out to establish whether there were systematic patterns in returns associated with the many stock dividend payments made by companies listed on the ISE, and whether these resembled the patterns observed around stock splits and dividends in the US market.

Stock dividend payments on the ISE are not motivated by the same factors - such as past or prospective outperformance - which trigger stock splits in more developed markets. They are largely driven by accounting and regulatory considerations. However, the presence of stock dividend payments on the ISE do appear to lead investors to behave irrationally, to treat the stock dividends as substitutes for cash dividends and as an effective discount on the price of rights issues. We find that shares on the ISE which offer a stock dividend alongside a reduced cash dividend do not suffer the same adverse reaction as shares which simply cut their cash dividend.

Although there appears to be an anticipatory rise in the price of shares paying stock dividends similar to that observed in the US, this effect becomes statistically insignificant once proper account is taken of the way the return variance changes before and after the dividend is paid. This is consistent with the findings of Aydogan and Muradoglu (1998), who from a conventional event study methodology find no systematic price reactions around the announcement and payment of a number of stock dividends and rights issues on the ISE in the period 1988-93.

In contrast, cash dividend payments do have a significant impact on excess returns. There is no systematic movement in price in the weeks before the dividend payment date. But after the dividend date, the price of shares which pay an improved dividend rise, and the prices of shares which pay a lower dividend fall. This suggests that the ISE is informationally inefficient, in that news about cash dividends - which are announced from one to three months earlier - is absorbed only partially in advance of their actual payment.

The main technical innovation in the paper is the use of a GARCH model with event-dependent intercept terms to track changes in variances around event dates. The model reveals that share prices are exceptionally volatile on the day of a stock dividend payment. Prices are also volatile after the stock dividend payment, but this reflects a market reaction to the volatility around the dividend date - that is, conditional heteroscedasticity - rather than a post-event upward shift in the level of the returns variance. We conjecture that this reflects some confusion about whether the stock dividend will have a real effect on relative share prices, a confusion which is resolved in the two weeks following the dividend distribution.

This contrasts with the case of an increased cash dividend, where the level of the variance does rise temporarily before and after the dividend payment, a phenomenon which may reflect an increased trading in these shares, and which deserves further investigation in a model with volume-dependent volatility.

An increase in variance after stock splits has also been observed in the US stock market, but no good rationale has been provided. The GARCH effect identified here offers a possible explanation for this effect, and suggests that it may be productive to apply our methodology to other markets and other types of events where variance anomalies have appeared. This does of course beg the much larger question of why GARCH-type effects are so omnipresent in financial markets.

APPENDICES 8

Table 8.1. Characteristics of Leading ISE shares

Company	Market Value end-94, TL m	Daily Returns Mean/ SD	Market Model: α	β	γ	R^2/ SE
Arcelik	25000	0.2692 (4.32)	.7217 (.39)	1.0118 (0.02)	-2.9253 (1.75)	0.49 (3.10)
Bagfas	1620	0.1955 (4.66)	-0.3270 (0.42)	1.0942 (0.02)	1.3534 (1.88)	0.49 (3.33)
Celik Halat	1032	0.2090 (4.94)	0.2394 (0.50)	1.0055 (0.03)	-1.0571 (2.22)	0.37 (3.93)
Cimsa	5560	0.2332 (4.44)	0.3187 (0.44)	0.9222 (0.03)	-1.2290 (1.97)	0.38 (3.49)
Cukurova Elektrik	5000	0.2479 (4.69)	0.5409 (0.45)	1.0073 (0.03)	-2.2426 (1.04)	0.41 (3.60)
Doktas	1800	0.1903 (4.57)	0.5186 (0.45)	0.9714 (0.03)	-2.3687 (1.99)	0.40 (3.53)
Eczacibasi Yatirim	1064	0.3186 (4.86)	0.4554 (0.48)	1.0271 (0.03)	-1.5564 (2.13)	0.40 (3.77)
Ege Biracilik	16793	0.4118 (4.16)	0.5297 (0.41)	0.8845 (0.02)	-1.3410 (1.81)	0.40 (3.21)
Eregli Demir Celik	22176	0.2600 (4.47)	-0.2930 (.38)	1.0976 (0.02)	1.4867 (0.86)	0.54 (3.04)
Good-year	4332	0.1998 (4.42)	0.0309 (0.46)	0.8682 (0.03)	-0.0329 (2.02)	0.34 (3.58)
Guney Biracilik	3289	0.3176 (4.46)	0.1360 (0.43)	0.9667 (0.03)	-0.0654 (1.93)	0.42 (3.41)
Kartonsan	4995	0.2583 (4.11)	-0.0640 (0.40)	0.8911 (0.02)	0.6390 (1.77)	0.42 (3.13)
Koc Holdings	57000	0.2754 (4.22)	0.5215 (0.37)	1.0113 (0.02)	-2.0349 (1.66)	0.51 (2.94)
Koc Yatirim	5400	0.2636 (4.21)	0.6259 (0.39)	0.9783 (0.02)	-2.5289 (1.71)	0.48 (3.03)
Otosan	8448	0.2617 (4.58)	0.7546 (0.44)	1.0028 (0.02)	-3.1397 (1.96)	0.43 (3.47)
Sarkuysan	4253	0.2760 (3.99)	0.2946 (0.35)	0.9835 (0.02)	-0.9835 (1.53)	0.54 (2.71)
T. Is Bankasi	19587	0.3317 (5.03)	-0.3980 (0.53)	0.9628 (0.03)	2.4102 (2.33)	0.33 (4.13)
T. Siemens	4536	0.2118 (4.63)	-0.2370 (0.44)	1.0280 (0.03)	1.0809 (1.96)	0.44 (3.47)
T. Demir Dokum	5000	0.1930 (4.40)	0.4524 (0.42)	0.9751 (0.02)	-2.0617 (1.86)	0.44 (3.30)
Yasas	1154	0.2684 (4.70)	0.0648 (0.47)	0.9564 (0.03)	0.0430 (2.10)	0.37 (3.73)
ISE Market	891064	0.2029 (2.98)				

Note: Figures in parentheses under estimated coefficients are standard errors. SD is the standard deviation of daily percentage log-returns, and SE is the standard error of the regression residuals (excess returns).

Table 8.2. Dividend Events by Company

Company	Total Dividend Events	*Stock Dividend Only*	*Cash Dividend Up*	*Cash Dividend Down*	*Stock Dividend + Cash Up*	*Stock Dividend + Cash Down*	With Rights Issue
ARC	6	*1*	*0*	*0*	*3*	*2*	5
BAG	5	*0*	*3*	*1*	*1*	*0*	1
CEL	6	*1*	*1*	*2*	*0*	*2*	3
CIMS	5	*0*	*3*	*1*	*0*	*1*	1
CUK	5	*0*	*3*	*2*	*0*	*0*	4
DOK	5	*0*	*0*	*0*	*3*	*2*	4
ECZ	5	*0*	*0*	*1*	*3*	*1*	4
EGEB	5	*0*	*1*	*1*	*2*	*1*	1
ERE	5	*0*	*1*	*1*	*1*	*2*	3
GOOD	5	*0*	*0*	*0*	*3*	*2*	2
GUN	5	*0*	*1*	*1*	*2*	*1*	1
KAR	6	*1*	*1*	*1*	*3*	*0*	3
KOCH	6	*1*	*1*	*0*	*2*	*2*	5
KOCY	5	*0*	*0*	*0*	*5*	*0*	3
OTO	5	*0*	*0*	*2*	*3*	*0*	3
SAR	5	*0*	*1*	*1*	*3*	*0*	3
TIB	5	*0*	*3*	*2*	*0*	*0*	1
TSI	9	*4*	*3*	*2*	*0*	*0*	1
DUDD	7	*2*	*1*	*1*	*3*	*0*	5
YAS	5	*0*	*2*	*1*	*1*	*1*	2
Total Sample	110	*10*	*25*	*20*	*38*	*17*	54

Table 8.3. Cash Dividends, Stock Dividends and Rights Issues

Type of Event	Number of Events	Average Cash Dividend (%)	Average Stock Dividend (%)	Number with Rights Issue
Stock Dividend Only	10	-	83	4
Cash Dividend Up	25	232	-	4
Cash Dividend Down	20	76	-	1
Stock Dividend + Cash Dividend Up	38	102	96	32
Stock Dividend + Cash Dividend Down	17	46	53	13

Table 8.4. Mean daily excess return (100 r_{it}) and standard deviation of daily excess returns around event days

Event	No. of Events	11-30 days before	1-10 days before	Event day	1-10 days after	11-30 days after
Stock Dividend Only	10	-0.0845 (3.68)	0.7827 (3.72)	-0.6461 (7.20)	-0.3704 (4.14)	-0.0929 (3.48)
Cash Dividend Up	25	0.0204 (3.53)	0.1274 (3.46)	0.8051 (3.61)	0.7099 (4.25)	-0.1974 (3.76)
Cash Dividend Down	20	0.0126 (3.55)	-0.0208 (3.62)	1.0405 (3.91)	-0.3962 (4.27)	0.0301 (3.71)
Stock Dividend + Cash Dividend Up	38	0.1331 (3.61)	0.2294 (3.68)	1.4059 (4.30)	-0.0702 (3.79)	-0.0209 (3.50)
Stock Dividend + Cash Dividend Down	17	0.2037 (3.31)	0.4227 (3.25)	2.4941 (3.58)	0.1789 (3.86)	-0.5100 (3.21)

Note: standard deviation of returns in parentheses

Table 8.5. OLS model for excess returns around event dates

Variable		1-10 days before j = 2	Event day j = 3	1-10 days after j = 4
Constant (11-30 days before/ after)	-0.0264 (0.48)			
Stock Dividend		0.8089* (2.21)	-0.6185 (0.54)	-0.3444 (0.94)
Cash Dividend Up		0.1540 (0.65)	0.8312 (1.14)	0.7364* (3.12)
Cash Dividend Down		0.0055 (0.02)	1.0674 (1.31)	-0.3700 (1.41)
Stock Div + Cash Div Up		-0.7071 (1.50)	1.2193 (0.82)	-0.4361 (0.92)
Stock Div + Cash Div Down		-0.3653 (0.69)	2.0705 (1.25)	0.9199 (1.74)

Notes: Regression Statistics: R^2 = 0.0035, SE = 3.6214. Figures in parentheses under estimated coefficients are t-statistics. * indicates significance at the 5% level, ** at the 1% level.

Table 8.6. EV-GARCH model of excess returns around event dates

Variable		1-10 days before j = 2	Event day j = 3	1-10 days after j = 4
Equation for mean:				
Constant (11-30 days before/ after)	-0.035 (0.74)			
Stock Dividend		0.2828 (0.91)	-0.8484 (0.65)	-0.1977 (0.54)
Cash Dividend Up		0.0357 (0.16)	0.7394 (1.13)	0.7304* (2.67)
Cash Dividend Down		0.0429 (0.21)	1.0315 (1.42)	-0.5092* (2.39)
Stock Div + Cash Div Up		-0.0919 (0.22)	1.1143 (0.68)	-0.6148 (1.27)
Stock Div + Cash Div Down		0.2368 (0.51)	1.7003 (0.92)	0.5793 (1.14)
Equation for variance:				
Company-specific dummies: (mean/ range)	0.8629* 0.45 *- 1.43*			
Stock Dividend		-0.0531 (0.13)	11.0113* (2.08)	-0.6749* (2.48)
Cash Dividend Up		0.6484 (2.59)	-1.0906 (0.40)	1.4096** (4.65)
Cash Dividend Down		-0.2196 (0.86)	5.1366 (1.91)	-0.3129 (1.31)
Stock Div + Cash Div Up		-0.5293 (1.03)	-2.0353 (0.32)	-1.0263* (2.36)
Stock Div + Cash Div Down		0.7306 (1.30)	-15.0675* (2.22)	1.1261* (2.53)
v_{it-1}^2	0.1321** (14.23)			
h_{it-1}	0.7950** (60.80)			

Notes: see Table 5.

Figure 8.1. Cumulative Abnormal
Pure Stock and Cash Dividend Events

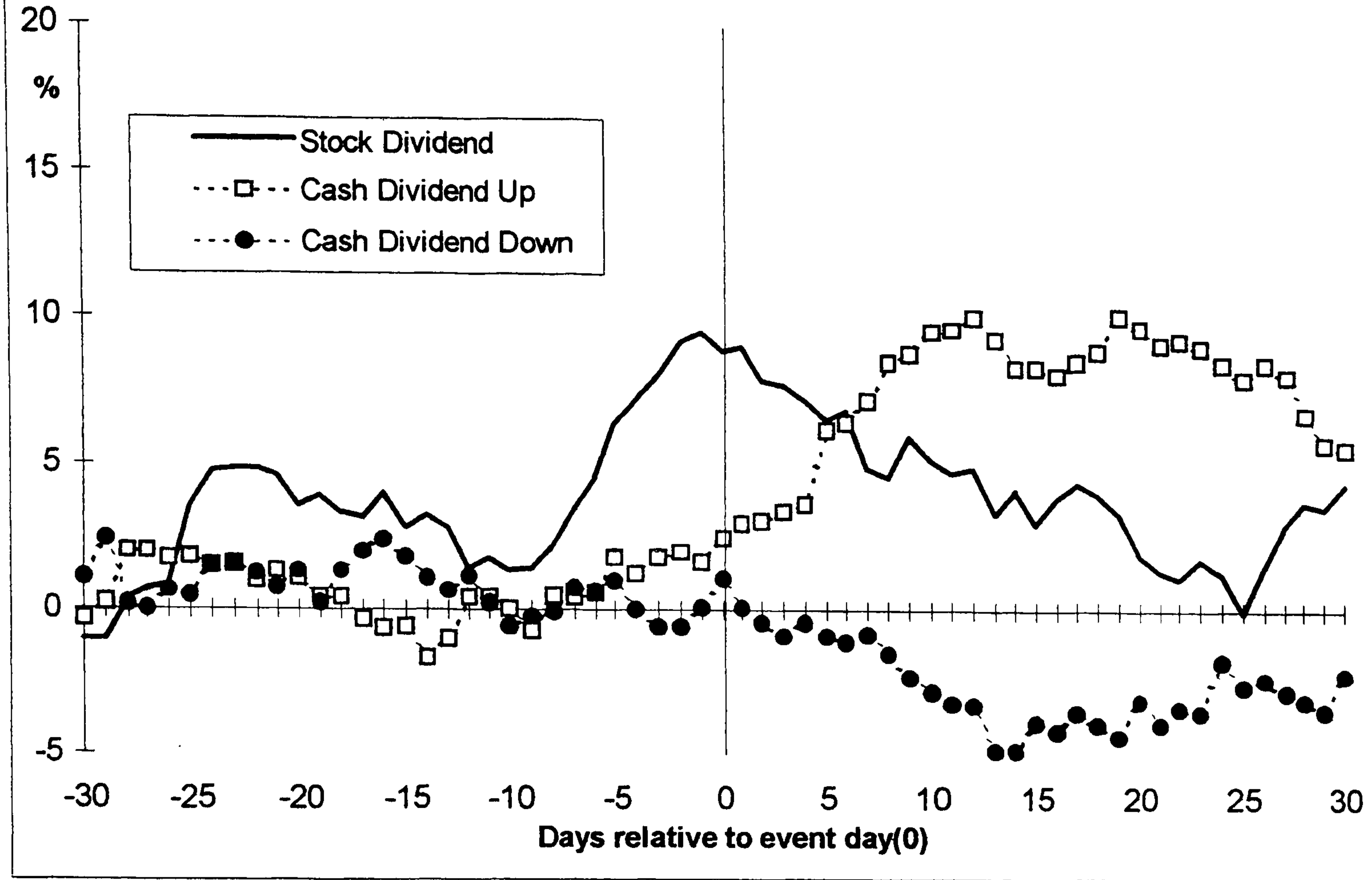
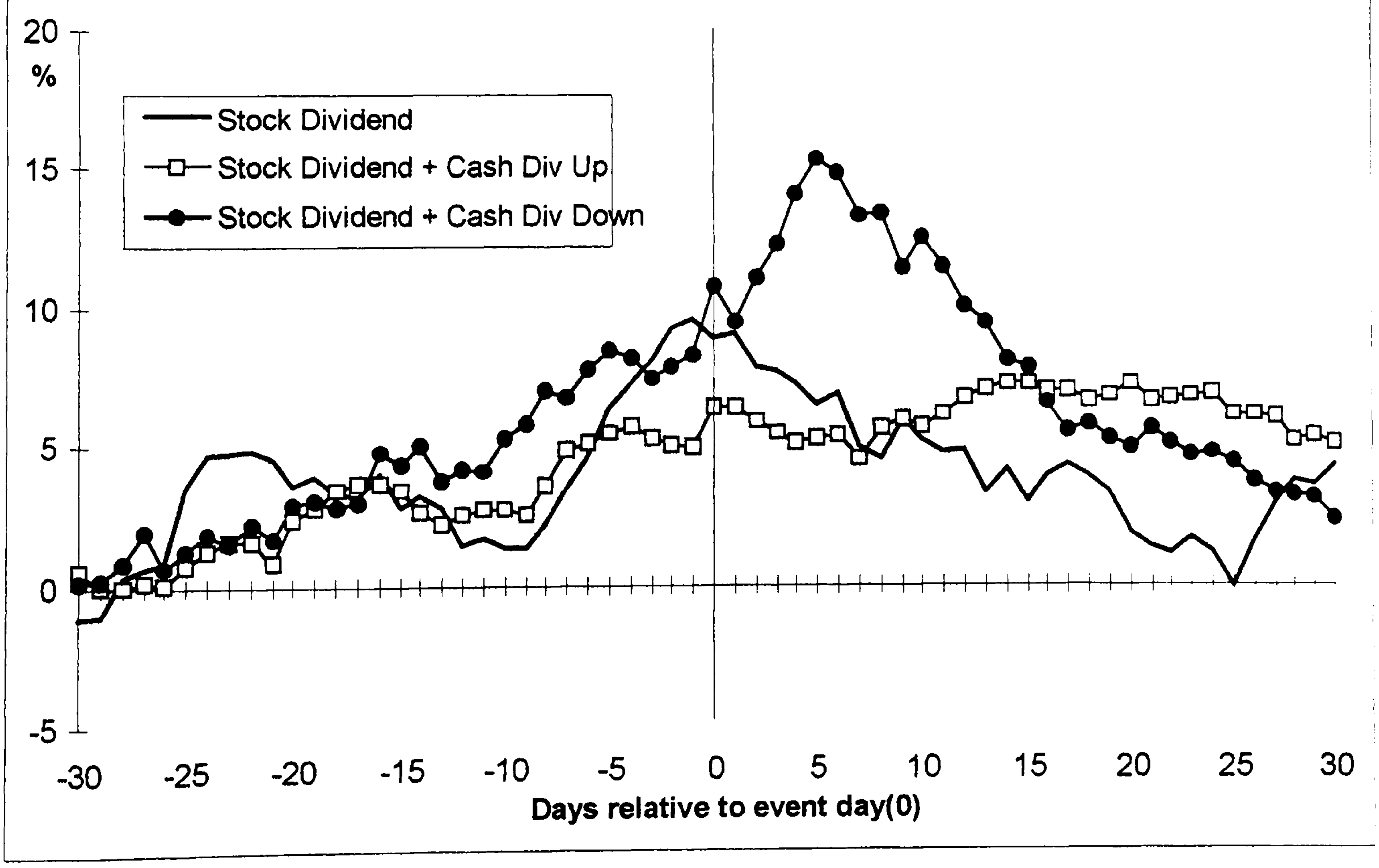


Figure 8.2. Cumulative Abnormal
Compound Stock and Cash Dividend Events



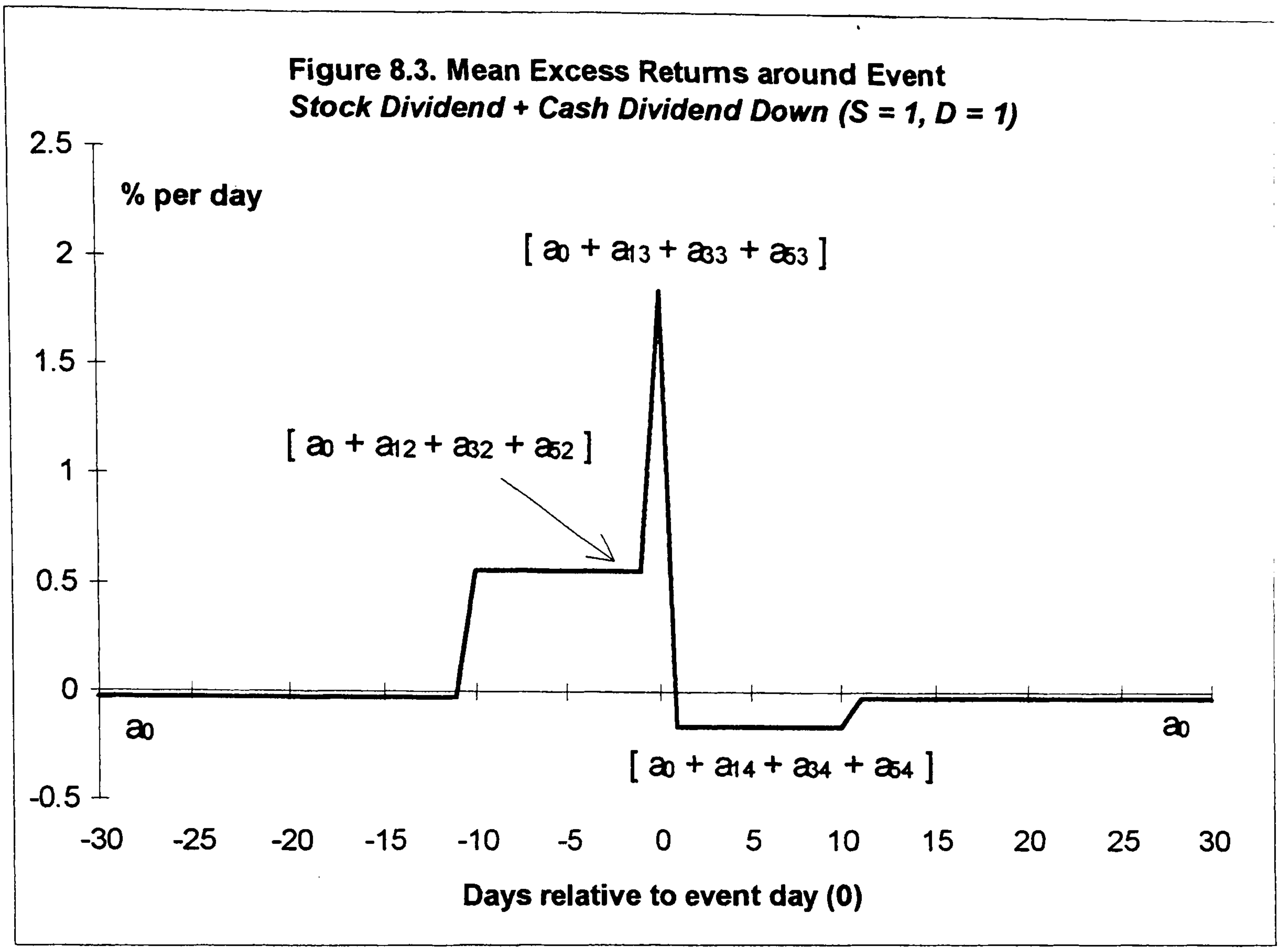


Figure 8.3. Mean Excess Returns around Event
Stock Dividend + Cash Dividend Down (S = 1, D = 1)
% per day
[a0 + a13 + a33 + a53]
[a0 + a12 + a32 + a52]
a0
a0
[a0 + a14 + a34 + a54]
2.5
2
1.5
1
0.5
0
-0.5
-30 -25 -20 -15 -10 -5 0 5 10 15 20 25 30
Days relative to event day (0)

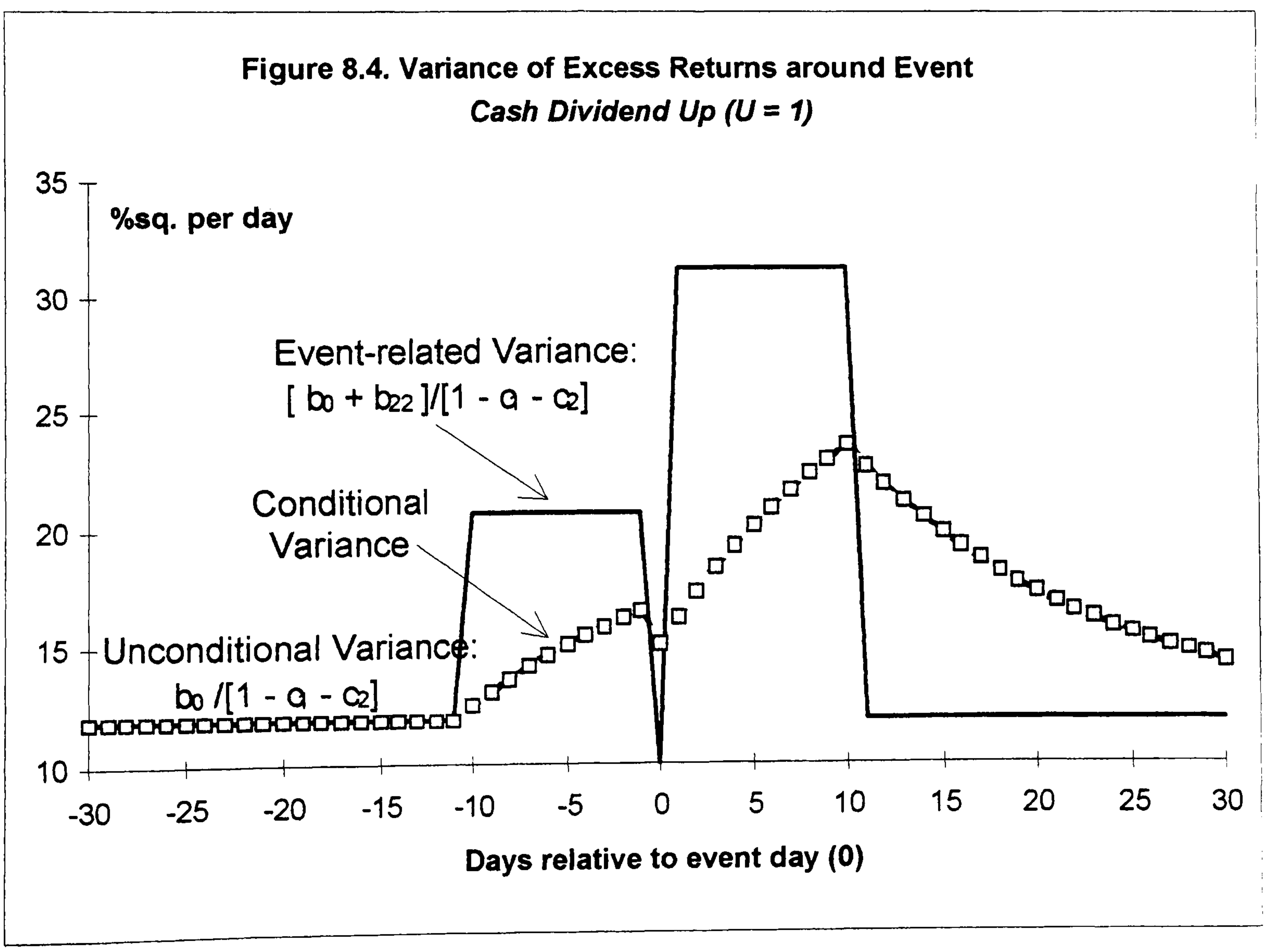


Figure 8.4. Variance of Excess Returns around Event
Cash Dividend Up (U = 1)
%sq. per day
Event-related Variance:
[b0 + b22]/[1 - c1 - c2]
Conditional Variance
Unconditional Variance:
b0 /[1 - c1 - c2]
35
30
25
20
15
10
-30 -25 -20 -15 -10 -5 0 5 10 15 20 25 30
Days relative to event day (0)

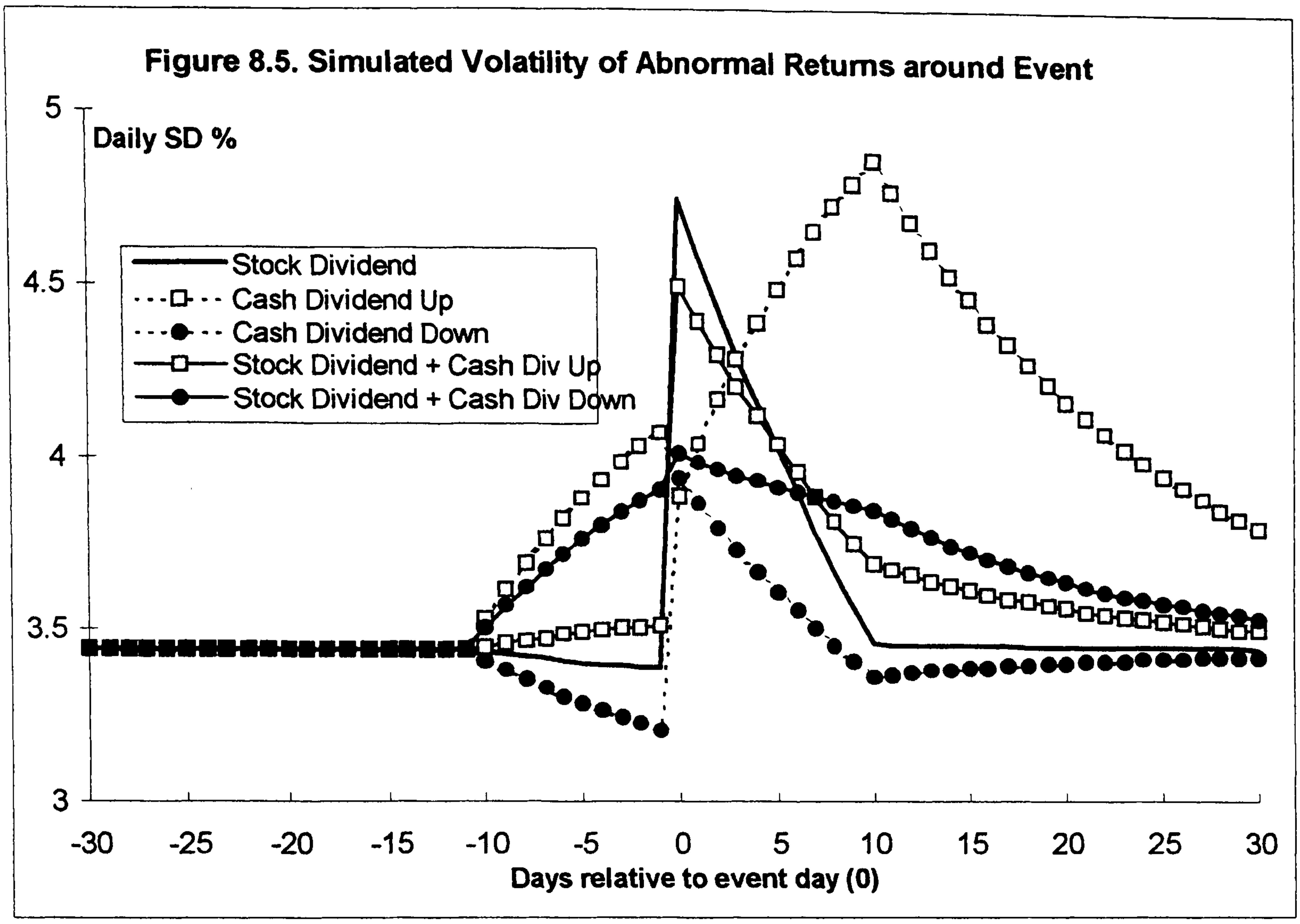


Figure 8.5. Simulated Volatility of Abnormal Returns around Event
Daily SD %
Stock Dividend
Cash Dividend Up
Cash Dividend Down
Stock Dividend + Cash Div Up
Stock Dividend + Cash Div Down
5
4.5
4
3.5
3
-30
-25
-20
-15
-10
-5
0
5
10
15
20
25
30
Days relative to event day (0)

CHAPTER NINE:

VOLATILITY FORECASTING IN THE ISE

9.1. INTRODUCTION

The aim of this chapter is to compare the performance of different volatility forecasting techniques in the context of Istanbul Stock Exchange.

The Turkish market is one of the most volatile in the world, and the measurement and prediction of volatility has obvious importance for risk management and the calculation of value-at-risk. As derivative markets evolve alongside the main market, volatility forecasting is also likely to become important for pricing options and warrants on the ISE index and individual stocks.

In Chapter 6 we found that the ISE index returns exhibited strong GARCH effects, and that these changed over time as the market became more efficient. While this suggests that volatility may be to some degree predictable, it does not mean that GARCH models are necessarily the best method to use for prediction. Many simpler alternatives, based on unweighted averages of past returns ("Historic Volatility") or weighted averages of past returns (such as "Exponential Smoothing") may adequately capture the time variation in the volatility process, and at less computational cost.

The first section of the Chapter sets out the five forecasting models considered. These are a GARCH model, an optimised exponential smoothing model (SES), a non-optimised "RiskMetrics" smoothing model (RM), a long term historic volatility model based on all previous daily returns (HMAX), and a short term historic volatility model based on the past 20 days of daily returns (H20).

The second section discusses estimation of the models, and compares their general features in the period 1991-98. In the case of the first two models care is taken to ensure that they are parameterised on data available before the beginning of each year being forecast. As might be expected from the results of Chapter 6, the structure of both these models changes through the sample period.

The third section assesses their accuracy in making out-of-sample 1-, 5-, 10- and 20-day ahead volatility forecasts. This replicates work on other markets by Akgiray (1989), Dimson and Marsh (1990), Tse (1991) and Tse and Tung (1992), Brailsford and Faff (1996). Like these studies, the error metric used is the mean absolute error in the standard deviation forecasts. By this criterion, differences across forecast methods are quite small and vary from year to year. Overall, methods which give more weight to recent data (GARCH, optimised SES, short term historic volatility) do better, especially at the longer horizons.

However, there are technical problems with the mean absolute error measure in assessing the 1-day forecasts. In addition it is unclear whether the implied linear loss function adequately reflects the costs of making errors in forecasting volatility.

In the third section we therefore complement conventional error measures by assessing the economic value of the different forecasts using a synthetic options market approach resembling that of Engle, Kane and Noh (1993). We imagine a market in options on the ISE index, with five different types of participant, each using one of the five forecasting methods to gauge the fair price of the option. The market price is set at the price implied by the median volatility forecast, and the other players take long or short positions in at-the-money straddles according as their forecasts are higher or lower than the median volatility.

Interestingly, the cumulative profits from the more accurate volatility forecasts (which give more weight to recent returns) tend to be lower than the profits from trading on long term historic volatility, or a RiskMetrics type smoothing model with a low smoothing parameter. This correlation is not particularly consistent across time, however, and the safest conclusion is that there is no correlation between the accuracy of different volatility forecasts and the profits made from trading options based on these forecasts. This parallels the finding in the mainstream forecasting literature, that there is no correlation between the accuracy of mean forecasts of interest rates and foreign exchange rates, and the profits made from trading interest rate and currency futures (Leitch and Tanner, 1991, Booth and Glassman, 1987).

The conclusion of this Chapter is that there is no simple answer to the question of which volatility forecasting method is best. It depends on the behaviour of the market. And it depends on the use to which the forecasts are to be put. A method may work well one year, and not the next. A method may be very relevant to value-at-risk calculations, which depends on accurate estimates of the variance, but not to options trading, which relies more on accurate directional signals. The final section of the paper considers these issues, and suggests some extensions to the current study.

9.2. VOLATILITY FORECASTING MODELS

Suppose the daily log-return of the ISE index is written $y_t = \ln(P_t/P_{t-1})$, where P_t is the index on day t, and the daily volatility (standard deviation) of returns is σ_t. The five models describing the possible evolution of this volatility over time are as follows:

Generalised autoregressive heteroscedasticity (GARCH):

This model has been discussed in previous Chapters, especially Chapter 6. The full specification used here is

$$y_t = c.\sigma_t + a_0 + a_1 y_{t-1} + a_2 y_{t-2} + u_t$$

$$u_t \sim N(0, \sigma_t^2) \text{ and serially independent}$$

$$\sigma_t^2 = b_0 + b_1 u_{t-1}^2 + b_2 \sigma_{t-1}^2$$

This is an AR(2) model for mean returns with a GARCH(1,1)-in-mean process for the error variance. The coefficient c measures the impact of volatility on returns, an effect we found in Chapter 6 to be significant in the early part of our data period when the ISE was less well integrated into the international capital market. The coefficients a_i relate to the AR process for daily returns. We found an AR(2) could adequately explain the systematic variation which occurred early in the period. As with c, we expect the coefficients a_1 and a_2 to be less significant in recent years as the market has become more efficient, and daily returns move closer to a random walk with drift.

The GARCH(1,1) process has a steady state when $\sigma_t^2 = u_{t-1}^2 = \sigma_{t-1}^2$, which implies a variance of

$$\sigma^2 = b_0 / \{1 - (b_1 + b_2)\}$$

For this "unconditional variance" to exist, we require $b_1 + b_2 < 1$. The steady state variance is not defined when $b_1 + b_2 = 1$ (an IGARCH process – similar to a random walk in the variance), and the model is unstable if $b_1 + b_2 > 1$.

Given estimates of the parameters of the model, k-day ahead forecasts starting from day T can be generated by the recursive formulae

$$\sigma_{T+1}^2 = b_0 + b_1 u_T^2 + b_2 \sigma_T^2 \text{ for } k = 1$$

$$\sigma_{T+k} = b_0 + (b_1 + b_2) \sigma_{T+k-1}^2 \text{ for } k > 1.$$

A feature of the GARCH model is that these forecasts converge towards the steady state variance. So if the most recent return was subject to a large shock (u_T^2 high), the 1-day ahead variance forecast will be high, but 2-, 3-, and 4-day ahead forecasts will be lower, and eventually converge on the steady state variance. Conversely volatility forecasts following an uneventful day will be low, but will rise towards the steady state variance as the forecast horizon increases.

As the forecast horizon lengthens, the range within which the underlying index may move will widen, and this depends on the sum of the variances of returns in the days between T+1 and T+k. So, corresponding to the set of 1- to k-day ahead forecasts for the variance of daily returns, we can calculate the variance of the log-index on day T+k as

$$\Sigma_{T+k}^{2} = \sum_{i=1}^{k} \sigma_{t+i}^{2}$$

The average daily variance from the GARCH model over the forecast period T+1 to T+k is then

$$\sigma_{T,k}^{2} = \sum_{i=1}^{k} \sigma_{t+i}^{2} / k.$$

Single Exponential Smoothing (SES and RM)

The GARCH model reflects an important "stylised fact" about financial market volatility, namely that if the returns are unexpectedly high or low on a particular day, this tends to lead to a series of abnormally high or low returns over the following days.

A reasonable "low-tech" way of expressing this relationship is to describe the evolution of the daily variance by the exponential smoothing model. The recursive form of this model is:

$$\sigma_t^2 = b\, y_{t-1}^2 + (1-b)\, \sigma_{t-1}^2$$

where $0 \leq b \leq 1$. That is, the variance on day t is a weighted average of the most recent squared return, and the most recent variance estimate, with the parameter b measuring how much weight is given to the recent "shock". This can alternatively be expressed as a infinite moving average of squared returns, with exponentially declining weights:

$$\sigma_t^2 = b\, y_{t-1}^2 + b.(1-b)\, y_{t-1}^2 + b.(1-b)^2\, y_{t-2}^2 + \ldots\, b.(1-b)^n\, y_{t-n}^2 + \ldots$$

Although superficially simple, this model makes a quite subtle assumption about the process driving squared returns – namely that they consist of the sum of permanent and transitory components – and the parameter b reflects the relative importance of the permanent component. If most changes to squared returns are permanent, an unexpectedly large market move would lead (through a high b value) to an immediate upward revision in the variance estimate. Conversely if most shocks to returns are transitory, b will be low, and a large market move will not be translated into an immediate rise in the estimated variance.

The SES model can be regarded as a special case of the GARCH process, in which the log index follows a random walk, and the variance process is IGARCH. The random walk implies that $c = a_0 = a_1 = a_2$, so that $y_t = u_t$, and the IGARCH process implies $b_0 = 0$, $b_1 = b$, and $b_2 = (1\text{-}b)$. While restrictive, these assumptions are not unreasonable in the context of high-frequency returns data.

Any violation of these assumptions means that the GARCH model is likely to fit our data better in-sample. However, this does not necessarily mean that it will perform better than SES out-of-sample, since the SES model is more parsimonious and is less sensitive to idiosyncrasies in the data used in estimation, and changes in the variance process over time.

Usually, the smoothing parameter b is estimated by minimising the sum of squared in-sample 1-step ahead forecast errors $(y_t^2 - \sigma_t^2)$. We term this an "optimised SES" model, and it is labelled SES in the results tables below.

An alternative approach was taken by the risk measurement firm RiskMetrics. This company was originally set up by J. P. Morgan to help financial services firms monitor and forecast volatility in market returns. It has come to focus on measures relevant to value-at-risk calculations, and has been extended over the years to incorporate correlation forecasts and credit risk assessment.

Risk Metrics forecasts are based on the exponential smoothing model described above, applied to returns series for all major stock markets. However, in the early days of the service RiskMetrics did not estimate the smoothing parameters by minimising the in-sample forecast error for each returns series individually. Instead they used a single estimate based on pooled time series data for all markets together. Their argument (since dropped) was that the pooled estimator was more robust in out-of-sample forecasting for the majority of markets.

In this study we have therefore "borrowed" the daily smoothing parameter of 0.06 from the early RiskMetrics model, as an alternative to a more conventional "optimised" smoothing model. In what follows this estimator is referred to as RM.

Given some parameter estimate based on data before day T, forecasts of the returns variance on day T+k are simply given by

$$\sigma_{T+k}^2 = b\, y_T^2 + (1-b)\, \sigma_{T-1}^2$$

That is, the variance forecasts are the same for all horizons. Hence the average daily variance between day T and day T+k is also

$$\sigma_{T,k}^2 = b\, y_T^2 + (1-b)\, \sigma_{T-1}^2$$

Historic Volatility (HMAX and H20)

As the smoothing constant $b \to 0$, the SES volatility estimator becomes an unweighted average of all past squared returns. Since the mean daily return is close to zero, this is very close to the sample variance of all observations up to day t:

$$\sigma_t^2 = \sum_{i=1}^{t} \{ y_i - \mu_t \}^2 / (t-1)$$

where

$$\mu_t = \sum_{i=1}^{t} y_i / t$$

is the mean return for all days up to t.

We call this volatility estimate HMAX, meaning "maximum term historic volatility". In contrast to the GARCH and SES models, which weight recent squared daily returns disproportionately, HMAX gives equal weight to all past squared daily returns, regardless of when they occurred.

An alternative scheme is to give the same weight to the last j observations, say, and a weight of zero to observations occurring earlier. The variance on day t is then the variance of the past j days returns, as

$$\sigma_t^2 = \sum_{i=t-j}^{t} \{ y_i - \mu_t \}^2 / (j-1)$$

where

$$\mu_t = \sum_{i=t-j}^{t} y_i / j$$

As a representative of this moving variance volatility measure we have set j = 20, so that the variance is estimated using only the last 20 trading days returns (roughly one month). This is termed H20.

Multiperiod forecasts for days following day T (sat day T+k) are again constant over all horizons for these forecasts, so in both cases

$$\sigma_{T+k}^2 = \sigma_T^2$$

and the average daily variance $\sigma_{T,k}^2$ in the interval (T, T+k) is similarly

$$\sigma_{T,k}^2 = \sigma_T^2$$

9.3 ESTIMATION

For this exercise our returns data are daily, starting at the beginning of 1988, and ending in September 1998. With around 250 trading days per year, this gives a total sample of 2500 observations.

The parameters of the GARCH and SES models have been fixed by estimating them based on daily data for two-year subsets of our data, and using the resulting estimates to forecast volatility through the following year. That is, data from 1988 and 1989 (around 500 observations) are used to parameterise the models, and these parameters are used to forecast variances in 1990. Then data from 1989 and 1990 are used to obtain updated parameter estimates, and these are used to forecast in 1991, Data from 1990 and 1991 are used to forecast 1992; and so on. This means that we do not use data from the forecast period in developing the volatility models. And we respect the changing structure of the market uncovered earlier, by discarding all except the most recent two years data.

Alternative approaches are of course possible. We could have updated the models on a daily basis, but this did not seem practicable. We could have used different past windows of data. However, we did not expect a window longer than 2 years to capture the changing parameter values well, whereas a shorter window of, say, 1 year might lead to too much instability in parameters. This is, however, a matter of judgement, and optimising the volatility forecasting process by experimenting with the data window is identified below as an issue for subsequent research.

Table 9.1 lists the parameter values for each 2-year data window for the GARCH models, and the corresponding SES smoothing parameters.

Some systematic changes appear in the coefficients of the models as time passes. For example, the coefficient c measuring the feedback of volatility on expected return is significant in the early years of our sample, but not after 1991. The significance of the coefficients on lagged returns in the AR(2) model for daily returns also falls progressively over time. Both of these features are consistent with our earlier picture of a market which has become steadily more efficient and internationally integrated over the past decade.

The coefficients of the GARCH(1,1) process also change after 1991, with the coefficient b_1, measuring the impact of shocks on volatility, falling, and the coefficient b_2, measuring persistence, rising. In recent years, one-off shocks have had a smaller impact on market volatility. But changes in volatility have been more long-lived. Calculation of the unconditional volatility implied by the GARCH coefficient estimates shows considerable variation in average returns volatility, from highs of over 23% per annum in the early 1990s to less than 10% after 1994.

The movements in b_1 are mirrored by changes in the coefficient b of the Single Exponential Smoothing model. This coefficient is very high in the late 1980s and early 1990s, but averages around 0.11 thereafter, with very low values in the low volatility years 1992-3 and 1995-7.

Accuracy of Volatility Forecasts

We have made volatility forecasts across four horizons - 1-day, 5-day, 10-day and 20-days ahead. To give a flavour of the data, Figure 9.1 shows daily returns and 20-day volatility predicted from the GARCH models year by year. The GARCH models display characteristic "saw-tooth" patterns, rising sharply after major market moves, and decaying slowly thereafter, and it captures high returns when there is a high standard deviation with in the 20-day ahead horizon.

To illustrate the difference between the multiperiod forecasts from GARCH as opposed to the other models, Figure 9.2 shows the 1- to 20-day ahead forecasts for all five models starting from one particular day (17 February 1993) when there was a large shock to the market. The returns series shows that the index rose over 8 per cent on that day. This caused the 1-day ahead GARCH volatility (standard deviation) estimate to rise from just over 2 per cent to almost 4 per cent. The 5-, 10- and 20-day ahead GARCH forecasts rose by less, with the 20-day ahead volatility rising to less than 3 per cent, reflecting the fact that the GARCH model expects volatility to track back towards its long run level following any shock.

The 1-day ahead SES volatility forecast also rises, but by less than the GARCH forecast, from just over 2 per cent to around 3 per cent. Since all k-period forecasts are equal for the SES model, this is also the level of volatility expected to obtain in 5days, 10 days and 20 days time. So while the 1-day GARCH volatility exceeds the 1-day SES volatility, positions are reversed for the 20-day ahead predictions. The other models are less affected by the exceptional market move, and barely at all in the case of the HMAX estimate. Like the SES, the volatility forecasts are the same for all horizons following the market shock.

We have measured the accuracy of volatility forecasts by comparing the forecast volatility with the standard deviation of daily returns in the forecast period. So for, say, k-day forecasts made on day T, realised volatility is defined as

$$s_{T,k} = \sqrt{\sum_{i=T+1}^{T+k} \{ y_i - \mu_T\}^2 / (k-1)}$$

where μ_T is the mean return over the days T+1 to T+k.

While this is the conventional way to measure "actual" volatility, it should be noted that when k is small, it produces biased estimates (see Lopez 1995). In the limit, when k=1, the daily variance is being proxied by the squared daily return. Since returns are assumed normally distributed, this squared return y_t^2 will have a $\chi^2(1)$ distribution, which is highly skewed. Although $E(y_t^2) = 1.00$, the median of the distribution is 0.46, so that in more than half of all daily observations we will find that $y_t^2 < \sigma_t^2/2$ even with an unbiased forecast σ_t^2 of volatility. This problem reduces as the asymmetry in the distribution of the variance falls with increasing sample size. But it does suggest that conventional comparisons of 1-day ahead, and possibly also 5-day ahead volatility forecasts are potentially flawed.

Subject to this caveat, a number of error metrics might be considered for assessing the accuracy of volatility forecasts. We have chosen to measure accuracy by the mean absolute error in forecasts of the standard deviation, as

$$MAE_k = \sum_{T=1}^{n} | s_{T,k} - \sigma_{T,k} |$$

where $\sigma_{T,k}$ is a standard deviation forecast produced by one of the five methods outlined above, and n is the number of forecasts. This assumes that losses from errors in volatility forecasts are symmetric, and increase linearly with the size of the error. Use of the mean squared error criterion, which assumes a quadratic loss function, can in principle produce different rankings of forecasting methods. However, in practice in our data the MAE and RMSE metrics produced the same pattern of results, so we report only the MAE figures here.

The full results by forecast horizon are set out in Table 9.2 below. Looking at the average errors across different methods, it is clear that for the longer 10- and 20-day horizons, the GARCH model performs better than the other models. In contrast, the maximum term historic volatility estimator HMAX is consistently less accurate than all the others. The short term historic volatility H20 performs a little worse than the exponential smoothing models. The optimised smoothing model SES, which by definition fits better in-sample, does not necessarily provide better out-of-sample forecasts than the non-optimised alternative RM.

At the 1-day and 5-day horizon, the noisiness of the data increases, and there is less to choose between the models, though the long-term historic volatility model HMAX is still clearly dominated.

Looking across years, there is some evidence that in the more volatile years, the smoothing models and the short term moving average models do well. On the other hand, in the more stable years towards the end of our sample period, the GARCH model performs better.

The final column of Table 9.2 shows the mean absolute errors for a pooled forecast formed by taking the unweighted average of the five individual volatility forecasts.

It is well established that averaging a number of unbiased forecasts of the expected value of some variable produces forecasts which have a lower root mean squared error than the majority of component forecasts (see for example Bates and Granger, 1969). Just as diversifying a portfolio of risky assets decreases the portfolio variance below the average variance of the assets, so diversifying forecasts reduces the expected forecast error. Suppose we have two variance forecasts σ_1^2 and σ_2^2, and form a pooled forecast

$$\sigma_p^2 = w.\ \sigma_1^2 + (1-w).\ \sigma_2^2$$

If the actual (realised) variance is σ^2, then

$$E\{(\sigma^2 - \sigma_p^2)^2\} < w.\ E\{(\sigma^2 - \sigma_1^2)^2\} + (1-w).\ E\{(\sigma^2 - \sigma_2^2)^2\}$$

And hence the MAE of the pooled forecast will be less than the average MAE of the individual forecasts. This result extends in a straightforward way to the case of n>2 component forecasts

As with portfolio diversification the size of the gain depends on the (lack of) correlation between errors made by the component forecasts. A set of very similar forecasts will not produce great gains from pooling. A set of very diverse forecasts, that make different kinds of errors, will be good material for pooling. In practice, the benefits of pooling are often substantial. Clemen (1989) surveys some of the empirical evidence. For forecasts of the expected values of economic variables, for example, the pooled forecast is more accurate than about 80% of the component forecasts.

However, none of the existing evidence relates to forecasts of variances, and the non-normal distribution of the target variable makes it interesting to see whether pooling helps in such problems.

In principle, the best way to combine forecasts is to weight them according to their degree of intercorrelation, just as optimal portfolio weights would be decided. However, the studies cited in Clemen (1989) show that in practice these error correlations are rarely stable enough to produce a robust weighting scheme, and it is hard to beat an equally weighted combination of forecasts.

The result on Table 9.2 show that in 20-day ahead forecasts the pooled model dominates all the individual methods. In 5- and 10-day ahead forecasts it produces errors comparable to those from the best method (GARCH). Only in the case of 1-day ahead forecasts are the benefits from pooling not evident. However, we have already noted that the calculation of MAE statistics for this horizon is problematical. We can therefore safely conclude that pooling produces benefits for variance forecasting, as in other applications.

Profitability of Volatility Forecasts

The value of any forecast can only properly be measured relative to the utility function of the user of the forecast. The mean absolute error metric used above assumes a particular loss function, without specifying exactly the activity into which the volatility forecasts might feed.

West and Cho (1993) take a different approach, and imagine the user of the volatility forecasts to be an investor who needs the forecasts to improve portfolio design. The forecasts are evaluated by asking how much an investor with a mean-variance utility function would be willing to pay to use the forecasts from each competing model.

In this Chapter we similarly assume the user of the forecast to have a specific use in mind for the forecasts – namely, trading options. Like the West and Cho (1993) approach, this will lead to a ranking of methods which is particular to this use of volatility forecasts. However, we are interested in whether changing the utility function leads to a change in rankings, and the nonlinear nature of the payoffs to options positions provides a tougher test of the robustness of conventional error metrics.

Our approach is similar to the artificial market constructed by Engle, Kane and Noh (1993). There are no options traded on the ISE index at present, although this is planned for the near future. We instead imagine an options market in which 1-day, 5-day, 10-day and 20-day calls and puts are traded each day.

In this market there are five groups of traders, each using one of the five forecasting methods described above. Since options premia are increasing functions of the forecast volatility, some of these groups will place a higher valuation on the options than others.

Specifically, we make the conventional assumption that the groups value calls and puts (C and P) in line with the Merton, dividend-adjusted, version of the standard Black Scholes option pricing model, as

$$C = S.e^{-qt}.N(d_1) - X.e^{-rt}.N(d_2)$$

$$P = X.e^{-rt}.N(-d_2) - S.e^{-qt}.N(-d_1)$$

where

$$d_1 = \{\ln(S/X) + (r - q - \sigma^2/2)\} / \sigma\sqrt{t}$$

$$d_2 = d_1 - \sigma\sqrt{t}$$

and S is the current index value, X the exercise price, r the riskless interest rate, q the dividend yield on the index, t the time to expiry of the option, and σ the forecast standard deviation.

As an aside, we should note that use of the Black-Scholes model is strictly inconsistent with the assumption we have made that volatility is time-varying. While there are models which embody GARCH processes for the underlying returns series, these are complex. We therefore follow the common practice of applying the Black-Scholes model, on the grounds that the resulting refinements to options prices are generally small.

Differences in volatility forecasts are the only source of differences of opinion about option values (aside from disagreements about the proper model). A trader whose forecast of volatility was higher than the volatility implied by the current options prices would naturally be a buyer of calls and puts. And vice versa.

In our artificial market we have five types of agent, corresponding to the five volatility forecasting models. To keep our calculations simple, we assume that the options prices are set day by day to reflect the median volatility forecast at each horizon. This means that two types of agent will want to buy options, and two sell, while for the median forecasters, the price will be just right. Again, for simplicity we assume that the agents with relatively high volatility forecasts each buy one at-the-money straddle – that is, buy a call and a put with exercise price = the current stock index price (X = S). This is a standard volatility trade, and will show a profit if the index rises or falls by more than the sum of the premia (C+P) at the expiry of the option.

Since positions must balance across the market, two groups of agents will have long straddle positions, and the other two, with relatively low volatility forecasts, will have short straddle positions. The short straddle will show a positive profit if at the expiry of the option, the index has moved by less than (C+P) away from its starting value S.

Since the market is a zero-sum game, in each trade there will be two winning groups and two losing groups (and one group which is out of the market).

Table 9.3 shows profits year by year, and over all years, from trading on the five volatility forecasting models. Because of the underlying high inflation rate in Turkey, the ISE index rises very strongly from year to year, and to adjust for this we have deflated the profits (which are in index points) by dividing by the value of the index itself. This gives a kind of "percentage return" to rolling single straddle positions. To give a visual impression of how the five groups fare, Figures 9.2 – 9.7 track the cumulative profits from the different forecasting methods, again on an inflation-corrected basis.

The results make a striking contrast with our findings on forecast accuracy. The GARCH model is consistently more accurate than the alternatives, especially at long horizons. However, looking at Table 9.3 and Figure 9.3, trading on GARCH forecasts of 10- and 20-day volatility makes consistent losses. The long term historic volatility model HMAX produces very inaccurate forecasts. However, looking at Table 9.3 and Figure 9.6 volatility trades based on the assumption that volatility will revert to its long term mean produce positive profits at all horizons.

The ordering of the other methods is also perverse. The non-optimised Risk-Metrics style model, for example, produces averagely accurate forecasts, but consistently good profits. The short term historic volatility model forecasts fairly well, but trading on its forecasts leads to losses.

The perverse correlation between accuracy and profitability is confirmed in Table 9.4, where we show simple and rank correlations across methods between MAE and profits. If higher accuracy (lower MAE) led to higher profits, these figures should be negative. While this is found in some years, the correlations are overwhelmingly positive, especially for options with a short time to expiry.

Table 9.5 asks whether for each method the years in which it performed well are also the years in which traders would have made most profit. For GARCH forecasts at the 5- to 20-day horizon this is broadly true. However, there is no such consistency with the other methods, not in the overall pattern of profitability over time. The safest conclusion is that, even if we knew in advance that a particular method would produce a low MAE in a particular year, we could not guarantee that profits would be above- (or below-) average in that year.

9.4. CONCLUSIONS

This Chapter has explored the value of different volatility forecasts for the ISE, defining "value" in two ways – accuracy and profitability.

In terms of accuracy the GARCH(1,1) model performs very well. Aside from the problematical 1-day horizon, it regularly dominates simpler alternatives based on simple or weighted averages of past squared returns.

Pooled forecasts work even better, however, suggesting that it is unwise to ignore completely the information in simpler and more traditional volatility forecasting methods. One contribution of this Chapter has been to show that the superiority of pooled forecasts, well documented in other applications in the forecasting literature, applies equally to volatility forecasts.

In terms of the profits generated by options traders, the picture is more cloudy. In an artificial options market with simple volatility trading, GARCH performs consistently less well than a simple historic volatility model, and a constant parameter non-optimised exponential smoothing model.

The idea that accuracy and profitability may be only weakly correlated is also now well established in the forecasting literature. This has been established for small sets of interest rate and exchange rate forecasts by Leitch and Tanner (1991) and Boothe and Glassman (1987) respectively. The reason such results can occur relates to the non-normality of financial market returns. Trading profits depend on correct forecasts of the directional change of the underlying variable, rather than its size. Moreover, these changes need to be correctly predicted only in the minority of days when there are large potential profits available (because the market moves very sharply in the forecast period).

Our contribution in this Chapter is again to show that this phenomenon characterises not only forecasts of mean returns, but also the volatility of these returns.

It is of course possible to argue with the way we have constructed the artificial options market. In common with the above studies of profitability we have had to assume a particular trading rule, and our results are conditional on the reasonableness of that rule. We would argue that buying and selling volatility through straddle trades is the most simple and intuitive way to use volatility forecasts, and is consistent with market practice. But other rules are of course possible, and might lead to different results. We could also have chosen a different method of market clearing, like the evolutionary approach of Engle, Kane and Noh (1993). However, this would be an unnecessary complication. Our approach is sufficient to show that at the very least it is unsafe to conclude that better volatility forecasting necessarily leads to better volatility trading.

Finally, it is important to note that this does not mean that volatility forecasts have no value. Simple exponential smoothing, for example, provided a good basis for trading in our sample period. And of course there are many users for volatility forecasts other than options traders. For example, there is a great current demand for value-at-risk measures relevant to emerging markets, and volatility forecasts are an important input into this process. Consideration of the value-at-risk implication of our modelling work, while important for future research, does take us well beyond the limited ambitions of this Chapter.

9.5. APPENDICES

Table 9.1 Coefficients of Volatility Models in Rolling Data Windows

Data Window	Coefficients: in-mean	AR(2) a_0	a_1	a_2	GARCH b_0	b_1	b_2	*Uncondit Vol %*	SES b
1988-9	0.04	-0.01	0.34	-0.10	0.23	0.44	0.55	*23.00*	0.24
t-stats	*1.37*	*0.04*	*6.57*	*2.20*	*2.83*	*7.30*	*12.91*		
1989-90	0.06	0.16	0.41	-0.14	0.47	0.35	0.63	*23.50*	0.15
t-stats	*2.56*	*0.62*	*8.00*	*2.97*	*3.60*	*5.55*	*12.34*		
1990-1	0.27	-0.74	0.30	-0.11	0.89	0.24	0.69	*12.71*	0.11
t-stats	*1.87*	*1.60*	*5.77*	*2.18*	*3.05*	*3.60*	*10.52*		
1991-2	0.25	0.69	0.16	0.09	0.43	0.15	0.80	*8.60*	0.11
t-stats	*1.37*	*1.50*	*3.23*	*2.02*	*2.57*	*4.01*	*17.26*		
1992-3	0.24	-0.32	0.12	-0.06	0.21	0.05	0.91	5.25	0.03
t-stats	*0.65*	*0.38*	*2.77*	*1.24*	*2.04*	*2.94*	*34.87*		
1993-4	-0.10	0.62	0.16	-0.04	0.26	0.09	0.89	*13.00*	0.11
t-stats	*0.48*	*1.12*	*3.11*	*0.72*	*1.61*	*3.41*	*27.00*		
1994-5	-0.05	0.28	0.18	-0.03	0.26	0.11	0.86	*8.67*	0.11
t-stats	*0.30*	*0.64*	*3.60*	*0.63*	*2.45*	*2.86*	*20.71*		
1995-6	0.08	0.06	0.08	0.02	0.26	0.08	0.87	*5.20*	0.05
t-stats	*0.29*	*0.10*	*1.78*	*0.43*	*1.90*	*2.72*	*19.24*		
1996-7	0.10	0.11	0.12	0.04	0.34	0.12	0.83	*6.80*	0.01
t-stats	*0.51*	*0.26*	*2.40*	*0.69*	*2.65*	*4.86*	*25.99*		

Table 9.2 Mean Absolute Errors in Volatility (Daily Standard Deviation) Forecasts

% per day

Target	1-day GARCH	SES	RM	HMAX	H20	Pooled
1991	2.11	2.05	2.14	1.99	2.11	*2.11*
1992	1.43	1.23	1.27	1.78	1.21	*1.43*
1993	1.46	1.45	1.44	1.58	1.41	*1.46*
1994	1.65	1.88	1.69	2.01	1.67	*1.65*
1995	1.49	1.41	1.41	1.73	1.41	*1.49*
1996	1.25	1.16	1.18	1.73	1.18	*1.25*
1997	1.63	1.75	1.76	1.78	1.80	*1.63*
1998	1.85	1.91	1.91	1.83	1.94	*1.85*
1991-98	*1.60*	*1.59*	*1.59*	*1.81*	*1.58*	*1.60*

Target	5day GARCH	SES	RM	HMAX	H20	Pooled
1991	1.38	1.31	1.40	1.35	1.36	*1.38*
1992	0.95	0.80	0.83	1.35	0.80	*0.95*
1993	0.93	0.93	0.90	1.03	0.92	*0.93*
1994	1.00	1.29	1.12	1.40	1.11	*1.00*
1995	0.93	0.88	0.86	1.26	0.93	*0.93*
1996	0.79	0.72	0.73	1.30	0.73	*0.79*
1997	1.00	1.12	1.11	1.26	1.20	*1.00*
1998	1.11	1.23	1.23	1.17	1.35	*1.11*
1991-98	*1.01*	*1.03*	*1.01*	*1.27*	*1.04*	*1.01*

Table 9.2 (ctd)

Target	***10 day*** ***GARCH***	***SES***	***RM***	***HMAX***	***H20***	***Pooled***
1991	1.27	1.15	1.18	1.06	1.22	*1.27*
1992	0.68	0.61	0.63	1.15	0.62	*0.68*
1993	0.65	0.70	0.64	0.71	0.73	*0.65*
1994	0.84	1.18	0.95	1.29	0.92	*0.84*
1995	0.71	0.73	0.72	1.05	0.84	*0.71*
1996	0.57	0.58	0.57	1.10	0.59	*0.57*
1997	0.95	1.05	1.04	1.16	1.16	*0.95*
1998	1.07	1.03	1.14	1.00	1.29	*1.07*
1991-98	*0.83*	*0.87*	*0.85*	*1.07*	*0.91*	0.83

Target	***20 day*** ***GARCH***	***SES***	***RM***	***HMAX***	***H20***	***Pooled***
1991	1.18	1.12	1.14	0.75	1.22	*1.18*
1992	0.53	0.59	0.61	1.07	0.60	*0.53*
1993	0.65	0.66	0.59	0.54	0.66	*0.65*
1994	0.86	1.11	0.94	1.27	0.93	*0.86*
1995	0.55	0.64	0.60	0.90	0.74	*0.55*
1996	0.48	0.54	0.51	1.04	0.56	*0.48*
1997	0.96	1.00	1.01	0.98	1.16	*0.96*
1998	1.03	0.74	0.95	0.74	1.08	*1.03*
1991-98	*0.77*	*0.81*	*0.79*	*0.92*	*0.86*	0.72

Table 9.3 Profits from Straddle Trades

(100*index points/end-year-index)

Target	*1-day GARCH*	*SES*	*RM*	*HMAX*	*H20*
1991	10	7	-39	31	-9
1992	-6	-4	-2	1	10
1993	-6	-22	23	11	-6
1994	21	-82	84	-68	44
1995	0	-15	-13	25	3
1996	11	3	6	-15	-5
1997	37	-21	6	25	-47
1998	70	10	-28	39	-91
1991-98	132	-34	-7	69	-159

Target	*5day GARCH*	*SES*	*RM*	*HMAX*	*H20*
1991	-73	-146	7	206	6
1992	5	-105	23	158	-81
1993	-3	-111	54	110	-50
1994	-93	-179	418	-294	148
1995	56	-110	-52	205	-99
1996	85	-86	7	87	-92
1997	42	-28	8	307	-328
1998	-92	-159	248	-124	127
1991-98	4	-293	308	389	-409

Table 9.3 (ctd)

Target	*10 day* *GARCH*	*SES*	*RM*	*HMAX*	*H20*
1991	-31	-298	145	406	-223
1992	73	-145	-49	262	-141
1993	-264	-309	197	480	-104
1994	-330	-84	635	-335	114
1995	127	-50	-248	532	-360
1996	160	-163	1	204	-201
1997	-128	166	-55	590	-573
1998	-317	-685	989	-639	650
1991-98	-480	-560	959	439	-358

Target	*20 day* *GARCH*	*SES*	*RM*	*HMAX*	*H20*
1991	-59	-798	310	715	-168
1992	-31	-137	-7	654	-479
1993	-684	-322	354	744	-93
1994	-913	271	902	-365	105
1995	232	-335	-315	1150	-733
1996	-169	-394	247	659	-343
1997	-177	314	-160	825	-802
1998	-923	-853	2245	-1176	706
1991-98	-1391	-622	2200	588	-775

Table 9.4 Correlation of accuracy and profitability across methods

Year	*Horizon* *1-day*	*5-day*	*10-day*	*20-day*
1991	-0.84	0.18	-0.57	-0.66
1992	-0.14	0.91	0.90	0.86
1993	0.31	0.54	0.10	-0.88
1994	-0.85	-0.57	-0.33	-0.02
1995	0.89	0.89	0.65	0.53
1996	-0.74	0.63	0.59	0.78
1997	-0.66	0.12	0.09	-0.71
1998	-0.87	0.53	0.80	0.47
1991-98	0.42	0.54	0.27	0.10

Rank correlation:

Year	*Horizon* *1-day*	*5-day*	*10-day*	*20-day*
1991	-0.70	0.30	-0.30	-0.40
1992	-0.30	0.80	1.00	0.60
1993	-0.10	0.10	0.10	-0.60
1994	-0.50	-0.60	-0.30	0.30
1995	0.30	0.70	0.10	0.00
1996	-0.30	0.70	0.10	0.20
1997	-0.60	0.00	0.00	-0.40
1998	-0.80	0.50	0.80	0.30
1991-98	0.80	0.10	0.20	0.30

Table 9.5 Correlation of accuracy and profitability across years

Horizon	*Method* *GARCH*	*SES*	*RM*	*HMAX*	*H20*	*All*
1-day	0.44	-0.18	-0.28	-0.32	-0.45	*-0.15*
5-day	-0.69	-0.51	0.35	-0.14	0.26	*0.13*
10-day	-0.36	-0.07	0.53	-0.24	0.28	*0.15*
20-day	-0.33	0.24	0.34	-0.08	0.24	*0.12*

Rank Correlation:

Horizon	Method *GARCH*	*SES*	*RM*	*HMAX*	*H20*	*All*
1-day	0.50	0.17	-0.33	0.10	-0.62	*-0.08*
5-day	-0.62	-0.69	0.43	-0.10	0.36	*0.14*
10-day	-0.45	0.19	0.31	-0.05	0.10	*0.10*
20-day	-0.43	0.07	0.14	-0.26	0.10	*0.06*

Figure 9.1 20-day volatility forecasts from the GARCH(1,1) model

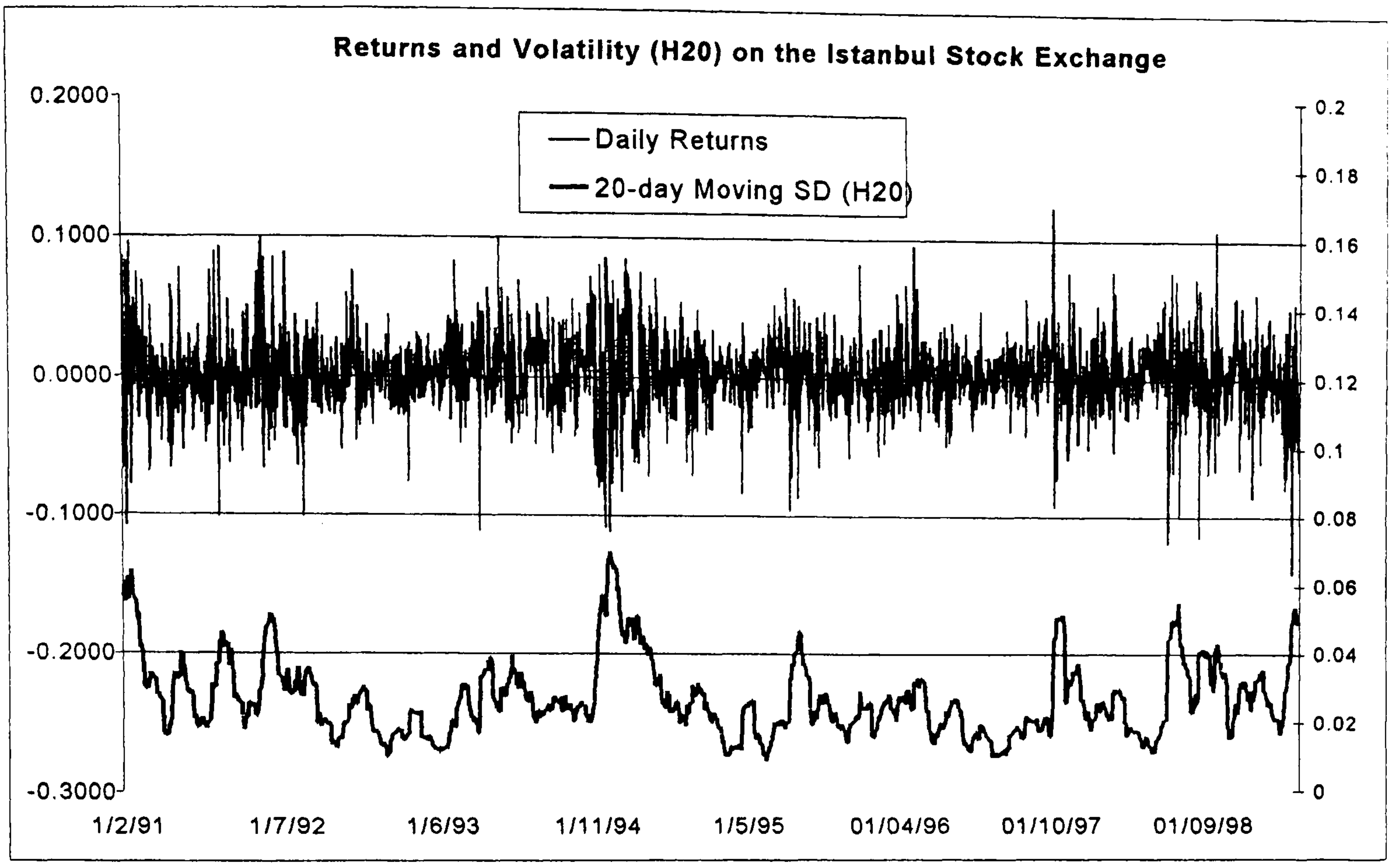


Figure 9.2 Multiperiod forecasts from GARCH model

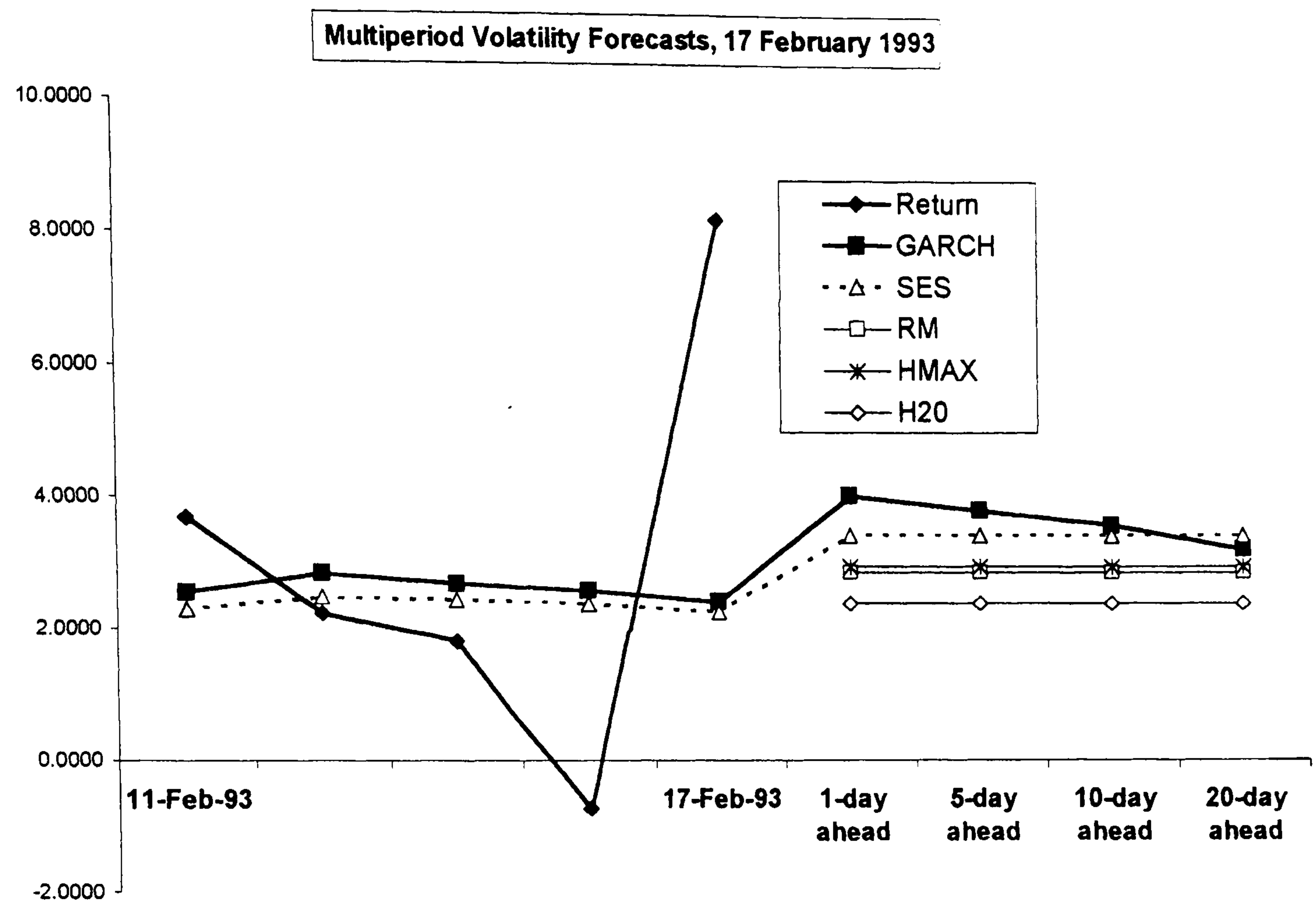


Figure 9.3

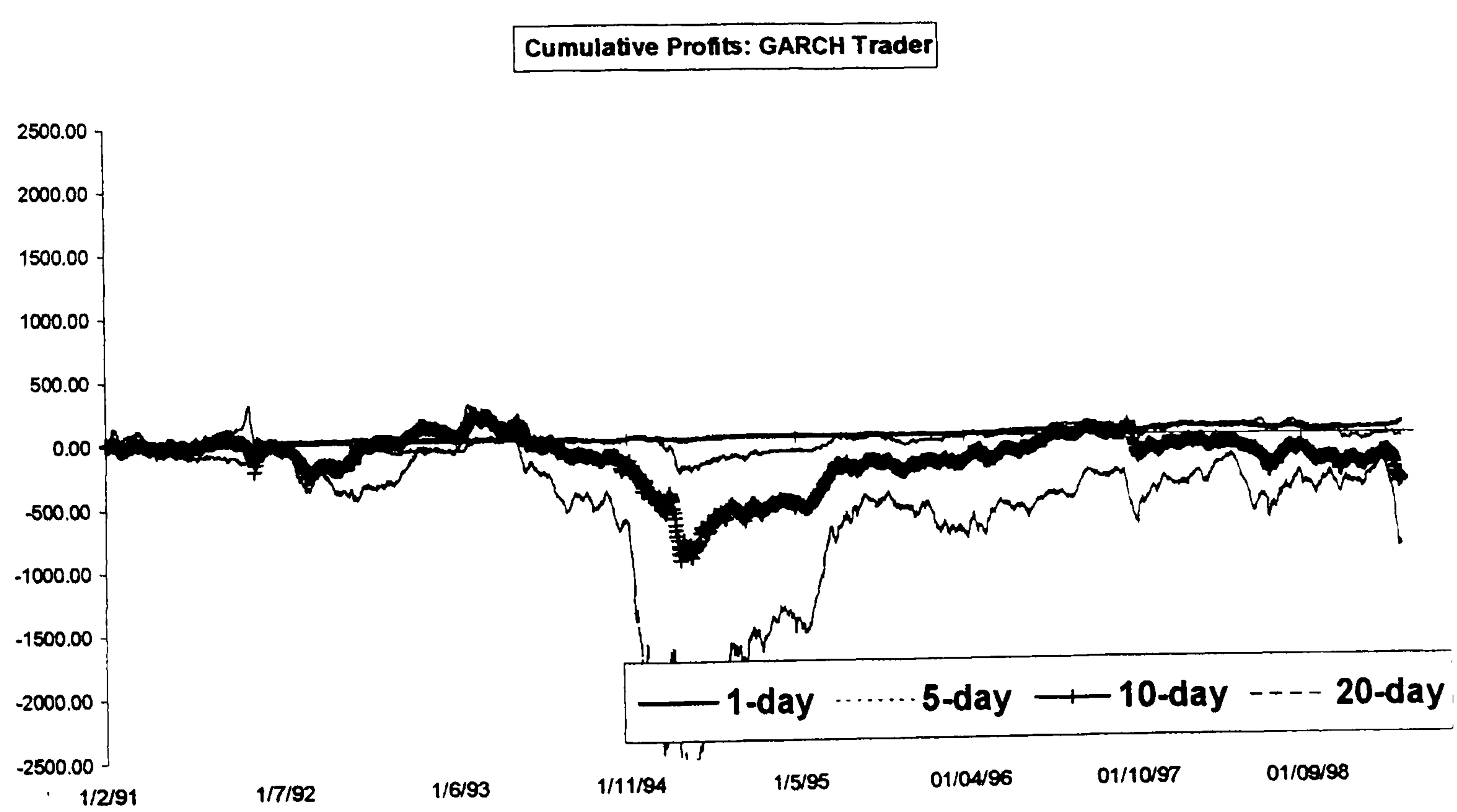


Figure 9.4

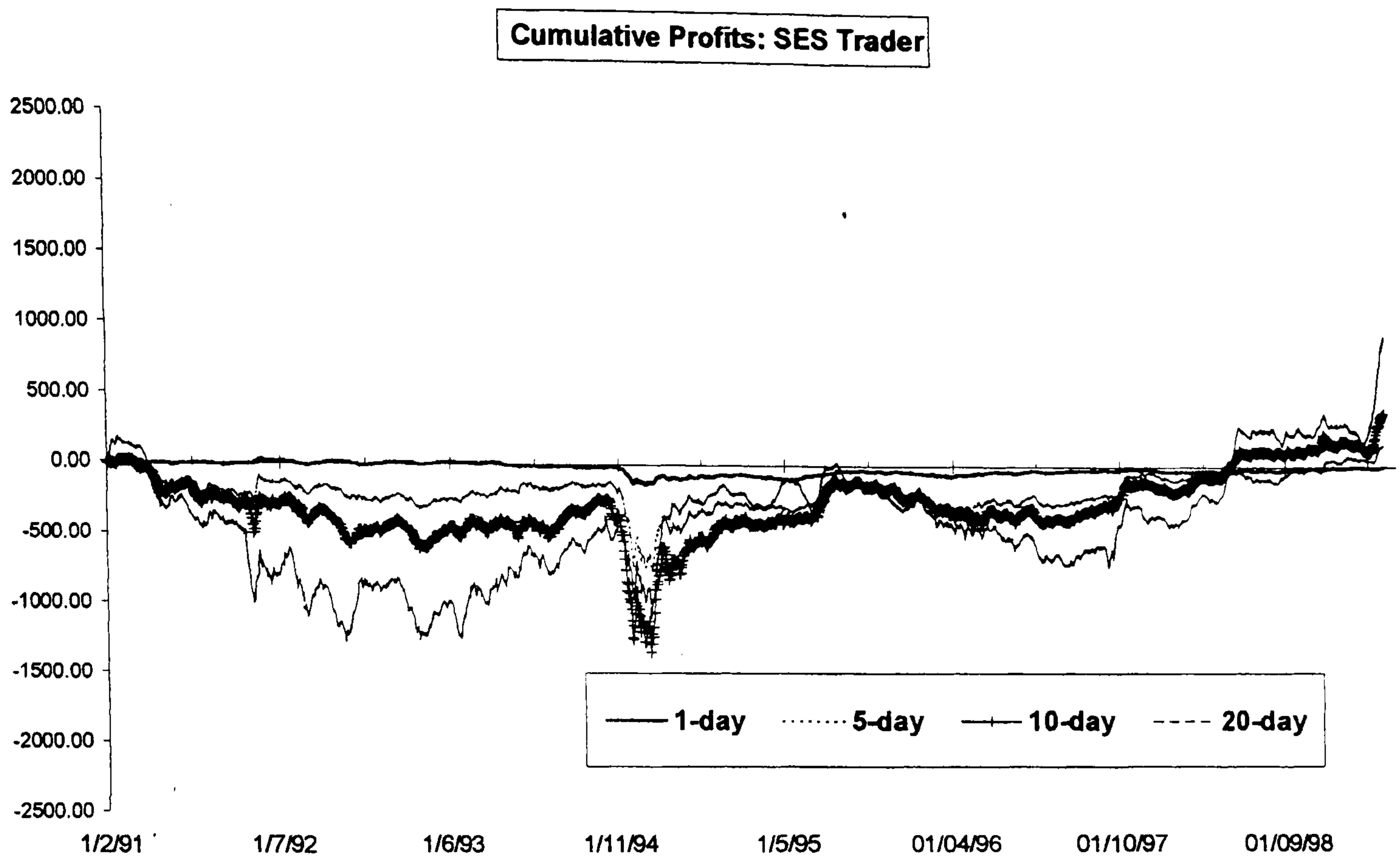


Figure 9.5

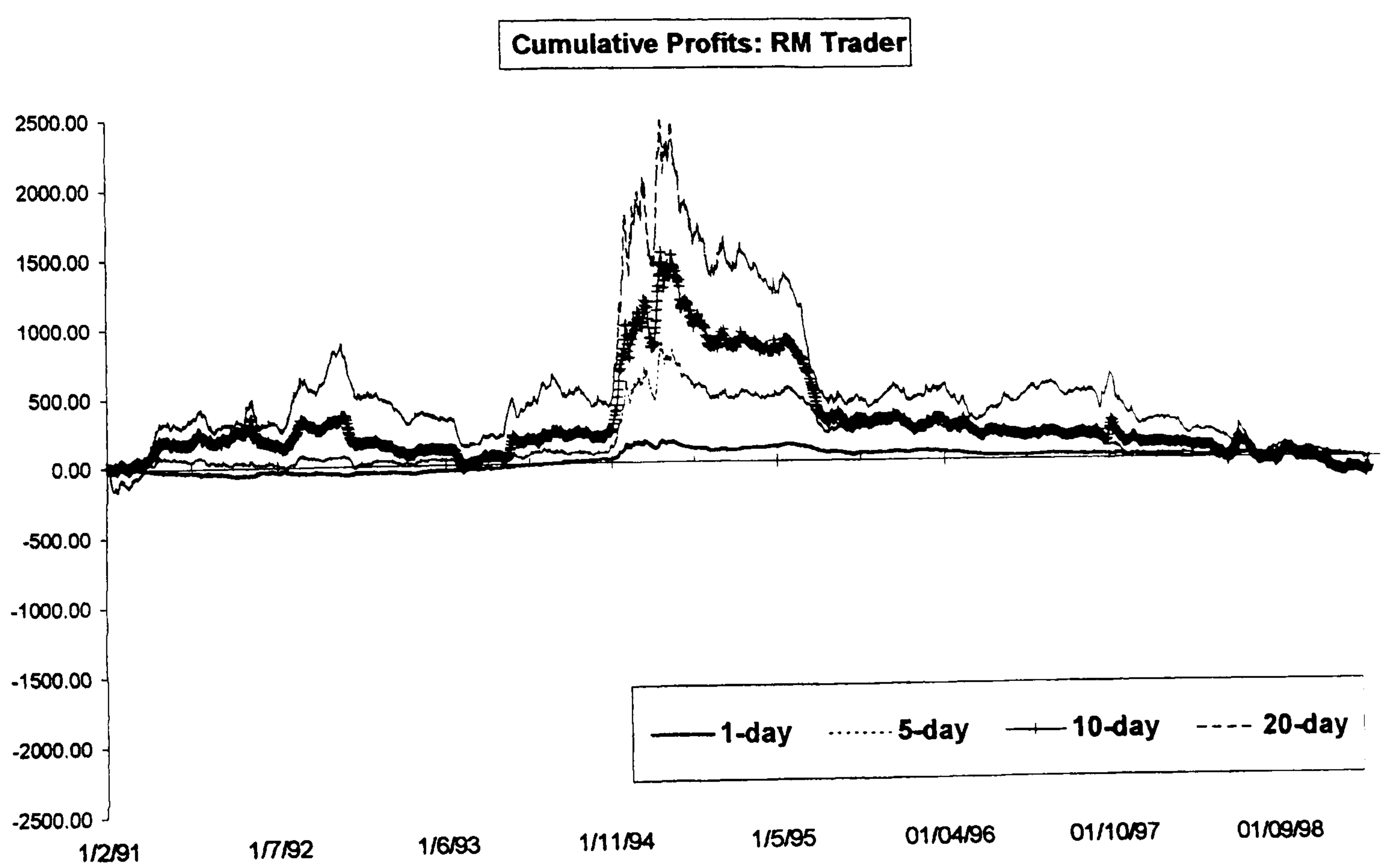


Figure 9.6

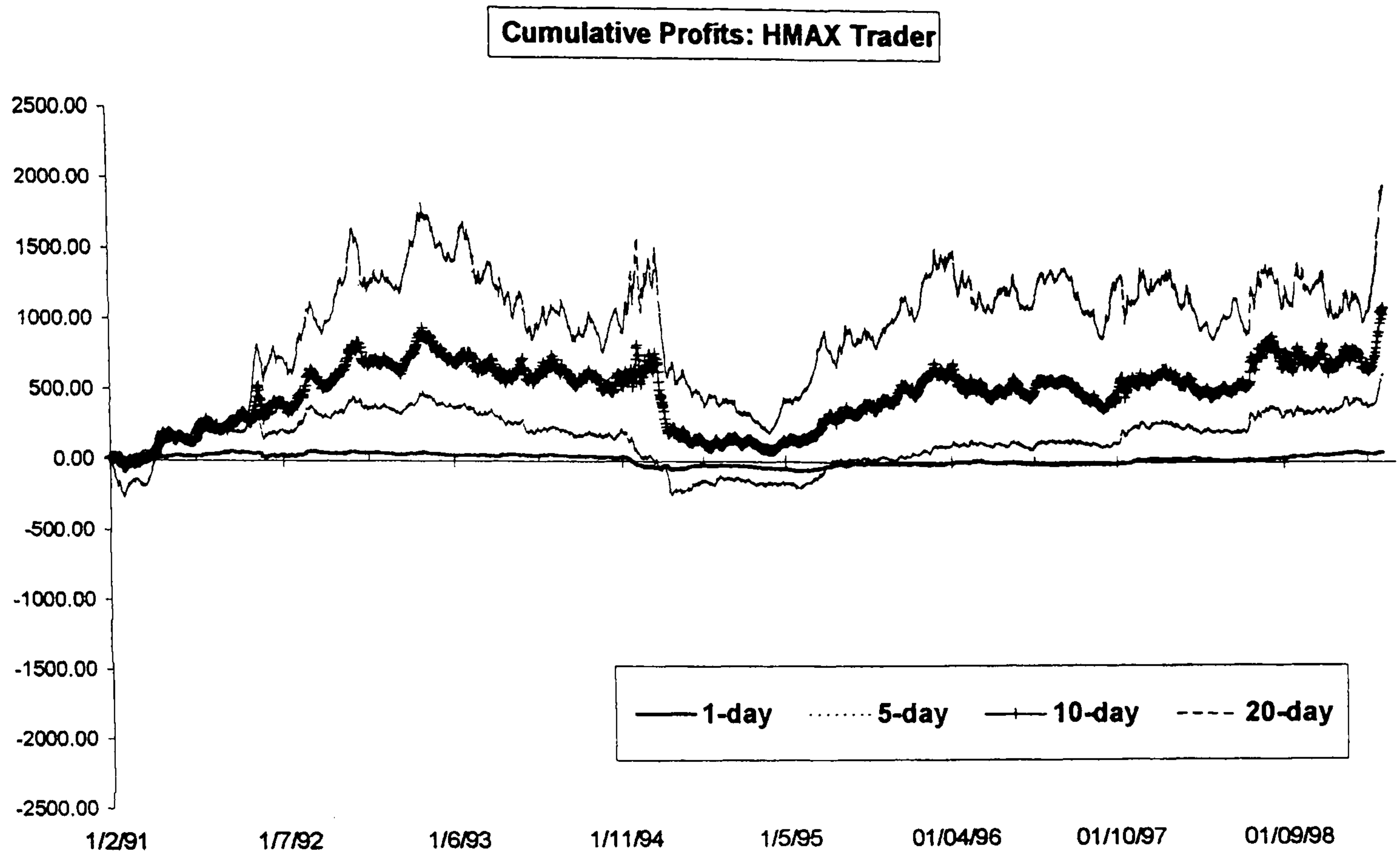
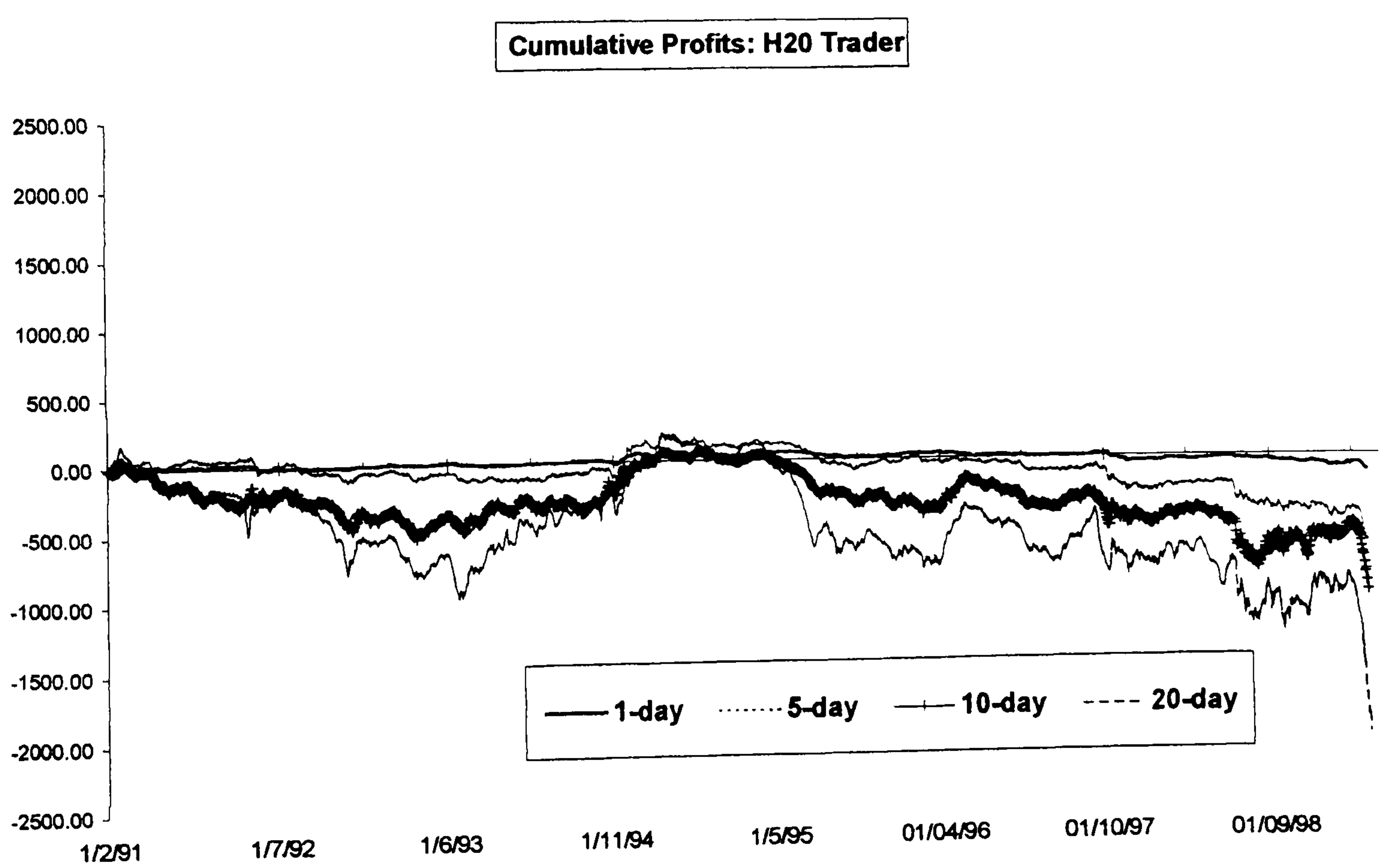


Figure 9.7



CHAPTER TEN:

CONCLUSION

The objective of this thesis was to conduct a number of empirical tests on the Istanbul Stock Exchange index, designed to assess how efficient the market is, and how efficiency has changed over time.

We have done this by applying a number of conventional tests to the ISE index, and the prices of its main constituent shares. We have also devised at least two novel approaches to analysing the performance of the market, in the form of the EV-GARCH model for stock splits in Chapter 8, and the synthetic options market approach to measuring the value of volatility forecasts in Chapter 9.

The thesis has produced a number of findings, some straightforward and uncontroversial, others more unusual or unexpected.

The straightforward conclusions include the finding of strongly fat-tailed leptokurtic distributions of daily returns in Chapter 3; the systematic variation of returns through the trading week uncovered in Chapter 7; and the presence of GARCH effects in the daily returns variance, discussed in Chapter 6.

Less straightforward, though possibly also characteristic of exchanges at a similar stage of development, are the findings that these patterns are not constant over time. Return predictability has declined as shown in Chapter 5. The day-of-the-week effect has become much weaker (Chapter 7). Volatility has become more persistent, and less affected by one-off shocks, as shown in Chapters 6 and 9. The average return expected by investors has become less related to volatility on the ISE.

Most of these effects we interpret as evidence of increased efficiency. This in turn we ascribe to increasing trading volume, and the relaxation of capital controls in Turkey. The disappearance of the GARCH-in-mean effect is exactly what one would expect in a market which was becoming more integrated into the international capital market, so that for most investors ISE-specific risk could be diversified away.

Finally, some of our findings are likely to be unique to the Turkish market. The prime example is the result of Chapter 9, where we find significant confusion (higher volatility) in the market for individual shares following stock splits. The motivation for the splits is the high rate of inflation in Turkey, rather than any signalling rationale which might drive a stock split in a more developed market. Interestingly, because these splits coincide with dividend payments, the confusion seems to spread to mean returns, with high/ low returns following high/ low cash dividend payments, even when these were announced well in advance. This again contrasts strongly with the experience of other markets, where effects have been observed following dividend announcements, but not subsequently.

Looking over the thesis as a whole, there seem to be two avenues for further research. One is on the ISE itself, which presents a growing and moving target for researchers. The other is on the refinement and applications of the new research techniques developed in Chapters 8 and 9.

The most recent data used in the thesis end in 1998. Since then, the ISE has experience continuing volatility. From the end of 1988 to April 1999, the index rose by around 60 per cent in real (dollar) terms. Between April and July 1999, the index fell by about 20 per cent. Then, following the imposition of a stronger counterinflationary policy, which helped stabilise the dollar echange rate, the index more than double from November 1999 to April 2000.

At the same time, the number of shares listed on the exchange has continued to grow, with over 30 new companies added to the exchange in the years 1999 and 2000 (to date). The trading systems and information systems of the exchange have become more automated. The Exchange has started to develop regional markets, and a second tier market for smaller stocks. It has put in place regulations ahead of trading in futures and options.

These changes in the economic environment and market structure underline our earlier observation that it is unsafe to assume that the processes governing returns and volatility on the ISE are stable. It is unlikely that the statistical relations uncovered in this thesis will continue to hold in the future, and there will continue to be a need for the kind of basic analysis conducted in the thesis, updated as the market evolves.

On the other hand, we are more optimistic that the tools of analysis developed here will find applications in the future.

The event study methodology is widely used in finance. This involves pooling data short strips of non-contemporaneous time series data, usually on returns, and usually from a number of different companies. It has long been recognised that the differences in the variance of the strips of data mean that standard analysis of variance and regression techniques cannot be directly applied to this kind of data set. The most popular solution is to give the more volatile strips of data less weight, by using a heteroscedasticity-adjusted estimator, or by standardising the data case by case before conducting conventional statistical tests.

In Chapter 8 we point to a further complication in event studies – namely the presence not only of differences in variance, but of GARCH effects in the variances of the strips of time series returns. We also offer a novel solution to the problems this poses for statistical inference, in the form of the EV-GARCH model. The way we have applied the model involves quite strong coefficient restrictions, and there is scope to develop more general forms of the model. The model has been used to help in a piece of applied analysis, and there is also scope to develop the statistical theory of inference in cross-sectional time series data with time-varying variances. Finally, the model has been applied to a very specific issue, the performance of the ISE around stock splits. There is obvious scope to use the EV-GARCH model to revisit some more standard problems, such as the performance of IPOs, on more intensively studied markets in the US and Europe.

The synthetic options market approach used in Chapter 9 to evaluate volatility forecasts is fairly original, with only Engle et. al. (1993) using a similar approach. It illustrates very nicely the general idea that forecasts can be properly evaluated only from the perspective of the utility function of the user of the forecasts. In this case, an options trader would have quite a different ranking of ISE volatility forecasts from a market participant with a more conventional linear (or quadratic) utility function. Since it is hard to identify players in any market with conventional utility functions, we would argue that the options-based approach is intrinsically useful, and deserves application to other markets, including those with fully developed derivatives products.

There are, however, many users of the ISE who have utility functions unrelated to options payoffs. Risk managers, for example, are likely to be interested in value-at-risk, and hence interested in volatility forecasts only to the extent that they can be used to anticipate extreme downside movements in the market.

A useful extension of our work on volatility rankings would therefore be to compare the options-based results with rankings based on, say, the costs of failing to anticipate extreme market falls. Sellier-Moiswitsch and Dawid (1993), Diebold and Mariano (1995), and Lopez (1995) have also developed techniques to compare probabilistic forecasts based on the shape of the whole distribution function (rather than just the extreme left tail). It might also be useful to compare volatility measures using these metrics, though it is not clear whose utility function they reflect.

Among the many innovations of the Istanbul Stock Exchange, the exchange launched in 1997 the *ISE Review*, which publishes academic-style research into the data which are now flowing from the exchange. While predicting the ISE index is hard, and according to our results is getting harder, it seems very safe to predict, on the basis of this thesis, that there will be no problem in filling the ISE Review with interesting and relevant empirical research.

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