TESTING THE RISK AND RETURN TRADE-OFF IN THE ATHENS STOCK EXCHANGE

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ABSTRACT

The present thesis is focused on the examination of the relationship between specific variables with the application of asset pricing models as well as the employment of (G)ARCH models, unit root and cointegration analysis. A theoretical and empirical review on the models is presented and, more specifically, there is an empirical examination of the validity of the Capital Asset Pricing Model (CAPM) and the two main forms of the Arbitrage Pricing Theory (APT) in the Athens Stock Exchange (ASE) during the period 1989–2006. Furthermore, there is an empirical application of specific (G)ARCH models on the variables under examination and an investigation of whether there are long-run relationships between different sets of financial and macroeconomic variables – whether the variables are cointegrated.

The results of the tests show the inability of the CAPM to explain the behaviour of stocks for the period under examination, as well as for the sub-periods (1989–1994, 1995–2000, and 2001–2006 respectively). This means that the (optimal) market portfolio used in the CAPM presents a poor explanatory power on the returns of stocks. On the contrary, the results of the statistical APT model show that there may be factors other than the market portfolio that can explain the behaviour of stocks. Similarly, the results from the application of the macroeconomic APT model show that specific macroeconomic variables can partially explain stocks' behaviour. Finally, the existence of long-run relationships between macroeconomic and financial variables, based on a series of cointegration tests, is evidence that there are different factors that can affect stocks, leading to a possible weak-form inefficiency of the Greek market.

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Chapter One

INTRODUCTION

1.1 The Aim and Objectives of the Study

The aim of the study is to investigate for the existence of factors that affect the behaviour of stock returns in the Athens Stock Exchange (ASE) for the period between 1989 and 2006. Furthermore, the study examines whether these potential factors are correlated or present any similarities in their influence on stock returns. In order to achieve the objectives of the study different models are constructed and employed. These models can be divided in two main groups.

The first group is related to asset pricing models and, specifically, to the Capital Asset Pricing Model (CAPM) and the two versions of the Arbitrage Pricing Theory (APT) model, the statistical and the macroeconomic one. By applying these models we proceed to an analysis of publicly available financial data of listed companies in the ASE and macroeconomic data of the Greek economy.

Moreover, the second category is comprised of more contemporary models that are widely used in the examination of the behaviour of time series. These are the family of (G)ARCH models and the unit root and cointegration techniques. The (G)ARCH models are interesting and relatively easy to use models in estimating the variance of the residuals of a time series, in case this series is characterised by heteroscedasticity (time-varying volatility). Cointegration analysis is used when a number of time series exhibit unit root (they are non-stationary) in their levels, but are becoming integrated (stationary) in their first differences ($I\,(1)$). When these series become $I\,(1)$ we examine whether they are cointegrated, which means that there may exist at least one linear vector that could relate, on the long-run, the time series of the variables under examination.

The objectives of the study are a) to review the literature and the empirical studies that took place in the Greek and foreign stock exchanges concerning the relationship between risk and return with the employment of the CAPM and APT models as well as (G)ARCH models, unit root and cointegration analysis; b) to evaluate the validity of the CAPM, the statistical and the macroeconomic APT model, in order to examine if the factors of the models are related; c) to investigate whether some specific types of (G)ARCH models appear to influence the behaviour of stock returns and to compare the results of these models; d) to employ a number of unit root tests and cointegration analysis, so as to investigate whether the variables of the analysis exhibit any relationship on the long-run, and e) to analyse the inferences of the tests, discuss possible managerial implications and suggest proposals for future research for any potential academic or investor in the ASE.

1.2 A Brief Literature Review on Asset Pricing Models

The development of asset pricing models is based on the early studies of Markowitz (1952) and Tobin (1958). Markowitz observed that, in the case that a number of risky assets constitute a portfolio, the total standard deviation of the portfolio is less that the sum of any individual risky asset. These findings led to the development of portfolio analysis and to the construction of models adequate to price assets (Elton *et al.*, 2003).

A major model for the analysis of the risk and return between individual securities or portfolios is the Capital Asset Pricing Model (CAPM). CAPM was developed by Treynor (1962), Sharpe (1964), Lintner (1965) and Mossin (1966). It implies that the return of an asset is proportional to a non-diversifiable (systematic) risk which is measured by the covariance between the asset's return and the return of the market portfolio for all assets in the market, divided by the variance of the market portfolio return. In other words, the efficiency of the (optimal) market portfolio implies that there exists a positive linear relationship between *ex-ante* security returns and the market beta (the coefficient of systematic risk), and that variables other than beta should not have any power in the explanation of the behaviour of stock returns (Diacogiannis, 1994).

After the development of the model, several empirical studies tried to test the validity of the CAPM. Some of these studies were those of Jacob (1971) and Miller and Scholes (1972), who used individual assets, while the studies of Black *et al.* (1972), Blume and Friend (1973) and Fama and MacBeth (1973) constructed portfolios for testing the validity of the model. Since the development of the CAPM a variety of different forms of asset pricing models have been developed and many empirical studies have focused on the examination of these models. The main reason for modifications on the original model or the development of different models was the critique that the traditional CAPM received, mostly because of its inability to verify that the market beta is the sole proxy for the risk-return trade-off between stock returns and the market portfolio.

The critique has its roots in the study of Roll (1977). He criticised all previous empirical tests of the CAPM while explaining that the market portfolio, as defined by the traditional CAPM, is not some single index equity market. It includes foreign assets, bonds and other property which is important in the maximisation of wealth. This means that the proxies employed in all those previous studies could not be the true proxies of the market. Consequently, the APT model, proposed by Ross (1976), was employed in the examination of the behaviour of securities, as an alternative to the CAPM. The restrictions on the model were fewer and it considered a number of factors, different than the market portfolio, that could influence stock returns. Several empirical studies followed since then (for instance, Roll and Ross, 1980; Reinganum, 1981; Chen, 1983; Chen *et al.*, 1986; Chen and Jordan, 1993). However, there is still evidence of dispute regarding the empirical verification of the model, which led to further modifications as well as different estimation techniques.

The main problem regarding the application of the APT model is which and how many are the factors that influence the stock returns. There were two main approaches of the empirical examination of the APT model for the solution of this problem: The development of the statistical APT (Roll and Ross, 1980; Chen, 1983) and the macroeconomic APT model (Chen *et al.*, 1983; Clare and Thomas, 1994). These two versions of the APT model are presented and analysed in chapter two and three, while chapter four presents the empirical results of both models regarding their validity in the ASE.

1.3 A Brief Literature Review on (G)ARCH Models and Cointegration Analysis

Although the contribution of the CAPM and the APT model has played a significant role in the explanation of the behaviour of security returns, a reason that there were mixed results between the models is their inability to test for, and model of, the time-varying volatility (variance and covariance) of security returns.

A solution to the problem came with the introduction of Autoregressive Conditional Heteroscedastic (ARCH) models in finance and, more specifically, in asset pricing. The ARCH model was developed by Engle (1982) so as to test the behaviour of inflation in the UK and, afterwards, several researchers worked on the model leading to many modifications. For example, Bollerslev (1986) developed the Generalised ARCH (GARCH) model while Engle *et al.* (1987) developed the ARCH "in mean" (ARCH-M) model. In chapter three the family of ARCH models is presented and analysed.

One of the initial studies of ARCH models in asset pricing is the study of Bollerslev *et al.* (1988). In their tests, the market beta was modelled in terms of a time-varying volatility, something which gave stronger inferences regarding the validity of the CAPM. Furthermore, in our study we will employ some specific (G)ARCH models which proved to be useful in asset pricing through the last decades, that is the simple form of Bollerslev's (1986) GARCH model and the EGARCH model of Nelson (1991). Our choice of models was based mostly on their significance in previous studies, especially in the examination of the ASE (Koutmos *et al.*, 1993; Chortareas *et al.*, 2000; Siourounis, 2002; Siokis and Kapopoulos, 2007).

The possible long-run relationship between specific financial and economic variables, such as the stock market index and the inflation rate, led to the development of cointegration techniques. These techniques aimed to the examination of the existence of linear vectors between the series under investigation. The most famous techniques are the Engle and Granger (1987) two-stage test and Johansen's (1988; 1991) and Johansen and Juselious (1990) cointegration analysis using a vector autoregressive (VAR) model. Cointegration analysis is employed in case that the time series of the variables have become stationary in their differences. An important assumption of cointegration analysis is that the variables under examination should be integrated (stationary) of the same order. Moreover, cointegration analysis follows, which shows if there exists at least one certain linear combination between the variables. In this case the series are *cointegrated.*

1.4 The Contribution of the Study

The study examines several aspects that could offer new information regarding the way that the ASE functions. The Greek stock exchange is one of the capital markets which proved to be extremely attractive over the last ten years to international investors, as during the 1990s it had started the transition to become a developed market. Investors and analysts have tried to benefit from possible abnormal returns as well as from the diversification of portfolio risk. The general reforms in the ASE from the late 1980s and early 1990s, that is capital market liberalisation, automated trading system and a relative political stability (Chortareas *et al.*, 2000) made the ASE a place of interest, so as to compare its evolution with that of other emerging or even developed markets. Although these markets are becoming the centre of several studies, they encounter problems that have to do mostly with data availability. This obstacle can lead to biased statistical results that cannot be easily overcome.

Several studies have been conducted in the ASE using different methodologies depending on the goal of each study, focusing mostly on the behaviour of stocks, the efficiency of the market and the reaction to announcements or events (Karanikas, 2000; Niarchos and Alexakis, 2000; Siourounis, 2002). However, almost none of these studies have combined in such a way traditional and modern financial and econometric models in order to come to some robust inferences regarding the behaviour of stock returns in Greece. The analysis can contribute in many ways to the explanation of the risk-return trade-off, as new and older models using several variables are combined so as to give the best unbiased results.

More specifically, in our work the statistical version of the APT model (Chen, 1983) is employed using historical data for the period between 1989 and 2006. We decided to employ the model so as to examine if there are any (artificial) factors that may explain the behaviour of stocks in the ASE. No similar empirical studies are evident for Greece, at least during this period under examination. The same holds for the application of the macroeconomic APT model (Chen *et al.*, 1986). We used a number of macroeconomic variables and applied the model for the same period, and as there are no similar studies in Greece, we compared our results with those of other stock markets.

Furthermore, after the application of the APT models, we proceeded to the comparison of the models. Specifically, we examined the relationship between the macrovariables and the artificial factors generated from the methodology of the statistical APT model. The methods used, like the Davidson and Mackinnon (1981) test for specification error and the canonical correlation analysis (Chen and Jordan, 1993; Cheng, 1995) have not been used in similar studies for the ASE. It is interesting to mention that all the models mentioned above, have been employed for the whole period (1989–2006), as well as for the sub-periods (1989–1994, 1995–2000, 2001–2006), which is a large period under examination, at least for the ASE standards.

Moreover, the use of specific ARCH models on the CAPM during the 18-year period under examination gives new evidence regarding the validity of the model after the estimation of time-varying volatility of the time series of stock returns. We have selected these models based on their significance in previous empirical studies and, during the testing procedure, we tried to compare them so as to use the best model in the examination of the validity of the CAPM, a procedure not evident in similar studies for the Greek market.

As far as the cointegration analysis is concerned, we tried to combine different sets of financial as well as macroeconomic variables, based on economic theory and data availability. Although, there are studies that have used similar variables for different time periods, such as the inflation rate (Niarchos and Alexakis, 2000), in our study we have added variables which are not so usually employed in asset pricing studies, that is the retail sales index, and examined their possible long-run relationships with other variables.

Finally, after we have completed the cointegration analysis we proceeded to a combination between cointegration and regression analysis, which is a procedure that is not usually visible in empirical studies (Maysami *et al.*, 2004) for any stock market, although it is a relatively easy procedure and can give very interesting results regarding the direction of these relationships between the variables.

There are several empirical studies that have used daily (Jeon and Seo, 2003), weekly (Michailidis *et al.*, 2006), or monthly (Fifield *et al.*, 2000) data for the examination of capital markets. In chapter five we use both daily and monthly observations when examining the relationship between stock returns and the market portfolio, so as to have more solid inferences regarding the behaviour of stocks. Moreover, in case that some indices were unavailable for the whole period (1989–2006) under investigation, e.g. the industrial production index in the tests of chapter four and five, the study is divided in specific sub-periods that could lead to interesting results without the need to subtract any variable from the analysis.

1.5 Methodology and Organisation of the Study

The study utilises a number of models (CAPM, APT) that have been employed for many decades in asset pricing. However, they still seem to be popular in the examination of the behaviour of stock returns and portfolio formation. By adding specific econometric techniques (ARCH process, unit root and cointegration analysis) it would be even more challenging to examine the relationships between specific variables. For the study we have incorporated secondary data beginning from January

1989 until December 2006. It is a relatively long period of stock returns examination (for the ASE standards) and this research may motivate scholars to extend their studies in the ASE.

After the introductory chapter one, the work continues with the presentation of asset pricing models. Chapter two begins with the CAPM of Sharpe (1964) and Lintner (1965) and its modifications. After an examination of the model, its critiques are presented that led to the development of the APT model. Furthermore, the chapter examines the two forms of the APT model, the statistical an the macroeconomic one. Following the presentation of the models, a sufficient number of empirical studies is presented both for the CAPM and the APT model. Moreover, chapter two examines the phenomenon of heteroscedasticity and the ARCH process is presented, focusing on its significance in finance. The respective empirical studies using ARCH models in financial issues follow and, then, there is a presentation of unit root analysis in time series. The chapter ends with the introduction of cointegration analysis and there is a sufficient examination of empirical studies that have employed specific cointegration techniques. We should mention that all the empirical studies include cases both for the ASE and foreign stock exchanges.

The work continues with chapter three where the methodology is presented and analysed. We explain how the two-stage procedure of the CAPM (Chen, 1983) is employed and, then, we examine the empirical procedure of the statistical APT model (Chen and Jordan, 1993). Moreover, we explain how the tests of comparison between the two models are applied so as to come to some first inferences regarding the validity of each model in the ASE. Consequently, the following sections examine the way that the macroeconomic APT model is employed in the tests, but, as there are observed variables to be used, we extensively depict the time series analysis of Box and Jenkins (1976), which has already been used in prior studies (Chen *et al.*, 1986;

Chen and Jordan, 1993). Similarly with the previous sections, we explain how a test of comparison is applied so as to examine the validity of the two forms of the APT model.

Chapter three continues with an examination of the procedure concerning the application of GARCH models on the CAPM. This procedure is followed by a mathematical presentation of several ARCH models most of which are employed for the tests of this work. After the ARCH processes we extensively explain the steps that are followed so as to apply specific unit root tests and cointegration analysis on a number of time series in order to examine their potential relationships on the long-run. Then, there is a brief introduction to unit root analysis and there is a presentation of the models that the study utilises regarding the stationarity of the time series of variables. Chapter three ends with a brief examination of the two most famous cointegration techniques, the Engle-Granger (1987) two-stage test and Johansen's (1988; 1991) multi-variate analysis.

Furthermore, chapter four and five present the empirical results. We decided to separate the tests in two chapters so as to examine, at first (chapter four), what are the results of more traditional models in the ASE, while the next chapter (chapter five) presents the results of relatively more contemporaneous tests using financial and macroeconomic secondary data for the examination of the ASE. The results gave evidence of the superiority of the statistical APT model in comparison to the CAPM. It is interesting to mention that the CAPM failed to show any adequacy as a model in the explanation of portfolio returns during the whole period (1989–2006) and the three sub-periods. This result has also implications for the efficiency of the ASE which seems to be in doubt. Moreover, the tests between the statistical and the macroeconomic APT model gave mixed results that are extensively examined in chapter four.

As far as chapter five is concerned, the results showed that the phenomenon of heteroscedasticity is evident both for monthly and daily observations of stock returns and the correction for heteroscedasticity with the employment of specific GARCH models did not help the validity of the CAPM in the ASE. Finally, the second part of chapter five shows that all the variables used in the tests become stationary in their first differences and can be used in cointegration analysis. For these tests we employed a sufficient number of variables, more than those used in chapter four, as the methodology at this point, and the studies on which we were based, led us to this decision. The results of cointegration analysis gave evidence that prove the existence of common linear vectors between the groups of variables under examination, verifying several conclusions of prior studies (Maysami *et al.*, 2004).

Chapter six summarises the empirical results regarding the ability of the models to explain the relationships of variables in the ASE. Furthermore, there is a presentation of the managerial implications of the study, which could be useful for any individual investor or company. After the implications we explain the limitations that this work had and we conclude the chapter with proposals for future research.

Chapter Two

LITERATURE REVIEW

2.1 Introduction

The aim of this chapter is to explore the principles of the traditional CAPM, with its main versions, and the principles of the APT model. The CAPM was developed by Treynor (1962) and Sharpe (1964), while Lintner (1965), Mossin (1966) and Black (1972) had made further extensions of the model (French, 2003). Other developments were the Consumption-based CAPM (Breeden, 1979) and the conditional CAPM based on up and down markets distinction (Pettengill *et al.*, 1995; Fletcher, 1997). Ross (1976) developed the APT model, which is a multi-variate and a not-so-restrictive model in comparison to the traditional CAPM. Finally, Roll's (1977) critique on the traditional CAPM has played a major role to the extended applications of the APT model, especially in the areas of macroeconomics and finance.

We should mention at this point that, for the construction of the macroeconomic APT model, the Box-Jenkins (1976) methodology was employed using as variables the inflation rate index, the industrial production index and the manufacture of coke, refined petroleum products and nuclear fuels index. In chapter three the Box-Jenkins approach and the ARIMA models are presented extensively.

Moreover, chapter two presents the importance of (G)ARCH models in financial markets. And this holds because many time series in different sectors of an economy exhibit the so-called "volatility clustering" phenomenon. This phenomenon is even more evident in finance because of the series' variability across time. A series' volatility clustering phenomenon shows that large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes

(Engle, 2001; Bollerslev *et al.*, 1992). The researchers, in order to analyse the phenomenon of volatility, have developed different models that can identify and explain the volatility of a time series. In order to examine the volatility clustering phenomenon, we investigate the "heteroscedasticity" of a variable. Heteroscedasticity refers to the conditional variance of a variable, which means that the variance in the present depends on its past values.

As our work focuses on financial theory and financial models (CAPM and APT) it is crucial for the reader to understand the meaning of time-varying volatility in asset pricing. An individual investor or a company expects an asset with high variance to give a higher return (for example, Fama, 1970; 1991). The meaning of uncertainty is of great importance in finance. In asset pricing theory the risk premium is determined by the covariance between the future return on the asset and one or more benchmark portfolios, that is the market portfolio according to the theory of the CAPM.

While the examination of time-varying volatility and the problem of uncertainty have found applications in many time series, it attracts most attention in the area of financial markets where a very important and interesting empirical literature has been generated, which shows changes through the decades in the development of models. Time-varying volatility is also evident in many stock market indices around the globe. The forms of volatility on these indices show similarities in its persistence and affect each stock market in a specific way. Financial models, as the CAPM, were taking into consideration the unconditional variance only (e.g. Black *et al.*, 1972; Black, 1972; Fama and MacBeth, 1973) which restricted the true potentials of the model.

With the development of different econometric tools one can measure the conditional variance of a series, e.g. in the case of pricing of individual stocks or portfolios in a market. These relatively contemporaneous models are the (G)ARCH models and their variations, which will be extensively examined in the present chapter.

Apart from (G)ARCH models, chapter two presents the unit root and cointegration analysis of time series. The long-run features in economic and financial data are usually associated with nonstationarity in time series and are called trends, while short-run features are associated with stationary time series and are called cycles. Most of the economic and financial time series can be viewed as combinations of these components of trends and cycles. Typically, a shock to a stationary time series would have an effect which would gradually disappear, leaving no permanent impact on the series, while a shock to a non-stationary time series would permanently alter the way that this series moves. Moreover, there could be a common trend shared by two time series. If there is no further trend which exists in only one time series, then it is said that these two time series are cointegrated (Gourieroux and Jasiak, 2001).

The rest of chapter two presents a review on the models employed in our work. Specifically, we begin with a review on asset pricing models, that is the standard CAPM and the statistical and macroeconomic APT model, which are the main models applied in our work as presented in chapter four. After the presentation of the models, we depict a number of empirical studies using these models. Moreover, the following sections present the theory behind GARCH models as well as their respective empirical studies. In the same way, there is a theoretical presentation of unit root and cointegration analysis and the empirical studies that are based on these techniques and the chapter ends with concluding remarks on the utility of the models.

2.2 A Review on Asset Pricing Models

A dynamic and healthy stock exchange is considered a crucial factor of a country's economy. In a stock exchange stock brokers and traders can trade stocks and other securities. Some of the roles that a stock exchange can play in an economy is the raising of capital for businesses or the creation of investment opportunities for small investors. The operations of a stock exchange can transform investor's money into investment. If this investment is profitable, it may give the opportunity to investors for further investments. Thus, besides the contribution of the stock exchange in a country's national economy, there is also a contribution to the investors individually (Elton *et al.*, 2003).

Based on the notion of the stock exchange, it is obvious that the pricing of assets is an issue that has been examined in the past and the research continues in the present with the use of different asset pricing models that will be investigated in our study.

2.3 The Capital Asset Pricing Model (CAPM)

The CAPM has become one of the main tools in the analysis of the risk-return trade-off of assets and can be considered as a contribution of academic research to finance. In finance dominates the notion that an investor can earn a higher return for his investment by taking a higher risk. This feature is what characterises the CAPM. It asserts that the return for any asset is a positive function of only one variable, its market beta, which can be defined as the ratio of the covariance between an asset's return and the market return to the variance of the market return. The CAPM can be used in several applications, such as in estimating the cost of capital of firms or evaluating the performance of managed portfolios (Diacogiannis, 1994; Campbell *et al.*, 1997).

The CAPM summarises the concept that the only reason investors would expect a higher return on an asset, would be to compensate them for bearing the higher risk associated with this asset. The model is based on the researches of Markowitz (1952; 1959) and Tobin (1958), which have developed the risk-return portfolio theory.

According to the CAPM, the mean-variance efficiency of the market portfolio implies that a positive linear relationship between the *ex-ante* expected returns and the market beta exists, and that there are no other variables, except the market beta, that can have power in the examination of the time-series and the cross-sectional tests of asset returns (Alexander *et al.*, 2001).

The development of the CAPM is based on some specific and, simultaneously, restrictive assumptions. These assumptions are (Diacogiannis, 1994; French, 2003):

1. All investors have homogeneous expectations;

2. All investors are expected to be utility maximisers of future wealth;

3. Utility is represented as a function of return and risk;

4. All investors prefer more return to less and they are risk-averse, as measured by the variance of the assets' returns;

5. The variance (or standard deviation) is the measure of security risk;

6. The capital market is in equilibrium;

7. The deviations from a least squares regression line of the variance of an asset's return against this asset's return follow a normal distribution;

8. There are no taxes;

9. There are no transaction costs (no frictions in the market);

10. There is a riskless asset, according to the belief of all investors in the market;

11. Short sales are allowed;

12. Leverage is allowed;

13. Each security has a number of shares that is constant through time; and

14. Fractional shares may be held;

The main implications of the CAPM are that a) there is a linear relationship between risk (measured by the market beta) and return; b) beta is the only risk that is related to the return of a security or portfolio, and c) the risk premium of the market index is positive (Diacogiannis, 1994).

Generally, the assumptions above express the notion that the market is efficient and all potential investors have the same expectations regarding the return from an investment. Their actions are based on the relationship between risk (measured by the market beta) and return and there are no other factors that can have an effect on this relationship. This is one of the reasons that different models were developed, such as the APT models (Ross, 1976; Roll and Ross, 1980; Chen *et al.*, 1986; Cheng, 1995) who showed that there are more factors, except the return of the market portfolio, that may affect the behaviour of security returns.

2.3.1 The Sharpe-Lintner CAPM

As mentioned before, the CAPM represents the relationship between the beta coefficient (which measures a security's risk to the market portfolio) and the return of an asset. In chapter three we present and extensively examine the Sharpe-Lintner CAPM and its components, as it is the first model that is employed for testing the behaviour of stock returns. In order to differentiate the model from later versions we will name it the "Sharpe-Lintner CAPM" although there were more scholars, like Treynor and Mossin, that have contributed in the development of the model (French, 2003). The CAPM of Sharpe (1964) and Lintner (1965) was a development on the mean-variance portfolio models of Tobin (1958) and Markowitz (1952; 1959). The Markowitz mean-variance analysis is concerned with the allocation of wealth among the various assets that are available in the market, given that the investor is a utility maximiser for one specific period of investment. Thus, the CAPM of Sharpe (1964) and Lintner (1965) utilises the characteristics of an investor's wealth allocation decision to derive the equilibrium relationship between risk and return from an investment on individual assets or portfolios. The model can be represented by the following linear equation:

$$E(R_{it}) = R_{ft} + b_{it}(E(R_{mt}) - R_f) \tag{1}$$

where $E(R_{it})$ is the expected return of a security at time t, R_f is a risk-free rate of return, b_{it} is the beta of the security at time t and $E(R_{mt})$ is the expected return of the market portfolio at time t. With the assumptions that there are risk-free borrowing and lending opportunities available in the market and that all consumers can borrow or lend as much as they like at the risk-free rate of return, R_{ft}, the efficient set becomes a straight line, since the expectations and portfolio opportunities are homogeneous in the market for all investors (Alexander *et al.*, 2001).

2.3.2 The Black CAPM

In the absence of a risk-free asset, Black (1972) suggested the use of a zero-beta portfolio, R_{zt}, as a proxy for the risk-free asset, whose covariance with the return of the market portfolio is equal to zero $(\text{cov}(R_{zt}, R_{mt}) = 0)$. Thus, this version of the CAPM depends upon two factors: A beta coefficient and a zero-beta one. This is the reason that it is called the two-factor CAPM, which can be represented as:

$$E(R_{it}) = E(R_{zt}) + b_{it}[E(R_{mt}) - E(R_{zt})] \qquad \textbf{(2)}$$

Moreover, the two-factor model of Black (1972) explains that the equilibrium expected return of an asset is a function of the market beta, which is defined by the return on the market portfolio, R_{mt}, and a second factor, defined by the return on a zero-beta portfolio, R_{zt}, which is uncorrelated with the market portfolio (Campbell *et al.*, 1997). If $E(R_{zt})$ is equal to zero, it implies that the traditional CAPM holds.

The zero-beta portfolio plays the role equivalent to the risk-free rate of return in the traditional Sharpe-Lintner model, when there is a relaxation from one of the assumptions of the traditional model, that is the relaxation of the assumption that riskless borrowing and lending opportunities are available (Black *et al.*, 1972).

2.3.3 The Consumption-based CAPM

The Consumption-based CAPM (CCAPM) is a single-beta model, which was developed by Breeden (1979), based on the concept of the Intertemporal CAPM (ICAPM) of Merton (1973). ICAPM states that the expected excess return of an asset is given by a multi-beta version of the CAPM. This number of betas is equal to one plus a number of variables e.g. the labour income or the prices of consumption goods, which are needed in order to explain the features of the investment set. And because of the fact that these variables cannot be easily identified, the model cannot be easily applied in empirical tests (Breeden, 1979).

This is the main reason that this multi-beta model was modified into a single-beta one, where the expected excess returns of an asset is proportional to its beta with respect to the aggregate real consumption rate. This is also the main difference with the standard CAPM: the betas of assets are measured in relation to the changes in the aggregate real consumption rate and not in relation to the market. The CCAPM can be represented as follows:

$$E(R_{it}) = R_{ft} + b_{cit}[E(R_{ct} - R_{ft})] \qquad \textbf{(3)}$$

where all the variables are familiar with the standard form of the CAPM, except from R_{ct}, which is the return on every portfolio whose total dividend is equal to the aggregate consumption c and b_{cit}, which is the beta of asset i with respect to the portfolio paying aggregate consumption.

We should mention here that, like in the case of the standard CAPM, if a riskless rate of return does not exist, then a zero-beta model is derived. In the case of the CCAPM, investor's wealth is not directly relevant to stock returns and one does not need to worry about defining the exact market portfolio. On the other hand, in order for the CCAPM to be employed by researchers, one must estimate the aggregate consumption and its changes. The empirical studies of Lucas (1978), Breeden (1979), Grossman and Shiller (1981), and Hansen and Singleton (1982; 1983) showed how a simple relationship between consumption and asset returns can capture the implications of a complex multi-factor asset pricing model. But the truth is that the CCAPM has failed perhaps the most important test of all, which is the test of time. More than twenty-five years after the development of the CCAPM, almost all applied work in finance still uses portfolio-based models to correct for risk, to explain the anomalies of the market and/or to produce cost of capital estimates (Campbell and Cochrane, 2000).

The CCAPM does poorly in practice relative to other factor models that use different risk factors. A CCAPM could hold in many cases, but there is evidence that the CAPM outperforms the specification of the CCAPM, and that multi-factor extensions of the standard CAPM perform even better (Campbell and Cochrane, 2000). In the following sub-section the conditional CAPM is presented, which has developed a separate theory on its own after several significant applications in finance (see: Pettengill *et al.*, 1995).

2.3.4 The Conditional CAPM based on Up and Down Markets Distinction

In 1974, Levy made a suggestion regarding the computation of betas for bull and bear markets separately. This concept was originally tested by Fabozzi and Francis (1977). They estimated betas over the bull and bear markets and the results showed no sign of beta instability. Later, Fabozzi and Francis (1978) suggested that the downside risk, which is measured by the beta reflecting the bear market, is a more valid measure of portfolio risk than the single beta of the standard version of the model.

Kim and Zumwalt (1979) examined the variation in the returns of portfolios in up and down markets and the results showed similarities with those of Fabozzi and

Francis (1978). Specifically, Kim and Zumwalt (1979) found that the downside risk is a more valid measure of risk than the standard single beta. Chen (1982) also found the same results regarding the significance of downside risk.

In their study, Pettengill *et al.* (1995) suggested that when realised returns are used in an analysis, the relationship between the systematic risk and the expected returns is conditional on the excess return of the market. The model employed in their research in order to complete the cross-sectional analysis was the following:

$$R_{it} = a_{0t} + a_{1t} D b_{it} + a_{2t}(1 - D) b_{it} + e_{it} \qquad \textbf{(4)}$$

where $D = 1$, if $(R_{mt} - R_{ft}) > 0$ (the market excess return is positive) and $D = 0$, if $(R_{mt} - R_{ft}) < 0$ (the market excess return is negative).

Their results showed a positive (negative) relationship between betas and returns during an up (down) market. Later empirical studies, based on the work of Pettengill *et al.* (1995), came to similar results regarding the significance of beta in bull and bear markets (Crombez and Vander Vennet, 2000).

All the models presented above are some of the most popular capital asset pricing models applied in finance. The major reason that several versions of the CAPM were developed, was its poor performance in the explanation of the behaviour of assets returns to a significant degree. These inferences led to the critiques on the model, which are presented in the next section.

2.4 The Critiques on the CAPM

Roll (1977) criticised the empirical applications of the CAPM on the basis that they are mean-variance tautological and that the market portfolio is unobservable. That is, suppose that the index used in the model is not the "market portfolio" but some other portfolio that lies on the efficient set. Then, there will always exist a linear relationship between the expected return of an asset and its beta with this efficient portfolio. Portfolios, which are uncorrelated with the index portfolio, will have a zero beta (though they may have specific risk), and the expected return on the index will have a beta equal to one. All assets' expected returns would lie on the straight line between these two points. The only test of the CAPM is whether the index portfolio is efficient. Does this mean that the CAPM should not be applied in tests? The answer is negative, since the index portfolio we chose may not have been the market portfolio, as the returns of all possible investments are unobservable. In summary, Roll's (1977) critique claims that the CAPM cannot be tested.

Other studies suggested that the CAPM was miss-specified in that additional factors could explain the variability of stock returns. Basu (1977) identified the earnings-to-price (E/P) ratio as an explanatory variable: low E/P ratios can predict higher returns. Fama and French (1988) found that dividend yields are good predictors of long horizon returns: high dividend yields are able to predict higher returns. Banz (1981), Reinganum (1981) and Fama and French (1992) described a size effect in security returns: small firms returns are higher than those predicted by the CAPM. Fama and French (1992) also claimed that the CAPM is miss-specified in the US stock market as, during the period between 1963 and 1990, beta does not explain the cross-section of expected returns, but size and book-to-market ratio do.

2.5 The CAPM and the Anomalies of the Market

Although initial empirical studies supported the CAPM (Black *et al.*, 1972; Fama and MacBeth, 1973), subsequent research has shown that market beta does not carry a risk premium (Reinganum, 1981). Furthermore, other variables like the market value of equity (MVE) ratio, the earnings-to-price (E/P) ratio and the book-to-market (B/M) equity ratio have been reported to have explanatory power beyond market beta on the returns of assets (Banz, 1981; Basu, 1983; Rosenberg *et al.*, 1985). All these variables have commonly been regarded as *anomalies* or *characteristics* of the market, as they do not have a clear role in the formation of an asset pricing model.

Fama and French (2003) in their work have shown that the standard CAPM cannot explain stock returns. As the CAPM has so many assumptions and the failure of one of them threatens its validity, the results of Fama and French (2003) should not surprise anyone. According to the CAPM, expected stock returns are assumed to be constant for any period of analysis. If this assumption does not hold – the expected returns of stocks are time-varying – the returns of stocks or portfolios can be determined by the covariance with other variables that can explain the behaviour of stock returns and not only by the covariance with the return of the market (Merton, 1973; Campbell, 1993). The results of Campbell and Vuolteenaho (2004) were similar to the above, that is the time-variation of expected returns is related to the failure of the CAPM.

In their study, Fama and French (1989) argued that stock market returns can be predicted. These results contrast the market efficiency hypothesis of Fama (1970). Fama and French (1992; 1993) reported that value stocks, stocks of high B/M value ratio, can have higher expected returns than growth stocks, which are stocks of low B/M value ratio. Other scholars showed that the momentum strategy of buying the past winners and selling the past losers can have positive results for the investors (Jegadeesh and Titman, 1993).

Scholars who believe in the efficiency of the market argued that these market characteristics (anomalies) are possible examples of data snooping, that is a set of macroeconomic variables is likely to have an effect on stocks returns for a specific period of time. But, in this case, there must always be a persistence effect, in order for the investors to achieve abnormal returns. Bossaerts and Hillion (1999) showed that although there are variables that can predict stock returns in-sample, the out-of-sample results were quite different. The results of Malkiel (2003), using US data, showed that there is no evidence of persistence and there might be strong efficiency in the stock market as the abnormal returns disappear quickly. Of course, data snooping is not the only possible reason for the prediction of stock returns. Jegadeesh and Titman (2001) showed in their results that momentum strategies were persistent during the last decade and gave profitable results, while Campbell (2000) found that there are some variables in a stock market that can really predict abnormal returns.

From the above, we can understand that scholars believe that several theories of modern finance should be developed and examined from the beginning (Shiller, 2003). Although there are different results from different analyses, the common interest of economists is the predictability of stock returns and not the reasons that led to the appearances of anomalies in a stock market. Barberis and Thaler (2003) argued that researchers should first explain the reasons behind the rationality or irrationality in the stock markets and then try to develop new theories on asset pricing. Campbell and Cochrane (1999) explained that, during recessions of the economy, investors are not so risk tolerant and demand a larger premium from their investments, while Fama (1991) and Campbell and Vuolteenaho (2004) explained that the examination of the time-variation of stock returns can give more accurate cross-sectional results.

2.6 The Arbitrage Pricing Theory (APT)

The arbitrage pricing theory (APT) was originally proposed by Ross (1976) and latter extended by Huberman (1982), Connor (1982), Chamberlain and Rothschild (1983), Chen and Ingersoll (1983), Chen (1983), Connor and Korajczyk (1988), Lehmann and Modest (1988), and so on. During that period the APT model had attracted considerable attention as a testable alternative to the CAPM of Sharpe (1964), Lintner (1965) and Black (1972).

Specifically, the APT model can be considered as an alternative concept to the CAPM for explaining risk and return in the market. APT has two claimed advantages over the CAPM (Alexander *et al.*, 2001): a) Its assumptions on investor preferences towards risk and return are less restrictive and b) it is argued that APT is empirically testable. Although these assumptions hold in several markets under investigation, there is still some dispute regarding the empirical verification of APT.

The APT assumes that security returns are generated by a "multi-factor" model, which is linear (Elton *et al.*, 2003):

$$R_{it} = a_{it} + b_{1t}F_{1t} + b_{2t}F_{2t} + \ldots + b_{kt}F_{mt} + e_{it} \qquad \textbf{(5)}$$

where the betas, b_s, are the sensitivities of each security to the factors, while the e_s are the firm-specific components of the return. F_{1t} to F_{mt} are proxies for new information about e.g. macroeconomic variables such as industrial production, inflation, interest rates, oil prices, and so on. In other words, it is believed that all security returns depend on the movements in these factors.

The APT model is a way to improve upon the CAPM, especially in light of the evidence on CAPM's poor performance in describing expected returns. APT, as a factor model, specifies that the return on each risky investment is determined by: a) a relatively small number of common factors, which are proxies for those factors in the economy that affect a large number of different investments, and b) a risk component that is unique to the investment.

The APT rests on fewer assumptions than the CAPM. The assumptions for the APT are: a) returns can be described by a factor model, just like the one presented above; b) there are no arbitrage opportunities, and c) there is a large number of securities, so it is possible to form portfolios that diversify away the firm-specific risk of individual stocks (Alexander *et al.*, 2001; Elton *et al.*, 2003). The big question regarding the APT model is what exactly these "factors" that influence stock returns are. There are at least two major approaches so as to answer this question: The statistical and the macroeconomic approach (Diacogiannis, 1994).

"Factor analysis" is a statistical technique which determines the factors in the data and explains the existing covariance between stocks in the sample. For example, Roll and Ross (1984) found that there are 4 or 5 factors that can explain the behaviour of stock returns. They also found that as the number of securities included in the analysis increases, so does the number of significant factors. It is important to mention that there is no good way to associate any of the estimated factors with any underlying theoretical constructs. This means that there is no clear economic interpretation for any of the empirical results (Campbell *et al.*, 1997).

Regarding the macroeconomic version of the model, the problem with this approach is that there is no theoretical reason or identification for any of the factors involved. This approach, however, hypothesizes that certain factors are important, based on theoretical considerations, and uses these factors to price the variation of stock returns. For example, Chen *et al.* (1986) used unanticipated changes in four variables as the factors that affect stock returns: a) the difference in the yield on long-term and short-term treasury bonds; b) the rate of inflation; c) the difference in yields on BB-rated corporate bonds and treasury bonds, and d) the growth rate in industrial production.

The problem with the macroeconomic approach of the APT model is that it is difficult to know if someone has *a priori* chosen the right factors, no matter how interesting the results of the model might be. This approach is best used by individuals who believe that APT holds and they think they know what type of risk factors the market prices. This makes the theory easy to use, but almost impossible to test (Diacogiannis, 1994).

2.7 A Review of the Empirical Studies of the CAPM and its Variations

Many empirical tests have been applied for the examination of the implications of CAPM, using historical rates of returns of securities and historical rates of return of a proxy for the market portfolio. Some early researchers on the topic were: Lintner (1965), Douglas (1968), Jacob (1971), Black *et al.* (1972), Miller and Scholes, (1972), Blume and Friend (1973) and Fama and MacBeth (1973). In order to solve the problem of error biases, Blume (1970), Friend and Blume (1970), and Black *et al.* (1972) grouped stocks into portfolios. The results showed that estimates of beta for diversified portfolios are much more precise than estimates for individual stocks. In other words, this was a method for the reduction of the error-in-variables problem.

In the late 1970s, new empirical studies contradicted even more the Sharpe-Lintner version of the CAPM (Breeden, 1979). There was solid evidence that much of the variation in expected returns was unrelated to market beta. The first major argument against the validity of the CAPM was Basu's (1977) evidence that when common stocks are sorted based on E/P ratios, future returns on high E/P stocks are higher than predicted by the CAPM.

Banz (1981) reported a size effect, which meant that, when stocks are sorted on market capitalisation, average returns on small stocks are higher than predicted by the CAPM. Rosenberg *et al.* (1985) argued that stocks with high B/M value ratio have high average returns that are not captured by the beta of the market. Finally, Bhandari (1988) showed that the high debt-equity ratio is associated with returns that are too high relative to their betas. Additionally, Chan *et al.* (1991) found a strong relationship between the B/M value ratio and stock returns in the Japanese stock market. Capaul *et al.* (1993) have shown a similar B/M value effect in four European stock markets and the Japanese market.

Fama and French (1992) reported the significance of size and B/M value ratio in the explanation of the behaviour of the US stock returns. In other words, size and B/M value ratio tended to explain the cross-section of average stock returns. Specifically, Fama and French (1992) claimed that the CAPM is miss-specified in the examined period between 1963 and 1990 because a) beta does not explain the cross-section of expected returns, while b) a combination of size and B/M value seemed to explain average returns. Fama and French (1996) reached similar conclusions with the use of a time-series testing approach.

Fama and French (1993) suggested a three-factor model so as to explain the expected returns of stocks. The three independent variables used in the model were a) the expected premium on the excess return of a broad market portfolio; b) the expected premium on the difference between returns on a portfolio of small stocks and the returns on a portfolio of large stocks and c) the expected premium on the difference between the returns on a portfolio of high B/M value stocks and the returns on a portfolio of low B/M value stocks.

Furthermore, Kothari *et al.* (1995) found that betas estimated from annual rather than monthly returns produced a stronger positive relationship between average returns and beta. Jagannathan and Wang (1996) examined whether the cross-section of returns can be explained by a conditional CAPM, that is, where betas and expected returns are allowed to vary over the business cycle. They reported that, when betas and returns are allowed to vary over time, by assuming that the CAPM holds period by period, the size effect, according to the findings of Fama and French (1992), is much weaker. Additionally, when a proxy for human capital is included in the return on aggregate wealth, the size effect vanishes.

Based on Black's (1972) version of the CAPM, Gibbons (1982), Stambaugh (1982) and Shanken (1985) have tested CAPM by first assuming that the market model is true, that is, the return of an asset is a linear function of a market portfolio proxy. Specifically, Stambaugh (1982) estimated the market model and, with the use of the Langrage multiplier test, found evidence supporting Black's (1972) CAPM.

A very interesting study during that period was the one by Kim and Wu (1987). Based on the concept of the standard CAPM, they developed a multi-factor version of the model. Specifically, they employed a CAPM-based model where factors from macroeconomic variables were added. The aim of the study was to heal the misspecifications of the statistical APT model, as it is not entirely able to give to the derived factors a proper economic meaning for the explanation of stocks' behaviour. The study used US data for the period 1959–1985 and the model was applied on individual stocks and portfolios. The results showed that there were three factors (related to production, investment and employment) at least, which played a major role in the explanation of stock returns and the most interesting part was that the measure of market return (the market beta) was not one of them.

In the paragraphs that follow there is a presentation of more recent empirical studies – studies that took place during the 1990s but mostly after the millennium. Particularly, MacKinlay (1995) examined the validity of the CAPM by employing its standard form and alternative multi-factor models. The results showed that alternative models can be useful in comparison to the traditional CAPM, although these models cannot significantly explain the deviations from the CAPM.

Fletcher (1997) examined the conditional relationship between beta and return in the UK stock returns. The results were insignificant regarding the unconditional relationship between beta and returns, while, when the data sample was divided into sub-periods, according to whether there is an up or down market – the excess market return is positive or negative – based on the study of Pettengill *et al.* (1995), there was a significant relationship between stock returns and market beta.

Ramchand and Susmel (1998), using an International CAPM (ICAPM), examined the relationship between stock returns and a world index for ten stock markets. These results for the six markets gave evidence that the world market beta is a non-linear function of domestic volatility. The results also showed that, for the Pacific and North American markets, the beta coefficient is time-varying, while, in most of the European markets, the world market beta is not related with the domestic market's volatility.

Heston *et al.* (1999) investigated whether beta and size have the ability to explain the variation in the returns of 12 European countries between 1980 and 1995. The results showed that returns are positively related to beta and negatively related to the size of firms. Additionally, Hodoshima *et al.* (2000) examined the relationship between stock returns and beta by employing cross-sectional regression tests. The results of the regression without differentiating positive and negative market excess returns gave flat relationships between stock returns and beta, while, by differentiating between positive and negative market excess returns (Pettengill *et al.*, 1995; Fletcher, 1997), there were significant conditional relationships between returns and beta. Specifically, the conditional relationship between the stock returns and beta was more robust when the market excess return was negative than positive in terms of goodness of fit of the model under examination.

Gonzalez (2001) examined the CAPM in the Caracas Stock Exchange using data for the period between 1992 and 1998. The results of the analysis showed that the CAPM has not any explanatory power in assessing the financial performance of the local market, while the APT model showed that there are factors that can be used in the explanation of stock returns.

Connor and Sehgal (2001) investigated the Fama and French (1993) three-factor model on stock returns for the Indian market. The results showed that the market beta, the B/M value ratio and the market value (size) influence the market. In other words, these factors explained the cross-sectional mean returns, while the market factor did not have such power by itself. On the other hand, the results were quite different regarding the influence of these factors on earnings and this was the reason that there was no accurate link between the factors on earnings and the factors on stock returns. Overall, the results of this study support the validity of the Fama and French (1993) three-factor model.

Lam (2002) examined the relationship between stock returns and a set of factors, namely, the market beta, the leverage, the size of firms, the B/M value ratio and the E/P ratio in the Hong Kong stock market for the 1984–1997 period. The study showed that the size of firms, the B/M value and the E/P ratio captured the variation of average stock returns. On the contrary, the market beta seemed to be weak in the explanation of stock returns behaviour.

Lau *et al.* (2002) investigated the relationship between stock returns and beta, size, cash flow-to-price ratio, E/P ratio, B/M value ratio and the growth of sales in Singapore and Malaysia. They used monthly data of stock returns for the period 1988–1996 and their inferences gave evidence of a conditional relationship between the returns of stocks and beta for both countries and, specifically, during the months with positive market excess returns, there was a positive relationship between the variables. The alternative occurred for the months with negative market excess returns. The results have also shown a negative relationship between stock returns and size for both countries, while, for Singapore only, there was a negative relationship between stock returns and the growth of sales. Finally, for Malaysia the results have shown a positive relationship between the returns of stocks and the E/P ratio. The main conclusion was that emerging markets such as the ones under examination, present similarities and differences in comparison to developed markets, like the US one.

Tai (2003) employed the ICAPM so as to investigate if the existence of pricing anomalies represented compensation for bearing extra-market risks by allowing for both time-varying first and second moments of asset returns. The MGARCH-M model was used in the analysis, as it does not only allow both the first and second moments of asset returns to be time-varying, but also links the conditional covariances to the conditional expected returns. The results gave significant evidence of the validity of the model with the use of the MGARCH-M model, while the unconditional version of the model gave poor results.

Chen (2003) compared the traditional CAPM with the CCAPM, so as to analyse which of the two coefficients – the market or the consumption beta – is a better measure of risk. The data sample used was seven financial market sectors in the emerging Taiwan stock market. The results of the analysis showed that, while the consumption beta is a better measure theoretically, the traditional CAPM is proved to be a better model in the prediction of assets' returns.

Carmichael and Samson (2005) applied a linear factor model so as to analyse the relationships between the returns of assets from the Toronto Stock Exchange and the Canadian bond market and two observable risk factors. The market portfolio was used as proxy in the model, according to the theory of CAPM, and the consumption growth, according to the theory of the CCAPM. The results showed that the market risk premium explained a significant part of the assets, while the consumption risk premium had a reduced impact on the assets under examination.

Ng (2004) applied an International CAPM that nested the standard CAPM, the International CAPM and the Dynamic CAPM. The model's performance was acceptable as far as the explanation of the average foreign-exchange and stock market returns in the US, Japan, Germany and the UK is concerned. However, it was evident that the model was not better in comparison to the traditional form of the CAPM, as they both failed in the prediction of average returns on portfolios of high B/M value stocks.

Drew *et al.* (2004) investigated whether idiosyncratic volatility was priced for stocks in the stock market of Shanghai. The results have shown that volatility was priced and, after a comparison between a multi-factor model and the standard CAPM, it was evident that the multi-factor model explained to a higher degree the returns of stocks. Moreover, they suggested that the size of firms and the idiosyncratic volatility should be used as proxies of systematic risk when an asset pricing model is employed.

Tang and Shum (2004) investigated the relationship between expected returns and risk in the stock exchange of Singapore for the period between 1986 and 1998. The results presented a weakness of market beta in the explanation of stock returns, but, when a conditional methodology of up and down markets was employed, there was a significant performance from the market beta – a significant positive (negative) relationship between beta and stock returns when the market excess returns were positive (negative). Finally, they suggested that other variables should also be added in such studies as beta is not the only factor capable of explaining the cross-sectional variation of stock returns.

Wang (2004) investigated the stock market of China for the period between 1994 and 2000. The results have shown that the market beta, the size of firms and the B/M value ratio did not have any power in the explanation of stock returns behaviour. In other words, the study presented evidence of rationality in the Chinese stock market. Moreover, Ho *et al.* (2005) investigated the pricing of beta, B/M value ratio and size of firms under conditions of up and down markets in the Hong Kong stock exchange. The results of the study showed that the three factors were significantly priced under these conditions. It is interesting to mention that, during that time, this conditional analysis was the first for the Hong Kong stock market.

2.8 A Review of the Empirical Studies of APT Models

The APT model of Ross (1976) was a breakthrough in the development of specific multi-factor models for the explanation of the variation of asset returns. In this section we present past and recent studies which are based on the theory of arbitrage pricing. Roll and Ross (1980) investigated the US stock market using the statistical specification of the APT model. The data sample was daily stock returns and the period of analysis extended from 1962 to 1972. The maximum likelihood estimation was used in the application of the model and the results showed that there were at least three priced factors for the period under examination. The study of Roll and Ross (1980) was one of the main studies that our work was based on so as to apply the statistical APT model in the ASE. The results of our tests, presented in chapter four, show that there is a number of significant factors that can explain the behaviour of portfolio returns during the whole period and the sub-periods under examination.

Chen (1983) also examined the US stock market for the period 1963–1978 by applying the statistical APT model using maximum likelihood estimation. The data sample needed for the analysis was daily stock returns and, after the application of the APT model, it was compared with the CAPM. The results showed that the APT model performed quite well, a result also similar to the results of our work. Alternatively, Chen *et al.* (1986) used a number of macroeconomic factors so as to examine the validity of the model for the US stock market. The period used for the analysis extended between 1953 and 1983. The results gave evidence of several priced macroeconomic variables, which means that they played a significant role in the explanation of the behaviour of stock returns. It is important to mention that both the stock market index and the variable of aggregate consumption gave insignificant results.

Faff (1988) employed a statistical APT model in the Australian stock market so as to examine possible derived factors. Based on the studies of Chamberlain and Rothschild (1983) and Beggs (1986), principal components analysis was used for the derivation of factors. After the application of the APT model, it was compared with the standard CAPM and the results were mixed for the period between 1974 and 1985.

Additionally, Chen and Jordan (1993) examined the power of the statistical and the macroeconomic APT model in the US stock market using monthly returns for the period between 1971 and 1986. The results of the analysis exhibited small differences between the models but it is important to mention that, during the application of the Davidson and MacKinnon (1981) method for the comparison between the models, the results of Chen and Jordan (1993) were the same with the results of our study, that is the statistical APT is a better model compared to the macroeconomic APT model.

Furthermore, Clare and Thomas (1994) investigated the cross-sectional variation of stock returns using two different methods of ordering stocks into portfolios. The period of analysis extended from 1983 to 1990 for the UK stock market and the results of the tests showed that only two factors were priced while ordering stocks according to size. On the other hand, more sources of risk (more macroeconomic variables) were found to be priced while ordering stocks according to beta. These statistical inferences might be a reason of the differences in the spread of returns and risk between the two methods of portfolio formation.

Cheng (1995) investigated the relationship between a set of factors derived from factor analysis and a number of macroeconomic variables. The study was applied on UK data for the period between 1965 and 1988 using monthly stock returns. Canonical correlation analysis was employed so as to examine the link between the factor scores of the security returns and the factor scores of the macroeconomic variables. The results showed that stock returns were positively correlated with several macroeconomic variables while there was also a small negative correlation between stock returns and some of the variables.

Diacogiannis and Diamandis (1997) developed three multi-factor risk-return models based on Ross's (1976) APT model. These models could use factors generated from a number of observable macroeconomic variables. The interesting part of this analysis was to help scholars investigate the possible pricing of risk premia in a market, using a sample of securities and a set of macroeconomic variables. Furthermore, Antoniou *et al.* (1998) examined the validity of the APT model in the UK stock market. They used two data samples of stock returns and the inferences of the study exhibited three variables that influenced both samples: the supply of money, the inflation rate and the excess return of the stock market, results that are also partially evident in our work for the ASE presented in chapter four.

Zhou (1999) investigated the best combinations of economic variables that can forecast stock factors. Based on previous studies (Chen *et al.*, 1986; Fama and French, 1993) they compared a five-, a four- and a three-factor model, so as to examine which is the best forecasting model and if the number of variables play a major role in the validity of the models. The results showed that the three-factor model was the one that had the best out-of-sample performance.

Fifield *et al.* (2000) examined the influence of local and world factors on a number of emerging stock markets (ESMs) including the stock markets of Hong Kong, Mexico, India, Greece and Turkey, during the period between 1987 and 1996. Some of the variables employed for the analysis were the inflation and money supply, as the local factors, and the world market return and world inflation, as world factors. After the application of factor analysis on the macroeconomic variables, the derived factors were used as independent variables in a series of multi-factor regressions so as to examine whether they can explain the behaviour of the indices of the ESMs. The results of the regressions showed that a selective number of world and local variables exhibited a significant influence on stock returns, but, because of the fact that the total variance explained from the factor analysis was relatively small, it was suggested that more variables should be used in similar tests.

Bilson *et al.* (2001) examined if a set of macroeconomic variables had explanatory power over stock returns in emerging markets. The results gave evidence of the existence of relationships between the variables but the influence of the factors was relatively poor. Additionally, Garcia and Bonomo (2001) investigated the Brazilian stock market by applying a conditional CAPM and APT model for the period between 1976 and 1992. The results showed that the APT model performed better as it included a factor that captured the risk of inflation and proved to be important in the pricing of portfolios.

Fletcher (2001) investigated if conditional asset pricing models are adequate to explain the UK stock returns predictability. The results gave evidence of the adequacy of a domestic APT model to explain a significant part of predictability in stock returns and performed better than the domestic CAPM. There is also evidence of a better performance of domestic asset pricing models in comparison to their international ones.

Finally, Cauchie *et al.* (2004) compared the statistical and the macroeconomic APT model using monthly data from the Swiss stock market between 1986 and 2000. The results showed that the statistical APT model provided more robust results in the explanation of stock returns behaviour, a result which is also similar to the results of our work. Moreover, stock returns in the Swiss market are influenced by both local and global factors.

2.9 A Review of the Empirical Studies of Asset Pricing Models in Greece

In the present section we present a brief number of studies that examined the risk-return relationship in the ASE.

Karanikas (2000) examined the cross-sectional relationship between firm-specific characteristics and average stock returns in the ASE having as independent variables the capitalisation size, the B/M value ratio and the dividend yields for the period 1991−1997. After using the Fama and Macbeth (1973) methodology with the adjustments of Shanken (1992) in order to avoid the error-in-variables problem, a statistically significant relationship between the B/M value ratio, the dividend yields and the average stock returns came as the main results of the analysis. Specifically, the performance of the B/M value ratio was not changeable by the inclusion of other variables during the tests and had the strongest influence on average stock returns in comparison to the dividend yields and the market capitalization.

Diacogiannis *et al.* (2001) investigated the pricing of possible risk premia in the ASE by applying a different form of APT model, which used observable macroeconomic and financial variables for the construction of the factors used in the analysis. They used quarterly data for the period 1980–1992 and the results showed the existence of two, at least, common factors for the 1980–1986 and the 1986–1992 sub-period under examination. The main conclusion of the study was that the variables had an effect on the pricing of risk premia. Furthermore, the results of the tests showed that, with the use of a significant number of observed variables, the tests based on factor analysis may give very interesting results regarding the behaviour of portfolios and individual stocks.

Theriou *et al.* (2005) examined the cross-sectional relationship between risk and return in the ASE during the period 1993–2001. They investigated whether there are anomalies in the Greek stock exchange by testing the CAPM and by constructing a model using firm-specific factors which were the B/M value ratio and the size (market value) of firms. The results of the tests showed the inability of the CAPM to explain the behaviour of monthly stock returns (the market beta was insignificant), while, in contrast to the CAPM, the firm-specific factors were statistically significant. This is evidence that there are firm-related factors which can influence the behaviour of stock returns.

Furthermore, Michailidis *et al.* (2006) examined the CAPM in the ASE during the period between 1998 and 2002. The data sample consisted of 100 listed stocks and, in order to enhance the precision of the beta estimates, the stocks were grouped into portfolios. The results of the tests did not verify the validity of the model. However, the linear structure of the CAPM is supported, an inference that is similar to the results of our work.

Finally, it is important to mention that there is a number of studies that have employed the standard CAPM or variations of it in the ASE (Theriou *et al.*, 2004a; 2004b) and there are other studies that have investigated for seasonal anomalies, that is the holiday effect in the ASE (Coutts *et al.*, 2000) or used econometric models on specific time series such as the ASE composite index (Chortareas *et al.*, 2000) but these studies have not compared the CAPM with different forms of APT models. Moreover, these models have not been recently investigated with the use of high frequency data (daily stock returns) which will be used during the application of (G)ARCH models.

2.10 (G)ARCH Models and Conditional Variance

2.10.1 Unconditional and Conditional Variance in Stock Returns

The distinction between unconditional and conditional variance has a significant empirical impact, especially in financial econometrics. First of all, one should consider how stock prices are determined. The rational valuation formula states that the price of a stock at time t, P_t, is the expected discounted present value of future dividend streams:

$$P_t = E_t\left[\sum_{i=1}^{\infty} b_{t+i} D_{t+i}\right] \qquad \textbf{(6)}$$

where E_t is the expectation formed at time t, D_{t+i} is the dividend in period $t+i$ and b_{t+i} is the factor that discounts to the present dividends that are received at some future time. Specifically, b_{t+i} is a function of the risk-free rate and a risk premium, which can explain the risk of expected returns (Cuthbertson, 1996). An increase in perceived risk leads to a decline in the stock price, so that the return of the stock declines. It is obvious from the above that the risk from an investment directly impacts upon the price of a stock.

A possibility for the assessment of risk is related to the variance of the forecast errors of stock returns. It should be mentioned that the variance is assessed at time t, which means that it is conditional on time t information. If there is an increase in the conditional variance there will be an increase in the risk premium and the stock price declines. It is obvious that a model could be developed, which would estimate the conditional variance of the forecast errors of returns.

Engle (1982) developed the *ARCH model*, which has the ability to model the conditional variance of errors. It was firstly used in the examination of whether the variance of inflation in the UK was higher in some periods than in others. There was also the separation of the predictable (mean) movements in inflation from the unpredictable (residuals) ones. The purpose of the application of the model was to make the variance of the residuals predictable (Engle, 2001). The shocks have an autoregressive characteristic, which means that volatility is based on past values of shocks and this is the reason that Engle's (1982) model allows the conditional variance to vary over time driven by past shocks. Later, the ARCH model, and its variations, were used in asset pricing, hedging and other popular areas of finance.

2.10.2 The Contribution of Econometrics in the Field of Finance

Financial time series are often available at a higher frequency than other time series (that is macroeconomic time series such as the inflation rate) and exhibit a statistically significant correlation between observations whose values are at a large distance (Susmel and Engle, 1994; Tay and Zhu, 2000). Another characteristic of the financial time series is the time-varying volatility, or the heteroscedasticity, of time series (Bollerslev *et al.*, 1988; Booth *et al.*, 1997; and for a survey of studies on finance Bollerslev *et al.*, 1992; Bera and Higgins, 1995). In this case the time series, that is of returns from investing in a financial asset, contain periods of high (low) volatility followed by even higher (lower) volatility periods, independent of the sign (the volatility clustering phenomenon).

During the last decades several studies have examined the "conditional variance" of time series (Engle, 1982; Bollerslev, 1986; Engle *et al.*, 1987). In other words, they have investigated the phenomenon of heteroscedasticity, which is usual in the case of financial time series. As it is already mentioned, the ARCH model developed by Engle (1982) provided a precise way of investigating the volatility issue of economic variables, and it was initially used to model inflation. Friedman (1977) had tested the hypothesis that higher inflation is more volatile. Using data from the UK as sample for his analysis, Engle (1982) supported Friedman's (1977) hypothesis of the volatility of inflation by applying the then innovative ARCH model.

Chapter three presents Engle's (1982) ARCH model and its most popular variations are examined: The GARCH model of Bollerslev (1986), the ARCH-in-mean (ARCH-M) model of Engle *et al.* (1987) and Nelson's (1991) Exponential GARCH (EGARCH) model. These models are employed in our empirical tests and the results are presented in chapter five.

2.11 The Sources of ARCH Effect

There are several reasons for the presence of ARCH effects in a series under examination and one of these possible explanations is the existence of a serially correlated news arrival process. Interpreting shocks as news means that the "news arrival process" is serially correlated. For example, especially in financial markets, information which was not incorporated into asset prices comes to the market in an "aggregated form" – small (large) changes tend to be followed by smaller (larger) changes, independent of the sign.

Diebold and Nerlove (1989) confirmed the presence of serial correlation of news as a reason for the volatility clustering phenomenon. It would be important to mention the two major forms that we can understand the arrival of news (shocks) and its effect on a market. According to the first form, information arrives regularly but may contain surprises that is published information on consumers' expenditures, inflation and unemployment are available at specific times of the month or quarter and may present deviations from what was originally expected. According to the second form, the arrival of information is not predictive and the shocks are almost unexpected, like earthquakes and changes in a government's policy through the year.

News from different parts of the world can affect asset prices significantly at discrete intervals. Today there are companies that cooperate at an international level and the financial markets are linked and affect each other, which means that there are spillo*ver news phenomena* from one market to another. These effects can also increase by the internal market behaviour as traders may iterate to a common view. Engle *et al.* (1990) and Ito *et al.* (1992) examined the serially correlated news arrival phenomenon and their results confirmed the hypothesis, but their explanations lacked of power.

It is important to mention that there are several studies that investigated the reasons for the phenomenon of ARCH as it is the main focus of our tests using (G)ARCH on asset pricing models in chapter five. Some of the studies are those of Ng (1988), Giovannini and Jorion (1989a; 1989b), Bollerslev and Domowitz (1991), Ng (1991), Bodurtha and Mark (1991), Chou *et al.* (1992), Gallo and Pacini (1998), Dillen and Stoltz (1999), Kim and Rui (1999), McKenzie *et al.* (2000), Ortiz and Arjona (2001), Koutmos and Knif (2002), Morelli (2002), Friedmann and Sanddorf-Kohle (2002) and Gardeazabal and Regulez (2004). It is obvious that there is an interest on the examination of ARCH effects and this is also the reason that we employ the (G)ARCH models in our work.

2.12 A Review of the Empirical Studies of (G)ARCH Models

2.12.1 The Empirical Studies of (G)ARCH Models in Asset Pricing and Stock Returns Analysis

Most of the studies examining for ARCH effects have found significant results regarding the capture of conditional heteroscedasticity in stock markets. For example, French *et al.* (1987) examined daily S&P stock index data for the period 1928–1984 in order to capture possible heteroscedastic effects. Akgiray (1989), having as data indices returns, found significant inferences regarding the effects of volatility clustering on these indices, while Engle and Mustafa (1992) applied the ARCH models on option prices. Likewise, Noh *et al.* (1994) and Nelson (1991) examined the effects of shocks on the market risk premium and all found similar results: A shock can affect the variance of stock market returns at a single point at time.

It should be noted here that, for such analyses, models with high orders of lag lengths are not necessary. For example, models like the GARCH(1,0) and

GARCH(1,2) are enough for such analyses. Of course, there were cases where higher orders of lag lengths were used. Bodurtha and Mark (1991) and Attanasio (1991) applied ARCH(3) models to examine the portfolios of monthly NYSE returns and monthly excess returns from the S&P 500 index.

Morgan and Morgan (1987) examined the validity of several market models by applying the ARCH models. Specifically, in their study of the small firm effect, they found that when correcting for the conditional variance in returns from portfolios long in small firms and short in large firms, there is a reduction in the coefficients of market risk and an increase in the coefficients of abnormal returns. Many other studies followed trying to use market models by applying ARCH processes (Bera *et al.*, 1988; Connolly, 1989; Diebold *et al.*, 1989; Schwert and Seguin, 1990).

The importance of ARCH models in asset pricing was born because of the trade-off relationship between risk and return from an investment on an asset. For example, a variation of the ARCH model (a multi-variate GARCH-M model) was applied to the original CAPM of Sharpe (1964), Lintner (1965) and Mossin (1966) by Bollerslev *et al.* (1988) and Koutmos and Theodossiou (1993) employed the standard GARCH model on the macroeconomic APT model of Chen *et al.* (1986).

The *ARCH-M* model developed by Engle *et al.* (1987) provides a tool for the estimation of the linear relationship between the return and the variance of an asset. The model had several applications in asset pricing: French *et al.* (1987) used it on the daily S&P index, Chou (1988) on the weekly NYSE value-weighted returns, and Friedman and Kuttner (1988) for the examination of quarterly US stock indices. Moreover, Campbell and Shiller (1989) estimated the relative risk aversion parameter using annual data from the Cowles/S&P index during the 1871−1986 period and a value-weighted index for the NYSE during the 1926−1986 period. Grossman *et al.* (1987) applied the ARCH-M model on the Consumption CAPM and Engel and

Rodrigues (1989) applied the model on a multi-variate CAPM. The ARCH-in-Mean model was used in the studies as it directly reflects the presence of the conditional variance in the conditional mean of the returns.

In contrast to its advantages, there is evidence of a *sensitivity* of the parameter estimates in the ARCH-M model with respect to different model specifications as in the work of Bailie and DeGennaro (1990). They used both daily and monthly portfolio returns and, by changing the conditional distribution from normal to student-t, the parameter for the conditional variance entering the mean equation changed from significantly positive, at the five per cent level, to insignificant and of either sign. Similar results can be found in the studies of Bollerslev and Wooldridge (1992), French *et al.* (1987) and Cocco and Paruolo (1990). Additionally, the problem of *constancy* of the linear relationship between the expected return and the conditional variance in the ARCH-M model has also been under question by several authors. For example, on introducing additional instruments over the past squared residuals in estimating the conditional variance, Harvey (1989) reports the coefficient to be significantly time-varying of either sign, depending on the stage of the business cycle.

It is evident that ARCH models have been successfully applied to the pricing of individual stocks and options (Jorion, 1988; Choi and Wohar, 1992; Lamoureux and Lastrapes, 1991; Engle and Mustafa, 1992; Day and Lewis, 1992). Ng (1991) examined an asset pricing model in which the Sharpe-Lintner CAPM and the zero-beta CAPM are used as special cases. The model allows the conditional expected excess returns and the risks to change over time. Significant time variability is shown in the conditional expected excess asset returns and risks and also in the reward-to-risk ratio. This paper reports the results of multi-variate tests on a conditional capital asset pricing model that allows time variation in the conditional expected asset returns, asset variances and covariances. The time-varying covariance matrix of asset returns is assumed to follow a multi-variate GARCH process.

Empirical results based on time-series and cross-sectional tests on beta-ranked portfolio returns do not reject the conditional efficiency of the market proxy portfolio. But when tests are based on size-sorted portfolios, the tests suggest rejecting the model. These results show a consistency with the results of Harvey (1989) and Schwert and Seguin (1990) but contradict the results of Bollerslev *et al.* (1988), Bodurtha and Mark (1991), and Fama and MacBeth (1973).

Bodurtha and Mark (1991) applied the ARCH-M model to formulate a conditional CAPM with time-varying risk and expected returns using data from the US stock market. In the conditional CAPM, an asset's beta is the ratio of the conditional covariance between the return of the asset and the return of the market and the conditional variance of the market return. They showed how these ARCH features can be estimated using the generalised method of moments (GMM). The estimation strategy offers some concrete advantages over maximum likelihood methods in that it frees the investigator from having to parameterise many features of the ARCH model that could be of incidental interest only.

Relative to other recent tests of models with time-varying risk and returns, the results of Bodurtha and Mark (1991) appeared to be more supportive of the conditional CAPM. Their model differs from the model used by Ng (1991) in several ways: Ng (1991) used market value weights as data and nested the model of Bollerslev *et al.* (1988) and Harvey (1989), which assumed a constant market price of risk. It was assumed that the innovations from her model followed a GARCH(1,1), while Bodurtha and Mark (1991) adopted a third order ARCH process. Another difference is that Ng (1991) had estimated her model by maximum likelihood, while they adopted the GMM methodology. Bodurtha and Mark (1991) found strong evidence of time variation in the conditional first and second moments of excess stock returns. The results suggested that monthly and quarterly variability components were priced in equity excess returns, which is evidence of an information effect corresponding to the quarterly release of news in possible corporate and governmental reports of statistical data.

Koutmos and Theodossiou (1993) examined the influence of the standard GARCH model on the macroeconomic APT in the US stock market for the period between 1970 and 1988, using similar observed factors with the ones used by Chen *et al.* (1986). The results showed that the conditional heteroscedasticity is evident in the monthly returns of stocks and the econometric model employed for the analysis gave accurate estimates of the time-varying volatility of the returns. Alternatively, Dillen and Stoltz (1999) examined the classic market model using the original ARCH model. The purpose was to examine the distribution of the residuals under different assumptions. The research was held on the Stockholm Stock Exchange for a data sample of 20 stocks. They found that the residuals have a leptokurtic distribution and that changes in the assumed distribution of the residuals can change the beta coefficient in comparison to the standard OLS estimation process.

McKenzie *et al.* (2000) analysed the phenomenon of large beta observations so as to understand if this is a result of a response by the market to the arrival of news or if it is a result of the model when it picks up noise from the mean of the series. For their analysis they applied a *Multi-variate GARCH (M-GARCH)* model to generate the time-varying beta coefficients. They used as investigation sample daily data from the US deposit taking institutions for the 1976–1994 period. The results of the study confirmed that the time-varying coefficients of risk are affected by economic factors which have to be investigated.

Furthermore, Ortiz and Arjona (2001) examined several Latin-American stock markets: Argentina, Brazil, Chile, Colombia, Mexico, and Venezuela. They applied different variations of GARCH models (EGARCH, GARCH-M) in their study. Their data sample consisted of weekly data between 1989 and 1994. Their results were very interesting as all the models that were applied in the study did not capture the volatility of the markets' series under examination. Specifically, the models rejected the autocorrelation of the series, the distribution of the residuals was normal in almost all cases and heteroscedasticity was just rejected for all econometric models.

Koutmos and Knif (2002) estimated time-varying betas in the Finnish Stock Exchange using a bivariate version of an asymmetric GARCH model. They used as data sample daily returns of five Finnish size-based equally-weighted portfolios for the 1991−1997 period. The inferences showed a significant time variation in the beta estimates. There was also evidence that time-varying betas are asymmetric in up and down markets.

Morelli (2002) examined the relationship between the conditional volatility of the UK stock market index and the volatility of a number of *macroeconomic* variables. These macrovariables included inflation, industrial production, real retail sales, money supply and an exchange rate variable. For his study monthly UK data was used over the period 1967−1995. At first, (G)ARCH models were employed in order to capture the conditional volatility of the stock market index and the conditional volatility of the macrovariables. Then, cointegration and multiple regression analysis was applied so as to investigate for possible relationships between the conditional volatilities of the variables under examination. While the cointegration results confirmed a significant relationship between the stock market and macroeconomic volatility, the results of the multiple regression tests showed that no macroeconomic volatility showed any significance in explaining the behaviour of stock market volatility. However, it should be noted that the inclusion of the conditional volatility of inflation in the conditional volatility of the stock market index resulted in an improvement in the goodness of fit of the model. Overall, Morelli (2002) suggested that, as stock returns change rapidly, (G)ARCH models should be applied so as to capture their conditional volatility and that the conditional volatility of specific macrovariables have no power to explain the volatility of the stock market.

Bollerslev *et al.* (1988) applied a multi-variate GARCH-M model on a conditional CAPM. Specifically, a multi-variate generalised autoregressive conditional heteroscedastic process conditional on the mean was estimated for returns to bills, bonds and stocks where the expected return was proportional to the conditional covariance of each return with that of the market portfolio. It was found that the conditional covariances were quite variable over time and were significant determinants of time-varying risk premia. The results also showed that the estimated betas were also time-varying.

The findings of Bollerslev *et al.* (1988) suggested that the conditional covariance matrix of the asset returns was strongly autoregressive. The data of the analysis clearly rejected the assumption that the matrix of returns was constant over time. The expected returns or the risk premia for the assets were significantly influenced by the conditional second moments (variance) of returns. The information, in addition to past innovations in asset returns, was important in explaining risk premia and the phenomenon of heteroscedasticity. Particularly, *lagged* excess holding yields and innovations in consumption appeared to have some explanatory power on asset returns. In other words, there were other variables, like the innovations in consumption, that should also be considered in the investor's information set when estimating the conditional distribution of returns.

A similar approach was used in a series of papers which analysed the mean-variance trade-off across both domestic and international equity markets (Engle and Rodrigues (1989) examined several countries by applying an International CAPM, De Santis and Sbordone (1990) examined the Italian stock market, Harvey (1991) examined the markets of 17 countries also with the employment of an International CAPM, McCurdy and Stengos (1992) examined the Japanese stock market and Engle *et al.* (1995) the US market).

2.12.2 A Review of the Empirical Studies of (G)ARCH Models with Volatility Spillovers

King *et al.* (1990) applied an ARCH model in an international asset pricing model to study the link between international markets. This linkage is investigated further by Hamao *et al.* (1990), who examined the effect of volatility spillovers among international markets using an ARCH-M model on daily open and close prices. Their inferences showed volatility spillovers from New York to Tokyo and London to Tokyo, but not from Tokyo to either New York or London. Cheung and Ng (1996) confirmed their results using a GARCH (1,1) model. Following the crash of October 1987, Hamao *et al.* (1991) found that their results were even stronger than before.

Additionally, Ng *et al.* (1991) found significant spillover effects in the Pacific-Rim countries, while Chou *et al.* (1999) tested the hypothesis that there are spillover changes of the short-term volatility and the price from developed to emerging markets using US and Taiwan data. Their results confirmed the presence of a substantial volatility spillover effect from the US stock market to the Taiwan stock market. There is also evidence supporting the existence of spillovers in price changes.

Kim and Rui (1999) applied the GARCH model in order to examine the relationship between the US, Japan and UK daily stock market return volatility and trading volumes. The results showed extensive volatility spillovers in these markets and were consistent with those of Tay and Zhu (2000) who found similar dynamic relationships in returns and volatilities in Pacific-Rim stock markets.

Furthermore, Engle *et al.* (1990) and Lin *et al.* (1994) examined the clustering of news and volatility spillovers and opened the road for further studies on the subject: Aggarwal and Park (1994) examined the US and Japanese stock markets using daily returns, Karolyi (1995) investigated the US and the Canadian stock market, Booth *et al.* (1997) examined the Scandinavian stock markets using also daily returns and Brooks and Henry (2000) the US, the Japanese and the Australian stock market.

2.12.3 A Review of Empirical Studies of (G)ARCH Models in Different Areas of Finance

Engle and Ng (1993) investigated the news impact curve as a precise measure of how news can be incorporated into volatility estimates. In order to proceed in their investigation, they applied several models (GARCH, EGARCH, and so on), so as to compare their results and make some comments regarding their validity on the topic under investigation. These models allow several types of *asymmetry* in the impact of news on volatility. One of these models is a *partially nonparametric (PNP)* ARCH model which allows the data to determine the news impact curve directly.

The secondary data of analysis was collected from the Japanese stock exchange from 1980 to 1988. All the models found that negative shocks introduce more volatility than positive shocks, with this effect particularly apparent for the largest shocks. They have also proved that the asymmetry phenomenon was not adequate, according to the diagnostic tests. After a comparison, Engle and Ng (1993) explained why the best model for the analysis was the one proposed by Glosten *et al.* (1993). Specifically, for reasonable shock values the volatilities forecast by EGARCH, the asymmetric model of Glosten *et al.* (1993) and the PNP ARCH model were similar. For more extreme shocks their forecasts differed to a great degree. What is of great importance here is that the results have indicated that, of the variance parametric models, the model of Glosten *et al.* (1993) was the best at capturing the asymmetry effect to a satisfied degree. They also mentioned that the PNP ARCH model had the ability to reveal the shape of the news impact curve and it is a useful measure in modelling heteroscedasticity.

Gallo and Pacini (1998) investigated the characteristics of market *opening news* using a GARCH model in order to analyse the impact of news on the risk coefficients of the model used in the analysis. They found that the characteristics are not the same between the differences of the opening price of the present day and the closing price of the day before. In their model a news variable was included, which improved the out-of-sample forecasting in comparison to the original ARCH and GARCH models.

Friedmann and Sanddorf-Kohle (2002) examined the volatility clustering of stock returns in the Chinese Stock Market comparing the EGARCH of Nelson (1991) with the Glosten *et al.* (1993) asymmetric GARCH model. For the analysis of the impact of news on volatility they proposed a modification of the news impact curve. Using the concept of a conditional news impact curve it is shown that in periods of high volatility there is an acceleration of the news impact according to the results of the asymmetric GARCH model, while the impact of news does not change under the

EGARCH approach. However, depending on the parameter values, it cannot be proved that the EGARCH model is weaker than the asymmetric GARCH model.

Furthermore, Gardeazabal and Regulez (2004) introduced an extended Dummy Variable Approach (EDVA) which can explain stock market *seasonality* by leaving a lower fraction of stock returns unexplained. This model was an alternative to the original DVA as there was too much unexplained variability of stock returns. They examined possible seasonality effects in the Spanish stock market and the inferences, based on the EDVA using portfolio and individual regression equations, showed strong *seasonality* effects. On the other hand, the inferences regarding the seasonality using the DVA were weak. After they extended their analysis to a model with GARCH process, the results showed heavy daily *seasonality* in the conditional variances of the series. In other words, by modelling heteroscedasticity as a GARCH process it is confirmed that the series exhibit heavy daily seasonality in their conditional variances.

Furthermore, Koutmos (1992) examined the risk-return trade-off in a time-varying volatility environment. The aim was to capture possible asymmetric effects on the conditional variance and the EGARCH-in-Mean (EGARCH-M) model was applied on 10 stock market return indices. The results supported the objectives of the analysis after the application of the model.

Longin's (1997) research is based on the analysis of Kyle (1985) where there are three types of traders under examination. These traders are the liquidity traders, the informed traders and the market makers. Longin (1997) used an asymmetric GARCH model in order to capture information shocks, so that the large shocks are less persistent than the small shocks. This model was used in the applications as it can give more precise information regarding the market liquidity and the trading volume. Moreover, Shields (1997) applied the *threshold GARCH (TGARCH)* model to two

Eastern European markets. His results seemed to be interesting as there were no asymmetry effects in the conditional variance in response to shocks of different sign. These results contradict those of the developed stock markets. In developed markets negative shocks entering the market lead to a larger return volatility than positive shocks of similar magnitude.

Hussain (1998) applied a GARCH model so as to examine the Ramadan effect on stock returns in the Pakistani stock market. As Ramadan is the season of the holy month of fasting, it is logic to have possible effects on the behaviour of the stock market. His results confirmed that the market was tranquil during that period as the conditional variance declined and there did not seem to be any impact on the series' returns under examination. Moreover, Mecagni and Sourial (1999) applied a GARCH-M model to estimate four daily indices in the Egyptian stock market. Their results suggested that there was a tendency of volatility clustering in returns and an asymmetric link between risk and returns which was statistically significant during market downturns.

Brooks *et al.* (2000) used Ding *et al.*'s (1993) power ARCH (PARCH) model to examine stock market returns in 10 countries and a world index. In comparison to the original ARCH and GARCH models, a PARCH model has less restrictions in its application and has the ability to capture with more precision asymmetry and leverage effects. Their results showed that the PARCH model gave significant estimates of volatility effects on the data sample of the returns under examination.

Grier and Perry (1998) examined *inflation uncertainty* and found that inflation raises inflation uncertainty, as measured by the conditional variance of the inflation rate, for all G7 countries over the period 1948–1993. They examined the causal relationship between inflation uncertainty and inflation and showed that while in some countries increased inflation uncertainty lowers inflation, in other countries increased inflation uncertainty raises inflation. Finally, Nas and Perry (2000) examined the uncertainty of inflation and found that inflation raises inflation uncertainty in Turkey over the full sample period 1960−1998 and the results were also the same for the sub-periods. They mentioned that these results were due to institutional and political factors in the monetary policy-making process in Turkey between 1960 and 1998.

2.12.4 A Review of Empirical Studies of (G)ARCH Models in Greece

Alexakis *et al.* (1996) examined the impact of inflation uncertainty on stock prices in developed and emerging capital markets for the period between 1980 and 1993. In their analysis they used an ARCH model, which allowed for the variability of the inflation series. Their results showed a negative association between inflation uncertainty and stock prices in the stock markets under examination. These inferences, especially for the emerging capital markets, could be, among other reasons, a result of exogenous factors through trading and financial transactions, since these markets are usually very open to external economic activity.

Demos and Parissi (1998) investigated the time variation of asset returns in their first and second moments in the ASE for the period between 1987 and 1997. For this investigation a conditional CAPM was used. The model used for capturing the variability of the stocks' series was a *Quadratic GARCH (QGARCH)* model. The QGARCH model was used because it captures not only the autocorrelation in the stock market volatility, but allows also for asymmetric effects in the volatility response to positive and negative signs of the same size. The results of the analysis showed that the Greek value-weighted index is inefficient to a sufficient degree. Additionally, Niarchos *et al.* (1999) found that there are no spillovers in the means and the conditional variances between the US and the Greek stock market and suggested that the US stock market did not have a substantial influence on the Greek stock market. The results of this study were similar to the studies of Dunne (1999) and Darbar and Deb (1997).

Moreover, Chortareas *et al.* (2000) examined the daily returns of the ASE Composite Index between 1987 and 1997. They used Nelson's (1991) EGARCH model to investigate whether important time series characteristics have changed significantly over time as the ASE has matured. We should mention here that the period under examination was the one in which significant changes occurred in the ASE, as it started transitioning from an emerging to a developed market. The results showed that the distribution of the daily and weekly returns series was both leptokurtic and non-normal and that the series exhibited significant time dependencies in the first (mean) and second (variance) moments.

After the examination of the whole period they compared the time series for the 1987–1991 and the 1991–1997 sub-period. They found that the first-order autocorrelation in returns has decreased, the conditional variance continued to be priced by investors and the first-order autocorrelation in conditional volatility has decreased. Generally, the results of Chortareas *et al.* (2000) showed that the properties of the time series in an emerging market can change through time as it transitions to a developed one.

Apergis and Eleptheriou (2001) investigated the volatility of the ASE excess stock returns over the 1990–1999 period. For their research they used different conditional heteroscedastic models (GARCH, EGARCH, etc). These models were compared in order to understand which of them had the ability to explain the properties and characteristics of the distribution of excess stock returns, such as leptokurtosis and volatility clustering. When applied to daily excess returns data, the *asymmetric quadratic GARCH (1,2)* model was found to explain returns' volatility to a higher degree. The results showed also the presence of *persistence* in volatility clustering, something which implies the *inefficiency* of the ASE. This might be due to the low trading volume of assets or the lack of a properly organised stock exchange (Dockery and Kavussanos, 1996). In our work the investigation for the efficiency or not of the ASE during the 1989–2006 period is one of the main goals of this study.

2.13 A Review on Unit Root Analysis

If a time series is stationary, it is said to be integrated of order zero, or $I(0)$. If it needs to be differenced once, in order to achieve stationarity, it is said to be integrated of order one, or $I(1)$. An $I(0)$ time series has no roots on or inside the unit root circle, but an $I(1)$ or higher order integrated time series contains roots on or inside the unit circle. Generally, a time series is $I(k)$ if it is to be differenced for k times to achieve stationarity (Brooks, 2002).

Chapter three presents the mathematical perspective of unit root analysis with its most popular methods of unit root testing. At this point it is important to mention that these methods are the Dickey-Fuller (DF) and the Augmented Dickey-Fuller (ADF) test for unit root (Dickey and Fuller, 1979; 1981), the Phillips-Perron (PP) (1988) test, which is an extension of the ADF test, and the Kwiatkowski *et al.* (1992) test.

2.13.1 A Review of Empirical Studies on Unit Root Testing

Nelson and Plosser (1982) tested 14 macroeconomic time series for the US using the DF tests between 1860 and 1970. They analysed the logarithms of all series, except for the interest rates that were examined in levels, and found empirical evidence which supported the existence of unit roots for the 13 of the series (except unemployment). Moreover, Meese and Singleton (1982) could not reject the null hypothesis of a unit root in many exchange rate time series. Perron (1988) examined the data of Nelson and Plosser (1982) and other macroeconomic series by applying semi-parametric tests and found the same results as they did.

Alternatively, there were some studies that found contradictory results regarding the existence of unit roots in time series. Kwiatkowski *et al.* (1992) performed a test for the null hypothesis of stationarity against the alternative of a unit root and they could not reject the hypothesis of stationarity in many of the time series used by Nelson and Plosser (1982). Some of these time series were the employment, the unemployment rate and the wages. Cheung and Chinn (1996) could not reject the null hypothesis of a unit root in macroeconomic quarterly data while they found different results using annual data.

Furthermore, Schotman and Dijk (1991) examined the random walk hypothesis for real exchange rates using Bayesian analysis and found significant evidence in favour of a stationary model in comparison to the traditional unit root tests. Gil-Alana and Robinson (1997) examined the Nelson and Plosser (1982) data by applying a LM test for the existence of a unit root against fractional alternatives. Their results have shown a variation in the 14 series under examination and, specifically, they found extremely non-stationary evidence for the money stock series and the consumer index, trend stationary evidence for the industrial production and stationarity for the unemployment rate.

Except from the use of unit root tests in univariate systems, the tests became very popular while examining for the existence of cointegration. Many unit root tests, like the ADF one, were used in multi-variate time series in order to test for the existence of cointegrated processes using residual-based approaches. Many examples, like the research of Engle and Granger (1987) and Phillips and Ouliaris (1990) used the unit root tests but this time the main interest of the analysis was the alternative hypothesis of the existence of cointegration. Except for the residual-based approaches there were studies based on likelihood ratio methods in vector autoregression in order to test for cointegration between the variables, like in the work of Johansen (1988; 1991) and Johansen and Juselius (1990). In the following section we briefly present cointegration analysis and a number of empirical studies on cointegration while chapter three presents analytically the mathematical perspective of the most popular cointegration methods.

2.14 A Review on Cointegration Analysis and Empirical Studies

2.14.1 A Review of Empirical Studies of Cointegration Across Different Countries

Non-stationary $I(1)$ time series are cointegrated if a certain linear combination of these time series is stationary. There are two main tests for the existence or not of cointegration among a set of time series: a) The Engle and Granger (1987) two-step method and the Johansen (1988; 1991) and Johansen and Juselius (1990) method. Furthermore, the present sub-section focuses on the application of cointegration methods to a country's financial or macroeconomic sectors.

Cerchi and Havenner (1988) examined the behaviour of five US stock prices over the volatile 1972–1979 period, finding that the series are cointegrated with one dominant common trend. Specifically, they found that while each individual stock price series appeared to follow a random walk when illustrated graphically and tested separately, when they were modelled together these five series shared one common trend. After the cointegration relationship was evident between the stocks of the analysis, the model produced a set of one-month forecasts for the 24 months immediately following the estimation period.

Richards (1995) examined if there are any cointegrated vectors between national stock market indices and the results of the empirical tests presented a model in which the stock return indices of different countries are the sum of a common "world" return index and two country-specific components, a permanent and a transitory one. Specifically, the cointegration tests showed that national return indices are not cointegrated around this common component. This indicated that country-specific factors also influence the long-run relationship of stock markets, which meant that there is a permanent component, and, in addition to that, the evidence of relative return predictability from the regression tests implied the existence of a transitory component.

Moreover, Arize (1996) examined the impact of terms of trade on the trade balance in 16 countries for the 1973–1992 period using the cointegration tests of Engle and Granger (1987) and Johansen (1988; 1991). The results of the unit root tests showed that the series are non-stationary integrated and the results of the cointegration tests presented a positive and significant long-run relationship between the trade balance and the terms of trade for most of the countries under examination. The main conclusions of the analysis were that, because of the long-run relationship, the devaluation improves the true balance.

Muradoglu and Metin (1996) investigated a semi-strong form of the efficient market hypothesis in Turkey. The long-run relationship between stock prices and inflation was investigated and the results presented the inefficiency of the Turkish stock market as stock prices can be forecasted. The efficiency or not of the ASE is one of the main goals of our study using (G)ARCH and cointegration models.

Furthermore, He (1997) investigated the relationship between four security sub-markets of Hong Kong. The results exhibited a stable, long-run, linear relationship among these sub-markets. Moreover, all four sub-markets played a major role to the process of price discovery and, more specifically, that price changes in one sub-market have a significant impact on the other sub-markets under examination.

Kanas (1998) investigated for possible cointegration links between the US and six European equity markets during the period 1983–1996. The results exhibited evidence of the absence of cointegration between the US and the European markets, a result which contradicted previous findings. The main conclusion was that the absence of cointegration gives the opportunity to investors to diversify in the US and the European stock markets.

Olienyk *et al.* (1999) avoided the restrictions of *non-synchronous trading*, fluctuations in foreign exchange rates, trading restrictions and index replication by using the World Equity Benchmark Shares (WEBS) to represent the stock markets of the world. The results of the analysis exhibited a long-run relationship between the 18 market indices. They also exhibited a relationship between the individual closed-end country funds and their own country's WEBS. Finally, a short-term Granger causality (Granger, 1986) existed between the series, which meant that there was evidence of market inefficiency as well as evidence of short-term arbitrage opportunities.

Knif and Pynnonen (1999) examined the impact of the leading markets, that is the US and Japan, on small markets, like Finland and Norway. The results of the tests showed that US price changes had an impact on all the other markets of the analysis. Finally, price changes on the Asian-Pacific markets had a direct effect on the price changes of European countries, but not on the price changes of the US market.

Choi *et al.* (1999) examined the interactions between stock markets and macroeconomic variables, and their results suggested that stock markets help predict industrial production in the US, UK, Japan and Canada out of the G7. Nasseh and Strauss (2000) examined the same phenomena where not only domestic, but also international, macroeconomic variables enter the cointegration vectors to share long-run relationships with stock prices.

Pan *et al.* (1999) applied the Johansen (1988) and the Johansen and Juselius (1990) cointegration test and a modified cointegration test with generalised autoregressive conditional heteroscedastic (GARCH) effects in order to investigate the relationship between the United States and five Asian-Pacific stock markets during the period 1988–1994. The GARCH cointegration test examined the possible common time-varying volatilities between the series. While the results showed a strong integration between the six stock markets through their second moments (variances), the results were different through their first moments (means).

The aim of their study was to investigate whether international stock markets have long-run, common time-varying volatility. The results of the study exhibited the presence of ARCH effects in most of the stock price series, which meant that, when testing for cointegration, one needs to account for time-varying volatility. The main conclusions suggest that volatility transmissions among international stock markets exist not only in the short-run, which refers to the volatility spillovers, but also in the long-run, something which is explained by the common time-varying volatility of the series under examination.

Kwon and Shin (1999) investigated if the economic activities in Korea explained stock market returns using cointegration and causality tests. They found that cointegration is evident between stock market indices and macroeconomic variables, which are the production index, the exchange rate, the money supply and the trade balance. It should be noted here that, even though the stock market index and the production index affect each other, the stock market index is not a general leading indicator for economic variables. In our work unit root and cointegration analysis is employed so as to examine the relationship between financial and macroeconomic indices presented in chapter five.

MacDonald and Nagayasu (2000) investigated the long-run relationship between the real exchange rate and the real interest rate differentials with a set of panel data which consisted of 14 countries. The results of unit root and cointegration analysis showed that there was stationarity in the panel data and the analysis exhibited significant long-run relationships among the variables. Furthermore, Felmingham *et al.* (2000) examined the relationship between the Australian short-term real interest rates and the real interest rates of the US, Japan and other countries during the 1970–1997 period. The results of the analysis exhibited significant dependence among the interest rates of the countries.

Additionally, Lanne (2000) examined the term structure of interest rates by applying cointegration tests on US monthly data between 1952 and 1991. The tests were based on the assumption that interest rates followed a unit root process. The results exhibited weak cointegration links between the variables under examination.

Harasty and Roulet (2000) examined for possible cointegration in the stock markets of 17 countries. The results for the in- and out-of-sample tests of the models for future stock market returns forecasts showed that the error correction model could be crucial in decisions for the investment in securities. Moreover, Siddiki (2000) investigated the factors that determine *black market exchange rates* in India using annual data for the period between 1955 and 1994. The results showed that the most important factors of black market rates are the import capacity of official foreign exchange reserves and the restrictions on international trade. Specifically, black market rates were negatively affected by a low level of official foreign exchange reserves, while the same rates were positively affected by a high level of restrictions on international trade.

Wernerheim (2000) examined for the presence of unit roots, cointegration, and causality between the Canadian exports and the GDP using bivariate and trivariate models during the 1947–1996 period. The results showed bidirectional causality between the exports of Canada and its GDP and between the exports of Canada and the US GDP.

Huang *et al.* (2000) examined the relationship between the stock markets of the US, Japan and the South China Growth Triangle (SCGT). Specifically, they applied unit root and cointegration tests that allowed for structural breaks over the sample period (1992–1997) and found that there are no links between these markets except for that between the Shanghai and Shenzhen stock market. The results also showed a strong Granger causality between the US and the members of the SCGT. US price changes predicted day price changes in the Hong Kong and the Taiwan stock market while price changes in the Hong Kong market predicted price changes in the Taiwan market. There was also a strong feedback relationship between the Shanghai and the Shenzhen stock market.

Kim (2002) developed a model taking into account the fat tails of stock returns and possible cointegration relationships between the prices of stocks under examination. The results of the analysis showed that the model can explain the variations of the cross-sectional average returns without the use of firm-specific variables or anomalies of the market.

Moreover, Fukuta (2002) examined two conditions for the absence of rational bubbles. The first condition is that real stock prices and real dividends are cointegrated and the second condition is that the order of integration of stock prices is equal to the order of integration of the dividends for these stocks. The tests of the analysis gave evidence that rational bubbles are not included in Japanese stocks. According to the suggestions of Fukuta (2002), the analysis has limitations as more tests should be employed for the existence or not of intrinsic bubbles in Japanese stock prices.

Lyhagen and Lof (2003) developed a seasonal cointegration model using quarterly data. This model included variables with different numbers of unit roots, which meant that they needed different ways to achieve stationarity. This is the reason that a Monte Carlo simulation was used, in order to specify a seasonal error correction model in annual differences. Two seasonal unit root tests were applied in the analysis. The results showed that, when the true model is not known, a seasonal error correction model in annual differences is very useful in comparison to models which are specified based on seasonal unit root tests.

Cheung and Westermann (2003) examined the long-run and short-run sectoral movements and co-movements in Germany. The data used were seasonally and non-seasonally adjusted data from the country's sectors. The results showed evidence of weak cointegration relationship (long-run relationship) between the seasonally adjusted data, while, regarding the short-run links, the same data exhibited cyclical features. Alternatively, the non-seasonally adjusted data presented different results. The data of the sectors were cointegrated but they featured common cyclical components, just to a lesser degree. The main conclusion of the analysis was that the selection between the data – non-seasonally or seasonally adjusted – is the major factor for the long- or short-run interaction between the variables for the sectors of Germany.

Karamustafa and Kucukkale (2003) examined the relationship between stock returns and macroeconomic factors in the emerging market of Turkey. The cointegration empirical results gave evidence of the existence of cointegration vectors between the Istanbul Stock Exchange (ISE) and specific macroeconomic factors. They also applied causality tests which showed that, while macroeconomic factors are not indicators for the stock returns of ISE, the ISE is a leading indicator for the macroeconomic performance in Turkey. The main conclusion of the analysis was that the investors in the ISE have different strategies in their investments when compared to the investors of developed markets.

Hassan (2003) investigated for possible relationships between share prices in the gulf region and specifically, between weekly share price indices in the Kuwait, Bahrain and Oman stock market for the period 1994–2001. The results of the tests showed that there is one cointegrated vector that relates the Kuwait and the Bahrain stock market, which means that there exists a stable, long-run equilibrium relationship between the markets. This relationship between the two markets means that potential investors can benefit in the long-run from the information that exists in the Bahrain stock market and visa versa.

Christopoulos and Tsionas (2004) examined the long-run relationship between financial development and economic growth with the use of panel unit root and panel cointegration tests. Their tests were applied in data sets of 10 developing countries and the results provided a clear support for the existence of a single equilibrium relationship between financial development, growth, investment share and inflation. The results exhibited a cointegration relationship between financial development and economic growth and the absence of short-run links between the variables of the analysis. The main conclusion was that improvements on the markets will have a significant effect on economic growth.

Ma and Kanas (2004) examined the existence of intrinsic bubbles in the US stock market during the period between 1871 and 1996. The results presented a long-run non-linear relationship between stock prices and dividends for the market and the out-of-sample forecasting performance of the intrinsic bubbles model used in the study gave more significant results in comparison to other models.

AuYong *et al.* (2004) examined the relationship between foreign exchange rates in the Asian and emerging markets during the 1990s financial crises, using cointegration and causality techniques. The findings of the study had important implications, as the evidence of the existence of cointegration and causality effects between the variables undermined the benefits of international risk diversification.

Jones *et al.* (2004) investigated the intraday and daily pricing behaviour of the UK interest rate and equity index futures contracts. They applied cointegration tests and GARCH models and the results showed that the announcement of changes in domestic monetary policy is the most important of the factors used in the analysis. Moreover, the announcement of the changes in the US interest rates, the retail prices, the retail sales and the producer prices are factors that affect short-term interest rates. Two cointegration vectors were found between the examined markets of the UK and finally, the use of GARCH models on intraday returns showed that volatility shocks displayed a weak persistence in the markets under investigation.

Dritsakis and Metaxoglou (2004) examined whether the interest rate between the national currency of Austria and the US dollar affects the economic growth of the country. They used the gross domestic product (GDP) as the dependent variable and the ratio of government expenditure to GDP, the interest rate, the money supply and the terms of trade as the independent variables of the analysis. The Johansen test of cointegration was used for the period between 1964 and 1991 using quarterly data. The results showed the existence of cointegrating vectors among the variables, which meant that a long-run relationship is evident. The selected vector of the analysis had as a result an error correction term which was statistically significant in the examination of short-run links between the variables.

Maysami *et al.* (2004) examined the relationship between macroeconomic variables and stock returns in the Singapore stock exchange for the period between 1989 and 2001. They used as explanatory variables the consumer price index, the industrial production, long and short-run interest rates, a money supply index and exchange rates, while the dependent variables were Singapore's composite stock index and three sectoral indices, the finance, the property and the hotel index. The results of the tests showed that there was a significant relationship between the composite and the property index with the macrovariables, while, only selective macrovariables were related to the finance and the hotel index. These results show the inefficiency of the Singapore stock exchange as there are cointegration relationships between the variables which could give opportunities for profit to any potential investor.

Aggarwal and Kyaw (2005) examined for integration and cointegration links between three equity markets before and after the 1993 North American Free Trade Agreement (NAFTA), based on daily, weekly, and monthly data. The results of the unit root tests for the overall 1988-2001 period and for the two sub-periods (1988–1993 and 1994–2001) showed that, while stock prices were non-stationary, stock returns exhibited stationarity for all three markets and for all the periods of the analysis.

Furthermore, the cointegration tests showed, for daily, weekly, and monthly data, that the prices of stocks are cointegrated only for the post-NAFTA period. The main conclusion of the analysis was that the increased integration and cointegration between the markets after the NAFTA presents less opportunity for international portfolio diversification. This is evidence for the need of new strategy developments among investors and managers.

Moreover, Kanas and Kouretas (2005) developed a framework which illustrated how *lagged* information transmission may cause cointegrating relationships between the current price of small-firm portfolios and the *lagged* price of large-firm portfolios. Using UK data for three sets of monthly prices – the first two sets contained monthly prices of size-sorted portfolios of different size and the third one contained portfolios of the same size – of equity portfolios for the period 1955–2000, they found evidence of cointegration for the two sets of portfolios with different capitalisation size but no evidence for the portfolios of equal size. Because of the conclusion that large-firm portfolio prices are variables that affect small-firm portfolio prices, this means that the capitalisation size is a crucial factor in a long-run relationship.

Davies (2006) analysed the degree of equity market integration on an international environment. With the use of MSCI total return index data, he concluded that a long-run equilibrium across equity markets is important since it implies a violation of the weak-form market efficiency. It is interesting to mention that a regime switching cointegration relationship that allowed for multiple structural breaks was used in the analysis, leading to results in favour of the integration of the equity index.

Syriopoulos (2006) examined developed and emerging Central European stock markets for possible dynamic links and the effects of time-varying volatilities. He found that there was one cointegration vector between the variables, which presented long-run market co-movements. Specifically, the Central European markets presented strong links with the developed markets under examination. Moreover, the application of an asymmetric EGARCH model presented a time-varying volatility effect for these emerging stock markets. The main conclusions were that international portfolio diversification is not the best solution across these cointegrated markets, as risk is not so easy to be reduced and the returns present volatilities to international and domestic innovations.

2.14.2 A Review of Empirical Studies of Cointegration in Greece

Through the years many empirical studies from local and foreign researchers have come to some major inferences regarding the existence or not of integration and cointegration among different time series under examination. In the present sub-section, we review some empirical macroeconomic and financial studies in Greece.

Hondroyannis and Papapetrou (1996) examined if there was any relationship between government expenditure and government revenue. The period under investigation extended from 1957 to 1993 and cointegration and Granger causality tests were employed. The results exhibited evidence of a long-run relationship between government spending and government revenue and, according to the causality test, expenditures cause revenues.

Chletsos and Kollias (1997a) investigated the growth of public expenditures and the factors that have an effect on them. Public expenditure data were used over the 1958–1993 period and the results showed that cointegration was merely evident for the data under examination. Additionally, Chletsos and Kollias (1997b) examined for possible relationships between the employment level and specific macroeconomic variables during the 1960–1992 period. The results were in agreement with this objective only in non-agricultural output and military spending.

Kouretas and Zarangas (1998) examined the exchange rates with the presence of a "parallel" market for US dollars in Greece, using unit root and cointegration tests on monthly data. After the analysis, using the unit root tests for the order of integration in the series, the multi-variate cointegration test of Johansen (1988; 1991) was applied in order to examine the data for possible cointegration links. The results gave one significant cointegration vector. During the process of their work, they employed several other tests that gave one common result, the existence of cointegration between the variables.

Niarchos and Alexakis (2000) investigated whether it is possible to predict stock market returns with the use of macroeconomic variables in the ASE. They argued that there is a possibility that a predictive model exists, which results to the violation of the Efficient Market Hypothesis (EMH). They used as explanatory variables some specific macroeconomic factors which is believed that they influence stock returns. These variables were the inflation rate measured by the consumer price index, the exchange rate of US Dollar/Greek Drachmae and the M3 measure of money supply. Their results showed that the EMH is rejected in the ASE. Specifically, the results suggested that the monthly stock returns are positively correlated. From the error correction model results there was evidence that the *lagged* values of inflation rate have explanatory power on the returns of stocks.

Furthermore, Hondroyannis and Papapetrou (2001) examined the influence of specific economic movements in the ASE during the period between 1984 and 1999. The variables used for the analysis were the industrial production, an interest and exchange rate, a foreign stock market index, oil prices and the Greek general stock market index. The results of the cointegration tests showed that the macroeconomic indicators and the foreign stock market index exhibited little explanatory power on the ASE stock market, as substantial part of the market's variation remains unexplained. It is interesting to mention that the oil prices index explained the behaviour of the ASE stock market movements and, specifically, its relationship with the stock market was negative.

Apergis and Rezitis (2003) examined the relationship between specific macroeconomic variables that is the inflation and the money supply, and the pricing of new houses sold in Greece. For the analysis the cointegration methodology with a vector error correction model was employed and the results indicated that housing prices responded to all the variables used, with the housing loan rate having the highest explanatory power. It should be mentioned that the supply of money did not play a major role on the price of new houses.

Dritsakis (2004a) investigated for possible changes in the long-run demand for tourism to Greece by Germany and Great Britain. He used a set of macroeconomic variables, including income of origin countries, tourism prices in Greece, exchanges rates and transportation costs between the countries under investigation during the 1960–2000 period. The data used for the analysis of this period were annual data and the ADF tests were employed for the existence of a unit root in the series. Furthermore, Johansen's (1988; 1991) maximum likelihood procedure was used in order to test for possible cointegration links among the variables. After the verification of the existence of cointegration between the variables, an error correction model was estimated for the explanation of the demand for tourism from Germany and Great Britain.

Furthermore, Dritsakis (2004b) examined for possible cointegration and causality relationships between the defense spending and economic growth for Greece and Turkey. He applied Johansen's cointegration test with the development of an error correction model, so as to examine the relationships between the variables. The results presented the absence of any cointegration links, which meant that there is no long-run relationship between economic growth and defense spending for both countries, whereas the tests for causality exhibited a unidirectional relation between the variables for both countries and, finally, there was a bilateral relationship between the defenses spending of Greece and Turkey.

Finally, Alexakis *et al.* (2005) investigated for possible cointegration and causality relationships between mutual fund flows and stock returns in the ASE. The results showed the existence of cointegration between the variables of the analysis. Moreover, the development of an error correction model presented bidirectional causality between mutual fund flows and stock returns. The main conclusions of the investigation was that the expectations of the investors lead them to buy or sell mutual fund units after an increase or decrease in stock prices respectively. While at the same time, due to the causality results, mutual funds flows have also an effect on stock returns.

2. 15 Conclusions

In the present chapter there was a focus on the theoretical aspects and the empirical studies of the CAPM and the APT model. At first, the standard CAPM was explored so as to examine whether a proxy for the optimal market portfolio is adequate to explain individual stock or portfolio returns. Furthermore, different versions of the model were examined and, then, the critiques of the CAPM and the anomalies of the market were briefly presented. Moreover, there was a theoretical review on the macroeconomic and the statistical APT model and, then, a series of empirical studies using the CAPM and APT models was investigated, in order to see if there are any factors, other than the market portfolio, that may exhibit any explanatory power on stock returns.

Furthermore, the objective of this chapter was to review the theory behind (G)ARCH models, and their variations, and present a number of empirical studies. It has been shown that (G)ARCH models can have several applications in different areas of investigation e.g. macroeconomy and finance. After a theoretical introduction to the models, their empirical applications in several countries and sectors of the economy were presented. Finally, we presented a few empirical studies for the Greece market. As far as the use of (G)ARCH models is concerned, in chapter three we explain the methodology that is followed so as to examine their possible influence in asset pricing.

Moreover, we reviewed the theoretical and the empirical aspects of unit root and cointegration tests. We have begun our review by presenting the definition of a unit root and some empirical studies on unit roots and we continued with the definition of cointegration between $I(1)$ series and a number of empirical studies for the existence of cointegration between the variables. Finally, we presented several empirical studies using cointegration tests in the Greek economy. In chapter three we present the methodology that is used so as to come to some conclusions regarding the potential factors that have an effect on the ASE.

Chapter Three

METHODOLOGY

3.1 Introduction

In chapter two we have reviewed the principles of the traditional CAPM, with its main versions, and the principles of the APT model. The CAPM was developed by Treynor (1962) and Sharpe (1964) while Lintner (1965), Mossin (1966) and Black (1972) had made some improvements on the model. The model is based on the notion that the optimal market portfolio is adequate to explain stock returns. However, Ross (1976) developed the APT model, based on the empirical failure of the CAPM and the existence of other factors that have an effect on returns. Consequently, Roll (1977) criticised the traditional CAPM arguing that it is untestable and that there may exist factors adequate to explain stocks' behaviour. Furthermore, we have presented the unit root and cointegration analysis which is also employed in our work and, finally, a number of empirical studies based on unit root and cointegration analysis has been examined for different areas of finance and economics.

In this chapter we focus on the analysis of specific models that are employed for the tests in chapter four and five. We try to analyse how these models function, combined with the respective theory under examination, by depicting a number of studies whose selection of models was crucial for the empirical tests and the respective conclusions. These studies include, at first, the work of Roll and Ross (1980) who employed the statistical APT model and the work of Chen (1983) who compared the CAPM and the statistical APT model based on specific methods also employed in chapter four and analysed in this chapter. Moreover, there is the study of Chen *et al.* (1986) who applied a macroeconomic APT model with the use of US data, as well as the study of Chen and Jordan (1993) who compared the statistical with the macroeconomic APT model. Furthermore, there is the study of Morgan and Morgan (1987) and Soufian (2004) who examined the CAPM using (G)ARCH models and, finally, using similar tests such as those in the studies of Maysami *et al.* (2004) and Hondroyannis and Papapetrou (2001) we employ a number of unit root tests and cointegration analysis, so as to investigate whether stocks are affected by the behaviour of a number of variables, such as the inflation rate, industrial production exchange rates, and so on.

The rest of chapter three presents the standard Sharpe-Lintner CAPM, whose results are evident in chapter four, and the respective methodology of Chen (1983) that helps in the examination of the statistical APT model (Roll and Ross, 1980; Chen, 1983; Faff, 1988). The main reason that we employ the statistical APT model is that we want to see, besides the optimal market portfolio, whether there are any (unobserved) factors that affect stock returns. After the examination of the methodology of the CAPM and the APT model, we present the criteria of comparison between the models (Davidson and MacKinnon, 1981; Chen, 1983; Chen and Jordan, 1983). In the next section the methodology of the macroeconomic version of the APT model is depicted. Consequently, the reason that the macroeconomic model is employed in the tests is that we want to investigate if there are any (observable) factors that could have an effect on stock returns. Moreover, the respective criteria for comparison purposes between the statistical APT and the macroeconomic APT model are presented. In order to understand the criteria of comparison more clearly we also examine the way that Davidson and MacKinnon (1981) equation functions, as well as the way that residual analysis works.

Chapter three also presents the Box and Jenkins (1976) methodology which was employed in our study for the estimation of the residuals from specific macroeconomic variables for the application of the macroeconomic APT model, whose results are presented in chapter four. Finally, we explain the methodology that will be followed in the empirical tests presented in chapter five. Specifically, we examine the methodology which is based on a combination between (G)ARCH models and the CAPM. Consequently, the mathematical perspective of the ARCH model and its variations are presented. Moreover, there is a presentation of the methodology employed using specific unit root and cointegration tests, followed by the respective mathematical explanation of unit root and cointegration analysis.

3.2 The Capital Asset pricing Model (CAPM)

The CAPM which is applied in the tests has the following form (Sharpe, 1964; Lintner, 1965; Black *et al.*, 1972):

$$R_{it} - R_{ft} = a_{it} + b_{it}(R_{mt} - R_{ft}) + e_{it} \quad \textbf{(1)}$$

where R_{it} = The return of a security or portfolio i at time t

R_{ft} = The return of the risk-free security at time t

R_{mt} = The return of the market portfolio m at time t

e_{it} = The disturbance term at time t

a_{it} = The intercept term at time t and

b_{it} = The beta coefficient of a security or portfolio i, which is defined as the ratio of the covariance between the return of a security or portfolio i and the return of the market portfolio m to the variance of the return of the market portfolio m:

$$\mathrm{cov}(R_{it}, R_{mt}) / \mathrm{var}(R_{mt}) \qquad \textbf{(2)}$$

3.2.1 The Testing of the CAPM

Analytically, the methodology used for the CAPM is the following:

1) In the beginning the excess returns are estimated by subtracting for each stock the risk-free rate of return ($R_{it} - R_{ft}$). The market premium (excess market proxy) is also estimated by subtracting from the general market index the risk free-rate of return ($R_{mt} - R_{ft}$).

2) For the first stage of the analysis a regression follows between the excess return of each stock and the excess return of the stock market index. This specific regression was based on the following equation:

$$R_{it} - R_{ft} = a_{it} + b_i(R_{mt} - R_{ft}) + e_{it} \qquad \textbf{(3)}$$

where R_{it} is the return of each stock i for each period of analysis, R_{ft} is the risk-free rate of return and R_{mt} is the return of the general market index. In this way the betas are estimated and, based on past studies (e.g. Black *et al.*, 1972), portfolios of equal size are constructed. The number of 30 stocks into the portfolios is justified as a sufficient number of stocks by previous studies on the CAPM and the APT models (Chen, 1983).

3) After the first stage of the analysis, we proceed to the cross-sectional stage (second stage) of the analysis by regressing the returns of each of the constructed portfolios for each period on the estimated betas from the first stage of analysis. This second stage of regressions is based on the following equation:

$$\widetilde{R}_{it} = \gamma_0 + \gamma_1 b_i + e_{it} \qquad \textbf{(4)}$$

where $\widetilde{R}_{it}$ is the average monthly returns of each security i that constructs portfolio p for each period of analysis (the dependent variable) and the $b_i s$ are the estimated betas from the first stage of analysis (the independent variable).

4) Steps 2 and 3 were followed for all portfolios for the whole period and the sub-periods of the analysis.

3.3 The Statistical APT model

As mentioned in chapter two, Roll and Ross (1980) examined the US stock market using the statistical APT model. The data sample was daily stock returns and the results showed that there were at least three priced factors for the period under examination. Moreover, Chen (1983) examined the US stock market by applying the statistical APT model and there was a comparison with the CAPM. The results showed that the APT model performed better in the explanation of stock returns of the market.

3.3.1 The Testing of the Statistical APT

Specifically, the methodology used for the APT is the following:

1) Steps 1 and 2 are the same for the statistical APT as in the case of the CAPM. After the same portfolios were constructed based on beta sorting, a principal components analysis (PCA) was employed. The output of this analysis, that is of interest for the cross-sectional tests, is the number of artificial factors which are used in a series of regressions to produce the betas for the second stage. The decision of the

number of factors that will be retained for the analysis is based on the scree plots (Cattell, 1966), the Kaiser criterion (Kaiser, 1958), or the amount of total variance of the initial variables.

2) After the first stage of the analysis, we proceed to the cross-sectional stage by regressing the returns of each of the constructed portfolios for each period on the estimated betas from the first stage of analysis. Likewise, this second stage of regressions is based on the following equation:

$$\widetilde{R}_{it} = \gamma_0 + \gamma_1 b_{i1} + \gamma_2 b_{i2} + \dots \gamma_n b_{in} + e_{it} \qquad \textbf{(5)}$$

where $\widetilde{R}_{it}$ is the return of each portfolio p comprised by the average monthly excess returns of each security i for each period of analysis (the dependent variable) and the $b_i s$ are the estimated betas from the first stage of analysis (the independent variable).

3) Steps 1 and 2 were followed for all portfolios for the whole period and the sub-periods of the analysis.

3.3.1.1. Principal Components Analysis

The aim of principal components analysis is to seek the standardised linear combination of a set of x variables which has maximum variance (a linear combination $l'x$ is called standardized if $1'l = 1$). More generally, principal component analysis looks for a few linear combinations which can be used to summarise the data, losing in the process as little information as possible (Mardia *et al.*, 1979).

The result of PCA method is an orthogonal transformation of the original data into a set of new variables which are uncorrelated with each other. The i-th principal component of x may be defined as the i-th element of the vector y, namely as:

$$y_i = \gamma'_{(i)}(x - \mu) \qquad \textbf{(6)}$$

where $\gamma_{(i)}$ is the i-th column of the matrix Γ (the matrix of transformation coefficients or betas in our analysis) that were produced from the spectral decomposition theorem $\Lambda = \Gamma'\Sigma\Gamma$ on the covariance matrix Σ of the original variables. Also, the correlations between the original variables and the new ones are given by:

$$\rho_{ij} = \gamma_{ij}(\lambda_i / \sigma_{ii})^{1/2} \qquad \textbf{(7)}$$

where γ_{ij} is the j-th element of the i-th column of the matrix Γ, λ_i is the i-th eigenvalues in the diagonal matrix Λ (the variance of the new variable y_j) and σ_{ii} is the variance of the variable x_i (Mardia *et al.*, 1979).

As was already mentioned in section 3.3.1 the aim of PCA is to produce factors, which will be needed for the cross-sectional regressions of the statistical APT model (Chen, 1983; Roll and Ross, 1980). In our study we use SPSS 14.0 and its procedures concerning PCA. The results are based on the scree plot approach that was firstly proposed by Cattell (1966). It involves plotting the variance accounted for by each principal component from the largest to the smallest. Then we search for a possible "elbow" in the curve, which is the point after which the remaining eigenvalues decline in a linear fashion, and we retain only the components that are above the elbow. In this way the scree test calls for a judgment of the amount of variance accounted for by the retained components (Lattin *et al.*, 2003; Jackson, 1991).

In the case where a scree plot cannot be diagnostic, Kaiser's rule can be the most preferable solution so as to retain the component with the largest variance. Kaiser (1958) suggested retaining only the principal components whose eigenvalues are exceeding unity. This rule reflects the notion that any principal component, as a measure of variance, should account for at least as much variation as any one of the original variables of the analysis. In other words, Kaiser's rule calls for a judgment regarding the amount of variance accounted for by each of the components (Lattin *et al.*, 2003; Jackson, 1991).

3.4 Comparison of the CAPM and the Statistical APT Model

We use three criteria for the comparison between the models:

a) The adjusted R squared and the F significant is used for each portfolio after the cross-sectional regressions for both models.

b) The Davidson and MacKinnon (1981) equation is applied for the comparison of the models. This equation has the following form:

$$R_{p,t} - R_{SAPT,t} = a_t (R_{CAPM,t} - R_{SAPT,t}) + e_t \qquad \textbf{(8)}$$

In equation (8) R_{SAPT} and R_{CAPM} are the expected returns which are generated by each model and $R_{i,t}$ are the average monthly returns of each security i that comprise each portfolio p. The a coefficient is the measure of the effectiveness between the CAPM and the statistical APT model.

c) The last criterion of comparison is the residual analysis, which measures the performance of the models (Chen, 1983). At first, a regression model is used which has as dependent variable the residuals from the CAPM cross-sectional tests and the estimated betas from the principal components analysis (the output for the APT model) as the independent variables. Then, a new regression model is developed which has as dependent variable the residuals from the APT model and the estimated betas from the cross-sectional tests of the CAPM as the independent variables of the analysis. All the criteria used for the comparison between the models are applied for all the portfolios and the periods of examination.

3.5 The Macroeconomic APT Model

Chen *et al.* (1986) used macroeconomic factors in order to examine the validity oft the APT model for the US stock market. The results presented a significant role of some of the macroeconomic variables in the explanation of the behaviour of stock returns. Moreover, Chen and Jordan (1993) examined the power of the statistical and the macroeconomic APT model in the US stock market using monthly returns and the results of the analysis exhibited small differences between the models. Clare and Thomas (1994) investigated the cross-sectional variation of stock returns using two different methods of ordering stocks into portfolios. The results of the tests showed that only two factors were priced while ordering stocks according to size while more macroeconomic variables were found to be priced while ordering stocks according to market beta. In the following sub-section we present analytically the methodology employed so as to have the empirical results of the macroeconomic APT model in chapter four.

3.5.1 The Testing of the Macroeconomic APT Model

The statistical APT and the macroeconomic APT model are both linear models and their only difference comes from the difference in the nature of their systematic factors. In order to empirically test the validity of the macroeconomic APT model, or macrovariable model (MVM), we follow the two-step procedure described in the study of Groenewold and Fraser (1997):

1) Each security is sorted to some specific portfolio, according to the ranking of its beta, as in the studies of Blume (1970), Friend and Blume (1970), and others. Then, we regress each security on the number of macroeconomic variables that have been selected for the analysis based on equation (9):

$$R_{it} = b_{i0} + b_{i1}F_1 + b_{i2}F_2 + \ldots\ldots + b_{ik}F_n + e_{it} \qquad \textbf{(9)}$$

where F_n are the factors (macroeconomic variables) selected for the tests, b_{ik} represent the sensitivities that are estimated from the regression of each security's return, R_{it}, on the set of factors, and e_{it} is the random variable assuming that the mean of the variable is zero and its variance is constant ($E(e_i) = 0, Var(e_i) = \sigma^2$). It is also assumed that $E(e_i, e_k) = 0, i \neq k$ and $\text{cov}(e_i, F_n) = 0$ for all securities and factors.

This stage is called the time-series regression stage as it involves the use of time series data to estimate a set of sensitivities (factor betas) for each asset (see: Groenewold and Fraser, 1997; Chen and Jordan, 1993).

2) After the factor betas for each security have been estimated, during the time-series stage, we cross-sectionally regress these estimated factor betas on the average returns of securities for each portfolio that have been constructed. In our study we have a total of 21 portfolios: 17 of them are comprised of 30 securities each, one of them covers all stocks (60) for the whole period of analysis (from 1989 to 2006) and another one covers all stocks (60) for the first sub-period of analysis (from 1989 to 1994). Finally, there are two more portfolios, one that covers all stocks for the second sub-period (from 1995 to 2000) and which is comprised of 150 stocks and the last one that covers the third/last sub-period (from 2001 to 2006) which is comprised of 240 stocks in total.

This cross-sectional regression is based on equation (10) which is the same with equation (5) of the statistical APT model:

$$\widetilde{R}_{it} = \gamma_0 + \gamma_1 b_{i1} + \gamma_2 b_{i2} + \ldots \gamma_n b_{ik} + e_{it} \qquad \textbf{(10)}$$

where $\widetilde{R}_{it}$ is the return of each portfolio p, which is comprised by the average monthly excess returns of each security i for each period of analysis (the dependent variable) and the $b_i s$ are the estimated factor betas or sensitivities, from the first stage of analysis (the independent variable). The results of this regression are the values of the estimated risk premiums, γ, for each (macroeconomic) factor for each portfolio of analysis (Chen, 1983; Chamberlain and Rothschild, 1983; Lehmann and Modest, 1988; Faff, 1988; Groenewold and Fraser, 1997)

3) Steps 1 and 2 were followed for all portfolios for the whole period and the sub-periods of the analysis.

It is interesting to mention at this point that we use excess returns in the analysis of the APT models, as in the application of the CAPM, because APT models can also have a risk-free, or a zero-beta, representation. This suggestion is strongly supported by the results of Lehmann and Modest (1988) and Chen and Jordan (1993).

3.6 Comparison between the Statistical APT factors and the Macroeconomic APT Variables

3.6.1 Fisher's Joint Test

Fisher's (1948) method is a "meta-analysis", which means that we can analyse data after they have already been analysed and have given specific results. Fisher's analysis is applied on these results. Specifically, it is a technique that combines the results from a variety of independent tests bearing upon the same overall hypothesis (H_0) as if in a single test.

Fisher's method combines the value probabilities, p, or "p-values", into one test statistic (x^2), having a chi-square distribution using the following equation (11):

$$x_{2k}^2 = -2\sum_{i=1}^{k} \log_e(p_i) \quad \textbf{(11)}$$

The p-value for the x^2 distribution itself can then be interpolated from a chi-square table using $2k$ "degrees of freedom", where k is the number of tests being combined. As in any similar test, H_0 is rejected for small p-values, usually < 0.05.

Fisher's joint test is applied in the p-values from the time-series regressions of the factor scores (estimated for the statistical APT during the factor analysis for each portfolio under examination) on the set of the macroeconomic variables selected for the analysis (Chen and Jordan, 1993). The purpose of the tests is to verify if there is truly an overall significant relationship between the factor scores from the statistical APT model and each macrovariable from the macroeconomic APT model (The cumulative results from the joint test of Fisher (1948) are presented in chapter four). Appendix VIII presents the results from the time-series regressions between the factor scores of the statistical APT and the macroeconomic variables of the macroeconomic APT model with the respective results from the joint tests for all periods and portfolios.

3.6.2 Canonical Correlation Analysis

Canonical Correlation is an extension of multiple regressions. In multiple regression analysis the variables are partitioned into a x-set containing q variables and a y-set containing $p=1$ variable. The regression solution involves finding the linear combination $a'x$ which is most highly correlated with y. In canonical correlation analysis the y-set contains $p \geq 1$ variables and we look for vectors a and b for which the correlation between $a'x$ and $b'y$ is maximised (Mardia *et al.* 1979).

Let us suppose that x is a q-dimensional random vector having mean μ and y is a p-dimensional random vector having mean ν and that:

$$E\{(x-\mu)(x-\mu)'\} = \Sigma_{11} \quad \textbf{(12)}$$

$$E\{(y-\nu)(y-\nu)'\} = \Sigma_{22} \quad \textbf{(13)}$$

$$E\{(x-\mu)(y-\nu)'\} = \Sigma_{12} = \Sigma'_{21} \quad \textbf{(14)}$$

Now consider the two linear combinations $\eta = a'x$ and $\phi = b'y$. The correlation between η and ϕ is:

$$\rho(a,b) = \frac{a'\Sigma_{12}b}{(a'\Sigma_{11}ab'\Sigma_{22}b)^{1/2}} \tag{15}$$

The correlation $\rho(a,b)$ varies with different values of α and b, hence one might ask what values of α and b maximise this correlation. Equivalently, we can solve the problem:

$$\max_{a,b} a'\Sigma_{12}b \text{ subject to } a'\Sigma_{11}a = b'\Sigma_{22}b = 1 \tag{16}$$

The solutions to this problem are vectors a_i and b_i which are called the i-th canonical correlation vectors for x and y, respectively, while the random variables $\eta_i = a_i'x$ and $\phi_i = b_i'y$ are called the i-th canonical correlation variables or canonical variates (Lattin *et al.*, 2003) and the $\rho(a,b)$ is the i-th canonical correlation coefficient between the canonical variates. The correlations between the canonical variates and the original variables x and y are called canonical loadings and are used for the characterisation of the new canonical variates (selected results from canonical correlation analysis are presented in chapter four, while in Appendix VIIII the results are presented analytically for each portfolio under examination).

3.7 Comparison of the Statistical APT and the Macroeconomic APT Model

The following criteria are used for the comparison between the models:

a) The adjusted R square and the significance of the F statistic are used for each portfolio after the cross-sectional regressions for both models.

b) The Davidson and MacKinnon (1981) equation is applied for the comparison of the models. This equation has the following form:

$$R_{p,t} - R_{MAPT,t} = a_t(R_{SAPT,t} - R_{MAPT,t}) + e_t \quad \textbf{(17)}$$

In equation (17) R_{SAPT} and R_{MAPT} are the expected returns which were generated by the models respectively. If the null hypothesis H_0 is not rejected and the coefficient a is equal to zero, it means that the macroeconomic APT is the better model, which shows that there might be observed variables able to explain the behaviour of stock returns. As in the comparison between the CAPM and the statistical APT model, the same comparison criteria are applied for all the portfolios and the periods of examination.

3.7.1 The Davidson and Mackinnon Test for Specification Error

According to the work of Davidson and Mackinnon (1981), we consider initially the case of a single-equation the validity of which we want to test:

$$H_0 : y_i = f_i(X_i, b) + e_{0i} \quad \textbf{(18)}$$

where y_i is the i-th observation on the dependent variable, X_i is a vector of observations on exogenous variables, b is a k vector of parameters to be estimated and the error term e_{0i} is assumed to be $NID(0, \sigma_0^2)$. If, according to economic theory, an alternative hypothesis is suggested:

$$H_1 : y_i = g_i(Z_i, \gamma) + e_{1i} \quad \textbf{(19)}$$

where Z_i is a vector of observations on exogenous variables, γ is an l vector of parameters to be estimated and e_{1i} is $NID(0,\sigma_1^2)$ if H_1 is true. It is also assumed that H_1 is not nested within H_0 and that H_0 is not nested within H_1. This means that the validity of H_0 implies the falsity of H_1 and vice versa.

In the case of a possibly non-linear regression:

$$y_i = (1-a)f_i(X_i,b) + a\hat{g}_i + e_i \qquad \textbf{(20)}$$

where $\hat{g}_i = g_i(Z_i,\hat{\gamma})$ and $\hat{\gamma}$ is the ML estimate of γ. If H_0 is true then the true value of α is zero. $\hat{g}_i$ is a function of the exogenous variables Z_i and the parameter estimates $\hat{\gamma}$. The former are independent of e_i by assumption.

Asymptotically, the latter are also independent of e_i because the influence of any particular error term on the estimates tends to zero as the sample size tends to infinity. Thus, asymptotically, $\hat{g}_i$ will be independent of e_i so that one may validly test whether $a = 0$ in equation (20) by using an asymptotic t-test or a likelihood ratio test.

An even simpler way to test the truth of H_0 would be to estimate

$$y_i = (1-a)\hat{f}_i + \hat{a}_i + e_i \qquad \textbf{(21)}$$

or

$$y_i - \hat{f}_i = a(\hat{g}_i - \hat{f}_i) + e_i \qquad \textbf{(22)}$$

where $\hat{f}_i = f_i(X_i,\hat{b})$, according to equation (20).

Equation (22) is the equation that has been used in our tests so as to compare the standard CAPM with the statistical APT model and, during the progress of this work, the statistical APT with the macroeconomic APT model.

If we set $y_i = R_{p,t}, \widehat{f}_i = R_{SAPT,t}$ and $\widehat{g}_i = R_{CAPM,t}$ we have the following equation:

$$R_{p,t} - R_{SAPT,t} = a_t(R_{CAPM,t} - R_{SAPT,t}) + e_t \tag{23}$$

so as to compare the statistical APT model and the CAPM, where R_{SAPT} and R_{CAPM} are the expected returns which were generated by the models respectively. The a coefficient measured the effectiveness of the models. Hence, in our work the two hypotheses are: $H_0 : a = 0$ and $H_a : a \neq 0$. So if the null hypothesis H_0 is not rejected and the coefficient a is equal to zero, it means that the statistical APT is the better model.

Furthermore, in order to compare the statistical APT and the macroeconomic APT model we developed the following equation:

$$R_{p,t} - R_{MAPT,t} = a_t(R_{SAPT,t} - R_{MAPT,t}) + e_t \tag{24}$$

where R_{SAPT} and R_{MAPT} are the expected returns which were generated by the models respectively. If the null hypothesis H_0 is not rejected and the coefficient a is equal to zero, it means that the macroeconomic APT is the better model, which shows that there might be observed variables able to explain the behaviour of stock returns.

3.7.2 Residual Analysis

The residuals of a model as in the case of the CAPM can be used for performance measurement (Chen, 1983). If the model is specified then the expected return of an asset i can be captured by the coefficient b_i and the residual n will behave like white noise with a mean equal to zero. Hence, if the expectations in the market are rational, the realised return is written as:

$$r_i = E_i + k_i \tag{25}$$

where E_i is the rational expected return of the market and k_i is the respective error term. Moreover, if the model is specified, r_i can be written as:

$$r_i = E_i(CAPM) + n_i \tag{26}$$

which means that

$$n_i = \left\lfloor E_i - \widehat{E}_i(CAPM) \right\rfloor + k_i \tag{27}$$

where $\widehat{E}_i(CAPM)$ is the expected return from the CAPM. Thus, if the model is correct, $E_i = \widehat{E}_i(CAPM)$ and $n_i = k_i$ should behave like white noise and should not be priced by any other model – this means that there is no information captured by any other model except the CAPM. Alternatively, if n_i can be priced by some other model – there is information captured by another model – it means that E_i contains information which is not captured by $\hat{E}_i(CAPM)$ and, thus, the CAPM is not the correct model for the analysis.

In our work, the method that was used based on residual analysis so as to test the validity of the CAPM, was to run a regression having as dependent variables the residuals of the model, n_i, and as independent variables the factor betas, which were estimated from the principal components analysis, of the statistical APT model. Furthermore, we regressed the residuals of the APT (dependent variable), which were estimated during the cross-sectional regression tests, on the beta (independent variable) estimated from the cross-sectional regressions, in order to examine if the CAPM captures information which is missed by the statistical APT model.

3.8 Time Series Analysis and the Box-Jenkins (1976) Methodology

For the time series models we use the standard notation of ARIMA (p,d,q) (P,D,Q), where p is the order of autoregression (AR), d is the order of differencing or integration (I), and q is the order of moving-average (MA), and (P,D,Q) are the respective seasonal counterparts.

There are three basic components to an ARIMA model: autoregression (AR), differencing or integration (I), and moving-average (MA). All of them are based on the concept of random disturbances or shocks. When a disturbance occurs between two observations in a series, it somehow affects the level of these series. The aim is to explain significant correlations found in the autocorrelation (ACF) and partial autocorrelation (PACF) plots and to handle trends (Bowerman and O΄Connel, 1993).

The first of the three processes included in the ARIMA models is autoregression. In an autoregressive (AR) process, each value in a series is a linear function of the preceding value or values. In a first-order autoregressive process, only the single preceding value is used; in a second-order process, the two preceding values are used, and so on. These processes are commonly indicated by the notation $\mathrm{AR}(n)$ or $\mathrm{ARIMA}(n,0,0)$, where the number in parentheses indicates the order (Vandaele, 1983).

For example, an $\mathrm{AR}(1)$ or $\mathrm{ARIMA}(1,0,0)$ process has the following functional form:

$$\text{value } (t) = \text{coefficient} * \text{value } (t-1) + \text{disturbance } (t) \qquad \textbf{(28)}$$

where value (t) is the value of the series at time t, the coefficient is a value that indicates how strongly each value depends on the preceding value. The sign and magnitude of the coefficient are directly related to the sign and magnitude of the partial autocorrelation at lag 1. When the coefficient is greater than -1 and less than $+1$, the influence of earlier observations dies out exponentially. Moreover, disturbance (t) is the error associated with the series value at time t.

An autoregressive process is one with a "memory", in that each value is correlated with all preceding values. In an $\mathrm{AR}(1)$ process, the current value is a function of the preceding value, which is a function of the one preceding it, and so on (Vandaele, 1983; Mills, 1992).

As far as the second component of ARIMA models is concerned, the differencing or integration component (I) tries, through differencing, to make a series stationary. Time series often reflect the cumulative effect of some process that is responsible for changes in the level of the series but is not responsible for the level itself. A series that measures the cumulative effect of something is called integrated.

One can study an integrated series by looking at the changes, or differences, from one observation to the next. When a series wanders, the difference from one observation to the next is often small. Thus, the differences of even a wandering series often remain fairly constant. This steadiness, or stationarity, of the differences is highly desirable from a statistical point of view (Vandaele, 1983; Mills, 1992).

The standard shorthand for integrated models, or models that need to be differenced, is $\mathrm{I}(1)$ or the $\mathrm{ARIMA}(0,1,0)$. There is also the needs to look at differences of the differences. Differencing beyond the second or third order is relatively rare. Usually, when a series exhibits such extreme trends, it is not stationary due to the variance which is not constant. The application of a log or square root transformation to the series, before the estimation of the model, will generally stabilise the variance (Vandaele, 1983; Mills, 1992).

Finally, the moving-average (MA) component of an ARIMA model tries to predict future values of the series based on deviations from the series mean observed for previous values. In this case, each value is determined by the weighted average of the current disturbance and one or more previous disturbances. The order of the moving-average process specifies how many previous disturbances are averaged into the new value. In the standard notation, an $\mathrm{MA}(n)$ or $\mathrm{ARIMA}(0,0,n)$ process uses n previous disturbances along with the current one (Vandaele, 1983; Mills, 1992; Bowerman and O'Connel, 1993).

An $\mathrm{MA}(1)$ or $\mathrm{ARIMA}(0,0,1)$ has the functional form:

$$\text{value } (t) = \text{coefficient} * \text{disturbance } (t-1) + \text{disturbance } (t) \qquad \textbf{(29)}$$

where value (t) is the value of the series at time t, coefficient is a term that indicates how strongly each value depends on the preceding disturbance terms. The sign and magnitude of the coefficient are directly related to the sign and magnitude of the autocorrelation at lag 1. Moreover, disturbance (t) is the error associated with the series value at time t (Box *et al.*, 1994).

The difference between an autoregressive process and a moving-average process is subtle but important. Each value in a moving-average series is a weighted average of the most recent random disturbances, while each value in an autoregression is a weighted average of the recent values of the series. Since these values in turn are weighted averages of the previous ones, the effect of a given disturbance in an autoregressive process dwindles as time passes. In practical terms, MA processes are more useful for modelling short-term fluctuations, while AR processes are more useful for modelling longer-term effects (Bowerman and O'Connel, 1993; Box *et al.*, 1994).

The full notation of an ARIMA model is ARIMA(p,d,q) (P,D,Q) where P, D, and Q are the seasonal AR, I, and MA components respectively. Seasonal components work just like their non-seasonal counterparts, but they "skip over" the seasonal interval. Since the three types of random processes in ARIMA models are closely related, there is no algorithm that can determine the correct model. Instead, there is a model-building procedure, the so-called Box and Jenkins methodology (Box and Jenkins, 1976), that allows constructing the best possible model for a series (Vandaele, 1983).

The first and most subjective step is the identification of the processes underlying the series. The three integers p, d, and q must be determined representing respectively the number of autoregressive orders, the number of differencing orders, and the number of moving-average orders of the ARIMA model. In the case of a seasonal model, the seasonal counterparts must also be specified to these parameters. The identification process for the autoregressive and moving-average components requires a stationary series. A stationary series has the same mean and variance throughout. Autoregressive and moving-average processes are inherently stationary, whereas integrated series typically are not (Vandaele, 1983; Mills, 1992).

In the case where a series is not stationary, it must be transformed until a stationary one is obtained. The most common transformation is differencing, which replaces each value in the series by the difference between that value and the preceding value (for seasonal differencing "preceding" means the value one seasonal lag prior to the current value). Differencing is necessary when the mean is not stationary. Logarithmic and square-root transformations are useful when the variance is not stationary, such as when there is more short-term variation with large series values than with small series values (Vandaele, 1983; Mills, 1992; Bowerman and O′Connel, 1993).

When a stationary series is obtained, the second ARIMA parameter, d, is already known – it is simply the number of times you had to difference the series to make it stationary. Diagnosing an ARIMA model is a crucial part of the model-building process and involves analysing the model residuals. A residual is the difference, or error, between the observed value and the model-predicted value. A large residual means that the model did a poor job of fitting that particular point. If the model is a good fit for the series, the residuals should be random. Generally, the following checks are essential (Vandaele, 1983; Box *et al.*, 1994):

1) The autocorrelation function and partial autocorrelation function of the residual series should not be significantly different from 0. One or two high-order correlations may exceed the 95 per cent confidence level by chance; but if the first- or second-order correlation is large, you have probably incorrectly specified the model.

2) The residuals should be without pattern. A common test for this is the Box-Ljung Q statistic, also called the modified Box-Pierce statistic. You should look at Q at a lag of about one-quarter of the sample size (but no more than 50). This statistic

should not be significant. If the autocorrelation at a particular lag exceeds the confidence level but the Box-Ljung statistic at that lag isn't significant, then you can ignore the autocorrelation as a chance occurrence (Bowerman and O'Connel, 1993).

According to the methodology of Box and Jenkins (1976):

If the seasonal autocorrelation has spikes at lags L, 2L, 3L,..., PL and cuts off after lag PL, while the seasonal partial autocorrelation dies down, we use a seasonal moving average operator of order P. In case that the seasonal autocorrelation dies down, and the seasonal partial autocorrelation has spikes at lags L, 2L, 3L,..., SL and cuts off after lag SL, we use a seasonal autoregressive operator of order S. Moreover, if the seasonal autocorrelation has spikes at lags L, 2L,..., PL and cuts off after lag PL, while the seasonal partial autocorrelation has spikes at lags L, 2L, 3L,..., SL and cuts off after lag SL, we choose either a seasonal moving average operator of order L or a seasonal autoregressive operator of order S in order to find the best model. If the seasonal autocorrelation contains small sample autocorrelation (it has no spikes) at all seasonal lags and the seasonal partial autocorrelation contains small sample partial autocorrelations (it has no spikes) at all seasonal lags, we do not use any seasonal operator. Finally, in case that the seasonal autocorrelation dies down quickly at the seasonal level and the seasonal partial autocorrelation also dies down quickly at the seasonal level, we use both operators mentioned above (Bowerman and O'Connel, 1993).

Respectively, as far as the non-seasonal autocorrelation and non-seasonal partial autocorrelation are concerned:

If the non-seasonal autocorrelation has spikes at lags 1, 2, 3,..., p and cuts off after lag p, while the non-seasonal partial autocorrelation dies down, we use a non-seasonal moving average operator of order p. In case that the non-seasonal autocorrelation dies down and the non-seasonal partial autocorrelation has spikes at lags 1, 2, 3,..., q and cuts off after lag q, we use a non-seasonal autoregressive operator of order q. Furthermore, if the non-seasonal autocorrelation has spikes at lags 1, 2, 3,..., p and cuts off after lag p and the non-seasonal partial autocorrelation has spikes at lags 1, 2, 3,..., q and cuts off after lag q, we choose one of the operators mentioned above. If the non-seasonal autocorrelation contains small sample autocorrelation (it has no spikes) at all lags and the non-seasonal partial autocorrelation contains small sample partial autocorrelations (it has no spikes) at all lags, we do not use any non-seasonal operator. Finally, in case that the non-seasonal autocorrelation dies down and the non-seasonal partial autocorrelation dies down, we use both operators (Bowerman and O'Connel, 1993).

Moreover, during the final stage we estimate the autocorrelation and the partial autocorrelation of the residuals of the selected model(s) and, in case there is a need for any correction in the series, we repeat the previous step – the examination of the seasonal and non-seasonal autocorrelations and partial autocorrelations of the first differences of the series, according to the Box-Jenkins (1976) methodology.

3.9 The Application of (G)ARCH Models on the CAPM

The following steps are followed so as to examine if the use of (G)ARCH models is of any significance in the application of the CAPM:

1) At first we run, using the ordinary least squares (OLS) method, a regression of each stock return on the stock market return, so as to estimate the respective coefficients (betas). This procedure is applied for both monthly and daily stock returns.

2) Furthermore, we examine the results from the diagnostic tests of the regression to see if there is an ARCH effect (Engle, 1982; Bollerslev, 1986) in the series (for monthly and daily stock returns).

3) In case there is a heteroscedasticity problem (ARCH effect), we apply a number of specific (G)ARCH models and examine if the results of each model are in agreement with the restrictions of the respective model, according to the econometric theory. For example, the coefficients of the GARCH(1.1) and ARCH(1)-M model should be non-negative because of the non-negative estimated conditional variance (Engle, 1982; Bollerslev, 1986). Only in the case that the restrictions hold the respective coefficients of the conditional mean equation of each model are of any use for the analysis. Alternatively, if the results contrast the restrictions of a model, it is excluded from the comparison.

4) We select the new coefficient (beta) of the mean equation based on the results of the (G)ARCH model that give the smallest value of the Akaike (1974) and Schwarz (1978) criterion.

5) Except for using the new coefficients after the application of (G)ARCH models, we examine whether there is evidence of risk-return trade-off, based on the results of the -M (in mean) models. According to the work of Engle *et al.* (1987) we employ the ARCH-M model, as well as the EGARCH-M model based on the study of Nelson (1991) plus the "in mean" factor. Moreover, we examine whether there is an asymmetry effect between negative and positive shocks in a time series. This is achieved by examining the coefficients significance of the conditional variance equation in the EGARCH and EGARCH-M model.

6) After we have all the new coefficients for all stocks, we construct a number of portfolios based on the ranking of each of the new beta estimates.

7) After the construction of the portfolios based on the new betas, we calculate the average return of each portfolio.

8) We run the respective cross-sectional regression tests having as dependent variable the average return of each portfolio and as independent variable the respective new beta coefficients for the same time period (Chen, 1983).

9) We examine the results of the diagnostic tests after the cross-sectional regressions. In this way we can come to some conclusions regarding the validity of the CAPM in the ASE after the application of a number of specific (G)ARCH models.

3.9.1 The ARCH Model

As we are mostly interested in regression models (CAPM, APT) our research continues in modelling the volatility of the time series (variables) under investigation. This means that the conditional variance of the series is also of interest for us as it may affect the conditional mean which gives rise to a regression model for the mean that includes some function of the conditional variance. That is, if an investor holds a financial asset and wants to model the respective returns of this asset, the conditional variance is likely not to remain constant over time. This might be due to small or even large shocks (change in government, stock market crash), which may affect the returns of the asset to a significant degree (Patterson, 2000).

The problem of modelling volatility so that it can respond to time-varying shocks was solved with the development of the Autoregressive Conditional Heteroscedasticity (ARCH) model developed by Engle (1982).

In case there is a conditional mean equation with two variables (as in the case of the CAPM):

$$y_{it} = a_{it} + b_{it}x_{it} + \varepsilon_{it} \tag{30}$$

then the ARCH model needed to capture the information from the time-varying volatility will have the following form:

$$\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 \tag{31}$$

where σ_t^2 is the conditional variance of the residuals ε_{it} from equation (30) and ε_{t-1}^2 are the past values of ε_{it} at time $t-1$.

As σ_t^2 is a variance it should not be negative and is mostly positive, otherwise the model is rejected according to Engle (1982). More specifically, the need for non-negativity leads to the following assumptions regarding the validity of ARCH model:

1) $a_0 \geq 0$. In case $a_1 = 0$, then the conditional variance σ_t^2 is $a_0 = 0$, which means that this coefficient must be non-negative.

2) $a_1 \geq 0$. Because ε_{t-1}^2 is always non-negative, a_1 should be equal or larger that zero so as $a_1\varepsilon_{t-1}^2$ to be non-negative.

3) $a_1 < 1$. In case a_1 is larger that 1, then the process cannot be covariance stationary (nonstationarity of ARCH effects).

To summarise, the ARCH model shows that the value of the conditional variance of the present period is a function of the squared error term from the previous period. It is always necessary to place restrictions on a_0 and a_1, which must be both positive. If one of the parameters were negative, then the estimation of the conditional variance could give a negative value, which contrasts the theory of ARCH models.

3.9.2 Variations of ARCH Models

3.9.2.1 The Generalised ARCH (GARCH) Model

A major problem of the application of ARCH model is that a large number of lagged squared error terms for the estimation of the conditional variance is found to be significant on the basis of pre-testing. In this case, in order to avoid problems associated with negative conditional variances it is necessary to impose restrictions on the model's parameters.

For this reason Bollerslev (1986) developed the *Generalised ARCH (GARCH)* model. This model is an extension of the original ARCH model as it allows for a more flexible lag framework. This conditional heteroscedasticity model includes lags of the conditional variance $(h_{t-1,}h_{t-2},...h_{t-n})$ as regressors for the conditional variance, which are added to the lags of the squared error term $u_{t-1}^2, u_{t-2}^2,...u_{t-q}^2$.

The GARCH model is based on the following equation:

$$u_t = e_t(\alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j-1}^{p} b_j h_{t-j})^{1/2} \tag{32}$$

where $e_t \sim NID(0,1); p \geq 0, q > 0; a_0 > 0, a_i \geq 0, i = 1,2,3,...,q$ and $b_j \geq 0, j = 1,2,3,....p$

In this case the conditional variance of the error term u_t, h_t, is a function of lagged values of u_t^2 and lagged values of h_t:

$$h_t = a_0 + \sum_{i=1}^{q} a_i u_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j} \tag{33}$$

The simplest GARCH model is the GARCH(1,1) model and its conditional variance is represented by the following equation:

$$h_t = a_0 + a_1 u_{t-1}^2 + b_1 h_{t-1} \qquad \textbf{(34)}$$

As in the case of Engle's (1982) ARCH model the conditional variance h of the GARCH model should not be negative. The assumptions that verify the validity of GARCH model are: $a_0 \geq 0$, $a_1 \geq 0$ and $b_1 \geq 0$. The GARCH model shows that the value of the conditional variance of the present period is a function of the squared error term from the previous period and previous period's conditional variance. Moreover, it is always necessary to place restrictions on the coefficients which must be both non-negative.

Engle and Bollerslev (1986) examined the case where the variance process allowed for unit roots in the lag polynomials. In this case the model is referred to as the Integrated GARCH (IGARCH) model, where:

$$a_1 + a_2 + \ldots + a_q + b_1 + b_2 + \ldots + b_p = 1 \qquad \textbf{(35)}$$

In their study, Bollerslev *et al.* (1992) suggested that a low order GARCH model can be a good representation of financial time series, while Koutmos and Theodossiou (1993) verified this suggestion with specific tests. This is the main reason that the GARCH(1.1) is employed in our work so as to examine whether the model can estimate the conditional variance of the residuals from the regression of each stock return on the general market index.

3.9.2.2 The ARCH-in-Mean (ARCH-M) Model

According to the theory of finance an individual expects that the variance of the returns from investing in a risky asset adds significantly to the explanation of the behaviour of the returns' conditional mean. And this holds because of the fact that risk-averse investors require higher returns so as to invest in riskier assets.

Engle *et al.* (1987) developed the following model in order to examine the excess return on a long-term bond in relation to a one-period treasury bill rate:

$$y_t = m_t + e_t \tag{36}$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i e_{t-i}^2 \tag{37}$$

$$m_t = b + k h_t^{1/2} \tag{38}$$

where y_t is the excess return on the long-term bond, m_t is the risk premium from the investment in the long-term bond, e_t is the difference between the *ex-ante* and *ex-post* rate of return and h_t is the conditional variance of e_t. When the return of the bond is volatile, risk-averse agents will select less risky assets, in order for the risk premium to move upward. The result will be a positive relationship between h_t and y_t, as it was also evident in the work of Engle *et al.* (1987). Their model was defined as the *ARCH-in-Mean (ARCH-M)* model, which reflects the presence of the conditional variance in the conditional mean of the returns. After a series of manipulations a GARCH-M model can be developed to satisfy different market requirements. In chapter two the presentation of the empirical studies with the use of ARCH-M model showed the significance of the model in asset pricing. The model is utilised in chapter five, so as to see whether the risk-return relationship between stock returns and the stock market index is verified.

3.9.2.3 The Exponential GARCH (EGARCH) Model

One significant limitation of ARCH and GARCH models is the difficulty in capturing the *asymmetry effect*. According to the asymmetry effect positive and negative shocks do not have the same effect on the conditional variance. The asymmetry effect is defined as the feature of time series on asset prices where an unexpected drop could increase volatility more than an unexpected increase of the same size – *bad news* tends to increase volatility more than *good news*. Furthermore, ARCH and GARCH models do not have the power to capture this effect, since the lagged error terms are squared for the estimation of the conditional variance, and a positive as well as a negative error have the same effect on the conditional variance of returns. This is the reason that a different model was developed by Nelson (1991).

According to Nelson's (1991) *Exponential GARCH (EGARCH)* model, the logarithm of the conditional variance varies over time as a function of the lagged error and not the lagged squared error terms. The model can be written as:

$$\ln(h_t) = k + [1 - b(L)]^{-1}[1 + a(L)]f(u_{t-1} / h_{t-1}^{1/2}) \tag{39}$$

where

$$f(u_{t-1} / h_{t-1}^{1/2}) = \pi u_{t-1} + \rho(| u_{t-1} / h_{t-1}^{1/2} | - E | u_{t-1} / h_{t-1}^{1/2} |) \tag{40}$$

In equation (39) a(L) and b(L) are q-order and p-order lag polynomials.

If p and q are set equal to 1, we can have the following equation:

$$\ln(h_t) = k + (1 + a_1 L) f(u_{t-1} / h_{t-1}^{1/2}) + b_1 \ln h_{t-1} \tag{41}$$

which has many similarities with the GARCH(1,1) model of equation (34).

As it is obvious, according to the EGARCH model, the natural log of the conditional variance is always positive, even if the parameters are negative. This is the reason that this model does not need parameter restrictions in comparison to the previous ones. According to the model, the volatility depends not only on the magnitude of the past surprises (shocks) in returns but also on its corresponding signs. An empirical support for this specification of ARCH models is documented in Nelson (1991).

In order to understand the contribution of the EGARCH model, it would be suitable to make a comment regarding the asymmetry effect. In our study we employ, in addition to Nelson's EGARCH model, a modified one. This model is the EGARCH-M model, which has already been utilised in the ASE (Chortareas *et al.*, 2000). The study presented interesting results regarding the asymmetric response of the conditional variance to innovations of different signs and the relationship between risk and return in the mean equation.

3.9.3 Other Variations of (G)ARCH Models

As it was shown previously, in the EGARCH model we use the natural logarithm of the conditional variance to capture the asymmetry effect. This effect can also be explained with some modifications on the original GARCH model with the use of a dummy variable.

In this way, Glosten *et al.* (1993) developed a new equation for the conditional variance of the error terms:

$$h_t = a_0 + a_1 u_{t-1}^2 + k_1 u_{t-1}^2 I_{t-1} + b_1 h_{t-1} \quad \textbf{(42)}$$

where $I_{t-1} = 1$ if $u_{t-1} > 0$ and $I_{t-1} = 0$ if $u_{t-1} \leq 0$.

Equation (42) shows that the ARCH parameter in the conditional variance changes between $a_1 + k_1$ and a_1. This change depends on whether the previous period's error term is positive or negative.

There is also evidence regarding the development of another model in order for the analysts to capture the asymmetry effect. This model captures the various asymmetric specifications so as to determine the specific form of asymmetry. It was developed by Ding *et al.* (1993) and is defined as the *asymmetric power ARCH* (APARCH) model. According to the APARCH model, the equation for the conditional variance is the following:

$$h_t^{k/2} = a_0 + \sum_{i=1}^{q} a_i (| u_{t-i} | - g_i u_{t-i})^k + \sum_{j=1}^{p} b_j h_{t-j}^{k/2} \quad \textbf{(43)}$$

where $k > 0$ and $-1 < g_i < 1$.

Many different model specifications can be the result of the variation of k and g, as in the case of the model of Zakoian (1994), which is called the *threshold GARCH (TGARCH)* model, $k = 1$.

Of course, there are several other models which have been developed for different statistical or financial reasons: The Integrated GARCH (IGARCH) model, briefly mentioned before, the Fractionally IGARCH (FIGARCH) model, developed by Bailie *et al.* (1996), the Multi-variate GARCH-M model, developed by Bollerslev *et al.* (1988) in order to examine the traditional form of the CAPM and so on.

In this study, we will emphasise on the group of models that are adequate for our objectives' completion in our research on asset pricing models. Generally, a single-lag length ARCH process can be extended to higher-order ARCH processes and to other univariate time series models, bivariate and multi-variate regression models or even systems of equations.

For example, the ARCH(q) multiple regression model can be written as:

$$y_t = a_0 + \sum_{i=1}^{q} a_i x_{it} + u_t \tag{44}$$

and

$$u_t = e_t (a_0 + \sum_{t=1}^{q} a_i u_{t-i}^2)^{1/2} \tag{45}$$

where $e_t \sim IID(0,1)$ and the x_{it} are exogenous explanatory variables of y_t.

We should mention at this point that by generalising the concept of ARCH models to systems of equations (Multi-variate (G)ARCH or M-(G)ARCH models), it can only be an extension of the original specifications of the model.

3.10 Unit Root and Cointegration Analysis between Financial and Macroeconomic Indices

The following steps are followed so as to employ unit root and cointegration analysis between a number of observed financial and macroeconomic time series based on the studies of Hondroyannis and Papapetrou (2001) and Maysami *et al.* (2004):

1) We examine for the existence of a unit root in each one of the series that will be used in the analysis of cointegration.

2) If there is a unit root in the series, which means that the series is not stationary, based on the Dickey-Fuller (1981), Phillips and Perron (1988) and Kwiatkowski, Phillips, Schmidt and Shin-KPSS (1992) procedures, we examine the first differences of the series.

3) Subsequently, we follow again the Dickey-Fuller (1981), Phillips and Perron (1988) and the KPSS (1992) procedures so as to examine the first differences of the series – if the series are integrated of order 1 $(I(1))$.

4) If the tests show that the series are $I(1)$ we proceed to cointegration analysis so as to examine if there is at least one linear combination between the series (the series are cointegrated).

5) If there is at least one linear combination between the series it means that there is at least one long-run relationship that connects the variables of the analysis.

More specifically, after we see that the variables under examination are $I(1)$ we investigate whether there is any relationship between the general market index and a number of macrovariables during the period 1989–2006. Moreover, we search for possible relationships between specific sectoral indices and a number of macrovariables for the period between 1989 and 2005 (the last year of data availability for the sectoral indices). Finally we examine if there is any relationship between the general market index and two different sets of variables – the set of variables also used for the whole period (1989–2006) and a set of new variables available only for the third period (2001–2006). The following sub-sections present the unit root and the respective tests of unit root hypothesis employed in our work.

3.10.1 Unit Root Analysis

The presence of a unit root can be presented using a first-order autoregressive process:

$$y_t = l + ky_{t-1} + e_t, e_t \sim N(0, \sigma_e^2) \quad \textbf{(46)}$$

where l is a constant of the equation, k is the coefficient of the first difference of y_t and e_t is the error term which has a mean of zero and variance σ_e^2.

In this case the variance of y_t is:

$$Var(y_t) = \frac{1-k^n}{1-k}\sigma_e^2 \quad \textbf{(47)}$$

If $k \geq 1$, then there is no finite variance for y_t. If $k < 1$ the variance is $\sigma_e^2/(1-k)$.

It is verified that equation (46) has a unit root $r = 1/k$. When y_t is non-stationary, it has a root on or inside the unit circle, which means that $r \geq 1$. While a stationary variable y_t has a root $r < 1$, which means that it is out of the unit circle. As it was mentioned before, when someone tests for stationarity, he/she tests if there is a unit root in a time series.

3.10.2 The Dickey-Fuller/Augmented Dickey-Fuller Test

The Dickey-Fuller (DF) test (Dickey and Fuller, 1979; 1981) can be written as:

$$\Delta y_t = l + (k-1)y_{t-1} + e_t = l + py_{t-1} + e_t \tag{48}$$

after the subtraction of y_{t-1} from both sides of equation (46)

In this test the null hypothesis says that there is a unit root in the time series, which means that $H_0 : p = 0$, while $H_1 : p < 0$, which is the alternative hypothesis and means that there is no unit root in the time series. Equation (48) gives the simplest case of a DF test where the residual is white noise. In fact, the residuals exhibit serial correlation most of the time and Δy_t can be rewritten as:

$$\Delta y_t = l + py_{t-1} + \sum_{t=1}^{c} f_i \Delta y_{t-i} + e_t \tag{49}$$

Equation (49) is the equation for the so-called Augmented Dickey-Fuller (ADF) test. This is the improved version of the Dickey-Fuller test as it accommodates higher-order autoregressive processes in e_t (Greene, 2003). The ADF test is one of the unit root tests that are used in the analysis.

3.10.3 The Phillips-Perron Test

The Phillips-Perron (PP) (1988) test is an extension of the ADF test. This test is more robust in the case of weak autocorrelation and heteroscedastic regression residuals. The PP test appears to be more valid for aggregate data in comparison to the

ADF test (Choi, 1992). It is based on equation (49) and examines its component at zero frequency. The t-statistic of the PP test is:

$$t = \sqrt{\frac{r_0}{h_0}} t_p - \frac{(h_0 - r_0)}{2 h_0 \sigma} \sigma_p \tag{50}$$

where

$$h_0 = r_0 + 2\sum_{\tau=1}^{v} (1 - \frac{j}{T}) r_j \tag{51}$$

is the variance of the v – period differenced series $(y_t - y_{t-v})$, r_j is the autocorrelation function at lag j, t_P is the t-statistic of p, σ_p is the standard error of p and σ is the standard error of the test regression. Finally, r_0 is the variance of the difference of one period $(\Delta y_t = y_t - y_{t-1})$.

It is important to mention that the Phillips and Perron test reduces the significance of the p estimate as k moves from zero to unity – or as p moves from -1 to 0 – in order to correct for the effect of non-conventional t-distributions.

3.10.4 The Kwiatkowski, Phillips, Schmidt and Shin Test

In the ADF test the null hypothesis supports the existence of a unit root in a time series. This hypothesis is not supported in the case that there is strong evidence against it. If there is evidence of stationarity near unit roots processes, then the ADF tests cannot give precise results and the model has a relative low power.

Due to lack of power in the ADF test (Elliott *et al.*, 1996) another stationarity test was applied. Particularly, the Kwiatkowski, Phillips, Schmidt and Shin (KPSS)

(1992) test was used with the null hypothesis of the existence of stationarity against the alternative of a unit root. The KPSS test is based on the following equation:

$$y_t = \alpha + \delta_t + x_t + v_t, x_t = x_{t-1} + u_t \qquad \textbf{(52)}$$

where y_t = the sum of the deterministic trend, a random walk x_t and a stationary error v_t, $u_t \sim (0, \sigma_u^2)$.

According to equation (52) v_t is assumed to be stationary and for the null hypothesis that y_t is trend stationary we simply require that $\sigma_u^2 = 0$.

Many empirical studies have employed the KPSS test in order to achieve stationarity in the series under examination. Examples of financial or macroeconomic time series are the interest rate and the unemployment rate, which, according to the economic theory, must be stationary in order for researchers to have more precise results. Another example of a time series under examination is the Purchase Power Parity (PPP) whose theory is less restrictive and the empirical results may contribute to different policy implications.

3.10.5 The Engle-Granger Cointegration Test

Analytically, the Engle-Granger (1987) procedure estimates the cointegrating regression between the variables and the residuals of the regression are obtained. Then, the ADF unit root test is applied to the residuals, in order to examine their stationarity. If the series under examination are found to be non-stationary, but integrated of the same order (e.g. I(1)), the cointegration test is applied. Equations (53a) and (53b) illustrate the cointegrating regressions:

$$x_t = l + k_1 y_t + e_{x,t} \qquad \textbf{(53a)}$$

$$y_t = l + k_1 x_t + e_{y,t} \qquad \textbf{(53b)}$$

After the residuals are obtained, equation (54) is used for the ADF test, which is the same with equation (49), after a little modification for the two variables example:

$$\Delta \hat{e}_t = l_1 \hat{e}_{t-1} + \sum_{i=1}^{v} a_1 \Delta \hat{e}_{t-1} + \varepsilon_t \qquad \textbf{(54)}$$

where Δe_t contains the $e_{x,t}$ or the $e_{y,t}$ processes and the null hypothesis $H_0 : l_1 = 0$ of no cointegration is examined. The test statistics that are obtained from the analysis, are compared against the table developed by McKinnon (1991).

3.10.6 The Johansen Multi-variate Cointegration Test

In case there is a vector y_t of non-stationary first-order integrated variables which can be expressed by a vector autoregressive (VAR) model, based on the studies of Johansen (1988; 1991) and Johansen and Juselius (1990):

$$y_t = A_1 y_{t-1} + \ldots + A_k y_{t-k} + BX_t + e_t \qquad \textbf{(55)}$$

where $A_1, \ldots, A_k$ = the matrices of the coefficients of the model.

e_t = the vector of the residuals of the system that has a mean equal to zero, constant variance and its values are not serially correlated.

Equation (55) can also be presented in its first differences as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} a_i \Delta y_{t-i} + BX_t + e_t \tag{56}$$

where

$$\Pi = \sum_{i=1}^{p} A_i - I \text{ and } a_i = -\sum_{j=i+1}^{p} A_j \tag{57}$$

The rank of the matrix Π is the one that determines the existence of cointegration (long-run relationship) between the variables of the vector. If the rank is equal to 0, then this means that there is no cointegration between the variables. Two tests statistics are used in the test, developed by Johansen (1988; 1991). These are the trace test statistic and the maximum eigenvalue test statistic. The trace statistic tests the null hypothesis that $r = 0$, which means that there is no cointegration, against the alternative hypothesis of $r \geq 1$. The maximum eigenvalue statistic tests the null hypothesis that the number of the vectors of cointegration is equal to zero ($r = 0$) against the alternative of $r = 1$.

We should mention here that, in addition to the panel data unit root tests, there were developments of methods on panel cointegration tests. The researches of Kao and Chiang (1998) and Moon and Phillips (1999) are examples of the use of panel cointegration tests.

3.11 Conclusions

Our focus is on the standard Sharpe-Lintner CAPM and the two main versions of the APT model. Regarding the CAPM, Chen's (1983) methodology will be followed using monthly data having as the prime goal of this part of the study a process that may give the most accurate results regarding the true relationship between stock returns and the factor(s) that affect them in a stock market during specific periods under examination.

Although it will be mentioned later in more details, it is important to explain that the analysis extends from 1989 to 2006, which is a period of great changes/reforms in the Greek stock market and so far there is no similar analysis that has used a data sample for this period under examination, plus the fact that the sample has been divided into sub-periods for comparison purposes between the models under examination as well as between the results of the non-overlapping sub-periods.

Regarding the application of the statistical APT model, our work is based on prior studies (Roll and Ross, 1980; Chen, 1983; Chamberlain and Rothschild, 1983; Faff, 1988) so as to examine if the factors comprising the model have any influence on the behaviour of stocks' portfolios. Moreover, as far as the macroeconomic APT model is concerned, the methodology that is followed is based on prior studies which used a number of macroeconomic indices (that is Chen *et al.*, 1986; Chen and Jordan, 1993; Clare and Thomas, 1994; Cauchie *et al.*, 2004) to examine if these variables can explain stocks' behaviour.

During the progress of the empirical tests the derivation of factors, and their respective significance, from the statistical version of the model, will be combined with the variables used in the macroeconomic APT model through the use of canonical correlation analysis (McGowan *et al.*, 1993; Cheng, 1995). It is also interesting to mention that no such test has been employed for the ASE and its empirical applications are generally minimal.

After this exploration of the CAPM and APT models, in a subsequent chapter (chapter five) the analysis continues based at first on the application of (G)ARCH on asset pricing models. Our aim, regarding the use of (G)ARCH models, is to examine their possible influence on asset pricing models. The tests that will be used in this part of the analysis have been widely used in asset pricing. The selection of (G)ARCH models will be based on their already significant contribution on asset pricing that is the ARCH-M model of Engle *et. al.* (1987) and the standard GARCH model of Bollerslev (1986) used e.g. in the work of Koutmos and Theodossiou (1993) to examine the macroeconomic APT model, as well as several models developed later which played a significant role in different areas of financial analysis. For example, in order to investigate the impact of news on the volatility of stocks, Friedmann and Sanddorf-Kohle (2002) compared the EGARCH model of Nelson (1991), which was initially developed to capture possible asymmetric effects, and the asymmetric GARCH model of Glosten *et al.* (1993).

Furthermore, based on the theory and the empirical studies of unit roots and cointegration, we will focus on the existence of stationarity of the series under examination (Nelson and Plosser, 1982; Kwiatkowski *et al.*, 1992). Then, we will investigate whether there are any long-run relationships between market indices and specific macroeconomic indices in order to be able to identify possible associations between the variables (Niarchos and Alexakis, 2000; Kim, 2002; Yong *et al.*, 2004; Dritsakis, 2004a; 2004b). Chapter four presents the empirical results based on the applications of the CAPM and the APT models.

Chapter Four

EMPIRICAL TESTS AND RESULTS OF THE CAPM AND APT MODELS

4.1 Introduction

In chapter three we have reviewed the methodology that is followed so as to come to some conclusions regarding the existence of factors that affect the behaviour of stock returns. In the present chapter we begin our analysis by applying the CAPM and the two APT models. The main purpose is to investigate whether the stock market index, that is used as a proxy for the market portfolio, is adequate to explain the returns of stocks. Specifically, at the beginning of the chapter we present the data sample used for the empirical tests and the respective restrictions of this choice. Then we test whether the empirical application of the Sharpe-Lintner CAPM and the statistical APT model (Roll and Ross, 1980; Chen, 1983) can explain the behaviour of stock returns in the ASE. Moreover, there are some criteria that are used so as to compare these two models. The results showed that the APT model performs better than the CAPM, a result that contradicts the (weak-form) efficiency of the ASE (Fama, 1991) as the development of the CAPM is in agreement with the efficiency of the market.

Furthermore, the time series analysis of the inflation rate is presented and we examine in details the procedure that leads to the selection of the ARIMA model used so as to estimate the final time series (the unexpected and the change in the expected inflation) needed for the application of the macroeconomic APT model. In Appendix V the calculated results from the inflation time series are presented, while Appendices IV and V depict the procedure, based on the Box-Jenkins (1976) methodology, that leads to the needed time series of the rest of the macroeconomic variables (the industrial production index and the petroleum and other fuels derivatives index). After the Box-Jenkins procedure on the inflation rate, we focus on the examination of the macroeconomic APT model. Specifically, we investigate whether the empirical application of the macroeconomic APT model, which is comprised of a number of observed macroeconomic indicators used in previous studies (Chan *et al.*, 1985; Chen *et al.*, 1986) can explain the behaviour of stock returns in the ASE. Then tests of comparison between the macroeconomic and the statistical APT model are presented and examined so as to see if the observed factors of the macroeconomic APT model are related to stock returns.

The results of the tests confirm that the stock market index has a sufficient explanatory power on the returns of portfolios. Additionally, the inflation variables that are also used in the tests prove to play an interesting role in asset pricing, a finding that contradicts prior studies (Chen and Jordan, 1993), but is in agreement with others (Chen *et al.*, 1986). Finally, the index of petroleum and other fuels derivatives series and the industrial production series seem to have a small effect on the explanation of cross-sectional stock returns, a result that is also in agreement with prior studies (Chen *et al.*, 1986; Chen and Jordan, 1993).

4.2 Data Collection

The research examines the monthly return series of listed Greek firms in the ASE. The data was obtained from the ASE databanks and it is comprised of daily closing prices of common stocks traded in the ASE. They are raw prices in the sense that they do not include any dividends but are adjusted to stock splits. These common stocks were listed in the ASE during the 1989–2006 period of analysis. The data set of 216 months was divided in three non-overlapping sub-periods (three sub-periods of

72 months each) for the needs of the analysis based on prior empirical studies (Chen, 1983; Roll and Ross, 1980). The stocks that were included in the sub-periods had a complete price history, which means that they had no missing values for this specific period of analysis due to temporary delisting or suspension or just because of missing data (Chen, 1983). The return on the market was obtained from the ASE Composite (General) Share Price Index. Finally, the three-month Government Treasury Bill Rate, which is considered to be a short-term interest rate, was used as the risk-free interest rate and was obtained from the Central Bank of Greece.

The daily returns of stocks were calculated using the logarithmic approximation:

$$R_{i,t} = \log\left(P_{i,t} \big/ P_{i,t-1} \right) \qquad \textbf{(1)}$$

where $P_{i,t}$ is the closing price of day t for asset i (Coutts *et al.*, 2000; Chortareas *et al.*, 2000). Then the daily returns were aggregated to compose the monthly return series used as the input of the analysis.

While in previous empirical studies like the one of Roll and Ross (1980) the stocks were sorted alphabetically into portfolios, in our study the portfolios were constructed based on the ranking of betas, a procedure similar to the studies of Blume (1970) and Friend and Blume (1970). The purpose was to eliminate the diversifiable risk and to reduce the error-in-variables problem (Clare and Thomas, 1994; Campbell *et al.*, 1997).

The variables explained above were used for the application and the comparison between the CAPM and the statistical APT model. For the application of the macroeconomic APT model a number of macroeconomic variables were also collected based on previous theory in order to test the model and compare the results with prior studies (Chen *et al.*, 1986; Groenewold and Fraser, 1997). In section 4.4 we examine the procedure followed as far as the selection of the macrovariables is concerned for the application of the macroeconomic APT model.

4.3 Data Analysis

The stocks that are examined have no missing values during the whole period and the sub-periods. According to the methodology that is followed, for the three sub-periods sample sizes of 72, 166 and 259 were produced respectively, while for the whole period the sample size was comprised by 62 stocks – the only stocks with no missing values during the period 1989–2006. According to prior studies (Roll and Ross, 1980) portfolios of equal size were constructed. The number of 30 stocks in each portfolio is justified as a sufficient number of stocks for the application of APT models (Roll and Ross, 1980).

The two-stage methodology was used for the analysis. This methodology has been adopted by scholars in the past and has given significant results regarding the behaviour of stock markets (Chen, 1983; Cheng, 1995; Groenewold and Fraser, 1997). As far as the CAPM is concerned, during the first stage the stock betas are estimated by regressing the excess returns of each stock (the dependent variable) for each period of analysis on the excess market index of the ASE (the independent variable) for the same period. In this way the stocks are sorted into portfolios of equal size. The stocks with the smallest betas were excluded from the analysis since complete portfolios were required (Chen, 1983; Black *et al.*, 1972). For the testing of the statistical APT model, and after stocks are sorted into portfolios as explained above, with the use of principal components analysis a set of factor betas are estimated for each portfolio of each period of analysis. During the second stage (the cross-sectional stage) we regress the mean excess returns of each portfolio on the estimated betas for the CAPM, and we regress the mean excess returns of the same portfolio on the factor betas for the statistical APT model. The procedure is similar for the macroeconomic APT model as explained in chapter three.

4.4 The Selection of Macroeconomic Data Series and the Construction of the Macroeconomic Variables

According to several prior studies (Chen *et al.*, 1986; Chen and Jordan, 1993; Clare and Thomas, 1994; Cheng, 1995; Groenewold and Frazer, 1997), if someone wants to examine the validity of a macroeconomic APT model, a set of macroeconomic data series should primarily be selected. In the following sub-sections we present the macroeconomic variables that have been selected and the way they have been estimated.

4.4.1 Unexpected Inflation

As far as the inflation variables are concerned, and in order to employ the Box-Jenkins time series approach explained in chapter three, we primarily calculated the monthly inflation rate as the change in the natural log of the Greek monthly Consumer Price Index during the period 1989–2006. There is an agreement to the proposition that the rate of return of common stocks moves with the rate of inflation (Niarchos and Alexakis, 2000). This agreement, in addition to the fact that the inflation rate and its variations have been used several times in asset pricing (Chan *et al.*, 1985; Chen *et al.*, 1986; Chen and Jordan, 1993; Niarchos and Alexakis, 2000) led us to use the inflation rate index in order to estimate the expected inflation, the unexpected inflation and the change in the expected inflation based on the Box-Jenkins (1976) approach.

The monthly inflation rate was calculated as the change in the natural log of the Greek monthly Consumer Price Index during the period 1989–2006. This calculation of the inflation rate is similar to that of previous studies (Chen *et al.*, 1986; Lakshman and Horton, 1999). Specifically, the calculation was based on the following equation:

$$I_t = \log(CPI_t / CPI_{t-1}) \qquad \textbf{(2)}$$

where I_t is the inflation rate at month t and CPI_t is the consumer price index at the respective month t. The unexpected inflation rate was calculated as in the study of Chen and Jordan (1993):

$$UI_t = I_t - E(I_t) \qquad \textbf{(3)}$$

where I_t is the realised monthly Greek inflation rate for period t. The series of the expected inflation $E(I_t)$ was estimated after the development of an ARIMA (0,1,5) (0,0,1) model, following the Box-Jenkins (1976) methodology, already used in prior studies (Fama and Gibbons, 1982; 1984).

4.4.2 Change in Expected Inflation

The change in the expected inflation was used in the analysis as it is partially unanticipated and has an influence which is separate from the influence of UI_t (Chen *et al*, 1986; Chen and Jordan, 1993). The equation that is used for the calculation of this variable is the following:

$$CEI_t = E(I_{t+1}) - E(I_t) \tag{4}$$

From equation (4) it becomes clear that the series of the change in the expected inflation, CEI_t, is the series of first differences of the expected inflation estimated after the development of the respective ARIMA model.

4.4.3 Growth Rate of Industrial Production

Based on the general hypothesis that the returns of stocks can be influenced by real domestic activity (Groenewold and Fraser, 1997) and based on previous studies on the application of APT models (Chan *et al.* 1985; Chen and Jordan, 1993; Clare and Thomas, 1994; Cheng, 1995) we collected the Industrial Production Index from the National Statistical Service of Greece. If IP_t is the index of the industrial production at month t, then the monthly growth rate in industrial production, $GRIP_t$, was calculated based on equation (5):

$$GRIP_t = \log_e(IP_t / IP_{t-1}) \tag{5}$$

The series of the growth rate of industrial production, $GRIP_t$, was used as the observed data series in the development of an ARIMA (9,0,1) (1,1,0) model in order to estimate the expected change in the growth rate in industrial production, $EGRIP_t$, based, as in the case of the inflation rate, on the Box-Jenkins (1976) methodology. Then we calculated the unexpected change in the growth rate in industrial production, $UGRIP_t$, which is the difference between the observed and the expected values (the residuals) of the series of growth rate of the industrial production (Chen and Jordan, 1993).

4.4.4 Manufacture of Coke, Refined Petroleum Products and Nuclear Fuels

The index of manufacture of coke, refined petroleum products and nuclear fuels, which is comprised mostly by products that are constructed based on petroleum, was also collected from the National Statistical Service of Greece. It was used in the analysis for comparison purposes as similar indices were used in the studies of Chen *et al.* (1986) and Chen and Jordan (1993) and its significance was justified by Pari and Chen (1984). CPS_t is the change in the petroleum series at month t and was calculated based on the following equation:

$$CPS_t = \log_e(PS_t / PS_{t-1}) \qquad \textbf{(6)}$$

where PS_t is the petroleum prices index – we use the term "petroleum" not only for abbreviation purposes but because of the fact that the index is comprised mostly by refined petroleum derivatives. The series of the change in the petroleum index was used in the development of an ARIMA (0,0,2) (0,0,0) model in order to estimate the expected change in the petroleum series and, then, to calculate the unexpected change in the petroleum series, $UCPS_t$, based on the Box-Jenkins (1976) methodology and used in the respective studies of Chen *et al.* (1986) and Chen and Jordan (1993).

It is important to mention at this point that, as there is no crude petroleum in Greece, there is no such index available from the National Statistical Service and the only index that has any similarity with the methodologies that are followed and the respective variables that are used is this index, which presents the trend of constructed products, mainly by refined petroleum.

4.4.5 Stock Market Index

Finally, as explained in section 4.2, the general market index of the ASE was used also in the set of the variables for the application of the macroeconomic APT model. The return on the market was obtained from the ASE Composite (General) Share Price Index. It was also used in the study for comparison purposes with previous studies (Chan *et al.*, 1985; Chen *et al.*, 1986). Chen *et al.* (1986) pointed that although a stock market index explains a significant part of the variability of stock returns, its role is almost insignificant in the pricing of stocks when it is compared with other variables. In table 4.1 the basic data series and the derived series are presented:

***Table 4.1*: The presentation and measurement of the macrovariables**

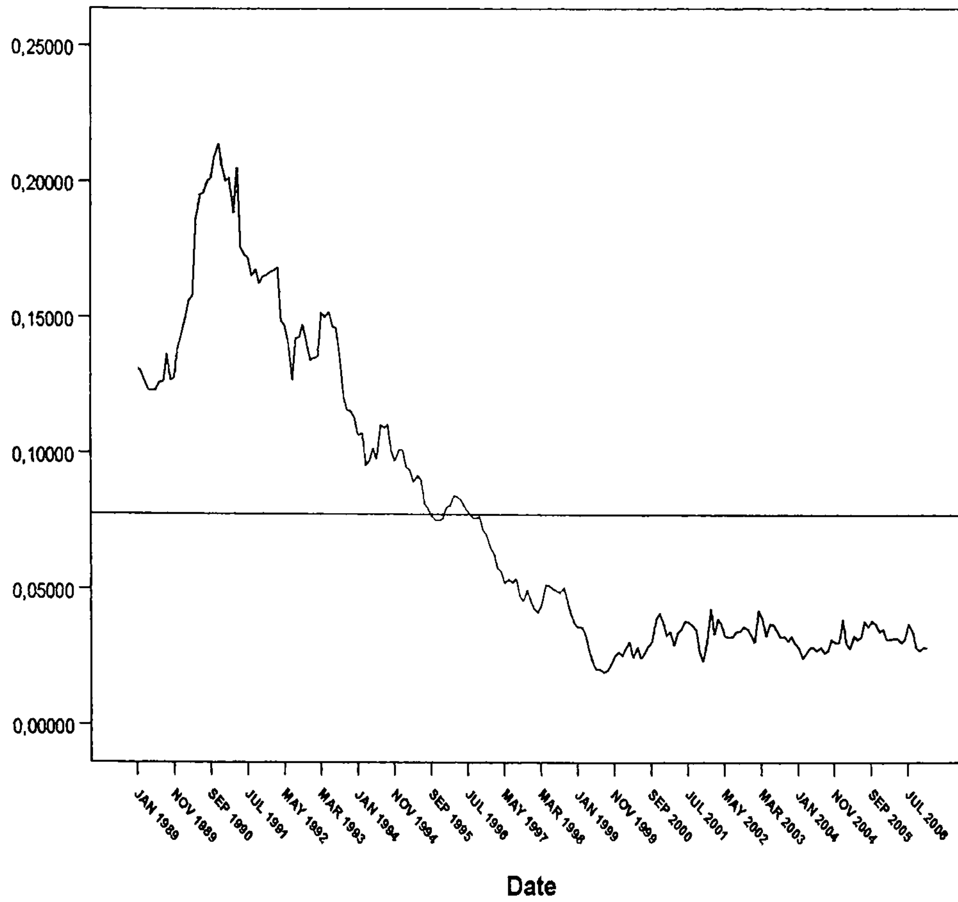
Macroeconomic Variables		
a. Basic Data Series		
Symbol	**Variable**	**Measurement**
I_t	Inflation	Consumer Price Index
IP_t	Industrial Production	Total Index of Industrial Production

PS_t	Petroleum Series	Producer Price Index: Manufacture of Coke, Refined Petroleum Products and Nuclear Fuels
RMI_t	Stock Market Index Return	Return on an equally-weighted market portfolio of the ASE
b. Derived Series		
Symbol	**Variable**	**Measurement**
$E(I_t)$	Expected Inflation	Estimated from an ARIMA (0,1,5)(0,0,1) model, based on the Box-Jenkins (1976) methodology
UI_t	Unexpected Inflation	$UI_t = I_t - E(I_t)$
CEI_t	Change in Expected Inflation	$CEI_t = E(I_{t+1}) - E(I_t)$
$GRIP_t$	Growth Rate in the Industrial Production	$GRIP_t = \log_e(P_t / P_{t-1})$
CPS_t	Change of the Petroleum Series	$CPS_t = \log_e(PS_t / PS_{t-1})$

4.5 Time Series Analysis of the Inflation Rate (1989–2006)

Initially we examine the stationarity of our data by plotting the values of the rate of inflation in Greece during the period 1989–2006. Figure 4.1 shows that the time series is not stationary as there is a trend and the variance of the observed values is not constant. Specifically, the inflation series exhibits numerous peaks, many of which appear to be equally spaced, as well as a clear trend. The equally spaced peaks suggest the presence of a periodic component to the time series. As far as the trend is concerned, at the beginning of the series there is an immediate increase and, then, a decreasing course follows until to the point that the series becomes more stable. This increase and decrease in the series confirms the properties of a stochastic process and shows that the application of the first differences is proposed as the correct method so as to transform a series from a non-stationary to a stationary one.

Figure 4.1: **The rate of inflation in Greece (1989–2006)**



The autocorrelations and partial autocorrelations were examined with the use of Box-Ljung statistic for their significance. If the p-value is less than 0.05 (<0.05) then the autocorrelation is significant. Table 4.2 presents the autocorrelations and it can be seen that each one of them is statistically significant. The Box-Ljung statistic varies between 214.771 (df=1) and 2969.282 (df=16) and the p-values are all less than 0.001. Also the values of the autocorrelations are greater than two times the standard error for all of them. These findings suggest that we have to take the first differences of our data.

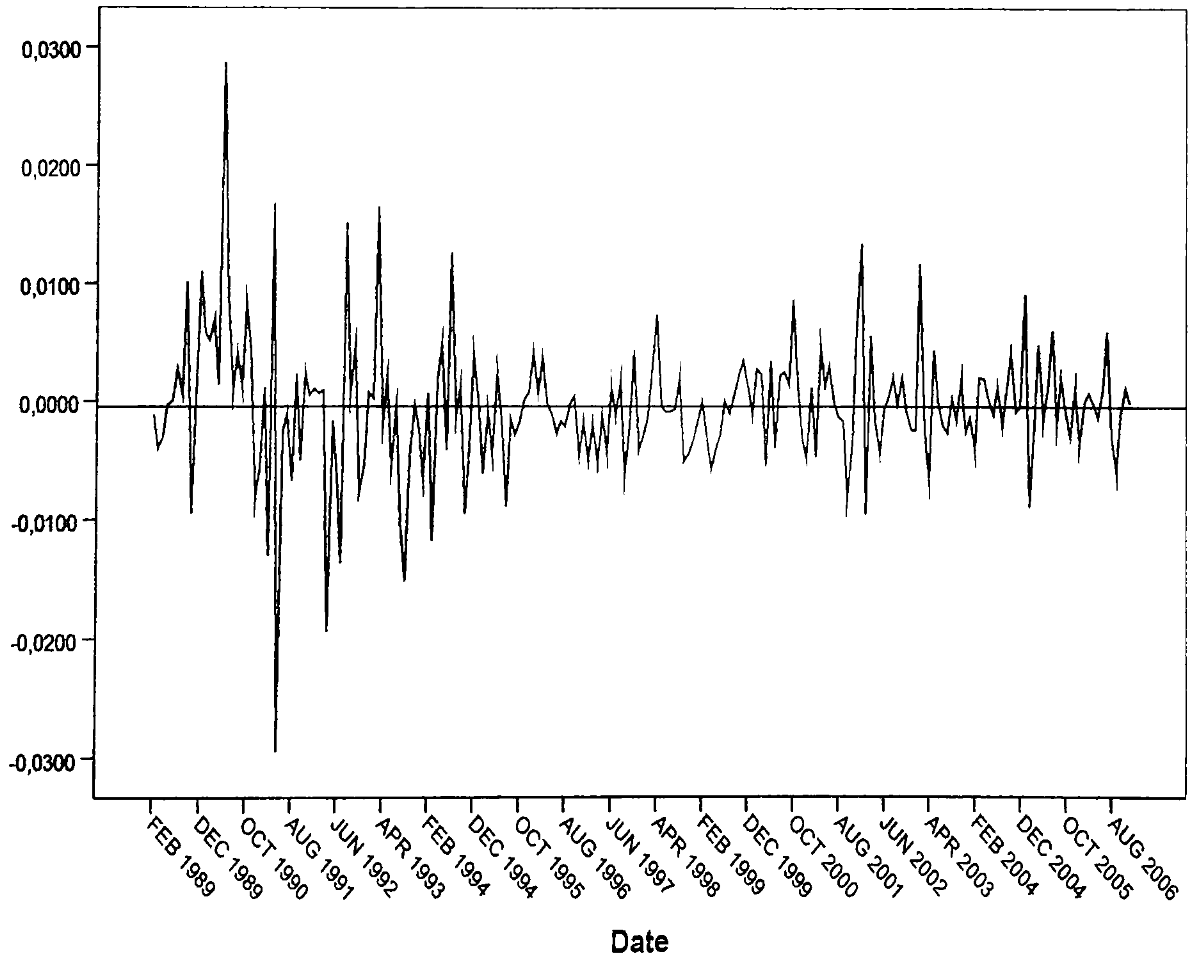
Table 4.2: **The autocorrelations of inflation rate series in Greece (1989–2006)**

Lag	Autocorrelation	Std. Error(a)	Box-Ljung Statistic		
			Value	Df	Sig.(b)
1	.990	.068	214.771	1	.000
2	.981	.067	426.564	2	.000
3	.971	.067	634.872	3	.000
4	.960	.067	839.360	4	.000
5	.949	.067	1040.505	5	.000
6	.938	.067	1237.602	6	.000
7	.925	.067	1430.364	7	.000
8	.912	.066	1618.803	8	.000
9	.899	.066	1802.479	9	.000
10	.885	.066	1981.610	10	.000
11	.873	.066	2156.562	11	.000

12	.858	.066	2326.633	12	.000
13	.848	.066	2493.328	13	.000
14	.836	.065	2656.167	14	.000
15	.822	.065	2814.633	15	.000
16	.810	.065	2969.282	16	.000

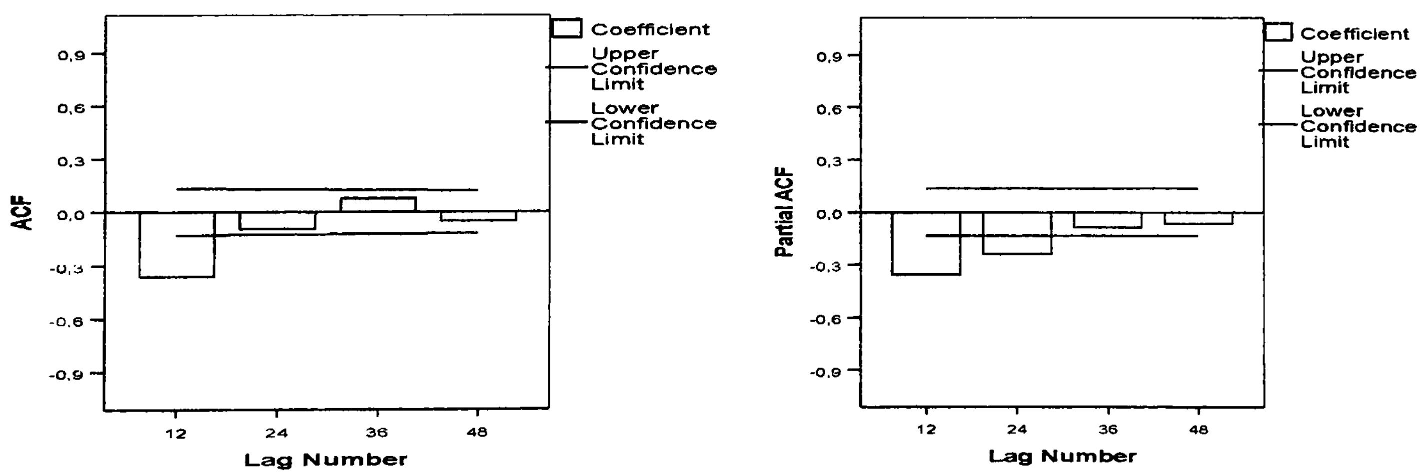
The first non-seasonal differences $z_t = y_t - y_{t-1}$ of our observations were computed and the plot of the new time series against time (for the same period 1989–2006) is presented in figure 4.2 below. It can be seen that the new series is stationary as there is no obvious trend in the new observations. It is also noticeable to mention the existence of peaks which represent significant deviations from the neighbouring data points. These points are identified as outliers. Moreover, we can observe the existence of a large positive difference between May 1990 and April 1990 and the existence of large negative differences between March 1991 and February 1991, May 1991 and April 1991, April 1992 and March 1992 and, finally, between July 1992 and June 1992.

***Figure 4.2*: The first difference series of the inflation rate (1989–2006)**



During the next step the autocorrelations and partial autocorrelations were computed for the new data, in order to estimate the parameters of the seasonal ARIMA model. According to the Box-Jenkins methodology (1976) we are looking at the seasonal autocorrelations and partial autocorrelations figures which are combined with the estimates of the Box-Ljiung statistic for them. We are interested in those lags which are outside the line limits or have p-values of the Box-Ljiung statistic less than 0.05. The existence of such values verifies that the model does not fit well to the observations. As it can be observed for lag=12 in figure 4.3, which is the seasonal autocorrelations graph (figure 4.3, left graph) and for lags=12 and 24 in figure 4.3, which is the partial autocorrelations graph (figure 4.3, right graph) the statistic shows a significant autocorrelation, hence, according to Box and Jenkins (1976) methodology we estimate the following seasonal ARIMA models: the ARIMA (0,1,0) (2,0,0) and the ARIMA (0,1,0) (0,0,1).

***Figure 4.3*: The seasonal autocorrelations and partial autocorrelations of the first differences of the series**



In table 4.3 the Box-Ljiung statistic is presented, which shows that there is not any clear view concerning the parameters of the non-seasonal part of the series and this is why we will start the analysis with the estimation of the seasonal ARIMA (0,1,0) (2,0,0) and ARIMA (0,1,0) (0,0,1) models.

***Table 4.3*: The autocorrelations of the first difference of the inflation rate series in Greece (1989–2006)**

Lag	Autocorrelation	Std. Error(a)	Box-Ljung Statistic		
			Value	Df	Sig.(b)
1	-.047	.068	.485	1	.486
2	.124	.068	3.866	2	.145
3	.099	.067	6.038	3	.110
4	-.061	.067	6.870	4	.143
5	.170	.067	13.270	5	.021
6	-.001	.067	13.271	6	.039
7	-.015	.067	13.320	7	.065
8	.029	.067	13.510	8	.095
9	.029	.066	13.695	9	.134
10	-.089	.066	15.490	10	.115
11	.076	.066	16.823	11	.113
12	-.363	.066	47.058	12	.000
13	.062	.066	47.939	13	.000
14	.088	.066	49.734	14	.000
15	-.135	.065	54.001	15	.000
16	.150	.065	59.243	16	.000

4.5.1 The ARIMA (0,1,0) (2,0,0) Model

In table 4.4 the statistics of the ARIMA (0,1,0) (2,0,0) model are presented:

***Table 4.4*: The model statistics of the ARIMA (0,1,0) (2,0,0)**

Model	Number of Predictors	Model Fit statistics			Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	MaxAPE	Statistics	DF	Sig.	
First Differences of the Rate of Inflation	0	.195	5.863	27.301	45.893	16	.000	0

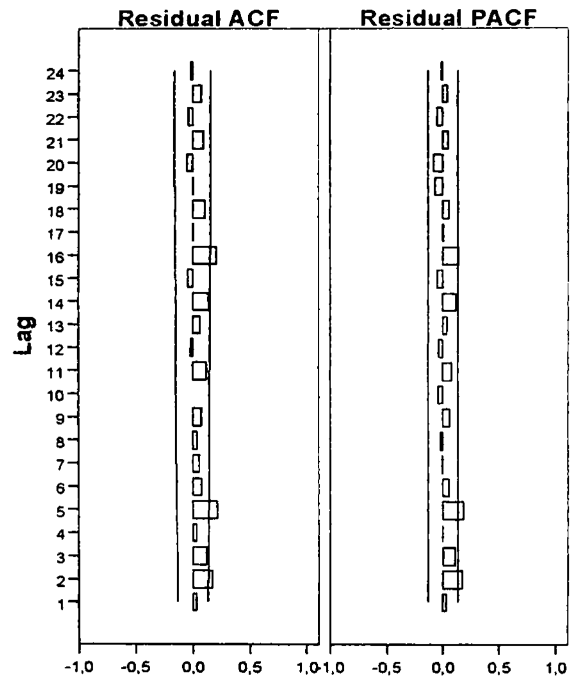
The model statistics table (table 4.4) provides summary information and goodness-of-fit statistics for the estimated ARIMA (0,1,0) (2,0,0) model. The stationary R^2=0.2 (0.195) value is a statistic that provides an estimate of the proportion of the total variation in the series that is explained by the model and is preferable to the ordinary R-squared value when there is a trend or a seasonal pattern, as in the case here. Larger values of stationary R^2 (up to a maximum value of 1) indicate a better fit.

Moreover, the Ljung-Box statistic, which is also known as the modified Box-Pierce statistic, provides an indication of whether the model is correctly specified. A value of significance which is less than 0.05 (here $p<0.001$) implied that there is structure in the observed series which is not accounted for by the model (an indication of no good fit to the data).

The absolute percentage error is a measure of the uncertainty in one's predictions. From the results of table 4.4, it is evident that the mean uncertainty in our model's predictions is about 5.8 per cent and the maximum uncertainty is around 27.3 per cent (the MAPE and MaxAPE respectively). Whether these values represent an acceptable amount of uncertainty depends on the degree of risk one is willing to accept.

Moreover from figure 4.4 it is seen that some of the autocorrelation and partial autocorrelation values are significant (for lags=2 and lag=5 the values cross the line limits), hence our first model needs to be corrected.

Figure 4.4: **The autocorrelations and the partial autocorrelations of residuals of the ARIMA (0,1,0) (2,0,0) model**



After the results of the ARIMA (0,1,0) (2,0,0) we proceed to the examination of the ARIMA (0,1,0) (0,0,1) presented in the following section.

4.5.2 The ARIMA (0,1,0) (0,0,1) Model

Similarly, table 4.5 presents the statistics of the ARIMA (0,1,0) (0,0,1) model:

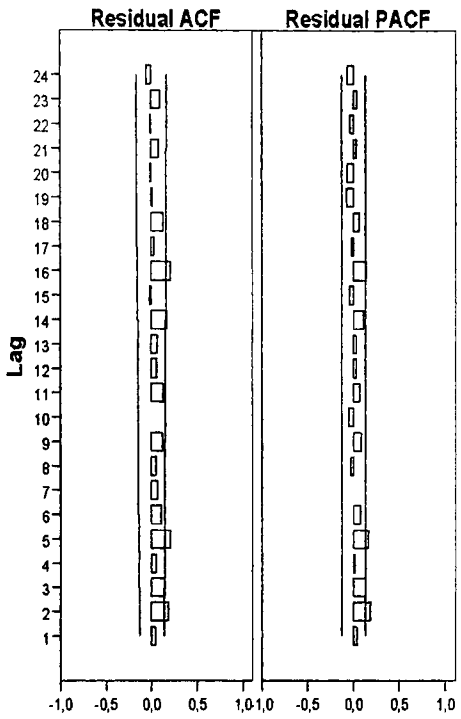
Table 4.5: **The model statistics of the ARIMA (0,1,0) (0,0,1)**

Model	Number of Predictors	Model Fit statistics			Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	MaxAPE	Statistics	DF	Sig.	
First Differences of the Rate of Inflation	0	.202	5.986	29.933	56.089	17	.000	0

As in table 4.4, this table provides respectively its summary information and goodness-of-fit statistics for the ARIMA (0,1,0) (0,0,1) model. The stationary R^2=0.2 (0.202), Q=56.089, p<0.001, hence we reject the null hypothesis that the model fits the data. It is also evident from the respective statistics that the mean uncertainty in the model's predictions is about 6 (5.986) per cent and the maximum uncertainty is around 30 (29.933) per cent (the MAPE and MaxAPE respectively).

Furthermore, figure 4.5 shows that some of the autocorrelation and partial autocorrelation values are significant (for lags=2 and lag=5 the values cross the line limits), hence this model also needs to be corrected.

***Figure 4.5*: The autocorrelations and the partial autocorrelations of residuals of the ARIMA (0,1,0) (0,0,1) model**



Based on the results presented above, and following the Box-Jenkins (1976) methodology (presented in chapter three), we analysed the ARIMA (5,1,0) (2,0,0), the ARIMA (0,1,5) (2,0,0), the ARIMA (5,1,0) (0,0,1) and the ARIMA (0,1,5) (0,0,1) models in the same way, so as to improve the initial ARIMA (0,1,0) (2,0,0) and ARIMA (0,1,0) (0,0,1) models. The best model after the analysis was the ARIMA (0,1,5) (0,0,1), as this was the one with insignificant autocorrelations. In the following section we present the statistics concerning the selected model.

4.5.3 The ARIMA (0,1,5) (0,0,1) Model

Table 4.6 provides respectively summary information and goodness-of-fit statistics for the ARIMA (0,1,5) (0,0,1) model. The stationary R^2=0.26 (0.259), Q=16.505, p=0.169>0.05 hence we cannot reject the null hypothesis that the model fits the data well. It is also evident from the respective statistics that the mean uncertainty in the model's predictions is about 6 (5.979) per cent and the maximum uncertainty is around 31 (31.473) per cent (the MAPE and MaxAPE respectively).

***Table 4.6*: The model statistics of the ARIMA (0,1,5) (0,0,1)**

Model	Number of Predictors	Model Fit statistics			Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	MaxAPE	Statistics	DF	Sig.	
First Differences of the Rate of Inflation	0	.259	5.979	31.473	16.505	12	.169	0

In table 4.7 below the coefficients that are significantly different from 0 are those concerning the constant (p=0.001), lag=2 (p=0.02<0.05), lag=5 (p=0.007<0.05) for the first differences moving average component and the seasonal lag=1 (p<0.001) for the seasonal moving average component.

***Table 4.7*: The model parameters of the ARIMA (0,1,5) (0,0,1)**

					Estimate	SE	T	Sig.
First Differences of the Rate of Inflation	The Rate of Inflation	No Transformation	Constant		-.001	.000	-3.401	.001
			Difference		1			
			MA	Lag 1	.009	.069	.135	.893
				Lag 2	-.160	.068	-2.339	.020
				Lag 3	-.100	.069	-1.450	.148
				Lag 4	.007	.069	.100	.921
				Lag 5	-.187	.068	-2.740	.007
			MA, Seasonal	Lag 1	.644	.064	10.132	.000

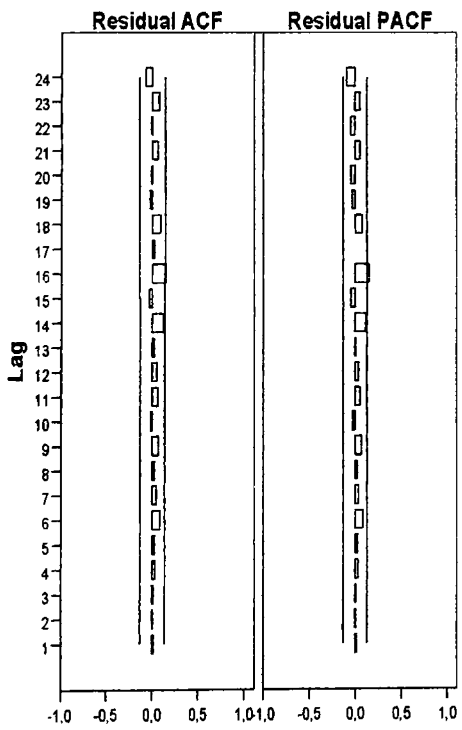
As it can be seen in Table 4.8, which contains the Box-Ljung Statistic for the autocorrelation function and the standard errors, each value of the autocorrelation function is non-significant (p>0.05 in column Sig. (b)).

Table 4.8: **The autocorrelation of the residuals of the ARIMA(0,1,5) (0,0,1) model**

Lag	Autocorrelation	Std. Error(a)	Box-Ljung Statistic		
			Value	Df	Sig.(b)
1	.015	.068	.052	1	.820
2	.008	.068	.068	2	.967
3	.011	.067	.094	3	.992
4	.029	.067	.277	4	.991
5	.024	.067	.410	5	.995
6	.083	.067	1.929	6	.926
7	.042	.067	2.316	7	.940
8	.025	.067	2.452	8	.964
9	.071	.066	3.602	9	.936
10	-.014	.066	3.645	10	.962
11	.061	.066	4.503	11	.953
12	.050	.066	5.079	12	.955
13	.023	.066	5.198	13	.971
14	.120	.066	8.563	14	.858
15	-.029	.065	8.760	15	.890
16	.155	.065	14.417	16	.568

Moreover, figure 4.6 shows that the values of the autocorrelation and partial autocorrelation functions are insignificant, as no one of them is crossing the line limits that represent the 95 per cent confidence interval.

Figure 4.6: **The autocorrelations and the partial autocorrelations of residuals of the ARIMA (0,1,5) (0,0,1) model**



Following the procedure above, we concluded to a moving average (MA) first differences model which is the ARIMA (0,1,5) (0,0,1) model.

4.5.4 Three-Month Inflation Forecast

We test whether the model that we have selected is proper so as to forecast the first three months of 2007 (January–March). Figure 4.7 below depicts the observed, the fitted and the forecasted values for the model that uses all the coefficients of the ARIMA (0,1,5) (0,0,1). Furthermore, the results of the three-month forecast are presented in table 4.9 (below) and, on average, they are seemingly good.

***Figure 4.7*: The observed, the fitted and the forecasted values of the inflation rate series (1989–2006)**

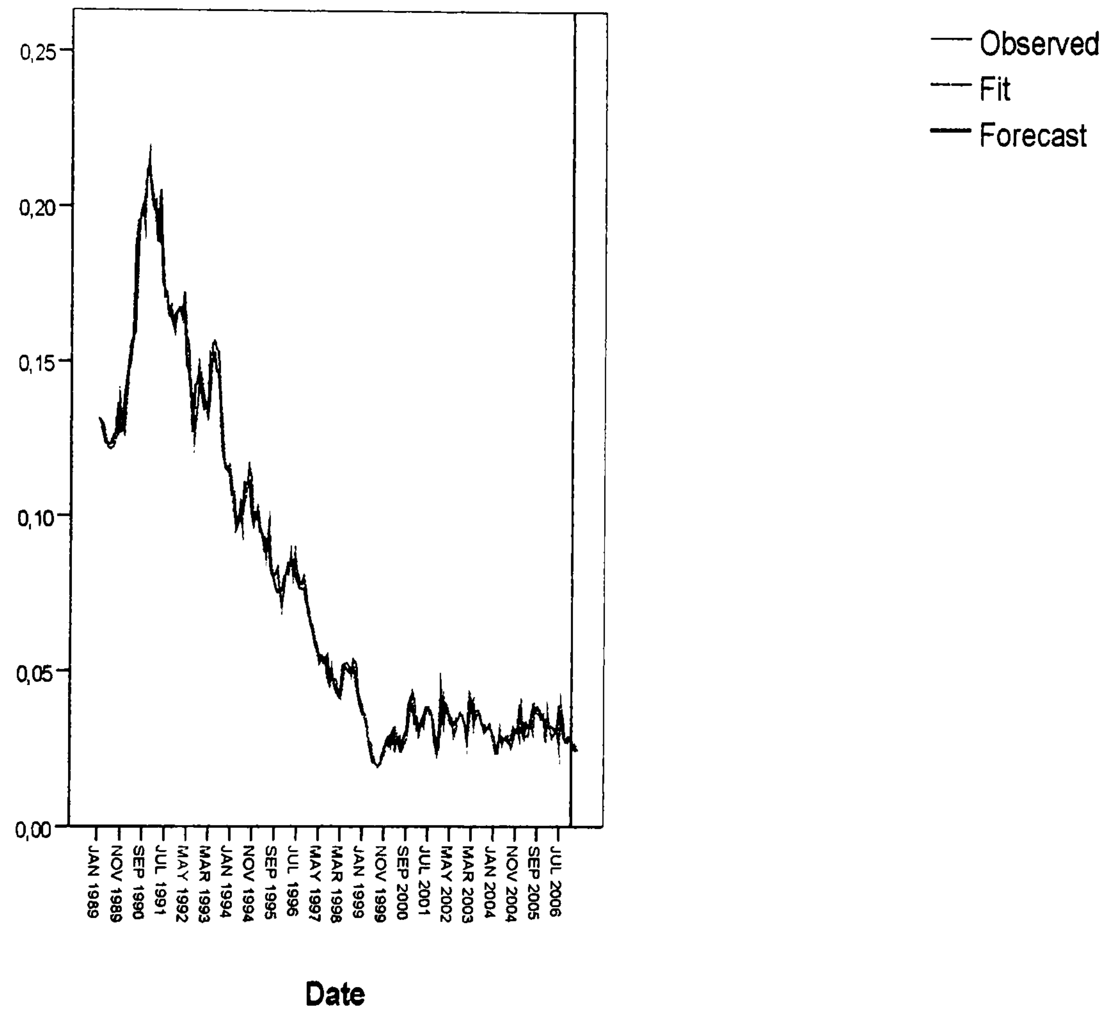


***Table 4.9*: The forecast results of the ARIMA (0,1,5) (0,0,1) model for the inflation rate series (1989–2006)**

Model		JAN 2007	FEB 2007	MAR 2007
First Differences of the Rate of Inflation	Forecast	0.02496	0.02607	0.02429
	UCL	0.03458	0.03961	0.04178
	LCL	0.01535	0.01254	0.00681
	Observed	0.02690	0.02640	0.02600

After the development of the model that best fits the data, we estimated the values of the expected and the unexpected (residuals) inflation, based on previous studies (Fama and Gibbons, 1984) and the change (difference) of the expected inflation (Chen *et al.*, 1986; Chen and Jordan, 1993). These values are presented in Appendix V in addition to the observed inflation values and the respective time period of investigation. The unexpected inflation and the change in the expected inflation will be used as variables in the application of the macroeconomic APT model, in addition to other variables (the general market index and the industrial production index). The results of the tests will lead us to understand the significance – or insignificance – of specific factors in the ASE. We should note at this point that the respective analytical procedures for the industrial production index and the petroleum derivatives index are presented in Appendix VI and VII.

4.6 Normal Distribution of Returns

Table 4.10 presents some statistics regarding the normal distribution of the time series of analysis. It is evident that the null hypothesis of normal distribution cannot be rejected at the 5 per cent confidence interval in 35 per cent, 30 per cent and 55 per cent of stock returns for the three sub-periods respectively. It is of interest to mention that only 1 of the 60 stock returns for the whole period (1989–2006) follows the normal distribution.

***Table 4.10*: Sample size and normal distribution for all the periods**

Period	Number of stocks	Normal Distribution (%)
1989–2006	60	1.6
1989–1994	60	35
1995–2000	150	30
2001–2006	240	55

The results from the descriptive statistics of Table 4.10 show that, for the three sub-periods, there is a sufficient number of normally distributed returns, which may lead to more reliable conclusions regarding the behaviour of stock returns in the ASE. Appendix III presents the distribution of the stock returns for each period of investigation.

4.7 Empirical Findings of the CAPM in the ASE

4.7.1 CAPM Cross-sectional Test Results

Table 4.11 reports the results of the tests, which are not in favour of the CAPM. At the first row of each portfolio the intercept term, the beta coefficient, the adjusted R^2, the Durbin-Watson (DW) statistic and the F statistic are presented, while below each intercept and beta the p-values for the t-tests of significance are presented in italics and show if the coefficients are statistically significant (priced) or not for each portfolio or group of portfolios (the sum of stocks for each period).

For the whole period (1989–2006) it is obvious that the CAPM cannot explain the behaviour of stock returns, as it can be seen from the adjusted R^2. It is almost close to zero and, especially in the case of the 2nd portfolio, it has a negative value. A confirmation that the linear model (CAPM) used for the analysis is not correct and we might need a non-linear model to explain the relationship between the average excess returns and the market portfolio. The beta coefficients are all insignificant for all the portfolios and the F statistic shows that the independent variable (the market proxy) is not valid for the explanation of the variation in the dependent variable. The only interesting part here is that the intercept term is statistically equal to zero (>0.05) for each of the two portfolios, which means that the market proxy selected is not totally invalid for the explanation of stock returns.

As far as the first sub-period (1989–1994) is concerned, the results seem to be a little better as for portfolio 2 and for both portfolios, the adjusted R^2 is 14.5 per cent and 18.1 per cent and the F statistic is 0.022 and 0.000 respectively. This means that the model present a small adequacy so as to predict the behaviour of stock returns. In other words, the developed model using the general market index as a proxy for the market portfolio has some explanatory power. Moreover, although the beta coefficients are statistically significant for portfolio 2 and for the group of portfolios (0.022 and 0.000 respectively), the intercept term is also statistically significant (statistically different from zero), meaning that the model cannot be verified during this period.

For the period between 1995 and 2000 the results show that stock returns were victims of the most turbulent period of the ASE for the last 15 years. The trouble with the so-called "bubbles" in the ASE and the ultimate breakdown during the period 1999–2000 is evidence that no linear model would really had the ability to predict the behaviour of stocks. The adjusted R^2 are all negative, except for portfolio 4 and the beta coefficients are all statistically insignificant. Interestingly, the intercept term is not statistically different from zero for all the portfolios, which means that the market proxy used in the application of the CAPM exhibit some explanatory power.

Finally, for the last sub-period 2001–2006, the CAPM does not perform any better. Almost all portfolios have a negative adjusted R^2, except portfolio 2 and 6 (if this really means anything as they are all close to zero) and the beta coefficients are still insignificant.

Table 4.11: **The cross-sectional test results of the CAPM**

Period	Portfolios	γ_0	γ_1	Adjusted R^2	DW	F Sig.
1989–1994	Portfolio 1	-0.020 *0.047*	0.019 *0.054*	0.096	1.799	0.054
	Portfolio 2	-0.031 *0.003*	0.042 *0.022*	0.145	1.841	0.022
	All portfolios	-0.020 *0.000*	0.020 *0.000*	0.181	1.801	0.000
1995–2000	Portfolio 1	0.014 *0.635*	-0.006 *0.802*	-0.033	1.926	0.802
	Portfolio 2	0.012 *0.729*	-0.004 *0.911*	-0.035	1.922	0.911
	Portfolio 3	0.028 *0.558*	-0.022 *0.674*	-0.029	1.704	0.674
	Portfolio 4	1.546 *0.056*	-1.959 *0.062*	0.087	2.307	0.062
	Portfolio 5	0.004 *0.829*	0.007 *0.798*	-0.033	2.071	0.798
	All portfolios	0.041 *0.145*	-0.028 *0.340*	-0.001	1.986	0.340
2001–2006	Portfolio 1	-0.018 *0.480*	0.001 *0.954*	-0.036	2.323	0.954
	Portfolio 2	0.083 *0.255*	-0.082 *0.164*	0.035	2.141	0.164
	Portfolio 3	0.047 *0.582*	-0.055 *0.471*	-0.016	2.262	0.471
	Portfolio 4	0.047 *0.509*	-0.057 *0.411*	-0.011	2.564	0.411
	Portfolio 5	0.040 *0.522*	-0.058 *0.392*	-0.008	2.397	0.392
	Portfolio 6	-0.792 *0.268*	0.966 *0.254*	0.012	2.204	0.254
	Portfolio 7	0.010 *0.788*	-0.033 *0.536*	-0.021	2.046	0.536
	Portfolio 8	-0.009 *0.526*	0.000 *0.990*	-0.036	2.018	0.990
	All portfolios	0.003 *0.850*	-0.012 *0.390*	-0.001	2.041	0.390
1989–2006	Portfolio 1	-0.011 *0.162*	0.012 *0.153*	0.039	2.629	0.153
	Portfolio 2	-0.004 *0.181*	0.005 *0.470*	-0.016	1.879	0.470
	All portfolios	-0.005 *0.029*	0.006 *0.059*	0.044	2.201	0.059

Furthermore, it is interesting to mention the results of the DW statistic. The results show that the problem of autocorrelation of the regression residuals seems to be relatively small, as its value is around two, for most of the portfolios. But there are a few cases (portfolios) where the problem of autocorrelation is more evident, as in the case of portfolio 1 for the whole period (1989–2006) and portfolio 4 for the third sub-period (2001–2006).

All the results reported in table 4.11, are examples of the lack of power of the CAPM to explain the relationship between stock returns and risk across time. The use of linear models with only one factor, even if this is considered as a proxy for the market portfolio according to the theory of the CAPM, is very difficult to provide researchers with really reliable results. The results are very similar to those of past studies (Fama and French, 1992; Chen, 1983; Groenewold and Fraser, 1997). Generally, based on the restrictions of the CAPM that the intercept should be equal to zero, if a correct market portfolio has been selected, and that the coefficient of the market proxy (average market premium) should be statistically significant (significantly different from zero), our main conclusion is that the model is rejected in the ASE.

4.7.2 CAPM Non-linearity Results

In table 4.12 we present the results of the CAPM after its equation was modified so as to test whether the returns of each portfolio and the returns of the market index are linearly related. The equation is based on the study of Fama and MacBeth (1973):

$$\widetilde{R}_{it} = \gamma_0 + \gamma_1 b_i + \gamma_2 b_i^2 + e_{it} \qquad \textbf{(7)}$$

where $\widetilde{R}_{it}$ is the average monthly returns of each security i that constructs portfolio p for each period of analysis, the $b_i s$ are the estimated betas from the time-series stage of analysis (see chapter three) and the $b_i^2 s$ are the same betas in exponential form (so as to test for possible non-linearities between the variables). In this form of the CAPM, if the exponential coefficient proves to be statistically equal to zero, the returns of the portfolios and the beta coefficients are linearly related.

As in section 4.7.1 the results of the tests do not seem to be in favour of the CAPM. At the first row of each portfolio the intercept term, the beta coefficient, the exponential beta coefficient, the adjusted R^2, the DW statistic and the F statistic are presented, while below each intercept and beta the p-values for the t-tests of significance are presented in italics and show if the coefficients are statistically significant or not for each portfolio or group of portfolios (the sum of stocks for each period).

The results for the whole period (1989–2006) show that the beta coefficient, in its simple or exponential form, of the market index is statistically insignificant for all portfolios, the adjusted R^2 is very low (or negative), and the F statistic also proves that the market proxy is not valid for the explanation of the variation in the dependent variable. It is interesting to mention that the intercept term is equal to zero, a result that is in agreement with the assumptions of the CAPM. Consequently, the insignificance of the exponential beta coefficient shows that there may be a linear relationship between the variables.

The results for the first sub-period (1989–1994) portfolio are a little better as the F statistic, for portfolio 2 and for the group of portfolios, seems to be significant and it is a sign that the market proxy has some explanatory power. But, overall, the results are similar to the results of the whole period. Moreover, the second sub-period

(1995–2000) gives no better results, with some exceptions e.g. the significance of the F statistic in portfolio 4 and the significance of the two forms of the beta coefficient at the 5 per cent level of significance in portfolio 1. Finally, the results for the third sub-period (2001–2006) show once more that the market index has no influence on the behaviour of stocks. In all sub-periods the exponential beta coefficient is statistically insignificant (except for portfolio 1 during the second sub-period), which is a sign that portfolio returns and the beta coefficients are linearly related, a result which is consistent with the theory of the CAPM.

***Table 4.12*: The non-linearity test results of the CAPM**

Period	Portfolios	γ_0	γ_1	γ_2	Adjusted R^2	DW	F Sig.
1989–1994	Portfolio 1	0.004 *0.944*	-0.028 *0.798*	0.022 *0.665*	0.069	1.798	0.146
	Portfolio 2	0.007 *0.846*	-0.118 *0.408*	0.159 *0.262*	0.154	1.954	0.040
	All portfolios	-0.025 *0.018*	0.033 *0.209*	-0.008 *0.599*	0.170	1.810	0.002
1995–2000	Portfolio 1	0.677 *0.033*	-1.040 *0.035*	0.400 *0.035*	0.093	2.088	0.102
	Portfolio 2	-0.511 *0.549*	1.006 *0.541*	-0.486 *0.539*	-0.058	1.945	0.820
	Portfolio 3	-0.228 *0.858*	0.556 *0.847*	-0.326 *0.841*	-0.066	1.704	0.898
	Portfolio 4	34.688 *0.067*	-89.283 *0.073*	57.415 *0.080*	0.157	2.600	0.038
	Portfolio 5	0.042 *0.782*	-0.126 *0.811*	0.115 *0.799*	-0.069	2.085	0.937
	All portfolios	0.029 *0.751*	-0.002 *0.992*	-0.014 *0.896*	-0.007	1.986	0.629
2001–2006	Portfolio 1	0.044 *0.884*	-0.081 *0.839*	0.027 *0.837*	-0.072	2.334	0.977
	Portfolio 2	-0.813 *0.718*	1.368 *0.708*	-0.586 *0.691*	0.005	2.155	0.357
	Portfolio 3	-0.612 *0.877*	1.124 *0.873*	-0.527 *0.867*	-0.053	2.263	0.764
	Portfolio 4	2.171 *0.428*	-4.214 *0.432*	2.031 *0.438*	-0.024	2.599	0.528

	Portfolio 5	0.068	-0.022	3.338	-0.009	2.397	0.393
		0.488	*0.462*	0.262			
	Portfolio 6	19.389	-47.546	29.081	0.026	2.304	0.269
		0.269	*0.259*	*0.250*			
	Portfolio 7	0.591	-1.713	1.209	-0.034	2.106	0.600
		0.419	*0.417*	*0.426*			
	Portfolio 8	0.031	-0.179	0.189	-0.059	2.067	0.830
		0.650	*0.548*	*0.545*			
	All portfolios	-.017	0.031	-0.022	-0.004	2.044	0.579
		0.640	*0.676*	*0.552*			
1989–2006	Portfolio 1	0.055	-0.119	0.064	0.069	2.798	0.145
		0.269	*0.221*	*0.178*			
	Portfolio 2	-0.002	-0.018	0.031	-0.014	1.933	0.458
		0.671	*0.433*	*0.310*			
	All portfolios	-0.003	-0.004	0.008	0.045	2.235	0.100
		0.434	*0.665*	*0.305*			

As in table 4.11, the DW statistic shows that the problem of autocorrelation of the regression residuals seems to be relatively small for most of the portfolios. The general results reported in table 4.12, are once more examples of the lack of power of the CAPM to explain the relationship between stock returns and risk across time. The inclusion of the beta coefficient in its exponential form did not add any power in the equation proving that there may be a linear relationship between the variables.

4.8 Empirical Findings of the Statistical APT Model

4.8.1 APT Principal Components Analysis Results

As we have demonstrated, the number of factors and the estimated betas of the APT model, used later in the cross-sectional tests, are determined through principal components analysis. Varimax rotation is used so as to minimise the number of variables who may have high loadings on some factors. In this section we present one of the portfolios of the analysis. We have randomly chosen portfolio 1 from the 1st sub-period (1989–1994). The procedure is the same for all the other portfolios for each period of analysis.

Table 4.13 shows that the Kaiser-Meyer-Olkin test value is high (0.887) and the Bartlett's test is statistically significant (0.000), which means that the factor analysis followed is the proper technique for this data. The KMO test values between 0.8 and 0.9 are described as excellent, something which is verified in table 4.13. The Bartlett's test of sphericity tests the hypothesis that there is no shared variance in the component matrix under examination. In this test a significant chi-square statistic explains that factor analysis is appropriate as a method for the data (Jackson, 1991). In the present portfolio, as well as at the rest of the portfolios for all periods (presented in Appendix IV), the KMO test value and the test of sphericity are high and significant respectively.

***Table 4.13*: KMO and Bartlett's test for portfolio 1 of the first sub-period (1989–1994)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.887
Bartlett's Test of Sphericity	Approx. Chi-Square	2091.037
	Df	435
	Sig.	.000

***Table 4.14*: Total variance explained for portfolio 1 of the first sub-period (1989–1994)**

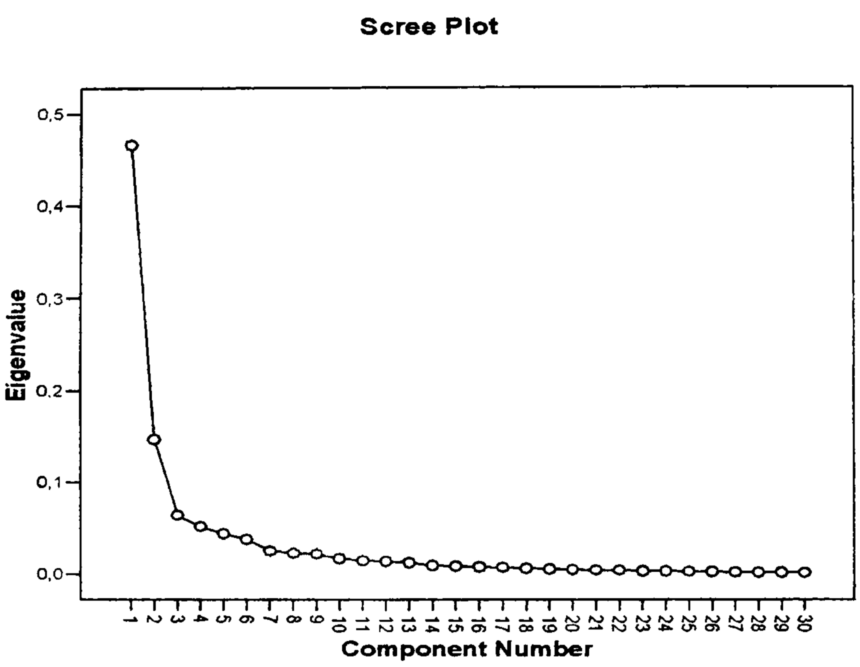
	Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
		Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Raw	1	466	46.313	46.313	466	46.313	46.313	.217	21.549	21.549
	2	.147	14.579	60.893	.147	14.579	60.893	.143	14.178	35.727
	3	.064	6.373	67.265	.064	6.373	67.265	.158	15.716	51.443
	4	.052	5.152	72.418	.052	5.152	72.418	.080	7.936	59.379
	5	.044	4.368	76.786	.044	4.368	76.786	.157	15.624	75.003
	6	.038	3.733	80.518	.038	3.733	80.518	.055	5.515	80.518
	7	.025	2.477	82.996						
	8	.023	2.239	85.235						
	9	.022	2.153	87.388						
	...	...	...	...						
	...	...	...	...						
	...	...	...	...						

25	.002	.237	99.296							
26	.002	.185	99.481							
27	.002	.155	99.636							
28	.001	.147	99.784							
29	.001	.120	99.904							
30	.001	.096	100.000							

Table 4.14 presents the eigenvalues representing the proportion of total variance in all variables that is accounted for by that specific factor. In order to decide the number of factors that will be retained, we examine the scree plot (figure 4.8) and the possible maximum amount of variance explained. Based on the results of table 4.14 we can see that there are six significant factors. As far as the scree plot is concerned, which presents the eigenvalues for each of the components under examination, figure 4.8 shows that after the sixth factor the eigenvalues are decreasing slowly and we decide to retain the six factors (Cattell, 1966).

From the observations above and according to Jackson (1991), we come to the conclusion to retain the first six significant factors that account for over 80 per cent of the total variance. In other words, the results from the tests show that there are six factors that have an effect on the behaviour of ASE stock prices. We should mention here that the first factor alone explains more that 21 per cent of the total variance, according to the last column "*Rotation Sums of Squared Loadings*" of table 4.14.

***Figure 4.8*: Scree plot for portfolio 1 of the first sub-period (1989–1994)**



The factor analysis and the respective scree plots of each portfolio for each period are reported in Appendix IV.

4.8.2 APT Cross-sectional Test Results

After the factor analysis, we have proceeded to the cross-sectional tests according to the proposed methodology, which means that we examine the results after the regression of the average returns of stocks of each portfolio on the estimated betas computed from the principal components analysis (Chen, 1983; Chen and Jordan, 1993; Clare and Thomas, 1994). In table 4.15 the results of the tests are reported. The results are different from the results of the CAPM for the same periods under examination. Specifically, during the whole period (1989–2006) it is obvious that, in contrast with the case of the CAPM, the APT has an adjusted R^2 equal of 56.8 per cent, 38.8 per cent and 42.3 per cent for portfolio 1, 2 and for their group respectively. This means that this model has a better structure as a model in comparison to the CAPM, as it explains to a sufficient degree the relationship between average excess returns and a number of unobserved variables. Although the coefficients are all insignificant, except for factor 6 for the 2nd portfolio (sig. = 0.010) and factor 9 for the group of the portfolios (sig. = 0.015), the F statistic shows that the independent (unobserved) variables are valid variables in the explanation of the variation in the dependent variable.

As far as the 1st sub-period is concerned, the results are in favour of the application of the APT model, as all the portfolios and their group have a significant adjusted R^2, the F statistic shows that the factors can explain the variation in the average excess returns and several coefficients are statistically significant. Overall, during this period, the APT performs well. It is also important to mention at this point that this is the same period that the CAPM shows also a good performance, which means that the prediction of the behaviour of stock returns is not always a matter of model functionality.

For the period between 1995 and 2000 the results are much better for the APT model than for the CAPM. In contrast to the case of the CAPM, the results from the APT model report sufficient values of the adjusted R^2, except for portfolio 3 and for the group of the portfolios. This means that the model provides a better explanation between the behaviour of average excess returns and the effect of the statistical factors. The F statistic is significant (the variation of the dependent variables can be explained to a sufficient degree by the independent ones) and some coefficients are statistically significant, as in the case of factor 5 in the 4th portfolio.

Finally, for the last sub-period 2001–2006, the APT model outperforms the CAPM as it can be seen from the values of the adjusted R^2 and the F statistic. They are sufficient and significant, respectively, for all the portfolios of this period and only when the portfolios are grouped their values are small and insignificant. Additionally, several beta coefficients are statistically significant, something which did not happen with the application of the CAPM at the same portfolios. Section 4.9 presents a comparison between the models via the Davidson and Mackinnon (1981) analysis, so as to verify which is the best model for the explanation of the behaviour of portfolio returns.

As far as the DW statistic is concerned, in several cases (portfolios) its value is around two. This means that the autocorrelation of the regression residuals is not significant, although in many cases, as in the case of the 1st portfolio during the period 1995–2000 and the 7th and 8th portfolio during the period 2001–2006, the deviations from the value of two are larger. Nevertheless, the application of factor analysis on the portfolios of stocks shows that the autocorrelation of the regression residuals, as well as the problem of multicollinearity, can be reduced so as not to have any spurious regressions (Roll and Ross, 1980; Fifield *et al.*, 2000).

***Table 4.15*: The cross-sectional test results of the statistical APT model**

Period	Portfolios	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	γ_9	γ_{10}	γ_{11}	γ_{12}	γ_{13}	Adjusted R^2	DW	F Sig.
1989—1994	P1	-0.006	0.054	0.018	0.056	0.037	0.041	-0.008								0.433	1.442	0.003
		0.342	*0.480*	*0.770*	*0.352*	*0.257*	*0.030*	*0.683*										
	P2	-0.012	0.036	-0.016	0.024	0.015	0.013	0.001	0.047	0.000	0.049					0.515	1.538	0.003
		0.032	*0.546*	*0.587*	*0.426*	*0.567*	*0.644*	*0.966*	*0.023*	*0.989*	*0.007*							
	All Ps	-0.011	0.170	0.099	0.074	0.057	0.002	0.046	0.010	0.023	0.059	0.004	0.058	0.058	0.025	0.497	1.569	0.000
		0.002	*0.031*	*0.041*	*0.118*	*0.164*	*0.950*	*0.025*	*0.690*	*0.247*	*0.000*	*0.841*	*0.004*	*0.000*	*0.068*			
1995—2000	P1	0.010	-0.086	-0.017	-0.032	-0.019	-0.005									0.274	2.713	0.024
		0.413	*0.585*	*0.896*	*0.771*	*0.823*	*0.950*											
	P2	0.006	0.023	-0.018	0.050	0.026	0.011									0.481	1.749	0.001
		0.374	*0.742*	*0.792*	*0.468*	*0.669*	*0.761*											
	P3	0.012	-0.043	-0.063	-0.036	-0.035	-0.028	-0.003								-0.073	1.494	0.673
		0.452	*0.827*	*0.725*	*0.769*	*0.756*	*0.785*	*0.960*										
	P4	-0.167	2.355	2.167	2.143	1.436	0.773									0.132	1.986	0.135
		0.139	*0.053*	*0.056*	*0.055*	*0.098*	*0.009*											
	P5	0.010	-0.039	-0.036	-0.008	-0.013	0.023	0.001	-0.014							0.287	2.192	0.037
		0.036	*0.405*	*0.408*	*0.847*	*0.737*	*0.237*	*0.943*	*0.389*									
	All Ps	0.018	-0.235	-0.206	-0.152	-0.216	-0.156	-0.069	0.383	-0.135						0.035	1.933	0.110
		0.363	*0.813*	*0.780*	*0.839*	*0.765*	*0.804*	*0.900*	*0.472*	*0.789*								
2001—2006	P1	-0.001	-0.231	-0.215	-0.177											0.313	1.651	0.005
		0.859	*0.040*	*0.025*	*0.014*													
	P2	0.001	-0.234	-0.298	-0.211	-0.071	-0.099									0.576	2.296	0.000
		0.926	*0.003*	*0.000*	*0.002*	*0.019*	*0.001*											
	P3	0.001	-0.161	-0.154	-0.168	-0.164	-0.101	-0.058								0.244	2.061	0.048
		0.870	*0.020*	*0.021*	*0.012*	*0.011*	*0.043*	*0.060*										
	P4	-0.001	-0.118	-0.093	-0.084	-0.085	-0.091	-0.095								0.698	2.337	0.000
		0.882	*0.064*	*0.102*	*0.092*	*0.091*	*0.026*	*0.002*										

	P5	-0.007 *0.205*	-0.055 *0.349*	-0.078 *0.169*	-0.066 *0.074*	-0.054 *0.071*	-0.051 *0.106*	-0.052 *0.040*								0.390	2.589	0.006
	P6	-0.013 *0.829*	0.189 *0.781*	0.090 *0.870*	0.072 *0.876*	0.077 *0.774*	1.060 *0.000*	0.000 *0.999*	-0.024 *0.907*							0.803	2.067	0.000
	P7	-0.001 *0.579*	-0.100 *0.000*	-0.101 *0.000*	-0.082 *0.000*	-0.050 *0.001*	-0.060 *0.000*	-0.050 *0.000*	-0.069 *0.000*	-0.010 *0.260*						0.678	1.205	0.000
	P8	0.006 *0.081*	-0.135 *0.000*	-0.109 *0.000*	-0.051 *0.003*	-0.066 *0.000*	-0.025 *0.025*	-0.043 *0.002*	-0.052 *0.000*	-0.055 *0.000*	-0.049 *0.001*					0.579	1.149	0.001
	All Ps	0.005 *0.604*	-1.568 *0.069*	-0.915 *0.202*	-1.191 *0.046*	-0.841 *0.116*	-0.351 *0.314*	-0.216 *0.281*								0.018	2.043	0.119
1989—2006	P1	0.004 *0.302*	-0.024 *0.631*	-0.052 *0.181*	-0.058 *0.068*	-0.040 *0.172*	-0.012 *0.387*	-0.003 *0.733*								0.568	2.443	0.000
	P2	0.002 *0.515*	-0.019 *0.457*	-0.019 *0.339*	-0.037 *0.085*	-0.028 *0.144*	-0.023 *0.089*	-0.029 *0.010*	0.009 *0.231*	0.002 *0.735*						0.388	1,959	0.013
	All Ps	0.000 *0.936*	0.017 *0.693*	-0.028 *0.340*	-0.015 *0.551*	-0.033 *0.087*	-0.018 *0.288*	-0.012 *0.466*	-0.014 *0.218*	0.005 *0.726*	-0.027 *0.015*	-0.013 *0.220*	-0.001 *0.922*	0.007 *0.314*	0.009 *0.250*	0.423	2.199	0.000

4.9 Comparison Criteria between the CAPM and The Statistical APT Model

4.9.1 Davidson and MacKinnon Analysis

The Davidson and MacKinnon (1981) equation was applied on the notion that the two models are non-nested. This means that the statistical APT model is being considered with artificial factors, while the CAPM has as its unique factor the market portfolio. This is the reason that the models are non-nested, unless there is a rotation of the factors such that one of them is the market portfolio.

Equation (23) of chapter three is the equation that has been used in our tests so as to compare the standard CAPM with the statistical APT model and, during the progress of this work, we compare the statistical APT with the macroeconomic APT model, based on equation (24) of chapter three. Analytically, based on the following equation:

$$R_{i,t} - R_{SAPT} = a(R_{CAPM} - R_{SAPT}) + e_i \qquad \textbf{(8)}$$

we compare the statistical APT model and the CAPM, where R_{SAPT} and R_{CAPM} are the expected returns which were generated by the models respectively. The a coefficient measured the effectiveness of the models. If the null hypothesis H_0 is accepted and the coefficient a is equal to zero it means that the statistical APT is the better model according to the study of Davidson and MacKinnon (1981).

According to equation (8), table 4.16 shows that for almost all the portfolios the APT model provide more reliable results in comparison to the CAPM. These can be seen by the p-values which can be seen at the second row of the column with the values of coefficient a. Even for the turbulent period of the ASE (1995–2000), the coefficient a also seems to be insignificant for all the portfolios, which also confirms that, according to the theory behind the statistical APT model, there is a number of unobserved factors, which have to be found so as to explain the behaviour of stock returns.

***Table 4.16*: The Davidson and MacKinnon results**

Period	**Portfolios**	a	R^2	**Adjusted** R^2
1989–1994	Portfolio 1	0.075 *0.675*	0.006	-0.028
	Portfolio 2	0.126 *0.344*	0.031	-0.002
	All portfolios	0.033 *0.786*	0.001	-0.016
1995–2000	Portfolio 1	-0.001 *0.996*	0.000	-0.034
	Portfolio 2	-0.001 *0.994*	0.000	-0.036
	Portfolio 3	0.059 *0.891*	0.001	-0.034
	Portfolio 4	0.235 *0.410*	0.024	-0.010
	Portfolio 5	-0.002 *0.992*	0.000	-0.032
	All portfolios	0.032 *0.905*	0.000	-0.007
2001–2006	Portfolio 1	0.003 *0.990*	0.000	-0.034
	Portfolio 2	0.036 *0.798*	0.002	-0.032
	Portfolio 3	0.026 *0.911*	0.000	-0.034
	Portfolio 4	0.005 *0.965*	0.000	-0.034
	Portfolio 5	0.017 *0.925*	0.000	-0.036
	Portfolio 6	0.004 *0.962*	0.000	-0.036
	Portfolio 7	-0.010 *0.921*	0.000	-0.034
	Portfolio 8	1.246 *0.000*	0.576	0.561

	All portfolios	0.045 *0.888*	0.000	-0.004
1989–2006	Portfolio 1	0.035 *0.798*	0.002	-0.032
	Portfolio 2	0.009 *0.959*	0.000	-0.032
	All portfolios	0.029 *0.811*	0.001	-0.016

4.9.2 Residual Analysis

Residual analysis has been used as a performance measure in the past (Chen, 1983). If the CAPM is not miss-specified the expected return of a security i would be captured by the estimated beta and the residuals e_i of the model would behave as white noise with zero mean. If there is rationality in expectations in the market, the realised return of an asset has the following equation:

$$R_i = E_i + k_i \tag{9}$$

where E_i is the expected return of the market and k_i is the error term of the equation.

In other words, if the model is not miss-specified, the return of an asset can be estimated with the use of the following equation:

$$R_i = E_i(CAPM) + e_i \tag{10}$$

which means that

$$e_i = [E_i - E(CAPM)] + k_i \tag{11}$$

In equation (11), $E(CAPM)$ is the expected return from the CAPM with the market proxy. If the CAPM is correct as a model, then $E_i = E(CAPM)$ and $e_i = k_i$, which means that e_i would behave as white noise with zero mean across time. This means that the residuals would not be priced by the factors of any other model. If there is pricing by other models, then there is information in the E_i that is not captured by $E_i(CAPM)$. This means that the CAPM is not correct.

In order to test these possible implications there is a test on the CAPM by regressing the residuals of the CAPM e_i (dependent variable) on the betas estimated from the principal components analysis of the APT model (independent variables). Then, we regress the residuals of the APT model on the estimated beta from the CAPM, so as to examine if the CAPM explains information which is missed by the APT model.

The results from table 4.17 show that the market betas do not seem to explain the variance which is not captured by the APT factor betas. This result is evident in every portfolio, suggesting once more that the CAPM is not a reliable model. Specifically, the adjusted R^2 has a negative value for almost all of the portfolios and the F statistic is insignificant in all the periods.

On the contrary, the results from table 4.18 present a much better performance from the APT model as in almost all cases it performs very well in the explanation of the variance left unexplained by the CAPM. For example, the results for the 1st sub-period show that the factor betas explain 40.7 per cent, 54.8 per cent and 39.6 per cent for portfolio1, 2 and the group of the portfolios respectively.

***Table 4.17*: Residual analysis: APT residuals on the market beta**

Period	Portfolios	γ_0	γ_1	Adjusted R^2	F Sig.
1989–1994	Portfolio 1	-0.006	0.006	-0.011	0.413
		0.421	*0.413*		
	Portfolio 2	-0.010	0.020	0.085	0.065

		0.073	*0.065*		
	All portfolios	-0.001 *0.704*	0.001 *0.684*	-0.014	0.684
1995–2000	Portfolio 1	-0.001 *0.947*	0.001 *0.947*	-0.036	0.947
	Portfolio 2	-0.006 *0.795*	0.006 *0.795*	-0.033	0.795
	Portfolio 3	0.030 *0.493*	-0.034 *0.492*	-0.018	0.492
	Portfolio 4	0.912 *0.189*	-1.189 *0.189*	0.027	0.189
	Portfolio 5	0.002 *0.890*	-.003 *0.889*	-0.035	0.889
	All portfolios	-0.014 *0.440*	0.016 *0.425*	-0.002	0.425
2001–2006	Portfolio 1	-0.015 *0.443*	0.010 *0.441*	-0.014	0.441
	Portfolio 2	0.034 *0.442*	-0.027 *0.442*	-0.014	0.442
	Portfolio 3	0.034 *0.608*	-0.030 *0.608*	-0.026	0.608
	Portfolio 4	0.008 *0.808*	-0.008 *0.808*	-0.033	0.808
	Portfolio 5	0.018 *0.685*	-0.019 *0.685*	-0.030	0.685
	Portfolio 6	-0.055 *0.845*	0.065 *0.845*	-0.034	0.845
	Portfolio 7	-0.013 *0.479*	0.018 *0.478*	-0.017	0.478
	Portfolio 8	-0.014 *0.077*	0.028 *0.073*	0.079	0.073
	All portfolios	0.010 *0.397*	-0.010 *0.377*	-0.001	0.377
1989–2006	Portfolio 1	-0.004 *0.462*	0.004 *0.457*	-0.015	0.457
	Portfolio 2	-0.001 0.798	0.001 0.778	-0.033	0.778
	All portfolios	-0.001 *0.519*	0.001 *0.481*	-0.008	0.481

Table 4.18: **Residual analysis: CAPM residuals on the APT betas**

Period	Portfolios	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	γ_9	γ_{10}	γ_{11}	γ_{12}	γ_{13}	Adjusted R^2	F Sig.
1989–1994	P1	0.004	-0.073	-0.074	-0.030	-0.012	0.007	-0.035								0.407	0.005
		0.427	*0.314*	*0.209*	*0.606*	*0.698*	*0.675*	*0.076*									
	P2	0.006	-0.087	-0.068	-0.028	-0.033	-0.035	-0.043	0.012	-0.040	0.016					0.548	0.001
		0.180	0.108	0.014	0.287	0.160	0.159	0.051	0.469	0.050	0.284						
	All Ps	0.004	-0.101	-0.043	-0.057	-0.059	-0.074	0.002	-0.055	-0.029	0.022	-0.040	0.005	0.023	0.004	0.396	0.000
		0.271	*0.185*	*0.360*	*0.221*	*0.145*	*0.022*	*0.918*	*0.028*	*0.141*	*0.088*	*0.041*	*0.807*	*0.124*	*0.740*		
1995–20000	P1	0.001	-0.053	0.009	-0.010	-0.003	0.012									0.270	0.025
		0.947	*0.734*	*0.943*	*0.926*	*0.976*	*0.882*										
	P2	-0.003	0.029	-0.012	0.056	0.031	0.014									0.479	0.001
		0.678	*0.685*	*0.858*	*0.420*	*0.614*	*0.702*										
	P3	0.004	-0.035	-0.060	-0.033	-0.032	-0.025	-0.003								-0.060	0.632
		0.809	*0.861*	*0.735*	*0.786*	*0.773*	*0.800*	*0.964*									
	P4	-0.196	2.132	2.149	1.923	1.387	0.628									0.087	0.212
		0.074	0.068	0.050	0.073	0.097	0.025										
	P5	0.002	-0.040	-0.038	-0.009	-0.014	0.022	0.000	-0.014							0.281	0.040
		0.640	*0.393*	*0.381*	*0.832*	*0.708*	*0.262*	*0.991*	*0.381*								
	All Ps	-0.009	0.462	0.188	0.295	0.288	0.240	0.218	0.706	0.177						0.033	0.117
		0.666	*0.640*	*0.799*	*0.691*	*0.690*	*0.701*	*0.690*	0.185	*0.725*							
2001–2006	P1	0.015	-0.236	-0.219	-0.180											0.316	0.005
		0.030	*0.036*	*0.023*	*0.012*												
	P2	0.015	-0.172	-0.245	-0.169	-0.050	-0.082									0.547	0.000
		0.013	*0.022*	*0.002*	*0.012*	*0.089*	*0.004*										
	P3	0.016	-0.162	-0.154	-0.164	-0.163	-0.100	-0.057								0.237	0.052
		0.025	*0.019*	*0.021*	*0.013*	*0.011*	*0.044*	*0.065*									
	P4	0.011	-0.120	-0.096	-0.087	-0.084	-0.094	-0.094								0.673	0.000

		0.070	*0.066*	*0.102*	*0.088*	*0.103*	*0.025*	*0.002*									
	P5	0.006 *0.226*	-0.046 *0.435*	-0.067 *0.237*	-0.062 *0.097*	-0.051 *0.086*	-0.044 *0.157*	-0.047 *0.066*								0.370	0.008
	P6	0.012 *0.848*	-0.329 *0.657*	-0.372 *0.536*	-0.354 *0.485*	-0.160 *0.582*	0.883 *0.000*	-0.080 *0.667*	-0.206 *0.360*							0.755	0.000
	P7	0.011 *0.000*	-0.096 *0.000*	-0.098 *0.000*	-0.080 *0.000*	-0.049 *0.002*	-0.056 *0.000*	-0.047 *0.000*	-0.067 *0.000*	-0.008 *0.402*						0.636	0.000
	P8	0.015 *0.000*	-0.135 *0.000*	-0.109 *0.000*	-0.051 *0.002*	-0.066 *0.000*	-0.026 *0.025*	-0.043 *0.002*	-0.052 *0.000*	-0.055 *0.000*	-0.049 *0.001*					0.580	0.001
	All Ps	0.007 *0.497*	-0.778 *0.368*	-0.283 *0.693*	-0.661 *0.268*	-0.425 *0.426*	-0.083 *0.811*	-0.028 *0.890*								0.009	0.228
1989—2006	P1	0.009 *0.035*	-0.089 *0.079*	-0.093 *0.019*	-0.092 *0.005*	-0.071 *0.018*	-0.025 *0.077*	-0.016 *0.121*								0.560	0.000
	P2	0.005 *0.100*	-0.029 *0.246*	-0.025 *0.218*	-0.044 *0.039*	-0.035 *0.071*	-0.024 *0.071*	-0.029 *0.009*	0.009 *0.264*	0.004 *0.624*						0.384	0.014
	All Ps	0.003 *0.086*	-0.053 *0.203*	-0.068 *0.021*	-0.042 *0.090*	-0.058 *0.003*	-0.040 *0.017*	-0.031 *0.047*	-0.019 *0.085*	-0.010 *0.454*	-0.035 *0.001*	-0.023 *0.023*	-0.013 *0.205*	0.006 *0.356*	0.000 *0.950*	0.420	0.000

4.10 Empirical Findings of the Macroeconomic APT Model

4.10.1 The Correlation between the Variables

Tables 4.19, 4.20, 4.21 and 4.22 present the correlation coefficients between the final variables used in the analysis. Table 4.19 depicts the correlation coefficients for the whole period of analysis (1989–2006) and tables 4.20, 4.21 and 4.22 present the correlation coefficients of the first (1989–1994), second (1995–2000) and third sub-period (2001–2006) respectively.

Most of the correlations are small or almost non-existent. It should be noted that the return on the stock market index is not correlated with any of the other variables for all the periods under examination. These findings contrast those of Chen *et al.* (1986) and Chen and Jordan (1993), who found that the return on the market index (RMI_t) is correlated with some of the other variables e.g. there is a significant correlation between the stock market index and the unexpected inflation (UI_t) (Chen and Jordan, 1993). The fact that the stock market index is not correlated with the other variables may be a sign of the independent course that the index follows and cannot be easily affected by the behaviour of the rest of the macroeconomic variables.

Further, we notice a significant correlation (at the 1 per cent level) between the petroleum series ($UCPS_t$) and the unexpected inflation (0.269) for the whole period of analysis, for the second sub-period (0.477) and for the third sub-period (0.424). This correlation is probably due to the international changes such as the increase of the crude petroleum prices and the increase or the already high inflation rates in many economies around the world, that is Turkey, Romania, Bulgaria, etc. Consequently, these changes have an impact of the correlation of these variables in the Greek economy, especially during the last few years that these changes seem to be more rapid.

Additionally, there is a significant negative correlation (at the 0.05 level) between the unexpected growth rate in the industrial production ($UGRIP_t$) and the unexpected change in the petroleum series (-0.244). This finding contrasts the findings of Chen and Jordan (1993) but shows the impact that petroleum products have on industrial production, especially during the period before the year 2000.

Finally, there is a correlation (at the 5 per cent level) between the unexpected inflation and the change in the expected inflation (CEI_t), a finding similar to Chen *et al.* (1986), although this is evident only for the third sub-period (-0.290). A reason may be that both series contain a part of the characteristics of the $E(I_t)$ series. The series of expected inflation, because of its significant autocorrelation and, simultaneously, its significant correlation with the change in the expected inflation, a finding similar to the work of Chen and Jordan (1993), was not used in the tests on the APT model. Generally, tables 4.19, 4.20, 4.21 and 4.22 show that the variables are not perfectly correlated and none of them can be replaced with any other.

***Table 4.19*: Correlation of the final variables, January 1989–December 2006**

	CEI_t	UI_t	$UCPS_t$	RMI_t
CEI_t	1.000	-0.023	0.054	0.046
UI_t	-0.023	1.000	**0.269****	0.106
$UCPS_t$	0.054	**0.269****	1.000	-0.082
RMI_t	0.046	0.106	-0.082	1.000

Note: **Indicates significance at the 1 per cent level.

Table 4.20: **Correlation of the final variables, January 1989–December 1994**

	CEI_t	UI_t	$UCPS_t$	RMI_t
CEI_t	1.000	0.076	0.096	0.155
UI_t	0.076	1.000	0.162	0.117
$UCPS_t$	0.096	0.162	1.000	-0.183
RMI_t	0.155	0.117	-0.183	1.000

Table 4.21: **Correlation of the final variables, January 1995–December 2000**

	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
CEI_t	1.000	-0.100	-0.044	-0.009	-0.172
UI_t	-0.100	1.000	0.029	**0.477****	0,149
$UGRIP_t$	-0.044	0.029	1.000	**-0.244***	0.109
$UCPS_t$	-0.009	**0.477****	**-0.244***	1.000	0.111
RMI_t	-0.172	0,149	0.109	0.111	1.000

Notes: *Indicates significance at the 5 per cent level.
**Indicates significance at the 1 per cent level.

Table 4.22: **Correlation of the final variables, January 2001–December 2006**

	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
CEI_t	1.000	**-0.290***	0.130	0.012	0.027
UI_t	**-0.290***	1.000	-0.109	**0.424****	0.063
$UGRIP_t$	0.130	-0.109	1.000	0.018	-0.147
$UCPS_t$	0.012	**0.424****	0.018	1.000	-0.077
RMI_t	0.027	0.063	-0.147	-0.077	1.000

Notes: *Indicates significance at the 5 per cent level.
**Indicates significance at the 1 per cent level.

4.10.2 The Autocorrelation of the Macrovariables

Table 4.23 presents the autocorrelations of the variables and a standard Box-Ljung statistic is estimated for each one of these variables used in the tests. The estimated autocorrelations are presented up to 12 lags while the Box-Ljung statistics are up to 24 lags. The findings support the previous work of Chen and Jordan (1993) that the variables selected are not autocorrelated, even in the case of CEI_t, which although seems to have a significant statistic (at the 1 per cent level) of the presence of autocorrelation, according to the theory of statistics the autocorrelation of the series (-0.087) for 24 lags does not exceed two times its respective standard error (0.064).

We should recall at this point that the unexpected inflation, the unexpected change in the growth rate in industrial production and the unexpected change in the petroleum series are the residuals from the fitted process which was previously used in studies such as the one of Fama and Gibbons (1984).

***Table 4.23*: The autocorrelation of the final variables**

Autocorrelations														
Series	**Lag 1**	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 5**	**Lag 6**	**Lag 7**	**Lag 8**	**Lag 9**	**Lag 10**	**Lag 11**	**Lag 12**	**X^2** (24 lags)	**Sig.**
CEI_t	0.108	0.074	-0.014	0.133	-0.026	0.067	-0.090	0.071	0.019	-0.077	-0.360	0.024	51.504**	0.001
UI_t	0.015	0.008	0.011	0.029	0.024	0.083	0.042	0.025	0.071	-0.014	0.061	0.050	19.909	0.702
$UGRIP_t$	0.007	0.013	-0.014	0.035	-0.011	-0.039	-0.022	-0.025	-0.033	-0.002	-0.115	0.000	15.199	0.915
$UCPS_t$	-0.007	-0.018	0.067	0.051	-0.046	0.082	-0.136	-0.019	0.029	-0.051	-0.015	0.049	24.695	0.423
RMI_t	0.132	0.119	-0.012	-0.095	-0.130	0.013	0.115	0.108	-0.003	0.143	-0.011	-0.038	28.403	0.243

Notes: The table above presents the autocorrelations of the final variables used in the application of the macroeconomic APT model, for 12 lags and the Box-Ljung Statistic for 24 lags.

**It shows that the Box-Ljung statistic is significant at the 1 per cent level.

All analytical tables (up to 24 lags) are available on request

4.11 Time-series Regression Analysis between the Factor Scores and the Macrovariables

In this section we investigate for possible relationships between the macrovariables that are used in the analysis and the factor scores that were generated during factor analysis (Chen and Jordan, 1993). As already mentioned in chapter two and three, factor analysis has been extensively used in the application of the APT model (Roll and Ross, 1980; Chen, 1983; Groenewold and Frazer, 1997). Moreover, the present section examines the extent that the macrovariables are related to the factors that underline security returns for all periods and portfolios under investigation.

In order to verify if there is truly any significant macrovariable for all of the regressions of each portfolio, Fisher's (1948) joint test is applied based on the hypothesis that the coefficient on that variable is jointly equal to zero. At the last row for each of the twenty one tables (see Appendix VIII) the p-values (significance) from Fisher's joint test are presented for all macrovariables (Chen and Jordan, 1993). A more detailed explanation of the joint test of Fisher was presented in chapter three.

Table 4.24 below presents the most important results (the p-values) from the joint tests for each variable for each portfolio. Although there is a significant relationship between several variables and the respective factor scores for many of the portfolios, the results from the joint tests show that, overall, only the stock market index has a strong relationship with the factor scores generated from the factor analysis of stock returns e.g. for the first portfolio of the whole period (1989–2006) the p-value is 0.013, while for the second portfolio it is 0.092. This finding is the same with that of Chen *et al.* (1986) and Chen and Jordan (1993). Additionally, the two inflation variables, while they generally present insignificance in almost all the portfolios, at least one of them seems to play a significant role for the first portfolio of the whole period (0.007 for the change in expected inflation) the first portfolio of the second sub-period and the second portfolio of the third sub-period, as it can be seen in table 4.24. This result of the weak performance of the inflation variables is in agreement with the findings of Chen *et al.* (1986).

While in the work of Chen and Jordan (1993) the unexpected growth rate in the industrial production presents a small significance, in our case this variable is insignificant at all levels of significance (see table 4.24). On the contrary, other variables, such as the stock market index, are based more directly on market prices (Chen and Jordan, 1993) and this may be a reason of significance based on the results from the joint test.

As far as the unexpected change in the petroleum series in concerned, which is used here as a similar index to the one used by Chen *et al.* (1986) and Chen and Jordan (1993), only for the first and the second portfolio of the third sub-period (2001–2006) the variable seems to be significant at the 10 and 5 per cent level (0.098 and 0.030 respectively). This result may be due to the fact that we use a similar and not the same index (i.e. crude petroleum index) used in previous studies (Chen *et al*, 1986; Chen and Jordan, 1993; Clare and Thomas, 1994).

Table 4.24: **Selected results of the time-series regressions of factor scores on the macrovariables**

Period	Portfolios	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1989—1994	P1	0.523	0.519	-	0.746	**0.018***
	P2	0.298	0.135	-	0.897	**0.006****
	All Ps	0.133	0.351	-	0.937	**0.083*****
1995—2000	P1	**0.079*****	**0.013***	0.433	0.986	0.719
	P2	0.220	0.553	0.686	0.699	**0.014***
	P3	0.264	0.400	0.260	0.921	**0.014***
	P4	0.619	0.349	0.218	0.450	0.172
	P5	0.740	0.708	0.817	0.874	0.421
	All Ps	0.380	0.244	0.311	0.469	0.227
2001—2006	P1	0.539	0.826	0.323	**0.098*****	0.102
	P2	0.209	**0.015***	0.292	**0.030***	0.434
	P3	0.347	0.255	0.191	0.530	**0.000****
	P4	0.394	0.843	0.290	0.298	**0.002****
	P5	0.437	0.578	0.785	0.460	0.466
	P6	0.205	0.466	0.715	0.657	**0.000****
	P7	0.176	0.313	0.774	0.429	**0.016***
	P8	0.306	0.909	0.259	0.228	**0.015****
	All Ps	0.576	0.561	0.554	0.120	**0.000****
1989—2006	P1	**0.007****	0.102	-	0.314	**0.013***
	P2	0.671	0.309	-	0.303	**0.092*****
	All Ps	0.504	0.121	-	0.583	0.971

Notes: *Indicates significance at the 5 per cent level for the joint test
**Indicates significance at the 1 per cent level for the joint test
***Indicates significance at the 10 per cent level for the joint test

4.12 Canonical Correlation Analysis between the Set of Factor Scores and the Set of Macroeconomic Variables

After the application of the multiple time-series regression model of the factor scores on the macrovariables, we apply a canonical correlation analysis so as to examine the extent of possible relationships between linear combinations of sets of dependent and independent variables (see: McGowan and Dobson, 1993; Cheng, 1995). In this test, the dependent variables are the factor scores, generated from the factor analysis for each portfolio and the independent variables are the respective macrovariables for each period under examination.

The purpose of this test is to find the linear combinations that maximise the correlations between the members of each *canonical variate pair* (see chapter three). This pair consists of different combinations between two sets of variables, one set of dependent variables and the other set of independent variables. In our case, we have different combinations of sets of factor scores and macroeconomic variables. It should be noted that, according to the theory of canonical correlation analysis, the maximum number of linear combinations between two sets of variables should not exceed that of the set with the smallest number of variables. Table 4.25 depicts the cumulative canonical correlation results for all the portfolios.

Specifically, table 4.25 presents *only* the significant linear combinations between the two sets with the respective squared canonical correlations that show the percentage of variance shared between the two sets of variables, the p-value, which shows the significance of the correlation between the two sets (we present the squared canonical correlations and the p-values of the first and the second linear combination only, as in all cases these were the significant combinations at most) and the macrovariables with their respective significant loadings for each set of macrovariables. For example, for the first portfolio of the whole period (1989–2006) the squared canonical correlation is equal to 0.912 which means that approximately 91.2 per cent of the total variance of the first linear combination of the factor scores is explained by the total variance of the respective linear combination of the macrovariables. The second set of linear combinations adds 30.9 per cent explanatory power to the rest of the unexplained variance of the second linear combination of the set of factor scores.

The canonical loadings for almost all the portfolios (except for the case of the fifth portfolio in the second sub-period 1995–2000 and the seventh portfolio in the third sub-period 2001–2006 where no variable was significant) show that the first linear combination is due almost to the return on the stock market index (e.g. for the group of the portfolios of the whole period 1989–2006 and for the first portfolio of the whole period the sig. of the first linear combination is equal to 0.000), a finding which is exactly the same as in the work of Chen and Jordan (1993). This is another confirmation that the stock market index still has the power to absorb the necessary amount of information so as to explain the behaviour of securities, even when it is compared to other variables, something which contradicts, up to a point, the findings of Chen *et al.* (1986), although this conclusion was a result of multiple regression and not of canonical correlation analysis.

Except from the significance of the stock market index, the second linear combination seems to be, although in a very few cases (only for the second portfolio of the third sub-period 2001–2006, the first portfolio of the whole period 1989–2006 and the group of portfolios also for the whole period), due to the change in the expected inflation and the unexpected inflation. The relative high loadings of these variables for each case are 0.625, -0.717 and -0.689 for the change in the expected inflation and -0.520, -0.660 and -0.676 for the unexpected inflation respectively. While these results contradict the findings of Chen and Jordan (1993), there are similarities with our results from Fisher's joint test as in the case of the first portfolio for the whole period (1989–2006) and the second portfolio of the third sub-period (2001–2006). In these two cases the two inflation measures seem to be statistically significant from the results of the joint test and the results of the canonical correlation analysis. This result is in accordance with the fact that the inflation measures that is the change in the expected inflation, have relatively more power to affect the behaviour of stock returns, especially when these variables are more volatile during specific periods. The findings of the relatively small but interesting role of the inflation variables in the ASE, confirms the conclusions of Chen *et al.* (1986) about the small but interesting performance of these variables in stock markets.

However, our results contradict those of Chen and Jordan (1993) where at least one of the two other variables, the unexpected growth rate in the industrial production and the unexpected change in the petroleum series, is significant for any of the portfolios under examination. Our results from the joint test and the canonical correlation analysis verify that these two variables are statistically insignificant for the explanation of the variance of any set of factor scores. Specifically, while each time-series regression of each factor score on the macrovariables proves to give a significant p-value separately, during the meta-analysis (joint test) the sum of p-values for all the factor scores for the same macrovariable for each portfolio seem to diminish the power of this specific macrovariable.

The only exception of significance is the case of the first and the second portfolio during the third period (2001–2006) and this phenomenon can easily, but partially, be explained by the fact that several similar indices, that include petroleum, have become much more volatile through the years because of several reasons that is the increase in the price of crude petroleum which affects petroleum products and it may have an effect, on an international level, on a country's economy to a lesser or a higher degree. Appendix IX presents the empirical results of canonical correlation analysis for each portfolio for all the periods under examination.

Table 4.25: **Selected results of canonical correlation analysis between the set of artificial factors and the set of macrovariables**

Period	**Portfolios**	**Squared canonical correlation (1st linear combination)**	**Squared canonical correlation (2nd linear combination)**	**1st linear combination (Sig.)**	**2nd linear combination (Sig.)**	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1989—1994	P1	0.957	-	**0.000****	-	-	-	-	-	-0.999
	P2	0.844	-	**0.000****	-	-	-	-	-	-0.996
	All Ps	0.966	-	**0.000****	-	-	-	-	-	-0.999
1995—2000	P1	0.945	-	**0.000****	-	-	-	-	-	1.000
	P2	0.870	-	**0.000****	-	-	-	-	-	0.984
	P3	0.940	-	**0.000****	-	-	-	-	-	0.998
	P4	0.805	-	**0.000****	-	-	-	-	-	0.978
	P5	-	-	-	-	-	-	-	-	-
	All Ps	0.952	-	**0.000****	-	-	-	-	-	0.997
2001—2006	P1	0.760	-	**0.000****	-	-	-	-	-	-0.984
	P2	0.734	0.492	**0.000****	**0.010****	0.625	-0.520	-	-	0.913
	P3	0.738	-	**0.000****	-	-	-	-	-	-0.927
	P4	0.766	-	**0.000****	-	-	-	-	-	-0.986
	P5	0.724	-	**0.001****	-	-	-	-	-	0.924
	P6	0.779	-	**0.000****	-	-	-	-	-	0.918
	P7	-	-	-	-	-	-	-	-	-
	P8	0.609	-	**0.072*****	-	-	-	-	-	0.830
	All Ps	0.766	-	**0.000****	-	-	-	-	-	0.970
1989—2006	P1	0.912	0.309	**0.000****	**0.009****	-0.717	-0.660	-	-	-0.997
	P2	0.725	-	**0.000****	-	-	-	-	-	-0.993
	All Ps	0.919	0.387	**0.000****	**0.015***	-0.689	-0.676	-	-	-0.998

Notes: *Indicates significance at the 5 percent level.
**Indicates significance at the 1 per cent level.
***Indicates significance at the 10 per cent level.

4.13 The Cross-Sectional Test Results of the Macroeconomic APT Model

After the examination of the results of the statistical APT model, we proceed to the explanation of the cross-sectional results from the application of the macroeconomic model. Specifically, table 4.26 presents the results from the regression of the average returns of stocks of each portfolio on the sensitivities (factor betas) estimated from the time-series stage of regressions (Chen *et al.*, 1986; Chen and Jordan, 1993; Groenewold and Fraser, 1997). The first row of each cell for each factor depicts the beta coefficient of each factor, while in the second row of the same cell the respective p-value is presented.

As far as the portfolios for the whole period (1989–2006) are concerned, the macroeconomic APT model seems to have the power to explain stock returns. For example, in the case of the first portfolio the adjusted R^2 is 0.421 and the F statistic is equal to 0.001, which means that the model is constructed well as it includes observed factors that have the ability to affect the behaviour of stocks. The results of the macroeconomic APT model for the whole period are similar, but not the same, to the results of the statistical APT model, as for the second portfolio of the same period the macroeconomic APT model shows its poor performance to explain asset returns (adjusted R^2 equal to 0.080 and F statistic equal to 0.198).

In the first sub-period (1989–1994) the results of the models are even more similar as they both seem to have the potential to affect stocks (adjusted R^2 equal to 0.417, 0.400 and 0.393 for the first, the second and for the group of the portfolios respectively). In all these cases the F statistic is also significant at the 1 per cent level (0.001, 0.002 and 0.000 respectively). This might be a sign of concurrence between the artificial factors and the observed macrovariables. This period of investigation is characterised by several reforms in the ASE in order to overcome the difficulties in its functionality, so it is very interesting to see that such concurrence may be feasible.

During the turbulent second period (1995–2000) on a domestic and an international level the results are different between the models. If we see the F statistics for each portfolio in both tables, we can see that at the cells that the one model has the ability to explain stock returns, in the respective cell of the other table the other model performs poorly (for example, while portfolio 4 in table 4.15 of the statistical APT model shows an adjusted R^2 equal to 0.132 and F statistic equal to 0.135, table 4.26 shows that for the same portfolio the adjusted R^2 is equal to 0.277 and the F statistic is 0.023). These results might be, as already mentioned, the aftermath of macroeconomic crises around the world, for instance in Brazil and Russia, and other economic problems that have occurred domestically and internationally. These phenomena motivate the use of more variables, mostly international, in these tests.

Finally, in the last sub-period (2001–2006), the macroeconomic APT model seems to explain stock returns less in comparison to the statistical APT model, a result which is evident by the F statistics (which in more than half the cases are insignificant at the 5 per cent level) and the adjusted R^2s which are relatively small. This is a sign that, as the ASE has become a developed market in the new millennium new factors may affect stocks' behaviour. This is why the artificial factors of the statistical APT model seem to be more significant in comparison to the macroeconomic model. It includes a number of significant (unobserved) factors and the only problem is to be identified and used in the tests.

As far as the variation inflation factor (VIF) for multicollinearity is concerned, its value is on average less than 5, which means that there is no multicollinearity between the macroeconomic variables for all periods and portfolios. Moreover, the cross-sectional regressions depict the true influence of the macrovariables on the portfolios of stock returns.

Furthermore, as the Olympic Games took place in Greece in 2004, significance is observed in the industrial production factor according to the results of portfolio 8. This inference is in agreement with the results of Veraros *et al.* (2004) that, during the preparation of the event, positive effects were observed at specific stocks related to infrastructure development. Specifically, portfolio 8 contains stocks of firms that belong to the industrial production sector whose work had increased before the period of the Games due to the need for new constructions, that is new buildings and stadiums, reconstruction of older ones and so on.

***Table 4.26*: The cross-sectional test results of the macroeconomic APT model**

Period	Portfolios	γ_0	CEI_t γ_1	UI_t γ_2	$UGRIP_t$ γ_3	$UCPS_t$ γ_4	RMI_t γ_5	Adjusted R^2	VIF	F Sig.
1989—1994	P1	-0.008	0.001	0.001		0.026	0.008	0.417	1.293847	0.001
		0.386	*0.032*	*0.356*	-	*0.004*	*0.366*			
	P2	-0.024	-0.001	0.002		0.014	0.030	0.400	1.213813	0.002
		0.005	*0.158*	*0.056*	-	*0.148*	*0.050*			
	All Ps	-0.018	0.000	0.002		0.020	0.018	0.393	1.028523	0.000
		0.000	*0.627*	*0.000*	-	*0.004*	*0.000*			
1995—2000	P1	0.011	0.000	0.000	0.002	-0.004	-0.003	-0.176	2.119706	0.984
		0.651	*0.690*	*0.937*	*0.703*	*0.623*	*0.865*			
	P2	0.003	0.000	0.000	0.005	0.001	0.012	0.017	1.921119	0.385
		0.945	*0.751*	*0.347*	*0.215*	*0.761*	*0.754*			
	P3	0.068	0.000	-0.001	0.007	0.007	-0.066	0.243	2.444862	0.036
		0.149	*0.673*	*0.193*	*0.046*	*0.363*	*0.203*			
	P4	0.599	0.022	-0.021	-0.022	-0.173	-0.753	0.277	2.053938	0.023
		0.452	*0.051*	*0.005*	*0.661*	*0.004*	*0.465*			
	P5	0.016	0.001	0.000	-0.005	0.007	-0.011	0.065	2.888322	0.259
		0.414	*0.271*	*0.946*	*0.237*	*0.085*	*0.736*			
	All Ps	0.036	0./003	-0.004	0.003	-0.047	-0.026	0.056	1.39209	0.020
		0.202	*0.061*	*0.004*	*0.736*	*0.003*	0.376			
2001—2006	P1	-0.016	-0.001	0.001	-0.005	0.014	0.005	0.117	1.317862	0.158
		0.511	*0.269*	*0.068*	*0.167*	*0.036*	*0.750*			
	P2	0.134	0.000	0.001	0.003	0.031	-0.111	0.530	2.045815	0.000
		0.039	*0.492*	*0.086*	*0.429*	*0.000*	*0.033*			
	P3	0.068	0.000	0.000	0.001	0.005	-0.071	-0.055	2.322695	0.629
		0.458	*0.631*	*0.790*	*0.821*	*0.489*	*0.385*			

	P4	-0.028 *0.685*	0.001 *0.115*	0.000 *0.842*	0.000 *0.949*	0.018 *0.022*	0.025 *0.715*	0.295	2.319409	0.018
	P5	0.064 *0.274*	0.000 *0.563*	0.000 *0.583*	-0.005 *0.283*	0.005 *0.397*	-0.077 *0.217*	0.186	2.38431	0.074
	P6	-0.597 *0.381*	-0.004 *0.697*	-0.007 *0.450*	-0.066 *0.470*	-0.319 *0.014*	0.670 *0.412*	0.141	1.528682	0.122
	P7	0.050 *0.223*	0.000 *0.770*	-0.001 *0.233*	0.003 *0.630*	0.003 *0.667*	-0.088 *0.135*	-0.050	1.823479	0.613
	P8	0.004 *0.710*	0.000 *0.607*	0.001 *0.386*	-0.006 *0.085*	0.025 *0.001*	-0.009 *0.696*	0.358	2.071917	0.007
	All Ps	0.004 *0.791*	-0.001 *0.659*	-0.001 *0.193*	-0.004 *0.560*	-0.012 *0.351*	-0.017 *0.256*	-0.004	1.218736	0.531
1989—2006	P1	-0.007 *0.338*	0.001 *0.154*	0.001 *0.061*	-	0.016 *0.004*	0.011 *0.133*	0.421	1.310447	0.001
	P2	-0.003 *0.458*	0.001 *0.447*	0.000 *0.626*	-	0.010 *0.075*	0.008 *0.199*	0.080	1.355591	0.198
	All Ps	-0.002 *0.431*	0.001 *0.045*	0.000 *0.358*	-	0.012 *0.003*	0.005 *0.066*	0.257	1.247452	0.000

4.14 A Comparison Criterion between the Macroeconomic APT and the Statistical APT Model

4.14.1 Davidson and MacKinnon Analysis

According to past studies (Chen, 1983, Chen and Jordan, 1993), the Davidson and MacKinnon (1981) equation was applied on the notion that the two models are non-nested. This means that the macroeconomic APT model is being considered with a number of observed factors while the statistical APT model has only artificial factors. This is the reason that the models are non-nested, unless there is a rotation of the artificial factors such that one of them is one of the macroeconomic factors used in the analysis.

Equation (12) was used in order to compare the statistical APT with the macroeconomic APT model:

$$R_{i,t} - R_{MAPT} = a(R_{SAPT} - R_{MAPT}) + e_i \qquad \textbf{(12)}$$

where R_{SAPT} and R_{MAPT} are the expected returns which were generated by the models respectively. If the null hypothesis H_0 is accepted and the coefficient a is equal to zero it means that the macroeconomic APT is the better model (Davidson and MacKinnon, 1981).

Table 4.27 shows that for most of the portfolios the statistical APT is the better model. This is clear from the p-values, presented in the second row of the cell of the coefficient, which show that the coefficient is significant in most cases. As in the case of the comparison between the CAPM and the statistical APT model, the results justify that there might be other factors – unobserved at the moment – or combinations of new factors with the existent ones that could play a major role in asset pricing. Alternatively, there are some cases as in the case of portfolio 1, 3 and 4 during the sub-period 1995–2000 as well as in portfolios 7 and 8 of the 2001–2006 sub-period of analysis, where the macroeconomic factors seem to be able to explain the cross-section of stock returns. These might be due to the fact that the high volatility of some of the variables, like in the case of the inflation variables, plays a crucial role in asset pricing, a conclusion similar to that of Chen *et al.* (1986). This is also evident during the turbulent period of the ASE (1995–2000) which confirms the findings that the macroeconomic APT model includes factors that have the ability to explain the behaviour of stock returns.

***Table 4.27*: The Davidson and MacKinnon results**

Period	**Portfolios**	a	R^2	**Adjusted** R^2
1989–1994	Portfolio 1	0.635 *0.028*	0.155	0.126
	Portfolio 2	0.765 *0.000*	0.389	0.368
	All portfolios	0.788 *0.000*	0.330	0.319
1995–2000	Portfolio 1	0.262 *0.186*	0.059	0.027
	Portfolio 2	0.866 *0.000*	0.484	0.466
	Portfolio 3	0.071 *0.807*	0.002	-0.032
	Portfolio 4	0.344 *0.132*	0.077	0.045
	Portfolio 5	0.783 *0.001*	0.327	0.303
	All portfolios	0.497 *0.013*	0.041	0.035
2001–20 06	Portfolio 1	0.855 *0.025*	0.162	0.134
	Portfolio 2	0.594	0.184	0.156

		0.016		
	Portfolio 3	0.994 *0.001*	0.313	0.290
	Portfolio 4	0.940 *0.000*	0.591	0.577
	Portfolio 5	0.762 *0.001*	0.313	0.289
	Portfolio 6	1.018 *0.000*	0.790	0.782
	Portfolio 7	-0.100 0.634	0.008	-0.026
	Portfolio 8	-0.117 0.308	0.036	0.003
	All portfolios	0.777 *0.010*	0.028	0.023
1989–2006	Portfolio 1	0.788 *0.001*	0.338	0.315
	Portfolio 2	0.828 *0.000*	0.488	0.470
	All portfolios	0.810 *0.000*	0.371	0.361

4.15 Further Cross-Sectional Test Results of the Macroeconomic APT Model

In this section we present the cross-sectional results of the macroeconomic APT model after we have added to the previous macroeconomic variables the time series of new ones. These new variables will also be used in the application of Johansen's (1988; 1991) multivariate cointegration model (presented in chapter five). Moreover, after the presentation of the empirical tests, based on the two-stage methodology presented in chapter three, we present the results of a macroeconomic APT model that contains only the new variables. Tables 4.28 and 4.29 (below) depict the main statistical results of each model.

The additional variables are comprised of the money supply ($M1_t$), the retail price index (RL_t), the exchange rate between US Dollar and Euro ($USEURO_t$) and the exchange rate between GB Pound and Euro ($GBPEURO_t$). Following the methodology of Box-Jenkins (1976) we have obtained the unexpected changes (residuals) in the money supply ($UM1_t$), the unexpected changes in the USD/Euro exchange rate ($UUSEURO_t$) and the unexpected changes in the retail price index (URL_t). For the case of the GBP/Euro exchange rate we used the observed changes according to the Box-Jenkins methodology (insignificant autocorrelations and partial autocorrelations of the time series).

Tables 4.28 and 4.29 present the results from the regression of the average returns of stocks of each portfolio on the sensitivities (factor betas) estimated from the time-series stage of regressions (Chen *et al.*, 1986; Chen and Jordan, 1993). The first row of each cell for each factor depicts the beta coefficient of each factor, while in the second row of the same cell the respective p-value is presented.

The period under examination for the application of these two models extended from January 2001 to December 2006 due to data availability limitations of the new variables. The results of table 4.28 show that with the addition of the new variables the statistics of the model have slightly improved. More specifically, the adjusted R^2 is in several cases (portfolios) higher than in table 4.26 and the F statistic is in four cases significant at the 5 per cent level (in comparison to the three cases of table 4.26) for the period between 2001 and 2006. The significant F statistic shows that the model has the ability to explain stock returns with the inclusion of the specific variables. But, while examining the p-values of each variable it is evident for most of the cases that the most significant are the initial ones (the variables that are presented in table 4.26). The results show that the power of the model increases when along with the market beta and the other initial variables, a number of new ones is included in the equation. These results imply that the initial variables provide a relatively efficient mechanism of examining stock returns, and, when they are combined with additional variables in a multi-factor model, they can enhance the quality of the model in terms of increased explanatory ability (Theriou *et al.*, 2005). As it is a period that the ASE has transtitioned to a developed market there might be alternative factors that can affect stocks' behaviour.

Furthermore, the variation inflation factor (VIF) for multicollinearity shows that, as its value is on average less than 5, there is no multicollinearity between the macroeconomic variables for all the portfolios. This means that the cross-sectional regressions depict the true influence of the macrovariables on the portfolios of stock returns.

As far as table 4.29 is concerned the results are much worse for the APT model. Only in the case of portfolio 2 and 4 the adjusted R^2 and the F statistics are significant at the 5 per cent level. Additionally, only for a few cases (portfolios) some of the variables exhibit any significance. These results might be one of the reasons that variables such as the retail price index and the money supply (M1) have not been so widely used in prior empirical studies regarding the two-stage macroeconomic APT model (Chan *et al.*, 1985; Chen *et al.*, 1986; Chen and Jordan, 1993; Zhou, 1999). Finally, the VIF for multicollinearity shows again that there is no multicollinearity between the macroeconomic variables for all the portfolios.

Table 4.28: **The cross-sectional test results of the macroeconomic APT model (all variables)**

Period	Portfolios	γ_0	CEI_t γ_1	UI_t γ_2	$UGRIP_t$ γ_3	$UCPS_t$ γ_4	RMI_t γ_5	$GBPEURO_t$ γ_6	$UM1_t$ γ_7	$UUSEURO_t$ γ_8	URL_t γ_9	Adjusted R^2	VIF	F Sig.
2001—2006	P1	-0.015	-0.001	0.001	-0.007	0.009	0.008	0.000	0.006	0.001	-0.010	0.233	2.939	0.098
		0.270	*0.307*	*0.053*	*0.127*	*0.365*	*0.410*	*0.955*	*0.083*	*0.877*	*0.080*			
	P2	0.007	0.000	0.000	-0.003	0.019	-0.005	0.002	0.001	-0.003	0.003	0.588	4.182	0.001
		0.619	*0.677*	*0.797*	*0.438*	*0.017*	*0.634*	*0.405*	*0.734*	*0.473*	*0.558*			
	P3	0.015	-0.001	0.001	-0.001	0.017	-0.011	-0.004	-0.005	-0.010	-0.003	0.317	2.740	0.043
		0.302	*0.125*	*0.062*	*0.678*	*0.045*	*0.399*	*0.181*	*0.047*	*0.076*	*0.602*			
	P4	0.018	0.001	0.000	-0.007	0.022	-0.014	0.001	-0.002	-0.004	-0.002	0.732	2.286	0.000
		0.042	*0.049*	*0.603*	*0.024*	*0.000*	*0.138*	*0.479*	*0.340*	*0.115*	*0.581*			
	P5	-0.005	0.000	0.001	-0.011	0.005	0.001	-0.001	0.002	0.003	0.005	0.270	2.756	0.069
		0.534	*0.513*	*0.187*	*0.006*	*0.404*	*0.912*	*0.621*	*0.416*	*0.301*	*0.198*			
	P6	-0.009	-0.003	-0.001	-0.009	-0.274	-0.077	0.006	-0.024	0.053	-0.109	0.210	2.051	0.120
		0.926	*0.755*	*0.881*	*0.903*	*0.042*	*0.612*	*0.812*	*0.448*	*0.293*	*0.133*			
	P7	-0.013	0.001	0.000	-0.010	0.003	0.015	0.001	-0.002	0.000	0.004	0.331	3.528	0.036
		0.133	*0.130*	*0.798*	*0.006*	*0.510*	*0.293*	*0.605*	*0.178*	*0.938*	*0.351*			
	P8	-0.003	0.000	0.000	-0.007	0.023	-0.002	0.003	-0.001	0.009	0.002	0.255	2.961	0.080
		0.609	*0.591*	*0.663*	*0.106*	*0.016*	*0.864*	*0.184*	*0.834*	*0.088*	*0.787*			
	All Ps	0.002	0.000	-0.001	-0.005	-0.009	-0.015	0.003	-0.003	0.000	-0.012	0.025	1.904	0.092
		0.877	*0.702*	*0.254*	*0.442*	*0.430*	*0.225*	*0.380*	*0.432*	*0.977*	*0.153*			

***Table 4.29*: The cross-sectional test results of the macroeconomic APT model (additional variables)**

Period	**Portfolios**	γ_0	$GBPEURO_t$ γ_1	$UM1_t$ γ_2	$UUSEURO_t$ γ_3	URL_t γ_4	**Adjusted** R^2	**VIF**	**F Sig.**
2001—2006	P1	-0.019	-0.002	0.002	-0.006	-0.011	0.030	1.879	0.327
		0.023	*0.508*	*0.633*	*0.270*	*0.049*			
	P2	-0.008	0.004	0.000	-0.003	0.005	0.414	2.076	0.001
		0.326	*0.018*	*0.952*	*0.466*	*0.428*			
	P3	-0.007	-0.003	-0.003	-0.010	-0.004	0.079	1.924	0.199
		0.186	*0.314*	*0.234*	*0.041*	*0.551*			
	P4	-0.006	0.005	0.001	-0.001	-0.002	0.357	1.848	0.004
		0.203	*0.015*	*0.808*	*0.817*	*0.700*			
	P5	-0.010	0.001	0.000	0.000	0.004	-0.104	1.365	0.864
		0.005	*0.739*	*0.937*	*0.952*	*0.320*			
	P6	-0.029	0.015	-0.034	0.056	-0.135	0.127	1.159	0.118
		0.571	*0.533*	*0.246*	*0.274*	*0.032*			
	P7	-0.009	0.003	-0.002	0.001	0.004	0.063	1.943	0.236
		0.033	*0.269*	*0.231*	*0.665*	*0.326*			
	P8	-0.009	0.001	-0.004	0.001	0.003	0.038	1.701	0.302
		0.060	*0.575*	*0.108*	*0.791*	*0.705*			
	All Ps	-0.008	0.004	-0.004	0.001	-0.010	0.014	1.515	0.118
		0.237	*0.267*	*0.224*	*0.830*	*0.198*			

4.16 Conclusions

At the end of the 1980s there were several significant changes/reforms in the ASE, especially after 1992, that led to an increase in its liquidity and efficiency as a stock exchange. These changes contributed to the ability of the ASE to respond faster to any kind of information that had to do with investments and possible gains for any individual investor. Additionally, the fact that the number of listed stocks has rapidly increased during the last years, as it transitions from an emerging to a developed market (Chortareas *et al.*, 2000), means that nowadays it can play a more significant role in the Greek economy and may affect other stock markets, especially those who are also in a transition stage.

The empirical findings of the tests show that the performance of the CAPM is relatively poor during all the sub-periods and the whole period. This could mean that the market beta may not be a significant factor in the ASE, something which also shows that the model is not the best one so as to examine if the efficiency of the ASE holds. In contrast, the statistical APT model performs better for all the sub-periods and the whole period under examination. It shows that there is a number of variables, except from the stock market index, that could explain the behaviour of the returns of assets. The following step, regarding the application of the macroeconomic APT model, was just to identify these factors, something that has been the main goal of many studies in the past (Chen *et al.*, 1986; Chen and Jordan, 1993; Clare and Thomas, 1994; Cheng, 1995).

It is also important to mention that, although there might be some power in the market, according to the CAPM, the stock exchange in Greece is complex and the behaviour of the returns of assets could depend on additional factors, that is macroeconomic (Chen *et al.*, 1986) and financial (Fama and French, 1992), or even psychological factors, as explained by Niarchos and Alexakis (2000). Finally, the results show that the statistical APT model fails to explain the behaviour of returns at some portfolios, especially when they are investigated as a group for specific periods, something which could be due to several reasons. One reason is that the risk and the return of assets may not be stationary during the periods under examination, while one of the assumptions of the APT model is that risk and return are assumed to be stationary. Another reason may be the lack of the application of non-linear models in the examination of the relationship between the APT model and the factors, as the linear relationship assumption seems to be too strong in order to hold in a stock market.

As far as the macroeconomic APT model is concerned, at the beginning, a number of observed variables were selected for the application of the model on a number of portfolios for different time periods. During these sub-periods of examination there was an increase in the liquidity of securities and the information was easier to be absorbed which had to do with new investments and possible gains for the investors. Of course, this is not evidence of market efficiency in Greece, as it can be seen from the empirical results of the CAPM in section 4.7. However, it might be a sign of partial market efficiency as time passes in comparison to the past. This conclusion is also empirically verified by the results of the tests as the return on the stock market index seems to play a relatively more significant role in portfolio returns explanation compared to the macroeconomic variables used in the application of the APT model (section 4.13).

These conclusions are evident in the work of Chen and Jordan (1993) and partially evident in the work of Chen *et al.* (1986). Specifically, the time-series regression tests of the factor scores on the macrovariables for each portfolio, the canonical correlation analysis between the two sets of variables and the cross-sectional regression results show that the return on the stock market index can be a more important factor in comparison to other variables in the ASE.

Additionally, in the case of the time-series regression tests of the factor scores on the macrovariables and from the canonical correlation results it is evident that the two inflation variables, the change in the expected inflation and the unexpected inflation, seem to have the ability to explain the behaviour of stock returns. Finally, while for the time-series tests and the canonical correlation analysis the results on the unexpected change in the growth rate of the industrial production and the unexpected change in the petroleum series are generally poor, the cross-sectional regression tests show that these variables may have some explanatory power on stocks' behaviour. These findings are in accordance with the findings of Chen and Jordan (1993) and Chen *et al.* (1986).

When the two APT models are compared based on the Davidson and MacKinnon (1981) analysis, it is clear that in the most cases the statistical APT model performs better. These findings can also be verified by the fact that the variables that are used for the application of the macroeconomic model are observed variables and not artificial (Clare and Thomas, 1994; Cheng, 1995; Groenewold and Fraser, 1997). This means that the artificial factors were generated mathematically as a linear combination of the variables (stock returns) used in the analysis (Roll and Ross, 1980; Chen, 1983), while in the case of the macroeconomic model there is not a really specific theory that explains which of the factors are truly the best for the application of the model (Chan *et al.*, 1985; McGowan and Dobson, 1993; Clare and Thomas, 1994; Cheng, 1995) and in many cases scholars select a number of such variables based on past studies, previous experience, curiosity and logic.

We have already mentioned that the CAPM performs poorly in most of the portfolios and the stock market index cannot be a crucial factor in asset pricing. However, for some of the tests employed, like in the tests of the time-series regression of factor scores on the macrovariables, the significance of this variable seems to be large when it is compared with other variables such as the unexpected inflation and the change in the expected inflation. This result contradicts the suggestion of Chen *et al.* (1986) who argued that when the stock market index is compared to other variables its significance becomes small. The findings of our tests show that there might be other variables, except the ones used in the tests that could play an important role in asset pricing, such as the exchange rates or even international stock indices.

During the cross-sectional multiple regression tests the results seem to be in agreement with the work and suggestions of Chen *et al.* (1986). The stock market index loses much of its power, although it does not become totally insignificant and the unexpected change in the industrial production, for some portfolios, but most of all, the unexpected change in the petroleum series seems to be the best factor for the pricing of stock returns, especially for the second and the third sub-period (1995–2000 and 2001–2006, respectively).

Overall, although the results show that there might be some power in the stock market, the stock returns in the ASE seem to be dependent on several additional factors like the ones used in this study. Of course, these differences between the results of the tests are due to the methodologies that are used, the factors that are compared each time and the criteria that are used to explain the results, such as the level of significance. On an international level, the differences on the results between several studies is caused because of different time periods of analysis, the different measurement between the same variables used in these studies, the use of different variables for the same goal and, of course, the methodologies and techniques that each scholar use to explain asset prices (Chen *et al.*, 1986; Clare and Thomas, 1994; Niarchos and Alexakis, 2000).

Generally, the weak performance of the macroeconomic APT – in comparison to the statistical APT model based on the Davidson and MacKinnon (1981) results – seems to argue that stock prices are affected by other factors, which may be exogenous to the ASE. For instance, during the period 1997–1998 the crises in Asia, Brazil and Russia and the problem of recession in the US might had an effect on stock prices. We should also mention that, as the Olympic Games took place in Greece in 2004, a weak significance was observed in the industrial production factor from the results of portfolio 8 according to table 4.26 (at the 10 per cent level of significance). This might be due to the fact that this portfolio contains stocks of firms that belong to the industrial production sector and their work had increased before the period of the Games because of the need for new constructions, that is new stadiums because of the enhanced need of athletic activities during that period. Another factor might be the devaluation of the Greek drachma in comparison to euro in 1998 which was one of the criteria necessary for Greece to be an equivalent member of the European Economic and Monetary Union, in 1999, and affected the inflation rate so as to make the Greek products more competitive.

Finally, as far as the (weak-form) efficiency of the market is concerned, it seems that it cannot hold in the ASE as the CAPM, whose theory is based on the efficiency of the market, is unable for almost all the portfolios and the periods of investigation to explain the behaviour of stocks' returns. In the following chapter, we will try, with the use of (G)ARCH models and cointegration analysis, to verify whether these conclusions hold in the ASE.

Chapter Five

EMPIRICAL TESTS AND RESULTS WITH (G)ARCH MODELS, UNIT ROOT AND COINTEGRATION ANALYSIS

5.1 Introduction

In chapter three we presented the steps that will be followed so as to use the (G)ARCH models in asset pricing as well as the unit root and cointegration analysis. When heteroscedasticity exists, which means that the variance of the residuals of a time series is not constant, a specific (G)ARCH model is applied so as to capture this phenomenon (Engle, 1982; Bollerslev, 1986; Engle *et al.*, 1990; Nelson 1991). As far as the structure of the present chapter is concerned, at the beginning we present the data sample used for tests using specific types of (G)ARCH models. Further, we present the respective data sample used so as to examine possible relationships in the ASE by employing specific unit root tests and cointegration analysis. The results of the empirical tests showed that, as far as the application of (G)ARCH models is concerned, the phenomenon of heteroscedasticy was evident for almost all stocks under examination. The contribution of the models was significant and the comparison between the models showed that the GARCH(1,1) model is the preferred one, as it is the most adequate to estimate the time-varying volatility of stock returns for most of the tests, followed by the EGARCH and the EGARCH-M model. The ARCH-M proved to be the most insignificant of all. The importance of these models in the examination of a financial time series is another strong sign which contradicts the validity of the CAPM and, consequently, the ability of the model to justify the (weak-form) efficiency of the Greek stock market (Fama, 1970; 1991). The empirical results showed that there were similarities with the results of the CAPM in chapter four.

Furthermore, the results of the unit root tests and cointegration analysis showed that there are cointegrated vectors between the variables under examination, which means that, on the long-run, the variables are related, an inference which contradicts the (weak-form) efficient market hypothesis (EMH) that future prices of variables, such as stock indices, are not influenced by past (historical) prices (Fama, 1970; 1991; Diacogiannis, 1994).

5.2 Data Collection

As mentioned in chapter four, monthly time series of stock returns of Greek firms listed in the ASE were used for the empirical tests. The data was obtained from the ASE databanks and it is comprised of daily closing prices of common stocks traded in the ASE. They are raw prices in the sense that they do not include any dividends but are adjusted to stock splits. These common stocks were listed in the ASE during the 1989–2006 period of analysis. The return on the market was obtained from the ASE Composite (General) Share Price Index. Finally, the three-month Government Treasury Bill Rate, which is considered to be a short-term interest rate, was used as the risk-free interest rate and was obtained from the Central Bank of Greece.

The daily returns of stocks were calculated using the logarithmic approximation:

$$R_{i,t} = \log\left(P_{i,t} / P_{i,t-1} \right) \qquad \textbf{(1)}$$

where $P_{i,t}$ is the closing price of day t for asset i (Coutts, *et al.*, 2000; Chortareas, *et al.*, 2000). Then, the daily returns were aggregated to compose the monthly return series used as the input of the analysis. It is important to mention that, for the application of (G)ARCH models on the market model, except for monthly returns, daily returns of stocks were also used. The reason was that for the sub-periods under examination (1989–1994, 1995–2000 and 2001–2006) the number of observations was relatively small for the application of (G)ARCH models while, on a daily basis, the results would give a more detailed view of the series' diagnostic tests e.g. heteroscedasticity or normality results.

As far as the unit root and cointegration tests are concerned, the raw price of the stock market index, was also used in the tests, along with a number of other sectoral indices e.g. the insurance and the banking index. Furthermore, the raw prices of a number of macroeconomic indices were employed for the unit root test, based on the studies of Dickey and Fuller (1979; 1981), Phillips and Perron (1988) and Kwiatkowski *et al.* (1992). Several indices are similar to the ones used in the tests of the APT model, such as the consumer price index (used in the calculation of the inflation rate in chapter four) and the index of industrial production.

5.3 Data Analysis

The monthly stock returns that are examined have no missing values during the whole period (1989–2006) under examination. Portfolios of equal size were constructed and the number of 30 stocks in each portfolio is justified as a sufficient number of stocks for the application of APT models (Roll and Ross, 1980). For the application of the market model on portfolios of daily stock returns, the stock market index was appropriately calculated on a daily frequency so as to have a large number of observations for the application of (G)ARCH models (in case we had to encounter the problem of heteroscedasticity in the data).

The two-stage methodology was employed for the analysis, as in prior studies (Chen, 1983; Chen *et al.*, 1986; Cheng, 1995; Groenewold and Fraser, 1997). Specifically, during the first stage the stock betas are estimated by regressing the excess returns of each stock (the dependent variable) for each period of analysis on the excess market index of the ASE (the independent variable) for the same period. In case the diagnostic tests show that there is a heteroscedasticity (time-varying volatility) problem, we employ specific types of (G)ARCH models so as to capture the ARCH effect and estimate the time-varying volatility.

After the application of the models, we compare them so as to see which is the preferred one (using the Akaike (1974) and Schwarz (1978) criteria). After we have selected the best model for each regression (each stock return on the stock market index) we gather the respective new beta coefficient (after the application of the best ARCH model) and sort the stocks into portfolios of equal size. The stocks with the smallest new beta coefficients were excluded from the analysis since complete portfolios were required (Chen, 1983; Black *et al.*, 1972).

It is interesting to mention that, except for the new beta coefficients, it was our concern to see whether there was any risk-return trade-off in the time-series regressions of stock returns on the return of the stock market. This was achieved, as it will be seen more clearly in the forthcoming tables, after the examination of the coefficients of ARCH-M and EGARCH-M model whose ability is also to estimate the conditional mean of the equation. Moreover, we investigated whether there are any asymmetry effects between the positive and the negative shocks, by examining the coefficients of the EGARCH and EGARCH-M models. Finally, during the second stage (the cross-sectional regression stage) we regressed the mean excess returns of each portfolio on the estimated new beta coefficients (the betas of the best ARCH model).

Furthermore, for the unit root tests, the raw prices of all the indices under examination were tested for a possible unit root (non-stationarity) in their levels. In case there was a unit root, we calculated the first differences of the indices' time series. If the series became stationary in their first differences, they were used in cointegration analysis (Johansen, 1988; 1991; Johansen and Juselius, 1990). The results would prove whether there is a long-run relationship between the variables and whether the efficiency of the ASE is justified or not.

5.4 The Selection of Variables for the Application of Unit Root and Cointegration Analysis

Based on several prior studies (Hondroyannis and Papapetrou, 2001; Maysami *et al.*, 2004) a number of financial and macroeconomic variables were employed for the unit root and cointegration tests. In the following sub-sections we present the variables that were selected for the examination of possible long-run relationships.

5.4.1 General Stock Market Index and Sectoral Indices

As in the case of the application of CAPM and APT model in chapter four based in prior studies (Chan *et al.*, 1985; Chen *et al.*, 1986; Chen and Jordan, 1993), we employ the general stock market index of the ASE so as to proceed to unit root and cointegration analysis. The monthly prices of the stock market index were obtained from the database of the ASE, along with the monthly prices of a number of sectoral indices (Maysami *et al.*, 2004). These indices were chosen for the analysis because of data availability and their significance in the economy of Greece. Specifically, the indices cover the investment, industrial, construction, insurance and banking sector of the Greek economy.

5.4.2 USD/Euro and GBP/Euro Exchange Rates

As there is an increase in economic globalisation, several businesses are affected by international activities. This means that the changes in the exchange rates may have an effect on the position of companies and industries on an international level. Furthermore, these effects of the exchange rates may lead to changes in the cash flows of companies, so it would be useful for the potential investors to use them in their portfolio evaluation (Gunsel and Cukur, 2007).

According to Maysami *et al.* (2004) it is hypothesised that there is a positive relationship between exchange rates and stock prices. If the euro is expected to appreciate, the Greek market will attract new investments. This appreciation will cause an increase in the stock market level, meaning that the stock market returns will be positively correlated to the exchange rate changes. Alternatively, in case of the depreciation of euro, this change will decrease the stock market level, leading to a negative correlation between stock prices and exchange rates (Mukherjee and Naka, 1995).

In our work we used the USD/Euro and the GBP/Euro exchange rate, so as to investigate whether these variables are related, on the long-run, to financial and macroeconomic indices, such as the general stock market index and the Consumer Price Index (CPI).

5.4.3 Money Supply (M1)

A money supply index is employed for the tests based on the notion that the growth rate of money supply has an effect on a country's economy and on the expected stock returns. Specifically, an increase in the supply of money indicate excess liquidity available for buying securities, which leads to higher stock prices (Hamburger and Kochin, 1972; Kraft and Kraft, 1977).

In our tests we use the M1 money supply index as in the study of Cheng (1995). The M1 index is a measure of the money supply which combines any liquid or cash assets held within a central bank and the amount of physical currency circulating in the economy plus demand deposits, which are checking accounts. It is the index that is used as a measurement for economists in order to quantify the amount of money in circulation because of its liquidity as it contains cash and assets that can quickly be converted to currency.

5.4.4 Consumer Price Index (CPI)

The results of prior studies (Nelson, 1976; Chen *et al.*, 1986) showed that there is a negative relationship between inflation rate and stock prices. This proposition is also verified by the study of Niarchos and Alexakis (2000) who verified that the stock returns are influenced by the inflation rate. Based on the notion of a possible negative relationship we use the CPI by hypothesising that an increase in the rate of inflation is likely to lead to more tight policies, which increases the nominal risk-free rate and raises the discount rate which, consequently, leads to stock prices reduction (Niarchos and Alexakis, 2000). Inflation forecasts are important for a country's economy. At the macroeconomic level, policy makers examine the forecasts of inflation indices in order to set the proper monetary policy. Alternatively, at the microeconomic level, banks examine inflation forecasts so as to use them in their business decisions, such as in case of interest rate policies.

We should recall that the CPI is the index which was calculated so as to have as output the inflation rate for the tests in chapter four based on the studies of Chen *et al.* (1986), Chen and Jordan (1993) and Lakshman and Horton (1999). Specifically, the monthly inflation rate was calculated as the change in the natural log of the Greek monthly Consumer Price Index.

5.4.5 Industrial Production

The industrial production index is used as a proxy for the level of real economic activity, which means that a rise in industrial production would signal economic growth. This was the hypothesis of prior studies (Fama, 1990; Geske and Roll, 1983) who investigated for a possible positive relationship between the industrial production and expected future cash flows. The results of Chen *et al.* (1986) showed that the growth in industrial production was a crucial factor in the explanation of the behaviour of stock returns, which meant that there is a positive relationship between real economic activities and stock prices. Based on this hypothesis we use the prices of the industrial production index which was obtained from the National Statistical Service of Greece, in order to examine its possible long-run relationship with the other variables of the analysis.

5.4.6 Manufacture of Coke, Refined Petroleum Products and Nuclear Fuels

Finally, the index of Manufacture of Coke, Refined Petroleum Products and Nuclear Fuels comprised mostly by products that are constructed based on petroleum, was also used in unit root and cointegration analysis. As we mentioned in chapter four, we use the term "petroleum" not only for abbreviation purposes but because of the fact that the index is comprised mostly by refined petroleum derivatives. The index, obtained from the National Statistical Service of Greece, was previously used in the tests of chapter four for comparison purposes as similar indices were used in the studies of Chen *et al.* (1986) and Chen and Jordan (1993) and its significance was justified by Pari and Chen (1984). Based on prior studies that used petroleum prices (Gay, 2008), we examine the hypothesis that the index is negatively related to stock prices as measured, in the present chapter, by the stock market indices. Raw prices of all the indices are used, as in the case of the other variables, so as to examine, at first, whether they are stationary (existence of unit root or not) and whether they can be used in the tests of long-run relationships (cointegration analysis).

5.4.7 Interest Rate

The changes in short- and long-term government bond rates have an effect on the nominal risk-free rate and, consequently, on the discount rate (Mukherjee and Naka, 1995). In our study we assume that there might be a possible relationship between interest rates and stock prices as the interest rates influence the level of corporate profits which in turn influence the price that investors are willing to pay for the stock through expectations of higher future dividends payment. Because of the fact that several firms finance their capital equipments and inventories through borrowings, a reduction in the interest rates will reduce the costs of borrowing and thus serves as a motive for expansion, leading to a positive effect on future expected returns for the firm. Another reason is that as a substantial amount of stocks is purchased with borrowed money, an increase in interest rates would cause a rise in the cost of stock transactions. Consequently the investors will require a higher rate of return before investing and this will cause a reduction to the demand and lead to the depreciation of price.

Except for the variables mentioned above we have also included the retail price index, as it has been used in prior studies (Clare and Thomas, 1994) and was found to be a significant risk factor. The retail price index was also obtained from the National Statistical Service of Greece and it was used as a proxy for real consumption (Breeden, 1979). Finally, all the variables' prices were expressed in logarithms, so as to easily achieve stationarity of the data (Hondroyannis and Papapetrou, 2001; Maysami *et al.*, 2004). Table 5.1 below presents the variables used in unit root tests and cointegration analysis.

Table 5.1: **The basic and derived variables for unit root and cointegration**

Macroeconomic Variables		
a. Basic Data Series		
Symbol	**Variable**	**Source**
CPI_t	Consumer Price Index	National Statistical Service of Greece
IP_t	Industrial Production	National Statistical Service of Greece
PS_t	Petroleum Series	National Statistical Service of Greece
RMI_t	Stock Market Index	ASE
ISI_t	Insurance Sectoral Index	ASE
BSI_t	Banking Sectoral Index	ASE
$INSI_t$	Investments Sectoral Index	ASE
$INDSI_t$	Industrial Sectoral Index	ASE
$M1_t$	Money Supply	National Statistical Service of Greece
$USDEEXR_t$	USD/Euro Exchange Rate	National Statistical Service of Greece
$GBPEEXR_t$	GBP/Euro Exchange Rate	National Statistical Service of Greece
RPI_t	Retail Price Index	National Statistical Service of Greece
$3MTBR_t$	3-Month Treasury Bill Rate	Central Bank of Greece
b. Derived Series		
Symbol	**Variable**	**Source**
$LCPI_t$	Logarithmic Consumer Price Index	National Statistical Service of Greece
LIP_t	Logarithmic Industrial Production	National Statistical Service of Greece
LPS_t	Logarithmic Petroleum Series	National Statistical Service of Greece
$LRMI_t$	Logarithmic Stock Market Index	ASE
$LISI_t$	Logarithmic Insurance Sectoral Index	ASE
$LBSI_t$	Logarithmic Banking Sectoral Index	ASE
$LINSI_t$	Logarithmic Investments Sectoral Index	ASE
$LINDSI_t$	Logarithmic Industrial Sectoral Index	ASE

$LM1_t$	Logarithmic Money Supply	National Statistical Service of Greece
$LUSDEEXR_t$	Logarithmic USD/Euro Exchange Rate	National Statistical Service of Greece
$LGBPEEXR_t$	Logarithmic GBP/Euro Exchange Rate	National Statistical Service of Greece
$LRPI_t$	Logarithmic Retail Price Index	National Statistical Service of Greece
$L3MTBR_t$	Logarithmic 3-Month Treasury Bill Rate	Central Bank of Greece

5.5 The Diagnostic Tests Results regarding ARCH Effects on Stock Returns

Table 5.2 presents some statistics regarding the frequency of ARCH effect as a result of the regression of each stock return on the return of the stock market index as explained in chapter three. At the first row of the table we present the results of ARCH effect for the whole period (1989–2006) using monthly data. It is evident that most of the regressions present an ARCH effect (69.35 per cent), which means that the residuals of each regression have time-varying volatility which need to be estimated by specific models (GARCH models) as it will be seen in the following sections. This period using monthly data was chosen as it is the whole period investigated during the application of CAPM and APT models in chapter four and, as in prior studies (Morgan and Morgan, 1987; Soufian, 2004) most of the regression results using financial data present ARCH effects.

By applying linear regression analysis using daily data for each stock return and the return of stock market index for the whole period (1989–2006) and the three sub-periods as in chapter three (1989–1994, 1995–2000, 2001–2006) the results are similar: for the whole period 86.66 per cent exhibited an ARCH effect while for the three sub-periods the ARCH effects were evident in the 91.54 per cent, the 99.39 per cent and the 84.29 per cent of stocks respectively. These results lead to the conclusion that the conditional variance should be appropriately estimated in order to solve the heteroscedasticity problem. Section 5.6 presents the best model results as well as the risk-return trade-off and the asymmetry results.

***Table 5.2*: Sample size and ARCH effect in each period**

Period	Number of Stocks	ARCH Effect (%)
1989—2006 (monthly)	62	69.35
1989—2006 (daily)	60	86.66
1989—1994 (daily)	71	91.54
1995—2000 (daily)	164	99.39
2001—2006 (daily)	242	84.29

5.6 The Frequency of the Best Model for Each Period, the Risk-Return Relationship and the Asymmetry Effect

Table 5.3 below presents the frequency that each model, used in the tests for estimating the time-varying volatility of each regression residuals (GARCH(1.1), ARCH(1)-M, EGARCH(1.1) and EGARCH(1.1)-M), was the best one in each period under examination. We should recall, based on the steps explained in chapter three, that the best model was chosen based on the Akaike (1974) and Schwarz (1978) criteria (their values for the preferred model should be algebraically the smallest compared to the values of all the other models). Except that, our results were also based on the restrictions of each model. For example, for the GARCH(1.1) and ARCH(1)-M model their coefficients should be non-negative because of the non-negative estimated conditional variance, as explained in chapter three. In case that the results contrasted the restrictions of a model, the model was excluded from the comparison.

The results show that the GARCH(1.1) and the EGARCH(1.1) model are the preferred models for estimating the conditional variance of the regression residuals. For example, for the period between 1995 and 2000 (second sub-period using daily observations) the GARCH(1.1) was the preferred model in 64 of the 163 cases and the EGARCH(1.1) was the preferred one for 60 cases. These results verify the studies of Bollerslev (1986) and Nelson (1991) regarding the significance of their models in financial econometrics.

***Table 5.3*: Size of stocks with ARCH effect and frequency of the best model for each period**

Period	Stocks with ARCH Effect	GARCH(1.1)	ARCH(1)-M	EGARCH(1.1)	EGARCH(1.1)-M
1989—2006 (monthly)	43	20	3	14	6
1989—2006 (daily)	52	10	0	32	10
1989—1994 (daily)	65	20	1	35	9
1995—2000 (daily)	163	64	1	60	38
2001—2006 (daily)	204	83	7	59	55

Furthermore, table 5.4 shows the number of cases that the coefficients of the EGARCH(1.1)-M and ARCH-M are significant regarding the relationship between risk and return in the conditional mean equation of each model. We should recall at this point that the -M (in Mean) models have the ability to estimate not only the conditional variance of the regression residuals like any other ARCH model, but they also estimate the values of the coefficients in the conditional mean equation (Engle *et al.*, 1987). The results give evidence of the significance of the models verifying that the risk is associated with the expected return for an adequate number of stocks during each period under examination. Specifically, while for only a relatively small number of monthly stocks returns the relationship is justified, the use of daily observations verifies the risk-return significance in several cases (stocks) in each period.

***Table 5.4*: Size of stocks with ARCH effect and evidence of risk-return trade-off**

Period	Stocks with ARCH Effect	ARCH-M	EGARCH(1,1)-M
1989—2006 (monthly)	43	9 (at 5 per cent level of significance) 6 (at 10 pr cent level of significance)	9 (at 5 per cent level of significance) 3 (at 10 per cent level of significance)
1989—2006 (daily)	52	43 (at 5 per cent level of significance)	13 (at 5 per cent level of significance) 7 (at 10 per cent level of significance)
1989—1994 (daily)	65	28 (at 5 per ccnt level of significance) 8 (at 10 per cent level of significancc)	16 (at 5 per cent level of significance) 7 (at 10 per cent level of significancc)
1995—2000 (daily)	163	93 (at 5 per cent level of significance) 14 (at 10 per cent level of significance)	44 (at 5 per cent level of significance) 24 (at 10 per cent level of significance)
2001—2006 (daily)	204	112 (at 5 per cent level of significance) 36 (at 10 per cent level of significance)	88 (at 5 per cent level of significance) 42 (at 10 per cent level of significance)

Finally, table 5.5 presents the number of cases where the EGARCH(1.1) and the EGARCH(1.1)-M model verify an asymmetry effect between the negative and positive shocks in each time series of stock returns. We should mention that the significance (different from zero) of the coefficients of the models prove, for example, that negative shocks have a larger effect on the behaviour of a time series compared to the effect of positive shocks. In table 5.5 the results show that generally the shocks are either of the same magnitude (no asymmetry effect found), or the models are only partially capable of capturing the asymmetry effect on the time series. These results are justified by the fact that for a relatively small number of cases, compared to the total number of stocks with ARCH effect for each period, the two models have significant coefficients at the 5 or 10 per cent level of significance.

Table 5.5: **Size of stocks with ARCH effect and evidence of asymmetry effect**

Period	Stocks with ARCH Effect	EGARCH(1,1)	EGARCH(1.1)-M
1989–2006 (monthly)	43	9 (at 5 per cent level of significance) 1 (at 10 per cent level of significance)	9 (at 5 per cent level of significance) 1 (at 10 per cent level of significance)
1989–2006 (daily)	52	6 (at 5 per cent level of significance)	6 (at 5 per cent level of significance) 2 (at 10 per cent level of significance)
1989–1994 (daily)	65	6 (at 5 per cent level of significance) 2 (at 10 per cent level of significance)	8 (at 5 per cent level of significance) 5 (at 10 per cent level of significance)
1995–2000 (daily)	163	18 (at 5 per cent level of significance) 6 (at 10 per cent level of significance)	18 (at 5 per cent level of significance) 7 (at 10 per cent level of significance)
2001–2006 (daily)	204	27 (at 5 per cent level of significance) 11 (at 10 per cent level of significance)	25 (at 5 per cent level of significance) 8 (at 10 per cent level of significance)

5.7 Empirical Findings of the CAPM in the ASE after the Application of (G)ARCH Models

Table 5.6 reports the results of the tests, not in favour of the CAPM. At the first row of each portfolio the intercept term, the beta coefficient, the adjusted R^2, the DW statistic and the F statistic are presented, while below each intercept and beta the p-values for the t-tests of significance are presented in italics and show if the coefficients are statistically significant or not for each portfolio or group of portfolios (the sum of stocks for each period).

During the whole period (1989–2006) using monthly stock returns it is obvious that the CAPM exhibit poor explanatory power. Specifically, for portfolio 1 and for both portfolios the adjusted R^2 is equal to 0.178 and 0.102 and the F statistic is 0.012 and 0.07 respectively. Moreover, the beta coefficients of portfolio 1 and the group of portfolios are statistically significant, which shows that the proxy of he market portfolio has an effect on portfolio returns, but the respective intercept terms are also statistically significant, a result that contradicts the validity of the model.

As far as the whole period (1989–2006) using daily stock returns is concerned, the results are even worse regarding the verification of the CAPM. The adjusted R^2 and the F statistic of the portfolios prove that the model is not adequate to explain the behaviour of portfolio returns, the beta coefficients are statistically insignificant (>0.05) for all portfolios while the intercept term for portfolio 2 and for the group of the portfolios is significant (<0.05), contradicting once more the validity of the model.

In the first sub-period (1989–1994), the results show that only for portfolio 2 the results are relatively in agreement with the model as the adjusted R^2 in equal to 0.102 and the F statistic is 0.048. This proves a small explanatory power of the model. However, the beta coefficients are insignificant (except for portfolio 2 but even in this case the value of the coefficient is negative) and the intercept term is, except for portfolio 1, in contrast with the implications of the model, as it is statistically different to zero (<0.05).

For the second sub-period (1995–2000) the results are against the validity of the CAPM as in most cases (portfolios) the adjusted R^2 has negative value or it is close to zero and the F statistic is not different to zero (>0.05) proving that the proxy for the market portfolio in not adequate to explain portfolio returns behaviour. Moreover, the beta coefficients are in all cases statistically insignificant, while, interestingly, the intercept term is not statistically different from zero (except for portfolio 5 and for the group of portfolios), which is in agreement with the utility of the model. Finally, the results are the same for the last sub-period between 2001 and 2006). Almost all portfolios have a negative adjusted R^2 and in all cases the F statistic is statistically insignificant.

***Table 5.6*: The cross-sectional test results of the CAPM after the selection of the best (G)ARCH model**

Period	Portfolios	γ_0	γ_1	Adjusted R^2	DW	F Sig.
1989–2006 (monthly)	Portfolio 1	-0.018 *0.014*	0.020 *0.012*	0.178	2.718	0.012
	Portfolio 2	-0.005 *0.062*	0.006 *0.319*	0.001	2.404	0.319
	All portfolios	-0.006 *0.002*	0.007 *0.007*	0.102	2.417	0.007
1989–2006 (daily)	Portfolio 1	-7.740 *0.795*	0.001 *0.090*	0.067	1.925	0.090
	Portfolio 2	0.000 *0.002*	0.000 *0.420*	-0.012	2.084	0.420
	All portfolios	0.000 *0.003*	0.000 *0.229*	0.008	1.941	0.229
1989–1994 (daily)	Portfolio 1	0.000 *0.403*	0.001 *0.110*	0.056	2.418	0.110
	Portfolio 2	0.001 *0.004*	-0.003 *0.048*	0.102	1.632	0.048
	All portfolios	0.000 *0.007*	0.000 *0.357*	-0.002	1.633	0.357
1995–2000 (daily)	Portfolio 1	0.002 *0.184*	-0.001 *0.376*	-0.007	1.944	0.376
	Portfolio 2	0.001 *0.764*	4.501 *0.987*	-0.036	2.207	0.987
	Portfolio 3	0.002 *0.410*	-0.001 *0.620*	-0.026	1.678	0.620
	Portfolio 4	-0.002	0.004	0.024	1.745	0.200

		0.356	*0.200*			
	Portfolio 5	0.001 *0.001*	-0.001 *0.375*	-0.006	2.226	0.375
	All portfolios	0.001 *0.000*	0.000 *0.064*	0.016	1.902	0.064
2001–2006 (daily)	Portfolio 1	0.068 *0.479*	-0.022 *0.358*	-0.005	2.328	0.358
	Portfolio 2	-0.035 *0.562*	0.018 *0.457*	-0.012	2.180	0.457
	Portfolio 3	0.088 *0.338*	-0.023 *0.962*	-0.035	2.420	0.962
	Portfolio 4	-0.067 *0.796*	0.028 *0.223*	0.018	1.923	0.223
	Portfolio 5	0.044 *0.522*	-0.005 *0.462*	-0.015	2.223	0.462
	Portfolio 6	0.077 *0.499*	-0.008 *0.918*	-0.032	2.388	0.918
	Portfolio 7	0.089 *0.223*	-0.002 *0.883*	-0.036	2.382	0.883
	Portfolio 8	0.012 *0.682*	-0.058 *0.485*	-0.021	2.280	0.485
	All portfolios	-0.008 *0.775*	0.003 *0.337*	-0.001	1.986	0.337

Finally, the results of the DW statistic show that the problem of autocorrelation of the regression residuals is relatively small, as for several portfolios its value is around two. However, there are many cases where the problem of autocorrelation is more evident, as in the case of portfolio 1 for the whole period 1989–2006 using monthly observations (DW = 2.718), portfolio 1 for the first sub-period 1989–1994 (DW = 2.418) and portfolio 3 for the third sub-period 2001–2006 (DW = 2.42).

Once more, as in chapter four regarding the validity of the CAPM, the application of specific (G)ARCH did not change the fact that the CAPM is not applicable in the ASE. Almost all the results reported in table 5.6 are examples of the lack of power of the CAPM to explain the relationship between stock returns and risk across time. The results are very similar to those of past studies (Fama and French, 1992; Chen, 1983) suggesting that there are factors different from potential market proxies that influence the behaviour of stock returns.

5.8 The Unit Root Test Results

After the employment of specific (G)ARCH models on the market model and the evidence of the inability of the model to explain the behaviour of portfolios returns we come to the conclusion that there may be more and different factors that have an effect on the Greek market. Based on the results of the partial explanatory power of other variables, such as the unexpected inflation to explain stock returns (in chapter four), in the subsequent sections we follow a different procedure so as to examine whether there are factors that affect the general stock market index, as well as the sectoral market indices. This is achieved with the application of unit root tests (tests of stationarity of a time series) and Johansen's (1988; 1991) cointegration analysis based on a vector autoregressive (VAR) model (analysis of the existence of possible linear long-run relationships between the series).

Moreover, we test, as in the previous chapter, whether the efficient market hypothesis (EMH) holds in the ASE. By employing a number of specific unit root tests, based on the studies of Dickey and Fuller (1979; 1981), Phillips and Perron (1988) and Kwiatkowski *et al.* (1992), we have constructed the following tables so as to see which one of the variables is stationary (does not have a unit root) in its levels (prices), or it had a unit root (non-stationary) and had to be estimated in its first differences so as to become stationary.

Tables 5.7 to 5.9 present the results of the unit root tests. In table 5.7 the first four rows present the variables in their levels in logarithmic form, while the following four rows present the same variables in their first differences. Next to the name of each variable the respective ADF, PP and KPSS test statistics are presented by applying the models without a constant and a trend, then only with a constant and, finally, both with a constant and a trend. If we recall, based on the Augmented Dickey-Fuller (ADF) test, the acceptance of the null hypothesis means that there is a unit root in the series. The same holds for the Phillips-Perron (PP) test. In the case of the KPSS test (Kwiatkowski *et al.*, 1992) the acceptance of the null hypothesis means that the series is stationary. Finally, the significance of each model is presented in bold numbers.

The results show that during the whole period 1989–2006 the statistics of ADF, PP and KPSS verify in most cases the nonstationarity of the variables in their levels. More specifically, the ADF and PP unit root tests show that the null hypothesis of non-stationarity (unit root) based on the critical values of MacKinnon (1991) is accepted in most cases. Moreover, the results of the KPSS tests show that the null hypothesis of level and trend stationarity is rejected for the variables based on the critical values of Kwiatkowski *et al.* (1992) (the critical values of each level of significance are depicted in table 1 of their study). To facilitate the examination of the tables, as far as the ADF and PP tests are concerned, we should mention that a series is $I(1)$ when a) the test statistics verify that the coefficient of each unit root model is not significant after it is applied on the levels of this series, and b) the models are applied on the first differences of the series and there is significance. Then the series becomes integrated of order one ($I(1)$). Exactly the opposite holds for the KPSS test as the null hypothesis of the test is reversed.

The results of our tests are similar with those in the work of Hondroyannis and Papapetrou (2001) where the same variables were employed for a different time period so as to examine possible relationships in the ASE. The variables presented in table 5.7 are the variables that were also employed for the tests in chapter four and their data was available for the examination of the whole period (1989–2006), except the industrial production index. The data of this index was not available for the whole period (as it can be seen in the tests of chapter four where it was used only in the second and third sub-period) and its unit root results are depicted in table 5.9 along with the new variables for the third sub-period (2001–2006). Generally the results of table 5.7 verify that the series are $I(1)$ and can be used in cointegration analysis.

Furthermore, table 5.8 shows the unit root results for the sectoral indices during the time period of their data availability (1989–2005). The results are even more clear that all series are $I(1)$. Finally, in the case of the variables used for the period between 2001 and 2006 (table 5.9) the results show that, as in table 5.7, in most cases the hypotheses of the models are verified and the series become integrated of order one ($I(1)$). Only in the case of the industrial index the half of the unit root models did not verify the integration of the series, however, we have included it in the cointegration procedure based on the ADF tests (the only group of tests that verified the integration of the series).

***Table 5.7*: Unit root tests of the initial variables (1989-2006)**

	ADF			PP			KPSS	
Variables	None	Const	const/trend	None	Const	const/trend	Const	const/trend
LRMI	1.327	-2.147	-2.717	1.599	-1.987	-2.339	**1.47****	**0.139*****
LCPI	0.089	**-4.707****	**-5.751****	-5.101	**-10.07****	**-3.73***	**1.714****	**0.44****
LPS	1.691	-1.386	**-3.541***	1.369	-1.467	**-3.5***	**1.715****	0.066
L3MTBR	-1.559	-0.417	-1.995	-1.66	-0.374	-1.943	**1.7****	**0.307****
DLRMI	**-9.754****	**-9.906****	**-9.925****	**-9.644****	**-9.7****	**-9.679****	0.142	0.094
DLCPI	**-1.749*****	-1.213	-1.57	**-10.392****	**-14.936****	**-14.066****	**1.072****	0.171
DLPS	**-12.371****	**-12.566****	**-12.544****	**-13.247****	**-13.349****	**-13.323****	0.034	0.029
DL3MTBR	**-15.752****	**-15.902****	**-15.877****	**-15.713****	**-15.873****	**-15.869****	0.209	0.181

Notes: *Indicates significance at the 5 per cent level.

**Indicates significance at the 1 per cent level.

*** Indicates significance at the 10 per cent level.

***Table 5.8*: Unit root tests of the sectoral indices**

	ADF			PP			KPSS	
Variables	None	Const	const/trend	None	Const	const/trend	const	const/trend
LISI	0.259	-2.429	-2.326	0.284	-2.262	-2.121	0.287	**0.136*** **
LBSI	1.305	-1.928	-2.454	1.745	-1.795	-1.773	**1.437** **	**0.153* **
LINSI	0.77	-1.836	-2.095	0.817	-1.75	-1.984	**0.794** **	0.161
LINDSI	1.096	-2.478	-2.443	1.151	-2.359	-2.24	**1.168** **	**0.199* **
DLISI	**-9.201** **	**-9.197** **	**-9.209** **	**-9.136** **	**-9.133** **	**-9.147** **	0.127	0.074
DLBSI	**-9.225** **	**-9.385** **	**-9.401** **	**-8.979** **	**-9.09** **	**-9.116** **	0.221	0.127
DLINSI	**-9.729** **	**-9.771** **	**-9.75** **	**-9.754** **	**-9.838** **	**-9.816** **	0.083	0.079
DLINDSI	**-10.023** **	**-10.123** **	**-10.182** **	**-9.979** **	**-10.131** **	**-10.192** **	0.186	0.073

Notes: *Indicates significance at the 5 per cent level.

**Indicates significance at the 1 per cent level.

*** Indicates significance at the 10 per cent level.

***Table 5.9*: Unit root tests of the new variables (2001-2006)**

	ADF			PP			KPSS	
Variables	None	Const	Const/trend	None	Const	const/trend	const	const/trend
*LM*1	5.516	0.721	-3.439	5.922	0.545	-3.317	**1.125****	**0.168***
LUSDEEXR	0.038	-0.578	-1.978	0.33	-0.679	-1.692	**0.968****	**0.215***
LGBPEEXR	-0.717	-1.253	-1.296	-0.66	-1.394	-1.683	**0.736***	**0.185***
LRPI	15.316	0.46	-0.3	2.154	-2.43	**-7.098****	**1.102****	0.068
LIP	1.000	-1.479	-1.631	0.393	**-8.103****	**-8.101****	0.124	0.024
*DLM*1	-1.122	**-6.609****	**-6.66****	**-7.507****	**-10.633****	**-10.688****	0.117	0.044
DLUSDEEXR	**-5.79****	**-6.006****	**-5.963****	**-5.709****	**-5.759****	**-5.698****	0.11	0.114
DLGBPEEXR	**-7.808****	**-7.789****	**-7.766****	**-7.889****	**-7.867****	**-7.84****	0.116	0.083
DLRPI	-0.779	**-3.25***	**-3.205*****	**-17.492****	**-26.133****	**-26.315****	0.276	0.164
DLIP	**-17.622****	**-17.649****	**-17.42****	**-44.478****	**-44.215****	**-43.767****	0.251	0.19

Notes: *Indicates significance at the 5 per cent level.

**Indicates significance at the 1 per cent level.

*** Indicates significance at the 10 per cent level.

5.9 The Johansen Cointegration Analysis Results

After we come to the conclusion that the series are $I(1)$ (stationary in their first differences) based on the ADF, PP and KPSS test statistics, we proceed to the examination of possible long-run relationships between the variables. The cointegration procedure of Johansen (1988; 1991) was employed in our tests, instead of the two-step test of Engle and Granger (1987), as it yields more efficient estimators of cointegrating vectors (Niarchos and Alexakis, 2000; Maysami *et al.*, 2004). Johansen's test allows for testing cointegration between variables in a whole system of equations in one step, without requiring to normalise a specific variable. Consequently, we can avoid to carry over the errors from the first to the second step (as in the case of the Engle-Granger (1987) test).

As explained in chapter three, our main purpose is to investigate whether there is any relationship between the general market index and the macrovariables already used in chapter four during the period 1989–2006. Moreover, we search for possible relationships between specific sectoral indices (as presented in table 5.1) and a number of macrovariables for the period between 1989 and 2005 (the last year of data availability for the sectoral indices). Finally we examine if there is any relationship between the general market index and two different sets of variables – a set of variables also used for the whole period and a set of new variables available only for the third period (2001–2006).

Tables 5.10 to 5.16 present the results of cointegration analysis between the different sets of variables. Specifically, table 5.10 (below) shows that between the general share market index and the macrovariables used for the whole period (1989–2001) there is one cointegrating vector as the p-value is less than 0.05 and rejects the null hypothesis of no cointegration. As there are two statistics in Johansen's procedure that test for possible cointegrating vectors (the maximum eigenvalue and the trace statistic), in case there are differences in their results, the trace statistic is preferred. The reason is that it shows more robustness to skewness and kurtosis in the residuals (Cheung and Lai, 1993).

***Table 5.10*: Johansen's cointegration test on the general market index, 3-month treasury bill rate, consumer price index and petroleum series index (1989–2006)**

Maximum Eigenvalue Test			
Null	Maximum Eigenvalue Statistic	Critical Values (at 5%)	Prob.
$R=0$*	126.7211	27.58434	**0.0000**
$R \leq 1$	14.44813	21.13162	0.3294
$R \leq 2$	5.481329	14.2646	0.6802
$R \leq 3$	1.967995	3.841466	0.1607

Note: *Indicates significance at the 5 per cent level.

Trace Test			
Null	Trace Statistic	Critical Values (at 5%)	Prob.
$R=0$*	148.6185	47.85613	**0.0000**
$R \leq 1$	21.89745	29.79707	0.3042
$R \leq 2$	7.449324	15.49471	0.526
$R \leq 3$	1.967995	3.841466	0.1607

Note: *Indicates significance at the 5 per cent level.

As there is at least one cointegrating vector in each set of variables we proceed to the examination of this relationship. As far as the first set of variables is concerned (table 5.10), the normalised cointegrating coefficients for the general market index during the whole period (1989–2006) are:

$$Y_t = (LRMI_t, LCPI_t, L3MTBR_t, LPS_t)$$

$$b = (1.000, 14.3326, -0.7506, -7.2681)$$

In order to investigate whether the existence of one cointegrating vector in the set can lead to more solid conclusions regarding the relationship between the variables, we express the set in the form of a linear regression model (the t-statistics are presented below the equation):

$$LRMI_t = -14.3326LCPI_t + 0.7506L3MTBR_t + 7.2681LPS_t \quad \textbf{(2)}$$
$$[8.600] \qquad [-1.307] \qquad [-3.385]$$

It is evident from the results of equation (2) that there is a negative and significant relationship between the general stock market index and the consumer price index, which is in agreement with the hypothesis of Nelson (1976) and Chen *et al.* (1986). The petroleum series seems to have a positive relationship with the market index, while it is interesting to mention that the interest rate also shows a positive relationship with the stock market index, a result that contradicts our hypothesis but is in agreement with prior studies (Bulmash and Trivoli, 1991; Mukherjee and Naka, 1995). A reason might be that a short-term interest rate (3-month) is not a good proxy for the risk-free component used in valuation models. A long-term rate (1-year) might prove to be a better proxy.

Table 5.11 shows that there are two cointegrating vectors (two linear combinations) between the sectoral banking index, the consumer price index, 3-month treasury bill rate and petroleum series.

***Table 5.11*: Johansen's cointegration test on the sectoral banking index, 3-month treasury bill rate, consumer price index and petroleum series index (1989–2005)**

Maximum Eigenvalue Test			
Null	Maximum Eigenvalue Statistic	Critical Values (at 5%)	Prob.
$R = 0$*	121.6452	27.5843	**0.0000**
$R \leq 1$*	25.17394	21.13162	**0.0127**
$R \leq 2$	4.427773	14.2646	0.8117
$R \leq 3$	0.210575	3.841466	0.6463

Note: *Indicates significance at the 5 per cent level.

Trace Statistic			
Null	Trace Statistic	Critical Values (at 5%)	Prob.
$R=0*$	151.4575	47.85613	**0.0000**
$R\leq 1*$	29.81229	29.79707	**0.0498**
$R\leq 2$	4.638347	15.49471	0.846
$R\leq 3$	0.210575	3.841466	0.6463

Note: *Indicates significance at the 5 per cent level.

The results of table 5.12 show that for the sectoral insurance index and the same macrovariables there is one cointegrating vector as in the case of the general market index (table 5.10).

***Table 5.12*: Johansen's cointegration test on the sectoral insurance index, 3-month treasury bill rate, consumer price index and petroleum series index (1989–2005)**

Maximum Eigenvalue			
Null	Maximum Eigenvalue Statistic	Critical Values (at 5%)	Prob.
$R=0*$	118.2682	27.58434	**0.0000**
$R\leq 1$	17.70641	21.13162	0.1412
$R\leq 2$	4.99791	14.2646	0.7421
$R\leq 3$	0.135547	3.841466	0.7127

Note: *Indicates significance at the 5 per cent level.

Trace Statistic			
Null	Trace Statistic	Critical Values (at 5%)	Prob.
$R=0*$	141.1081	47.85613	**0.0000**
$R\leq 1$	22.83986	29.79707	0.254
$R\leq 2$	5.133457	15.49471	0.7945
$R\leq 3$	0.135547	3.841466	0.7127

Note: *Indicates significance at the 5 per cent level.

In table 5.13 the results for the sectoral investment index are different between the two statistics. While the maximum eigenvalue statistic verify the existence of two cointegrating vectors, the trace statistic verify only one. Thus, we accept the fact that there is only one cointegrating vector, based on the result of the trace statistic (Cheung and Lai, 1993).

***Table 5.13*: Johansen's cointegration test on the sectoral investment index, 3-month treasury bill rate, consumer price index and petroleum series index (1989–2005)**

Maximum Eigenvalue			
Null	Maximum Eigenvalue Statistic	Critical Values (at 5%)	Prob.
$R = 0*$	119.9714	27.58434	**0.0000**
$R \leq 1*$	24.17996	21.13162	**0.018**
$R \leq 2$	5.435027	14.2646	0.6862
$R \leq 3$	0.168326	3.841466	0.6816

Note: *Indicates significance at the 5 per cent level.

Trace Statistic			
Null	Trace Statistic	Critical Values (at 5%)	Prob.
$R = 0*$	149.7547	47.85613	**0.0000**
$R \leq 1$	29.78331	29.79707	0.0502
$R \leq 2$	5.603352	15.49471	0.7418
$R \leq 3$	0.168326	3.841466	0.6816

Note: *Indicates significance at the 5 per cent level.

Finally, table 5.14 shows one cointegrating vector between the sectoral industrial index and the macrovariables.

***Table 5.14*: Johansen's cointegration test on the sectoral industrial index, 3-month treasury bill rate, consumer price index and petroleum series index (1989–2005)**

Maximum Eigenvalue			
Null	Maximum Eigenvalue Statistic	Critical Values (at 5%)	Prob.
$R = 0*$	119.8068	27.58434	**0.0000**
$R \leq 1$	20.28584	21.13162	0.0653
$R \leq 2$	4.944994	14.2646	0.7488
$R \leq 3$	0.21374	3.841466	0.6438

Note: *Indicates significance at the 5 per cent level.

Trace Statistic			
Null	Trace Statistic	Critical Values (at 5%)	Prob.
$R = 0*$	145.2513	47.85613	**0.0000**
$R \leq 1$	25.44457	29.79707	0.1462
$R \leq 2$	5.158734	15.49471	0.7918
$R \leq 3$	0.21374	3.841466	0.6438

Note: *Indicates significance at the 5 per cent level.

As far as the second set of variables is concerned (tables 5.11 to 5.14) the results are similar with those of the previous case. For the banking index and the macrovariables, the normalised cointegrating coefficients during the period (1989–2005) are:

$$Y_t = (LBSI_t, LCPI_t, L3MTBR_t, LPS_t)$$
$$b = (1.000, 14.70114, -0.934294, -9.296012)$$

The above relationship with the normalised coefficients can be re-expressed as:

$$\underset{}{LBSI_t} = -14.70114\underset{[8.221]}{LCPI_t} + 0.934294\underset{[-1.575]}{L3MTBR_t} + 9.296012\underset{[-3.463]}{LPS_t} \quad \textbf{(3)}$$

The results as in the previous case show that the banking sector has negative relationship with the consumer price index and a positive relationship with the interest rate and petroleum series.

Moreover, the results of the sectoral insurance index and the macrovariables are:

$$Y_t = (LISI_t, LCPI_t, L3MTBR_t, LPS_t)$$
$$b = (1.000, 30.43464, -1.359545, -12.47712)$$

which can be expressed as:

$$LISI_t = -30.43464\underset{[8.435]}{LCPI_t} + 1.359545\underset{[-1.149]}{L3MTBR_t} + 12.47712\underset{[-2.395]}{LPS_t} \quad \textbf{(4)}$$

The results for the insurance index are the same with those in the previous cases. Moreover, the results of the sectoral investment index regarding the normalised coefficients are the following:

$$Y_t = (LINSI_t, LCPI_t, L3MTBR_t, LPS_t)$$
$$b = (1.000, 16.01136, -0.832926, -8.592847)$$

also expressed as:

$$\underset{}{LINSI_t} = -16.01136\underset{[8.714]}{LCPI_t} + 0.832926\underset{[-1.370]}{L3MTBR_t} + 8.592847\underset{[-3.153]}{LPS_t} \quad \textbf{(5)}$$

Finally, as far as the sectoral industrial index is concerned, the coefficients of the relationship are the following:

$$Y_t = (LINDSI_t, LCPI_t, L3MTBR_t, LPS_t)$$
$$b = (1.000, 10.23537, -0.528742, -4,697293)$$

which can be expressed as:

$$LINDSI_t = -10.23537\underset{[7.875]}{LCPI_t} + 0.528742\underset{[-1.220]}{L3MTBR_t} + 4.697293\underset{[-2.412]}{LPS_t} \quad \textbf{(6)}$$

The main conclusion of equations (2) to (6) is that all the market indices present a negative relationship with the consumer price index (Chen *et al.*, 1986; Niarchos and Alexakis, 2000), and a positive relationship with the interest rate (Bulmash and Trivoli, 1991; Mukherjee and Naka, 1995) and the petroleum series.

After the examination of the sectoral indices we proceed to the examination of the relationship between the general stock market index and two different sets of variables for the period between 2001 and 2006, which is the third period of analysis (as in chapter four). This time period was chosen because there is a number of new variables used in the tests and their data was available only during this period. Tables 5.15 and 5.16 (below) present the cointegration results between the general market index and the respective groups of variables.

***Table 5.15*: Johansen's cointegration test on the general market index, consumer price index, industrial production index and petroleum series index (2001–2006)**

Maximum Eigenvalue			
Null	Maximum Eigenvalue Statistic	Critical Values (at 5%)	Prob.
$R=0*$	30.32896	27.58434	**0.0217**
$R\leq 1$	13.84196	21.13162	0.3782
$R\leq 2$	10.53395	14.2646	0.1792
$R\leq 3$	0.009148	3.841466	0.9234

Note: *Indicates significance at the 5 per cent level.

Trace Statistic			
Null	Trace Statistic	Critical Values (at 5%)	Prob.
$R=0*$	54.7102	47.85613	**0.0099**
$R\leq 1$	24.38507	29.79707	0.1846
$R\leq 2$	10.5431	15.49471	0.2412
$R\leq 3$	0.009148	3.841466	0.9234

Note: *Indicates significance at the 5 per cent level.

***Table 5.16*: Johansen's cointegration test on the general market index, retail price index, money supply (M1), GBP/Euro exchange rate and USD/Euro exchange rate and 3-month treasury bill rate (2001–2006)**

Maximum Eigenvalue			
Null	Maximum Eigenvalue Statistic	Critical Values (at 5%)	Prob.
$R=0*$	42.59052	40.07757	**0.0255**
$R\leq 1$	29.59967	33.87687	0.149
$R\leq 2$	17.8366	27.58434	0.5088
$R\leq 3$	15.32792	21.13162	0.2666
$R\leq 4$	3.898654	14.2646	0.8699
$R\leq 5$	2.30123	3.841466	0.1292

Note: *Indicates significance at the 5 per cent level.

Trace Statistic			
Null	Trace Statistic	Critical Values (at 5%)	Prob.
$R=0*$	111.5549	95.75366	**0.0026**
$R\leq 1$	68.96438	69.81889	0.0583
$R\leq 2$	39.3647	74.85613	0.246
$R\leq 3$	21.52811	29.79707	0.3255
$R\leq 4$	6.200184	15.49471	0.6719
$R\leq 5$	2.30153	3.841466	0.1292

Note: *Indicates significance at the 5 per cent level.

Moreover, the results between the general market index and the first set of variables for the period between 2001–2006 are:

$$Y_t = (LRMI_t, LCPI_t, LIP_t, LPS_t)$$
$$b = (1.000, 12.4621, -31.9698, -3.649762)$$

and re-expressed as a linear regression model in the following form:

$$LRMI_t = -12.4621LCPI_t + 31.9698LIP_t + 3.649762LPS_t \qquad (7)$$
$$[1.774] \qquad [-5.495] \qquad [-1.697]$$

Once more there is a negative relationship between the market index and the consumer price index, although in this case the relationship is insignificant, and a positive relationship with the petroleum series index. An interesting result at this point is that the stock market index shows a positive and significant relationship with the industrial production index. This result verifies that a rise in industrial production can signal economic growth and lead to an increase in expected future cash flows (Fama, 1990; Geske and Roll, 1983; Chen *et al.*, 1986).

$$Y_t = (LRMI_t, L3MTBR_t, LLM1_t, LRPI_t, LGBPEEXR_t, LUSDEEXR_t)$$
$$b = (1.000, -0.341028, 0.780099, -1.81824, -5.115774, 0.29476)$$

and re-expressed as:

$$LRMI_t = 0.341028L3MTBR_t - 0.780099LM1_t + 1.81824LRPI_t +$$
$$[-1.133] \qquad [1.196] \qquad [-2.347]$$
$$+5.115774LGBPEEXR_t - 0.29476LUSDEEXR_t \qquad \textbf{(8)}$$
$$[-2.136] \qquad [0.282]$$

Equation (8) shows that the (short-term) interest rate has a positive relationship with the general market index (Bulmash and Trivoli, 1991; Mukherjee and Naka, 1995) and that the index of money supply (M1) shows a negative relationship (although insignificant) with the general market index which is in agreement with Fama (1981) who argued that an increase in money supply would lead to inflation and to the reduction of stock prices. Moreover, the general market index presents a positive relationship with the retail price index, which has been proved to be a significant risk factor (Clare and Thomas, 1994).

Moreover, the GBP/Euro exchange rate presents a different relationship compared to the USD/Euro exchange rate. Specifically, the USD/Euro exchange rate shows that if the USD depreciates compared to euro, it will lead to new domestic investments and to an increase in stock prices (although this relationship is insignificant). Alternatively, in the case of the GBP/Euro exchange rate, if the GBP appreciates compared to euro, this change will decrease the stock market level, leading to a negative and significant correlation between stock prices and exchange rates (Mukherjee and Naka, 1995).

5.10 Conclusions

In chapter four we focused on the application of the CAPM and the two APT models in the ASE leading to some interesting results. These results centered around the existence of a number of observed factors and unobserved ones that could play a significant or partially significant role in the explanation of the behaviour of portfolio returns. Moreover, we came to the conclusion that the CAPM cannot be verified in the ASE during the whole period or the sub-periods of the analysis. All these results justify that the (weak-form) market efficiency may be rejected and that investors should have in mind that the examination of different factors may lead to better and more profitable decisions.

The present chapter of analysis verifies the fact that the CAPM cannot be applicable in the market, after the application of a number of (G)ARCH models. The chapter aimed to identify at the beginning the existence of heteroscedasticity at the residuals of the regression between each stock return and the return of the market index. As in most cases there was a heteroscedasticity problem (Koutmos and Theodossiou, 1993; Soufian, 2004; Michailidis *et al.*, 2006), we chose to employ a number of models that have proved their significance in the estimation of conditional volatility. The first model used was the GARCH(1.1) which has been proved to be a good representation of financial time series (Bollerslev *et al.*, 1992; Koutmos and Theodossiou, 1993). The second model was the "in mean" specification of the initial ARCH(1) model. This model was employed as its specification allows a practical implementation of the theoretical result, that is the mean return of any financial asset (stock) is affected by the volatility of shocks to this return. In other words, the ARCH(1)-M of Engle *et al.* (1987) not only models the heteroscedasticity process, but it also includes the resulting measure of volatility in the mean regression equation.

The last two models used were Nelson's (1991) EGARCH model and its modification, EGARCH-M, as they have also been developed to capture possible asymmetries (different impact between positive and negative shocks) on the volatility of financial assets. The best ARCH models were employed (based on the Akaike (1974) and Schwarz (1978) criteria) on monthly but, mainly, on daily stock returns (Apergis and Elepttheriou, 2001) to give the new beta coefficients. These coefficients were used in the construction of portfolios without heteroscedasticity problems but the market model did not seem to explain portfolio returns after the cross-sectional regressions for different time periods. These results contradicted the validity of the CAPM showing that other models could be more useful in the examination of stocks.

However, we should recall that at the end of the 1980s and during the beginning of the 1990s there were many reforms in the stock market that increased its liquidity and efficiency. This means that any investor would expect to be informed appropriately so as to be able to make the right choice and invest wisely. Moreover, the number of listed stocks has increased in comparison to the previous decade, that is the stocks without missing values were only 72 during the period 1989–1994, while they increased to 259 during the period 2001–2006. There might be some other reasons that justify the inefficiency of the market, like the lack of a proper technical organization which could lead to a spread of information reflected in stock prices (Dockery and Kavussanos, 1996). Other reasons of market inefficiency are possible delays of news on stock market prices as well as psychological factors that influence the decision of investors. For example, during a period of price increase an investor becomes optimist which leads to further price increase (Niarchos and Alexakis, 2000).

The second part of the present chapter focused on unit root tests and cointegration analysis. The reason that a number of unit root tests were employed was the need to examine the stationarity of the variables used in the analysis. Specifically, the application of the ADF, PP and KPSS tests led us to the conclusion that the variables are in most cases integrated of order one ($I(1)$), which means that they are stationary in their first differences. Consequently, these results led to the application of a number of tests based on Johansen's (1988; 1991) cointegration analysis. The same financial and macroeconomic variables were used (as in the tests of chapter four) with the addition of specific indices, based on data availability and the significance of these variables in prior studies (Chen *et al.* 1986; Chen and Jordan 1993; Clare and Thomas, 1994; Hondroyannis and Papapetrou, 2001: Gay, 2008).

The results of all the groups of variables showed that there is at least one cointegrating vector, which proves that the variables are linearly related on the long-run. Moreover, we expressed the groups of variables in the form of a linear regression model so as to examine the sign of each relationship based on specific hypotheses presented in section 5.4. The developed regression model had as a dependent variable the stock market index and the results were partially similar to prior studies. For example, in the case of the consumer price index, which is generally used in the calculation of the inflation rate, it seemed to be negatively related to all the market indices, verifying the notion that as inflation increases its impact is negative on stock prices (Nelson, 1976; Chen *et al.*, 1986). A possible reason for this relationship could be that an increase in the inflation rate causes government policy makers to react by changing their monetary policy. These reactions that can affect investments are the basis of the notion that inflation is generally harmful for business (Niarchos and Alexakis, 2000).

Furthermore, as far as other variables are concerned, the results regarding the relationship between industrial production and stock market indices were in agreement with prior studies (Fama, 1990; Geske and Roll, 1983), showing that a rise in industrial production can lead to economic growth and to an increase of stock prices. Moreover, the relationship between the petroleum products index and stock market indices was positive, a result that contradicts our hypothesis, that is as energy prices rise, the production and input costs will increase, decreasing gross profits and cash flows. However, this result is partially similar to the results of Gay (2008), showing that the petroleum prices during that period of examination did not play a significant role in the formation of stock prices that covered the period between 1989 and 2006. Perhaps the testing of stock prices during 2007 and 2008 might give more significant results because of the even more rapid increase of petroleum prices on an international level.

In chapter six, that concludes this work, we discuss the general findings, the managerial implications in the Greek market, as well as proposals for further examination of the relationship between financial and economic variables.

Chapter Six

CONCLUSIONS, MANAGERIAL IMPLICATIONS, LIMITATIONS AND PROPOSALS FOR FUTURE RESEARCH

6.1 Conclusions

The present study is focused on the investigation for the existence of factors that could offer new information regarding the way that the ASE functions. The ASE is one of the capital markets which proved to be extremely attractive over the last years to international investors, as during the 1990s it had started the transition so as to become a developed market (Chortareas *et al.*, 2000). It is interesting to mention that, in 2001, Morgan Stanley, which is an investment banking and global financial services corporation headquartered in New York City, upgraded the ASE giving it the status of a developed market (Argyropoulos, 2006). But it is also a fact that, so far, most empirical studies have treated the Greek market as an emerging one, mostly because of data availability, as contemporary data are more difficult to be gathered.

Although there are several studies conducted in the ASE using different methodologies depending on the goal of each study (Karanikas, 2000; Niarchos and Alexakis, 2000; Siourounis, 2002), none of these studies have combined traditional and modern models in order to come to some robust inferences regarding the behaviour of stocks in Greece. This analysis has contributed in many ways to the explanation of the relationship between stocks and a number of economic factors, as new and older models were utilised to give the best results.

Specifically, we have employed the statistical version of the APT model (Chen, 1983) using historical data for the period between 1989 and 2006. The model was selected so as to examine if there are any (unobserved) factors that may explain the behaviour of stock returns in the ASE as no similar empirical studies are evident for Greece, at least during this period under examination. Moreover, we have employed the macroeconomic APT model (Chen *et al.*, 1986) so as to investigate whether there are any (observed) factors that could influence stock returns. Specific macroeconomic variables were applied for the same period and sub-periods, and as there are no similar studies in Greece, we have compared our results with those of other stock markets (Chen, 1983; Chen *et al.*, 1986; Chen and Jordan, 1993; Cheng, 1995).

After the application of each APT model, we have compared them in order to see if there is any relationship between the selected macrovariables and the artificial factors generated from the methodology of the statistical APT model. Methods of comparison, such as the Davidson and Mackinnon (1981) test for specification error and the canonical correlation analysis (Chen and Jordan, 1993; Cheng, 1995) have not been used in similar studies for the ASE. We should recall that the period examined extends from January 1989 to December 2006, which could be characterised as a large period under examination (for the ASE standards), as it includes periods of economic and social changes in Greece that is reforms in the ASE, several elections and the Olympic Games of 2004 held in the city of Athens.

Furthermore, the use of specific (G)ARCH models on the CAPM during the 18-year period under examination gave new evidence regarding the validity of the model. We have selected these specific (G)ARCH models based on their significance on previous empirical studies, and, after comparing them, we have used the one that was the best for each case, so as to examine the explanatory power of the CAPM, a procedure not evident in similar studies for the Greek market.

Moreover, we have combined different sets of financial as well as macroeconomic variables, based on economic theory and data availability, so as to employ specific unit root and cointegration tests. Although there are studies that have used similar variables for different time periods, such as the inflation rate (Niarchos and Alexakis, 2000), the present study has added variables which are not so usually employed in asset pricing studies, that is the retail sales index, and examined their possible long-run relationships with other variables.

After we have gathered all the results from the cointegration tests for the different sets of variables, we proceeded to a combination between cointegration and regression analysis. This is a procedure that is rarely visible in empirical studies (Maysami *et al.*, 2004) for any stock market, although it is a relatively easy procedure and can give interesting results regarding the direction of the linear relationship between the variables.

Finally, there are several empirical studies that have used daily (Jeon and Seo, 2003), weekly (Michailidis *et al.*, 2006), or monthly (Fifield *et al.*, 2000) data for the examination of financial or macroeconomic variables. In our study, both daily and monthly observations were used in the examination of the relationship between stock returns and the market portfolio. The comparison of results based on a different frequency of observations could lead to more solid inferences when utilising a model.

The results of prior studies based on the CAPM and the two forms of the APT model are mixed for different stock markets, even for different periods of the same market. But, the general conclusion is in most cases the same: It is difficult for the traditional CAPM to hold, especially during the last decades. The main reason is that, in agreement with the critique of Roll (1977), the general market index of a stock exchange does not contain all the necessary information so as to proxy for the market portfolio, according to the theory behind the development of the CAPM (Markowitz, 1952; 1956; Sharpe, 1964; Lintner, 1965; Treynor, 1962). This result contradicts the notion that all information is immediately reflected to the prices of securities, implying the inefficiency of capital markets (Fama, 1970; 1991).

Another general conclusion based on past studies (Chen, 1983; Chan *et al.*, 1985; Faff, 1988; Clare and Thomas, 1994; Chen *et al.*, 1986; Chen and Jordan, 1993, and so on) is that there is a number of specific factors, observed or unobserved, that could play a significant role in the explanation of stock returns. As far as the unobserved factors are concerned, the results showed that the number of these factors varies and this may depend on the frequency of data availability or the specification of the variables under examination. Similarly, the significance or not of specific observed factors is a result of a number of variables that are used in order to specify a financial model that could explain the way that a stock exchange or, generally, an economy functions. Variables such as the inflation rate, petroleum prices, consumption, industrial production, the supply of money, the proxy for the *a priori* optimal market portfolio, are some of the factors that have been used in the application of the APT model.

In the present work the objective was to examine if there are indeed factors that can have any explanatory power on the behaviour of stock returns. We primarily examined the validity of the traditional CAPM and the cross-sectional results showed that the proxy for the market portfolio, which was the ASE general stock market index, was insignificant in the explanation of stock returns and this result was not only evident for the whole period under examination (1989–2006) but also for the three sub-periods (1989–1994, 1995–2000 and 2001–2006).

The implications of the CAPM, which show that a) the market beta is the only systematic risk of stock returns, a) the risk premium should be positive and c) the relationship between stock returns and beta is linear, were rejected for almost all stock portfolios (see chapter four). The only inference that supports the validity of the CAPM is that the intercept term of the equation was, in some cases, consistent with the theory behind the model, as it shows that if a correct market model is selected, the regression intercepts for portfolios, or individual stocks, are equal to zero. This might be a sign that the CAPM is not entirely invalid for the examination of the ASE but, overall, the results indicate that the Greek stock market index should not be used as a proxy for the optimal market portfolio. These conclusions led us to the application of the APT models for the same periods under investigation.

We primarily examined the statistical version of the APT model in order to produce a number of artificial factors as different, from the market beta, sources of systematic risk. The results have shown that a different number of independent (orthogonal) factors was produced in each case (portfolio), meaning that specific combinations of variables (stock returns) gave specific and independent information through the produced factors. The results of cross-sectional regressions, so as to see whether the returns of each portfolio are related to the estimated factor betas, were very interesting as in most cases there was a significant relationship with the returns of the portfolios. These findings show that several (unobserved) factors exist that should be specified so as to see if they are truly related to stock returns (Chen, 1983).

This conclusion led to the application of the macroeconomic APT model for the same time period using the two-stage procedure of time-series and cross-sectional regressions (Chen and Jordan, 1993). The first variables employed, related to the inflation rate, were the unexpected inflation rate and the change in expected inflation rate, which were already used in prior studies (Chen *et al.*, 1986; McGowan and Dobson, 1993; Diacogiannis *et al.*, 2001). The results have shown that their influence was partial for specific periods and portfolios.

Other variables used were the unexpected change in the petroleum derivatives series, which was estimated by applying the Box-Jenkins (1976) time series analysis. We should recall that the series of petroleum derivatives was the closest variable to petroleum prices that was available for the Greek market. Petroleum prices were used in prior studies (Chen *et al.*, 1986; Chen and Jordan, 1993) and, in our case, the results have shown that its influence was relatively weak on portfolio returns, a result similar to the results of Chen *et al.* (1986). This might be a result of the impact of a more general crisis that increases nowadays and can affect any emerging or developed market. Finally, the unexpected change in the growth rate in industrial production was used in the tests (Chen and Jordan, 1993). Its results were even weaker in the ASE, with a few exceptions, and this might be due to the fact that Greece is not a highly industrialised country (in relation to other European countries, the US and Japan). Finally, the variable that proved to be the most significant was the general market index, whose power was combined with the macroeconomic variables so as to examine the validity of the APT model.

This relative significance of the market index was also verified by the joint test between the factors scores and the macroeconomic variables, and by the results of canonical correlation analysis, which examined for possible linear relationships between different sets of factor scores and macroeconomic variables (chapter four). Finally, the tests of comparison between the CAPM and the statistical APT model, as well as between the statistical APT and the macroeconomic APT model (residual analysis (Chen, 1983) and Davidson and MacKinnon (1981) test for specification error) verified the inability of the CAPM to function as a model in the ASE and the existence of factors (unobserved and observed) that show some explanatory power on stocks returns.

Moreover, chapter five verified that although specific GARCH models were selected to estimate the new beta coefficients of the regression equation so as to avoid the problem of heteroscedasticity and the case of spurious regressions, the main inference was that the CAPM could not have any significant influence on stock returns using both monthly and daily observations of returns. At the final part of the empirical tests (sections 5.8 and 5.9), we gathered a number of variables so as to examine whether they are related on the long-run based on several prior studies (Hondroyannis and Papapetrou, 2001; Hassan, 2003; Maysami *et al.*, 2004). The variables were grouped in order to examine for possible long-run relationships, as well as the direction of these relationships. In most cases the results were in agreement with results of prior studies (Niarchos and Alexakis, 2000; Maysami *et al.*, 2004), that is the inflation rate is negatively related to the market indices, the (short-term) interest rate is positively related to market indices (although, based on previous studies the results are not the same for long-term rates) and the industrial production index is also positively related to the same indices.

The inability of the CAPM and the possible relationships between the variables also led us to the conclusion that the Greek market seems to be inefficient as there are variables, like the stock market indices, that depend on the past values of other variables, based on the theory of cointegration analysis (Kuhl, 2007). Although Euro was introduced in 2001 in the Greek market, the empirical results seemed to be unaffected by this monetary change, which might be a result of the existence of other factors that influence the decision of investors. These factors could be psychological, which means that they may be related to the theory of behavioural finance (Fama, 1998; Barberis and Thaler, 2003). Moreover, the development of behavioural models as well as a combination between financial models might lead investors and analysts to even more accurate inferences. The addition of the psychological factor of each investor (Niarchos and Alexakis, 2000) to the list of all the factors presented in this study could show that the optimal market portfolio cannot explain stocks by itself.

6.2 Managerial Implications

It is evident that the market beta cannot explain the cross-section variation of average stock returns of the ASE firms for the period between 1989 and 2006, when beta is the only explanatory variable based on the theory of the CAPM. Moreover, during the application of the macroeconomic APT model it can be seen that the power of the model increases significantly when along with the market beta, a number of variables are included in the equation. These results imply that the market beta alone cannot provide us with an efficient mechanism of examining stock returns, but, when it is combined with other variables in a multi-factor model, it enhances the quality of the model in terms of increased explanatory ability (Theriou *et al.*, 2005).

However, the CAPM is still widely used by many practitioners. Although the theoretical problems with the model have been documented through the decades (Roll, 1977), it is still one of the most common approaches employed for valuation purposes. The model is taught in most undergraduate corporate finance classes and, even though its weaknesses have been documented, practitioners are typically left with no alternative to replace it with, so it is generally accepted.

Many brokerage firms, financial institutions, and financial consulting firms can develop their own model to aid their investment decision-making process. These models have become increasingly popular because they allow risk to be more tightly controlled and they allow the investor to be protected against specific types of risk to which he or she is more sensitive. The findings of this study, which indicate that there are variables others than beta that can explain the cross-section of average stock returns, suggest that the APT models can be broadly applied in the explanation of stock returns behaviour, especially when the variables can be determined *a priori* based on a more theoretical context.

A useful tool for any financial institution would be to understand the direction of the relationship between different groups of indices. Specifically, it has been shown in our work that the short-term interest rates are positively associated with the market indices. It is argued that, in contrast to the short-term interest rate, the long-term one exhibit a negative influence on the indices (Maysami *et al.*, 2004). This might be a result of the negative influence of the inflation on the market indices. In case that a rise in inflation leads to a rise in the interest rates the investors will want to sell their stocks.

Generally, the findings of the tests have important applications for investors' portfolio formation and performance evaluation, as most of the investors care about long-term security returns. By adding the fact that there is not a solid theoretical background on these relationships, as most of them are results of statistical analysis, we tried to employ an adequate number of (observed and unobserved) variables so as to come to some inferences regarding the way that the ASE functions.

6.3 Limitations of the Research

This work had some drawbacks as far as the data collection process is concerned. Although a sufficient sample period has been used, an even larger sample would lead to a more complete examination of the ASE with its respective changes through the years. The lack of information from the ASE databank is due to the fact that most of the data were not available in electronic form, especially until the beginning of the 1990s. This is one of the reasons that we started collecting the data sample from January 1989. The data of stocks are row prices, which means that they do not include any dividends and are adjusted for stock splits. We decided to work with the largest number of stocks (for the ASE standards) that we could gather so as to understand what is the general trend in the market and who the factors are that could have an effect on it.

The employment of individual stocks (especially during the application of (G)ARCH models) aimed to keep our inferences safe from biased results. Furthermore, the correction of stocks and macrovariables for possible diagnostic problems such as autocorrelation, heteroscedasticity, or even multicollinearity, with the use of specific methods (principal components analysis, time series analysis and (G)ARCH processes) led to the avoidance of potential spurious regressions during the cross-sectional stage.

6.4 Proposals for Future Research

The conclusions of the study are beneficial so that it could be clearer whether there exist any potential opportunities for profit from the inefficiency of the stock market mechanism. The presence of cointegrating relationships between macroeconomic variables and stock prices led to the conclusion that the efficient market hypothesis is in doubt. Factors may indeed exist that can predict the behaviour of stock market and the investors or policy makers may need to reevaluate their economic policies.

Moreover, although it has been documented in several studies that there are relationships between the macroeconomic variables and stock markets, there is evidence which shows that this is not universally accepted. There are stock markets that are affected by both local and global factors (Cauchie *et al.*, 2004) while other studies only by global ones, leading to the suggestion that researchers should gather a sufficient number of variables so as to be even more precise when they come to such economic conclusions. For instance, in the case of the ASE, the Gross Domestic Product (GDP) and the long-term (1-year) interest rate would be two interesting factors in order to examine their interaction with stock returns. Alternatively, different variables could be used, such as the general stock market indices of foreign capital markets that were also in a transition stage during the last decade.

An initial analysis on the correlation between the ASE general index and the respective stock market indices of NASDAQ (National Association of Securities Dealers Automated Quotations), NYSE (New York Stock Exchange), LSE (London Stock Exchange), the Mexican stock exchange and the Italian stock exchange showed that only the Italian market is related to the ASE during the period between 1995 and 2006. Specifically, the results showed a weak linear relationship (the Pearson correlation coefficient was equal to 0.256) but statistically significant ($p = 0.002$). This result might be based on the fact that, except that Greece and Italy are neighbour countries, they are both not so highly industrialised in comparison to other developed countries, such as the US and Japan.

There is another proposition for future research in asset pricing and this is related to investor sentiment. Specifically, Baker and Wurgler (2006) found that when sentiment is estimated to be high, the returns tend to be relatively low for small, young or high volatility stocks, as most of the Greek stocks are, while, when sentiment is low, the returns of the same stocks tend to be relatively high. Although it is not expected these results to be the same for the ASE, as most of these inferences are based on studies applied in more developed markets, that is the US market, it would be interesting to see what the results would be for the Greek market.

Overall, the results of the tests suggest that stock risks are multi-dimensional. For example, one of this dimensions of risk could be proxied by the (optimal) market portfolio, another one by the inflation rate, while others could be proxied by other local or global indices or even psychological factors, which could lead to different decisions regarding the formation of portfolios by firms or individual investors. The CAPM will always be applied in similar tests using the stock market index as the proxy for the market portfolio.

Furthermore, along with the CAPM, the utility of APT models is crucial as it has been depicted in several empirical studies. Perhaps the development of a different form of equation such as an exponential one could lead to even more acurate results as the linear relationship used is not always the best for each case. In our study we have already employed a polynomial equation so as to test for the existence of non-linearity between portfolio returns and the market beta (chapter four). The studies depend a lot on data availability and the avoidance of sampling bias could lead to more interesting clues regarding the investor profile during different time periods.

Finally, the existence of long-run relationships between macroeconomic variables and sectoral indices does not prove that the variables are also related in the short-run. So, it would be interesting to examine such relationships in the future using the same variables by employing an error correction model (Niarchos and Alexakis, 2000; Apergis and Rezitis, 2003).

6.5 Summary

We conclude this chapter by stressing the main findings of our study related to the examination of the ASE during the period between 1989 and 2006. The results showed that the (weak-form) efficiency of the ASE is in doubt, as it claims that all past prices of a stock are reflected in today's stock price, and, therefore, technical analysis cannot be used to predict and beat a market. This is not totally true, as there are factors (observed or unobserved) according to the results of the APT models that have a (partial) effect on stock returns.

Moreover, the view that stock prices may be influenced by a variety of unexpected changes is supported, as it has been shown by the results of the APT models (chapter four). Additionally, the existence of long-run relationships between the stock indices and the economic factors (chapter five) show that past prices have an effect on present prices, an inference that contrasts the market efficiency and shows that the investors can benefit from the information that exists in these factors.

However, as the stock market index, proxied for the optimal market portfolio, has a sufficient explanatory power relative to other macroeconomic factors, is a sign that the CAPM may not be the best model for the examination of stock returns in the

ASE, but this does not mean that there is any other specific model that could substitute it (Michailidis *et al.*, 2006).

The inefficiency of the ASE may hold due to several reasons. These reasons may be related to the existence of a combination of different economic factors or even psychological factors, which can easily affect each investor (Niarchos and Alexakis, 200). As psychology catalogues the deviations from full rationality (Barberis asnd Thaler, 2003), the existence of such factors may automatically lead against the notion of market efficiency. The psychological factor, along with the theory of limited arbitrage, which shows that if irrational investors deviate the fundamendal value of a security, rational investors will not be able to react, are components of the behavioural finance theory.

Because of the advances in information technology, the markets are becoming more efficient. Technology allows for a more effective means to disseminate information, and electronic trading allows for prices to adjust more quickly to news entering the market. However, according to the above, it is obvious that there is not any clear view regarding the best model so as to examine the behaviour of securities. The mixed empirical results between a sufficient number of studies (Black *et al.*, 1972; Fama and MacBeth, 1973; Chen, 1983 and so on) show that there seems to be a gap between theory and practice. This inference may necessitate the development of new theories in finance.

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APPENDICES

Appendix I
Normality Test Results

***Table I.1*: Tests of normality for all the portfolios of the whole period (1989–2006)**

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	Df	Sig.
VAR00001	.107	216	.000	.904	216	.000
VAR00002	.084	216	.001	.962	216	.000
VAR00003	.091	216	.000	.950	216	.000
VAR00004	.131	216	.000	.915	216	.000
VAR00005	.193	216	.000	.601	216	.000
VAR00006	.123	216	.000	.883	216	.000
VAR00007	.065	216	.029	.976	216	.001
VAR00008	.087	216	.000	.921	216	.000
VAR00009	.095	216	.000	.944	216	.000
VAR00010	.082	216	.001	.967	216	.000
VAR00011	.123	216	.000	.937	216	.000
VAR00012	.126	216	.000	.912	216	.000
VAR00013	.058	216	.073	.990	216	.127
VAR00014	.087	216	.000	.968	216	.000
VAR00015	.131	216	.000	.905	216	.000
VAR00016	.084	216	.001	.955	216	.000
VAR00017	.131	216	.000	.916	216	.000
VAR00018	.099	216	.000	.952	216	.000
VAR00019	.086	216	.000	.955	216	.000
VAR00020	.092	216	.000	.952	216	.000
VAR00021	.099	216	.000	.927	216	.000
VAR00022	.111	216	.000	.932	216	.000
VAR00023	.091	216	.000	.955	216	.000
VAR00024	.087	216	.000	.959	216	.000
VAR00025	.127	216	.000	.918	216	.000
VAR00026	.075	216	.005	.970	216	.000
VAR00027	.129	216	.000	.917	216	.000
VAR00028	.147	216	.000	.750	216	.000
VAR00029	.098	216	.000	.938	216	.000
VAR00030	.127	216	.000	.826	216	.000
VAR00031	.094	216	.000	.941	216	.000
VAR00032	.144	216	.000	.866	216	.000
VAR00033	.123	216	.000	.915	216	.000
VAR00034	.126	216	.000	.945	216	.000
VAR00035	.132	216	.000	.928	216	.000
VAR00036	.147	216	.000	.900	216	.000
VAR00037	.110	216	.000	.921	216	.000
VAR00038	.055	216	.200(*)	.975	216	.001
VAR00039	.068	216	.016	.971	216	.000

VAR00040	.102	216	.000	.961	216	.000
VAR00041	.152	216	.000	.877	216	.000
VAR00042	.087	216	.000	.968	216	.000
VAR00043	.137	216	.000	.928	216	.000
VAR00044	.062	216	.043	.954	216	.000
VAR00045	.133	216	.000	.856	216	.000
VAR00046	.125	216	.000	.824	216	.000
VAR00047	.120	216	.000	.917	216	.000
VAR00048	.072	216	.008	.964	216	.000
VAR00049	.088	216	.000	.964	216	.000
VAR00050	.102	216	.000	.940	216	.000
VAR00051	.173	216	.000	.854	216	.000
VAR00052	.108	216	.000	.938	216	.000
VAR00053	.203	216	.000	.778	216	.000
VAR00054	.069	216	.014	.974	216	.000
VAR00055	.193	216	.000	.779	216	.000
VAR00056	.126	216	.000	.951	216	.000
VAR00057	.100	216	.000	.982	216	.008
VAR00058	.073	216	.007	.966	216	.000
VAR00059	.161	216	.000	.900	216	.000
VAR00060	.090	216	.000	.970	216	.000

Note: *This is a lower bound of the true significance.

Note: The use of coding (VAR00001, VAR00002 etc.) was only necessary to facilitate this work. As far as the stock returns of the whole period (1989–2006) are concerned, in the next page we present the table with the ISIN code for each stock with its respective full name as it is depicted in the ASE databank. For the stocks presented in tables 2 to 4 (below) their names are available on request.

VARIABLE	ISIN CODE	SHARE NAME
VAR00001	GRS003013000	NATIONAL BANK OF GREECE S.A. (CR)
VAR00002	GRS018023002	ETHNIKI S.A. GENERAL INSURANCE CO (CR)
VAR00003	GRS006013007	EMPORIKI BANK OF GREECE S.A. (CR)
VAR00004	GRS001013002	BANK OF ATTICA S.A. (CR)
VAR00005	GRS117123000	LOULIS MILLS S.A. (CR)
VAR00006	GRS014013007	PIRAEUS BANK S.A. (CR)
VAR00007	GRS132003005	SHELMAN S.A. (CR)
VAR00008	GRS015013006	ALPHA BANK S.A. (CR)
VAR00009	GRS048004006	KLONATEX GROUP OF COMPANIES S.A. (PR)
VAR00010	GRS091103002	METKA S.A. (CR)
VAR00011	GRS083003012	F.G. EUROPE S.A. (CR)
VAR00012	GRS043003011	EUROHOLDINGS CAPITAL & INVESTMENT CORP S.A. (CR)
VAR00013	GRS002013001	GENERAL BANK OF GREECE S.A. (CR)
VAR00014	GRS046064002	ETMA RAYON S.A. (PR)
VAR00015	GRS004013009	BANK OF GREECE (CR)
VAR00016	GRS048003008	KLONATEX GROUP OF COMPANIES S.A. (CR)
VAR00017	GRS084103001	BIOSSOL S.A. (CR)
VAR00018	GRS135213007	VIOTER S.A. (CR)
VAR00019	GRS124153008	VIS S.A. (CR)
VAR00020	GRS090101007	N. LEVEDERIS S.A. (CB)
VAR00021	GRS073083008	HERACLES GEN.CEMENT COMPANY S.A. (CR)
VAR00022	GRS084104009	BIOSSOL S.A. (PR)
VAR00023	GRS124154006	VIS S.A. (PR)

VAR00024	GRS131171001	XYLEMPORIA S.A. (CB)
VAR00025	GRS097103006	SHEET STEEL S.A.(CR)
VAR00026	GRS066071002	PETZETAKIS S.A. (CB)
VAR00027	GRS020023008	PHOENIX METROLIFE S.A.(CR)
VAR00028	GRS074083007	TITAN CEMENT COMPANY S.A. (CR)
VAR00029	GRS081103004	ALUMINIUM OF GREECE S.A. (CR)
VAR00030	GRS071003008	CERAMICS ALLATINI S.A. (CR)
VAR00031	GRS131176000	XYLEMPORIA S.A. (PB)
VAR00032	GRS070083001	KEKROPS S.A. (CR)
VAR00033	GRS116121005	ALLATINI IND &COM S.A. (CB)
VAR00034	GRS032043002	ALPHA LEASING S.A. (CR)
VAR00035	GRS085101004	VIOHALCO (CB)
VAR00036	GRS120131008	KARELIA TOBACCO COMPANY S.A. (C)
VAR00037	GRS103003000	ELAIS OLEAGINOUS PROD. S.A. (CR)
VAR00038	GRS110111002	J.BOUTARIS & SON HOLDING S.A. (CB)
VAR00039	GRS065001018	PLIAS CONSUMER GOODS S.A. (CB)
VAR00040	GRS127003002	IONIAN HOTEL S.A. (CR)
VAR00041	GRS146181003	ZAMPA S.A. (CB)
VAR00042	GRS044063006	ELFICO S.A. (CR)
VAR00043	GRS128003001	LAMPSA HOTEL S.A. (CR)
VAR00044	GRS110116001	J.BOUTARIS & SON HOLDING S.A. (PB)
VAR00045	GRS323013003	EFG EUROBANK ERGASIAS BANK S.A. (CR)
VAR00046	GRS144161007	ATTICA HOLDINGS S.A. (CB)
VAR00047	GRS096003009	FOURLIS S.A.(CR)

VAR00048	GRS149501009	IPPOTOUR S.A. (CB)
VAR00049	GRS106111008	REDS S.A. (CB)
VAR00050	GRS133003004	MULTIRAMA S.A.(CR)
VAR00051	GRS059063008	WOOL INDUSTRY TRIA ALFA S.A. (CR)
VAR00052	GRS019023001	ASPIS PRONIA GENERAL INSURANCES S.A. (CR)
VAR00053	GRS059064006	WOOL INDUSTRY TRIA ALFA S.A. (PR)
VAR00054	GRS046063004	ETMA RAYON S.A. (CR)
VAR00055	GRS118003003	C. SARANTOPOULOS FLOUR MILLS S.A. (CR)
VAR00056	GRS332073006	FIERATEX S.A. (CR)
VAR00057	GRS060063005	FINTEXPORT S.A. (CR)
VAR00058	GRS107003006	KATSELIS SONS S.A. BREAD IND. (CR)
VAR00059	GRS123143000	PARNASSOS ENTERPRISES S.A. (CR)
VAR00060	GRS047063003	LANAKAM S.A. (CR)

***Table I.2*: Tests of normality for all the portfolios of the first sub-period (1989–1994)**

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	Df	Sig.
VAR00001	.290	72	.000	.555	72	.000
VAR00002	.175	72	.000	.814	72	.000
VAR00003	.136	72	.002	.865	72	.000
VAR00004	.164	72	.000	.883	72	.000
VAR00005	.113	72	.024	.928	72	.001
VAR00006	.131	72	.004	.904	72	.000
VAR00007	.196	72	.000	.848	72	.000
VAR00008	.144	72	.001	.929	72	.001
VAR00009	.220	72	.000	.805	72	.000
VAR00010	.175	72	.000	.877	72	.000
VAR00011	.088	72	.200(*)	.981	72	.329
VAR00012	.122	72	.010	.953	72	.009
VAR00013	.136	72	.002	.884	72	.000
VAR00014	.187	72	.000	.818	72	.000
VAR00015	.095	72	.174	.956	72	.014
VAR00016	.123	72	.009	.971	72	.098
VAR00017	.096	72	.169	.952	72	.008
VAR00018	.102	72	.059	.960	72	.021
VAR00019	.092	72	.200(*)	.957	72	.015
VAR00020	.118	72	.015	.965	72	.043
VAR00021	.175	72	.000	.843	72	.000
VAR00022	.143	72	.001	.913	72	.000
VAR00023	.092	72	.200(*)	.954	72	.010
VAR00024	.070	72	.200(*)	.992	72	.923
VAR00025	.071	72	.200(*)	.973	72	.121
VAR00026	.077	72	.200(*)	.984	72	.481
VAR00027	.146	72	.001	.914	72	.000
VAR00028	.100	72	.074	.967	72	.054
VAR00029	.178	72	.000	.888	72	.000
VAR00030	.177	72	.000	.767	72	.000
VAR00031	.082	72	.200(*)	.969	72	.077
VAR00032	.222	72	.000	.708	72	.000
VAR00033	.104	72	.051	.950	72	.006
VAR00034	.142	72	.001	.925	72	.000
VAR00035	.135	72	.002	.954	72	.011
VAR00036	.150	72	.000	.924	72	.000
VAR00037	.088	72	.200(*)	.975	72	.154
VAR00038	.306	72	.000	.745	72	.000
VAR00039	.067	72	.200(*)	.984	72	.483
VAR00040	.064	72	.200(*)	.986	72	.635
VAR00041	.061	72	.200(*)	.976	72	.177
VAR00042	.139	72	.002	.912	72	.000
VAR00043	.109	72	.035	.969	72	.072
VAR00044	.088	72	.200(*)	.982	72	.408
VAR00045	.087	72	.200(*)	.958	72	.016
VAR00046	.125	72	.007	.912	72	.000

VAR00047	.208	72	.000	.870	72	.000
VAR00048	.128	72	.005	.962	72	.029
VAR00049	.149	72	.000	.905	72	.000
VAR00050	.138	72	.002	.938	72	.002
VAR00051	.114	72	.022	.946	72	.004
VAR00052	.114	72	.022	.923	72	.000
VAR00053	.093	72	.200(*)	.982	72	.381
VAR00054	.187	72	.000	.909	72	.000
VAR00055	.075	72	.200(*)	.981	72	.331
VAR00056	.141	72	.001	.918	72	.000
VAR00057	.088	72	.200(*)	.978	72	.235
VAR00058	.108	72	.037	.987	72	.653
VAR00059	.233	72	.000	.820	72	.000
VAR00060	.147	72	.001	.942	72	.002

Note: *This is a lower bound of the true significance.

Table I.3: **Tests of normality for all the portfolios of the second sub-period (1995–2000)**

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	Df	Sig.
VAR00001	.156	71	.000	.901	71	.000
VAR00002	.115	71	.021	.934	71	.001
VAR00003	.156	71	.000	.906	71	.000
VAR00004	.111	71	.031	.951	71	.008
VAR00005	.083	71	.200(*)	.959	71	.022
VAR00006	.115	71	.021	.955	71	.012
VAR00007	.119	71	.015	.958	71	.019
VAR00008	.112	71	.028	.962	71	.030
VAR00009	.111	71	.031	.971	71	.096
VAR00010	.124	71	.008	.958	71	.019
VAR00011	.134	71	.003	.954	71	.011
VAR00012	.152	71	.000	.885	71	.000
VAR00013	.130	71	.005	.926	71	.000
VAR00014	.112	71	.029	.953	71	.009
VAR00015	.152	71	.000	.905	71	.000
VAR00016	.174	71	.000	.905	71	.000
VAR00017	.091	71	.200(*)	.946	71	.004
VAR00018	.135	71	.003	.952	71	.009
VAR00019	.074	71	.200(*)	.984	71	.520
VAR00020	.122	71	.011	.956	71	.015
VAR00021	.148	71	.001	.920	71	.000
VAR00022	.137	71	.002	.946	71	.004
VAR00023	.107	71	.043	.974	71	.152
VAR00024	.105	71	.051	.965	71	.045
VAR00025	.113	71	.026	.951	71	.007
VAR00026	.140	71	.001	.944	71	.003
VAR00027	.144	71	.001	.925	71	.000
VAR00028	.120	71	.013	.925	71	.000
VAR00029	.164	71	.000	.943	71	.003
VAR00030	.170	71	.000	.907	71	.000
VAR00031	.121	71	.012	.970	71	.090
VAR00032	.137	71	.002	.940	71	.002
VAR00033	.086	71	.200(*)	.983	71	.428
VAR00034	.100	71	.078	.979	71	.275
VAR00035	.130	71	.005	.920	71	.000
VAR00036	.080	71	.200(*)	.963	71	.033
VAR00037	.106	71	.045	.943	71	.003
VAR00038	.185	71	.000	.902	71	.000
VAR00039	.101	71	.072	.970	71	.092
VAR00040	.097	71	.092	.958	71	.018
VAR00041	.076	71	.200(*)	.985	71	.560
VAR00042	.115	71	.021	.938	71	.002
VAR00043	.179	71	.000	.877	71	.000
VAR00044	.092	71	.200(*)	.971	71	.100
VAR00045	.142	71	.001	.905	71	.000
VAR00046	.132	71	.004	.947	71	.005

VAR00047	.132	71	.004	.921	71	.000
VAR00048	.122	71	.010	.949	71	.006
VAR00049	.073	71	.200(*)	.985	71	.531
VAR00050	.096	71	.170	.970	71	.082
VAR00051	.161	71	.000	.814	71	.000
VAR00052	.136	71	.002	.936	71	.001
VAR00053	.109	71	.036	.964	71	.040
VAR00054	.150	71	.000	.883	71	.000
VAR00055	.185	71	.000	.923	71	.000
VAR00056	.156	71	.000	.936	71	.001
VAR00057	.086	71	.200(*)	.982	71	.386
VAR00058	.118	71	.016	.938	71	.002
VAR00059	.186	71	.000	.842	71	.000
VAR00060	.065	71	.200(*)	.988	71	.750
VAR00061	.055	71	.200(*)	.989	71	.787
VAR00062	.122	71	.011	.919	71	.000
VAR00063	.141	71	.001	.888	71	.000
VAR00064	.127	71	.007	.923	71	.000
VAR00065	.120	71	.012	.892	71	.000
VAR00066	.053	71	.200(*)	.987	71	.674
VAR00067	.147	71	.001	.902	71	.000
VAR00068	.156	71	.000	.932	71	.001
VAR00069	.065	71	.200(*)	.984	71	.524
VAR00070	.084	71	.200(*)	.978	71	.245
VAR00071	.097	71	.098	.968	71	.065
VAR00072	.098	71	.087	.929	71	.001
VAR00073	.133	71	.003	.912	71	.000
VAR00074	.120	71	.013	.953	71	.010
VAR00075	.065	71	.200(*)	.991	71	.878
VAR00076	.135	71	.003	.872	71	.000
VAR00077	.086	71	.200(*)	.923	71	.000
VAR00078	.124	71	.009	.955	71	.013
VAR00079	.085	71	.200(*)	.961	71	.025
VAR00080	.090	71	.200(*)	.969	71	.080
VAR00081	.082	71	.200(*)	.976	71	.182
VAR00082	.165	71	.000	.891	71	.000
VAR00083	.106	71	.047	.973	71	.129
VAR00084	.066	71	.200(*)	.991	71	.881
VAR00085	.103	71	.058	.964	71	.042
VAR00086	.150	71	.000	.855	71	.000
VAR00087	.132	71	.004	.945	71	.004
VAR00088	.105	71	.051	.943	71	.003
VAR00089	.175	71	.000	.901	71	.000
VAR00090	.184	71	.000	.898	71	.000
VAR00091	.102	71	.067	.966	71	.055
VAR00092	.091	71	.200(*)	.964	71	.037
VAR00093	.114	71	.024	.935	71	.001
VAR00094	.197	71	.000	.807	71	.000
VAR00095	.168	71	.000	.892	71	.000
VAR00096	.120	71	.013	.963	71	.033
VAR00097	.118	71	.016	.870	71	.000

VAR00098	.074	71	.200(*)	.979	71	.278
VAR00099	.154	71	.000	.927	71	.000
VAR00100	.066	71	.200(*)	.993	71	.971
VAR00101	.191	71	.000	.815	71	.000
VAR00102	.200	71	.000	.855	71	.000
VAR00103	.143	71	.001	.938	71	.002
VAR00104	.112	71	.029	.947	71	.004
VAR00105	.133	71	.003	.950	71	.007
VAR00106	.148	71	.001	.920	71	.000
VAR00107	.118	71	.016	.954	71	.010
VAR00108	.090	71	.200(*)	.975	71	.178
VAR00109	.101	71	.072	.969	71	.072
VAR00110	.091	71	.200(*)	.958	71	.019
VAR00111	.054	71	.200(*)	.991	71	.895
VAR00112	.132	71	.004	.948	71	.005
VAR00113	.151	71	.000	.931	71	.001
VAR00114	.093	71	.200(*)	.972	71	.120
VAR00115	.074	71	.200(*)	.987	71	.683
VAR00116	.070	71	.200(*)	.980	71	.301
VAR00117	.115	71	.021	.965	71	.047
VAR00118	.123	71	.010	.907	71	.000
VAR00119	.167	71	.000	.870	71	.000
VAR00120	.119	71	.015	.945	71	.004
VAR00121	.115	71	.021	.912	71	.000
VAR00122	.149	71	.000	.908	71	.000
VAR00123	.168	71	.000	.898	71	.000
VAR00124	.103	71	.058	.972	71	.106
VAR00125	.172	71	.000	.871	71	.000
VAR00126	.177	71	.000	.923	71	.000
VAR00127	.123	71	.010	.914	71	.000
VAR00128	.174	71	.000	.893	71	.000
VAR00129	.107	71	.041	.951	71	.007
VAR00130	.186	71	.000	.848	71	.000
VAR00131	.139	71	.002	.910	71	.000
VAR00132	.099	71	.082	.976	71	.203
VAR00133	.140	71	.001	.874	71	.000
VAR00134	.171	71	.000	.867	71	.000
VAR00135	.160	71	.000	.914	71	.000
VAR00136	.117	71	.017	.957	71	.015
VAR00137	.086	71	.200(*)	.974	71	.154
VAR00138	.129	71	.005	.946	71	.004
VAR00139	.107	71	.042	.933	71	.001
VAR00140	.132	71	.004	.961	71	.026
VAR00141	.116	71	.019	.954	71	.011
VAR00142	.185	71	.000	.878	71	.000
VAR00143	.064	71	.200(*)	.988	71	.719
VAR00144	.071	71	.200(*)	.981	71	.337
VAR00145	.107	71	.042	.974	71	.148
VAR00146	.052	71	.200(*)	.988	71	.755
VAR00147	.235	71	.000	.748	71	.000
VAR00148	.120	71	.013	.958	71	.019

VAR00149	.152	71	.000	.927	71	.000
VAR00150	.249	71	.000	.757	71	.000

Note: *This is a lower bound of the true significance.

***Table I.4*: Tests of normality for all the portfolios of the third sub-period (2001–2006)**

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
VAR00001	.108	72	.037	.891	72	.000
VAR00002	.114	72	.021	.951	72	.007
VAR00003	.075	72	.200(*)	.980	72	.326
VAR00004	.094	72	.189	.948	72	.005
VAR00005	.123	72	.009	.926	72	.000
VAR00006	.113	72	.022	.940	72	.002
VAR00007	.093	72	.200(*)	.961	72	.025
VAR00008	.057	72	.200(*)	.984	72	.480
VAR00009	.070	72	.200(*)	.967	72	.057
VAR00010	.106	72	.043	.973	72	.122
VAR00011	.115	72	.019	.918	72	.000
VAR00012	.081	72	.200(*)	.966	72	.050
VAR00013	.079	72	.200(*)	.988	72	.737
VAR00014	.129	72	.005	.944	72	.003
VAR00015	.082	72	.200(*)	.969	72	.077
VAR00016	.067	72	.200(*)	.985	72	.566
VAR00017	.092	72	.200(*)	.978	72	.250
VAR00018	.070	72	.200(*)	.988	72	.717
VAR00019	.127	72	.006	.956	72	.013
VAR00020	.120	72	.012	.951	72	.007
VAR00021	.094	72	.186	.964	72	.036
VAR00022	.070	72	.200(*)	.968	72	.062
VAR00023	.098	72	.086	.954	72	.010
VAR00024	.074	72	.200(*)	.973	72	.125
VAR00025	.105	72	.046	.949	72	.005
VAR00026	.116	72	.018	.932	72	.001
VAR00027	.066	72	.200(*)	.976	72	.185
VAR00028	.087	72	.200(*)	.967	72	.057
VAR00029	.101	72	.064	.972	72	.111
VAR00030	.067	72	.200(*)	.992	72	.924
VAR00031	.124	72	.008	.950	72	.006
VAR00032	.140	72	.001	.900	72	.000
VAR00033	.111	72	.029	.923	72	.000
VAR00034	.067	72	.200(*)	.985	72	.566
VAR00035	.103	72	.058	.979	72	.264
VAR00036	.083	72	.200(*)	.970	72	.088
VAR00037	.100	72	.069	.962	72	.029
VAR00038	.100	72	.072	.941	72	.002

VAR00039	.091	72	.200(*)	.978	72	.239
VAR00040	.086	72	.200(*)	.977	72	.211
VAR00041	.118	72	.014	.973	72	.130
VAR00042	.105	72	.049	.965	72	.045
VAR00043	.147	72	.001	.865	72	.000
VAR00044	.100	72	.073	.963	72	.033
VAR00045	.111	72	.027	.954	72	.011
VAR00046	.116	72	.018	.968	72	.062
VAR00047	.066	72	.200(*)	.988	72	.704
VAR00048	.120	72	.012	.962	72	.029
VAR00049	.164	72	.000	.804	72	.000
VAR00050	.081	72	.200(*)	.915	72	.000
VAR00051	.085	72	.200(*)	.987	72	.642
VAR00052	.094	72	.195	.934	72	.001
VAR00053	.118	72	.014	.953	72	.009
VAR00054	.078	72	.200(*)	.991	72	.878
VAR00055	.083	72	.200(*)	.948	72	.005
VAR00056	.112	72	.026	.941	72	.002
VAR00057	.133	72	.003	.922	72	.000
VAR00058	.103	72	.057	.948	72	.005
VAR00059	.109	72	.034	.969	72	.076
VAR00060	.069	72	.200(*)	.969	72	.076
VAR00061	.086	72	.200(*)	.973	72	.130
VAR00062	.145	72	.001	.925	72	.000
VAR00063	.089	72	.200(*)	.970	72	.086
VAR00064	.132	72	.003	.948	72	.005
VAR00065	.084	72	.200(*)	.980	72	.309
VAR00066	.098	72	.085	.981	72	.343
VAR00067	.129	72	.005	.962	72	.030
VAR00068	.151	72	.000	.878	72	.000
VAR00069	.111	72	.028	.974	72	.149
VAR00070	.154	72	.000	.885	72	.000
VAR00071	.095	72	.180	.986	72	.614
VAR00072	.088	72	.200(*)	.970	72	.088
VAR00073	.105	72	.046	.960	72	.021
VAR00074	.083	72	.200(*)	.970	72	.088
VAR00075	.096	72	.099	.985	72	.526
VAR00076	.123	72	.009	.950	72	.006
VAR00077	.164	72	.000	.891	72	.000
VAR00078	.100	72	.074	.979	72	.266
VAR00079	.128	72	.005	.922	72	.000
VAR00080	.123	72	.009	.967	72	.054
VAR00081	.112	72	.026	.974	72	.150
VAR00082	.101	72	.064	.975	72	.164
VAR00083	.090	72	.200(*)	.968	72	.067
VAR00084	.122	72	.010	.952	72	.008
VAR00085	.123	72	.009	.895	72	.000
VAR00086	.116	72	.018	.947	72	.004
VAR00087	.127	72	.006	.971	72	.090
VAR00088	.068	72	.200(*)	.989	72	.775
VAR00089	.139	72	.002	.887	72	.000

VAR00090	.055	72	.200(*)	.990	72	.826
VAR00091	.076	72	.200(*)	.978	72	.253
VAR00092	.164	72	.000	.900	72	.000
VAR00093	.122	72	.010	.956	72	.013
VAR00094	.101	72	.064	.951	72	.007
VAR00095	.154	72	.000	.935	72	.001
VAR00096	.072	72	.200(*)	.970	72	.081
VAR00097	.069	72	.200(*)	.967	72	.058
VAR00098	.082	72	.200(*)	.956	72	.013
VAR00099	.094	72	.188	.928	72	.001
VAR00100	.088	72	.200(*)	.966	72	.051
VAR00101	.217	72	.000	.644	72	.000
VAR00102	.088	72	.200(*)	.991	72	.870
VAR00103	.095	72	.179	.971	72	.097
VAR00104	.121	72	.011	.854	72	.000
VAR00105	.060	72	.200(*)	.981	72	.356
VAR00106	.086	72	.200(*)	.983	72	.438
VAR00107	.073	72	.200(*)	.975	72	.166
VAR00108	.074	72	.200(*)	.991	72	.891
VAR00109	.128	72	.005	.813	72	.000
VAR00110	.120	72	.011	.974	72	.149
VAR00111	.071	72	.200(*)	.987	72	.690
VAR00112	.130	72	.004	.924	72	.000
VAR00113	.038	72	.200(*)	.993	72	.968
VAR00114	.102	72	.061	.957	72	.015
VAR00115	.082	72	.200(*)	.970	72	.085
VAR00116	.110	72	.030	.880	72	.000
VAR00117	.093	72	.200(*)	.938	72	.002
VAR00118	.086	72	.200(*)	.842	72	.000
VAR00119	.131	72	.004	.935	72	.001
VAR00120	.084	72	.200(*)	.968	72	.067
VAR00121	.133	72	.003	.925	72	.000
VAR00122	.105	72	.046	.961	72	.026
VAR00123	.118	72	.014	.959	72	.020
VAR00124	.135	72	.002	.921	72	.000
VAR00125	.115	72	.019	.967	72	.057
VAR00126	.153	72	.000	.795	72	.000
VAR00127	.115	72	.019	.938	72	.002
VAR00128	.116	72	.018	.969	72	.073
VAR00129	.101	72	.066	.985	72	.531
VAR00130	.089	72	.200(*)	.959	72	.019
VAR00131	.095	72	.176	.947	72	.004
VAR00132	.091	72	.200(*)	.965	72	.045
VAR00133	.104	72	.050	.943	72	.003
VAR00134	.054	72	.200(*)	.992	72	.930
VAR00135	.081	72	.200(*)	.966	72	.048
VAR00136	.081	72	.200(*)	.970	72	.078
VAR00137	.125	72	.008	.814	72	.000
VAR00138	.128	72	.005	.903	72	.000
VAR00139	.116	72	.018	.973	72	.119
VAR00140	.119	72	.013	.943	72	.003

VAR00141	.076	72	.200(*)	.988	72	.707
VAR00142	.087	72	.200(*)	.921	72	.000
VAR00143	.130	72	.004	.937	72	.001
VAR00144	.081	72	.200(*)	.958	72	.017
VAR00145	.101	72	.067	.959	72	.020
VAR00146	.092	72	.200(*)	.950	72	.007
VAR00147	.107	72	.039	.966	72	.049
VAR00148	.131	72	.004	.956	72	.014
VAR00149	.113	72	.023	.917	72	.000
VAR00150	.084	72	.200(*)	.984	72	.518
VAR00151	.055	72	.200(*)	.989	72	.779
VAR00152	.096	72	.097	.960	72	.021
VAR00153	.171	72	.000	.922	72	.000
VAR00154	.069	72	.200(*)	.989	72	.798
VAR00155	.164	72	.000	.814	72	.000
VAR00156	.100	72	.071	.986	72	.588
VAR00157	.059	72	.200(*)	.989	72	.792
VAR00158	.249	72	.000	.833	72	.000
VAR00159	.128	72	.005	.932	72	.001
VAR00160	.084	72	.200(*)	.972	72	.102
VAR00161	.125	72	.007	.921	72	.000
VAR00162	.180	72	.000	.882	72	.000
VAR00163	.061	72	.200(*)	.979	72	.259
VAR00164	.093	72	.200(*)	.964	72	.036
VAR00165	.093	72	.200(*)	.940	72	.002
VAR00166	.129	72	.005	.931	72	.001
VAR00167	.091	72	.200(*)	.917	72	.000
VAR00168	.079	72	.200(*)	.957	72	.015
VAR00169	.091	72	.200(*)	.954	72	.010
VAR00170	.100	72	.071	.970	72	.084
VAR00171	.110	72	.031	.956	72	.013
VAR00172	.127	72	.006	.930	72	.001
VAR00173	.121	72	.011	.918	72	.000
VAR00174	.118	72	.015	.945	72	.003
VAR00175	.145	72	.001	.908	72	.000
VAR00176	.115	72	.019	.946	72	.004
VAR00177	.120	72	.012	.965	72	.044
VAR00178	.072	72	.200(*)	.973	72	.120
VAR00179	.073	72	.200(*)	.975	72	.152
VAR00180	.059	72	.200(*)	.986	72	.612
VAR00181	.135	72	.002	.873	72	.000
VAR00182	.135	72	.002	.873	72	.000
VAR00183	.153	72	.000	.905	72	.000
VAR00184	.097	72	.087	.977	72	.223
VAR00185	.094	72	.188	.968	72	.067
VAR00186	.072	72	.200(*)	.983	72	.453
VAR00187	.147	72	.001	.933	72	.001
VAR00188	.128	72	.005	.940	72	.002
VAR00189	.111	72	.029	.879	72	.000
VAR00190	.170	72	.000	.810	72	.000
VAR00191	.094	72	.192	.985	72	.574

VAR00192	.093	72	.200(*)	.958	72	.017
VAR00193	.131	72	.004	.901	72	.000
VAR00194	.160	72	.000	.868	72	.000
VAR00195	.098	72	.083	.938	72	.002
VAR00196	.094	72	.190	.946	72	.004
VAR00197	.095	72	.181	.942	72	.002
VAR00198	.099	72	.076	.961	72	.026
VAR00199	.160	72	.000	.928	72	.000
VAR00200	.087	72	.200(*)	.967	72	.058
VAR00201	.106	72	.043	.936	72	.001
VAR00202	.084	72	.200(*)	.988	72	.751
VAR00203	.090	72	.200(*)	.978	72	.248
VAR00204	.064	72	.200(*)	.974	72	.140
VAR00205	.103	72	.057	.961	72	.025
VAR00206	.103	72	.056	.962	72	.028
VAR00207	.150	72	.000	.918	72	.000
VAR00208	.121	72	.010	.943	72	.003
VAR00209	.093	72	.196	.961	72	.025
VAR00210	.101	72	.066	.976	72	.185
VAR00211	.051	72	.200(*)	.994	72	.985
VAR00212	.090	72	.200(*)	.970	72	.083
VAR00213	.070	72	.200(*)	.976	72	.192
VAR00214	.111	72	.028	.974	72	.133
VAR00215	.120	72	.011	.911	72	.000
VAR00216	.093	72	.200(*)	.957	72	.015
VAR00217	.102	72	.061	.946	72	.004
VAR00218	.093	72	.200(*)	.968	72	.066
VAR00219	.097	72	.091	.978	72	.240
VAR00220	.101	72	.067	.961	72	.025
VAR00221	.081	72	.200(*)	.980	72	.309
VAR00222	.068	72	.200(*)	.987	72	.673
VAR00223	.063	72	.200(*)	.987	72	.647
VAR00224	.117	72	.017	.930	72	.001
VAR00225	.174	72	.000	.832	72	.000
VAR00226	.075	72	.200(*)	.974	72	.136
VAR00227	.072	72	.200(*)	.988	72	.717
VAR00228	.119	72	.013	.951	72	.007
VAR00229	.074	72	.200(*)	.970	72	.086
VAR00230	.112	72	.027	.947	72	.005
VAR00231	.143	72	.001	.921	72	.000
VAR00232	.098	72	.082	.936	72	.001
VAR00233	.193	72	.000	.738	72	.000
VAR00234	.080	72	.200(*)	.981	72	.344
VAR00235	.120	72	.012	.967	72	.059
VAR00236	.083	72	.200(*)	.962	72	.030
VAR00237	.125	72	.007	.883	72	.000
VAR00238	.139	72	.001	.944	72	.003
VAR00239	.112	72	.026	.905	72	.000
VAR00240	.145	72	.001	.945	72	.003

Note: *This is a lower bound of the true significance.

Appendix II
Normality Tests, Summary Statistics, Source, Frequency of Data and Availability of Financial and Macroeconomic Variables

***Table II.1*: First Group of Variables**

VARIABLE	STOCK MARKET INDEX*	CONSUMER PRICE INDEX**	INDUSTRIAL PRODUCTION INDEX**	TREASURY BILL RATE	OIL DERIVATIVES**
MEAN	1969.077	84.84756	70.66103	10.53954	83.30488
MEDIAN	1530.900	90.87998	68.06626	11.15000	75.63294
MAXIMUM	5712.260	122.6786	174.9672	25.50000	157.0023
MINIMUM	263.9000	31.87060	22.25952	2.030000	41.73798
STD. DEV.	1302.960	26.13077	39.20454	6.423826	27.02249
SKEWNESS	0.842956	-0.501190	0.611290	-0.038774	0.734121
KURTOSIS	2.836127	2.088297	2.547080	1.531599	2.973300
JARQUE-BERA	25.82237	16.52372	11.89886	19.45994	14.40800
PROBABILITY	0.00002	0.000258	0.002607	0.000059	0.000061
SOURCE	Athens Stock Exchange	National Statistical Service of Greece	National Statistical Service of Greece	Central Bank of Greece	National Statistical Service of Greece
DATA FREQUENCY	Daily	Monthly	Monthly	Monthly	Monthly
AVAILABLE FROM:	January 1989	January 1989	January 1993	January 1989	January 1989

***Table II.2*: Second Group of Variables**

VARIABLE	SECTORAL INVESTMENT INDEX*	SECTORAL INDUSTRIAL INDEX*	SECTORAL INSURANCE INDEX*	SECTORAL BANKING INDEX*	RETAIL PRICE INDEX**	MONEY SUPPLY (M1)**	US/EURO**	GBP/EURO**
MEAN	735.0473	1161.807	972.1339	3288.435	121.4468	2736.758	0.912227	1.509081
MEDIAN	616.1649	984.1346	704.5605	2267.392	119.5507	2702.250	0.845965	1.482500
MAXIMUM	2996.950	3614.072	4344.136	10678.57	199.4264	3746.600	1.171900	1.643200
MINIMUM	231.6141	238.7732	231.6141	271.2591	81.51689	2028.000	0.745850	1.402090
STD. DEV.	513.4132	680.9475	791.5093	2730.164	22.69532	528.1859	0.136182	0.071328
SKEWNESS	2.241290	1.428762	2.135222	0.896533	0.613224	0.339465	0.633427	0.566982
KURTOSIS	8.823947	5.058971	7.721642	2.624998	3.501470	1.762487	1.827513	1.816370
JARQUE-BERA	459.1011	105.4408	344.5100	28.52355	6.144760	5.977158	8.938935	8.060559
PROBABILITY	0.000000	0.000000	0.000000	0.000001	0.046311	0.050359	0.011453	0.017769
SOURCE	Athens Stock Exchange	Athens Stock Exchange	Athens Stock Exchange	Athens Stock Exchange	National Statistical Service of Greece	National Statistical Service of Greece	National Statistical Service of Greece	National Statistical Service of Greece
DATA FREQUENCY	Daily	Daily	Daily	Daily	Monthly	Monthly	Monthly	Monthly
AVAILABLE FROM:	January 19898	January 19898	January 19898	January 19898	January 2000	January 2001	January 2001	January 2001

*The financial indices and the prices of stocks were collected via order by the following department of the ASE:

Xygkaki Aggeliki,
Information Services Department,
Athens Exchange,
110 Athinon Avenue,
10442,
Athens – Greece,
Tel: (+30) 210 3366369.

**The economic indices were collected via order by the following department of the National Statistical Service:

Nektaria Tsiligaki
Head of Statistical Data Provision Section
Ministry of Economy and Finance,
National Statistical Service of Greece,
Pireos 46 and Eponiton Str.,
GR 185 10,
Pireas – Greece,
Tel: (+30) 210 4852022.

or by the respective statistical bulletins.

Appendix III
Sequence Plots of the Financial and Macroeconomic Variables

Figure III.1: **Stock Market Price Index (1989-2006)**

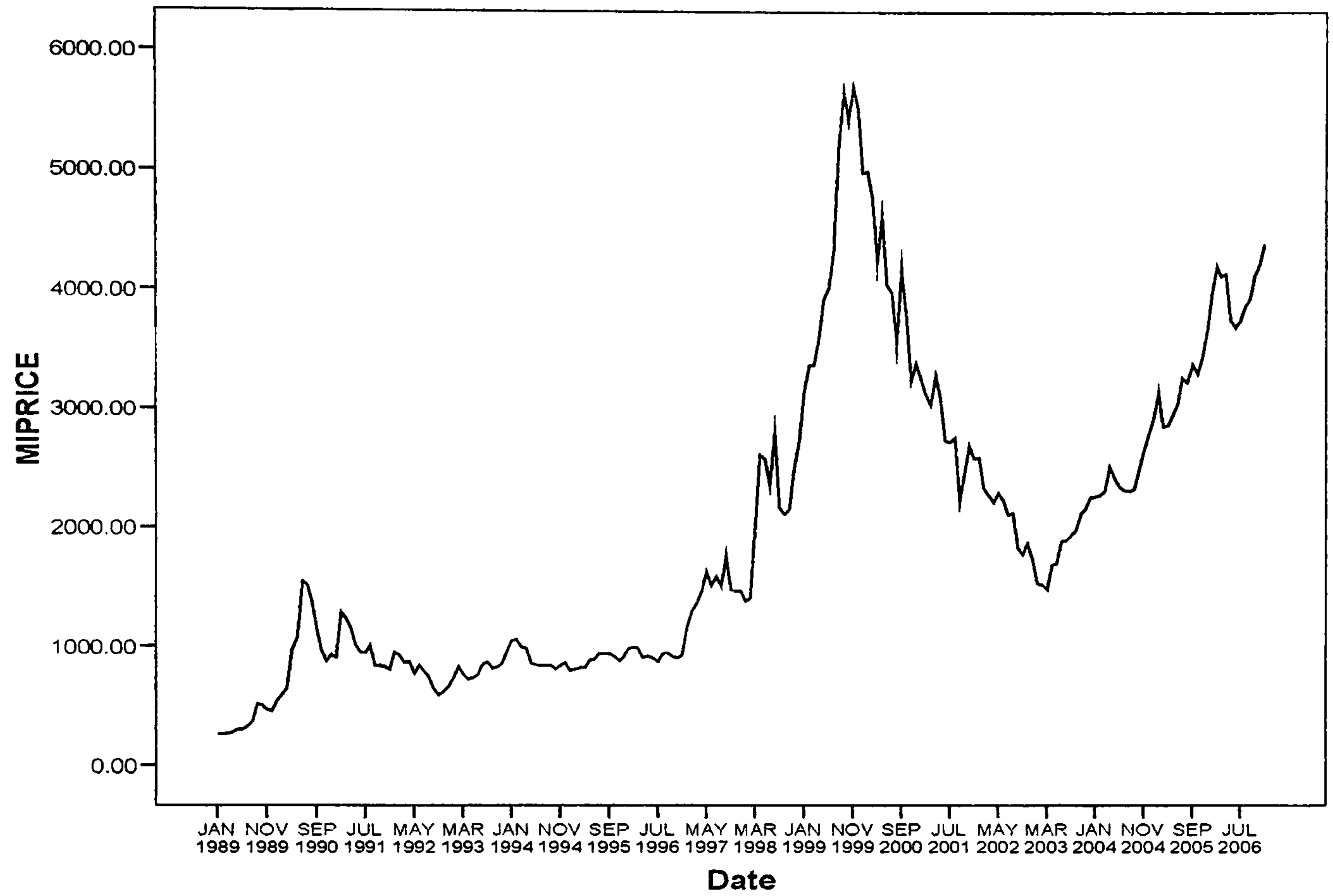


Figure III.2: **Consumer Price Index (1989-2006)**

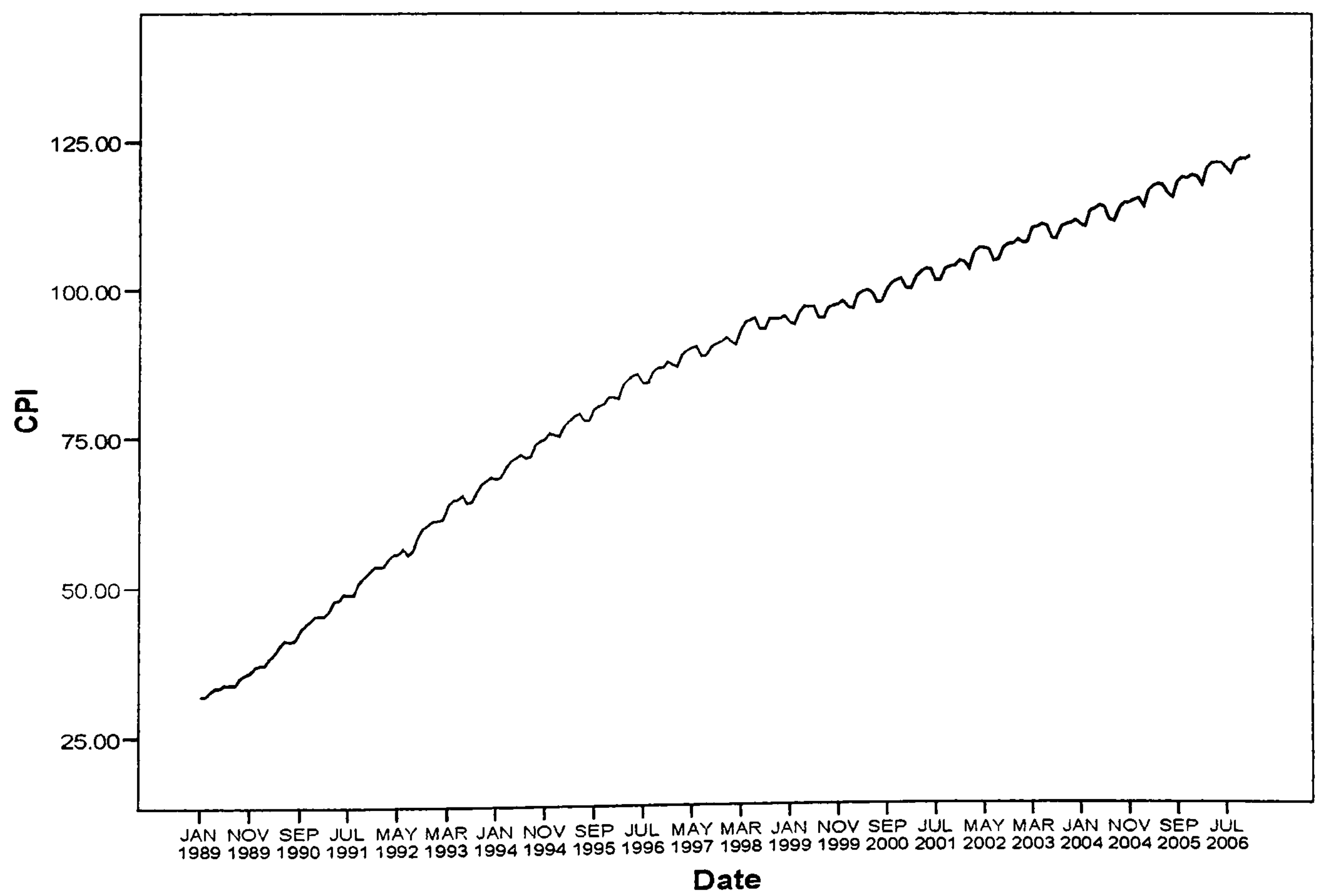


***Figure III.3*: Industrial Production Index (1993-2006)**

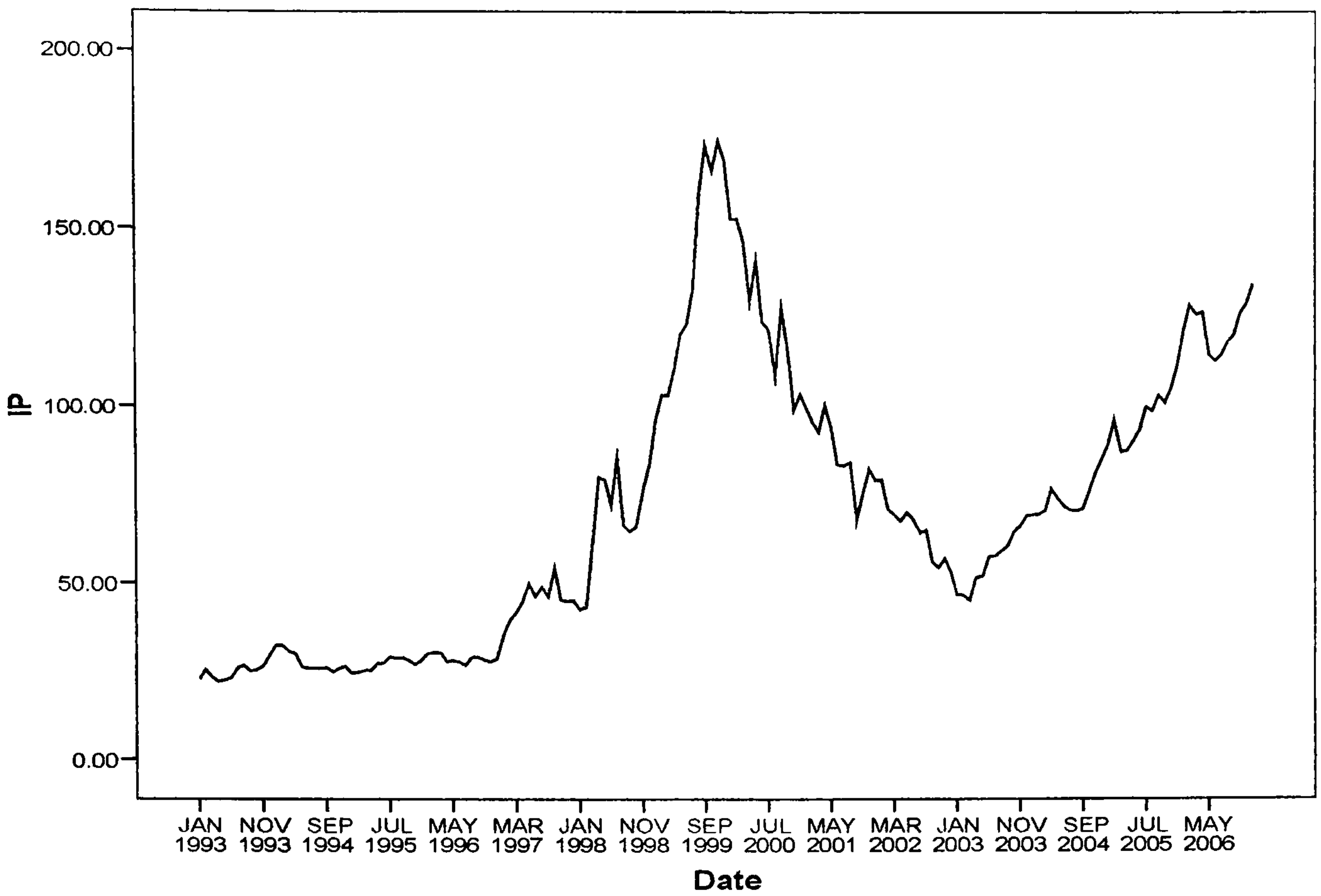


***Figure III.4*: Oil Derivatives Price Index (1989-2006)**

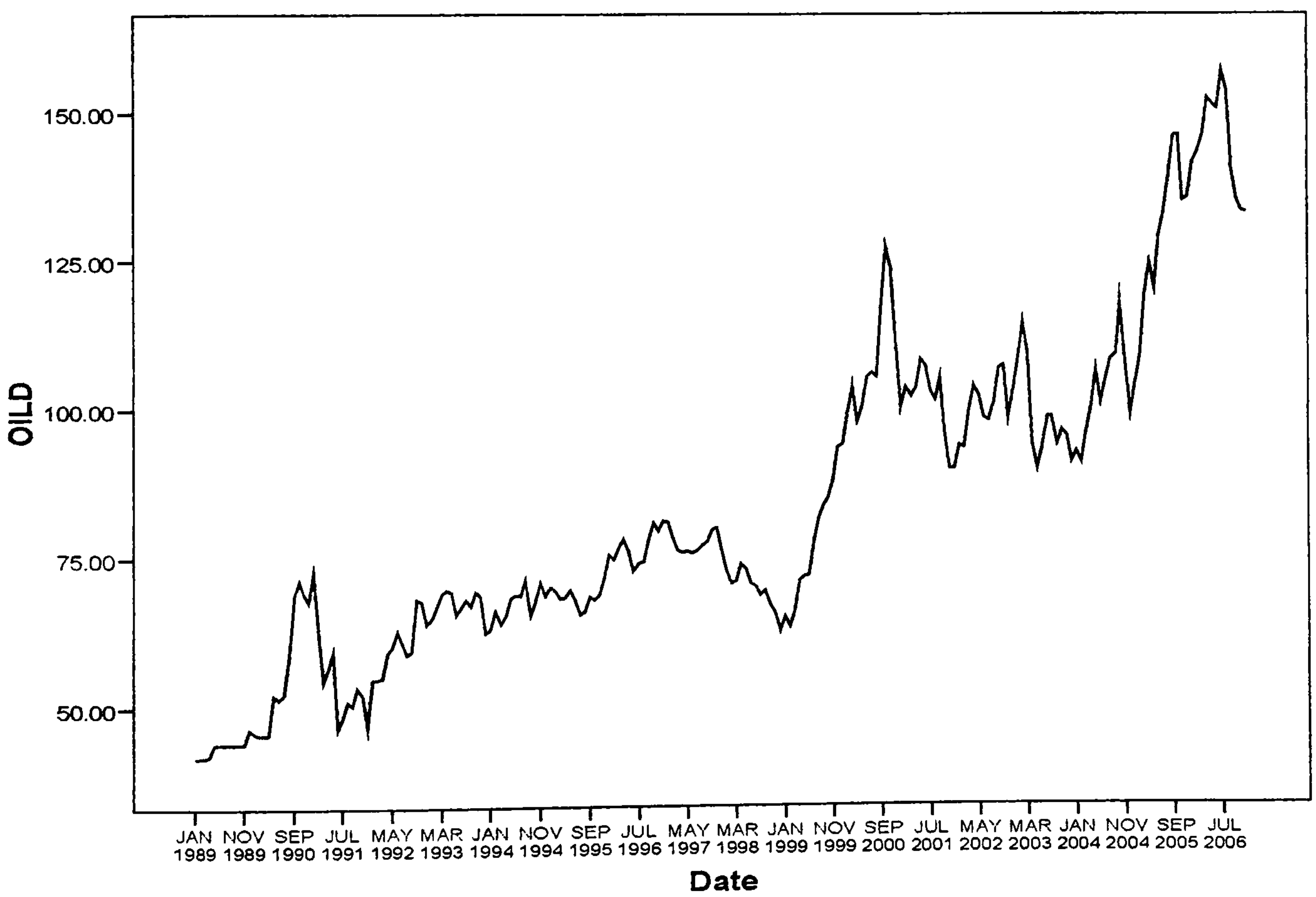


***Figure III.5*: Treasury Bill Rate (1989-2006)**

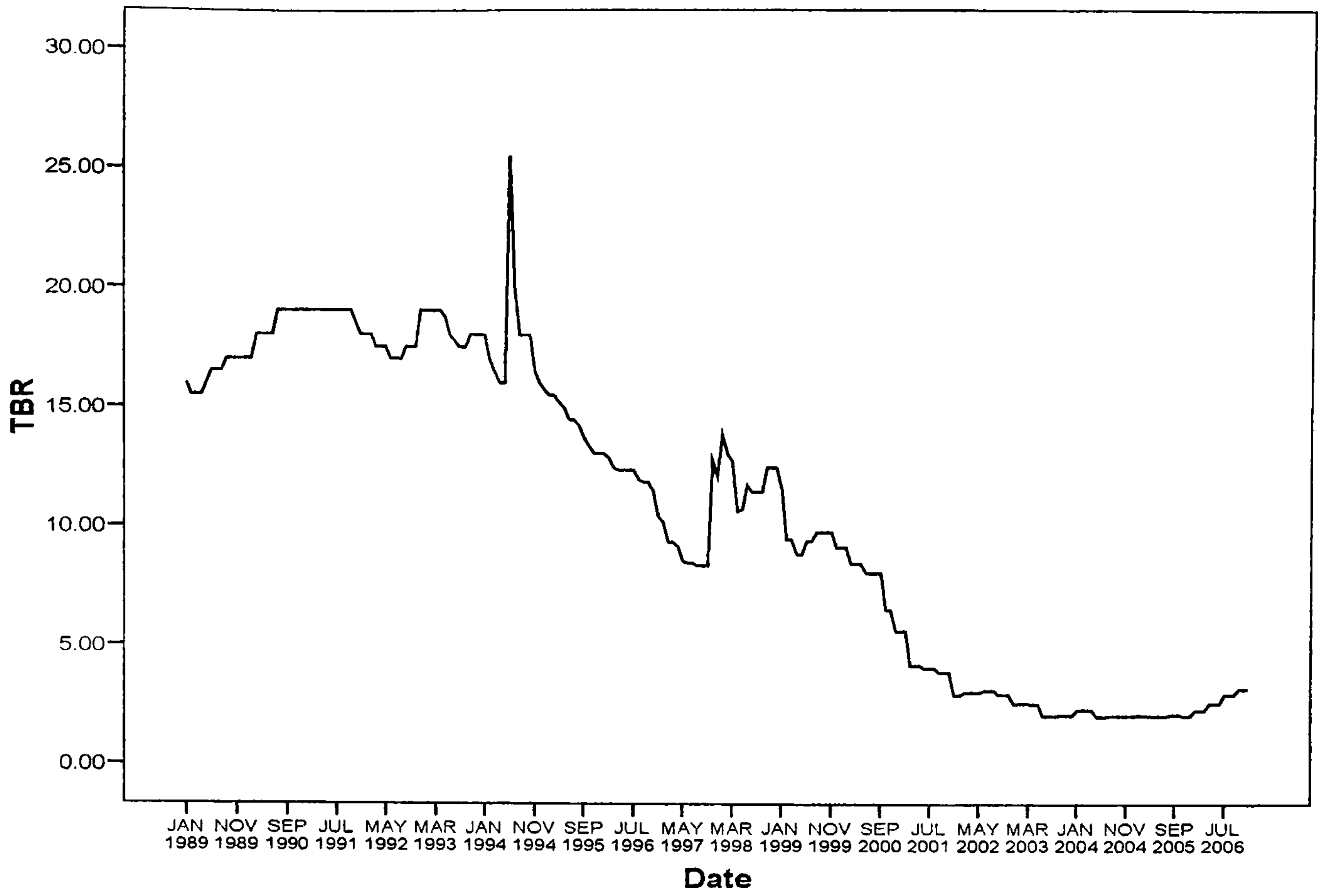


***Figure III.6*: Retail Price Index (2000-2006)**

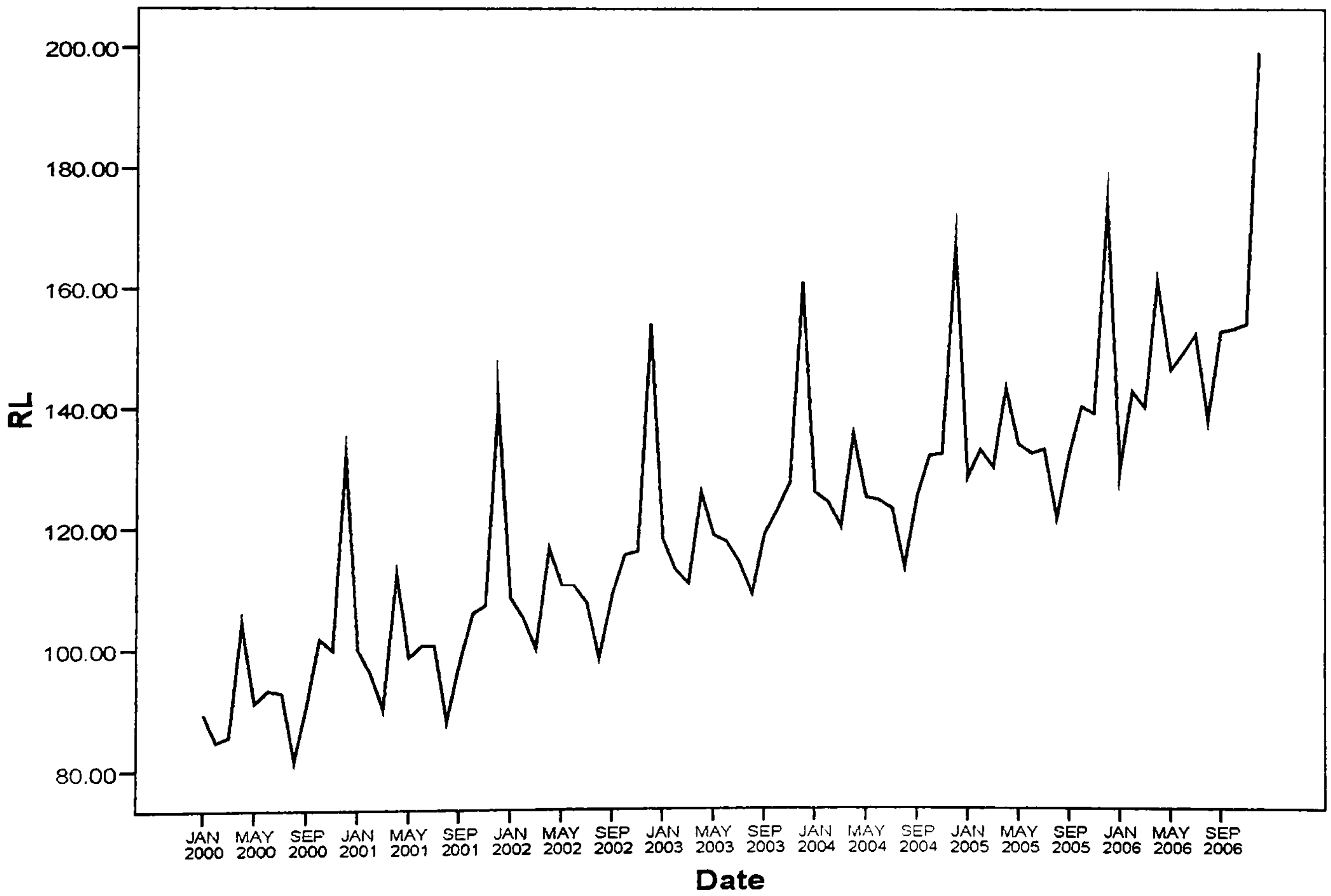


Figure III.7: **Money Supply (M1) (2001-2006)**

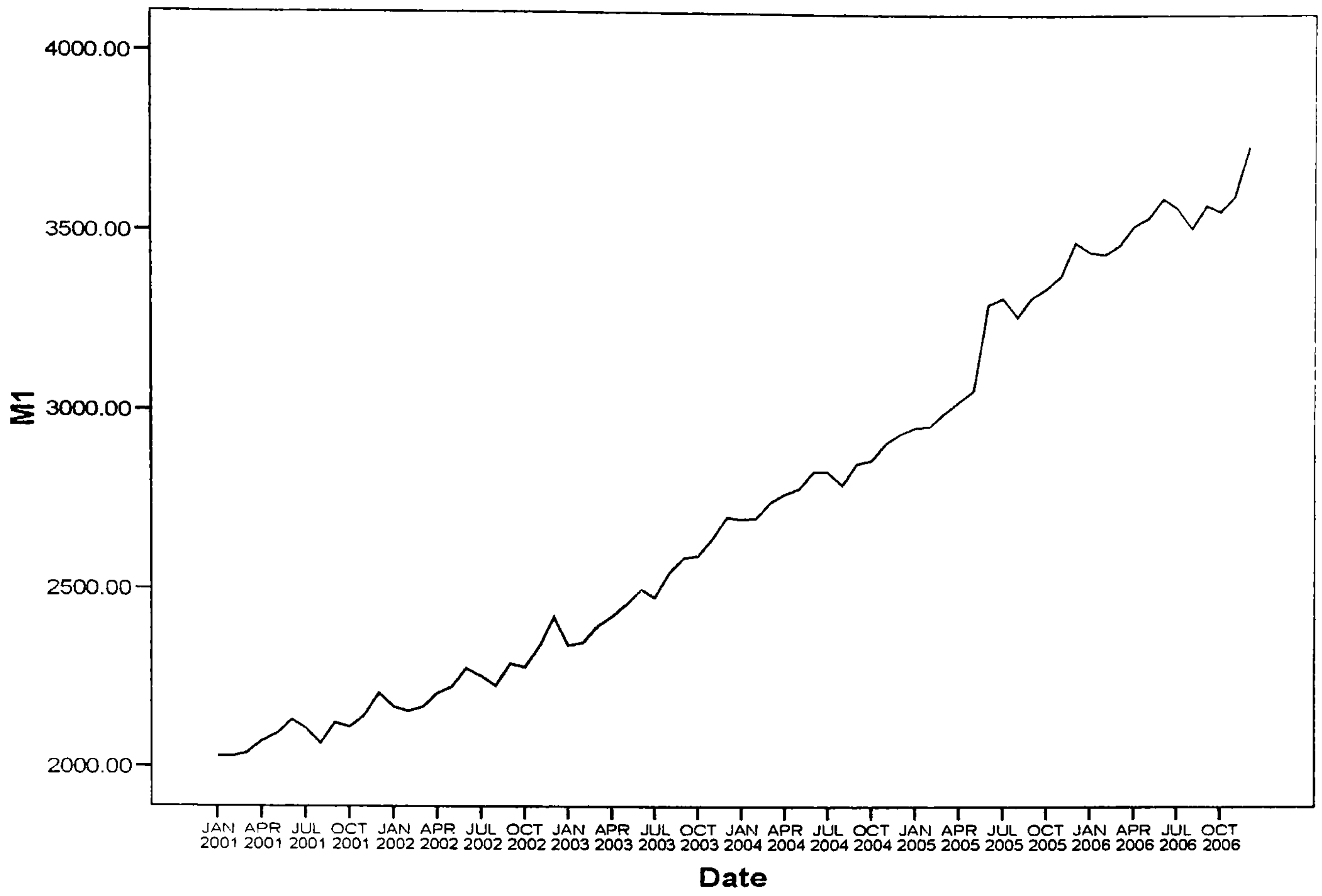


Figure III.8: **US Dollar/Euro Exchange Rate (2001-2006)**

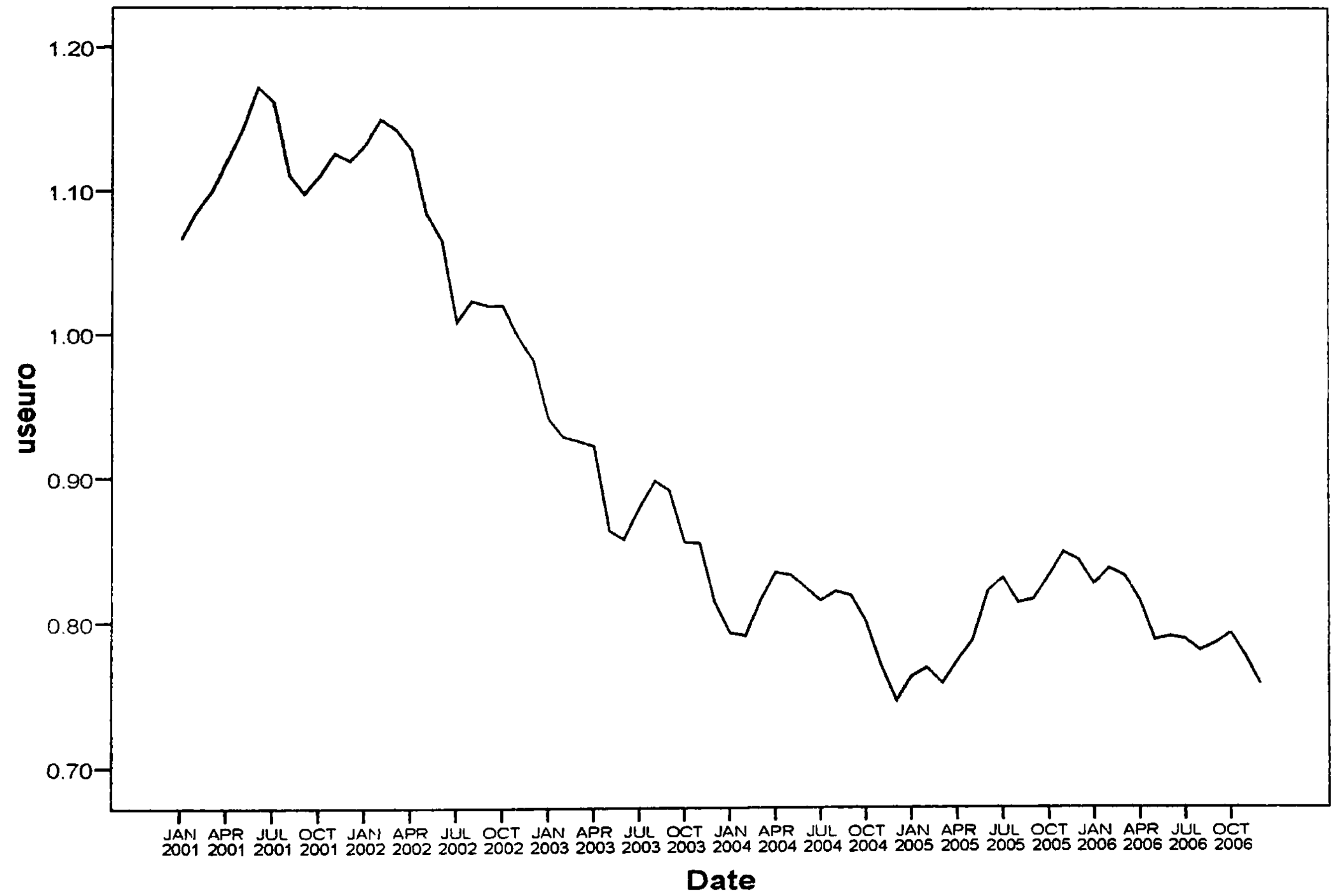


Figure III.9: **GB Pound/Euro Exchange Rate (2001-2006)**

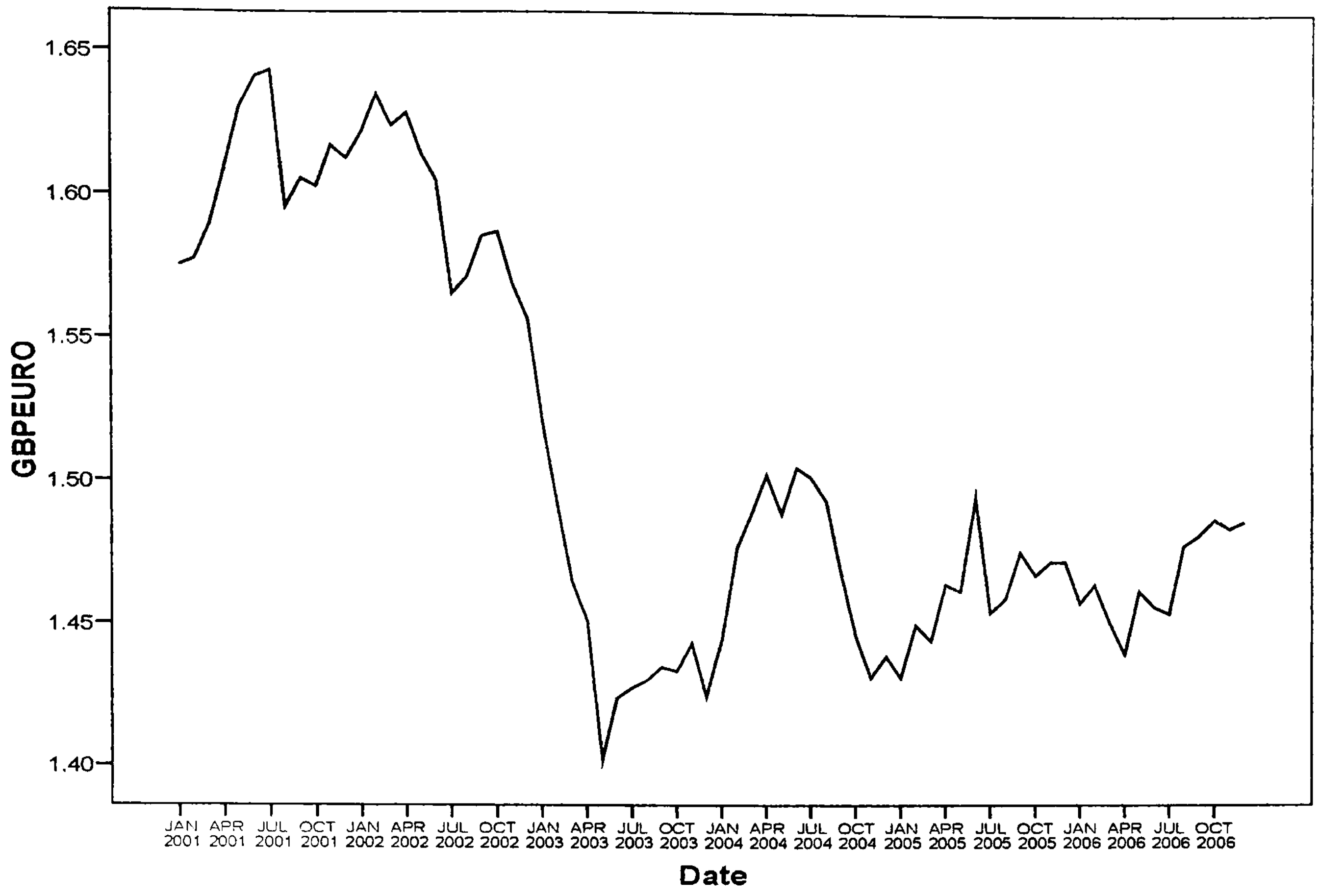


Figure III.10: **Sectoral Investment Index (1989-2005)**

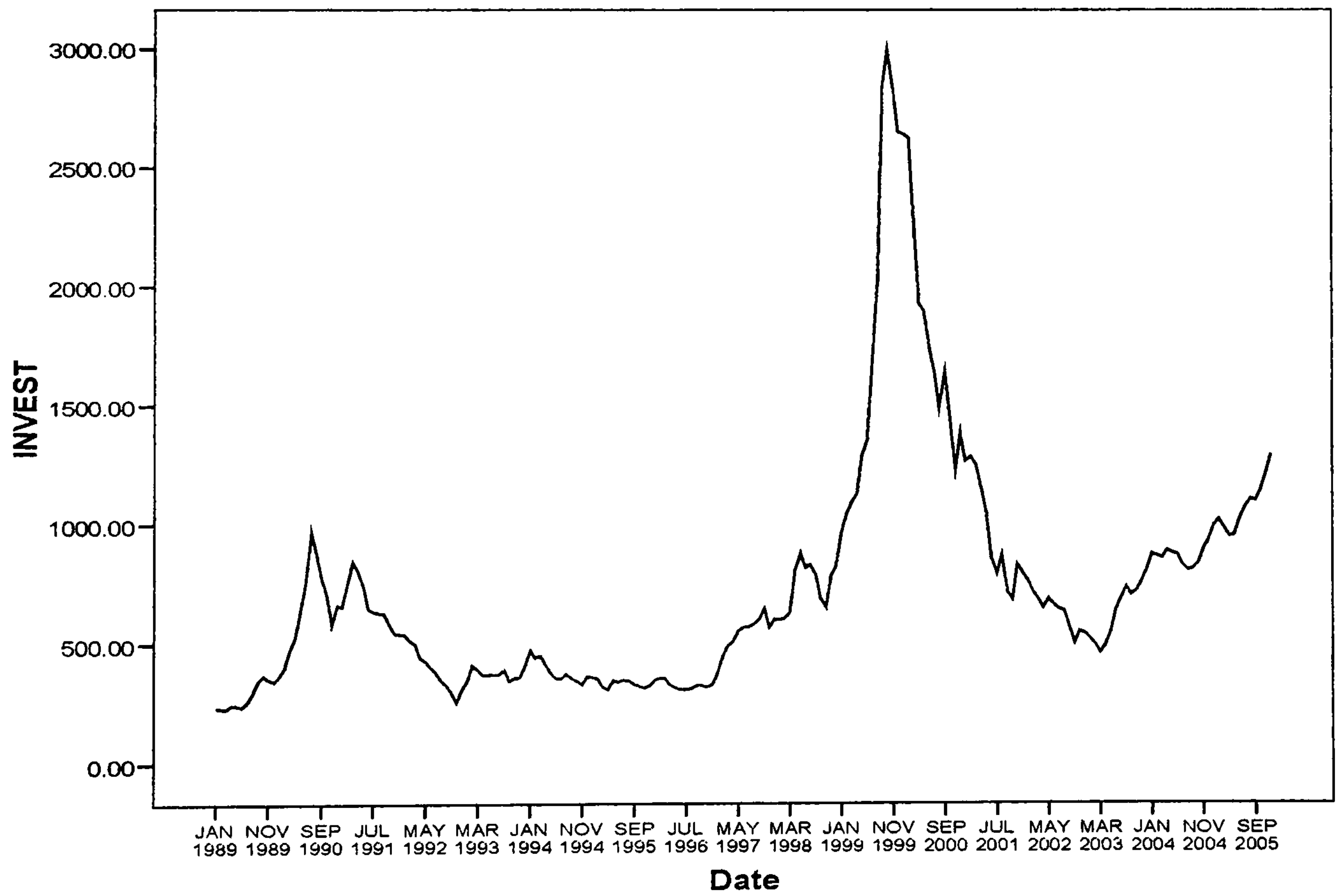


Figure III.11: **Sectoral Industrial Index (1989-2005)**

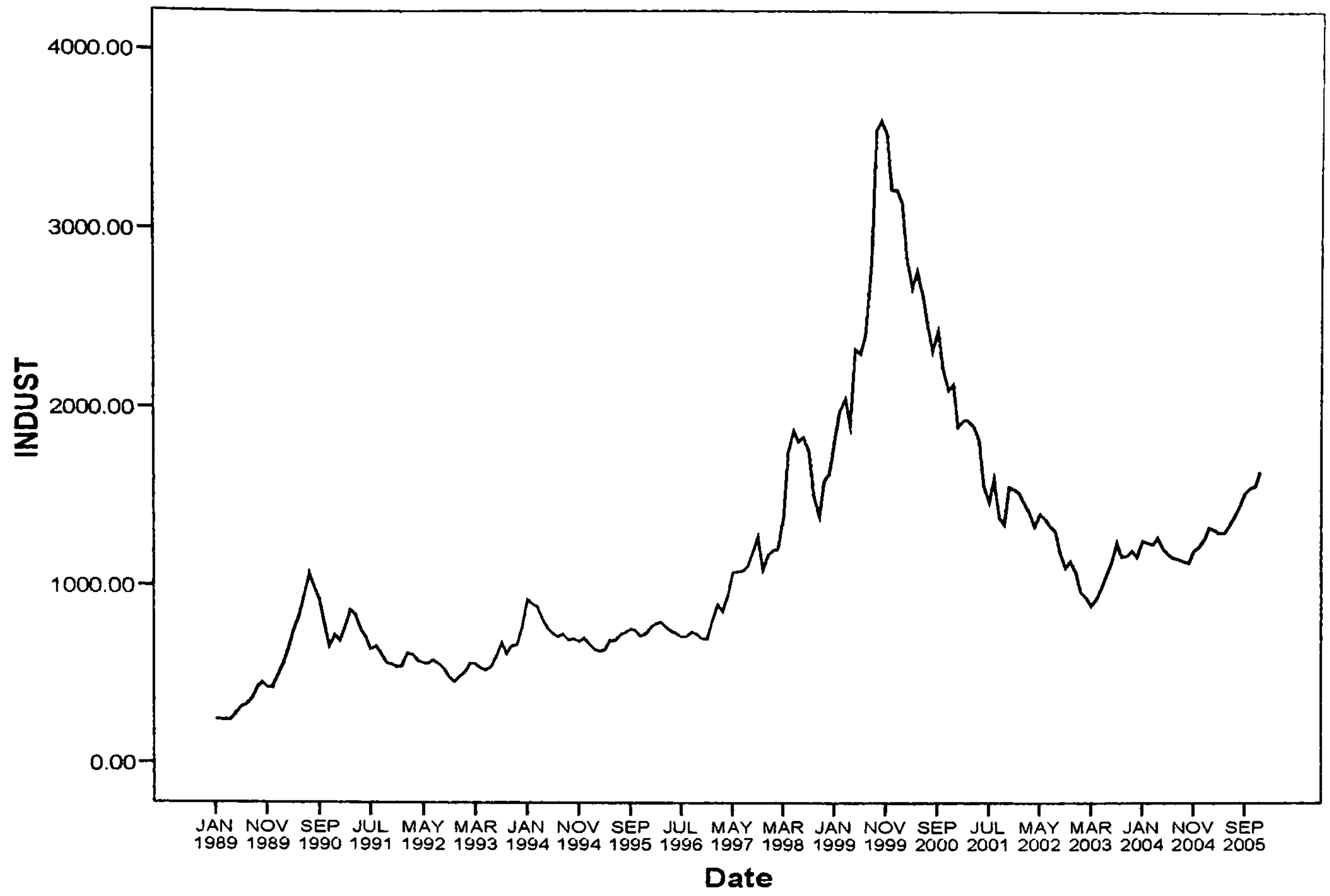


Figure III.12: **Sectoral Insurance Index (1989-2005)**

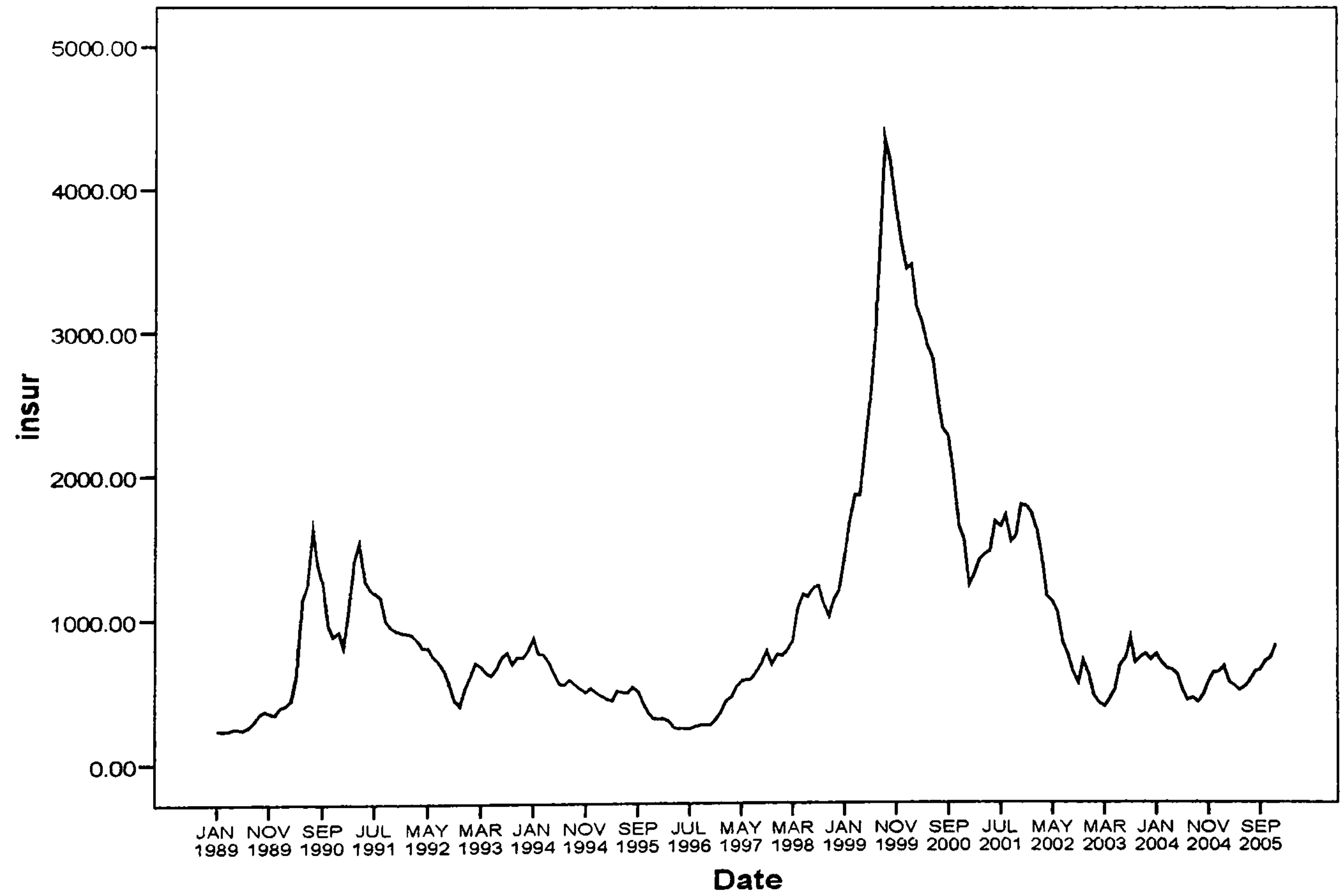
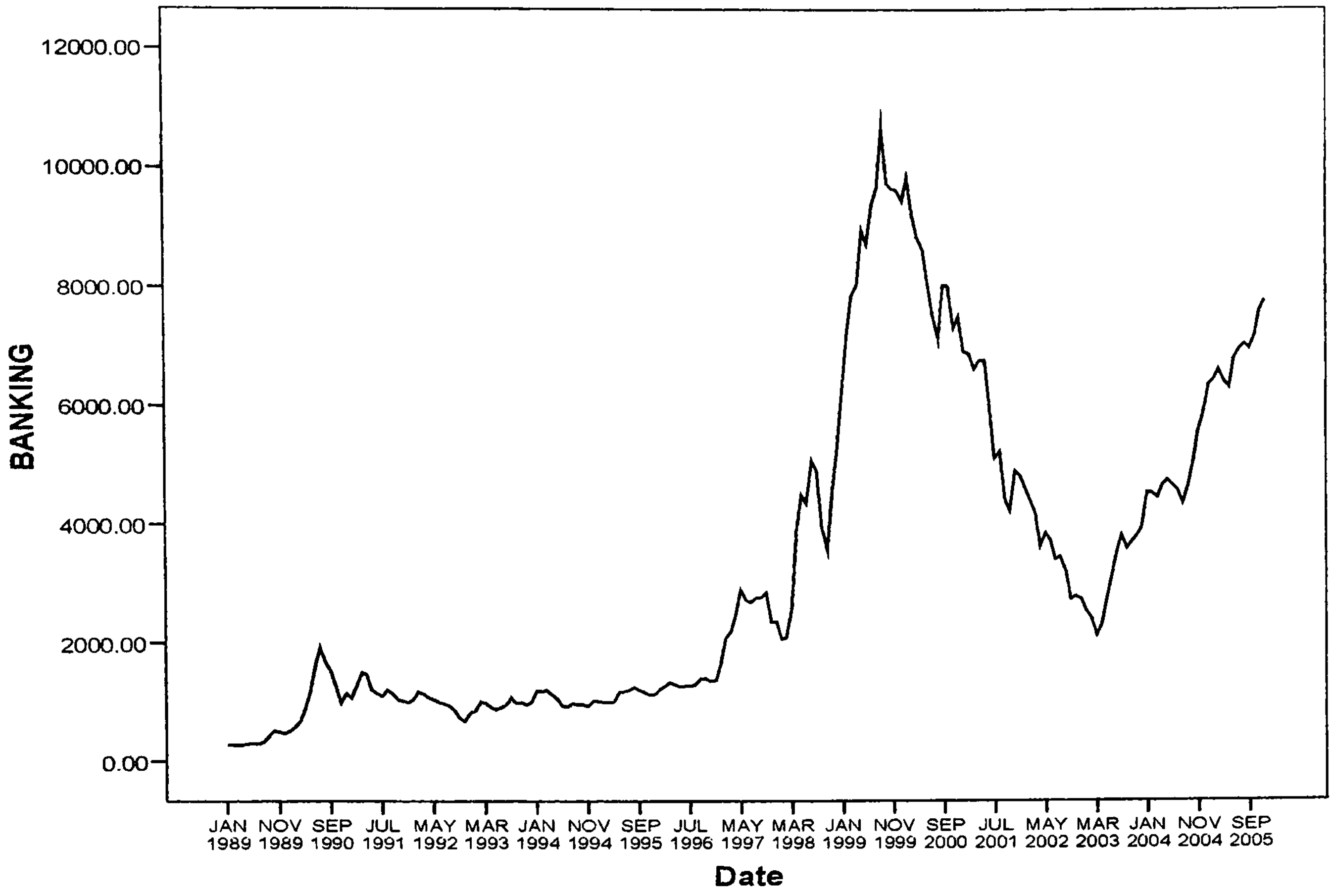


Figure III.13: **Sectoral Banking Index (1989-2005)**



Appendix IV
Factor Analysis Results

***Table IV.1*: KMO and Bartlett's test for all portfolios of the whole period (1989–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.908
Bartlett's Test of Sphericity	Approx. Chi-Square	8724.989
	Df	1770
	Sig.	.000

***Table IV.2*: Total variance explained results for all portfolios of the whole period (1989–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.626	33.722	33.722	.626	33.722	33.722	.255	13.754	13.754
2	.114	6.125	39.847	.114	6.125	39.847	.186	10.050	23.804
3	.074	4.012	43.860	.074	4.012	43.860	.152	8.188	31.992
4	.066	3.572	47.432	.066	3.572	47.432	.117	6.301	38.292
5	.062	3.321	50.752	.062	3.321	50.752	.087	4.708	43.000
6	.061	3.264	54.017	.061	3.264	54.017	.069	3.738	46.738
7	.057	3.097	57.113	.057	3.097	57.113	.065	3.478	50.216
8	.050	2.674	59.787	.050	2.674	59.787	.075	4.051	54.267
9	.046	2.494	62.281	.046	2.494	62.281	.069	3.692	57.959
10	.045	2.416	64.697	.045	2.416	64.697	.048	2.601	60.561
11	.040	2.153	66.850	.040	2.153	66.850	.065	3.528	64.089
12	.036	1.923	68.773	.036	1.923	68.773	.055	2.974	67.063
13	.031	1.677	70.449	.031	1.677	70.449	.063	3.387	70.449
14	.031	1.655	72.105						
15	.029	1.585	73.690						
...	...	...	...						
...	...	...	...						
...	...	...	...						
55	.003	.146	99.454						
56	.003	.136	99.590						
57	.002	.122	99.712						
58	.002	.112	99.824						
59	.002	.090	99.915						
60	.002	.085	100.000						

Figure IV.1: **Scree plot for all portfolios of the whole period (1989–2006)**

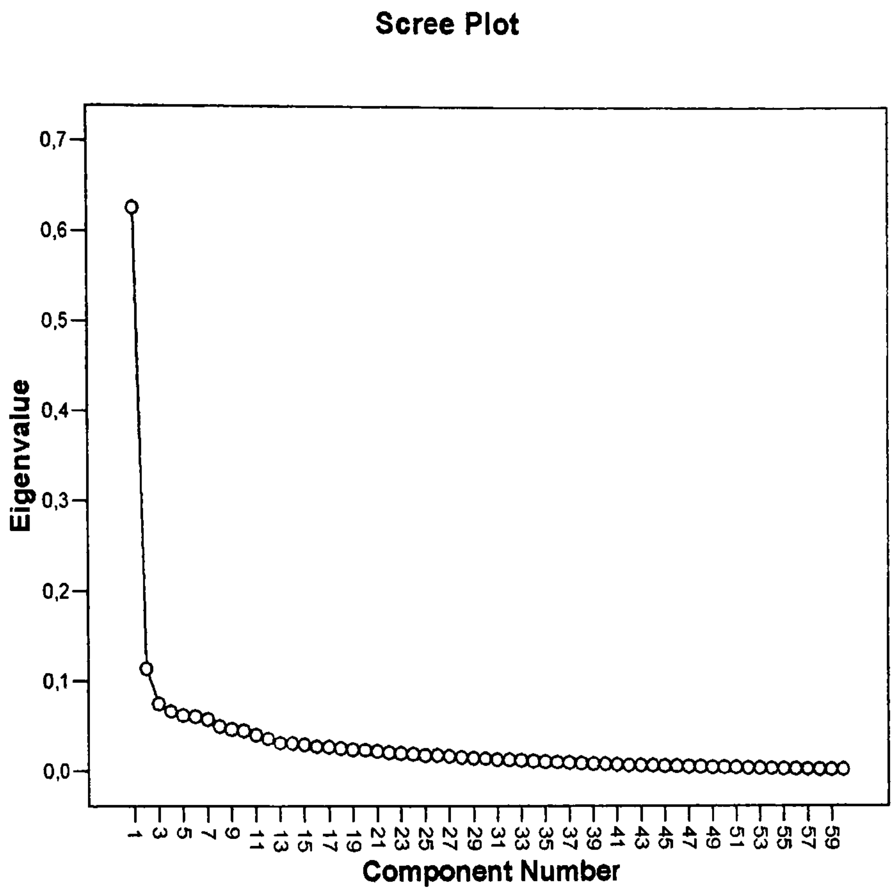


Table IV.3: **KMO and Bartlett's test for portfolio 1 of the whole period (1989–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.935
Bartlett's Test of Sphericity	Approx. Chi-Square	4834.336
	Df	435
	Sig.	.000

***Table IV.4*: Total variance explained results for portfolio 1 of the whole period (1989–2006)**

Component	Initial Eigenvalues(a)			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.436	43.980	43.980	.436	43.980	43.980	.178	17.903	17.903
2	.078	7.875	51.856	.078	7.875	51.856	.159	16.055	33.958
3	.057	5.781	57.637	.057	5.781	57.637	.139	13.985	47.943
4	.052	5.265	62.902	.052	5.265	62.902	.112	11.271	59.215
5	.049	4.948	67.850	.049	4.948	67.850	.066	6.650	65.865
6	.041	4.181	72.031	.041	4.181	72.031	.061	6.166	72.031
7	.028	2.862	74.893						
8	.025	2.561	77.454						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.005	.473	98.312						
26	.005	.458	98.770						
27	.004	.417	99.187						
28	.003	.313	99.500						
29	.003	.259	99.759						
30	.002	.241	100.000						

***Figure IV.2*: Scree plot for portfolio 1 of the whole period (1989–2006)**

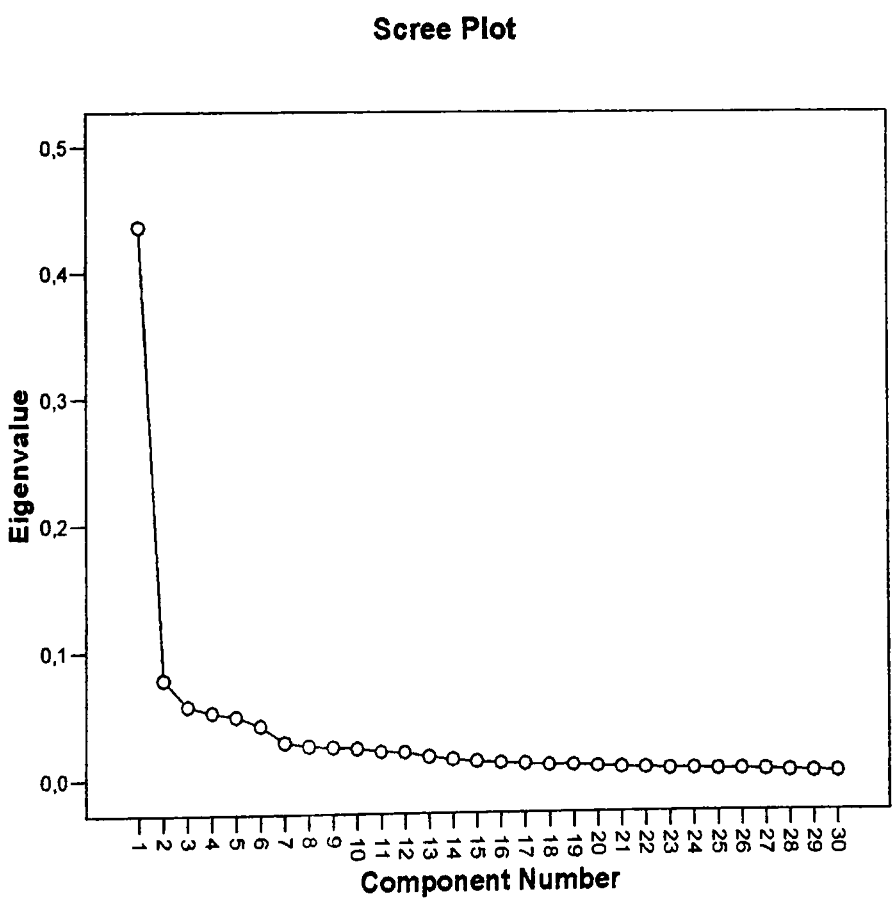


***Table IV.5*:** **KMO and Bartlett's test for portfolio 2 of the whole period (1989–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.839
Bartlett's Test of Sphericity	Approx. Chi-Square	2441.249
	Df	435
	Sig.	.000

***Table IV.6*:** **Total variance explained results for portfolio 2 of the whole period (1989–2006)**

Component	Initial Eigenvalues(a)			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.231	26.779	26.779	.231	26.779	26.779	.085	9.822	9.822
2	.064	7.385	34.164	.064	7.385	34.164	.104	12.052	21.873
3	.058	6.762	40.926	.058	6.762	40.926	.071	8.271	30.144
4	.056	6.459	47.385	.056	6.459	47.385	.074	8.527	38.671
5	.047	5.427	52.812	.047	5.427	52.812	.062	7.239	45.910
6	.041	4.803	57.615	.041	4.803	57.615	.060	6.962	52.872
7	.033	3.850	61.465	.033	3.850	61.465	.055	6.373	59.245
8	.032	3.725	65.190	.032	3.725	65.190	.051	5.945	65.190
9	.028	3.240	68.430						
10	.026	3.003	71.432						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.007	.840	97.265						
26	.006	.702	97.967						
27	.006	.665	98.632						
28	.005	.631	99.263						
29	.003	.375	99.638						
30	.003	.362	100.000						

Figure IV.3: **Scree plot for portfolio 2 of the whole period (1989–2006)**

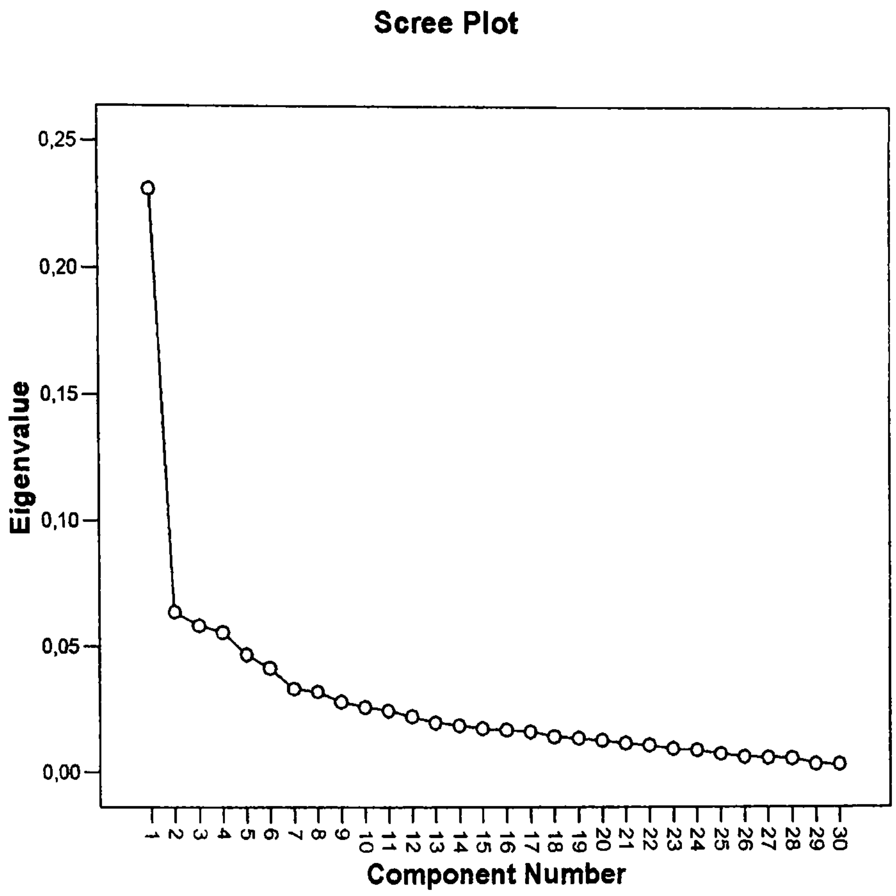


***Table IV.7*: KMO and Bartlett's test for all the portfolios of the first sub-period (1989–1994)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.691
Bartlett's Test of Sphericity	Approx. Chi-Square	4294.233
	Df	1770
	Sig.	.000

Table IV.8: **Total variance explained results for the all the portfolios of the first sub-period (1989–1994)**

Component	Initial Eigenvalues(a)			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.619	37.371	37.371	.619	37.371	37.371	.315	19.014	19.014
2	.166	10.027	47.399	.166	10.027	47.399	.146	8.841	27.855
3	.093	5.613	53.012	.093	5.613	53.012	.118	7.150	35.005
4	.076	4.605	57.617	.076	4.605	57.617	.101	6.083	41.087
5	.068	4.127	61.744	.068	4.127	61.744	.086	5.219	46.306
6	.058	3.497	65.240	.058	3.497	65.240	.082	4.957	51.262
7	.049	2.948	68.188	.049	2.948	68.188	.057	3.447	54.710
8	.044	2.654	70.842	.044	2.654	70.842	.055	3.299	58.009
9	.040	2.416	73.259	.040	2.416	73.259	.154	9.296	67.304
10	.037	2.219	75.478	.037	2.219	75.478	.044	2.632	69.936
11	.033	1.988	77.466	.033	1.988	77.466	.064	3.867	73.804
12	.029	1.768	79.234	.029	1.768	79.234	.078	4.711	78.514
13	.028	1.710	80.945	.028	1.710	80.945	.040	2.430	80.945
14	.025	1.492	82.436						
15	.025	1.488	83.924						
...	...	...	...						
...	...	...	...						
...	...	...	...						
55	.000	.020	99.957						
56	.000	.014	99.971						
57	.000	.012	99.982						
58	.000	.007	99.990						
59	.000	.006	99.995						
60	.000	.005	100.000						

Figure IV.4: **Scree plot for the all the portfolios of the first sub-period (1989–1994)**

Scree Plot

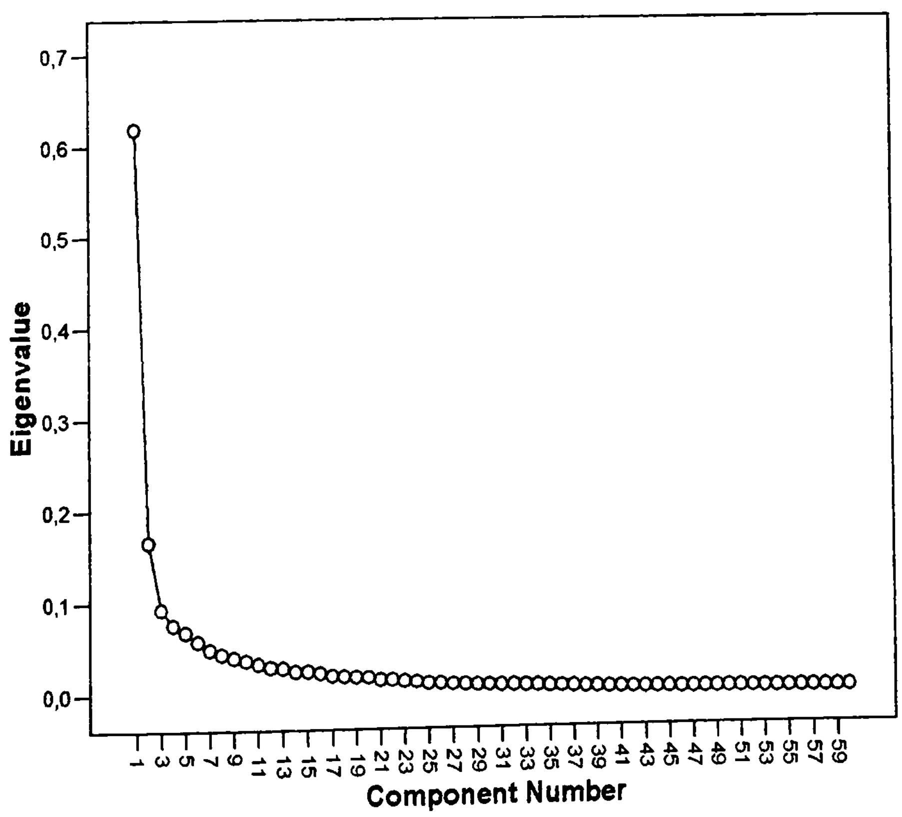


***Table IV.9*: KMO and Bartlett's test for portfolio 1 of the first sub-period (1989–1994)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.887
Bartlett's Test of Sphericity	Approx. Chi-Square	2091.037
	Df	435
	Sig.	.000

***Table IV.10*: Total variance explained results for portfolio 1 of the first sub-period (1989–1994)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.466	46.313	46.313	.466	46.313	46.313	.217	21.549	21.549
2	.147	14.579	60.893	.147	14.579	60.893	.143	14.178	35.727
3	.064	6.373	67.265	.064	6.373	67.265	.158	15.716	51.443
4	.052	5.152	72.418	.052	5.152	72.418	.080	7.936	59.379
5	.044	4.368	76.786	.044	4.368	76.786	.157	15.624	75.003
6	.038	3.733	80.518	.038	3.733	80.518	.055	5.515	80.518
7	.025	2.477	82.996						
8	.023	2.239	85.235						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.002	.237	99.296						
26	.002	.185	99.481						
27	.002	.155	99.636						
28	.001	.147	99.784						
29	.001	.120	99.904						
30	.001	.096	100.000						

Figure IV.5: **Scree plot for portfolio 1 of the first sub-period (1989–1994)**

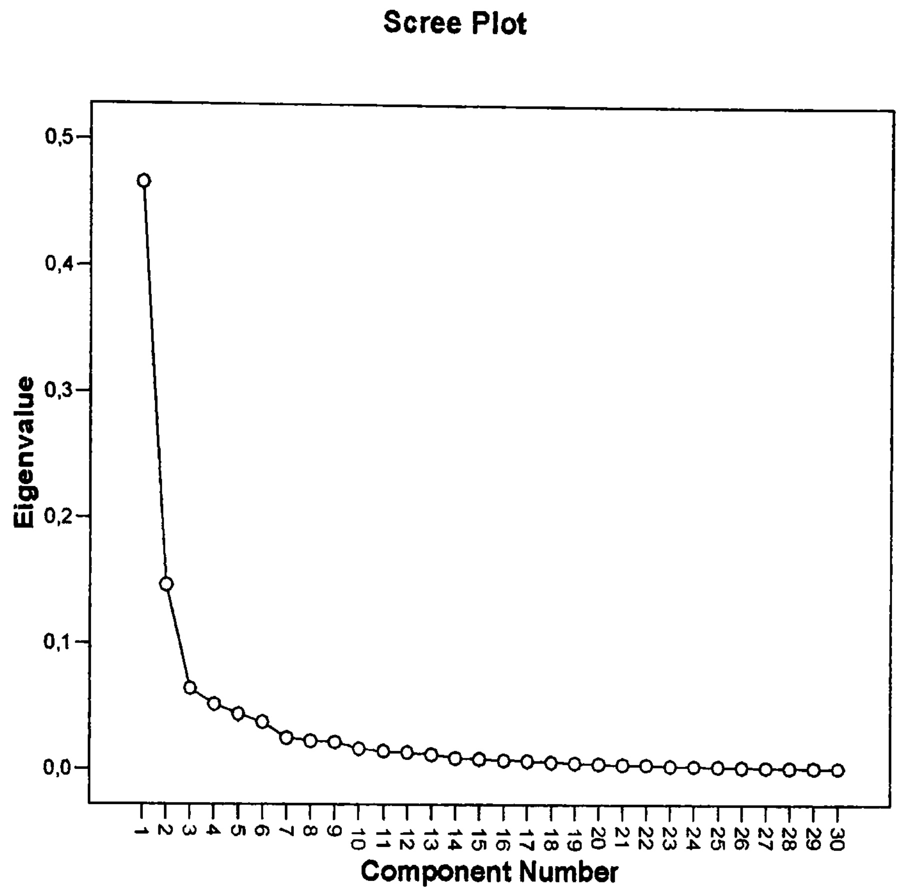


Table IV.11: **KMO and Bartlett's test for portfolio 2 of the first sub-period (1989–1994)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.760
Bartlett's Test of Sphericity	Approx. Chi-Square	1145.160
	Df	435
	Sig.	.000

Table IV.12: **Total variance explained results for portfolio 2 of the first sub-period (1989–1994)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.189	29.021	29.021	.189	29.021	29.021	.092	14.163	14.163
2	.067	10.279	39.300	.067	10.279	39.300	.058	8.982	23.145
3	.051	7.851	47.151	.051	7.851	47.151	.048	7.320	30.465
4	.041	6.259	53.410	.041	6.259	53.410	.048	7.445	37.910
5	.036	5.475	58.884	.036	5.475	58.884	.037	5.740	43.651
6	.029	4.474	63.358	.029	4.474	63.358	.040	6.155	49.806
7	.028	4.284	67.642	.028	4.284	67.642	.056	8.602	58.408
8	.024	3.755	71.397	.024	3.755	71.397	.037	5.737	64.146
9	.023	3.575	74.971	.023	3.575	74.971	.070	10.825	74.971
10	.022	3.328	78.299						
11	.018	2.744	81.043						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.003	420	98.735						
26	.002	.367	99.102						
27	.002	.313	99.415						
28	.002	.241	99.657						
29	.001	.207	99.864						
30	.001	.136	100.000						

Figure IV.6: **Scree plot for portfolio 2 of the first sub-period (1989–1994)**

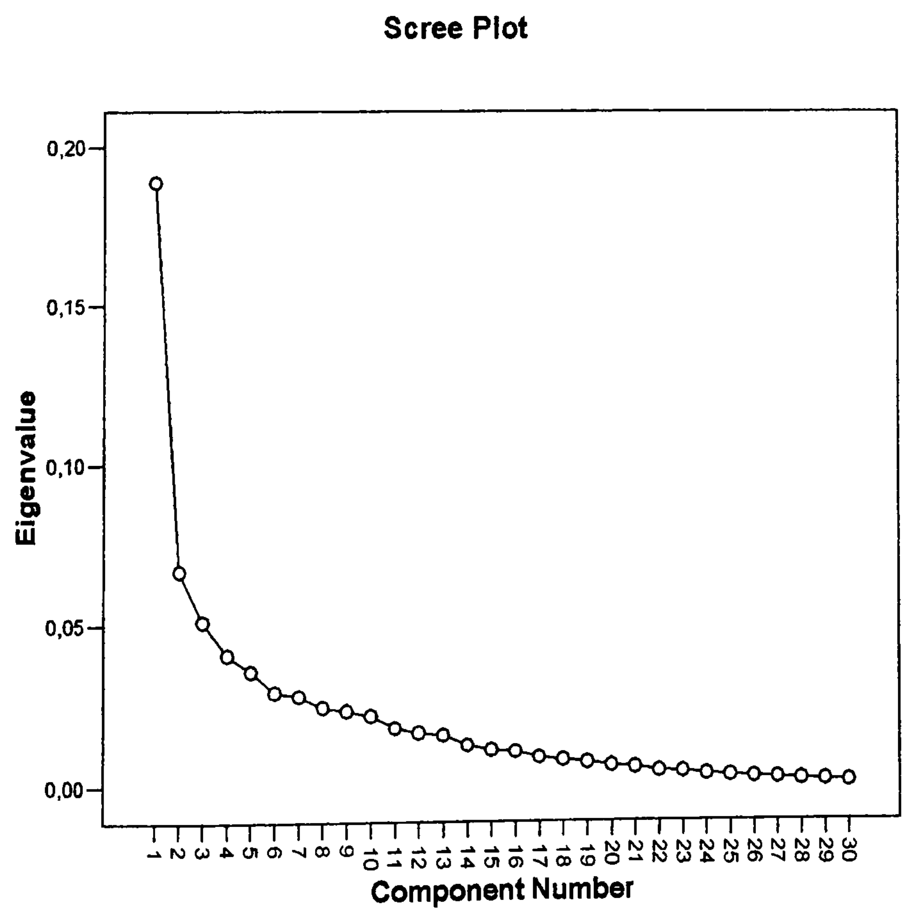


Table IV.13: **KMO and Bartlett's test for all the portfolios of the second sub-period (1995–2000)***

Note: *Because of the fact that the variables are more than the cases (observations) for this period, the KMO and Bartlett's test table is not available.

Table IV.14: **Total variance explained results for all the portfolios of the second sub-period (1995–2000)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.576	46.043	46.043	2.576	46.043	46.043	.642	11.475	11.475
2	.336	5.999	52.042	.336	5.999	52.042	.648	11.582	23.057
3	.224	4.011	56.053	.224	4.011	56.053	.535	9.564	32.621
4	.176	3.148	59.201	.176	3.148	59.201	.517	9.246	41.867
5	.162	2.891	62.092	.162	2.891	62.092	.441	7.880	49.746
6	.158	2.822	64.914	.158	2.822	64.914	.440	7.862	57.608
7	.127	2.270	67.184	.127	2.270	67.184	.322	5.758	63.366
8	.120	2.148	69.332	.120	2.148	69.332	.334	5.966	69.332
9	.098	1.755	71.087						
10	.094	1.674	72.762						
...	...	...	...						
...	...	...	...						
...	...	...	...						
145	.000	.000	100.000						
146	.000	.000	100.000						
147	.000	.000	100.000						
148	.000	.000	100.000						
149	.000	.000	100.000						
150	.000	.000	100.000						

Figure IV.7: **Scree plot for all the portfolios of the second sub-period (1995–2000)**

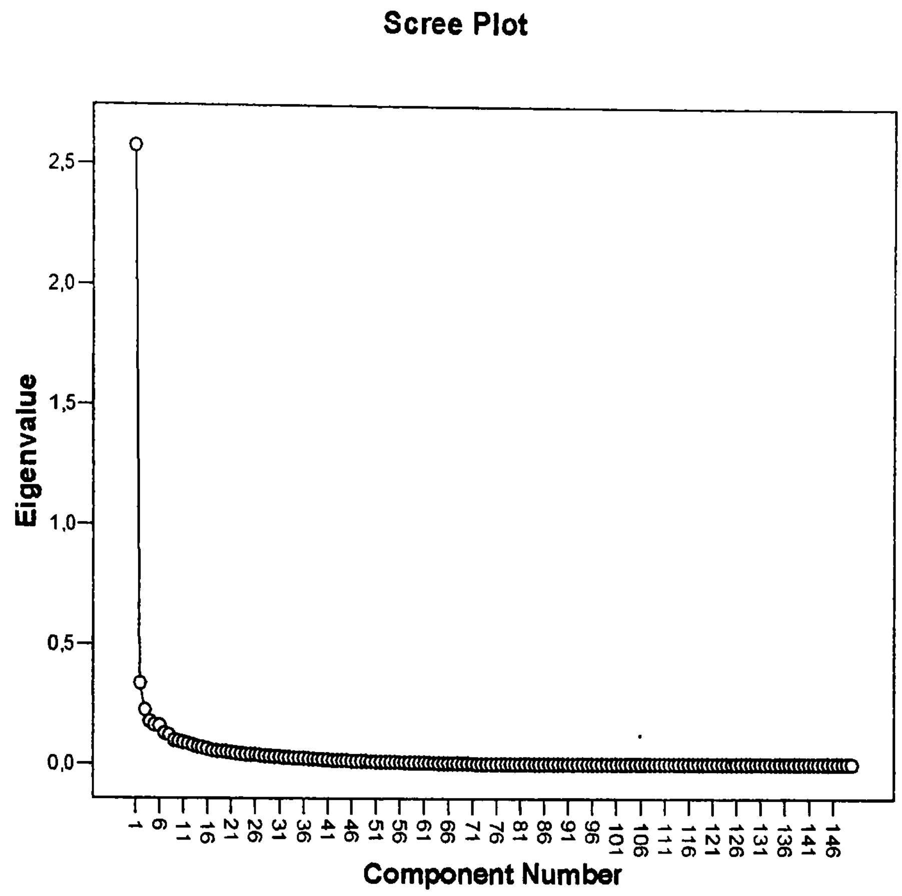


Table IV.15: **KMO and Bartlett's test for portfolio 1 of the second sub-period (1995–2000)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.875
Bartlett's Test of Sphericity	Approx. Chi-Square	2171.283
	Df	435
	Sig.	.000

***Table IV.16*: Total variance explained results for portfolio 1 of the second sub-period (1995–2000)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.752	56.928	56.928	.752	56.928	56.928	.307	23.258	23.258
2	.079	5.996	62.923	.079	5.996	62.923	.174	13.162	36.421
3	.066	5.027	67.951	.066	5.027	67.951	.208	15.730	52.151
4	.055	4.137	72.088	.055	4.137	72.088	.152	11.490	63.641
5	.052	3.966	76.054	.052	3.966	76.054	.164	12.412	76.054
6	.038	2.847	78.900						
7	.034	2.552	81.452						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.003	.247	99.312						
26	.003	.209	99.521						
27	.002	.182	99.703						
28	.002	.139	99.842						
29	.002	.122	99.964						
30	.000	.036	100.000						

***Figure IV.8*: Scree plot for portfolio 1 of the second sub-period (1995–2000)**

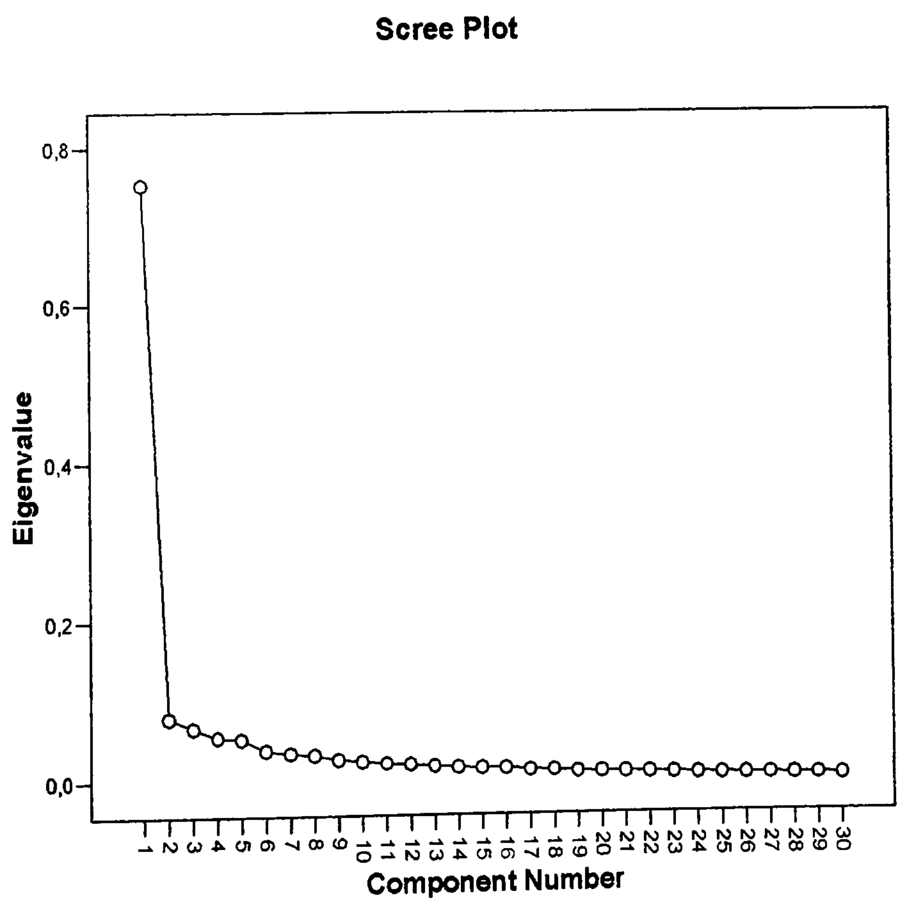


***Table IV.17*: KMO and Bartlett's test for portfolio 2 of the second sub-period (1995–2000)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.900
Bartlett's Test of Sphericity	Approx. Chi-Square	1971.271
	Df	435
	Sig.	.000

***Table IV.18*: Total variance explained results for portfolio 2 of the second sub-period (1995–2000)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.601	52.918	52.918	.601	52.918	52.918	.192	16.923	16.923
2	.078	6.861	59.778	.078	6.861	59.778	.210	18.485	35.408
3	.063	5.512	65.290	.063	5.512	65.290	.148	13.032	48.440
4	.057	5.025	70.315	.057	5.025	70.315	.188	16.570	65.010
5	.049	4.350	74.665	.049	4.350	74.665	.110	9.655	74.665
6	.038	3.332	77.997						
7	.029	2.523	80.520						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.004	.331	99.147						
26	.003	.221	99.368						
27	.002	.208	99.576						
28	.002	.160	99.736						
29	.002	.138	99.875						
30	.001	.125	100.000						

Figure IV.9: **Scree plot for portfolio 2 of the second sub-period (1995–2000)**

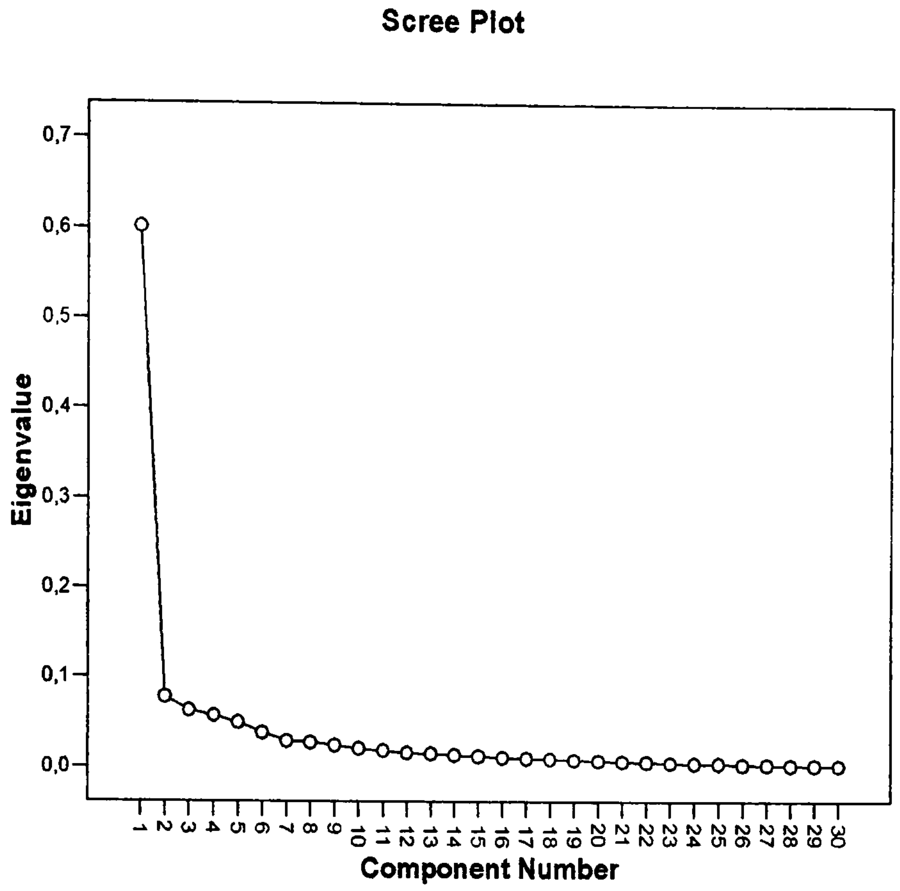


Table IV.19: **KMO and Bartlett's test for portfolio 3 of the second sub-period (1995–2000)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.891
Bartlett's Test of Sphericity	Approx. Chi-Square	1817.968
	Df	435
	Sig.	.000

***Table IV.20*: Total variance explained results for portfolio 3 of the second sub-period (1995–2000)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.398	49.363	49.363	.398	49.363	49.363	.124	15.456	15.456
2	.066	8.199	57.562	.066	8.199	57.562	.162	20.073	35.529
3	.047	5.890	63.452	.047	5.890	63.452	.126	15.691	51.221
4	.037	4.638	68.090	.037	4.638	68.090	.081	10.069	61.289
5	.032	3.992	72.082	.032	3.992	72.082	.064	7.903	69.193
6	.029	3.550	75.632	.029	3.550	75.632	.052	6.439	75.632
7	.024	2.954	78.586						
8	.021	2.589	81.174						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.002	.299	99.071						
26	.002	.277	99.348						
27	.002	.251	99.599						
28	.001	.172	99.771						
29	.001	.127	99.897						
30	.001	.103	100.000						

***Figure IV.10*: Scree plot for portfolio 3 of the second sub-period (1995–2000)**

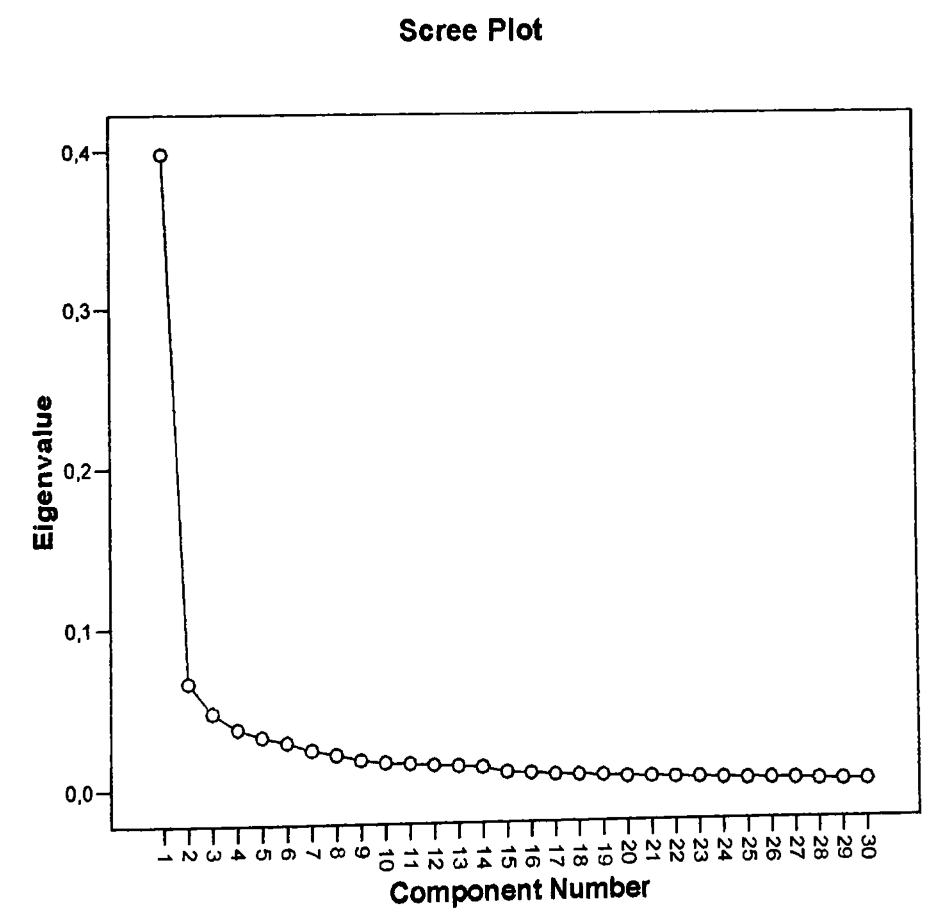


Table IV.21: **KMO and Bartlett's test for portfolio 4 of the second sub-period (1995–2000)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.853
Bartlett's Test of Sphericity	Approx. Chi-Square	1502.437
	Df	435
	Sig.	.000

Table IV.22: **Total variance explained results for portfolio 4 of the second sub-period (1995–2000)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.471	45.581	45.581	.471	45.581	45.581	.122	11.786	11.786
2	.101	9.764	55.345	.101	9.764	55.345	.220	21.294	33.081
3	.065	6.306	61.652	.065	6.306	61.652	.167	16.169	49.249
4	.050	4.857	66.509	.050	4.857	66.509	.145	14.075	63.325
5	.041	3.938	70.447	.041	3.938	70.447	.074	7.123	70.447
6	.034	3.297	73.745						
7	.029	2.826	76.571						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.004	.394	98.880						
26	.003	.296	99.176						
27	.003	.284	99.460						
28	.002	.238	99.699						
29	.002	.162	99.861						
30	.001	.139	100.000						

Figure IV.11: **Scree plot for portfolio 4 of the second sub-period (1995–2000)**

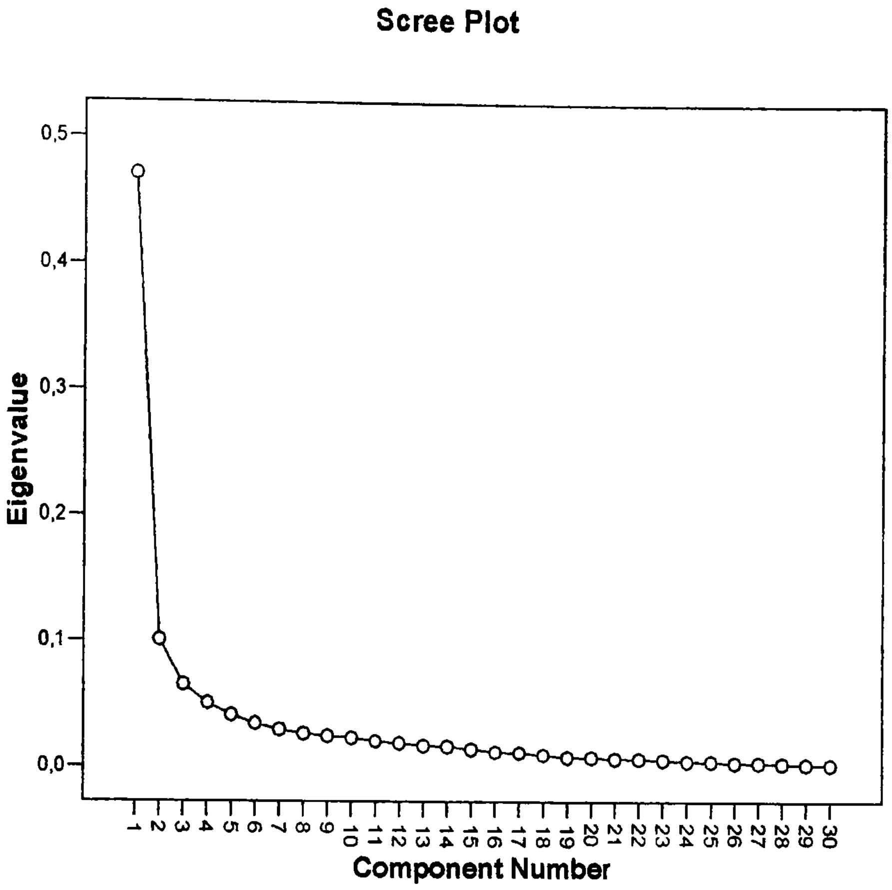


Table IV.23: **KMO and Bartlett's test for portfolio 5 of the second sub-period (1995–2000)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.849
Bartlett's Test of Sphericity	Approx. Chi-Square	1598.104
	Df	435
	Sig.	.000

***Table IV.24*: Total variance explained results for portfolio 5 of the second sub-period (1995–2000)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.584	44.973	44.973	.584	44.973	44.973	.160	12.360	12.360
2	.118	9.081	54.054	.118	9.081	54.054	.193	14.836	27.196
3	.076	5.833	59.887	.076	5.833	59.887	.243	18.718	45.914
4	.062	4.739	64.626	.062	4.739	64.626	.167	12.854	58.768
5	.059	4.556	69.182	.059	4.556	69.182	.075	5.812	64.580
6	.053	4.098	73.280	.053	4.098	73.280	.073	5.589	70.170
7	.044	3.352	76.632	.044	3.352	76.632	.084	6.462	76.632
8	.038	2.904	79.536						
9	.037	2.828	82.364						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.004	.334	99.098						
26	.003	.251	99.349						
27	.003	.222	99.571						
28	.002	.190	99.761						
29	.002	.142	99.903						
30	.001	.097	100.000						

***Figure IV.12*: Scree plot for portfolio 5 of the second sub-period (1995–2000)**

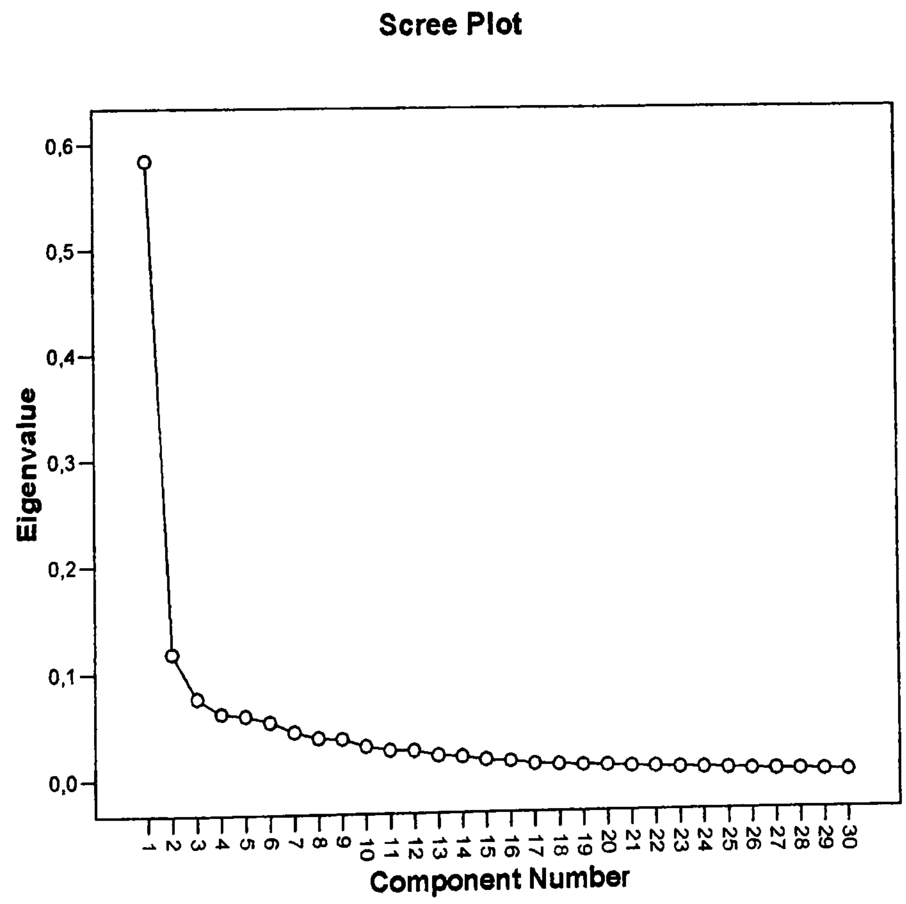


Table IV.25*: KMO and Bartlett's test for all the portfolios of the third sub-period (2001–2006)

Note: *Because of the fact that the variables are more than the cases (observations) for this period, the KMO and Bartlett's test table is not available

***Table IV.26*: Total variance explained results for all the portfolios of the third sub-period (2001–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.605	42.551	42.551	2.605	42.551	42.551	1.265	20.672	20.672
2	.270	4.409	46.960	.270	4.409	46.960	.767	12.531	33.203
3	.230	3.763	50.723	.230	3.763	50.723	.665	10.871	44.074
4	.184	2.999	53.722	.184	2.999	53.722	.451	7.366	51.440
5	.165	2.700	56.422	.165	2.700	56.422	.270	4.417	55.857
6	.160	2.618	59.040	.160	2.618	59.040	.195	3.183	59.040
7	.138	2.249	61.289						
8	.122	1.996	63.286						
...	...	...	...						
...	...	...	...						
...	...	...	...						
235	.000	.000	100.000						
236	.000	.000	100.000						
237	.000	.000	100.000						
238	.000	.000	100.000						
239	.000	.000	100.000						
240	.000	.000	100.000						

Figure IV.13: **Scree plot for all the portfolios of the third sub-period (2001–2006)**

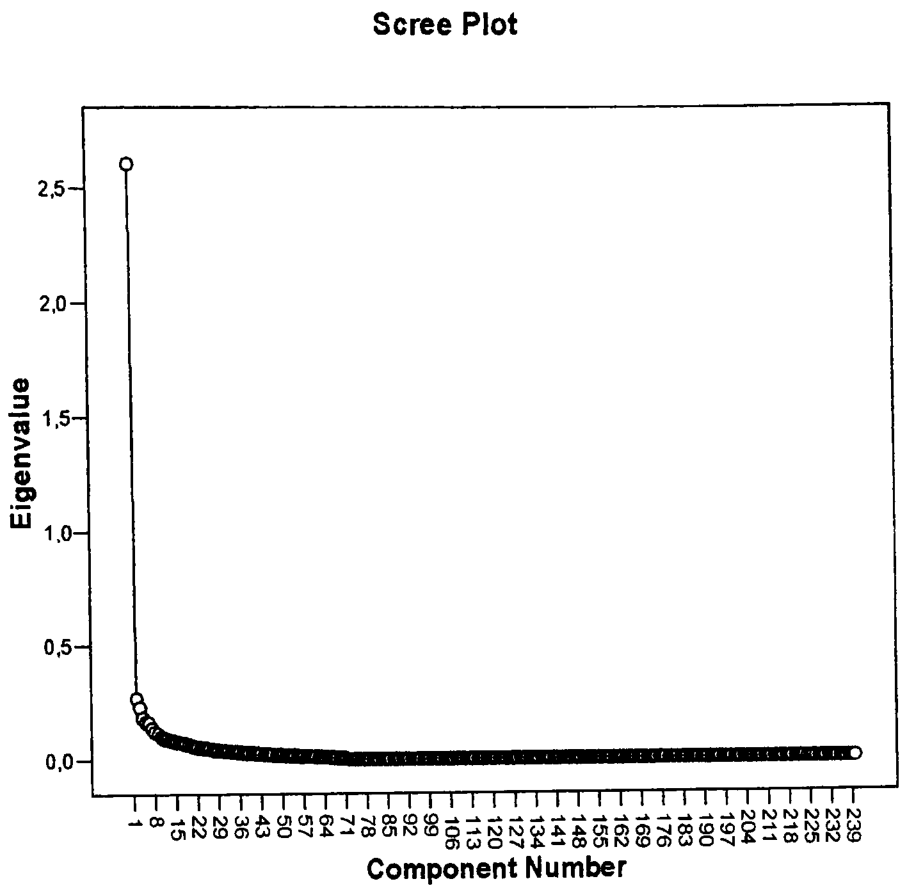


Table IV.27: **KMO and Bartlett's test for portfolio 1 of the third sub-period (2001–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.935
Bartlett's Test of Sphericity	Approx. Chi-Square	2090.942
	Df	435
	Sig.	.000

Table IV.28: **Total variance explained results for portfolio 1 of the third sub-period (2001–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.609	62.973	62.973	.609	62.973	62.973	.286	29.500	29.500
2	.044	4.513	67.486	.044	4.513	67.486	.244	25.248	54.747
3	.039	4.029	71.515	.039	4.029	71.515	.162	16.768	71.515
4	.030	3.054	74.569						
5	.025	2.607	77.175						
...	...	...	...						
...	...	...	...						
		...	...						
25	.003	.336	98.923						
26	.003	.308	99.231						
27	.003	.270	99.501						
28	.002	.199	99.700						
29	.002	.174	99.874						
30	.001	.126	100.000						

Figure IV.14: **Scree plot for portfolio 1 of the third sub-period (2001–2006)**

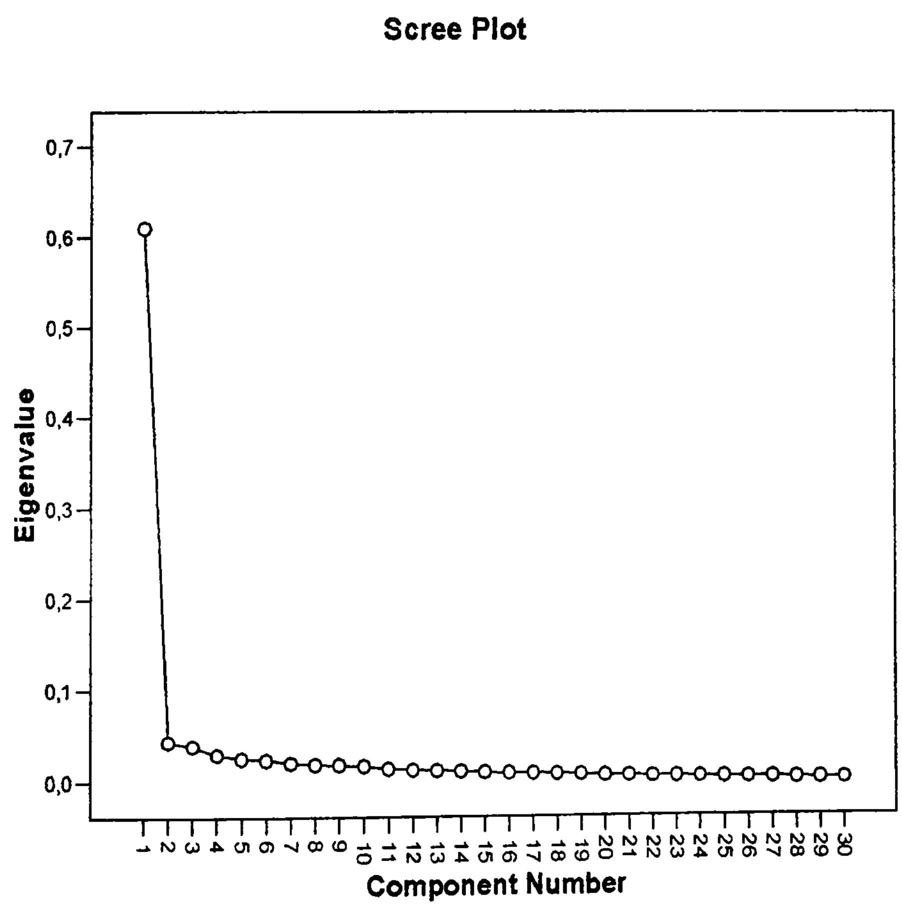


Table IV.29: **KMO and Bartlett's test for portfolio 2 of the third sub-period (2001–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.911
Bartlett's Test of Sphericity	Approx. Chi-Square	1930.095
	Df	435
	Sig.	.000

Table IV.30: **Total variance explained results for portfolio 2 of the third sub-period (2001–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.540	55.264	55.264	.540	55.264	55.264	.191	19.539	19.539
2	.083	8.457	63.721	.083	8.457	63.721	.269	27.486	47.025
3	.045	4.598	68.319	.045	4.598	68.319	.151	15.469	62.494
4	.043	4.429	72.748	.043	4.429	72.748	.080	8.138	70.632
5	.033	3.390	76.138	.033	3.390	76.138	.054	5.506	76.138
6	.025	2.572	78.710						
7	.023	2.364	81.074						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.003	.310	98.996						
26	.003	.287	99.282						
27	.002	.253	99.536						
28	.002	.208	99.743						
29	.001	.139	99.882						
30	.001	.118	100.000						

Figure IV.15: **Scree plot for portfolio 2 of the third sub-period (2001–2006)**

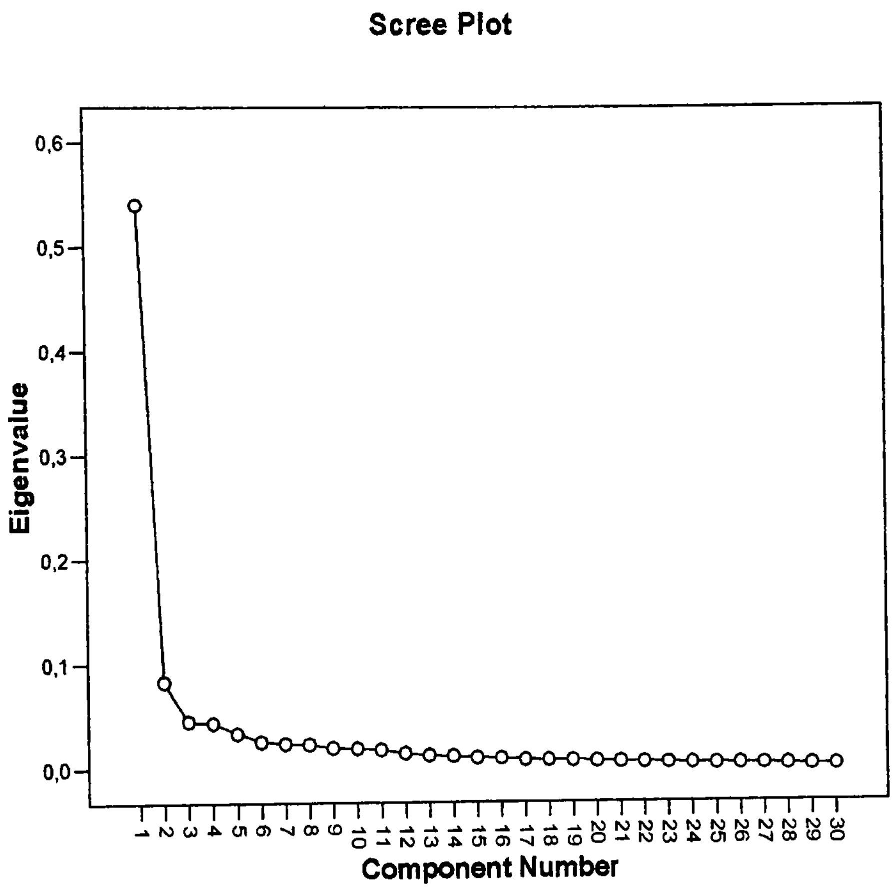


Table IV.31: **KMO and Bartlett's test for portfolio 3 of the third sub-period (2001–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.901
Bartlett's Test of Sphericity	Approx. Chi-Square	1648.533
	Df	435
	Sig.	.000

***Table IV.32*: Total variance explained results for portfolio 3 of the third sub-period (2001–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.375	50.523	50.523	.375	50.523	50.523	.101	13.615	13.615
2	.042	5.606	56.129	.042	5.606	56.129	.099	13.346	26.961
3	.036	4.861	60.990	.036	4.861	60.990	.095	12.877	39.838
4	.030	4.065	65.056	.030	4.065	65.056	.114	15.340	55.178
5	.028	3.768	68.823	.028	3.768	68.823	.073	9.827	65.005
6	.025	3.349	72.173	.025	3.349	72.173	.053	7.167	72.173
7	.024	3.189	75.362						
8	.021	2.894	78.256						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.003	.379	98.775						
26	.003	.353	99.129						
27	.002	.282	99.411						
28	.002	.260	99.671						
29	.002	.209	99.880						
30	.001	.120	100.000						

***Figure IV.16*: Scree plot for portfolio 3 of the third sub-period (2001–2006)**

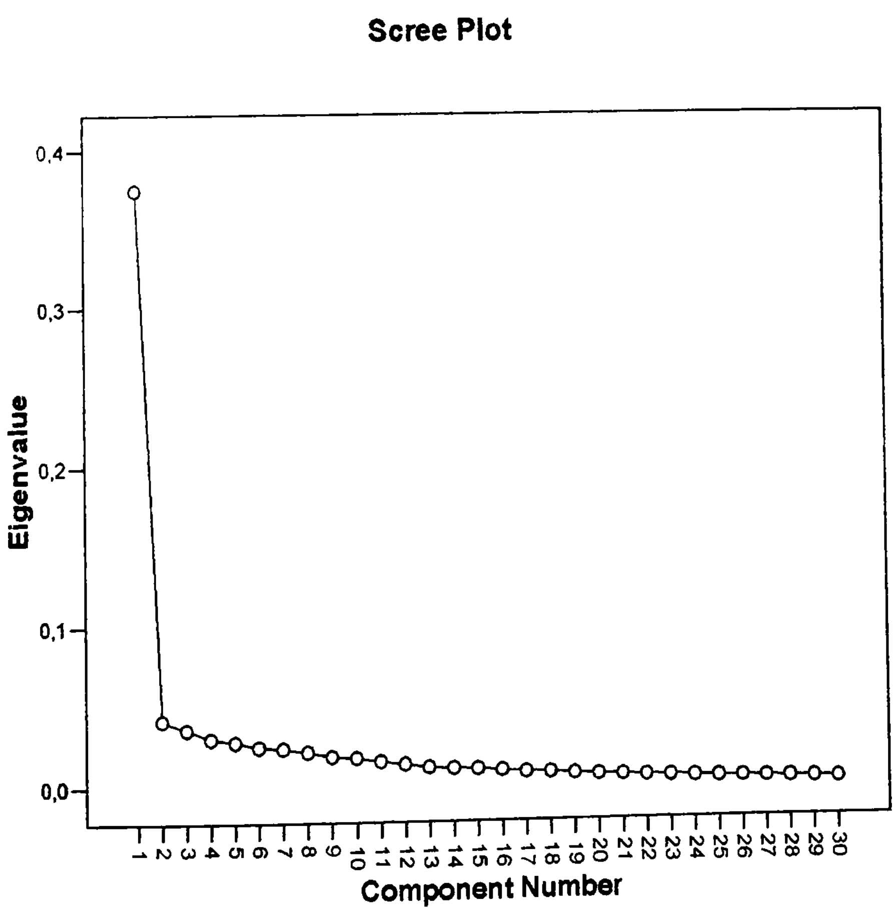


Table IV.33: **KMO and Bartlett's test for portfolio 4 of the third sub-period (2001–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.898
Bartlett's Test of Sphericity	Approx. Chi-Square	1675.195
	Df	435
	Sig.	.000

Table IV.34: **Total variance explained results for portfolio 4 of the third sub-period (2001–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.310	48.922	48.922	.310	48.922	48.922	.107	16.872	16.872
2	.048	7.640	56.561	.048	7.640	56.561	.072	11.328	28.200
3	.036	5.646	62.207	.036	5.646	62.207	.084	13.233	41.432
4	.029	4.571	66.779	.029	4.571	66.779	.088	13.848	55.281
5	.025	4.018	70.796	.025	4.018	70.796	.070	11.057	66.338
6	.025	3.886	74.683	.025	3.886	74.683	.053	8.344	74.683
7	.019	3.045	77.727						
8	.015	2.338	80.065						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.002	.368	98.811						
26	.002	.346	99.158						
27	.002	.267	99.425						
28	.002	.243	99.668						
29	.001	.187	99.855						
30	.001	.145	100.000						

Figure IV.17: **Scree plot for portfolio 4 of the third sub-period (2001–2006)**

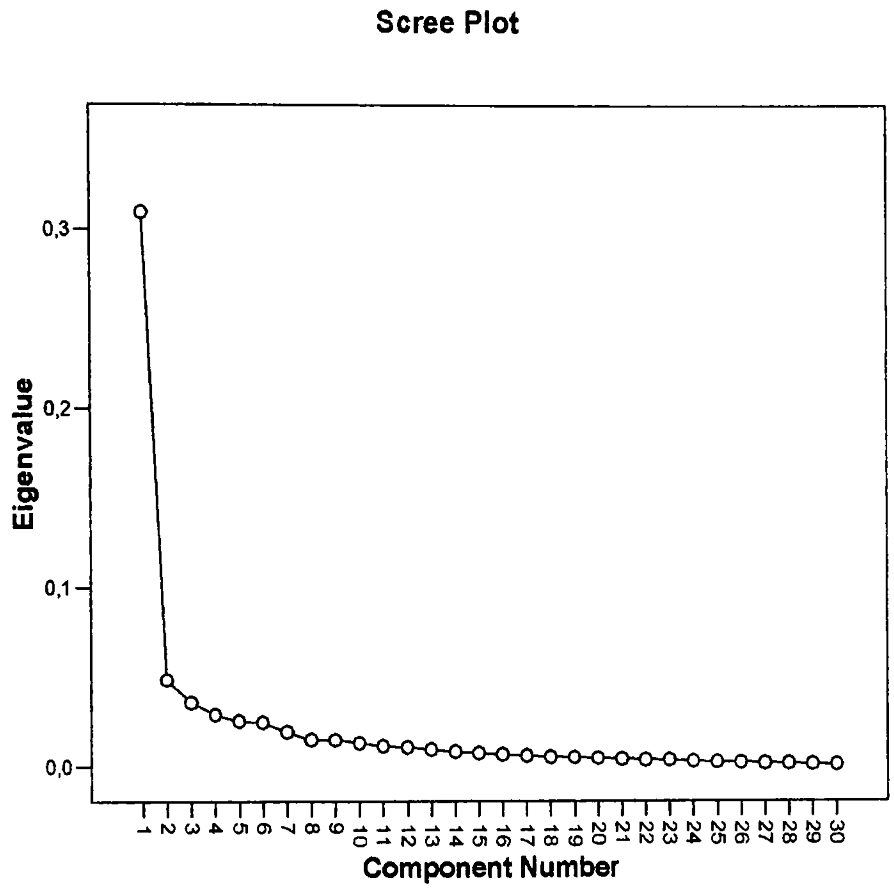


Table IV.35: **KMO and Bartlett's test for portfolio 5 of the third sub-period (2001–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.876
Bartlett's Test of Sphericity	Approx. Chi-Square	1487.637
	Df	435
	Sig.	.000

***Table IV.36*: Total variance explained results for portfolio 5 of the third sub-period (2001–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.332	43.548	43.548	.332	43.548	43.548	.108	14.169	14.169
2	.067	8.776	52.324	.067	8.776	52.324	.115	15.109	29.277
3	.046	6.006	58.330	.046	6.006	58.330	.085	11.095	40.373
4	.039	5.152	63.482	.039	5.152	63.482	.074	9.691	50.064
5	.031	4.084	67.566	.031	4.084	67.566	.079	10.353	60.417
6	.030	3.906	71.473	.030	3.906	71.473	.084	11.056	71.473
7	.024	3.181	74.653						
8	.023	3.011	77.664						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.003	.342	98.817						
26	.002	.316	99.133						
27	.002	.265	99.398						
28	.002	.246	99.644						
29	.002	.208	99.851						
30	.001	.149	100.000						

***Figure IV.18*: Scree plot for portfolio 5 of the third sub-period (2001–2006)**

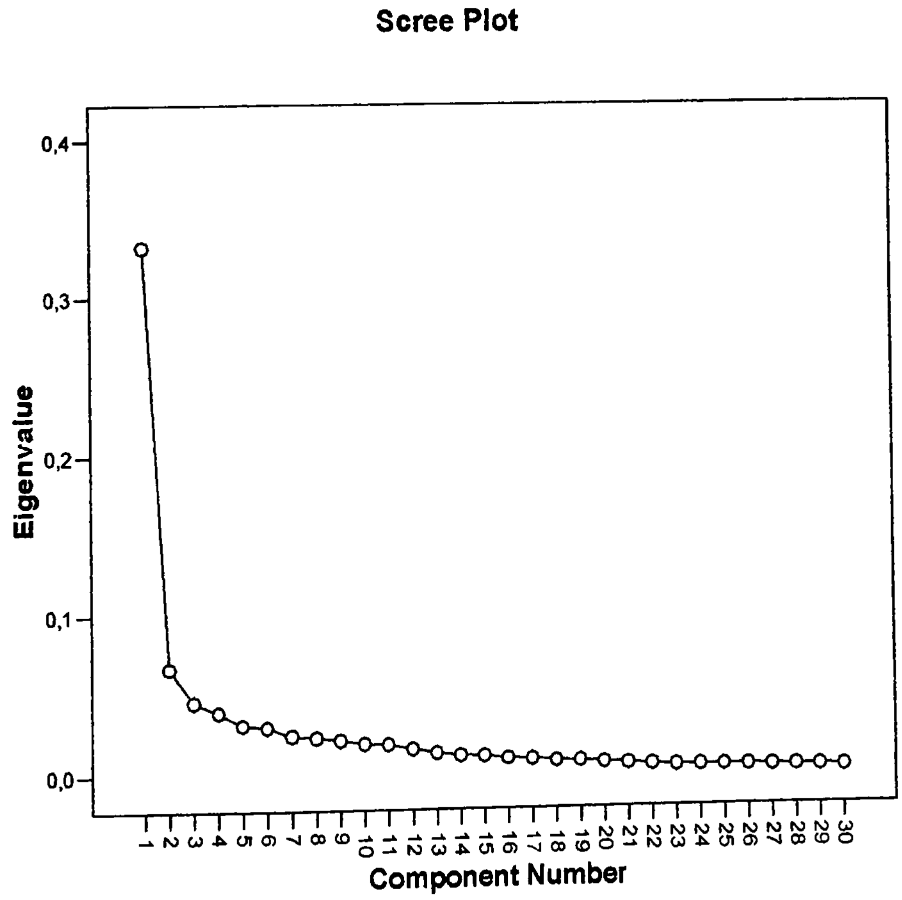


***Table IV.37*: KMO and Bartlett's test for portfolio 6 of the third sub-period (2001–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.832
Bartlett's Test of Sphericity	Approx. Chi-Square	1275.077
	df	435
	Sig.	.000

***Table IV.38*: Total variance explained results for portfolio 6 of the third sub-period (2001–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.233	37.189	37.189	.233	37.189	37.189	.112	17.945	17.945
2	.062	9.973	47.162	.062	9.973	47.162	.087	13.846	31.791
3	.043	6.890	54.053	.043	6.890	54.053	.058	9.203	40.994
4	.041	6.558	60.611	.041	6.558	60.611	.067	10.660	51.653
5	.031	4.970	65.580	.031	4.970	65.580	.037	5.837	57.491
6	.024	3.815	69.395	.024	3.815	69.395	.056	8.884	66.374
7	.022	3.574	72.969	.022	3.574	72.969	.041	6.595	72.969
8	.021	3.295	76.264						
9	.016	2.566	78.831						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.003	.445	98.565						
26	.002	.398	98.963						
27	.002	.370	99.333						
28	.002	.302	99.635						
29	.001	.235	99.869						
30	.001	.131	100.000						

Figure IV.19: **Scree plot for portfolio 6 of the third sub-period (2001–2006)**

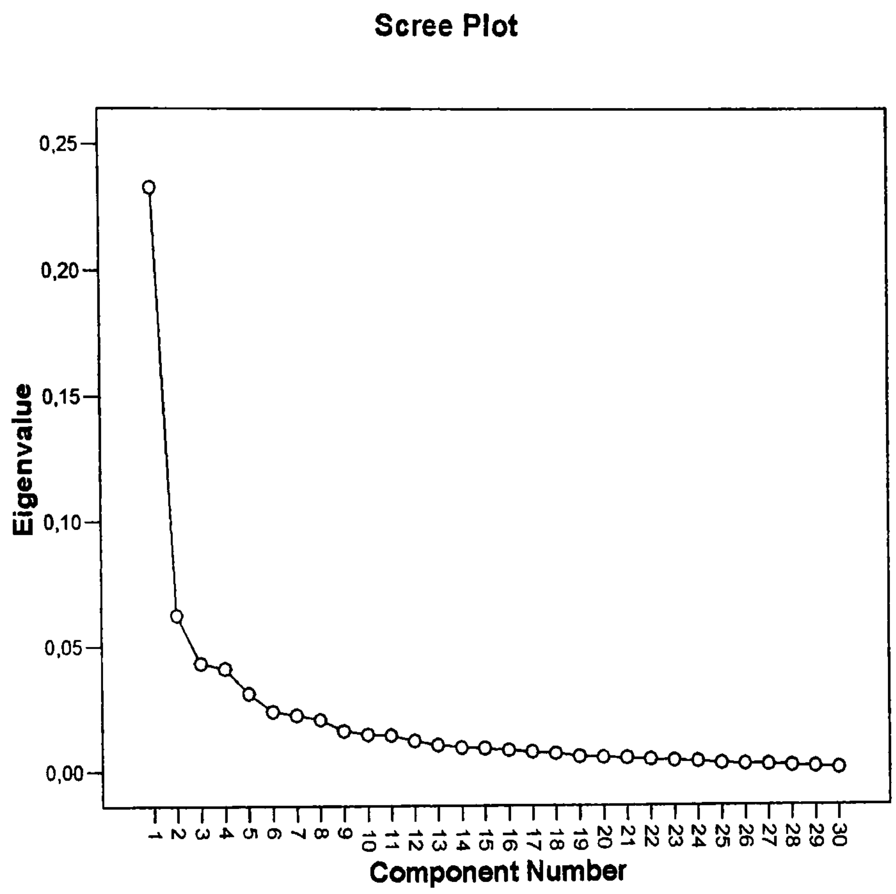


Table IV.39: **KMO and Bartlett's test for portfolio 7 of the third sub-period (2001–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.780
Bartlett's Test of Sphericity	Approx. Chi-Square	1086.156
	Df	435
	Sig.	.000

Table IV.40: **Total variance explained results for portfolio 7 of the third sub-period (2001–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.259	30.178	30.178	.259	30.178	30.178	.114	13.299	13.299
2	.101	11.703	41.881	.101	11.703	41.881	.080	9.251	22.551
3	.070	8.149	50.030	.070	8.149	50.030	.089	10.303	32.854
4	.069	7.981	58.011	.069	7.981	58.011	.086	10.052	42.906
5	.050	5.808	63.819	.050	5.808	63.819	.056	6.554	49.459
6	.042	4.902	68.721	.042	4.902	68.721	.072	8.334	57.793
7	.040	4.665	73.386	.040	4.665	73.386	.064	7.484	65.277
8	.035	4.104	77.490	.035	4.104	77.490	.105	12.212	77.490
9	.026	3.024	80.514						
10	.023	2.656	83.170						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.003	.375	98.893						
26	.003	.298	99.191						
27	.002	.267	99.457						
28	.002	.231	99.689						
29	.002	.194	99.883						
30	.001	.117	100.000						

Figure IV.20: **Scree plot for portfolio 7 of the third sub-period (2001–2006)**

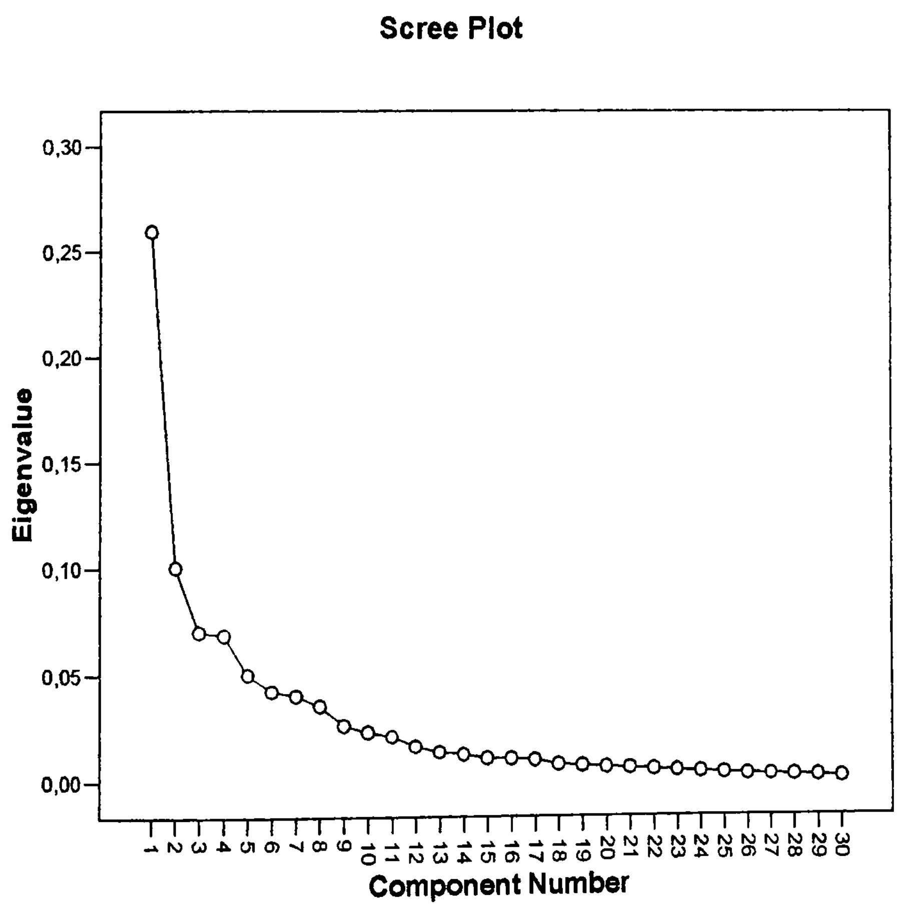


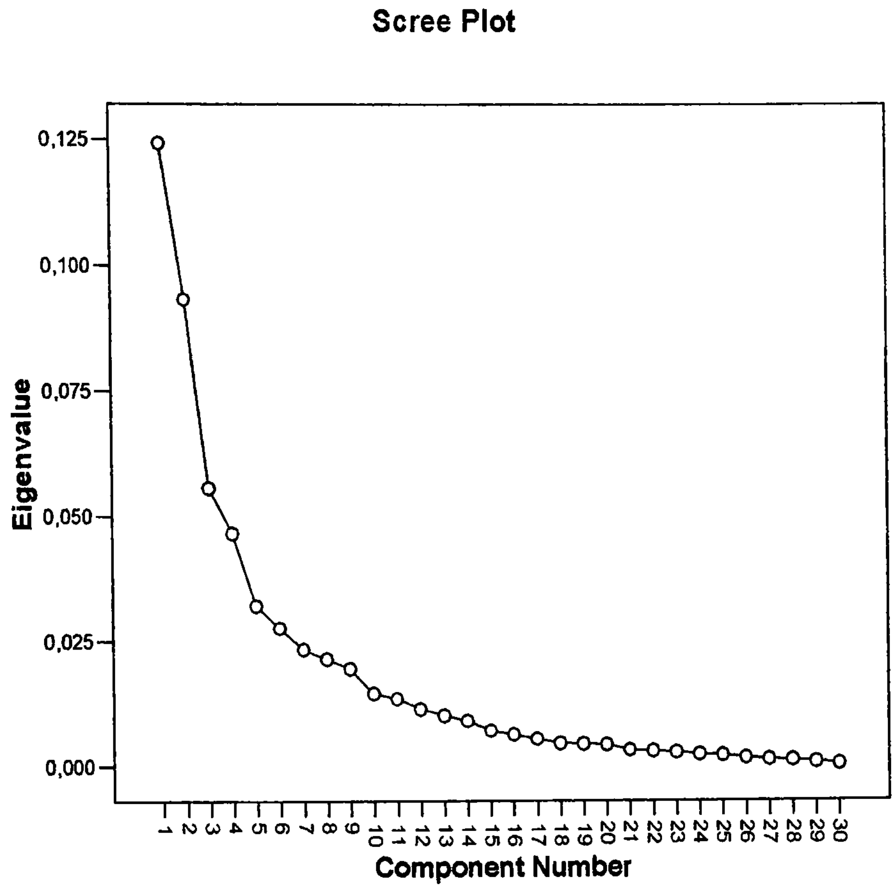
***Table IV.41*: KMO and Bartlett's test for portfolio 8 of the third sub-period (2001–2006)**

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.652
Bartlett's Test of Sphericity	Approx. Chi-Square	1047.764
	Df	435
	Sig.	.000

***Table IV.42*: Total variance explained results for portfolio 8 of the third sub-period (2001–2006)**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	.124	22.482	22.482	.124	22.482	22.482	.054	9.840	9.840
2	.093	16.875	39.357	.093	16.875	39.357	.059	10.727	20.567
3	.056	10.063	49.420	.056	10.063	49.420	.034	6.147	26.713
4	.047	8.424	57.844	.047	8.424	57.844	.051	9.172	35.885
5	.032	5.803	63.648	.032	5.803	63.648	.080	14.524	50.409
6	.028	5.001	68.648	.028	5.001	68.648	.050	9.135	59.544
7	.023	4.223	72.871	.023	4.223	72.871	.042	7.631	67.174
8	.021	3.871	76.743	.021	3.871	76.743	.044	8.048	75.222
9	.019	3.528	80.271	.019	3.528	80.271	.028	5.049	80.271
10	.015	2.629	82.900						
11	.013	2.439	85.339						
...	...	...	...						
...	...	...	...						
...	...	...	...						
25	.002	.378	99.077						
26	.002	.294	99.370						
27	.001	.231	99.601						
28	.001	.203	99.805						
29	.001	.136	99.940						
30	.000	.060	100.000						

Figure IV.21: **Scree plot for portfolio 8 of the third sub-period (2001–2006)**



Appendix V
Time Series Results of the Inflation Rate (1989–2006)

Table V.1: **The observed, expected, unexpected and the change in the expected inflation rate during the 1989–2006 period of investigation**

	observed	Expected	Residual	difference E(It+1)-E(It)	Date.
1	.131505	.	.		JAN 1989
2	.130403	.130861	-.000457		FEB 1989
3	.126418	.129757	-.003339	-.001104	MAR 1989
4	.123393	.125689	-.002296	-.004068	APR 1989
5	.123122	.122185	.000937	-.003504	MAY 1989
6	.123135	.121672	.001463	-.000513	JUN 1989
7	.125865	.122351	.003515	.000679	JUL 1989
8	.126494	.124943	.001551	.002592	AUG 1989
9	.136605	.126171	.010434	.001227	SEP 1989
10	.127067	.136884	-.009817	.010713	OCT 1989
11	.127470	.128974	-.001504	-.007910	NOV 1989
12	.138436	.126978	.011458	-.001996	DEC 1989
13	.144244	.137270	.006974	.010292	JAN 1990
14	.149358	.146748	.002611	.009477	FEB 1990
15	.156221	.150582	.005639	.003834	MAR 1990
16	.157608	.157316	.000292	.006734	APR 1990
17	.186314	.159669	.026645	.002353	MAY 1990
18	.195237	.186771	.008467	.027101	JUN 1990
19	.196133	.197668	-.001535	.010898	JUL 1990
20	.200144	.199946	.000198	.002278	AUG 1990
21	.201455	.195035	.006420	-.004911	SEP 1990
22	.209651	.209730	-.000079	.014695	OCT 1990
23	.214226	.211322	.002904	.001592	NOV 1990
24	.206069	.207931	-.001862	-.003391	DEC 1990
25	.200354	.203074	-.002720	-.004857	JAN 1991
26	.201484	.197662	.003823	-.005412	FEB 1991
27	.188355	.196755	-.008400	-.000907	MAR 1991
28	.205138	.188115	.017023	-.008640	APR 1991
29	.175619	.186113	-.010495	-.002002	MAY 1991
30	.173107	.170787	.002320	-.015327	JUN 1991
31	.172062	.171470	.000592	.000683	JUL 1991
32	.165318	.166046	-.000728	-.005424	AUG 1991
33	.167620	.164265	.003355	-.001781	SEP 1991
34	.162632	.162307	.000325	-.001958	OCT 1991
35	.165107	.159555	.005552	-.002752	NOV 1991
36	.165669	.165910	-.000241	.006355	DEC 1991
37	.166725	.167028	-.000303	.001118	JAN 1992
38	.167376	.164139	.003237	-.002890	FEB 1992
39	.168289	.172228	-.003938	.008089	MAR 1992
40	.148812	.158110	-.009298	-.014118	APR 1992

41	.147141	.155258	-.008117	-.002852	MAY 1992
42	.140765	.142272	-.001507	-.012986	JUN 1992
43	.127065	.137701	-.010636	-.004571	JUL 1992
44	.142223	.126703	.015519	-.010998	AUG 1992
45	.142814	.133610	.009204	.006907	SEP 1992
46	.147555	.143076	.004479	.009466	OCT 1992
47	.139962	.145716	-.005754	.002640	NOV 1992
48	.134547	.138792	-.004245	-.006924	DEC 1992
49	.135280	.136064	-.000784	-.002728	JAN 1993
50	.135515	.132321	.003194	-.003743	FEB 1993
51	.151997	.137705	.014292	.005384	MAR 1993
52	.150067	.155525	-.005458	.017821	APR 1993
53	.152130	.156592	-.004462	.001066	MAY 1993
54	.146738	.154063	-.007326	-.002529	JUN 1993
55	.146253	.153124	-.006871	-.000939	JUL 1993
56	.136094	.137976	-.001883	-.015148	AUG 1993
57	.120829	.129142	-.008313	-.008835	SEP 1993
58	.116127	.115752	.000375	-.013390	OCT 1993
59	.115857	.114530	.001327	-.001222	NOV 1993
60	.113460	.116089	-.002629	.001558	DEC 1993
61	.106937	.111762	-.004825	-.004327	JAN 1994
62	.107605	.102178	.005427	-.009584	FEB 1994
63	.095724	.096619	-.000895	-.005558	MAR 1994
64	.097505	.099696	-.002191	.003077	APR 1994
65	.102288	.098479	.003809	-.001217	MAY 1994
66	.098145	.104636	-.006492	.006157	JUN 1994
67	.110724	.103803	.006921	-.000833	JUL 1994
68	.109632	.109671	-.000039	.005868	AUG 1994
69	.110754	.116109	-.005355	.006438	SEP 1994
70	.101201	.112444	-.011244	-.003665	OCT 1994
71	.097369	.099506	-.002137	-.012938	NOV 1994
72	.101346	.098699	.002647	-.000807	DEC 1994
73	.101324	.102344	-.001019	.003644	JAN 1995
74	.095226	.097643	-.002417	-.004701	FEB 1995
75	.094206	.093849	.000357	-.003793	MAR 1995
76	.089802	.093636	-.003834	-.000214	APR 1995
77	.092147	.087088	.005059	-.006548	MAY 1995
78	.090601	.095777	-.005176	.008689	JUN 1995
79	.081666	.084589	-.002924	-.011188	JUL 1995
80	.080079	.081405	-.001325	-.003185	AUG 1995
81	.077233	.081135	-.003902	-.000270	SEP 1995
82	.075512	.083360	-.007848	.002225	OCT 1995
83	.075504	.075903	-.000399	-.007457	NOV 1995
84	.076236	.071635	.004600	-.004268	DEC 1995
85	.080346	.076072	.004274	.004436	JAN 1996
86	.081147	.081687	-.000539	.005615	FEB 1996
87	.084719	.081216	.003503	-.000471	MAR 1996
88	.084312	.087325	-.003012	.006109	APR 1996
89	.083324	.081552	.001772	-.005773	MAY 1996
90	.080524	.087174	-.006650	.005622	JUN 1996
91	.078809	.081665	-.002856	-.005509	JUL 1996

92	.076697	.078962	-.002265	-.002702	AUG 1996
93	.076493	.077994	-.001501	-.000968	SEP 1996
94	.076835	.080307	-.003472	.002313	OCT 1996
95	.072290	.075838	-.003548	-.004469	NOV 1996
96	.070365	.068896	.001469	-.006942	DEC 1996
97	.065436	.066347	-.000911	-.002549	JAN 1997
98	.063472	.064782	-.001311	-.001565	FEB 1997
99	.058261	.060166	-.001905	-.004616	MAR 1997
100	.056958	.058468	-.001510	-.001698	APR 1997
101	.052735	.054156	-.001421	-.004312	MAY 1997
102	.053888	.055367	-.001479	.001211	JUN 1997
103	.052703	.054537	-.001833	-.000830	JUL 1997
104	.054291	.052926	.001365	-.001611	AUG 1997
105	.048022	.054964	-.006942	.002038	SEP 1997
106	.045860	.049619	-.003759	-.005345	OCT 1997
107	.050148	.047363	.002785	-.002256	NOV 1997
108	.046066	.047652	-.001585	.000289	DEC 1997
109	.043032	.047257	-.004225	-.000395	JAN 1998
110	.041797	.042260	-.000463	-.004997	FEB 1998
111	.044724	.041220	.003503	-.001040	MAR 1998
112	.052026	.045669	.006357	.004448	APR 1998
113	.051567	.052573	-.001006	.006904	MAY 1998
114	.050638	.052835	-.002197	.000262	JUN 1998
115	.049775	.051941	-.002166	-.000894	JUL 1998
116	.049080	.048886	.000194	-.003054	AUG 1998
117	.050925	.053997	-.003072	.005111	SEP 1998
118	.045789	.052470	-.006681	-.001527	OCT 1998
119	.041334	.043320	-.001986	-.009151	NOV 1998
120	.037967	.041024	-.003056	-.002296	DEC 1998
121	.036299	.038893	-.002595	-.002131	JAN 1999
122	.036219	.035539	.000681	-.003355	FEB 1999
123	.033435	.032356	.001079	-.003182	MAR 1999
124	.027677	.028186	-.000510	-.004170	APR 1999
125	.023448	.027250	-.003803	-.000936	MAY 1999
126	.020652	.023410	-.002758	-.003840	JUN 1999
127	.020651	.020641	.000010	-.002769	JUL 1999
128	.019599	.019151	.000449	-.001491	AUG 1999
129	.020026	.020180	-.000154	.001029	SEP 1999
130	.022240	.023276	-.001036	.003096	OCT 1999
131	.025589	.022906	.002683	-.000370	NOV 1999
132	.027071	.027838	-.000767	.004932	DEC 1999
133	.025964	.029091	-.003127	.001253	JAN 2000
134	.028688	.025800	.002888	-.003291	FEB 2000
135	.030957	.027796	.003161	.001996	MAR 2000
136	.025424	.031595	-.006171	.003799	APR 2000
137	.028851	.028154	.000697	-.003441	MAY 2000
138	.024870	.028976	-.004106	.000822	JUN 2000
139	.027016	.024599	.002416	-.004377	JUL 2000
140	.029488	.026503	.002985	.001904	AUG 2000
141	.030935	.027955	.002980	.001451	SEP 2000
142	.039515	.032204	.007311	.004249	OCT 2000

143	.041580	.037378	.004202	.005174	NOV 2000
144	.038307	.043419	-.005112	.006041	DEC 2000
145	.033477	.041393	-.007916	-.002026	JAN 2001
146	.034603	.031059	.003544	-.010334	FEB 2001
147	.029844	.031978	-.002134	.000919	MAR 2001
148	.034393	.033383	.001010	.001405	APR 2001
149	.035702	.031934	.003768	-.001449	MAY 2001
150	.038580	.036933	.001647	.004999	JUN 2001
151	.038463	.037712	.000751	.000779	JUL 2001
152	.037158	.036107	.001051	-.001605	AUG 2001
153	.035462	.035811	-.000350	-.000296	SEP 2001
154	.027281	.030503	-.003223	-.005308	OCT 2001
155	.023732	.024363	-.000631	-.006140	NOV 2001
156	.029996	.024771	.005225	.000409	DEC 2001
157	.043406	.032896	.010511	.008124	JAN 2002
158	.033751	.040993	-.007241	.008097	FEB 2002
159	.039321	.036451	.002869	-.004541	MAR 2002
160	.037624	.037343	.000281	.000892	APR 2002
161	.033288	.035766	-.002479	-.001577	MAY 2002
162	.032565	.034976	-.002412	-.000790	JUN 2002
163	.032843	.028839	.004005	-.006138	JUL 2002
164	.034823	.031241	.003582	.002402	AUG 2002
165	.034619	.034556	.000063	.003315	SEP 2002
166	.036627	.035969	.000658	.001413	OCT 2002
167	.035773	.036026	-.000253	.000057	NOV 2002
168	.033317	.032866	.000450	-.003160	DEC 2002
169	.030875	.026772	.004103	-.006094	JAN 2003
170	.042482	.034501	.007981	.007729	FEB 2003
171	.039948	.039666	.000282	.005165	MAR 2003
172	.033198	.040938	-.007739	.001271	APR 2003
173	.037479	.034710	.002770	-.006228	MAY 2003
174	.037429	.036340	.001089	.001631	JUN 2003
175	.035291	.036461	-.001170	.000121	JUL 2003
176	.032647	.032995	-.000348	-.003466	AUG 2003
177	.032815	.030141	.002674	-.002855	SEP 2003
178	.031224	.031722	-.000498	.001581	OCT 2003
179	.032905	.031426	.001479	-.000296	NOV 2003
180	.030293	.031389	-.001096	-.000037	DEC 2003
181	.028852	.026675	.002177	-.004714	JAN 2004
182	.024787	.023516	.001270	-.003159	FEB 2004
183	.026789	.023600	.003189	.000084	MAR 2004
184	.028715	.030751	-.002036	.007151	APR 2004
185	.028916	.026098	.002818	-.004653	MAY 2004
186	.027806	.028271	-.000466	.002174	JUN 2004
187	.028943	.027641	.001302	-.000631	JUL 2004
188	.026876	.028962	-.002086	.001321	AUG 2004
189	.027823	.025282	.002542	-.003680	SEP 2004
190	.031844	.027601	.004244	.002319	OCT 2004
191	.030938	.029917	.001020	.002317	NOV 2004
192	.030461	.032205	-.001744	.002288	DEC 2004
193	.039519	.028537	.010982	-.003668	JAN 2005

194	.030506	.037931	-.007425	.009393	FEB 2005
195	.028515	.030163	-.001648	-.007768	MAR 2005
196	.033272	.028876	.004396	-.001286	APR 2005
197	.031828	.029085	.002743	.000209	MAY 2005
198	.032658	.033864	-.001206	.004779	JUN 2005
199	.038654	.030387	.008267	-.003477	JUL 2005
200	.036653	.038500	-.001847	.008113	AUG 2005
201	.038597	.036532	.002064	-.001968	SEP 2005
202	.037640	.036058	.001582	-.000474	OCT 2005
203	.034609	.036146	-.001538	.000088	NOV 2005
204	.035570	.036358	-.000789	.000212	DEC 2005
205	.031929	.027290	.004639	-.009068	JAN 2006
206	.031835	.036008	-.004173	.008718	FEB 2006
207	.032491	.031691	.000801	-.004317	MAR 2006
208	.032210	.028441	.003770	-.003250	APR 2006
209	.030837	.030228	.000609	.001787	MAY 2006
210	.031828	.030856	.000972	.000628	JUN 2006
211	.037730	.025855	.011875	-.005001	JUL 2006
212	.034740	.038719	-.003978	.012863	AUG 2006
213	.028884	.034197	-.005313	-.004521	SEP 2006
214	.027738	.027264	.000474	-.006933	OCT 2006
215	.028840	.027030	.001810	-.000234	NOV 2006
216	.028676	.029171	-.000495	.002140	DEC 2006
Total N	216.000000	215.000000	215.000000	214.000000	216

Note: *The results of the expected values from the industrial production index and the petroleum and other fuels index are available on request.

Appendix VI
Time Series Analysis of the Industrial Production Index

1. Monthly Trend of the Index

As in the case of the inflation rate (presented in chapter four), in order to employ the macroeconomic APT model, we examine the series of the growth rate of the industrial production index, based on the Box-Jenkins (1976) methodology (presented in chapter three). As in prior studies (Chen and Jordan, 1993; Chen *et al.*, 1986) the purpose is to calculate the unexpected change in the growth rate in the industrial production which is the difference between the observed and the expected values (the residuals) of the series of growth rate of the industrial production. Figures 1, 2 and 3 present the observations of the series, the first differences and the first seasonal differences respectively:

***Figure VI.1*: The industrial production index in Greece (1993–2006)**

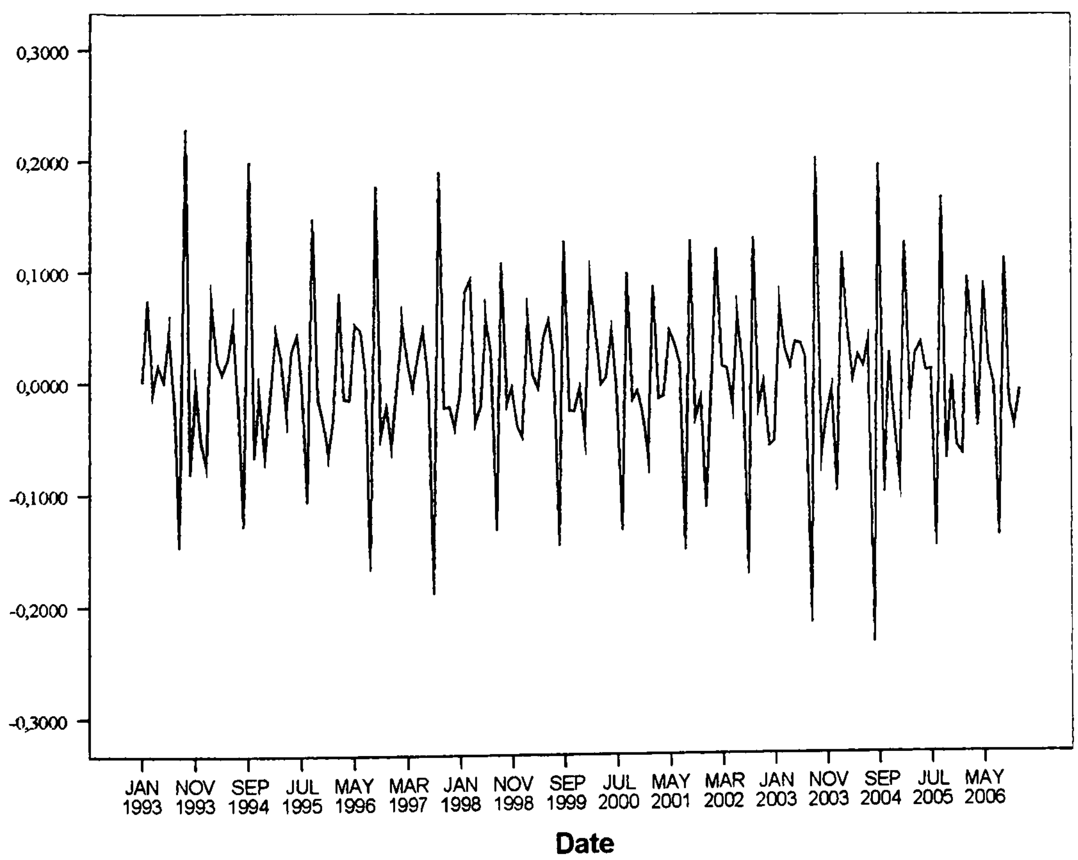


Figure VI.2: **The first difference series of the industrial production index (1993–2006)**

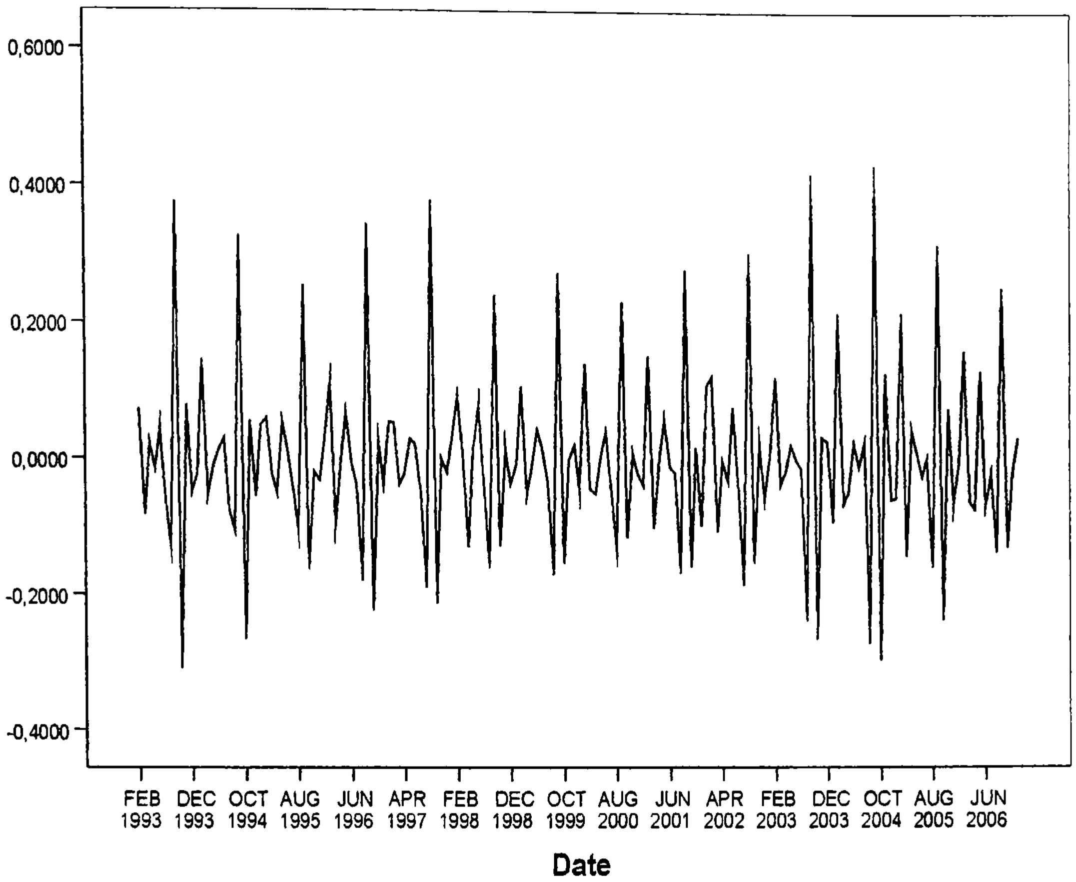
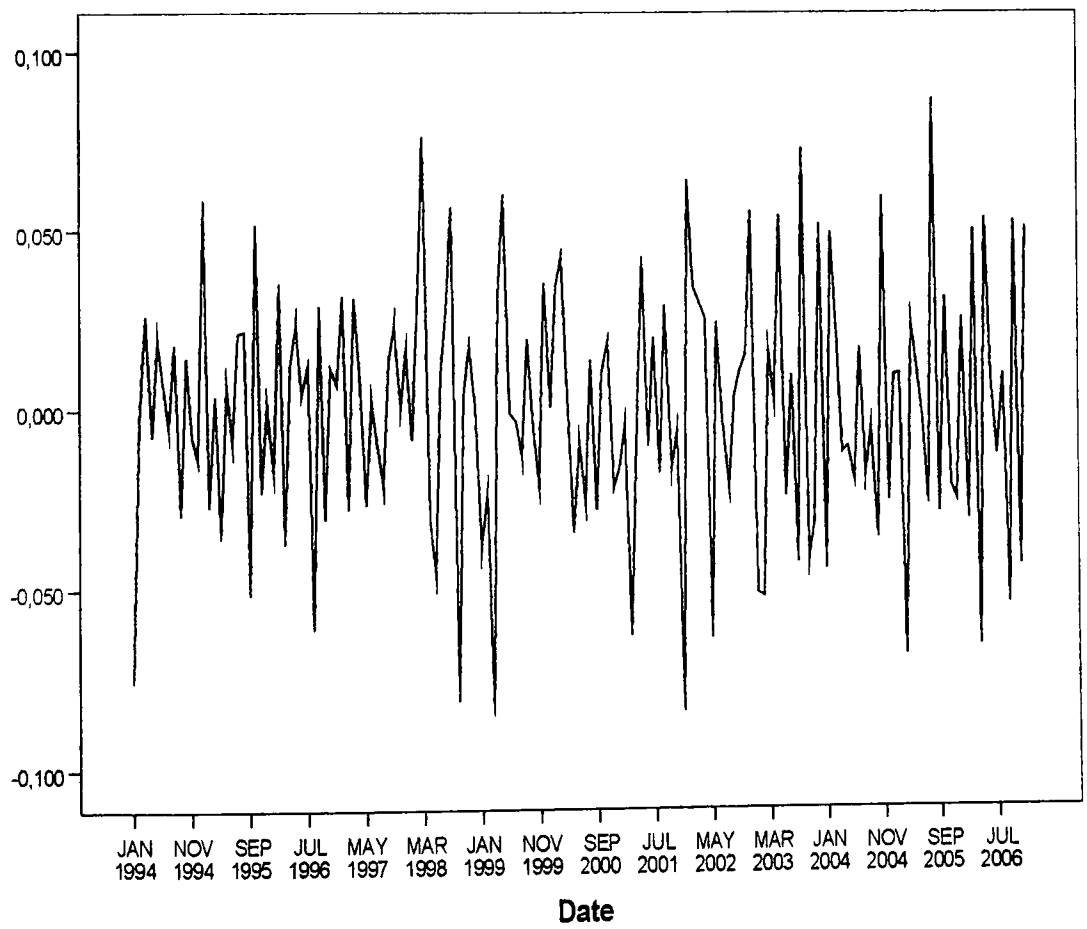


Figure VI.3: **The first seasonal difference series of the industrial production index (1993–2006)**



After the presentation of the seasonal first differences we examine the seasonal autocorrelation and partial autocorrelations of the series, so as to see whether they are significant or not (as in the case of the inflation rate in chapter four).

2. Seasonal Autocorrelations and Partial Autocorrelations

Figure VI.4: **The seasonal autocorrelations of the first differences of the series**

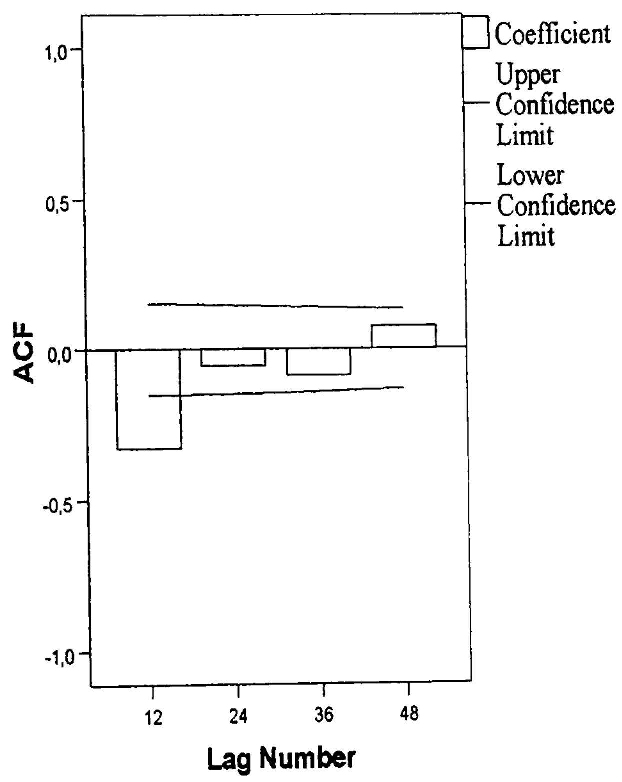
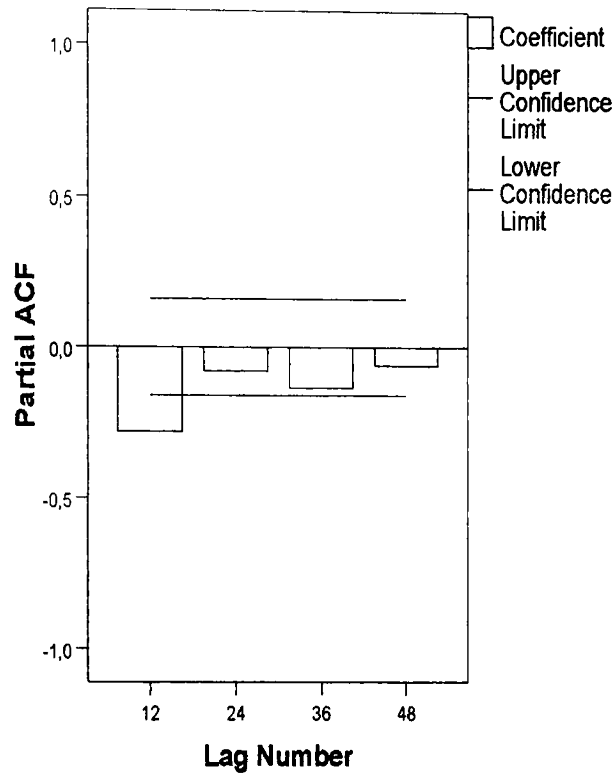


Figure VI.5: **The seasonal partial autocorrelations of the first differences of the series**



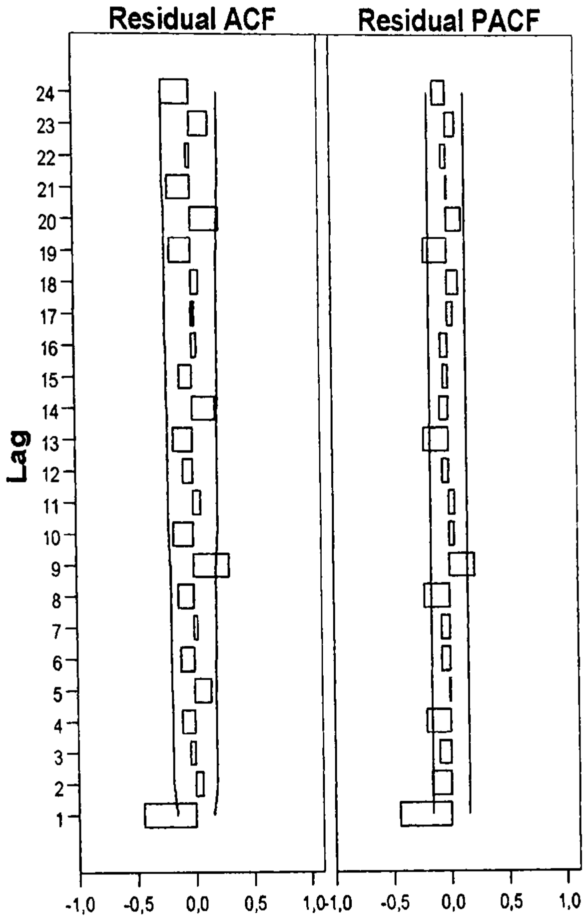
According to figures 4 and 5 that represent the seasonal autocorrelations and partial autocorrelations, and based on the Box-Jenkins (1976) methodology, the potential models are the ARIMA (0,0,0) (1,1,0) or the ARIMA (0,0,0) (0,1,1).

3. Autocorrelations and Partial Autocorrelations of the ARIMA (0,0,0) (1,1,0) and the ARIMA (0,0,0) (0,1,1) Models.

3.1 ARIMA (0,0,0) (1,1,0)

Figure 6 presents the autocorrelations and the partial autocorrelations of the residuals of the ARIMA (0,0,0) (1,1,0):

***Figure VI.6*: The autocorrelations and the partial autocorrelations of residuals of the ARIMA (0,0,0) (1,1,0) model**

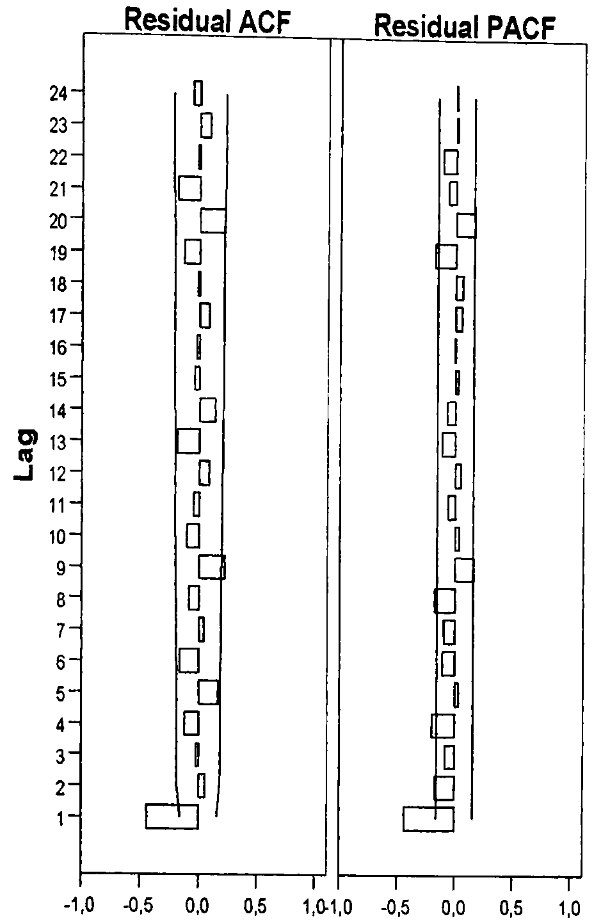


According to figure 6 the three potential models for the examination are the ARIMA (1,0,0) (1,1,0), the ARIMA (0,0,1) (1,1,0) or the ARIMA (9,0,1) (1,1,0).

3.2 ARIMA (0,0,0) (0,1,1)

Respectively, figure 7 presents the autocorrelations and the partial autocorrelations of the residuals of the ARIMA (0,0,0) (0,1,1):

Figure VI. 7: **The autocorrelations and the partial autocorrelations of residuals of the ARIMA (0,0,0) (0,1,1) model**



According to figure 7 the two more potential models for the examination are the ARIMA (1,0,0) (0,1,1) or the ARIMA (0,0,1) (0,1,1). From the group of all the potential models the most appropriate one is found to be the ARIMA (9,0,1) (1,1,0) (its autocorrelations were insignificant), which is presented below:

3.3 ARIMA (9,0,1) (1,1,0)

Table 1 presents the model statistics of the ARIMA (9,0,1) (1,1,0) model while table 2 presents the respective model parameters:

Table VI.1: **The model statistics of the ARIMA (9,0,1) (1,1,0)**

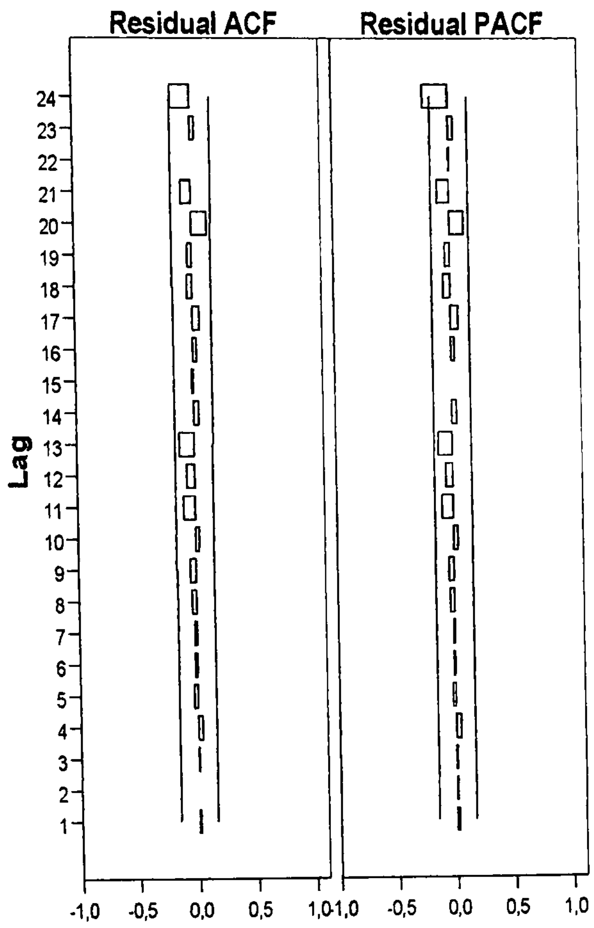
Model	Number of Predictors	Model Fit statistics				Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	MaxAPE	Normalized BIC	Statistics	DF	Sig.	
Ipi-Model_1	0	.437	108.785	1282.578	-6.855	7.751	7	.355	0

In this case, the model has R^2=43.7 per cent, Ljung-Box Q(18)=7.751 and p=0.355, which means that we cannot reject the null hypothesis that the model fits well to the data.

Table VI.2: **The model parameters of the ARIMA (9,0,1) (1,1,0)**

					Estimate	SE	T	Sig.
ipi-Model_1	Ipi	No Transformation	Constant		.000	.001	-.138	.891
			AR	Lag 1	-.463	.380	-1.220	.225
				Lag 2	-.228	.259	-.882	.379
				Lag 3	-.182	.163	-1.116	.266
				Lag 4	-.254	.136	-1.874	.063
				Lag 5	-.033	.152	-.219	.827
				Lag 6	-.121	.108	-1.128	.261
				Lag 7	-.099	.117	-.844	.400
				Lag 8	-.083	.116	.714	.476
				Lag 9	.253	.115	2.198	.030
			MA	Lag 1	.142	.393	.361	.719
			AR. Seasonal	Lag 1	-.481	.078	-6.162	.000
			Seasonal Difference		1			

***Figure VI.8*: The autocorrelations and the partial autocorrelations of residuals of the ARIMA (9,0,1) (1,1,0) model**



We can mention at this point that there are insignificant autocorrelations and partial autocorrelations, according to figure 8 and tables 3 and 4, where the autocorrelations and the partial autocorrelations of the residuals of the model are presented. Specifically, the Box-Ljung statistic in table 3 shows the insignificant autocorrelations of the series of the residuals.

***Table VI.3*: The autocorrelation statistics of residuals of the ARIMA (9,0,1) (1,1,0) model**

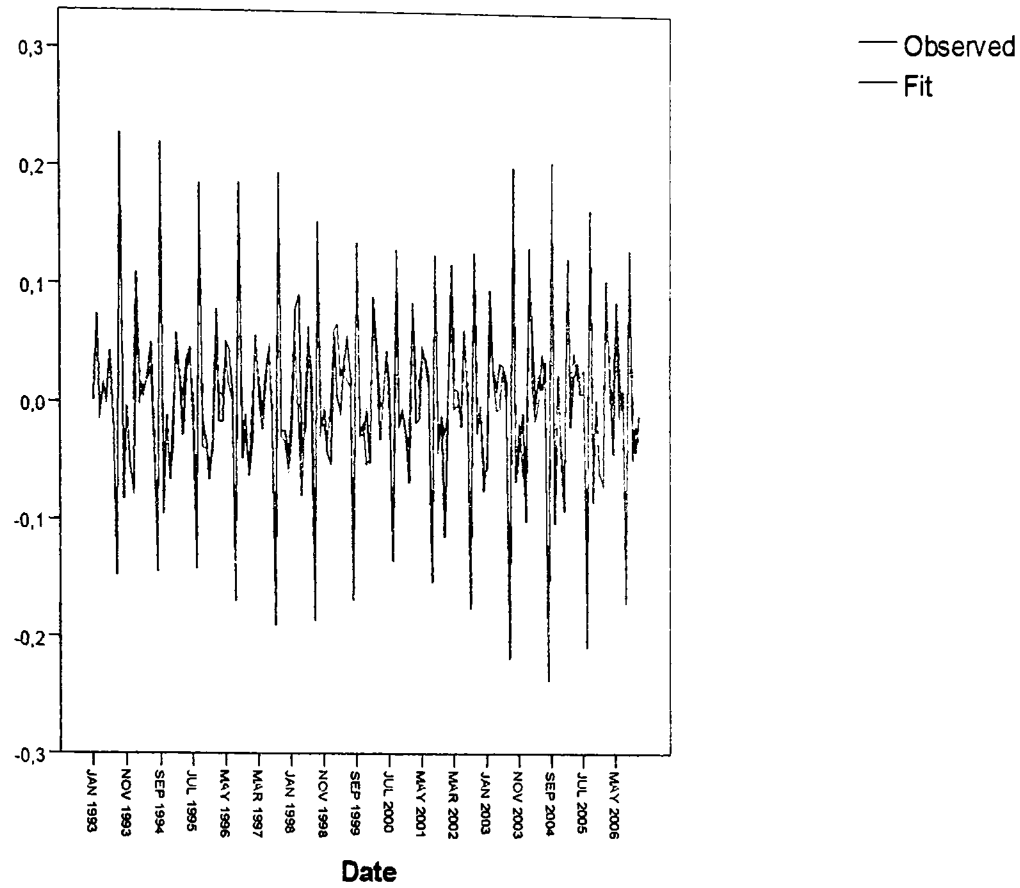
Lag	Autocorrelation	Std. Error(a)	Box-Ljung Statistic		
			Value	df	Sig.(b)
1	.007	.079	.007	1	.932
2	.013	.079	.035	2	.983
3	-.014	.079	.065	3	.996
4	.035	.079	.262	4	.992
5	-.011	.078	.280	5	.998
6	-.039	.078	.525	6	.998
7	-.022	.078	.606	7	.999

8	-.025	.077	.711	8	.999
9	-.033	.077	.892	9	1.000
10	-.002	.077	.893	10	1.000
11	-.115	.077	3.139	11	.989
12	.000	.076	3.139	12	.994
13	-.124	.076	5.792	13	.953
14	.035	.076	6.010	14	.966
15	-.011	.076	6.032	15	.979
16	.020	.075	6.104	16	.987

***Table VI.4*: The partial autocorrelation statistics of residuals of the ARIMA (9,0,1) (1,1,0) model**

Lag	Partial Autocorrelation	Std. Error
1	.007	.080
2	.013	.080
3	-.014	.080
4	.035	.080
5	-.011	.080
6	-.040	.080
7	-.020	.080
8	-.025	.080
9	-.032	.080
10	.001	.080
11	-.115	.080
12	.000	.080
13	-.124	.080
14	.031	.080
15	-.007	.080
16	.012	.080

Figure VI.9: **The observed and the fitted values of the industrial production series (1993–2006)**



As we have already explained in chapter four, what we need from the macroeconomic indices is the series of errors (the residuals). The residuals are calculated as the difference between the expected and the observed values of each index, as in the case of the inflation rate whose cumulative results were presented in Appendix V.

Appendix VII
Time Series Analysis of the Manufacture of Coke, Refined Petroleum Products and Nuclear Fuels Index (1989–2006)

1. Monthly Trend of the Index

The following figures 1, 2 and 3 present the observations of the series, the first differences and the first seasonal differences respectively:

***Figure VII.1*: The petroleum derivatives index in Greece (1989–2006)**

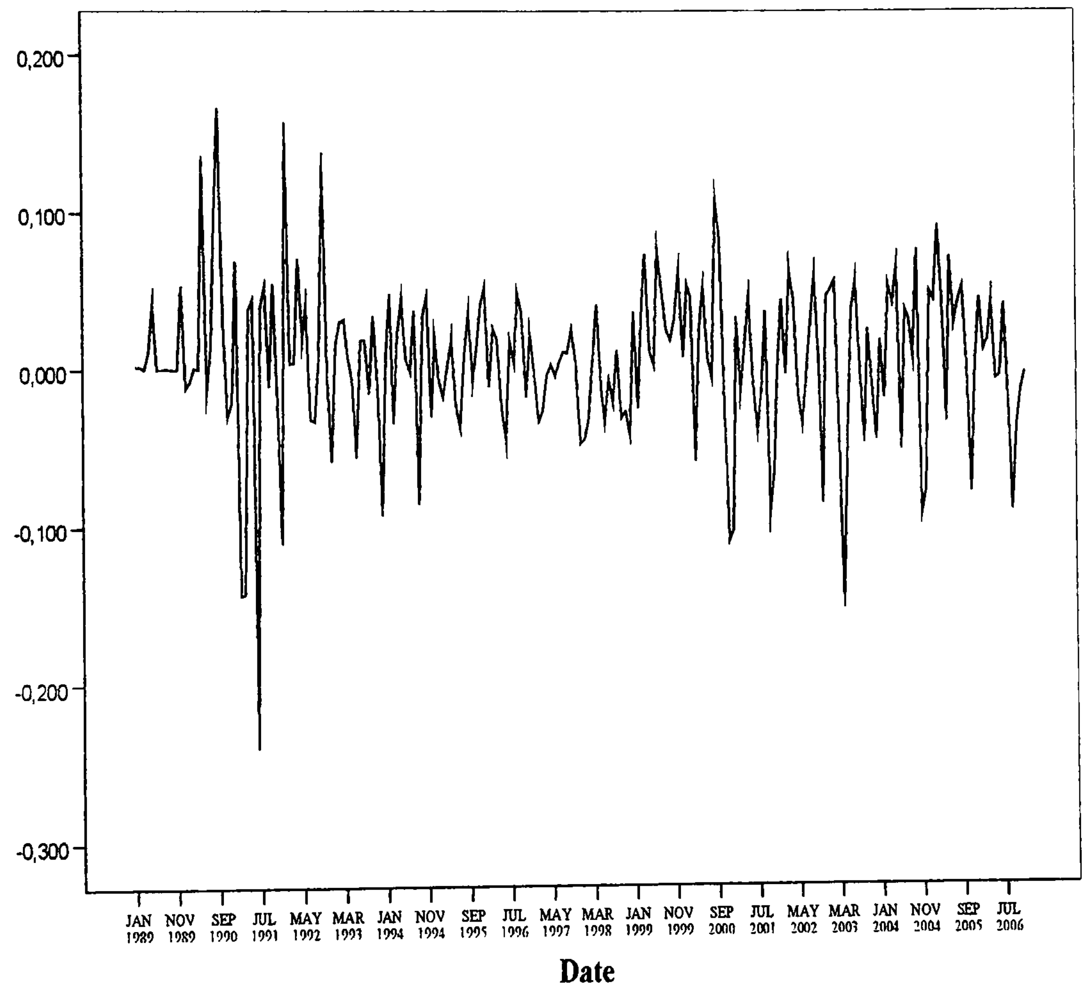


Figure VII.2: **The first difference series of the petroleum derivatives index (1989–2006)**

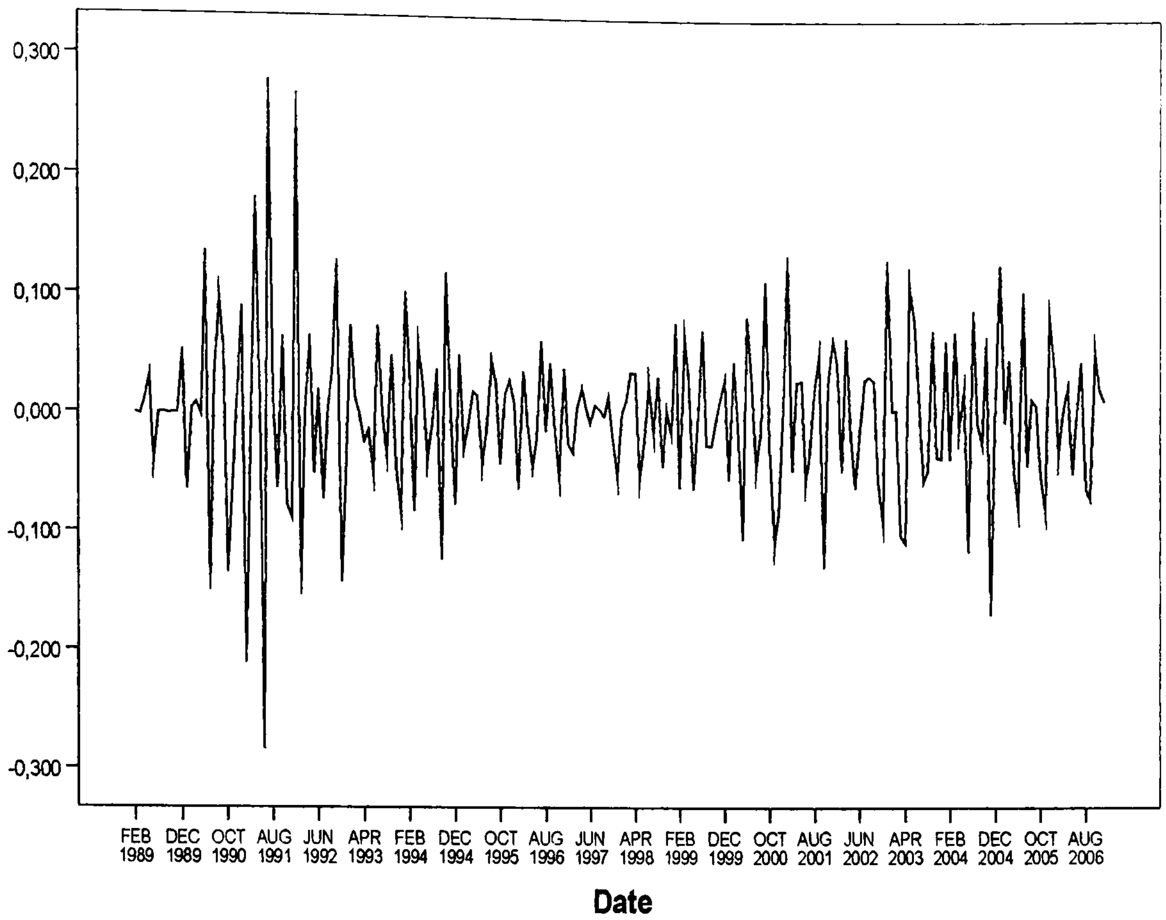
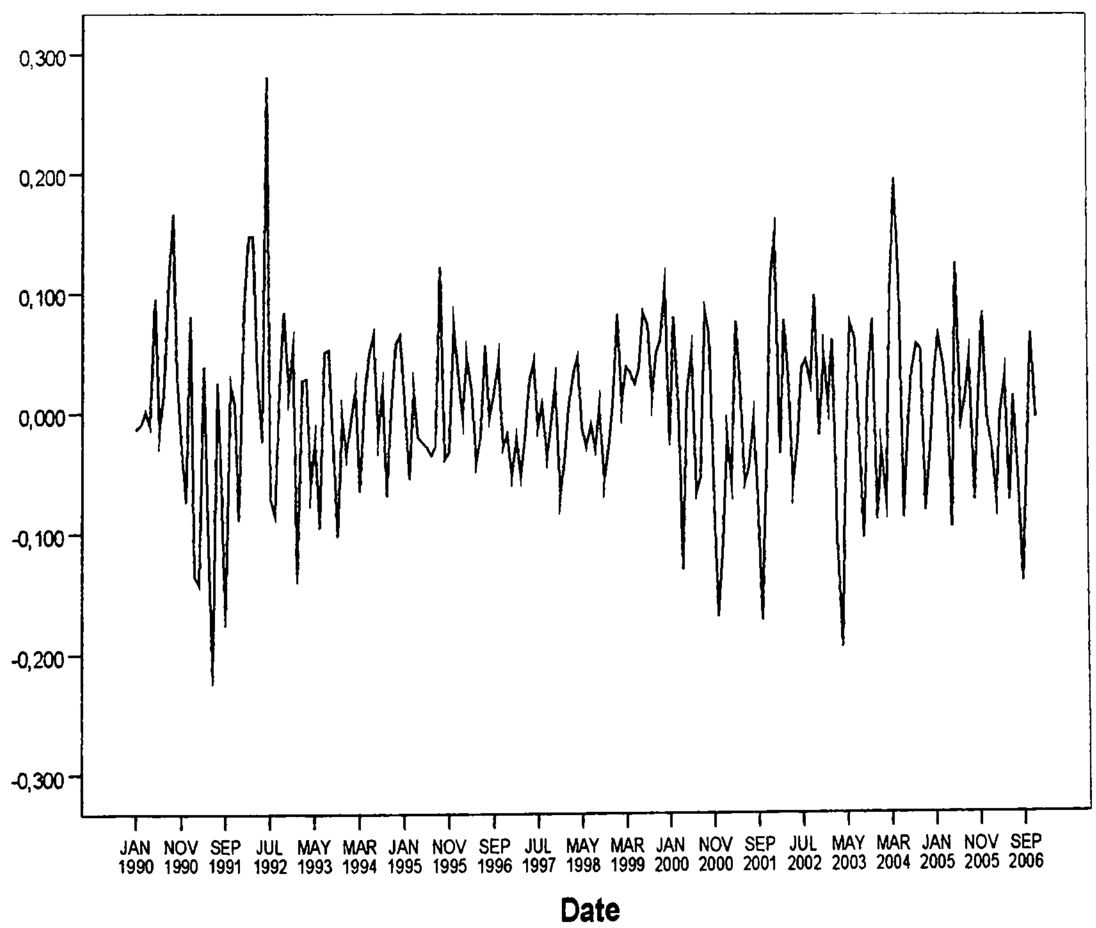


Figure VII.3: **The first seasonal difference series of the petroleum derivatives index (1989–2006)**



The figures presented above show that the series is already stationary as there is no trend in the observed values. This is the reason that we proceed to the examination of the index without the need to examine the first differences of the series.

2. Seasonal Autocorrelations and Partial Autocorrelations

Figure VII.4: **The seasonal autocorrelations of the series**

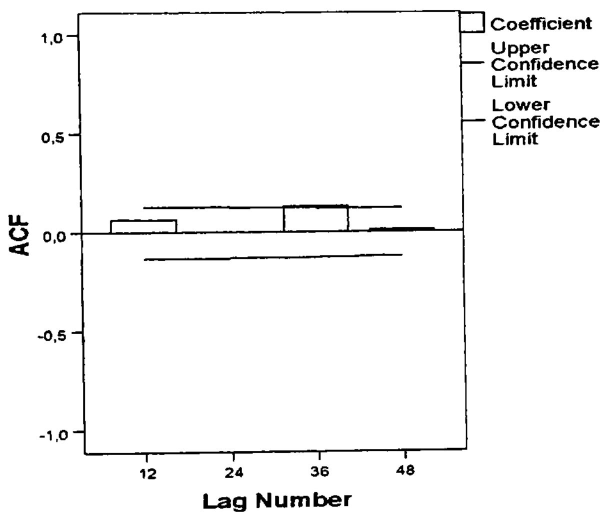


Figure VII.5: **The seasonal partial autocorrelations of the series**

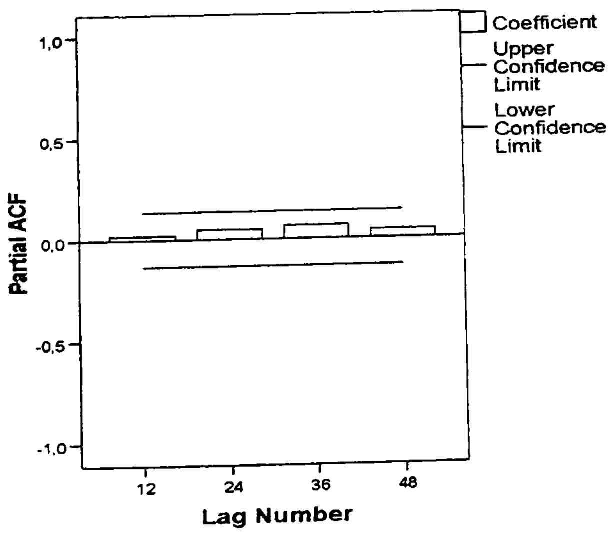


Table VII.1: **The seasonal autocorrelation statistics of the series**

Lag	Autocorrelation	Std. Error(a)	Box-Ljung Statistic		
			Value	Df	Sig.(b)
12	.064	.066	22.588	12	.031
24	.001	.064	38.285	24	.032
36	.131	.062	48.154	36	.085
48	.013	.060	60.111	48	.113

According to figures 4 and 5 and table 1, always based on the Box-Jenkins (1976) methodology, no model can be derived, so we proceed to the examination of the non-seasonal autocorrelations and partial autocorrelations of the series.

3. Non-seasonal Autocorrelations and Partial Autocorrelations

Figure VII.6: **The non-seasonal autocorrelations of the series**

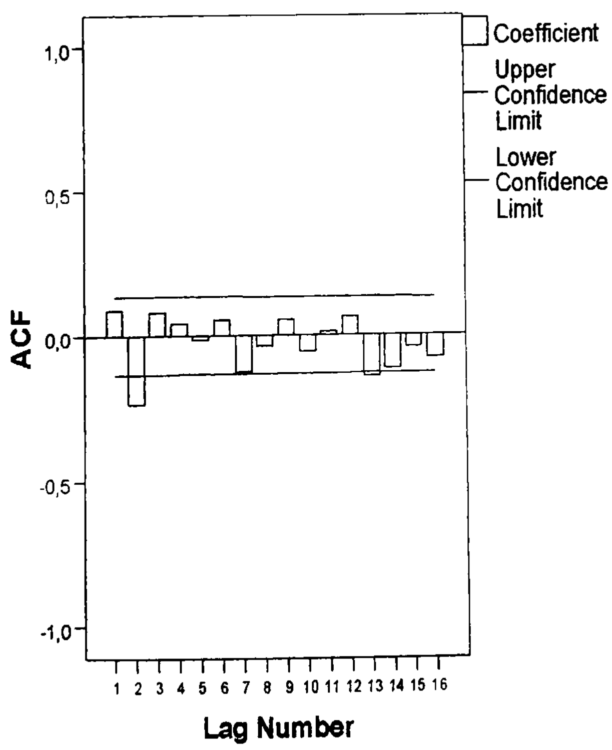
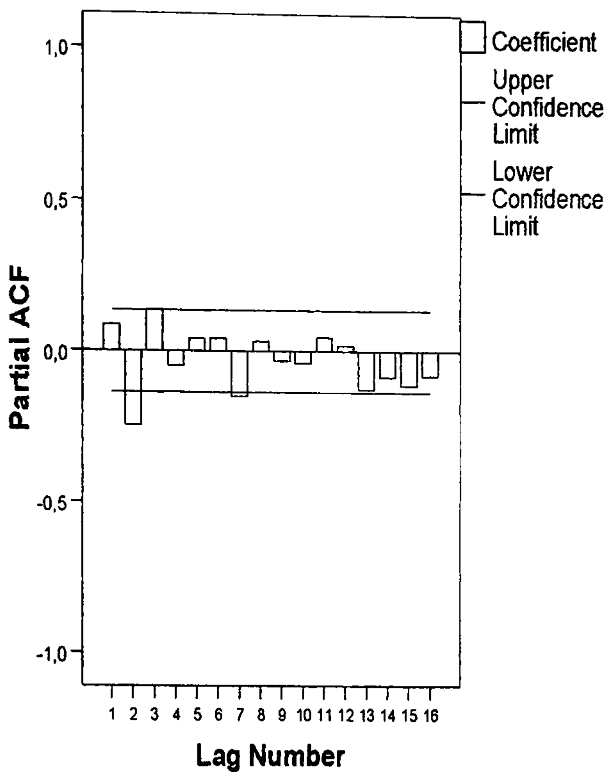


Figure VII.7: **The non-seasonal partial autocorrelations of the series**



According to the above, the potential models are the ARIMA (2,0,0) (0,0,0) and the ARIMA (0,0,2) (0,0,0). The examination of the two models led us to the conclusion that the best model is the ARIMA (0,0,2) (0,0,0).

3.1 ARIMA (0,0,2) (0,0,0)

Table 2 presents the model statistics of the ARIMA (0,0,2) (0,0,0) model while table 3 presents the respective model parameters:

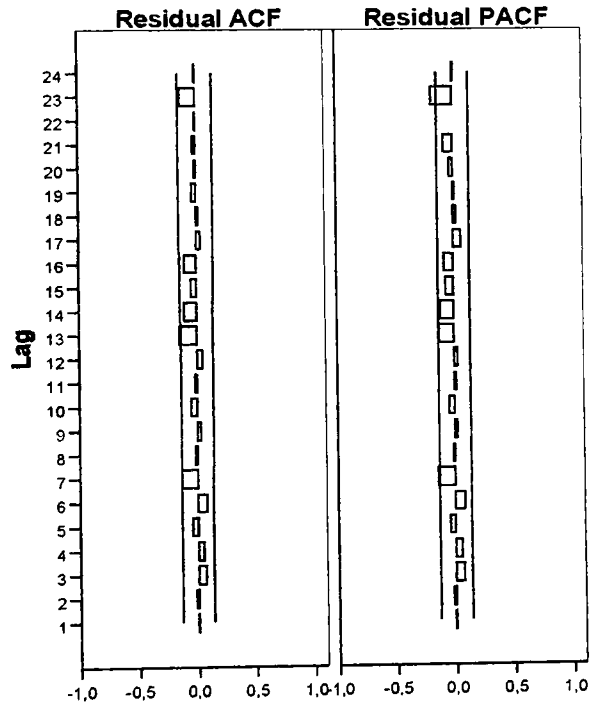
Table VII.2: **The model statistics of the ARIMA (0,0,2) (0,0,0)**

Model	Number of Predictors	Model Fit statistics			Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	MAPE	MaxAPE	Statistics	DF	Sig.	
Petroleum and Other Fuels Index	0	.077	216.840	12898.724	20.252	16	.209	0

Table VII.3: **The model parameters of the ARIMA (0,0,2) (0,0,0)**

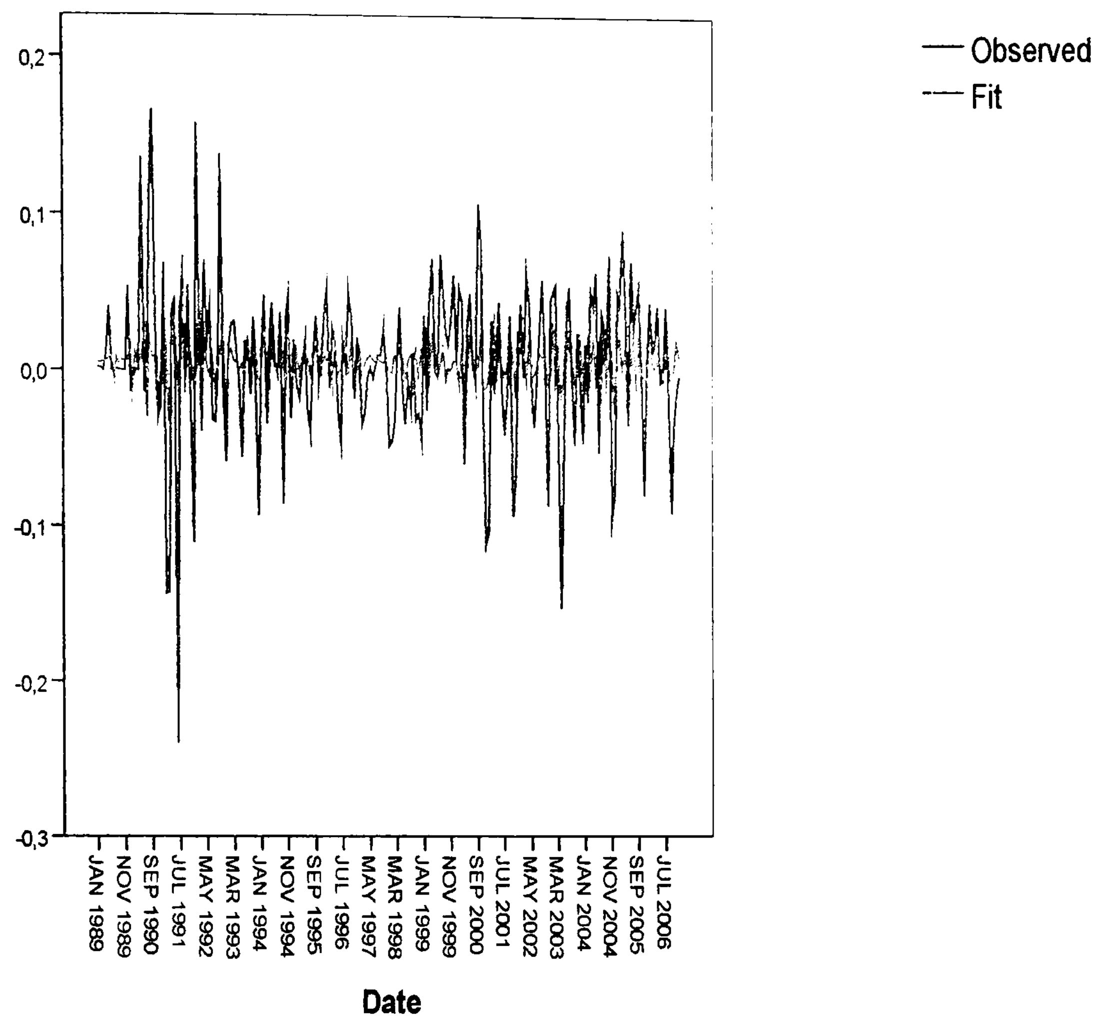
					Estimate	SE	t	Sig.
odi-Model_1	odi	No Transformation	Constant		.005	.003	1.756	.081
			MA	Lag 1	-.153	.067	-2.299	.023
				Lag 2	.231	.067	3.457	.001

***Figure VII.8*: The autocorrelations and the partial autocorrelations of residuals of the ARIMA (0,0,2) (0,0,0) model**



Although the final series is not the most satisfying one, it is the best that can be derived from an ARIMA model, giving us a series of residuals that is used in the application of the macroeconomic APT model. In figure 9 the observed and the fitted values of the index are presented.

***Figure VII.9*: The observed and the fitted values of the petroleum derivatives series (1989–2006)**



As in the case of the inflation rate (chapter four) and the industrial production index (Appendix VI), we need the series of errors (the residuals) which is calculated as the difference between the expected and the observed values of the index.

Appendix VIII
Time-series Regression Results and Joint Test Results for all Portfolios

***Table VIII.1*: Time-series regression results between the factor scores and the macrovariables (all portfolios, whole period 1989–2006)**

Factor	Constant	CEI_t	UI_t	$UCPS_t$	RMI_t	R^2
1	-0.012	12.994	49.318	-2.469	0.263	0.036
	-0.153	0.795	2.448	-1.193	0.266	
	0.879	0.428	0.015	0.234	0.791	
2	-0.019	-14.098	-19.274	-2.549	0.429	0.031
	-0.249	-0.929	-1.031	-1.328	0.466	
	0.804	0.354	0.304	0.186	0.642	
3	-0.018	-19.170	16.662	0.261	-0.877	0.018
	-0.214	-1.157	0.816	0.125	-0.874	
	0.831	0.249	0.415	0.901	0.384	
4	0.041	-10.352	-14.688	-1.308	0.465	0.013
	0.521	-0.658	-0.758	-0.657	0.488	
	0.603	0.512	0.450	0.512	0.626	
5	0.000	-2.779	7.726	0.184	-0.182	0.002
	-0.005	-0.182	0.410	0.095	-0.196	
	0.996	0.856	0.682	0.924	0.845	
6	0.018	10.700	37.358	1.517	-0.143	0.033
	0.223	0.644	1.825	0.722	-0.142	
	0.824	0.520	0.070	0.471	0.887	
7	-0.002	-13.440	2.903	-0.975	-1.174	0.014
	-0.032	-0.854	0.150	-0.490	-1.231	
	0.975	0.394	0.881	0.625	0.220	
8	0.052	24.078	-7.652	-2.895	0.334	0.030
	0.641	1.474	-0.380	-1.401	0.337	
	0.522	0.142	0.704	0.163	0.736	
9	0.008	1.818	7.048	-2.629	0.290	0.010
	0.095	0.113	0.354	-1.287	0.296	
	0.925	0.910	0.724	0.200	0.768	
10	-0.057	-23.313	-13.267	-1.405	0.566	0.022
	-0.705	-1.426	-0.659	-0.679	0.571	
	0.482	0.156	0.511	0.498	0.569	
11	0.038	4.465	40.948	-1.454	-1.230	0.039
	0.516	0.299	2.226	-0.770	-1359	
	0.607	0.765	0.027	0.442	0.176	
12	0.002	-25.653	22.680	-0.882	-0.018	0.025

	0.020 0.984	-1.572 0.118	1.128 0.261	-0.427 0.670	-0.018 0.986	
13	0.007 0.090 0.928	10.508 0.627 0.532	-14.853 -0.719 0.473	-2.451 -1.156 0.249	0.288 0.284 0.777	0.019
Joint Test		0.504	0.121	0.583	0.971	

Note: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.

***Table VIII.2*: Time-series regression results between the factor scores and the macrovariables (portfolio 1, whole period 1989–2006)**

Factor	Constant	CEI_t	UI_t	$UCPS_t$	RMI_t	R^2
1	-0.035 -0.919 0.359	11.759 1.728 0.085	3.302 0.406 0.685	-0.981 -1.201 0.231	8.646 21.256 0.000	0.696
2	-0.016 -0.230 0.818	-17.986 -1.503 0.134	-26.837 -1.878 0.062	1.038 0.723 0.471	2.234 3.123 0.002	0.061
3	-0.012 -0.177 0.860	-15.140 -1.258 0.210	-2.576 -0.179 0.858	-2.064 -1.428 0.155	1.646 2.288 0.023	0.045
4	-0.008 -0.121 0.904	-7.596 -0.641 0.522	-16.798 -1.186 0.237	-1.120 -0.787 0.432	2.605 3.675 0.000	0.073
5	-0.020 -0.289 0.773	-16.942 -1.401 0.163	19.001 1.316 0.190	1.987 1.369 0.173	0.537 0.743 0.458	0.034
6	0.007 0.099 0.921	32.716 2.742 0.007	26.978 1.893 0.060	0.355 0.248 0.804	1.006 1.410 0.160	0.065
Joint Test		**0.007***	0.102	0.314	**0.013***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

Table VIII.3: **Time-series regression results between the factor scores and the macrovariables (portfolio 2, whole period 1989–2006)**

Factor	Constant	CEI_t	UI_t	$UCPS_t$	RMI_t	R^2
1	-0.030	-2.509	8.561	-0.666	6.185	0.356
	-0.544	-0.253	0.724	-0.560	10.444	
	0.587	0.800	0.470	0.576	0.000	
2	-0.008	-9.637	5.131	0.686	0.362	0.006
	-0.114	-0.783	0.349	0.464	0.491	
	0.910	0.434	0.727	0.643	0.624	
3	-0.013	-4.632	-10.150	-1.485	3.056	0.095
	-0.202	-0.395	-0.724	-1.054	4.357	
	0.840	0.693	0.470	0.293	0.000	
4	-0.014	-3.117	4.967	0.159	2.210	0.046
	-0.203	-0.259	0.345	0.110	3.071	
	0.840	0.796	0.730	0.912	0.002	
5	-0.007	-17.781	-11.521	-2.584	0.614	0.038
	-0.105	-1.469	-0.797	-1.778	0.848	
	0.916	0.143	0.426	0.077	0.397	
6	-0.003	-11.976	-22.485	-0.750	0.196	0.021
	-0.046	-0.991	-1.558	-0.517	0.271	
	0.963	0.323	0.121	0.606	0.787	
7	0.004	-15.362	-33.371	-0.249	-1.538	0.062
	0.062	-1.286	-2.338	-0.174	-2.152	
	0.951	0.200	0.020	0.862	0.033	
8	0.002	-2.460	-1.794	3.266	-0.477	0.028
	0.031	-0.202	-0.123	2.235	-0.655	
	0.975	0.840	0.902	0.026	0.513	
Joint Test		0.671	0.309	0.303	**0.092***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
***Indicates significance at the 10 per cent level for the joint test.

***Table VIII.4*: Time-series regression results between the factor scores and the macrovariables (all portfolios, first sub-period 1989–1994)**

Factor	Constant	CEI_t	UI_t	$UCPS_t$	RMI_t	R^2
1	0.026	13.686	-3.926	-0.440	6.711	0.642
	0.345	1.380	-0.352	-0.349	10.022	
	0.732	0.172	0.726	0.728	0.000	
2	0.015	-9.186	-17.348	2.286	2.901	0.111
	0.131	-0.588	-0.986	1.151	2.750	
	0.896	0.559	0.328	0.254	0.008	
3	-0.028	-6.452	47.938	-0.312	1.722	0.160
	-0.244	-0.426	2.814	-0.162	1.686	
	0.808	0.671	0.006	0.872	0.097	
4	0.008	-10.609	-5.110	-1.744	2.193	0.089
	0.066	-0.673	-0.288	-0.870	2.060	
	0.948	0.504	0.774	0.387	0.043	
5	0.050	26.797	-17.384	-0.210	0.654	0.064
	0.422	1.707	-0.983	-0.105	0.617	
	0.675	0.093	0.329	0.916	0.540	
6	-0.002	-5.668	-0.139	-1.558	0.405	0.015
	-0.018	-0.344	-0.007	-0.744	0.364	
	0.986	0.732	0.994	0.460	0.717	
7	0.010	3.270	-17.625	-1.288	1.299	0.048
	0.083	0.204	-0.975	-0.632	1.199	
	0.934	0.839	0.333	0.530	0.235	
8	0.001	-24.583	-14.215	-1.922	0.514	0.070
	0.007	-1.535	-0.788	-0.945	0.476	
	0.994	0.130	0.433	0.348	0.636	
9	0.004	29.169	21.076	0.453	0.744	0.094
	0.033	1.846	1.184	0.226	0.697	
	0.974	0.069	0.241	0.822	0.488	
10	-0.005	-23.865	-2.601	0.792	1.372	0.048
	-0.043	-1.486	-0.144	0.388	1.266	
	0.966	0.142	0.886	0.699	0.210	
11	-0.002	-1.807	4.660	-0.046	1.086	0.017
	-0.018	-0.110	0.252	-0.022	0.978	
	0.986	0.913	0.802	0.982	0.332	
12	-0.035	-28.300	13.996	2.565	1.077	0.079
	-0.295	-1.787	0.785	1.274	1.007	
	0.769	0.079	0.436	0.207	0.318	
13	-0.024	-19.202	23.462	-1.061	0.610	0.053
	-0.195	-1.197	1.299	-0.521	0.564	
	0.846	0.235	0.198	0.604	0.575	
Joint Test		0.133	0.351	0.937	**0.083*****	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
***Indicates significance at the 10 per cent level for the joint test.

***Table VIII.5*: Time-series regression results between the factor scores and the macrovariables (portfolio 1, first sub-period 1989–1994)**

Factor	Constant	CEI_t	UI_t	$UCPS_t$	RMI_t	R^2
1	0.004	1.973	13.931	-0.735	5.862	0.498
	0,047	0.168	1.052	-0.492	7.384	
	0.963	0.867	0.297	0.625	0.000	
2	0.031	2.405	-11.185	-1.750	3.652	0.212
	0.282	0.164	-0.679	-0.941	3.697	
	0.779	0.870	0.500	0.350	0.000	
3	0.004	-17.545	-4.706	2.094	3.486	0.155
	0.032	-1.151	-0.274	1.081	3.386	
	0.975	0.254	0.785	0.284	0.001	
4	0.010	1.824	-7.227	0.881	2.184	0.062
	0.081	0.113	-0.399	0.432	2.013	
	0.936	0.910	0.691	0.668	0.048	
5	0.003	33.763	25.460	0.007	1.114	0.135
	0.022	2.187	1.464	0.004	1.068	
	0.983	0.032	0.148	0.997	0.289	
6	0.015	-6.038	-18.002	-1.942	0.951	0.050
	0.120	-0.375	-0.991	-0.948	0.873	
	0.905	0.709	0.325	0.347	0.386	
Joint Test		0.523	0.519	0.746	**0.018***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

Table VIII.6: **Time-series regression results between the factor scores and the macrovariables (portfolio 2, first sub-period 1989–1994)**

Factor	Constant	CEI_t	UI_t	$UCPS_t$	RMI_t	R^2
1	0.011 0.110 0.913	0.609 0.048 0.962	16.305 1.138 0.259	-0.959 -0.593 0.555	5.233 6.089 0.000	0.410
2	0.064 0.549 0.585	27.967 1.823 0.073	-22.570 -1.306 0.196	-0.626 -0.321 0.749	0.939 0.907 0.368	0.088
3	-0.018 -0.153 0.879	-8.956 -0.563 0.576	30.797 1.718 0.091	-0.313 -0.155 0.877	1.389 1.292 0.201	0.077
4	0.001 0.007 0.995	-20.898 -1.322 0.191	-7.794 -0.438 0.663	-2.575 -1.282 0.204	1.535 1.438 0.155	0.093
5	0.014 0.119 0.905	-10.828 -0.711 0.480	-17.535 -1.023 0.310	1.812 0.937 0.352	3.311 3.220 0.002	0.142
6	0.032 0.273 0.786	16.369 1.062 0.292	-35.205 -2.028 0.047	0.202 0.103 0.918	1.905 1.830 0.072	0.115
7	-0.007 -0.056 0.955	8.312 0.513 0.610	7.547 0.413 0.681	-0.674 -0.327 0.744	1.435 1.311 0.194	0.043
8	-0.030 -0.241 0.811	-4.257 -0.261 0.795	13.728 0.746 0.458	0.045 0.022 0.983	0.601 0.545 0.588	0.015
9	-0.037 -0.315 0.754	-29.464 -1.891 0.063	17.496 0.997 0.322	2.342 1.183 0.241	1.894 1.800 0.076	0.109
Joint Test		0.298	0.135	0.897	**0.006***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

Table VIII.7: **Time-series regression results between the factor scores and the macrovariables (all portfolios, second sub-period 1995–2000)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.074	26.785	3.156	3.937	0.030	8.768	0.770
	-1.148	1.810	0.148	1.616	0.015	14.285	
	0.255	0.075	0.883	0.111	0.988	0.000	
2	-0.062	-14.858	-44.981	-1.180	3.490	0.976	0.033
	-0.470	-0.490	-1.030	-0.236	0.846	0.776	
	0.640	0.626	0.307	0.814	0.401	0.441	
3	-0.048	-38.121	-22.621	-3.633	-2.257	1.397	0.061
	-0.366	-1.275	-0.526	-0.738	-0.555	1.127	
	0.715	0.207	0.601	0.463	0.581	0.264	
4	-0.045	-27.723	-18.524	-6.361	-1.559	3.089	0.128
	-0.357	-0.962	-0.447	-1.341	-0.398	2.585	
	0.722	0.339	0.657	0.185	0.692	0.012	
5	0.056	-11.468	64.780	-4.490	-1.211	0.924	0.063
	0.427	-0.384	1.506	-0.913	-0.298	0.745	
	0.671	0.702	0.137	0.365	0.767	0.459	
6	-0.029	-15.820	-16.378	-0.851	0.048	0.489	0.009
	-0.214	-0.515	-0.370	-0.168	0.011	0.384	
	0.831	0.608	0.712	0.867	0.011	0.702	
7	-0.126	-25.786	-86.029	4.379	3.898	1.036	0.081
	-0.974	-0.872	-2.020	0.899	0.968	0.844	
	0.333	0.387	0.047	0.372	0.336	0.402	
8	-0.070	-27.090	-66.493	-7.553	0.841	1.349	0.099
	-0.547	-0.925	-1.577	-1.566	0.211	1.110	
	0.586	0.358	0.120	0.122	0.833	0.271	
Joint Test		0.380	0.244	0.311	0.469	0.227	

Note: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.

Table VIII.8: **Time-series regression results between the factor scores and the macrovariables (portfolio 1, second sub-period 1995–2000)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.116	-25.146	-72.571	-5.126	0.166	4.994	0.293
	-1.022	-0.969	-1.943	-1.200	0.047	4.640	
	0.310	0.336	0.056	0.234	0.963	0.000	
2	-0.019	33.585	46.647	3.332	-0.493	7.853	0.662
	-0.241	1.873	1.807	1.128	-0.202	10.557	
	0.810	0.065	0.075	0.263	0.840	0.000	
3	-0.003	-29.488	41.032	1.088	-0.336	1.392	0.066
	-0.022	-0.989	0.956	0.222	-0.083	1.126	
	0.983	0.326	0.343	0.825	0.934	0.264	
4	-0.105	-27.320	-81.602	-2.483	3.469	1.525	0.087
	-0.819	-0.927	-1.923	-0.512	0.865	1.247	
	0.416	0.357	0.059	0.611	0.390	0.217	
5	-0.080	-50.555	-58.976	-6.125	0.774	0.805	0.097
	-0.629	-1.725	-1.398	-1.269	0.194	0.662	
	0.532	0.089	0.167	0.209	0.847	0.510	
Joint Test		**0.079*****	**0.013***	0.433	0.986	0.719	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test
***Indicates significance at the 10 per cent level for the joint test.

Table VIII.9: **Time-series regression results between the factor scores and the macrovariables (portfolio 2, second sub-period 1995–2000)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.081	-29.315	-42.408	-2.216	-2.308	3.252	0.142
	-0.649	-1.026	-1.031	-0.471	-0.594	2.743	
	0.519	0.309	0.306	0.639	0.555	0.008	
2	-0.058	-22.178	-27.855	-4.092	1.485	2.833	0.104
	-0.458	-0.759	-0.662	-0.851	0.374	2.338	
	0.649	0.450	0.510	0.398	0.710	0.022	
3	-0.090	26.070	-31.579	1.852	2.580	7.434	0.542
	-0.984	1.248	-1.050	0.539	0.908	8.579	
	0.329	0.216	0.297	0.592	0.367	0.000	
4	0.007	-34.283	29.176	-6.639	-3.379	1.943	0.090
	0.054	-1.165	0.689	-1.370	-0.844	1.591	
	0.957	0.248	0.494	0.175	0.402	0.116	
5	-0.063	-39.585	-26.664	0.415	3.114	0.333	0.036
	-0.479	-1.307	-0.612	0.083	0.756	0.265	
	0.633	0.196	0.543	0.934	0.453	0.792	

Joint Test		0.220	0.553	0.686	0.699	**0.014***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

***Table VIII.10*: Time-series regression results between the factor scores and the macrovariables (portfolio 3, second sub-period 1995–2000)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.057 -0.769 0.445	26.775 1.566 0.122	19.826 0.805 0.424	5.145 1.827 0.072	0.352 0.151 0.880	8.116 11.439 0.000	0.693
2	-0.009 -0.072 0.943	-2.684 -0.093 0.926	-9.424 -0.227 0.821	-8.913 -1.874 0.065	-1.706 -0.434 0.666	3.070 2.562 0.013	0.124
3	-0.060 -0.460 0.647	-20.854 -0.694 0.490	-51.582 -1.193 0.237	-4.366 -0.883 0.381	0.738 0.181 0.857	1.182 0.949 0.346	0.052
4	-0.121 -0.973 0.334	-50.836 -1.778 0.080	-76.537 -1.859 0.067	-2.989 -0.635 0.528	1.492 0.383 0.703	2.269 1.913 0.060	0.141
5	-0.055 -0.436 0.664	-40.561 -1.394 0.168	-3.531 -0.084 0.933	0.616 0.129 0.898	-3.201 -0.809 0.422	2.481 2.055 0.044	0.110
6	-0.061 -0.462 0.646	-3.360 -0.111 0.912	-40.242 -0.922 0.360	1.424 0.285 0.776	3.869 0.938 0.352	1.290 1.025 0.309	0.034
Joint Test		0.264	0.400	0.260	0.921	**0.014***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

Table VIII.11: **Time-series regression results between the factor scores and the macrovariables (portfolio 4, second sub-period 1995–2000)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.042	5.868	11.197	-3.584	-2.278	7.396	0.525
	-0.456	0.276	0.366	-1.023	-0.787	8.382	
	0.650	0.783	0.716	0.310	0.434	0.000	
2	-0.097	-21.573	-45.765	3.665	6.094	1.920	0.088
	-0.752	-0.732	-1.079	0.756	1.520	1.571	
	0.455	0.467	0.284	0.453	0.133	0.121	
3	-0.108	-44.038	-79.107	-5.353	1.600	1.907	0.130
	-0.857	-1.530	-1.909	-1.130	0.409	1.598	
	0.395	0.131	0.061	0.263	0.684	0.115	
4	0.003	-25.775	7.329	-7.520	-4.575	1.467	0.070
	0.027	-0.866	0.171	-1.535	-1.130	1.189	
	0.979	0.389	0.865	0.130	0.263	0.239	
5	-0.060	2.433	-39.554	5.151	-1.659	1.371	0.062
	-0.462	0.081	-0.920	1.047	-0.408	1.106	
	0.646	0.935	0.361	0.299	0.685	0.273	
Joint Test		0.619	0.349	0.218	0.450	0.172	

Note: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.

Table VIII.12: **Time-series regression results between the factor scores and the macrovariables (portfolio 5, second sub-period 1995–2000)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.016	-13.963	25.453	-2.933	-4.564	4.567	0.225
	-0.136	-0.514	0.651	-0.656	-1.235	4.053	
	0.892	0.609	0.517	0.514	0.221	0.000	
2	-0.160	-40.562	-118.633	0.280	1.827	2.083	0.176
	-1.308	-1.448	-2.942	0.061	0.479	1.792	
	0.195	0.152	0.004	0.952	0.633	0.078	
3	-0.042	-26.990	-16.997	-1.546	1.846	0.830	0.026
	-0.314	-0.887	-0.388	-0.308	0.446	0.657	
	0.755	0.379	0.699	0.759	0.657	0.513	
4	-0.008	-18.600	-4.323	-6.399	1.195	0.822	0.042
	-0.057	-0.616	-0.099	-1.287	0.291	0.657	
	0.955	0,540	0.921	0.203	0.772	0.514	
5	-0.023	9.605	-5.082	0.686	4.330	1.736	0.055
	-0.174	0.320	-0.118	0.139	1.061	1.394	
	0.863	0.750	0.907	0.890	0.293	0.168	
6	-0.047	17.213	-36.754	5.405	-0.788	1.262	0.055
	-0.363	0.574	-0.851	1.094	-0.193	1.014	

	0.718	0.568	0.398	0.278	0.848	0.314	
7	0.032	10.882	10.904	-3.144	0.521	-0.502	0.015
	0.240	0.355	0.247	-0.623	0.125	-0.395	
	0.811	0.723	0.805	0.535	0.901	0.694	
Joint Test		0.740	0.708	0.817	0.874	0.421	

Note: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.

***Table VIII.13*: Time-series regression results between the factor scores and the macrovariables (all portfolios, third sub-period 2001–2006)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.025	-6.294	-16.204	-0.327	-5.060	3.220	0.122
	-0.209	-0.234	-0.459	-0.066	-1.837	1.741	
	0.835	0.816	0.648	0.948	0.071	0.086	
2	-0.011	-37.913	-20.003	6.647	-0.049	5.966	0.168
	-0.096	-1.448	-0.582	1.377	-0.018	3.314	
	0.924	0.152	0.563	0.173	0.986	0.001	
3	-0.041	24.622	54.454	6.877	-1.220	2.191	0.078
	-0.333	0.893	1.504	1.354	-0.432	1.156	
	0.740	0.375	0.137	0.180	0.667	0.252	
4	-0.040	-18.294	-16.923	0.233	0.408	8.195	0.271
	-0.365	-0.746	-0.526	0.052	0.162	4.861	
	0.716	0.458	0.601	0.959	0.872	0.000	
5	-0.061	12.293	22.473	-4.272	-3.766	3.215	0.094
	-0.498	0.450	0.626	-0.848	-1.346	1.712	
	0.620	0.654	0.533	0.399	0.183	0.092	
6	0.031	-23.358	-35.967	4.005	6.605	4.120	0.135
	0.262	-0.875	-1.026	0.814	2.416	2.244	
	0.794	0.385	0.309	0.419	0.018	0.028	
Joint Test		0.576	0.561	0.554	0.120	**0.000***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

Table VIII.14: **Time-series regression results between the factor scores and the macrovariables (portfolio 1, third sub-period 2001–2006)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.054 -0.590 0.557	-27.207 -1.329 0.188	-27.215 -1.012 0.315	-1.088 -0.288 0.774	0.438 0.209 0.835	10.927 7.765 0.000	0.492
2	-0.008 -0.063 0.950	10.275 0.384 0.702	5.902 0.168 0.867	8.962 1.817 0.074	1.009 0.368 0.714	4.938 2.684 0.009	0.131
3	-0.030 -0.250 0.803	-13.662 -0.511 0.611	5.514 0.157 0.876	3.069 0.623 0.535	-7.474 -2.731 0.008	1.062 0.578 0.565	0.134
Joint Test		0.539	0.826	0.323	**0.098*** **	0.102	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
***Indicates significance at the 10 per cent level for the joint test.

Table VIII.15: **Time-series regression results between the factor scores and the macrovariables (portfolio 2, third sub-period 2001–2006)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.106 -1.017 0.313	-37.382 -1.598 0.115	34.631 1.128 0.264	-4.141 -0.961 0.340	-3.384 -1.413 0.162	7.390 4.596 0.000	0.336
2	-0.020 -0.158 0.875	-8.032 -0.288 0.774	3.620 0.099 0.922	2.896 0.563 0.575	-4.527 -1.585 0.118	1.296 0.676 0.502	0.056
3	0.054 0.492 0.624	2.172 0.087 0.931	-90.035 -2.757 0.008	3.429 0.748 0.457	3.266 1.282 0.204	6.538 3.824 0.000	0.250
4	-0.022 -0.191 0.849	58.804 2.239 0.029	52.854 1.533 0.130	10.593 2.189 0.032	-0.826 -0.307 0.760	2.293 1.270 0.209	0.163
5	-0.099 -0.851 0.398	-15.811 -0.605 0.547	64.158 1.869 0.066	0.513 0.106 0.916	-6.589 -2.461 0.016	3.410 1.897 0.062	0.171
Joint Test		0.209	**0.015***	0.292	**0.030***	0.434	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

Table VIII.16: **Time-series regression results between the factor scores and the macrovariables (portfolio 3, third sub-period 2001–2006)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.024	-5.403	-11.002	3.901	-1.869	5.794	0.150
	-0.207	-0.204	-0.316	0.800	-0.690	3.184	
	0.837	0.839	0.753	0.427	0.493	0.002	
2	-0.013	-17.951	3.781	13.769	-1.599	5.985	0.223
	-0.120	-0.709	0.114	2.952	-0.617	3.440	
	0.905	0.481	0.910	0.004	0.539	0.001	
3	0.035	12.701	-75.295	-1.652	1.630	5.041	0.175
	0.301	0.487	-2.199	-0.344	0.610	2.812	
	0.765	0.628	0.031	0.732	0.544	0.006	
4	-0.047	-45.005	14.651	-4.209	-2.748	0.838	0.086
	-0.382	-1.639	0.406	-0.832	-0.978	0.444	
	0.704	0.106	0.686	0.408	0.332	0.659	
5	-0.067	10.743	25.656	-0.879	-4.013	4.993	0.147
	-0.565	0.405	0.737	-0.180	-1.478	2.739	
	0.574	0.687	0.464	0.858	0.144	0.008	
6	-0.060	50.671	61.605	-1.489	-1.491	1.348	0.082
	-0.487	1.842	1.706	-0.294	-0.529	0.713	
	0.628	0.070	0.093	0.770	0.598	0.478	
Joint Test		0.347	0.255	0.191	0.530	**0.000***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

Table VIII.17: **Time-series regression results between the factor scores and the macrovariables (portfolio 4, third sub-period 2001–2006)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.029	10.399	23.561	10.427	-1.383	5.341	0.165
	-0.246	0.396	0.684	2.157	-0.515	2.962	
	0.806	0.693	0.496	0.035	0.608	0.004	
2	-0.067	-11.362	-5.923	-5.534	-0.897	8.191	0.317
	-0.637	-0.479	-0.190	-1.265	-0.369	5.020	
	0.526	0.634	0.850	0.210	0.713	0.000	
3	-0.063	10.460	15.407	-1.905	-4.138	5.275	0.166
	-0.540	0.399	0.447	-0.394	-1.541	2.926	
	0.591	0.691	0.656	0.695	0.128	0.005	
4	0.021	-40.004	-39.236	4.389	0.479	2.809	0.068
	0.167	-1.443	-1.078	0.859	0.169	1.474	
	0.868	0.154	0.285	0.393	0.866	0.145	
5	0.013	13.730	-31.061	-2.725	1.923	2.396	0.045

	0.101 0.920	0.489 0.626	-0.843 0.402	-0.527 0.600	0.669 0.506	1.243 0.218	
6	-0.021 -0.173 0.863	-51.023 -1.909 0.061	6.319 0.180 0.858	1.906 0.387 0.700	-5.815 -2.125 0.037	-1.286 -0.700 0.486	0.133
Joint Test		0.394	0.843	0.290	0.298	**0.002***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

***Table VIII.18*: Time-series regression results between the factor scores and the macrovariables (portfolio 5, third sub-period 2001–2006)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0,055 -0.523 0.603	-38.091 -1.619 0.110	-13.289 -0.430 0.668	1.409 0.325 0.746	-2.897 -1.203 0.233	8.287 5.125 0.000	0.329
2	-0.044 -0.378 0.707	-26.374 -1.016 0.313	-10.195 -0.299 0.766	-0.052 -0.011 0.991	-2.710 -1.020 0.312	5.986 3.355 0.001	0.183
3	-0.058 -0.469 0.641	29.998 1.079 0.284	67.621 1.853 0.068	2.752 0.537 0.593	-2.291 -0.805 0.424	1,026 0.537 0.593	0.063
4	0.023 0.182 0.856	15.438 0.551 0.584	-22.838 -0.620 0.537	5.041 0.975 0.333	-0.383 -0.134 0.894	1.869 0.970 0.336	0.046
5	0.038 0.304 0.762	4.178 0.148 0.883	-32.181 -0.867 0.389	4.070 0.781 0.437	-0.280 -0.097 0.923	-0.029 -0.015 0.988	0.031
6	0.021 0.173 0.863	-20.277 -0.732 0.466	-11.633 -0.320 0.750	5.468 1.072 0.288	4.625 1.632 0.107	2.152 1.131 0.262	0.071
Joint Test		0.437	0.578	0.785	0.460	0.466	

Note: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.

Table VIII.19: **Time-series regression results between the factor scores and the macrovariables (portfolio 6, third sub-period 2001–2006)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.024	-27.160	-4.261	5.321	1.215	6.369	0.172
	-0.211	-1.039	-0.124	1.105	0.454	3.545	
	0.834	0.302	0.902	0.273	0.651	0.001	
2	-0.018	-14.707	-17.241	4.125	-4.264	4.284	0.139
	-0.154	-0.552	-0.493	0.840	-1.563	2.339	
	0.878	0.583	0.624	0.404	0.123	0.022	
3	-0.075	2.235	24.123	-2.587	-1.589	6.720	0.214
	-0.662	0.088	0.722	-0.552	-0.610	3.841	
	0.510	0.930	0.473	0.583	0.544	0.000	
4	-0.031	48.356	50.787	3.068	-0.254	0.787	0.070
	-0.253	1.746	1.397	0.601	-0.090	0.413	
	0.801	0.085	0.167	0.550	0.929	0.681	
5	-0.003	-44.314	-51.207	0.507	-4.118	4.094	0.194
	-0.028	-1.719	-1.512	0.107	-1.560	2.310	
	0.977	0.090	0.135	0.915	0.124	0.024	
6	0.003	-21.002	-22.989	2.559	0.685	3.260	0.049
	0.028	-0.750	-0.625	0.496	0.239	1.694	
	0.978	0.456	0.534	0.622	0.812	0.095	
7	-0.013	-34.543	36.370	5.943	-0.587	-1.669	0.079
	-0.106	-1.253	1.005	1.170	-0.208	-0.881	
	0.916	0.214	0.318	0.246	0.836	0.381	
Joint Test		0.205	0.466	0.715	0.657	**0.000***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

Table VIII.20: **Time-series regression results between the factor scores and the macrovariables (portfolio 7, third sub-period 2001–2006)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.005	-28.611	-15.762	6.154	-2.162	3.550	0.092
	-0.045	-1.045	-0.439	1.220	-0.772	1.887	
	0.964	0.300	0.662	0.227	0.443	0.064	
2	0.011	-56.732	-53.601	2.220	1.664	5.461	0.170
	0.090	-2.168	-1.560	0.460	0.621	3.036	
	0.928	0.034	0.124	0.647	0.537	0.003	
3	-0.028	23.875	0.903	-1.665	-5.391	1.636	0.093
	-0.231	0.873	0.025	-0.330	-1.925	0.870	
	0.818	0.386	0.980	0.742	0.059	0.387	
4	-0.049	-3.005	33.910	2.779	-3.817	2.378	0.059

	-0.398	-0.108	0.927	0.541	-1.338	1.242	
	0.692	0.914	0.357	0.590	0.185	0.219	
5	-0.069	-10.731	72.410	2.927	-0.719	1.667	0.094
	-0.565	-0.393	2.018	0.581	-0.257	0.887	
	0.574	0.696	0.048	0.563	0.798	0.378	
6	-0.017	-2.727	-16.938	-3.683	-0.323	3.095	0.054
	-0.135	-0.098	-0.462	-0.716	-0.113	1.612	
	0.893	0.922	0.646	0.477	0.910	0.112	
7	-0.033	63.144	52.241	4.356	-1.607	1.228	0.104
	-0.274	2.323	1.464	0.870	-0.577	0.657	
	0.785	0.023	0.148	0.388	0.566	0.513	
8	-0.006	18.981	6.764	3.811	-3.242	0.642	0.038
	-0.050	0.674	0.183	0.734	-1.124	0.331	
	0.960	0.503	0.855	0.465	0.265	0.741	
Joint Test		0.176	0.313	0.774	0.429	**0.016***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

***Table VIII.21*: Time-series regression results between the factor scores and the macrovariables (portfolio 8, third sub-period 2001–2006)**

Factor	Constant	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t	R^2
1	-0.056	-8.686	12.175	-0.016	-1,432	6.133	0.165
	-0.479	-0.331	0.353	-0.003	-0.533	3.401	
	0.634	0.742	0.725	0.997	0.596	0.001	
2	-0.032	-21.437	19.592	11.191	-3.346	4.660	0.166
	-0.270	-0.818	0.569	2.316	-1.247	2.586	
	0.788	0.416	0.571	0.024	0.217	0.012	
3	-0.004	-10.778	-35.962	-5.032	-1.038	2.407	0.065
	-0.030	-0.388	-0.987	-0.983	-0.365	1.262	
	0.976	0.699	0.327	0.329	0.716	0.212	
4	-0.049	24.663	44.874	-0.234	-3.508	0.591	0.038
	-0.389	0.876	1.213	-0.045	-1.216	0.305	
	0.699	0.384	0.327	0.964	0.228	0.761	
5	0.013	-19.419	-27.342	-0.263	0.751	1.282	0.016
	0.101	-0.682	-0.731	-0.050	0.258	0.655	
	0.920	0.498	0.467	0.960	0.797	0.515	
6	-0.010	-58.041	2.718	2.965	0.486	0.833	0.074
	-0.079	-2.100	0.075	0.582	0.172	0.439	
	0.938	0.040	0.941	0.562	0.864	0.662	
7	0.014	-35.920	8.502	11.886	3.067	2.093	0.126
	0.115	-1.338	0.241	2.403	1.116	1.134	
	0.909	0.185	0.810	0.019	0.269	0.261	

8	-0.028 -0.225 0.823	3.208 0.114 0.910	19.580 0.529 0.599	-1.146 -0.221 0.826	-4.394 -1.522 0.133	-0.750 -0.387 0.700	0.036
9	-0.026 -0.213 0.832	41.515 1.538 0.129	22.823 0.644 0.522	4.689 0.943 0.349	-6.079 -2.200 0.031	1.197 0.645 0.521	0.117
Joint Test		0.306	0.909	0.259	0.228	**0.015***	

Notes: The first row in each cell indicates the beta coefficient, the second row the t-statistic and the third row the respective p-value.
*Indicates significance at the 5 per cent level for the joint test.

Appendix IX
Canonical Correlation Test Results for all the Portfolios

***Table IX.1*: Canonical correlation between artificial factors and macrovariables (all portfolios, whole period 1989–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UCPS_t$	RMI_t
1	0.919	0.118	437.723	52.000	**0.000**	-0.075	-0.088	0.143	**-0.998**
2	0.387	0.756	56.955	36.000	**0.015**	**-0.689**	**-0.676**	-0.414	-0.003
3	0.294	0.889	23.940	22.000	0.350	-0.444	0.230	0.854	0.069
4	0.163	0.973	5.490	10.000	0.856	0.568	-0.694	0.281	0.000

Definition of columns:

Linear combination = The number of combinations between the two sets of variables in ascending order.

Squared canonical correlation = A value that shows the percentage of variance shared between the two sets of variables which a linear combination accounts for.

Wilk's Λ = A statistic that provides a good and commonly used multi-variate test and the corresponding chi-square (x^2) value that points the significant canonical variates (the best combination of the one set of variables).

Chi-square (x^2) = The respective distribution.

DF = The degrees of freedom of the chi-square (x^2) distribution.

Sig. = The p-value (significance) of the correlation between the two sets of variables.

The remaining columns present the loadings for each set of macrovariables.

Note:

The definitions are the same for all the rest of the tables of the canonical correlation results.

***Table IX.2*: Canonical correlation between artificial factors and macrovariables (portfolio 1, whole period 1989–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UCPS_t$	RMI_t
1	0.912	0.145	400.635	24.000	**0.000**	-0.078	-0.068	0.151	**-0.997**
2	0.309	0.862	30.838	15.000	**0.009**	**-0.717**	**-0.660**	-0.362	-0.011
3	0.188	0.953	9.989	8.000	0.266	-0.599	0.535	0.681	0.077
4	0.110	0.988	2.532	3.000	0.469	-0.347	0.524	-0.618	-0.019

***Table IX.3*: Canonical correlation between artificial factors and macrovariables (portfolio 2, whole period 1989–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UCPS_t$	RMI_t
1	0.725	0.416	181.013	32.000	**0.000**	-0.012	-0.151	0.170	**-0.993**
2	0.313	0.877	27.163	21.000	0.166	-0.430	-0.735	-0.715	-0.034
3	0.147	0.972	5.866	12.000	0.923	0.427	0.300	-0.676	-0.087
4	0.081	0.993	1.347	5.000	0.930	-0.796	0.589	-0.047	-0.072

***Table IX.4*: Canonical correlation between artificial factors and macrovariables (all portfolios, first sub-period 1989–1994)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x2	DF	Sig.	CEI_t	UI_t	$UCPS_t$	RMI_t
1	0.966	0.035	200.522	52.000	**0.000**	-0.188	-0.135	0.199	**-0.999**
2	0.504	0.533	37.710	36.000	0.391	-0.901	0.343	-0.009	0.025
3	0.471	0.715	20.088	22.000	0.578	0.389	0.910	0.399	-0.022
4	0.283	0.920	5.013	10.000	0.890	-0.034	-0.190	0.895	0.027

***Table IX.5*: Canonical correlation between artificial factors and macrovariables (portfolio 1, first sub-period 1989–1994)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UCPS_t$	RMI_t
1	0.957	0.068	170.529	24.000	**0.000**	-0.175	-0.145	0.211	**-0.999**
2	0.369	0.810	13.357	15.000	0.575	0.743	0.682	0.305	-0.029
3	0.230	0.938	4.040	8.000	0.854	-0.383	0.315	0.825	0.030
4	0.096	0.991	0.593	3.000	0.898	0.520	-0.644	0.427	0.026

***Table IX.6*: Canonical correlation between artificial factors and macrovariables (portfolio 2, first sub-period 1989–1994)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UCPS_t$	RMI_t
1	0.844	0.189	103.303	36.000	**0.000**	-0.085	-0.157	0.205	**-0.996**
2	0.494	0.656	26.141	24.000	0.346	0.596	-0.742	-0.198	0.075
3	0.283	0.868	8.758	14.000	0.846	-0.763	-0.650	-0.010	-0.024
4	0.237	0.944	3.578	6.000	0.734	-0.234	-0.043	-0.959	-0.036

***Table IX.7*: Canonical correlation between artificial factors and macrovariables (all portfolios, second sub-period 1995–2000)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.952	0.065	174.694	40.000	**0.000**	-0.168	0.068	0.107	0.074	**0.997**
2	0.455	0.692	23.542	28.000	0.705	-0.471	-0.689	-0.466	-0.142	-0.059
3	0.313	0.873	8.713	18.000	0.966	-0.252	0.565	-0.668	0.105	0.047
4	0.135	0.968	2.092	10.000	0.996	0.479	0.061	-0.514	0.774	0.005
5	0.119	0.986	0.911	4.000	0.923	0.676	-0.445	-0.248	-0.603	-0.034

***Table IX.8*: Canonical correlation between artificial factors and macrovariables (portfolio 1, second sub-period 1995–2000)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.945	0.075	170.031	25.000	**0.000**	-0.163	0.129	0.094	0.111	**1.000**
2	0.515	0.700	23.334	16.000	0.105	-0.422	-0.712	-0.473	-0.117	-0.019
3	0.198	0.954	3.102	9.000	0.960	-0.851	0.563	-0.004	0.176	0.018
4	0.081	0.993	0.471	4.000	0.976	0.085	-0.017	-0.334	-0.701	0.000
5	0.024	0.999	0.039	1.000	0.844	0.252	0.399	-0.810	0.672	-0.007

***Table IX.9*: Canonical correlation between artificial factors and macrovariables (portfolio 2, second sub-period 1995–2000)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.870	0.206	103.461	25.000	**0.000**	-0.193	0.002	0.029	0.094	**0.984**
2	0.317	0.851	10.599	16.000	0.834	-0.801	-0.108	-0.460	-0.174	-0.072
3	0.167	0.946	3.646	9.000	0.933	0.259	0.552	-0.323	-0.211	0.096
4	0.150	0.973	1.790	4.000	0.774	-0.174	0.699	-0.268	0.939	0.051
5	0.067	0.995	0.297	1.000	0.586	-0.473	0.441	0.782	-0.185	0.118

***Table IX.10*: Canonical correlation between artificial factors and macrovariables (portfolio 3, second sub-period 1995–2000)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.940	0.087	158.702	30.000	**0.000**	-0.188	0.092	0.137	0.073	**0.998**
2	0.433	0.747	19.000	20.000	0.522	-0.521	-0.613	-0.522	-0.163	-0.033
3	0.224	0.919	5.515	12.000	0.939	0.597	0.082	-0.781	0.336	0.041
4	0.180	0.967	2.177	6.000	0.903	-0.215	0.329	-0.193	-0.552	0.018
5	0.026	0.999	0.045	2.000	0.978	0.539	-0.707	0.248	-0.742	-0.040

***Table IX.11*: Canonical correlation between artificial factors and macrovariables (portfolio 4, second sub-period 1995–2000)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.805	0.277	83.995	25.000	**0.000**	-0.245	0.013	-0.021	0.041	**0.978**
2	0.327	0.789	15.501	16.000	0.488	-0.515	-0.612	-0.503	-0.125	-0.197
3	0.271	0.884	8.110	9.000	0.523	0.055	0.324	-0.591	-0.299	-0.056
4	0.210	0.953	3.124	4.000	0.537	0.162	-0.589	0.456	-0.936	-0.036
5	0.053	0.997	0.183	1.000	0.669	0.803	-0.417	-0.435	0.130	-0.032

Table IX.12: **Canonical correlation between artificial factors and macrovariables (portfolio 5, second sub-period 1995–2000)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.587	0.504	44.182	35.000	0.137	-0.374	-0.198	0.045	-0.096	0.905
2	0.359	0.769	16.938	24.000	0.851	-0.070	-0.902	0.230	-0.394	-0.349
3	0.283	0.883	8.052	15.000	0.922	-0.421	-0.035	-0.782	0.492	-0.156
4	0.181	0.960	2.651	8.000	0.954	-0.375	-0.062	-0.170	-0.745	-0.187
5	0.089	0.992	0.511	3.000	0.916	0.733	-0.376	-0.552	-0.197	0.009

Table IX.13: **Canonical correlation between artificial factors and macrovariables (all portfolios, third sub-period 2001–2000)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.766	0.306	77.015	30.000	**0.000**	-0.118	-0.025	-0.025	-0.174	**0.970**
2	0.419	0.739	19.682	20.000	0.478	0.101	-0.251	-0.356	-0.901	-0.005
3	0.259	0.896	7.112	12.000	0.850	0.376	0.623	0.380	0.061	0.092
4	0.189	0.961	2.595	6.000	0.858	-0.274	-0.308	0.807	-0.389	-0.217
5	0.061	0.996	0.243	2.000	0.886	0.871	-0.673	0.278	-0.054	0.056

Table IX.14: **Canonical correlation between artificial factors and macrovariables (portfolio 1, third sub-period 2001–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.760	0.350	69.875	15.000	**0.000**	0.068	0.026	0.066	0.149	**-0.984**
2	0.354	0.828	12.590	8.000	0.127	-0.206	-0.328	0.036	-0.965	-0.091
3	0.232	0.946	3.689	3.000	0.297	-0.382	-0.029	-0.928	0.005	0.026

Table IX.15: **Canonical correlation between artificial factors and macrovariables (portfolio 2, third sub-period 2001–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.734	0.284	82.539	25.000	**0.000**	-0.227	0.121	-0.185	-0.364	**0.913**
2	0.492	0.614	31.937	16.000	**0.010**	**0.625**	**-0.520**	0.440	0.234	0.335

3	0.387	0.811	13.753	9.000	0.131	0.384	0.498	0.523	-0.049	-0.021
4	0.216	0.953	3.139	4.000	0.535	-0.014	0.657	-0.355	0.853	0.225
5	0.003	1.000	0.001	1.000	0.979	0.641	-0.188	-0.611	-0.290	0.057

***Table IX.16*: Canonical correlation between artificial factors and macrovariables (portfolio 3, third sub-period 2001–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.738	0.325	73.014	30.000	**0.000**	-0.081	0.144	-0.127	0.322	**-0.927**
2	0.350	0.713	21.971	20.000	0.342	-0.691	0.674	-0.104	-0.255	0.028
3	0.320	0.813	13.478	12.000	0.335	-0.545	-0.371	0.552	-0.024	-0.189
4	0.305	0.905	6.463	6.000	0.373	0.355	0.381	0.784	0.314	-0.110
5	0.041	0.998	0.111	2.000	0.946	0.306	-0.493	0.233	-0.855	-0.303

***Table IX.17*: Canonical correlation between artificial factors and macrovariables (portfolio 4, third sub-period 2001–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.766	0.298	78.762	30.000	**0.000**	-0.009	0.005	0.158	0.241	**-0.986**
2	0.402	0.721	21.292	20.000	0.380	-0.681	-0.084	0.121	-0.692	-0.126
3	0.302	0.860	9.811	12.000	0.633	-0.174	-0.091	-0.961	-0.116	-0.033
4	0.209	0.946	3.580	6.000	0.733	-0.388	-0.433	0.115	0.354	0.053
5	0.102	0.990	0.680	2.000	0.712	-0.596	0.893	-0.154	0.569	0.088

***Table IX.18*: Canonical correlation between artificial factors and macrovariables (portfolio 5, third sub-period 2001–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.724	0.387	61.679	30.000	**0.001**	-0.217	-0.057	-0.090	-0.351	**0.924**
2	0.272	0.815	13.336	20.000	0.863	-0.162	0.844	-0.462	0.033	0.077
3	0.263	0.880	8.336	12.000	0.758	-0.052	0.508	0.450	0.806	0.202
4	0.232	0.945	3.677	6.000	0.720	-0.734	0.063	-0.536	0.319	-0.083
5	0.036	0.999	0.086	2.000	0.958	0.621	-0.150	-0.537	0.352	0.305

Table IX.19: **Canonical correlation between artificial factors and macrovariables (portfolio 6, third sub-period 2001–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.779	0.283	81.449	35.000	**0.000**	-0.164	-0.141	-0.061	-0.376	**0.918**
2	0.403	0.719	21.263	24.000	0.623	-0.413	-0.649	0.009	-0.598	-0.373
3	0.293	0.859	9.817	15.000	0.831	-0.708	0.502	0.496	0.287	-0.078
4	0.194	0.940	4.007	8.000	0.856	0.366	0.000	0.571	-0.578	-0.107
5	0.153	0.977	1.532	3.000	0.675	0.410	-0.554	0.651	0.290	0.018

Table IX.20: **Canonical correlation between artificial factors and macrovariables (portfolio 7, third sub-period 2001–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.570	0.449	51.232	40.000	0.110	-0.264	-0.161	0.030	-0.435	0.850
2	0.425	0.666	26.053	28.000	0.570	-0.680	-0.133	-0.231	0.384	-0.128
3	0.353	0.813	13.272	18.000	0.775	0.362	-0.923	-0.159	-0.539	-0.181
4	0.197	0.929	4.741	10.000	0.908	0.503	0.008	-0.418	0.533	0.477
5	0.184	0.966	2.204	4.000	0.698	-0.289	0.322	-0.863	-0.299	0.036

Table IX.21: **Canonical correlation between artificial factors and macrovariables (portfolio 8, third sub-period 2001–2006)**

Linear Combination	Squared canonical correlation	Wilk's Λ	Chi-Square x^2	DF	Sig.	CEI_t	UI_t	$UGRIP_t$	$UCPS_t$	RMI_t
1	0.609	0.392	59.518	45.000	**0.072**	-0.185	0.088	0.260	-0.335	**0.830**
2	0.480	0.623	30.039	32.000	0.566	0.596	-0.343	-0.337	-0.676	0.115
3	0.349	0.810	13.407	21.000	0.894	0.310	0.159	0.800	-0.104	-0.403
4	0.219	0.922	5.169	12.000	0.952	0.702	0.026	0.101	0.601	0,356
5	0.178	0.968	2.037	5.000	0.844	0.149	-0.921	0.411	-0.242	-0.092