ASSET PRICING IN UK

KOULAFETIS, PANAYIOTA

DOCTOR OF PHILOSOPHY IN FINANCE

CITY UNIVERSITY BUSINESS SCHOOL

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ABBREVIATION LIST

ABBREVIATION	DEFINITION
AMEX	American Stock Exchange
APM	Arbitrage Pricing Model
APT	Arbitrage Pricing Theory
CAPM	Capital Asset Pricing Model
CCH	Chan, Chen and Hsieh
CRR	Chen, Roll, and Ross
EIV	Errors-in-variables
ERM	Exchange Rate Mechanism
FF	Fama and French
FMB	Fama-MacBeth
GLS	Generalized Least Squares
GMM	Generalized Method of Moments
GNP	Gross National Product
HJ	Hansen and Jaganathan
HML	High minus Low
LBS	London Business school
LSE	London Stock Exchange
LSPD	London Share Price Database
MV	Market Value
MSCI	Morgan Stanley Capital International
MSE	Mean Square Error
NASDAQ	National Association of Securities Dealers Automated Quotations
NLSUR	Non Linear Seemingly Unrelated Regression Estimates
NL3SLS	Non Linear Three Stage Least Squares
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
OTC	Over the counter
PE	Price Earnings

PL	Premium-Labour model
RMSE	Root Mean Square Error
SLB	Sharpe, Lintner and Black
SMB	Small minus Big
SUR	Seemingly Unrelated Regression model
UK	United Kingdom
US	United States

NOTATION LIST

SYMBOL	DEFINITION
α_i	A constant term
β_{ij}	The sensitivity of asset i to factor j
β_{RSRFT}	The beta of FTSE
β_{RSRSP}	The beta of S&P 500
β_{RSRTU}	The beta of the UK stock exchange turnover
β_{RSRMO}	The beta of the change in money supply
β_{RSIMP}	The beta of the change in imports
β_{RSINF}	The beta of the change in inflation
d_t	The dividend declared in month t
e_{it}	The zero mean idiosyncratic term
F_{jt}	The j_{th} factor in month t
INS_{t-1}	The instrumental variable in month t-1
k	The cost of capital
λ_{jt}	The price of risk of factor j in month t
λ_{RSRFT}	The price of risk of FTSE
λ_{RSRSP}	The price of risk of S&P 500
λ_{RSRTU}	The price of risk of the UK stock exchange turnover
λ_{RSRMO}	The price of risk of the change in money supply
λ_{RSIMP}	The price of risk of the change in imports
λ_{RSINF}	The price of risk of the change in inflation
p_t	The last traded price in month t
p_{t-1}	The last traded price in month t-1
R_{it}	The return of the i_{th} asset in month t
$R_{INDUSTRYit}$	The industry return in month t

R_{MVit}	The return of market value portfolio i in month t
R_{PEit}	The return of PE ratio portfolio i in month t
R_{DYit}	The return of dividend yield portfolio i in month t
$\otimes$	The kronecker or direct product operator of two matrices

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DECLARATION

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ABSTRACT

The thesis contributes to the literature in the following ways: First it contributes to the body of literature by extending our knowledge on the predictive ability of alternative Unconditional methodologies. Second it adds to the body of litareture by providing practical tests so as to assess the performance of Conditional models. Third the thesis extends our knowledge on the sensitivity of utilising different portfolio formation criteria, while testing both Unconditional and Conditional asset pricing inferences. Fourth it contributes to the body of literature by extending our knowledge on Unconditional and Conditional beta models and their comparative performance. Fifth the thesis adds to the existing literature by estimating the Industry cost of capital, using the following different models, Unconditional, Conditional, the Arbitrage Pricing Model and the Capital Asset Pricing model. Thus provides empirical evidence using a practical application, estimation of the Industry cost of capital, of which model provides a better description of UK returns.

Chapter 4 introduces the portfolio returns used in the thesis and examines the size, price earnings ratio, dividend yield effect and their interactions. The time-series of the primary portfolios start in 1956 and ends in 1996. We find that for the 1976-1996 period, that the dividend yield and PE effect subsume the size effect. However the PE effect subsumes the dividend yield effect and it is the PE effect that is the most dominant. The best documented of all stock market effects, the small-firm premium went into reverse during 1989-1996. The size effect lives on, but for the latest decade, it is the largest firms that outperform the smallest ones by 10.26% per annum.

Chapter 5, which examines Unconditional models, aims to examine the predictive ability of alternative Unconditional methodologies. Another objective that is explored is the sensitivity of results to different grouping techniques, of size; PE ratio and dividend yield portfolio groupings. The third issue examined entails the identification of priced factors in the UK market, over a twenty year of period, (1976-1996), and for a data-set (approximately 6000 companies), which provides a complete history of firms traded on the London Stock exchange, inclusive of Unlisted securities market. We find that that the choice of one methodology over another has important implications and that there is a sensitivity of results to different portfolio groupings.

Chapter 6, which examines Conditional models, i.e., conditioned on a set of instrumental variables, models the dynamic behaviour of portfolio returns using a Conditional Asset Pricing Model and examine the behaviour of macroeconomic risk premiums over time. We provide practical tests of Conditional Asset Pricing Models and forecast (i) the sign of the price of risk using the probit model, (ii) the magnitude of the price of risk and (iii) portfolio returns for the size, PE ratio and dividend yield portfolios. We find that the instrumental variables show ability to predict variation of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, inflation and portfolio returns.

Chapter 7 compares first Unconditional (constant) and Conditional (time-varying & conditioned on a set of instrumental variables) beta models and second the CAPM and the APM, estimates the industry cost of capital. We find differences, between constant-unconditional betas and conditional betas cost of capital. The average Mean Square Error (MSE) for the conditional betas are smaller compared to constant betas. Moreover we find that the CAPM has larger MSE not only compared to the APT model with conditional betas, but with APT with unconditional betas. The Conditional beta model provides the best description of UK returns. We also run Monte Carlo simulations and test the statistical significance of the errors of the Conditional beta model. We find the errors to be statistically insignificant.

CHAPTER 1

INTRODUCTION

A fundamental portion of the research effort in finance is directed towards improving our understanding of how investors measure risk and value risky assets. The Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Model (APM) are two models that enable us to price risky assets in equilibrium. Assets with the same sensitivities will have the same expected return according to equilibrium-based models. Within the CAPM framework the appropriate measure of risk is the covariance of returns between the risky asset in question and the market portfolio of all assets. However the only way to test the CAPM is to see whether or not the true market portfolio is efficient, and since the markėt portfolio contains marketable and nonmarketable assets, it is impossible to observe. The APM is more general, since many factors, not just the market portfolio may explain asset returns. Within the APT framework there is no special role for the market portfolio, whereas the CAPM requires the CAPM to be efficient. For each factor the appropriate measure of risk is the sensitivity of asset returns to changes in the factor. The APT assumes that the return on a security is sensitive to the movements of various factors or indices. The market model assumes that there is only one factor-the return on the market index. However the APT is potentially more useful than the market model, because it appears that the actual security returns are sensitive to more than movements to the market index, this implies that there is probably more than one pervasive factor in the economy that affect security returns. The APT starts by making the assumption that security returns are related to an unknown number of unknown factors. Securities or portfolios worth the same factor sensitivities should offer the same expected return. If not then "almost arbitrage" opportunities exist. Investors will take advantage of these opportunities causing their elimination. That is the essential logic underlying APT. The APT recognises that only a few systematic factors affect the long-term average returns of financial assets. While it does not deny the myriad of factors that affect the daily price variability of individual stocks, it focuses on the major forces. By identifying these forces we gain an intuitive appreciation of their influence of portfolio returns. Moreover since anticipated changes are expected and have already been incorporated into expected returns, the unanticipated are what determine the sensitivities, and their measurement is one of the most important components of the APT approach. The sensitivities (betas) measure the average response of a portfolio or an asset to anticipated changes in the respective economic factors.

The APT allows for a better description of security returns than the CAPM for reasons we have briefly explained, however another choice within Asset Pricing Models is whether one should use Unconditional or Conditional Asset Pricing Models. The research on time-series supports the intuition that the rates of return to holding common stocks and bonds are to some extent predictable over time, using interest rates, dividend yields and other variables. In an attempt to accommodate this time variation several Conditional models have been developed. The predictive ability of these variables has been the major stimulus to the development of Conditional asset pricing models.

The first time-series return predictability studies consist of univariate tests that examine individual securities and portfolios and where the forecasting power of past returns has been investigated. Researchers have examined whether the return autocorrelation is zero. Fama (1965) examine the autocorrelation of daily returns for the individual Dow 30 industrial stocks. He finds that 75% of the Dow 30 stocks had significantly positive autocorrelations in the 1957-1962 period. Foerster (1987) update these results for the 1963-1990 period and find that 80% are significantly positive. Their sample though small, is interesting because it represents a sample of stocks widely followed by analysts, these stocks are most actively traded stocks of all stocks and as a result have very tight bid-ask spreads. French and Roll (1986) compute autocorrelations for all NYSE and AMEX stocks and find that the estimated autocorrelations are inversely related to market capitalisation of the stock: small stock autocorrelation are the most negative, and the stocks in the largest decile of market capitalisation have positive autocorrelation on average. Due to variance reduction obtained from diversification, portfolio returns provide more powerful tests of the ability of past returns to predict future returns. On the other hand this increased power may be offset by biases induced autocorrelation caused by the nontrading of securities contained in the portfolios. Poon and Taylor (1991) find that the Financial Times All Share Price Index (FTSE)-a value weighted index- exhibit positive lag-one autocorrelation in daily returns (0.19) but insignificant positive lag one monthly autocorrelations (0.13) for the 1965-1989 period. Lo and Mackinlay (1988) examine weekly stock market returns. They find evidence of positive autocorrelation that is strongest for the portfolio of smallest stocks (0.42) and weakest for the portfolio of largest stocks (0.14).[1] In order to determine whether the autocorrelation results are affected by nontrading biases Corad and Kaul (1988) compute portfolio autocorrelations using weekly returns that were computed only with prices that were the result of actual transactions, that is stocks that did not trade were excluded. Corad and Kaul (1988) find very similar results with Lo and Mackinlay (1988), implying that significant positive autocorrelations are not due to nontrading. Keim and Stambaugh (1986) reinforce the results of Lo and MacKinlay (1988) and Corad and Kaul (1988) that the relation between autocorrelations and the size of the firms in the portfolio is not due to nonsynchronous or infrequent trading. They use monthly returns and find the same relation between market capitalisation and autocorrelations for monthly portfolio returns, though it is weaker than the evidence for shorter-interval returns. They find that between 1928-1978 period the return autocorrelation for the portfolio comprising the smallest (largest) quintile of market capitalisation was 0.17 (0.13).

The stream of literature in time-series predictability of stock returns apart from univariate tests also covers multivariate tests, where a number of ex-ante variables, other than past returns, are used to predict future returns. Although univariate tests are suggestive of time-variation in expected returns, the problem is that the variation in expected returns that we attempt to predict represents a small part of the total variation in returns. Thus more powerful tests exploit explanatory variables that convey more precise information about expected returns. Rozeff (1984) and Shiller (1984) investigate the explanatory power of dividend yields on annual stock returns. Rozeff finds that dividend yields explain 14% of the variation in S&P composite index over the 1926-1981 period. Shiller also examines the predictability of annual S&P composite returns and finds that dividend yields explain nearly 16% of the variation in 1946-1983 period. Additional research finds that the predictive power of dividend yields and earnings yields increases with the length of the return horizon. Fama and French (1988b) report that the dividend yields explain about 25% of the variation in 2- to 4-year returns. Harvey (1991) finds that US dividend yield and term structure variables predict monthly returns on a wide array of foreign common stock

[1] An Autocorrelation is the slope in a regression of the current return on the past return.

portfolios. Campbell and Hamao (1992) finds similar evidence for Japanese and US stocks.

Ferson and Harvey (1991b) empirically investigate the sources of predictability and shed light on the controversy over the predictability of returns, because some attribute predictability to market inefficiencies, while others to rational updating of investors' assessment of the required rate of return. Therefore they empirically attempt to calibrate the relative importance of these two sources of predictability. They express the predictable changes in portfolio returns as follows:

Predictable return= return predicted by the model + inefficiency

They use a multi-beta APT-type model, and claim that if the multi-beta model is the true model for required returns, then it should capture all predictable changes in return that are not due to market inefficiencies. However, since no model is perfect, the model may miss some sources of variation in required returns, therefore quotation marks are placed around inefficiency. They find that their model does a good job of capturing the predictability of the portfolio returns, which implies that the portion of predictability due to market inefficiency is relatively small.[2] Ferson and Harvey (1991b) examined both common stocks and fixed income portfolios. They formed 10 stock portfolios by ranking and then grouping NYSE stocks according to market value of equity capital at the beginning of each year. The 10 size portfolios were value-weighted averages of the stocks in each group. They also formed 12 NYSE industry portfolios, and also examined portfolios of long-term government bonds, long-term corporate and six-month Treasury bills. The data they utilise are monthly data over the 1959-1986 period, but since they used the first 5 years of data for initial beta estimates, the reported results refer to analyses of the 1964-1986 period. The predictor variables used were: the past excess returns of the equally weighted NYSE stock index; the excess return on the three-month Treasury bill; the past year's dividend yield on the Standard & Poor's 500; the yield spread between Baa and Aaa corporate bonds; the one-month Treasury bill rate and a dummy variable for the month of January. The use of the dummy variable for January helped a lot with the smaller forms; it is well known that small-stock returns are typically higher in January.

[2]Market Inefficiencies are defined as systematic departure of market prices or rates of return from the values implied by investment fundamentals. Some examples of market inefficiency may be considered: investors' overreaction to news, an investment fad that causes a large deviation between the market value of an asset and its rational investment value.

The multi-beta, APT-type model of Ferson and Harvey (1991b), capture most of the predictability of the returns, and the part not explained by the model is a tiny fraction of the total in most cases. The model's capturing predictability varies, for the utilities' portfolio, the model explains 55.9% of the predictability (the worst case of its performance), for the construction industry: 66.7%, and 95% of the predictability for the leisure, transportation and basic industries.

Given the evidence of studies that document that the returns and risks of stocks and bonds are predictable over time using dividend yields, interest rates and other variables, and that this predictability reflects changing required returns in equilibrium, Conditional models developed. Conditional models assume that the return distribution is conditional on a set of ex-ante observable variables. Thus the asset pricing models, that use these variables, and allow for the dynamic behaviour of asset expected returns to be a reflection of time-varying betas, time-varying risk premia or both time-varying betas and risk premia, are called Conditional asset pricing models.

1.1 OBJECTIVES AND MOTIVATION

The Capital Asset Pricing Model (CAPM) has long served as the backbone of academic finance, however studies have identified empirical deficiencies in the CAPM, such as market capitalisation and financial ratios that predict the cross-section of returns. As an alternative, Ross (1976) introduced the Arbitrage Pricing Model. The Arbitrage Pricing Theory (APT) has been the subject of empirical scrutiny, particularly in the United States. However many fundamental issues regarding the APT especially in the United Kingdom, have remained unresolved. These fundamental issues briefly consist of the adequacy of competitive methodologies to estimate the APT and the sensitivity of these results to different portfolio formation. In order to test and identify the systematic factors that affect security returns within the APT framework, there are two main unconditional methodologies, the Two-Step methodology [Fama MacBeth (FMB) (1972) methodology] and the Non-Linear Seemingly Unrelated Regression (NLSUR) methodology. However the comparative ability of these alternative methodologies to detect pricing relation has not been examined, thus this is one of the objectives of the thesis. The NLSUR has the advantage of avoiding the Error-in-variables problem; inherent in the two-step methodology, because it simultaneously estimates the sensitivities and the prices of risk, also it allows the APT's principle that the price of risk is equal across assets to be tested. Both Poon and Taylor (1991) and Claire and Thomas (1994) suggest such an investigation. Poon and Taylor (1991) who used the FMB methodology with the Chen Roll and Ross (CRR) (1986) factors, find none factor to be priced and claim that It could be that the FMB methodology is inadequate for detecting such pricing relationships. (Page 620). Moreover, Claire and Thomas (1994) claim that an important next step is to compare their results obtained form the two-step procedure with those obtained from non-linear least squares method. (Page 326). In addition we also examine the sensitivity of results to different portfolio formation. The motivation for such investigation stems from the study of Chen, Roll and Ross, (1986), who claim that the sensitivity of results to different grouping techniques is an important area for research (page395). Hence we aim to explore the sensitivity of results to different grouping procedures of size; price/earnings ratio and dividend yield portfolio groupings. Another objective, entails the identification of priced factors in the UK market, over a twenty year of period, (1976-1996), and for a dâta-set, which provides a complete history of firms traded on the London Stock exchange, inclusive of Unlisted securities market. This objective pursue the identification of significant macroeconomic factors in the UK market, free from data limitations and short-testing periods, which is an empirical question that we seek to answer.

Although Unconditional models have been the corner stone of theoretical and empirical finance given recent considerable empirical evidence documenting time-variation in returns, Conditional models have emerged. Conditional models assume that the return distribution is conditional in a set of ex-ante observable variables. Conditional asset pricing models utilise these information variables, and allow for the dynamic behaviour of asset expected returns to be a reflection of time-varying betas, time-varying risk premia or both time-varying betas and risk premia. Ferson and Harvey (1991), (1993), (1999), Ferson and Korajczyk (1995), He, Kan and Zuang (1996), Jaganathan and Wang (1996), Ferson and Stadt (1996), provide studies of Conditional Asset Pricing Models. However the focus of these studies are either the utilisation of different models or estimation procedures in order estimate conditional models and there is a lack of practical tests in order to assess the performance of Conditional Asset Pricing Models. Given this limitation another objective of this thesis is to carry out practical tests in order to assess the performance of Conditional Asset Pricing Models. These practical tests consist of providing forecasts of (i) the sign of the price of risk using the probit model, (ii) the magnitude of the price of risk, and (iii) portfolio returns for the size, price earnings ratio and dividend yield portfolios. Thus we model the dynamic behaviour of portfolio returns using a Conditional Asset Pricing Model and examine the behaviour of macroeconomic risk premiums over time. We examine whether the instrumental variables have ability to predict variation of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, inflation and portfolio returns for different groupings. So as to evaluate the performance of Conditional models we estimate the Root Mean Square Errors (RMSE) and also test the statistical significance of the errors of the Conditional model.

We utilize the Conditional methodology of Ferson and Harvey (1991), to estimate the conditional model. However given the fact that Ferson and Harvey (1991), mention that errors in variables affects their inferences when the fitted premiums are used as dependent variables in the time-series regressions to assess predictability we develop an alternative conditional methodology in an attempt to avoid this problem. We extend the Non-linear Seemingly Unrelated Regression (NLSUR) [McElroy and Burmeister (1988)], into Conditional NLSUR. The Conditional NLSUR theoretically avoids the Errors In Variables (EIV) problem of the Ferson and Harvey (1991) methodology. The Conditional NLSUR achieves that because the price of risk, which is regressed on a set of instrumental variables, is obtained from the NLSUR, which simultaneously estimates the price of risk and betas, without having to run cross-sectional regressions as in the two-step methodology.

Other objectives of this thesis are to provide empirical evidence and practical tests on whether Unconditional (constant) or Conditional (time-varying & conditioned on a set of instrumental variables) beta models provide a better description of returns. Moreover whether the Capital Asset Pricing Model or the Arbitrage Pricing Model provides a better description of returns. Thus we estimate the industry cost of capital, using Unconditional and Conditional beta models in order to examine which model provide better estimates. We also estimate the cost of capital using the CAPM in order to compare the CAPM estimates of cost of capital to the APT estimates of cost of capital and conclude on which model provide more accurate estimates of the cost of capital.

1.2 OVERVIEW

The thesis is organised as follows. Chapter 2 outlines Asset Pricing Models. It provides a review on Unconditional Asset Pricing models, and an analysis on the various methodologies used to estimate Conditional Asset Pricing models. Moreover summarise the main differences between Unconditional and Conditional Asset Pricing models. Chapter 3 describes the main hypotheses tested in the thesis and explains the main Unconditional and Conditional methodologies utilised in the thesis. Chapter 4 review the literature based on size; price/earnings ratio and dividend yield effects, explains the technical details of forming primary and secondary (combined) portfolios, examines the size, price earnings ratio, dividend yield effects and their interaction, discusses the results and provides graphs for the size; price/earnings and dividend yield effect, for the 1956-66, 1967-77, 1978-88, and 1989-96 sub-periods.

Chapter 5, the chapter that examines Unconditional models, discusses the factors that could proxy for the state variables in the APT model. These factors refer to the Chen Roll and Ross (CRR) (1986) factors and to other factors that could affect returns. It defines the macroeconomic factors and indexes utilised in the thesis. It derives the innovations of the series through Arima Box-Jenkins methodology. Chapter 5 tests whether the CRR factors estimated by the two-step methodology are significant for the size; price-earnings ratio and dividend yield portfolios. Then employs other macroeconomic factors, and investigates whether these are significant by using the two step-methodology; furthermore explores the sensitivity of these results to different ranking procedures of size, price-earnings ratio, and dividend yield. Chapter 5 examines whether the CRR factors estimated by NLSUR are significant for the size; price earnings ratio and dividend yield portfolios. Then employs other macroeconomic factors, and investigates whether these are significant by using the NLSUR methodology; furthermore explores the sensitivity of these results to different ranking procedures of size, price-earnings ratio, and dividend yield. The chapter concludes by discussing the two-step methodology versus the NLSUR.

Chapter 6, the chapter that examines Conditional models, models the dynamic behaviour of portfolio returns using a Conditional Asset Pricing model. It provides empirical results by utilising the Ferson and Harvey (1991) conditional methodology for the size; PE ratio and dividend yield portfolios. Then it outlines the development of the Conditional non-linear seemingly unrelated regression estimates methodology and provides empirical results for the size, price/earnings ratio and dividend yield portfolios. Chapter 6 describes the out-of-sample procedure that we utilise to forecast the sign of price of risk by using Probit, and summarises the empirical findings. Moreover it describes the out-of-sample procedure that we utilise to forecast the magnitude of price of risk, explains how we forecast portfolio returns and also provides the empirical results. Then the chapter provides estimates of the errors when portfolio returns are forecasted. Finally the chapter summarizes the results of Monte Carlo simulations, which are run to test the statistical significance of the errors.

Chapter 7, the chapter that provides comparisons first between the Unconditional (constant) and Conditional (time-varying & conditioned on a set of instrumental variables) beta model and second between the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Model (APM), reviews the literature on the cost of capital. It explains the estimation of the Unconditional and Conditional beta model. It discuses the Unconditional beta estimates of the cost of capital with the Conditional beta estimates of the cost of capital and in order to examine which have less errors we estimate the Mean Square Error of both models. Then the chapter discusses the APM estimates of the cost of capital and compares the APM cost of capital estimates with the CAPM estimates of the cost of capital and in order to examine whether the CAPM or the APM have less errors we estimate the Mean Square Error of both models. Finally the chapter summarizes the results of Monte Carlo simulations, which are run to test the statistical significance of the errors. Chapter 8 summarises the main conclusions of the thesis.

CHAPTER 2

ASSET PRICING MODELS

A substantial part of the research effort in finance is directed towards improving our understanding of how investors value risky cash flows. Several Asset Pricing Models have been suggested in the literature and describe how investors assess risk and value risky cash flows. Among them, the Capital Asset Pricing Model (CAPM), which shows that the equilibrium rates of return on all risky assets are a function of their covariance with the market portfolio.

However test of the CAPM is equivalent to tests of the market's mean-variance efficiency. If the only testable hypothesis of the CAPM is that the market portfolio is mean-variance efficient, then such test is infeasible. The reason for this not being feasible is the fact that we do not know the exact composition of the true market portfolio. So the CAPM theory is not testable unless all individual assets are included in the market. Using a proxy for the true market portfolio does not solve the problem for two reasons. First the proxy itself may be mean-variance efficient even when the true market portfolio is not, and second the chosen proxy may be inefficient even though the true market portfolio is actually efficient.

Furthermore over the past two decades a number of studies have empirically examined the performance of the static version of the CAPM in explaining the cross-section of realised average returns. These studies have identified empirical deficiencies in the CAPM. The most powerful challenges include market capitalisation and related financial ratios that can predict the cross-section of returns. For instance, portfolios containing stocks with relatively small capitalisation appear to earn higher returns on average than those predicted by the CAPM. Basu (1977) and Banz (1981) found that the ratio of price to earnings and the market capitalisation of common equity, respectively, provide considerably more explanatory power than beta. An alternative Asset Pricing Model is the Arbitrage Pricing Theory (APT). It is also an equilibrium model, whereas the return on any risky asset is a linear combination of various common factors that affect asset returns. It is more general than the CAPM because it allows numerous factors to explain the equilibrium return on a risky asset.

At the heart of Arbitrage Pricing Theory (APT) is the recognition that a few systematic factors affect the long-term returns of financials assets. Although the APT does not deny the various factors that influence the daily price variability of individual stocks, it focuses on the major forces that move aggregates of assets in large portfolios. The identification of these forces provides us an intuitive appreciation of their influence on portfolio returns. The returns on an individual stock in the coming year will depend on various anticipated and unanticipated events. However anticipated events will be incorporated by investors into their expectations of returns on individuals stocks thus will be incorporated into market prices. So the return ultimately realised will be the outcome of unanticipated events. Asset returns are also affected by influences that are not systematic to the economy as whole, influences that impinge upon individual firms or particular industries but are not directly related to overall economic conditions. Such forces are called "idiosyncratic" to distinguish them from the systematic factors that describe the major movements in market returns. However returns on large portfolios are influenced mainly by systematic factors alone, because through the process of diversification, idiosyncratic returns on individual assets cancel out.

The APT is much more robust than the CAPM for several reasons. The APT makes no assumption about the empirical distribution of returns. The APT also makes no strong assumption about individuals' utility functions. The APT allows the equilibrium returns on assets to be dependent on many factors, not just one. The APT yields a statement about the relative pricing of any subset of assets; thus one need not measure the entire universe of assets in order to test the theory. In the APT framework there is no special role for the market portfolio, whereas the CAPM requires the market portfolio to be efficient.

Although factor models, such as the Unconditional CAPM and APT have been the corner stone of theoretical and empirical finance there is now considerable empirical evidence documenting time-variation in returns, thus several Conditional models have been developed. Conditional models assume that the return distribution is conditional in a set of ex-ante observable variables. The ex-ante variables are referred to as information variables, or as instrumental variables. Therefore the asset pricing models, that utilise these information variables, and allow for the dynamic behaviour of asset expected returns to be a reflection of time-varying betas, time-varying risk premia or both time-varying betas and risk premia, are called Conditional asset pricing models. The concept of Conditional asset pricing models is that, since there is evidence documenting that the return distribution varies over time, more or less with certain ex-ante variables, then investors use this information to form their expectations. Conditional moments then change over time, since agents update their expectations using the latest information available in the market.

This remaining chapter is organised as follows. Section 2.1 reviews studies of Unconditional models. Section 2.2 reviews several Conditional models and methodologies. Section 2.3 concludes.

2.1 UNCONDITIONAL MODELS

Chen, Roll, and Ross (CRR) (1986), utilise the present discounted dividend formula as a rationale for identifying candidates for factors that may carry a risk premium. Stock prices (P_0) can be therefore expressed as the discounted sum of expected future dividend flows.

$$P_o = \sum_{t=1}^{\infty} \frac{E(D_t)}{(1+R)^t}$$

Where: E is the expectations operator, R is the appropriate discount rate, and D_t is the dividend paid at the end of period t. The discount rate is an average of rates over time, and it changes with both the level of rates and the term structure across different maturities. The rationale for choosing economic factors is that any variable that affects the discount rate or affects the future stream of dividends will affect the present stock price. Although the selection of the macroeconomic variables is arbitrary, to the extent that the formula does not identify the important variables, however this formula provides the theoretical framework from which the analyst can pre-specify likely candidates.

Many empirical tests of the APT have been based on the two-step methodology (Fama & MacBeth, 1973, Test of the CAPM) by creating a multiple-factor analogue of this procedure. In the initial stage, time-series regressions of asset returns are conducted on a proxy for the market portfolio to obtain estimates of the sensitivities, or betas and on the second stage cross-sectional regressions then use these estimates as the independent variables. So in the Second stage the reported risk premium is the average of the time series estimates obtained from the cross-sectional regression of the monthly returns on the estimated betas. This methodology, allows beta to vary across month by calculating it as the coefficient from the regression of the returns on the market portfolio return over the previous last (in most studies, 60) months and rolling the regression forward every month (first stage).

Chen, Roll and Ross (1986) used this methodology to test the APT (from 1958-1984), with the following ex ante observable variables as proxies for the systematic factors in the economy: 1) the monthly percentage change in industrial production, 2) a measure of unexpected inflation, 3) the change in expected inflation, 4) the difference in returns on low grade (Baa and under) corporate bonds and long term government bonds, and 5) the difference in returns on long-term government bonds and short-tern Treasury bills. At the first stage time-series observations (60 months, i.e., 5 years) are used to get the estimates of the asset's betas relative to the pre-specified factors. Then given these estimates of the sensitivities of the factors, Beta hat, cross sectional regressions of returns on these Beta hat, are estimated to get estimates of the returns on factor-mimicking portfolios. In order to reduce the EIV problem in the second stage regressions caused by the use of B hat instead of B, they form twenty portfolios.

CRR (1986), grouped securities into portfolios according to: a) their betas on a market index, b) the standard deviation of their return in a market model regression (i.e., residual variability), c) level of a stock price, and d) size. The first two techniques did not provide a spread of returns and were discarded. Sorting on stock price, spread returns, but the state variables were individually only marginally significant. Sorting on size, also spread returns, and the following factors were found significant: industrial production, risk premium, term structure, measures of unanticipated inflation and change in expected inflation when these variables were highly volatile. However these factors only for their second sub-period 1968-1977 of the three sub-periods produced results at the 5% level (see CRR, Table 4, Panel B, page 396).

So as to check how robust their results are to changes in the pre-specified factors, CRR replaced the industrial production factor with alternative factors. When the proxy of the market portfolio was included instead of the industrial production factor (either the equal-weighted or the value- weighted NYSE portfolio), they find that the risk premia on the market factors are not significant when other factors are included in the regression. Also the growth rate in per capita real consumption is added as a factor, (to replace the market portfolios). This growth rate is actually led by one period to reflect the fact that there are lags in data collection. They find that the risk premium on the consumption factor is not significant when the other factors are included. Moreover when the percentage change in the price of oil is included, they find that the estimated risk premium associated with oil price shocks is statistically insignificant for the two of the three sub-periods analysed. The sub-period in which the premium is statistically significant is the 1958-1967 period. Therefore they conclude that the five pre-specified factors provide a reasonable specification of the sources of systematic and priced risk in the economy.

The two-step methodology has been used by Chan, Chen and Hsieh (1985). They utilised the same set of factors as CRR (1986) in order to determine whether cross-sectional differences in factor risk are enough to explain the size anomaly. For each test year from 1958 to 1977, an estimation period is defined as the previous five-year interval (i.e., 1953-1957 is the estimation period for 1958, 1954-1958 for 1959, etc). Their sample consists of all NYSE firms that exist at the beginning of the estimation period and have price data at the end of the estimation period. Chan, Chen and Hsieh (1985) form twenty size portfolios, and estimate the factor sensitivities of the twenty size based portfolios relative to the pre-specified factors and the equal weighted NYSE portfolio over the estimation period. In the subsequent test year, cross sectional regressions of portfolio returns on the estimated factor sensitivities, Beta hat, are run each month, this is repeated for each test and yields a monthly time series of returns on factor mimicking portfolios from January 1958 to December 1977.

They find that the risk premium for the equal-weighted market portfolio is positive in each sub-period, but not significantly statistically, they find significant risk premia for the industrial production factor, the unexpected inflation factor, and the low-grade bond spread factor. They find that the average residuals are not significantly different across portfolios and that the difference in the average residuals between the portfolio of smallest firms and the portfolio of largest firms, while positive, is not significantly different from zero. The average difference in monthly returns between these two portfolios is 0.956%; 0.453% is due to low-grade bond risk premium, 0.352% is due to the NYSE market risk premium, 0.204% is due to the industrial production risk premium, and 0.102% is unexplained.

CCH (1985), use paired t tests and the Hotelling T^2 test to determine if the residuals have the same means across different size portfolios. When the Beta hat matrix includes the betas for the pre-specified factors and the equal-weighted NYSE portfolio, the coefficient of the firm size, δ, is statistically significant, on the other hand when Beta hat only contains betas for the pre-specified factors, then the coefficient of the firm size, δ, becomes insignificant. Based on that they conclude that the multi-factor model explains the size anomaly.

Poon and Taylor (1991), and Claire and Thomas (1994) have examined the APT in the UK market. Claire and Thomas (1994) used the Fama-MacBeth methodology and two ordering procedures, size and beta sorted portfolios over an eight years period (1983-1990) and a sample of 840 stocks to estimate an APT model. For their ordering of the beta-sorted portfolios, they find that the mean return of their portfolios does not vary with portfolio betas (technique failed to spread returns). For the size-sorted portfolios they have a better spread, but they do not find a size effect. Using beta-sorted portfolios Claire and Thomas (1994) find two measures of default to be priced at the 5% level. Using size sorted portfolios, they find the retail price index to be priced at the 5% level, but once they include the market, they find none significant factor at the 5% level.

Poon and Taylor (1991), test whether the results of CRR (1986) are applicable to UK stocks. They used the Fama-MacBeth methodology for their 1965-1984 period, and a large sample of 1570 UK-listed Company returns extracted from the LSPD. They formed 20 equally weighted portfolios, and consistent with Levis (1989), find a size effect. Their results show that variables similar to those of CRR do not affect prices in the UK. Poon and Taylor (1991), although incorporate potential lead/lag relationships up to fifteen months, find none significant factor, and in particular they suggest the following: It could be that other macroeconomic factors are at work or the methodology in CRR is inadequate for detecting such pricing relationships or possibly both explanations apply (Page 620).

The application of the two-step methodology with the cross-sectional regressions use estimates of betas instead of the true value, has the result of the independent variable in the cross-sectional regression being measured with error, so the second stage estimator is subject to an errors-in-variables (EIV) problem. EIV problem arises due to the estimation of betas in one period and the subsequent use of these betas as independent variables in another period. In response to this, Fama-MacBeth proposed the construction of portfolios, so as to minimise the measurement error.

However, Ferson and Harvey (1991), claim that even if the "true" betas are known, the second step, i.e., the cross-sectional regressions are complicated because returns are correlated and heteroskedastic. Conclusions based on the usual standard errors for these regressions are unreliable, since the betas are estimated with error; the regressions involve errors in the variables. The Fama-MacBeth "t-ratios" for testing the hypothesis that the average price of risk is zero should be interpreted with caution, given the possibility of correlated measurement errors in the beta and observations that may not be independent over time.

Kan and Zhang (1997) investigate the properties of the standard two-pass methodology of testing beta-pricing models with mispecified factors. In a setting where a factor is useless defined as being independent of all asset returns they provide theoretical results and simulation evidence that the second-pass cross-sectional regression tends to find the beta risk of the useless factor priced more often than it should. More surprisingly they find this mispecification bias exacerbates when the number of time-series observations increases

McElroy & Burmeister (1988) postulate macroeconomic variables as observable factors and use non-linear time-series regression to estimate the parameters of the factor model. This approach allows joint estimation of the parameters of the model in one step rather the two-step procedure. They use monthly returns on 70 individual stocks, from January 1972 through December 1982, as the set of test assets and five pre-specified factors that are similar to the factors used by Chen, Roll & Ross (1986). The factors used are 1) the difference in returns of long-term corporate bonds and long-term governments bonds. 2) The difference in returns on long-term government bonds and short-term Treasury bills, 3) a measure of unexpected deflation (the negative of unexpected inflation. 4) a measure of unexpected growth in sales and 5) either a return on market index (the S&P 500 portfolio) or a 'residual market factor' equal to the residual from a regression of the market index on the other four factors. The basis for this is that these market residuals should capture any factor that is not included in the proposed list of measured variables. They estimate $R_t=B\lambda+Bf_t+\varepsilon_t$, using (INLSUR) where the factor risk premia are constant through time ($\lambda_{t-1}=\lambda$ for all t) and find that the estimated risk premia are significantly different from zero at the 5% level, for each factor except for the unexpected deflation factor, which is significant at the 10% level.

The Fama & MacBeth (FMB) methodology, unlike the NLSUR allows the coefficients of the explanatory variables to vary across month. These coefficients are then averaged across time. Such aggregation, however, assumes that the coefficients are drawn from an underlying stationary distribution. Since the level of an independent variable affects the magnitude of its coefficient, a dramatic growth over time in the levels of the explanatory variables may invalidate the assumption of a stationary distribution.

McElroy and Burmeister (1988), introduces the NLSUR, which eliminates the problems of the FMB including non-robustness of the estimators with respect departures from normality and efficiency losses. They claim that if the errors are not jointly normal, the properties of the estimators for the factor loading (beta hat) obtained from FMB are unknown. Also there is no guarantee that factor 1 for the first portfolio will be the same as factor 1 for the second portfolio. The prices of risk obtain from FMB does not have any straightforward economic interpretation.

The methodology of McElroy & Burmeister (1988), provide an alternative and attractive econometric framework, which simultaneously estimates the sensitivities and the prices of risk, and a major advantage is that, unlike other techniques it allows the APT's principle conclusion that the price of risk is equal across assets to be tested.

The NLSUR also adjusts for the cross-sectional correlation in the residual returns (across assets, portfolios, etc). The NLSUR model consists of a series of equations linked because the error terms across equations are correlated, the NLSUR model involves generalised least squares estimation and achieves an improvement in efficiency by taking into account the fact that cross-equation error correlation may not be zero.

Claire, Priestley and Thomas (1997) test the robustness of the APT to alternative factor structures. Their data consists of 56 size-sorted portfolios comprising 15 equally weighted stocks from a random subset of the LSPD. Their sample period for the portfolios and the macroeconomic factors is January 1978 to December 1990. Their research indicates that the one-step and the two-step estimation techniques of the APT produce different results, which depend crucially upon the form of the covariance matrix of returns. They find that when the two-step procedure with a correction for the EIV is employed it lead to the conclusion that the APT is not an empirically valid model for the UK stock market. However they find that the two-step procedure is consistent with the results from a non-linear simultaneous equation estimator when they constrain the covariance matrix of the residuals to be diagonal. Finally they show that when they allow for the existence of an approximate factor structure, their five factors plus the market portfolio are price in the UK market.

Claire, Priestley and Thomas (1998), further continue their research on the alternative factor structures of the APT by testing the CAPM and the claims of the Fama and French (FF) (1992), about the explanatory power of alternative variables. Their data consists of month-end, dividend-adjusted stock return data on 100 stocks quoted on the LSE between January 1980 and December 1993. Claire, Priestley and Thomas (1998) claim that a number of authors have found that firm size and book-to-market-value capture the cross-sectional variation in average returns and that these variables have been found to out-perform the CAPM's beta coefficient in explaining the cross-section of average stock returns. However, these authors all employ variant of the two-step methodology. That imposes the restriction that the idiosyncratic returns are uncorrected. In contrast to the US findings, Claire, Priestley and Thomas (1998) find no role for the FF variables when the CAPM is estimated using the NLSUR with an unconstrained variance-covariance matrix.

Claire, Smith and Thomas (1997) test the mean variance efficiency of the UK stock market. Their paper provides an important link between formal asset pricing models and the empirical evidence for the predictability of excess returns. They form ten size and ten dividend yield portfolios. The stocks are equally weighted within each portfolio with the average number of stocks in each portfolio being 85. They show that excess returns on portfolios of stock traded on the LSE are predictable using a set of instruments, which contain information widely available to investors. Furthermore they suggest that researchers estimating asset pricing models using UK data should consider ranking stocks by dividend yield to achieve a satisfactory spread of risk and returns while simultaneously reducing the problem of thin trading.

Antoniou, Garrett and Priestley (1998) use the Non Linear Three Stage Least Squares (NL3SLS) to investigate the performance of the APT for 138 securities traded on the London Stock exchange, covering the period from January 1980 to August 1993. They analyse the performance in terms of the presence of common pervasive factors across two different samples, each containing 69 securities. They claim that it will always be possible to find companies that are relatively more sensitive to certain non-unique factors (in the sense that they carry different premia for different subsamples of assets). This in turn will increase the explanatory power of the models. However they claim that it may be worth sacrificing some explanatory power in order to obtain uniqueness in the return generating process. They also claim that since the market portfolio appears on the right side of the system equations, it should be treated as endogenous. Therefore they use the NL3SLS rather than NLSUR. The difference between the NLSUR and the NL3SLS is that by using the NL3SLS the market portfolio is treated as endogenous. In the estimation of the model the market portfolio is instrumented using the fitted and square fitted values from a regression of excess returns on the market portfolio on the other factors, other instruments used are the factors and their squares. They test a model consisting of ten factors, the unexpected inflation, expected inflation, industrial production, retail sales, money supply, commodity prices, term structure, default risk, exchange rate, and the market portfolio. They find that out of these factors, the unexpected inflation, money supply and excess return on the market portfolio are unique in the sense that they carry the same prices of risk in both of their samples.

Antoniou, Garrett and Priestley (1998) estimate the APT and use it to analyse the effects of Exchange Rate Mechanism (ERM) membership on the equity market risk premium. They base their results on a data set of 69 companies and data covering the period of January 1980 to August 1993. They use the NL3SLS so they treat the market portfolio as endogenous that appears on both the right and left sides of the system. They test a model consisting of ten factors, the unexpected inflation, expected inflation, industrial production, retail sales, money supply, commodity prices, term structure, default risk, exchange rate, and the market portfolio. However they conclude on model consisting of the following factors: the unexpected inflation, expected inflation, money supply, default risk, exchange rate, and the market portfolio. They find that prior to and during the first year of membership the equity market risk premium fell quite dramatically. However when conflict between domestic and ERM policy requirements arose at the turn of 1991, the equity risk premium increased and continued to do so until the sterling's exit, partially wiping out the benefits of ERM.

2.2 CONDITIONAL MODELS AND METHODOLOGIES

Ferson and Harvey (1991), analyze the predictable component of monthly stock and bond portfolio returns. For their analysis they utilize originally the Fama-MacBeth methodology, and then extended this to conditional models by regressing the individual risk premium on a set of instrumental variables. Ferson and Harvey (1993) also extend their work in international setting; they investigate the risk and predictability of international equity returns. They use a model in which conditional betas of the national equity market depend on local information variables, while global risk premia depend on global variables. They claim that most of the research on international asset pricing models has been conducted in terms of explaining differences in average returns, whereas average returns are the estimated of unconditional expected returns, formed using no information about the current state of the economy.

Unlike this approach Ferson and Harvey (1993) suggest that asset-pricing models can also be interpreted as statements about expected returns conditional on currently available information. Therefore they focus on the ability of beta pricing models to capture the predictability of international equity market returns through conditional expected risk premia and conditional betas. They assume that under rational expectations, actual returns differ from their conditional expected values in the model by an error term that is orthogonal to the conditioning information, Ω_{t-1}, assumed to be public knowledge at time t-1, and the predictability of reruns is attributed to the correlation between expected returns and the current information. So predictability should arise because betas or risk premia are correlated with the information variables.

They assume that conditional expected returns can be written as:

$E(R_{it}| \Omega_{t-1})=\lambda_0(\Omega_{t-1})+\Sigma b_{ij}(\Omega_{t-1})\lambda_j(\Omega_{t-1})$ (1)

where the $b_{ij}(\Omega_{t-1})$ are the conditional regression betas of the returns, R_{it}, measured in a common currency, on K global risk factors, j=1,...,K. The expected risk premia, $\lambda_j(\Omega_{t-1})$, j=1,...,K are the expected excess returns on mimicking portfolios for the risk factors.[1] The intercept $\lambda_0(\Omega_{t-1})$ is the expected return of portfolios with all of their betas equal to zero. If there is a risk-free asset available at time t-1, then its rate of return equals $\lambda_0(\Omega_{t-1})$. Equation (1) implies an expression for the expected excess returns:

$E(r_{it}| \Omega_{t-1})= \Sigma\beta_{ij}(\Omega_{t-1})\lambda_j(\Omega_{t-1})$ (2)

where $\beta_{in}(\Omega_{t-1})= b_{ig}(\Omega_{t-1})- b_{ufl}(\Omega_{t-1})$ are the conditional betas of the excess returns and $b_{ufl}(\Omega_{t-1})$, j=1,...,K, are the conditional betas of the Treasury bill. They let $\Omega_{t-1}=\{Z_{t-1}, Z^i_{t-1}, i=1,...,n\}$, where Z_{t-1} represents the global information variables and Z^i_{t-1}, the local information variables for country i.

Since Ferson and Harvey assume globally integrated markets, the risk premia should not be country specific, this is the reason they restrict the risk premia in (2) to depend on global variables, Z_{t-1}. They also suggest that the local information variables are related to country-specific betas, therefore they assume that the betas are functions only of the local information and model the predictable variance, using (2) as:

$Var\{ E(R_{it}| \Omega_{t-1})=Var\{\Sigma\beta_{ij}(Z^i_{t-1})\lambda_j(Z_{t-1})\}$.

Ferson and Harvey (1993) study equity returns for 18 national markets, provided by Morgan Stanley Capital International (MSCI). The a priori factors they choose are the U.S. dollar return of the world equity market in excess of a short-term interest rate. A global measure of exchange risk, which they define as the log first difference in the trade-weighted U.S dollar prices of the currencies of 10 industrialised countries.[2] The unexpected component of a monthly global inflation

[1]Mimicking portfolios are portfolios that can be substituted for the factors in a factor model regression, to measure the betas, and whose expected excess return are the risk premiums.
In general a factor-mimicking portfolio is defined as a portfolio whose return can be utilised in the place of the factors, both in the following factor model:
$R_{i,t+1}=\alpha_{it}+\Sigma b_{jt}F_{j,t+1}+u_{i,t+1}$, for all i,
where $E_t(u_{i,t+1}F_{j,t+1})= E_t(u_{i,t+1})=0$ for all i and j.
Also to identify the expected risk premiums in the following expressions:
$E_t(R_{i,t+1})=\lambda_{0t}+\Sigma b_{ijt}\lambda_{jt}$, for all i.
[2]They claim that a positive change in this factor implies depreciation of the dollar. Although they acknowledge that that there is little evidence of this factor being priced on average, there is some evidence for time-varying risk premia.

measure (Chen, Roll and Ross, 1986).[3] The monthly changes in expected inflation, (Chen, Roll and Ross, 1986).[4] The change in the spread between the 90-day Eurodollar deposit rate and the 90-day U.S. Treasury bill yield.[5] A measure of real interest rates, as a weighted average of short-term interest rates minus inflation rate. [6] The change in the monthly average U.S. dollar price per barrel of crude oil.[7] Finally the weighted average of industrial production growth rates.[8]

The predetermined instruments include the global information variables, Z_{t-1}, which are the yield of a one month U.S.Treasury bill, the dividend yield of the MSCI world stock market index, the spread between the yields to maturity of 10-year U.S.Treasury bonds and 90-day U.S. Treasury bills, the lagged value of the Eurodollar-U.S.Treasury (TED) spread, the lagged return on the MSCI world market index, and a dummy variable for the month of January. These variables represent readily available, global information that may influence expectations about future equity returns.

The predetermined instrumental variables, for the country-specific instruments, Z^i_{t-1}, are: the US Treasury bill is replaced with a short-term interest rate from the specific country, the world dividend yield is replaced with the dividend yield for the national stock market. The term spread is replaced with a yield spread of domestic long-term over short term, low-risk bonds. The lagged world index return is replaced with the lagged return of the national stock market index. These variables

[3]This is a weighted average of the % changes in the consumer price indices (CPI) in 7 countries, using relative shares of the total real, gross domestic product (GDP) as the weights. Ferson and Harvey (1993) claim that an inflation state variable can arise in a multi-beta model if inflation has real effects, since global inflation is correlated with marginal utility, for instance, higher inflation may signal higher levels of economic uncertainty which makes consumers worse off. So if national equity market returns differ in their exposures to changes in the global inflation outlook, there could be an inflation risk premium in global equity markets.

[4]Changes in expected inflation is formed by Ferson and Harvey by regressing a 48- month moving average of the unexpected inflation rate on their predetermined global information variables and taking the first difference of the fitted values.

[5]This is measure of measure of the premium on Eurodollar deposit rates in London, relative to the U.S. Treasury. Ferson and Harvey(1993) claim that fluctuations in the spread may capture fluctuations in global credit risks.

[6]Real interest rates are often used in economic models. For instance Merton (1973), Cox, Ingersoll, and Ross (1985), Chen, Roll and Ross (1986), Ferson and Harvey (1991).

[7]Also oil prices are proposed as a measure of economic risk in the U.S market by Chen, Roll and Ross (1986). Hamao (1988), Brown and Otsuki (1990b) study oil prices in the Japanese equity market.

[8]Also Chen, Roll and Ross (1986), Shanken and Weinstein (1990) examine the average pricing of U.S industrial production in the U.S market. Hamao (1988) studies domestic industrial production risk in the Japanese equity market. Bodurtha, Cho and Senbet (1989) estimate the average risk premia for domestic industrial production risk in several countries.

represent information specific to the domestic markets, to the extend that the global aggregates are not sufficient for the local market information.

In order to estimate the fraction of the predictable variation that the beta pricing model captures, they use a regression of the excess country return (measured in a common currency, the U.S. dollar) on the information variables as a base case. With a linear regression model for the conditional expected return given Z_{t-1}, $E(r_{it} \mid Z_{t-1})=Z'_{t-1}\ \delta_i$, where δ_i is the coefficient vector. The predictable variance of the return, using Z_{t-1}, is $Var[E(r_{it} \mid Z_{t-1})]=Var[Z'_{t-1}\ \delta_I]$. The predictable variation captured by the model depends on the conditional betas and risk premia. They utilise a linear regression to model the expected risk premia. They assume that $\lambda(Z_{t-1})= E(F_t \mid Z_{t-1})= \gamma' Z_{t-1}$, where γ is an L*K matrix of coefficients and the F_t are mimicking portfolio excess returns for the K risk factors. The conditional betas are approximated as linear functions of the local information variables: $\beta_{ij}\ (Z^i_{t-1}) = \kappa'_I\ Z^i_{t-1}$, where κ is an L*K matrix of coefficient that describe the conditional betas for country I as a linear function of the lagged, local market variables. Under these assumptions, the predictable variance of the return captured by the beta pricing model is $Var[\Sigma_j E(F_{jt} \mid Z_{t-1})\beta_{ij}(Z^i_{t-1})]= Var[Z'_{t-1}\gamma\kappa'_I Z^i_{t-1}]$.

They define this a proportion, defining the following variance ratio:

$VR1_i = Var[Z'_{t-1}\ \gamma\kappa'_I\ Z^i_{t-1}]\ /\ Var[Z'_{t-1}\ \delta_I]$

The variance ratio VR1 measures the fraction of the predictable variance in the return attributed to the model. While the following variance ratio $VR2_i$ measures the predictable variation in the return not captured by the model:

$VR2_i\ = Var[Z'_{t-1}\ \delta_I\ -Z'_{t-1}\ \gamma\kappa'_I\ Z^i_{t-1}]\ /\ Var[Z'_{t-1}\ \delta_I]$

Ferson and Harvey (1993) conduct their study by defining the following error terms for each country i.

$u1_{it} = (r_{it}-Z'_{t-1}\ \delta_i)$ (3a)

$u2_{it}= (F'_t\ -\gamma Z_{t-1})'$ (3b)

$u3_{it}= [(u2_{it}\ u2'_{it})\ (\kappa'_I Z^i_{t-1})-\ F_t\ u1'_{it})]$ (3c)

$u4_{it}= (Z'_{t-1}\ \delta_I-\theta_i)$ (3d)

$u5_{it}= (\gamma Z_{t-1})(\kappa'_I Z^i_{t-1})-\ \theta_I\ +\alpha_I$ (3e)

$u6_{it}= (u4^2_{it})VR1_I-\ u5^2_{it}$ (3f)

The parameters are $\{\theta_I,\ \alpha_I,\ VR1_I,\ \gamma,\ \delta_I,\ \kappa_I\}$, where the first three parameters are scalars. The parameter α_I is the difference between the unconditional mean return and the unconditional mean of the model fitted return. It is a measure of an 'average pricing error' analogous to the traditional α measure of performance, hence if the model is well specified, α_i should be zero. The model implies the orthogonality conditions $E(u1_{it} Z_{t-1}, u2_{it} Z'_{t-1}, u3_{it} Z^{i\prime}_{t-1}, u4_{it}, u5_{it}, u6_{it}) = 0$, the model is estimated for each country by using GMM (Hansen (1982).

Ferson and Harvey (1993) use 60 month rolling regressions as a simple way to approximate a factor model with time-varying betas. In these regressions, where each national equity market return is regressed over time on the eight global risk factors, they find that the average of the adjusted R^2's of the rolling regressions for each country range from 14% to 80% over the 1975-89 period. In the regressions that use the lagged information variables to predict the excess county returns, the predictable variation measured by the adjusted R^2's ranges across the countries, from virtually zero to 10%.

They estimate the average pricing errors α_i, its standard error, and the variance ratios for the one-factor model, in which the world market portfolio is the factor, for the two-factor model, in which exchange rate is the second factor, and for the five-factor model that consist of the following factors: the excess world market portfolio, exchange rates, the change in long-term expected inflation minus the treasury bill return, the change in the price of oil minus the treasury bill return and real interest rates. The world excess return is the only one used directly as a factor, while mimicking portfolios are constructed for the remaining factors. They constructed mimicking portfolios by using a variation of the approach of Breeden, Gibbons and Litzenberger (1989), and the Fama-MacBeth approach.

They find that that the single-factor model the average pricing error is smaller than the average excess return for all countries, but its standard errors are large. Regressing the pricing errors over time on the lagged global information variables, the adjusted R^2's are negative for 10 of the 18 countries. Regressing the pricing errors on the local versions of the information variables, 7 of the 18 adjusted R^2's are negative. The variance ratios VR1 are larger than the VR2's in 13 of the 18 countries, which suggests that the model captures more of the predictability than it leaves in the residuals. The average VR1 is 0.704 and the average VR2 is 0.456. The results for the two-factor model show some modest improvements over the single model. The average pricing error is reduced relative to the single-factor model in 11 of the countries. The estimates of the pricing error are more than two standard errors from zero in only 3 of the 37 cases. The adjusted R^2's from regression the pricing errors on the lagged variables present a similar pattern to the one-factor model. Twelve of 17 of the 18 VR1's are larger than the VR2's. The five-factor model point to a dramatic improvement relative to the single-factor model. Only 1 of the 36 (18 countries*2 two ways of mimicking portfolios=36) average pricing errors, α_i, is more than two standard errors from zero. Thirty-one of the 36 VR1's are larger than VR2's. The regression of the model residuals on the lagged world and lagged local market variables show little evidence of remaining predictability.

Further, Ferson and Harvey (1993) examine how important are movement in the betas and the risk premia for explaining return predictability. In order to examine this, they estimate the following decomposition:

$$Var\{E(\beta'\lambda| Z)\}=E(\beta)'Var\{E(\lambda| Z)\}E(\beta)+E(\lambda)'Var\{\beta(Z)\}E(\lambda)+\phi$$

The left-hand side is the predictable variation that is captured by the model. The first term on the right hand side is the part attributed to movements in expected risk premia. The second term is the part attributed to time-variation in the betas. The ϕ term represents interaction effects that arise because the expected risk premia and betas may be correlated through time. They employ GMM to estimate the above decomposition, using a system of equations. They find that there is only a small contribution of time-varying betas to the model variation in expected country returns, and most of the predictable variation is attributed to movements in the global time-varying risk-premia.

Ferson and Korajczyk (1995) present an approach for estimating how much of the predictability in security returns is explained by asset pricing and use the approach to evaluate conditional models for multiple return horizons. The asset-pricing hypothesis is a multi-beta arbitrage pricing (APT) model of the following form:

$$E(R_{i,t+1}| Z_t)=\lambda_0(Z_t)+\Sigma b_{ijt}\lambda_j (Z_t) \qquad (1)$$

Where $R_{i,t+1}$ is the rate of return on asset i between times t and t+1, and Z_t is a vector of instruments for the information available when prices are set at time t. The b_{i1t},..., b_{i1t} are the time t conditional betas that measure the systematic risk of asset I relative to the k risk factor. The $\lambda_j (Z_t)$; j=1,...,k are the market prices of systematic risk, or expected risk premiums. The conditional betas with respect to the risk factors $F_{j,t+1}$, j=1,...k are defined by a factor model regression:

$R_{i,t+1} = \alpha_i + \Sigma\beta_{ijt} F_{j,t+1} + u_{i,t+1}$ (2)

Their first set of tests uses time-series regressions of returns on the factor mimicking portfolios and a vector of predetermined instruments:

$r_{it} = \alpha_{i0} + \Sigma\alpha_{ip}Z_{p,t-1} + \Sigma\beta_{ijt} F_{j,t+1} + u_{i,t+1}$ (3)

They use excess returns $r_{it} = R_{it} - R_{ft}$, where R_{ft} is the return of the 1-month Treasury bill. The symbol $Z_{p,t-1}$ denotes the value of predetermined variable p at period t-1, and $F_{j,t}$ denotes the excess return of the factor mimicking portfolio for factor j at period t. They assume that the conditional betas are fixed parameters over time, where $\beta_{ij} = b_{ijt} - b_{fit}$, and b_{fit} is the conditional beta of the Treasury bill. Their model implies that $r_{it} - \Sigma\beta_{ij} F_{j,t}$ should have a conditional mean equal to zero, and the predetermined variables should not enter the equation. In particular, α_{i0} should be zero, and the predetermined variables should not enter the regression. They examine the joint hypothesis by testing the restrictions that the α_{i0} and the α_{ip}'s are equal to zero in (3). If the predetermined variables were not in the regression (3), the α_{i0} should be zero if the model explains the unconditional expected returns. However they claim that their main interest is the ability of the models to capture the predictable variation in returns over time. Therefore they focus on the restrictions that $\alpha_{ip}=0$, p=1,...,L. In essence they examine whether the violations of the model vary through time and are correlated with the lagged variables. If the hypothesis that the lagged variables may be excluded from regression (3), the joint hypothesis that included constant betas is rejected. A rejection of the model in (3) may be interpreted as indicating either time-varying betas or the need for additional factors.

Ferson and Korajczyk (1995) decompose the return predictability by estimating the following system with GMM.

$u1_{it} = (r_{it} - Z'_{t-1}\,\delta_i)$ (4a)

$u2_{it} = (F'_t - Z_{t-1}\gamma_i)'$ (4b)

$u3_{it} = [(u2_{it}\, u2'_{it})\beta_i - (F_t\, u1_{it})]\, Z'_{t-1}$ (4c)

$u4_{it} = (Z'_{t-1}\,\delta_i - \theta_i)$ (4d)

$u5_{it} = (Z'_{t-1}\,\gamma_i\,\beta_i + \alpha_i - \theta_i)$ (4e)

$u6_{it} = (u4^2_{it})VR1_i - u5^2_{it}$ (4f)

The parameters are $\{\theta_i, \alpha_i, VR1_i, \delta_i, \beta_i, \gamma_i\}$, where the first three parameters are scalars. The model implies the orthogonality conditions E $(u1_{it}\, Z_{t-1}, u2_{it}\, Z'_{t-1}, u3_{it}\, Z^{i\prime}_{t-1}, u4_{it}, u5_{it}, u6_{it}) = 0$. The first equation describes a regression of the excess asset return on the lagged instruments. The second equation is a system of regressions for the factor-mimicking portfolios on the lagged instruments. The fitted values are used to model the expected risk premiums. Equation (4c) defines the conditional betas, which are assumed to be fixed parameters. The predictable variance of the asset return that is captured by the model is the part attributed to betas and risk premiums: $Var[E(\Sigma_j \beta_{ij} F_{jt} | Z_{t-1}) = Var[Z'_{t-1}\gamma_i\beta_i]$. The last three equations [(4d)-(4f)] define the variance ratio: $VR1_i = Var[Z'_{t-1} \gamma_i \beta_i] / Var[Z'_{t-1} \delta_i]$. The variance ratio VR1 is the predictable variance in the return that is attributed to the model, relative to the total predictable variance in the return, given Z_{t-1}.

They test the models using portfolios grouped according to market capitalisation and industry affiliation. Ten value-weighted portfolios are formed by CRSP according to size deciles of the combined NYSE and AMEX sample, based on the market value of equity outstanding at the beginning of each year. They also form 12 portfolios according to the 2-digit Standard industry classification code.

They study monthly (quarterly, annual, 2-year) returns, their model assumes that the representative investor makes consumption and investment decisions at monthly (quarterly, annual, 2-year) frequencies.

They study predictability based on the following variables: the level of the 1-month treasury bill rate, the dividend yield of the CRSP value-weighted NYSE stock index, a detrended stock index price level, a measure of the slope of the term structure. Their list of economic factors consist of the following: The return on the SP500 stock index, a real interest rate factor (nominal 1-month treasury-bill rate less the rate of change in the consumer price index), an unexpected inflation factor, a corporate default risk factor, a term structure risk factor.

First they regress the asset returns on the predetermined variables. For horizons longer than 1 month, the return is the compounded multi-month return, and the lagged instruments are the level observed in the last month of the prior period. The repressors are therefore the same for each horizon, but there are observed less frequently for the longer-horizon regressions. They conduct much of their analysis over the 1927-88 period, and also report results for the 1961-88 period. They conduct an F-test of the hypothesis that excess returns are not predicted by the instruments. This test has an F-distribution under the assumption that the prediction errors are normal, independent, identically distributed. They also conduct a Wald Test of the hypothesis that excess returns are not predicted by the instruments. This test has a X^2 distribution and allows for conditional heteroskedasticity in the prediction errors, following White (1980) and Hansen (1982).

Ferson and Korajczyk (1995) find that for the monthly regressions, the F-tests reject the null hypothesis that there is no predictability at a 5% level, for 10 of the 12 (1927-888) and all of the (1961-88) industries. The test also rejects the null for 9 of the 10 (1927-88) and all 10 (1961-88) size portfolios. The Wald test tells the same story. For the quarterly horizons, the F-tests reject the null hypothesis for 7 of 12 (1927-88) and all 12 (1961-88) industry portfolios and 9 of the 10 (1927-88) and all 10 of the (1961-88) of the size portfolios. They find that the Wald test has a tendency to reject the null hypothesis more often than the F-test. For longer horizons the tests more frequently disagree, but the R^2s generally increase. Although the tests strongly reject the null of no predictability in the 1961-88 period, the evidence for the full sample is weaker.

Then they consider test based on the time-series regression of (3). The test examine the hypothesis that the $\alpha_j=0, j=1,\ldots,L$. The tests compare the sum of squares of regressions that include the Zs with regressions that exclude the Zs. They find that for the monthly observations and using the first five principal components as risk factors in (3), the tests provide evidence that the factors do not capture all of the predictability, when used in a constant-beta model. In quarterly data, the test reject the models from 4 to 7 of the 12 industry portfolios and from 7 to 10 size portfolios at the 5% level. Moving to annual data, the F-test rejects the models for only from 2 to 4 of the 12 industries and one of the size portfolios at the 5% level. They find that the results using mimicking portfolios for the economic variables as factors, are remarkably similar. In general they find that tests reject the models for monthly and quarterly data, but the evidence for longer horizons is more favourably to the models. However on the other hand, the tests may be of low power for the longer-horizons models. They also acknowledge that it is difficult to compare tests across investment horizons, because the tests for different horizons are likely to be correlated, and the tests may have low power given the smaller number of observations for the longer-horizons returns.

Ferson and Korajczyk (1995) estimate variance ratio tests for one-factor model and five-factor model. Using a single principal component the VR1 are in most cases larger than the VR2. They find however differences in the performance of the one-factor, principal-component, and the single-factor model using the SP500. The variance ratios reveal a size effect in the SP500 for the conditional returns. In monthly and quarterly data, the VR1 are often less than the VR2 for the smaller size portfolios. In contrast, the one- principal component model performs well for the size portfolios at all return horizons. However, the explanatory power of the one-principal component model for the industry portfolios at the longer return horizons is not as good as the SP500 model. Compared with the single-factor models, the estimates of the variance ratios of the five-factor models appear more precise, and the ability of the model to explain predictable variance is improved, this is especially for the industry portfolios. The multiple-factor results using economic variables are similar to the results using principal components.

Ferson and Korajczyk (1995) also estimate variance ratios in a multi-step procedure. In the first step the asset return is decomposed into model-fitted return and model residual return. This step involves the following: portfolio betas are obtained from rolling time-series regressions on the factors, and mimicking portfolios are formed as the coefficients in the cross-sectional regressions of the returns on the betas. The model fitted-part of the return is the product of the betas and the mimicking portfolio excess return. The difference between the return and its model-fitted component is the model residual. In the second step each component is regressed separately on the lagged instruments. In the third step variance ratios are taken from the sample variance of the fitted values (of the regressions on the lagged instruments). They also find that the five-factor model capture much of the predictable variation in the monthly and quarterly returns and the performance of the principle components models for the industry portfolios is worse than it is for the size portfolios.

Jaganathan and Wang (1996), develop a Conditional CAPM, which as he characterises is very different from what is commonly understood as the CAPM, and resembles the multi-factor model of Ross (1976). The model Jaganathan and Wang (1996) evaluate has three betas, whereas the standard CAPM has only one. However they assume that the conditionally expected return is linear in the conditional beta alone. From this they show that the unconditional expected return is linear in the market beta and the premium beta. Although they develop a conditional CAPM, their objective is to examine whether the unconditional expected returns are consistent with the conditional CAPM. When they consider unconditional returns they estimate the two parts of the conditional beta, which is the market beta and the premium beta, these reflect how market returns react to the market return on average (market beta) and how to the changes of the market risk premium (premium beta). [9]

Jaganathan and Wang (1996), create 100 portfolios of NYSE and AMEX stocks as in Fama and French (1992). For every calendar year, starting in 1963, they sort firms into size deciles based on their market value at the end of June. For each size decile, they estimate the beta for each firm, using 24 to 60 months of past-return data and the CRSP value-weighted index as the market index proxy. Following Fama and French (1992), this beta is denoted as "pre-ranking" beta estimate. They then sort firms within each size decile into beta deciles based on their pre-betas. This results in 100 portfolios, whose return is computed for the next 12 calendar months by equally weighting the returns on stocks in the portfolio. This is repeated for each calendar year, and gives a time series of monthly returns (July 1963-December 1990, i.e., 330 observations) for each of the 100 portfolios

Although they acknowledge that a number of variables help predict future economic conditions, and consequently the analyst should make use of the same variables that help predict the business cycle for forecasting the market risk premium as well, they restrict their attention to only one forecasting variable. They claim that since interest rate variables are more likely to predict the market risk premium, based on previous evidence, they chooses the yield spread between BAA-and AAA-rated bonds, denoted by R^{prem}_{t-1}, as a proxy for the market risk premium.

Jaganathan and Wang (1996), apart from the use of the return on the value-weighted portfolio of all stocks traded in the US as a proxy for the return on the portfolio of the aggregate wealth, denoted by R^{vw}_{t}, and the use of R^{prem}_{t-1}, as a proxy for the market risk premium, they also incorporate a proxy for the return on human capital, denoted by R^{labour}_{t}. The R^{labour}_{t} denotes the growth rate in labour income that becomes known at the end of month t. They construct the growth rate per capita monthly labour income series using the formula: $R^{labour}_{t}= [L_{t-1}+L_{t-2}]/ [L_{t-2}+L_{t-3}]$.
Labour Income is the difference between the total personal income and the dividend income; L_{t-1} denotes the per capita labour income for month t-1, which becomes

[9] Jaganathan and Wang (1996), claim that the conditional betas decomposes into three parts, the market beta, the premium beta and the residual beta, but when considering unconditional expected returns, they ignore the residual beta, because it does not affect unconditional expected returns, and concentrate on the two other parts of the conditional beta.

known at the end of month t. They use this dating convention to be consistent with the fact that monthly labour income data are typically published with one-month delay.

The basis for their empirical study is the Premium-Labour model (PL), according to which the unconditional expected return on any asset is a linear function of its vw-beta, prem-beta and labour-beta. In order to test whether data are consistent with the PL model, they investigate whether there are residual effects in the PL model. They define the size of a stock as the logarithm of the market value of the stock. Log(ME_i) denote the time-series average of size for asset i. If the PL model holds the coefficient c_{size} should be zero. They estimate the models using the cross-sectional regression of Fama and MacBeth (1973). They claim that since the standard errors computed in the Fama and MacBeth procedure are biased, they attempt to correct this biases following Shanken (1992). However in the process of this correction they made some strong assumptions that may not be satisfied in practise, they also evaluate their model using the Generalised Methods of Moments. The Hansen-Jaganathan distance, or simply HJ-distance is the pricing error for the portfolio that is most mis-priced by the model, (Hansen and Jaganathan (1994).

Jaganathan and Wang (1996), by using return data on the 100 portfolios, first examined the traditional CAPM:

$$E[R_{it}] = c_0 + c_{vw}\beta^{vw}_i$$

In the cross-sectional regressions they find c_{vw} to be insignificant (the t-value is -0.28), which remains the same after the correction to the standard errors for estimation errors in the betas, the R^2 is 1.35). When size is added to the model, the t-value for size is -2.30. This strong size effect suggests that the traditional CAPM is inconsistent with the data. In the GMM tests that use the HJ-weighting matrix, the estimated HJ-distance is 0.6548 and the pricing error is significantly different from zero.

When they allow betas to vary over time, i.e., assume that the conditional CAPM holds, but still use the stock index as a proxy for the market return:

$$E[R_{it}] = c_0 + c_{vw}\beta^{vw}_i + c_{prem}\beta^{prem}_i$$

In the cross-sectional regressions the t-value for c_{prem} is 3.28, the R^2 is 29.32% compared to the traditional CAPM , which was 1.35%. The GMM test with the HJ weighting matrix gives an estimated value of 0.6425 for the HJ-distance, so this specification reduces the pricing errors, but there are significantly different from zero.

Then they estimate the PL-model (Premium-labour), where the return on the market portfolio of all assets is assumed to be a linear function of the stock index and the growth rate per capita labour income:

$$E[R_{it}] = c_0 + c_{vw}\beta^{vw}{}_i + c_{prem}\beta^{prem}{}_i + c_{labour}\beta^{labour}{}_i$$

The estimated value c_{labour} is significantly different from zero in the cross-sectional regressions (t-value=2.31, the R^2 = 55.21%). When size is added to the model, the t-value for the size coefficient is -1.45. In the GMM test with the HJ weighting matrix, the estimated HJ distance drops to 0.6184. So the pricing errors of the PL-model are much smaller and are also found not significantly different from zero. They conclude that their specification to include the return on human capital performs well in explaining the cross-section of average returns.

Ferson and Schadt (1996), compare the Conditional and Unconditional versions of the CAPM and a Four-factor model. The value-weighted CRSP index for all stocks listed on NYSE is used as the market factor. The four-factor model uses large stocks, small stocks, government bonds, and low-grade government bonds. In this factor model, the S&P 500 total return is used to represent large market capitalisation (cap) equities. The small cap index from Ibbotson Associates represents stocks whose market values correspond to the ninth and tenth decile of market values on the NYSE. The third factor is the return to a long-term (20-year) US government bond from Ibbotson Associates. Low-grade government bond return are based on the return series in Blume, Keim and Patel (1991), updated using Merrill Lynch High Yield Composite Index return.

For the Unconditional CAPM, Ferson and Schadt (1996), estimate the following:

$$r_{pt+1} = \alpha_p + b_p r_{mt+1} + u_{pt+1}$$

They regress each fund's excess return on the excess return of the market factor. The slopes and coefficients are estimates of the Unconditional alpha and beta coefficients. The coefficients α_p and b_p are the intercept and the slope coefficient, where the r_{pt+1} is the excess return of a fund and r_{mt+1} is the excess return of the CRSP value weighted market index.

For the Conditional CAPM they consider a regression of the managed portfolio excess return on the market factor and the product of the market factor with the lagged information:

$$r_{pt+1} = \alpha_p + \delta_{1p} r_{mt+1} + \delta'_{2p} (Z_t r_{mt+1}) + \varepsilon_{pt+1}$$

This regression may also be interpreted as an unconditional multiple factor model, where the market index is the first factor and the product of the market and the lagged information variables are additional factors. Where Z_t is the vector of predetermined instruments, consisting of the dividend yield of the CRPS index, a Treasury yield spread (long minus short term bonds), the yield on a short -term Treasury bill, a corporate bond yield spread (low minus high grade bonds) and a dummy variable for January.

They find that R-squares are slightly higher for the conditional model. The F-test of the marginally explanatory power of Conditioning information in the CAPM can reject the hypothesis that the additional variables do not matter, at the 5% level, for 50 of the 67 individual funds, and the average p-value is 0.06. Heteroskedasticity-consistent Wald test produce similar results: the p-values are below 0.05 for 43 of the 67 funds. This is evidence of statistically significant movements in the Conditional market betas, which are related to the public information variables.

Ferson and Schadt (1996), test multiple factor models also. Their unconditional K-factor model (1,...,K are the market prices of systematic risk or the expected risk premiums) is a multiple regression of the excess returns on a constant and the K factor-portfolios, and the intercept is the unconditional alpha. In their Conditional K-factor model, the regression equation has (L+1)K+1 repressors. The repressors are a constant, the K factor portfolios, and the products of the L information variables in Z_t with the K factor-portfolios.

Ferson and Schadt (1996), measure the performance of their models also by the alphas, which are defined as follows. For the CAPM, the unconditional alphas are the intercepts in regressions for the excess returns of the funds on the excess returns of the CRSP value-weighted market index. The Conditional alphas are the intercepts in regressions of fund excess returns on the CRSP index and the product of the index with a vector of predetermined instruments. The Unconditional alphas in the four-factor models are the intercepts in regressions of the excess returns of the funds on the four factors. The Conditional alphas in the four-factor models are the intercepts when fund excess returns are regressed over time on the factors and the product of the factors with the vector of predetermined instruments.

Overall, in the Unconditional CAPM, about 2/3 of the point estimates of the alphas are negative. Of the 13 'significant' (absolute t-ratio larger than 2.0) alphas, 8 are negative. Ferson and Schadt (1996) claim that previous studies finding negative unconditional alphas interpreted them as indicating poor performance, however they continue that it is difficult to know where the distribution of the alphas should be centred under the hypothesis of no abnormal performance. In both of the unconditional models the left tails are thicker than the right tails. The distribution of the t-ratios shifts to the right when the conditioning information into the models. The negative unconditional alphas may reflect a bias caused by omitting public information that is correlated with the portfolio betas and the fact that the predetermined variables are significant. About half of the conditional alphas (34 of the 67) of these estimates are negative, and half positive. Thus a simple adjustment to condition on public information has removed the inference of the traditional approach that mutual funds alphas tend to be negative.

Moving from the simple CAPM to the four-factor model does not change the result that the unconditional alphas tend to be negative. Of the 67 point estimates of the unconditional models, 46 are negative. While only 38 are negative of the conditional model. Introducing the conditioning information seems to have a greater impact on the measures of performance than does moving from the single-factor to the four-factor model.

Ferson and Schadt (1996) conclude that traditional measures of performance (Unconditional alphas) are negative more often than positive. Both a simple CAPM and the four-factor model produce this. However using conditional models, the distribution of alphas shifts to the right and is centred near zero. The relatively pessimistic results of the traditional measure are attributed to common-variation in the conditional betas and the expected return.

Ghysels and Cirano (1997) examine whether time-varying betas help or hurt. To address this they compute the in-sample root mean square error (RMSE) of the conditional CAPM of Harvey (1991) and the conditional APT of Ferson and Korajczk (1995) and compare this with the RMSE of the fixed beta model. So they consider the RMSE from three models, the unconditional CAPM, the conditional CAPM, and the conditional APT using economic factors. These comparisons are performed for the ten size-based portfolios and the twelve industry-based returns. They find that the unconditional CAPM for six out of twelve industries has the smallest RMSE. They claim that a plausible explanation of these results is that betas change through time very slowly. The Conditional APT and CAPM models may have a tendency to overstate time variation and as a result produce beta risk, which is too volatile and changing too rapidly.

Ferson and Harvey (1999) test the empirical performance of the Fama and French (1993) model as an asset-pricing model. The FF model was developed to explain the unconditional mean returns. Ferson and Harvey (1999) test the FF model on conditional expected returns. They do not focus on alternative factors that may provide a better model of average returns, but concentrate on the ability of the model to capture common dynamic patterns in returns, modelled using a set of lagged, economy-wide predictor variables.

Ferson and Harvey (1999) start with the null hypothesis that the three-factor model identifies the relevant risk in a linear return generating process:

$$r_{i,t+1}= E_t(r_{i,t+1})+\beta_{it}'\{ r_{p,t+1}-E_t(r_{p,t+1})\}+\varepsilon_{i,t+1} \quad (1)$$

$$Et(\varepsilon_{i,t+1})=0$$

$$Et(\varepsilon_{i,t+1}\, r_{p,t+1})=0$$

Where $r_{i,t+1}$ is the return for any stock or portfolio I, net of the return to a one-month Treasury bill. $r_{p,t+1}$ is a vector of excess returns on the risk factor-mimicking portfolios. In the FF three-factor model, r_p is a 3*1 vector containing the market index excess return, high minus low (HML) and small minus big (SMB). The notation $E_t(.)$ indicates the conditional expectation, given common public information set at time-t. The factor model expresses the unanticipated return, $r_{i,t+1}-E_t(r_{p,t+1})$, as a linear function on the unanticipated parts of the factors. The third line says that that the coefficient vectors β_{it} are the conditional betas of the return r_i on the factors.

Equation (1) captures the idea that $r_{p,t+1}$ are risk factors, but it says nothing about the determination of expected returns. So they assume that the following general model for the conditional expected returns and the betas.

$$E_t(r_{i,t+1})=\alpha_{it} + \beta_{it}'\, E_t(r_{p,t+1}),$$

$$\beta_{it}=b_{0i}+b_{1i}'Z_t, \quad (2)$$

$$\alpha_{it}=\alpha_{0i}+\alpha_{1i}'Z_t$$

They allow the betas in equation (2) to depend on Z_t, the betas are modelled as a linear function of the predetermined instruments. In equation (2) the relation over time between the lagged instruments and the betas for a given portfolio is assumed to be a fixed linear function, as b_{1i} is a fixed coefficient. However they examine models estimated on rolling sample windows, an approach that allows b_{1i} to vary over time, thus relaxing the assumption of a fixed linear relation. The hypothesis that the FF model explains expected returns says that the "alpha" term, α_{it} in equation (2) is zero (that is the parameters α_{0i} α_{1i} are zero). Testing for $\alpha_{it}=0$ in system (2) asks whether the variables in Zt can predict returns over and above their role as linear instruments for the betas.

Combining equation (1) and (2), they derive the following econometric model.

$$r_{i,t+1}= (\alpha_{0i}+\alpha_{1i}'Z_t)+ (b_{0i}+b_{1i}'Z_t)\, r_{p,t+1}+\varepsilon_{i,t+1} \qquad (3)$$

In order to examine the issue of time-varying betas they report regressions in which they allow the lagged instruments to enter the models through the conditional betas. They carry out time-series regression of equation (3) for each of the 25 portfolio returns. They find the three-factor model, the F-tests for 11 of the 25 portfolios to produce p-values below 0.05 when the alphas are allowed to be time varying, and 12 cases reject constant betas on the assumption that the alphas are constant over time. The joint Benferoni test rejects the hypothesis that the betas are constant over time, in either specification. Since they find evidence that betas are time varying, the instruments could enter the model through the betas. In other words they claim that if the hold the betas fixed the tests may be biased against the FF model. So they allow the betas to be time varying. Each portfolio excess return is regressed on a constant intercept, the lagged instruments, the FF factors and the products of the FF factors with the lagged instruments. This allows the FF factors to vary as a linear function of the lagged instruments. The null hypothesis that the alphas are constant (the lagged instruments may be excluded from the model of alpha) is tested with an F-test. They find most of the p-values from this to be small. So they obtain a strong rejection of the FF three-factor model, even allowing for time varying betas that depend on the instruments. Fama and French (1993) find that the regression intercepts are close to zero for their three-factor model. However Ferson and Harvey (1999) find that conditional on the lagged instruments the alphas are time varying and thus not zero. This implies that the FF three-factor model does not explain the conditional expected returns of these portfolios. Even a conditional version of the FF model, with time varying betas can be rejected.

2.3 CONCLUSION

The main differences between Unconditional and Conditional asset pricing models are summarised in this section. Unconditional tests of asset pricing models assume that expected returns are constant, and asset's betas are stationary over a fixed period. However the betas are likely to vary over the business cycle. For example during a recession, financial leverage of firms in relatively poor shape may increase sharply relative to the other firms, causing their stock betas to rise. Further, to the extent that the business cycle is induced by technology or taste shocks, the relative share of different sectors in the economy fluctuates, inducing fluctuations in the betas of firms in these sectors. Therefore, betas and expected returns will depend on the nature of available information at any given point in time and vary over time.

Unconditional measures ignore the fact that risk and expected returns may vary with the state of the economy. They ignore the evidence that expected returns in the stock market are higher at the beginning of an economic recovery, when dividend yields are high and interest rates low. Unconditional models assume that the rates of return have a constant distribution and are serially iid, (independent, identical distributed returns). Also, as a consequence the return distribution is also assumed to be independent of any ex-ante information. Therefore the expected returns, variances, covariances, and risk premia are constant.

On the other hand Conditional models, assume that the return distribution is conditional in a set of ex-ante observable variables. The ex-ante variables are referred to as information variables, or as instrumental variables. Therefore the asset pricing models, that utilise these information variables, and allow for the dynamic behaviour of asset expected returns to be a reflection of time-varying betas, time-varying risk premia or both time-varying betas and risk premia, are called Conditional asset pricing models. The concept of Conditional asset pricing models is that, since there is evidence documenting that the return distribution varies over time, more or less with certain ex-ante variables, then investors use this information to form their expectations. Conditional moments then change over time, since agents update their expectations using the latest information available in the market. Conditional asset pricing models allow the variances, covariances, and risk premia to vary over time, and hence incorporate the dynamic behaviour of returns into asset pricing theory. Also Conditional asset pricing models have been motivated, apart from the time-series return predictability, by the belief that investors update their expectation using the latest available information in the market.

Although several Conditional models have been developed, one limitation in the literature is that practical tests to check the robustness of Conditional asset pricing models have not been carried out. Another limitation is that practical tests in order to compare the relative performance of Unconditional and Conditional models have not been carried out also. This thesis aims to shed light on these issues, by providing practical tests so as to examine the performance of Conditional asset pricing models, and also practical tests in order to make comparisons between Unconditional and Conditional beta models.

CHAPTER 3

HYPOTHESES AND METHODOLOGY

This chapter summarises the main hypotheses and describes the methodologies employed, to test these hypotheses. In the thesis we start our empirical examination by introducing the portfolio returns used in the thesis and examine the size, price earnings ratio and dividend yield effects. Given the fact that our data contains 41 years (1956-96) the examination of these effects over large time-period provide empirical evidence more robust. Combined portfolios are also formed to assess the interaction amongst these effects, over the time period (1976-1996) we utilise the portfolio returns to test asset-pricing inferences. Given the following limitations and gaps in the literature we form the following hypotheses. In terms of Unconditional asset pricing, there is a gap in the literature of whether the two-step methodology is adequate to detect a pricing relationship in the UK market [see, Poon and Taylor (1991)]. A related issue is to compare the two-step methodology with an alternative asset pricing methodology, the Non-Linear Seemingly Unrelated Regression methodology [see, Claire and Thomas (1994)]. Moreover another gap in the literature is to check the sensitivity of results to different portfolio grouping techniques [see, Chen, Roll and Ross (1986)]. Second in terms of Conditional asset pricing, the main gap in the literature relates to the lack of practical tests in order to test the performance of Conditional asset pricing models. Furthermore another gap in the literature is to check the sensitivity of results of Conditional asset pricing models to different portfolio grouping techniques. For example if there are differences in the results between different portfolio groupings when one uses Unconditional models, and there are no differences in the results between different portfolio groupings when one uses Conditional models, indirectly that implies that Conditional models are more robust. Third another limitation in the literature relates to the lack of practical test in order for someone to choose between Unconditional and Conditional beta models.

We form our hypotheses as follows:

Chapter 4 examines the following hypotheses:

Hypothesis: There is a significant size effect (small minus big market value portfolio) over the 1956-66, 1967-77, 1978-88, 1989-96 sub-periods.

Hypothesis: There is a significant price earnings ratio effect (low minus high PE ratio portfolio) over the 1956-66, 1967-77, 1978-88, 1989-96 sub-periods.

Hypothesis: There is a significant dividend yield effect (high minus low dividend yield portfolio) over the 1956-66, 1967-77, 1978-88, 1989-96 sub-periods.

Tests: Chapter 4 also examines the size; price earnings ratio and dividend yield interaction effects using Wald tests.

Chapter 5 examines the following hypotheses:

Hypothesis: The two-step methodology is not adequate to describe a pricing relation in UK market.

Hypothesis: The Non Linear Seemingly Unrelated Regression methodology is more adequate to capture a pricing relationship in UK market

Hypothesis: The results of Unconditional asset pricing models are not sensitive to different portfolio grouping techniques of size, price earnings ratio and dividend yield.

Chapter 6 examines the following hypotheses:

Hypothesis: The Conditional Non Linear Seemingly Unrelated Regression methodology is more robust than the Ferson and Harvey (1991) methodology.

Hypothesis: The results of Conditional asset pricing models are not sensitive to different portfolio grouping techniques of size, price earnings ratio and dividend yield.

Tests: In order to test the performance of Conditional models and the predictive ability of the Conditional-Instrumental variables, Chapter 6 provides the practical tests of Conditional asset pricing models and forecasts the sign of the price of risk using the Probit model, forecasts the macroeconomic risk premiums and also forecasts portfolio returns.

Chapter 7 examines the following hypotheses:

Hypothesis: The Conditional (time-varying & conditioned on a set of instrumental variables) beta model provides a better description of UK returns than the Unconditional (constant) beta model.

Hypothesis: The Arbitrage Pricing Model provides a better description of UK returns than the Capital Asset Pricing model.

This chapter summarises the basic methodologies used in the thesis. This are categorised as Unconditional methodologies and Conditional methodologies. The Unconditional methodologies are the Two-step methodology, and the Non Linear Seemingly Unrelated Regression Estimates methodology (NLSUR). These Unconditional methodologies are utilised in Chapter 5 to estimate the Unconditional Arbitrage Pricing Model. The Conditional methodologies are the Ferson and Harvey (1991) methodology and the Conditional Non Linear Seemingly Unrelated Regression Estimates methodology. The Conditional Non Linear Seemingly Unrelated Regression Estimates methodology is developed in this thesis with the aim to avoid the Error in Variables problem inherent in the Ferson and Harvey (1991) methodology. The Conditional methodologies are used in Chapter 6 to estimate the Conditional Arbitrage Pricing Model. This chapter is organised as follows: Section 3.1 explains the two-step methodology. Section 3.2 discusses the Non Linear Seemingly Unrelated Regression Estimates methodology. Section 3.3 discusses the Ferson and Harvey methodology and Section 3.4 explains the Conditional Non Linear Seemingly Unrelated Regression Estimates methodology.

3.1 THE TWO-STEP METHODOLOGY

The first step of this methodology involves estimation of the return portfolios' exposure (sensitivities or betas) to the factors. This is achieved by regressing the portfolio returns on the factors using time series regressions over an estimation period of 5 years, i.e., (60 months rolling). Thus the slope coefficients in the time-series regressions provide estimates of the betas.

$$R_{it} = \alpha_i + \beta_{F1}F1_t + \beta_{F2}F2_t + \beta_{F3}F3_t + \beta_4 F4_t + \beta_{F5}F5_t + e_{it}$$

where: R_{it} is the return for portfolio i, $i = 1,...,25$ at time t; α_i is a constant term; $\beta_{F1}, \beta_{F2}, \beta_{F3}, \beta_{F4}, \beta_{F5}$ are the betas; $F1_t, F2_t, F3_t, F4_t, F5_t$ are the factors at time t; e_{it} is the zero mean idiosyncratic term.

The betas used as independent variables in the cross-sectional regressions for a given month are estimated from prior data. We use the five-year period ending in December of the previous calendar year and update the estimates annually. The portfolio returns are the dependent variable. So at the second step, for each of the 12 months, the following cross-sectional regression is run. Since the time series start in 1976, the cross-sectional start in 1981 and end in 1996.

$$R_i = \lambda_0 + \lambda_{F1}\hat{\beta}_{F1} + \lambda_{F2}\hat{\beta}_{F2} + \lambda_{F3}\hat{\beta}_{F3} + \lambda_{F4}\hat{\beta}_{F4} + \lambda_{F5}\hat{\beta}_{F5} + u_i$$

Where $\lambda_{F1}, \lambda_{F2}, \lambda_{F3}, \lambda_{F4}, \lambda_{F5}$, are the estimates of the prices of risk; u_i is the zero mean idiosyncratic term. The result of the cross-sectional regressions; are the estimated time-series of the prices of risk associated with each of the factors. Significant average cross-sectional regression coefficient would suggest that an economic factor is priced. In order to see whether the APT has explanatory power in the cross-sectional regression we test the null hypothesis that $\lambda_{F1} = 0, \lambda_{F2} = 0, \lambda_{F3} = 0, \lambda_{F4} = 0, \lambda_{F5} = 0$.

In order to test this hypothesis, a t-ratio is calculated.

The t-statistics for the hypothesis that $\lambda_{Fj}=0$, for factor j=1,...5, is:

T-statistics: $t_\lambda = \dfrac{\hat{\lambda}_{Fj}}{S(\hat{\lambda}_{Fj}) / \sqrt{n}}$

where $\hat{\lambda}_{Fj}$ is the average of the month by month regression coefficient estimates, λ_{Fj} for economic variable j; $S(\hat{\lambda}_{Fj})$ is the standard deviation of the monthly estimates, and n is the number of months in the period.

3.2 THE NON-LINEAR SEEMINGLY UNRELATED REGRESSION METHODOLOGY

It is assumed that in a world of n assets the differences between actual and expected returns on the ith asset and the jth time period are generated by a linear factor model with k factors.

$$R_{it} = E_t[R_{it}] + \sum_{J=1}^{K} \beta_{ij} F_{jt} + \varepsilon_{it} \qquad (3.1)$$

Where Et is the expectation operator that conditions on information available at the beginning of the period and where R_{it} = the total return on the ith asset in period t; F_{ij} = the jth factor in period t; β_{ij} = the sensitivity of asset i to factor j; and ε_{it} = a random error specific to the ith firm/portfolio or the idiosyncratic disturbance, which satisfies

$$E_t[\varepsilon_{it}] = 0 \quad E_t\left[\varepsilon_{it}\varepsilon_{jt}'\right] = \sigma_{ij} \qquad t = t' \qquad (3.2)$$

$$E_t\left[\varepsilon_{it}\varepsilon_{jt}'\right] = 0 \qquad t \neq t'$$

The APT originated with Ross (1976,1977), the APT takes the form of (3.1) and its basic postulate is that, because of competition in asset markets, it is impossible for an investor to earn a positive expected rate of return on any combination of assets without undertaking some risk and without making some net investment. The common fundamental theorem of APT is that for each time period there exists k+1 constants λ_{0t} and $\lambda_t=(\lambda_{1t}\ldots\lambda_{Kt})'$, not all zero, such that expected return is approximately given by

$$E_t[R_{it}] = \lambda_{0t} + \sum_{J=1}^{K} \beta_{ij}\lambda_{jt} \qquad (3.3)$$

To write the APT as a multivariate regression model for a sample of N<n assets, we retain the error assumptions (3.2) and substitute (3.3) into (3.1) to obtain a system of N non-linear regressions over T time periods

$$R_{it} = \lambda_{0t} + \sum_{J=1}^{K} \beta_{ij}\lambda_{jt} + \sum_{J=1}^{K} \beta_{ij}F_{jt} + \varepsilon_{it} \qquad (3.4)$$

$i = 1,...,N \quad t = 1,...,T$

Equation (3.4) is a multivariate non-linear regression model with cross-equations restrictions, for which McElroy, Burmeister and Wall (1985), showed that with the NLSUR, we can obtain joint estimation of the sensitivities (β_{ij}'s) and the prices of risk (λ_{ij}'s)

Equation (3.4) can be written:

$$\rho_i = R_i = \lambda_0 + \sum_{J=1}^{K} \left(\lambda_{J\,IT} + F_i\right)\beta_{ij} + \varepsilon_i \qquad (3.5)$$

Using the matrix notation (3.5) becomes:

$$\rho_i = R_i = \lambda_0 + \left[(\lambda' \otimes i_T) + F\right]\beta_i + \varepsilon_i \qquad (3.6)$$

Where r_i= a T*1 vector; λ= a K*1 vector of prices of risk; IT a T vector of ones; F is a T*K matrix of observations on the K factors; B is a K*1 vector of sensitivities; ⊗ a kronecker or direct product operator of two matrices,

$$\underset{T*K}{X(\lambda)} = \left[(\lambda' \otimes i_T) + F\right]$$

Now stacking for N equations yields:

$$\begin{pmatrix} \rho_1 \\ \rho_2 \\ \vdots \\ \rho_N \end{pmatrix} = \begin{bmatrix} X(\lambda) & 0 & \dots & 0 \\ 0 & X(\lambda) & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & X(\lambda) \end{bmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_N \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_N \end{pmatrix}$$

or in obvious notation: $\rho = \left[I_N \otimes X(\lambda)\right]B + \varepsilon \qquad (3.7)$

where I_N is an N*N identity matrix, and via (2.2), $E\varepsilon = 0_{NT}$ and $E\varepsilon\varepsilon' = [\Sigma \otimes I_T]$

The NLSUR estimator, provide joint estimates of λ, B, chosen to minimise the following quadratic form.

$$Q(\lambda, b; \hat{\Sigma}) = \{\rho - [I_N \otimes X(\lambda)]\beta\}' * (\hat{\Sigma}^{-1} \otimes I_T)\{\rho - [I_N \otimes X(\lambda)]\beta\}$$

Where: $\hat{\Sigma}^{-1}$ is the residual variance-covariance matrix estimated from estimating (3.5) for all i=1,...,N. The (NLSUR) estimates are obtained by estimating a set of non-linear equations with cross-equation constraints imposed, but with a diagonal covariance matrix of the disturbances across equations. These parameters estimates are used to form a consistent estimate of the covariance matrix of the disturbances, which is then used as a weighting matrix when the model is re-estimated to obtain new values of the parameters. These estimates are consistent and asymptotically normal.

3.3 THE FERSON AND HARVEY (1991) METHODOLOGY

The Ferson and Harvey (1991) methodology is used to examine the ability of the instrumental variables *(INS1, INS2, INS3, INS4, INS5)* to predict variation of the individual risk premia associated with the macroeconomic variables. The instrumental variables that Ferson and Harvey (1991) use are: the equal-weighted NYSE index less the 1-month Treasury bill return, the 1-month return of a 3-month Treasury bill less the 1-month return of a 1-month bill, the average monthly yield to maturity of corporate bonds rated Baa by Moody's investor services less the Aaa corporate bond yield, the monthly dividend yield on the S&P 500 stock index, the nominal 1-month Treasury bill return. Having obtained the price of risk estimates λ_{Fj} from the cross-sectional regressions of the two-step methodology for each month t, we perform time-series regressions of each of the risk premiums on the instrumental variables *(INS1, INS2, INS3, INS4, INS5)*.

$$\lambda_{F1t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F2t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F3t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F4t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F5t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F6t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

Where $\lambda_{F1t}, \lambda_{F2t}, \lambda_{F3t}, \lambda_{F4t}, \lambda_{F5t}, \lambda_{F6t}$ are the prices of risk of the factors $F1, F2, F3, F4, F5, F6$, obtained from the cross-sectional regressions of the two-step methodology; $INS1, INS2, INS3, INS4, INS5$ are the instrumental variables; δ_0 is a constant term; e_t is the idiosyncratic term.

3.4 THE CONDITIONAL NON LINEAR SEEMINGLY UNRELATED REGRESSION METHODOLOGY

The Conditional NLSUR involves regressing the price of risk obtained from the NLSUR on a set of instrumental variables. The Conditional NLSUR methodology, avoids the Error in Variables problem, inherent in the Ferson and Harvey methodology, because, the price of risk of the factors is obtained from NLSUR, which simultaneously estimates betas and prices of risk. So according to the Ferson and Harvey (1991) methodology, first they run time-series regressions, to obtain the betas, then they run cross-sectional regressions with the betas used as independent variables to obtain the price of risk of certain factors. Then they use the price of risk of their factors and regress it to a set of instrumental variables. While according to the Conditional NLSUR, with just one step we obtain both betas and prices of risk for certain factors. Then we regress each price of risk to a set of instrumental variables. In that way we avoid the Error in Variables problem.

$$\lambda_{F1t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F2t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F3t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F4t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F5t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

$$\lambda_{F6t} = \delta_0 + \delta_1 INS1_{t-1} + \delta_2 INS2_{t-1} + \delta_3 INS3_{t-1} + \delta_4 INS4_{t-1} + \delta_5 INS5_{t-1} + e_t$$

Where $\lambda_{F1t}, \lambda_{F2t}, \lambda_{F3t}, \lambda_{F4t}, \lambda_{F5t}, \lambda_{F6t}$ are the prices of risk of the factors $F1, F2, F3, F4, F5, F6$, obtained from the Non Linear Seemingly Unrelated Regression Estimates methodology; $INS1, INS2, INS3, INS4, INS5$ are the instrumental variables; δ_0 is a constant term; e_t is the idiosyncratic term.

CHAPTER 4

INTRODUCTION OF THE DATA

THE SIZE, PE RATIO, DIVIDEND YIELD EFFECTS AND THEIR INTERACTIONS

This chapter introduces the portfolio returns used in the thesis. We sort stocks into groups to test asset-pricing references in the chapters that follow. We form primary portfolio on the basis of market capitalisation, price earnings ratio and dividend yield. These different rankings procedures are adopted in order to examine the sensitivity of asset pricing models to different ranking procedures. The time-series of the primary portfolios start in 1956 and ends in 1996. We split the sample in four sub-periods, 1956-66, 1967-77, 1978-88 and 1989-96 period. During these periods we examine the size, price earnings ratio and dividend yield effects, given the fact that our data contains 41 years, the examination of these effects over large time-period provide empirical evidence more robust. Combined portfolios are also formed to assess the interaction amongst these effects, over the time period (1976-1996) we utilise the portfolio returns to test asset-pricing inferences. This chapter reviews these effects; provides an empirical examination of their behaviour from 1956 to 1996 and their interaction effect over the testing period of the thesis. Although the size, price earnings ratio and dividend yield effects have been documented in the previous decades there is a lack of empirical evidence of their behaviour and interaction effects over the last decade. Thus this lack of evidence provides an additional motive of this chapter, given the fact that these phenomena have been shown to vary over.

The seminal studies of Banz (1981) and Reinaganum (1981) served as a springboard for much subsequent research that has confirmed the existence of the price earnings (PE) and size effect in stock market behaviour. The existence of the size effect has been documented in stock markets worldwide. A positive size premium has also been found in other countries, such as New Zealand, Australia, Canada, Japan, and seven European markets. Levis (1989) reports evidence documenting the presence of a significant PE effect on the London Stock exchange over the period April 1961 to March 1985. He reports an average monthly premium of 0.58% (7% annually). His results are similar to results reported by Basu (1977, 1983) and Reinaganum (1981). Levis (1989) also reports a size effect, which finds to be weaker than the PE effect. He finds that there is a large degree of interdependency between size and PE, but with the PE effect tending to subsume the size effect. The relation between dividend yield and stock returns has also received close scrutiny. Studies by Litzenberger and Ramaswamy (1979), Blume (1980), Gordon and Bradford (1980), Miller and Scholes (1982) and Elton, Gruber and Rentzer (1983), point to a positive and significant relation between dividend yield and returns. Levis (1985) also finds a positive relation between dividend yield and returns in the LSE between April 1961 to March 1985.

The objective of this chapter, apart from introducing the portfolio returns used in the thesis is to examine whether the size, price earnings ratio and dividend yield effects still exist and on what extent, whether they have reversed, or disappeared, and furthermore to examine the interaction amongst them. Chapter 4 is organised as follows. Section 4.1, 4.2 and 4.3 provides a review of the literature based on size; price earnings ratio and dividend yield effects. Section 4.4 provides some final considerations on the links between these anomalies with the joint hypothesis of market efficiency and asset pricing models. Section 4.5.1 explains the technical details of forming primary portfolios, and discusses the results. Section 4.5.2 explains how we form secondary (combined) portfolios, discusses the results, and provides graphs for the size; PE and dividend yield effect, for the 1956-66, 1967-77, 1978-88, and 1989-96 sub-periods. Section 4.6 concludes.

4.1 THE SIZE EFFECT

Banz (1981) was the first to document the size effect. For the 1931 to 1975 period, Banz estimated a model of the form: $E(Ri)= a_0+a_1\beta_i+a_2S_i$; where Si is a measure of the relative market capitalisation (size) for firm i. He found that the statistical association between returns and size is negative. Similar models have been estimated for Belgium (Hawawini, Michel & Corhay, 1989), Canada (Calvet & Lefoll, 1989), France (Hawawini & Viallet, 1987), Japan (Hawawini, 1991; Chan, Hamao & Lakonishok, 1991), Spain (Rubio, 1988), and the UK (Corrhay, Hawawini & Michell, 1987). In all countries except France and Japan there is no relation on average between return and market risk when all months of the year are considered (i.e., a_1 is statistically indistinguishable from zero). There is, however, a negative relationship between returns and size in all countries except Canada and France (i.e., a_2 is significantly less than zero).

The existence of the size effect has also been demonstrated by examining the returns of portfolios formed on the basis of market capitalisation. Reinaganum (1981) by using daily data over the period from 1963 to 1977 showed that portfolios of small firms have significantly higher average returns than larger firms. He found that the difference in returns between the smallest and the largest deciles of firms drawn from the NYSE and AMEX was about 30% annually. Regarding this findings Roll (1981) posits that the size effect may be a statistical artefact of improperly measured risk due to infrequent trading of small stocks. OLS estimates of beta coefficients of infrequently traded stocks are lower than their 'true' beta coefficients, and since small firms tend to trade relatively infrequently, their beta coefficients are underestimated. However, in response to the previous argument, Reinaganum (1982) estimated betas using methods designed to account for nonsyncrounous and infrequent trading (Scholes, 1977, Dimson (1979), and still found a significant size effect.

Reinaganum (1990) claims that the relative price behaviour of small and large firms may differ for Over-the Counter (OTC) stocks. He finds, by using data from 1973 to 1988, that small OTC stocks have significantly lower returns than NYSE and AMEX firms with the same size, and that the small-firm premium for OTC stocks is much lower than for NYSE and AMEX stocks. Reinaganum (1990), attribute these differences to differences in liquidity between the two markets, implying that differential costs of trading small stocks in these two types of markets. Therefore he suggests that market structure may be an important influence on the measured size effect. Therefore he suggests that market structure may be an important influence on the measured size effect.

He finds that among small firms, the average returns of NYSE securities exceed the average returns of similar-sized NASDAQ securities; and that the return differential between NYSE and NASDAQ securities diminishes as stock-market capitalisation increases; According to Amihud and Mendelson (1986), stocks with lower volume (and hence higher spreads and less liquidity) will have higher average returns than high-volume stocks, all else being equal. Reinaganum (1990), finds that among small companies, the NASDAQ appears to have a liquidity advantage, but among larger firms it has no such advantage. He claims that the NYSE specialist has an incentive to provide the best service and provide liquidity for securities that generate profits, that is, high volume securities.

The existence of the size effect has been have been documented in stock markets worldwide. Hawawini & Keim (1995) report a positive size premium (size premium is the difference between the average monthly return on the portfolio of smallest stocks and the average monthly return on the portfolio of largest stocks) in other countries, such as New Zealand, Australia, Canada, Japan, and seven European markets. Its magnitude varies across markets. It is most pronounced in Australia (5.73%) and Japan (1.20%).

Table 4.1, 4.2, 4.3, and 4.4 show that there is a wide range across the 13 markets in terms of the size (market capitalisation) differential between the largest and smallest size portfolios. In Spain the average market capitalisation of the stocks in the largest size portfolios is 228 times the average market capitalisation of the stocks in the smallest size portfolios, whereas in Taiwan the largest portfolio is only 17 times larger than the smallest one. Therefore because of the size and the number of portfolios as well as the sample periods differ across countries, it is difficult to gauge whether the magnitude of the size premium is significantly different across countries.

Table 4.1: The Size effect

Country	Australia	Belgium	Canada	Finland
Test Period	1958-81	1969-83	1973-80	1970-81
No of securities	281-937	170	391	50
No of size portfolios	10	5	5	10
Market value of largest portfolio of firms divided by market value of smallest portfolio of firms	NA	188	67	113
Average monthly return (%) on the smallest portfolio of firms	6.75	1.17	1.67	1.65
Average monthly return (%) on the largest portfolio of firms	1.02	0.65	1.23	0.89
Size premium (%) (small minus large)	5.73	0.52	0.44	0.76

[Source: Hawawini & Keim (1995)]

Table 4.2: The Size effect

Country	France	Germany	Ireland	Japan
Test Period	1977-88	1954-90	1977-86	1965-87
No of securities	529-460	All FSE	40	1st TSE
No of size portfolios	5	9	5	10
Market value of largest portfolio of firms divided by market value of smallest portfolio of firms	NA	NA	NA	NA
Average monthly return (%) on the smallest portfolio of firms	1.2	1.54	3.1	2.57
Average monthly return (%) on the largest portfolio of firms	0.3	1.05	2.63	1.37
Size premium (%) (small minus large)	0.9	0.49	0.47	1.2

[Source: Hawawini & Keim (1995)]

Table 4.3: The Size effect

Country	New Zealand	Spain	Switzerland	Taiwan
Test Period	1977-84	1963-82	1973-88	1979-86
No of securities	About 100	98-140	153	53 to 72
No of size portfolios	5	10	6	5
Market value of largest portfolio of firms divided by market value of smallest portfolio of firms	60	228	99	17
Average monthly return (%) on the smallest portfolio of firms	0.69	0.58	0.94	0.47
Average monthly return (%) on the largest portfolio of firms	0.18	0.02	0.42	-0.1
Size premium (%) (small minus large)	0.51	0.56	0.52	0.57

[Source: Hawawini & Keim (1995)]

Table 4.4: The Size effect

Country	UK
Test Period	1958-82
No of securities	All LSE
No of size portfolios	10
Market value of largest portfolio of firms divided by market value of smallest portfolio of firms	182
Average monthly return (%) on the smallest portfolio of firms	1.32
Average monthly return (%) on the largest portfolio of firms	0.9
Size premium (%) (small minus large)	0.42

[Source: Levis (1985), Hawawini & Keim (1995)]

Levis, (1985), provide an empirical analysis of the size effect on the London stock exchange. He utilises data from 1958 to 1982, and finds that the size effect is not confined to the US market, Australia and Canada, but also there are differences in performance between shares of various size firms. He finds that the smaller portfolio outperforms its largest counterpart by about 5% per annum, and that the average portfolio returns decline quite uniformly as firm size increases. Further he notes that the return on the largest UK portfolio is roughly the same as the equivalent U.S. and Australian portfolios over similar periods, but the lowest decile of British firms seem to earn a substantial lower return than their equivalent in these two countries.

Levis (1985) finds that the autocorelation coefficients indicate first and higher order serial correlation for most of his 10 size portfolios, and claims that since the lower order serial correlation are far more pronounced for the smaller portfolios suggest that they may be to be due to infrequent trading. Dimson claims that in the case of infrequently traded stocks, such as those of small firms are likely to be the last transaction may well have taken place some time before hand. Theoretically since ordinary beta estimates focus on the contemporaneous relationship with the market index, such betas would be biased downwards. With these facts taken in account, Levis (1985) computed both OLS betas and Dimson betas adjusted for thin trading. Summing up three lagged and the contemporaneous regression coefficients obtain the Dimson betas. He finds that although the adjusted betas for smaller portfolios are higher in comparison to the OLS betas, smaller firms still appear to be less risky than larger firms are.

To shed some light in this issue, Levis (1985) examined some beta estimates for individual firms provided by the London Business school Risk measurement Service. Over 22 quarters covering the period January 1979 to June 1984 only 29% of the eighty highest beta firms included in the service are firms with a total market capitalisation of less than £10 million, while the equivalent lowest comprises 76% of such firms. So he concludes that the lower betas for the smaller firms reported in his study are in line with LBS estimates. Furthermore in a later study Levis (1989), when he used five lagged and one leading market coefficients, to account for thin trading, [Dimson, (1979)], he also finds that smaller firms do not emerge as riskier than larger firms. Levis (1989) examines a number of irregularities in the stock price behaviour of firms on the London stock exchange, and finds that the size effect to be weaker then the P/E effect, and the dividend yield effects. In fact he documents that the dividend yield and PE ratios subsume the size and share price effects.

Banz (1985) also provides evidence of a significant size effect on the LSE. His analysis is based on 29 years of monthly returns (1955-1983) taken from the LSPD. With ten value-based portfolios, he reports a compounded annual return of 39% for the smallest portfolio versus 13% for the largest. Dimson and Marsh (1986) also report evidence of a size effect constructed from a sample of stocks taken from LSPD. Over the period 1977-1983, the portfolio of smallest stocks earned a compound annual return of 41% and the portfolio of largest stocks realised a compound annual return of 18%. Banz (1985) find that the compound annual return on the smallest portfolio exceeded that of the largest by 27%. Dimson and Marsh (1986) report that the difference is 23%, both before adjusting for risk.

Hawawini and Keim (1995) mention that in the US and Japan small firms have on average higher beta risk than large firms, but the higher beta risk is not enough to explain the size premium- the risk-adjusted size premium is still significantly different from zero. In the remaining countries the systematic risk of the smallest firms is about the same or lower than that of largest firms. A possible explanation may be the extreme illiquidity in some of these markets, especially for smaller stocks, that may result in downward-biased estimates of beta-even when betas are estimated with monthly returns. In countries where adjusted betas are computed, using the methods of Scholes & Williamms (1977) or Dimson (1979) the size effect remains.

Chan and Chen (1991) explore the fundamental risk characteristics of smaller companies. They claim that small firms are marginal firms in the sense that their prices tend to be more sensitive to changes in the economy and are more exposed to adverse economic conditions. Small firms are more likely to be inefficient producers, to have high financial leverage and limited access to capital markets particularly at periods of tight credit conditions. The outcome of such fundamental differences with larger (healthier) companies is that marginal companies react differently to the same macroeconomic news. They also claim that among the firms that have cut their dividends in half or more the year before, 50% are in the bottom size quintile. Furthermore the probability of a small company to be highly leveraged is almost four times higher than a large company. Queen and Roll (1987) show that there is a strong inverse relation between unfavourable mortality and size. About one-quarter of the smaller forms are halted, de-listed or suspended from trading within a decade, and about 5% actually meet this fate within a year. In contrast less than 1% of the largest firms expire from unfavourable causes even over the longest observation period. A firm of course may be de-listed as a result of different reasons, such as straight take-over, suspension or liquidation.

Levis (1999) shows that the probability of such incidents incurring is significantly higher for small to medium size companies. For example he finds during the period 1958 to 1988, that companies in deciles 3 to 6 are more likely to be targets of take-overs than companies in deciles 9 and 10. During the same period, 95% of the suspended companies belong to deciles 1 to 5, with a staggering 50% coming exclusively from the first smallest decile. Liquidations are also concentrated in deciles 1 to 6, with 45% from the first decile alone. So he concludes that there is little doubt that smaller companies are riskier than their larger counterparts to some type of event risk. However he claims that the positive size effects, is driven by a relatively limited number of small stocks, which are good performers and possess the following key characteristics. They have lower than average market-to-book and price earnings ratings. Their market value is higher than the average market capitalisation of the small cap sector; they have been listed in the market for longer than a year. They have not raised additional equity capital; in the last year, they have reasonable stable earnings growth profile. Furthermore they do not belong to sectors with excessive swings in analyst forecasts, their current ratings do not depend on hugely overoptimistic analyst forecasts, and they are relatively immune to the downturn of the business cycle.

4.2 THE PRICE / EARNINGS RATIO (P/E)

Nicholson (1960), examined the relation between P/E multiples and subsequent total returns, showing that low P/E stocks consistently provide returns greater than the average stock. The Asset Pricing Model of Sharpe (1964), Lintner (1965), and Black (SLB model) (1972) implies that the market portfolio of invested wealth is mean-variance efficient in the sense of Markovitz (1959). The efficiency of the market portfolio implies that expected returns on securities are positive linear function of their market betas and that market betas suffice to describe the cross-section of expected returns. However several empirical contradictions of the SLB model have been found. Basu (1983) shows that the earnings price ratios (E/P) help explain the cross section of average returns on US stocks in tests that also include size and market beta. Ball (1978) argues that E/P is a catchall proxy for unnamed factors in expected returns. Basu (1977) claims that P/E ratios may explain violations of the CAPM, and found that for his sample of NYSE firms, there was a significant negative relation between P/E ratios and average returns. Basu claims that if an investor followed his strategy of buying the quintile of lowest P/E stocks and selling short the quintile of the highest P/E quintile stocks based on annual rankings, the average annual abnormal return would have been 6.75% over the 1957 to 1975 period (before commissions and other transaction costs). Also Reinaganum (1981), by examining both NYSE and AMEX stocks, confirmed Basu's results.

Hawawini & Keim (1995), update the data file of Keim and Westerfield (1989) from 1987 to 1989. Hawawini & Keim (1995), find the average difference in returns between the highest and lowest portfolio E/P portfolios is on average 0.46% per month (Table 4.5). Then for purposes of comparisons, they also separately computed size portfolios for the same sample of firms. The average difference in returns between the smallest and largest size deciles for this same 1962-1989 period is 0.80% per month. Thus, size and E/P display similar abilities to sort firms according to expected returns.

Related to the relation between size, E/P and dividend yield in connection to the results of Table 4.5, Morgan and Thomas (1998) show that smaller firms are concentrated in the zero dividend yield portfolio, but both the highest and dividend yield quintiles have low average sizes. That high dividend yield stocks are small may suggest that they are shrinking (falling share prices), but are reluctant to cur dividends: eventually they will join the low- or zero-dividend groups. Levis (1989) finds that although there is a large interdependency between size, price/earnings ratio, dividend yield and share price, the dividend yield and price earnings ratio subsume the size and share price effects.

Table 4.5: The E/P effect

E/P portfolio	Mean return
Negative	1.55
Lowest	0.79
2	0.9
3	0.91
4	0.87
5	0.79
6	0.97
7	1.05
8	1.13
9	1.34
Highest	1.25

[Source: Hawawini & Keim (1995)]

Outside the U.S there limited studies examining the P/E effect, due to lack of computerised accounting data. Levis (1989) reports evidence documenting the presence of a significant P/E effect on the London Stock exchange over the period April 1961 to March 1985. He reports an average monthly premium of 0.58% (7% annually). His results are similar to results reported by Basu (1977, 1983) and Reinaganum (1981). Levis (1989) also reports a size effect, which finds to be weaker than the P/E effect. He finds that there is a large degree of interdependency between size and P/E, but with the P/E effect tending to subsume the size effect.

Aggarwal, Hiraki and Rao (1988), also finds a significant P/E effect in the Tokyo Stock exchange during the period from 1974 to 1983. They find that portfolios of low P/E stocks outperformed those with relatively higher P/E stocks even after controlling for differences in systematic risk and size across portfolios. For the Taiwan stock exchange, Chou and Johnson (1990) report a significant P/E effect from 1979 to 1988. Also Ma and Shaw (1990) report a weaker but significant P/E effect for the Taiwan stock exchange over the period 1979 to 1986.

We should also mention that the both the PE and Size effects exhibit some similar features. First, size and E/P are computed using a common variable-price per share. Blume & Stambaugh (1983), Stoll & Whaley (1983), report evidence suggesting a high rank correlation between size and price. Second, apart from the common denominator between these effects, all these effects also become most pronounced in the month of January. Which in turn suggests that these effects are associated with some common underlying factor. The January seasonal has been demonstrated for the size effect (Keim, 1983b), E/P effect (Cook & Rozeff, 1984), and Jaffe, Keim & Westerfield, 1989). Third in addition to the within-year variation the magnitude of these effects have been shown to vary over longer periods of time.

4.3 THE DIVIDEND YIELD

Keim (1985) analyse the relationship between returns and dividend yields of NYSE firms. He divides, in each month the sample securities into six groups of increasing dividend yield (one group containing all zero-dividend yield firms, the other five representing the quintiles of the positive-yield firms). He computes portfolio returns by combining the returns for the securities in each portfolio with equal weights. The time-series of portfolio returns cover the period January 1931 to December 1978.

Table 4.6 reports the mean returns for each dividend yield portfolio, along with the average dividend yields and average market value for each portfolio.

Table 4.6: The Dividend Yield effect

Dividend Yield portfolio	Average return	Average Dividend Yield	Average Market value of equity[1]
Lowest	1.11	2.12	422.2
2	1.10	3.71	339.9
3	1.06	4.81	259.6
4	1.23	5.93	245.9
Highest	1.40	8.25	202.7

[Source: Keim (1985)]

Keim (1985) finds that returns for dividend paying stocks tend to increase as dividend yield increases.[2] To further investigate the relation between yields and size he independently ranks all sample securities on the basis of both total market value of equity and dividend yield. He forms six dividend yield categories and five size categories (quintiles) based on the two rankings. This procedure results in thirty categories. Keim (1985) finds that a great number of smallest firms on the NYSE are concentrated in the highest dividend yield group, and that the high average returns of the highest yield groups may simply reflect the high returns of small firms.

Keim (1985) estimate the dividend yield coefficient in both January and non-January months using the Seemingly Unrelated Regression model (SUR), (Zellner, 1962). The dividend yield in month $_t$ is defined as the sum of dividends paid in the previous twelve months divided by the stock price in month $_{t-13}$. He finds for the overall period the yield coefficient to be positive and significant in both January and non-January months. The January yield coefficient is significantly larger than the non-January coefficient. Then given his evidence that the cross-sectional variability in yields is related to cross-sectional variability in market capitalisation, he investigated further the interrelation between dividend yield and size. He utilise the SUR model with a new variable included (the average of the natural logarithm of market capitalisation) for his thirty combined size-yield portfolios. He finds the estimate of the size coefficient significantly larger in January than in other months in the overall period and in every sub-period. When estimated over the entire period, the non-January size coefficient is insignificant. He also finds that the magnitude of the January dividend yield coefficient declines (relative

[1] Market values are in millions of dollars.
[2] Keim (1985) finds that zero dividend securities have on average the largest returns.

to the previous model without the variable of market capitalisation included) when estimates simultaneously with size. Keim (1985) claims that the attenuation of the yield coefficient suggests that dividend yields and size are related to the same asset-pricing factor. The yield coefficient remains significant though in both January and non-January months, after controlling size.

Keim (1985) claims that an obvious question concerns the robustness of the results. He reports that Litzenberger and Ramaswamy (1979) find coefficient on dividend yield to be insignificant in January and significantly positive in non-January months, whereas Miller and Scholes (1982) find the coefficients on yield to be significantly positive in January and significantly negative in non-January months. He claims the studies of Litzenberger and Ramaswamy (1979) & Miller and Scholes (1982), produce results from the Fama-MacBeth (1973) methodology, which are subject the errors–in-the variables problem, and do not account for cross-equations (i.e., cross-portfolio) correlation in the residuals when estimating the parameters.

In the UK market, Levis (1989) finds a dividend yield effect, for the period April 1961 to March 1985. He also examine the inter-relation between dividend yield and size by forming combined portfolios, and he also finds that a combination of small size and high dividend yield generates portfolios earning consistently higher abnormal returns. He finds a dividend yield effect at each level of market size; this effect however declines as one moves from the smallest portfolio to the largest portfolio. The dividend yield effect also increases gradually from dividend yield quintile 1 to 5. Levis (1989) examine whether a large proportion of smaller firms are concentrated in the high dividend yield categories, by computing the average dividend yield of each market size quintile. He finds that a high concentration of smaller firms within the higher dividend yield groups, but claims that the dividend yield is not a surrogate for size.

Morgan and Thomas (1998) test the tax-based theory which, when applied to US data, predicts a positive relation between stock returns and anticipated dividend yields. Their paper draws on unique features of the British tax system to reject the tax-based explanation for the relation between dividend yields and stock returns. The UK tax system is formed in such a way that tax-based models of the dividend yield-return relation do not imply a positive correlation between dividend yields and returns, as in the case in the US, despite this the yield-return relation in the UK has been shown to be similar to the US. Morgan and Thomas (1998) find that high-yielding stocks earn positive risk adjusted returns, whereas low yielding stocks earn negative risk adjusted returns. They also detect evidence of non-linearity in the performance of zero-dividend yield stocks. Controlling for firm size, seasonality and market risk they find a significant positive relation between dividend yields and returns. They conclude that their evidence is not consistent with a tax-based explanation.

4.4 ASSET PRICING MODELS, MARKET EFFICIENCY AND ANOMALIES

This section provides a discussion on the links between these anomalies with the joint hypothesis of market efficiency and asset pricing models. The Capital Asset Pricing model (CAPM) has occupied a central position in the science of finance, and states that the rate of return on any security is linearly related to that security's systematic risk (beta) measured relative to the market portfolio of all securities. If the model is correct and securities markets are efficient, security returns will on average conform to this linear relationship. Persistent departures, however, represent violations of the joint hypothesis that both the CAPM and the efficient market hypothesis are correct. The empirical attacks on the CAPM model begin in the late 1970's with studies that identify variables that contradict the model's prediction that market β's suffice to describe the cross section of expected returns [Basu (1977, 1983), Banz (1981), Fama and French (1991), etc]. Fama (1991) claims that the relation between expected returns and size, PE, dividend yield, book-to-market, etc, are usually interpreted as embarrassments for the CAPM model or the way it is tested, rather than evidence of market inefficiency. Actually, however the existing tests can't tell whether the anomalies result from a deficiency of the CAPM model or persistent mispricing of securities. Now if a past anomaly does not appear in future data it might be market inefficiency erased with the knowledge of its existence. On the other hand if the anomaly is explained by other asset pricing models then one is tempted to conclude that it is a rational asset-pricing phenomenon.

Fama and French (FF) (1993, 1995, 1996) advocate that their three factor model consisting of: (1) the return on a value weighted market portfolio in excess of the one-month Treasury bill return. The equal-weighted returns are affected more by small stocks, while value weighted towards large stocks; (2) the difference in returns on a small-firm portfolio and a large portfolio; (3) the difference in returns on a portfolio of firms with high book-to-market equity and a portfolio of firms with low book-to-market equity; does a much better job in explaining asset returns (i.e., values of a close to zero) than the CAPM. Fama and French (1997) use this model for calculating the cost of equity capital for US industry portfolios. However there is a controversy over why the firm-specific attributes that are used to form the FF model should predict returns. Some argue, Fama and French (FF) (1993, 1995, 1996) that the measures are proxies for exposure to underlying economic risk factors that are rationally priced in the market. For example Fama and French (1992) and Chen and Zuang (1998) claim that value stocks outperform their growth counterparts because they are fundamentally riskier. Thus the positive association between book to market and stock returns is consistent with efficient pricing in capital markets, since book to market and size are proxies for unobservable common risk factors. On the other hand other argue, Lakonishok, Shleifer and Vishy (1994), Daniel and Titman (1997), that such variables may be used to find securities hat are systematically mispriced by the market. They base their explanations on the behavioural finance paradigm and/or some type of inefficiency of the market to justify this phenomenon. Systematic errors in expectations about the future, that is the result either from a series of good or bad news, for example, has been suggested to justify the observed return deference between value and growth stocks. Expectation errors cause a certain degree of mispricing, which makes value stocks to be underpriced and growth stocks to be overpriced.

Chan, Chen and Hiesh (1985) argue that the business condition variables in the Chen, Roll and Ross, especially the difference between low-grade corporate and government bonds returns explain the size anomaly of the CAPM model. These successes of the multifactor model are however tempted by Shanken and Weinstein (1990) who find that the power of the economic factors in Chen, Roll and Ross (CRR) is sensitive to the assets used in the tests and the way factor loadings are estimated. Ferson and Harvey (1991) extend the CRR approach to study the links between the common economic factors in the cross section of returns and the variables (e.g., dividend yield, term structure) that track variation in expected returns through time. The Arbitrage Pricing Theory (APT) compared to the CAPM seems to fare well in the sense that it does a better job of explaining cross-sectional differences in asset returns [e.g., the nonested hypothesis tests of Chen (1983)]. However Connor and Korajczyk (1995) claim that given the inherent variability in asset returns, it is difficult to measure unconditional mean return with much precision and that this is a problem shared by all models of unconditional asset pricing and is not specific to the APT.

4.5 PORTFOLIO FORMATION

Following the review on the size, price earnings ratio, dividend yield and the brief discussion of the link between these effects with the joint hypothesis of market efficiency and asset pricing models, we proceed by explaining the procedure of forming our portfolios.

4.5.1 PRIMARY PORTFOLIO FORMATION

Primary portfolios are formed in order to test asset-pricing inferences in the following chapters. This section presents the procedure of forming these primary portfolios on the basis of size, price earnings and dividend yield. Section 4.5.2 also provides an analysis of how the size, price earnings ratio and dividend yield effects have developed over a large time period, from 1956 to 1996, and also during the period we use these portfolio returns to asset pricing inferences.

We form primary portfolios based on market value as follows: at the end of December each year all firms are ranked in ascending order and divided in 25 groups. Portfolio returns are computed for the 12-month period commencing the following January (equal weighted). The portfolios are formed in such a way so that portfolio 1 [Market Value 1 (MV1)] contains the smallest companies and portfolio 25 [Market Value 25 (MV25)] contains the largest companies. A firm needs data for market value at the end of the year and a valid rate of return for January next year to enter the sample. Firms enter or leave the sample due to new listings/mergers/ bankruptcies.

We also form portfolios based on dividend yield and PE ratios. The dividend yield is measured by the ratio of the dividends paid during the 12 months period to the market price of common stock at the end of December. Portfolios returns are computed for the 12-month period starting the following January. The portfolios are formed in such a way so that portfolio 1 [Dividend yield 1 (DY1)] contains the low dividend yield companies and portfolio 25 [Dividend yield 25 (DY25)] contains the higher dividend yield companies.

The earnings per share over the share price defines the PE ratio, where earnings per share are estimated as the 12 month earnings divided by the number of shares outstanding at the calendar year end. Ball (1978) posits that the earnings-price ratio is a catch-all for omitted risk factors in expected returns. If current earnings proxy for expected future earnings, high-risk stocks with high-expected return will have low prices relative to their earnings. Thus, E/P should be related to expected returns whatever the omitted sources of risk. This argument only makes sense, however, for firms with positive earnings. When current earnings are negative, they are not a proxy for the earnings forecasts embedded in the stock price, and E/P is not a proxy for expected returns. Following this argument, also Fama and French' (1992) slope of E/P in their regression is based only on positive earnings. Both Reinaganum (1981) and Basu (1983) excluded stocks in any year in which it had negative earnings. Studies by Basu (1977), Cook and Rozeff (1984), and Baumen and Dowen (1986) have found that the effects of portfolio return ranking are essentially the same, whether stocks with negative EPS are included or excluded from portfolio groups. Given the ambivalent interpretation of negative earnings and following the practice of previous studies, Levis (1989) excludes from his sample in any year firms that they had negative earnings. Levis and Liodakis (1999) also do not use stocks with negative M/B, CF/P or E/P when forming portfolios. Thus a firm was dropped from the sample in any year in which had negative earnings. The portfolios are formed in such a way so that portfolio 1 [PE ratio 1 (PE1)] contains the low PE ratio companies and portfolio 25 [PE ratio 25 (PE25)] contains the high PE ratio companies.

Table 4.7, 4.8 and 4.9 report the monthly average portfolio return for the twenty-five size, PE ratio and dividend yield portfolios, and the annual size, PE ratio and dividend yield premiums respectively. Table 4.7 shows that the average annual size premium for the 1956-66, 1967-77, and 1978-88 period is 10.27%, 12.24%, and 19% respectively. However the size effect for the 1989-96 has reversed (-10.26% annually), that means that there is a size effect, but on the reverse, large firms outperformed smaller ones. Dimson and Marsh (1999) also find that the size effect has reversed. Levis (1999) claims that the reversal of the size effect is associated with a large volume of equity issuing activity in the preceding months. Large volume of equity issuance activity is associated with high initial prices resulting from overoptimistic prices. Price overoptisism is associated with subsequent long-term under-performance. If new companies are searching for windows of opportunity to come to the market, their valuations are likely to be optimistic at the time of the floatation and are adjusted downwards when their true potential becomes better understood.

Table 4.7: Primary Market Value Portfolios

We form primary portfolios based on market value as follows: at the end of December each year all firms are ranked in ascending order and divided in 25 groups. Portfolio returns are computed for the 12-month period commencing the following January (equal weighted). The portfolios are formed in such a way so that portfolio 1 [Market Value 1 (MV1)] contains the smallest companies and portfolio 25 [Market Value 25 (MV25)] contains the largest companies. A firm needs data for market value at the end of the year and a valid rate of return for January next year to enter the sample. Firms enter or leave the sample due to new listings/mergers/ bankruptcies.

Table 4.7 *-continued-*

MARKET	VALUE			
PERIOD	1956-66	1967-77	1978-88	1989-96
MV1	1.529	1.758	2.924	0.238
MV2	1.266	1.428	2.128	0.019
MV3	1.071	1.057	2.175	-0.204
MV4	1.041	1.319	1.74	-0.790
MV5	1.155	1.283	1.598	-0.341
MV6	1.178	1.309	1.721	0.430
MV7	1.216	1.222	1.785	-0.025
MV8	0.887	1.227	1.461	-0.509
MV9	1.161	1.281	1.326	0.067
MV10	0.99	1.148	1.284	-0.173
MV11	0.999	1.288	1.371	0.030
MV12	0.991	1.117	1.421	-0.144
MV13	0.923	1.193	1.236	-0.040
MV14	1.009	1.067	1.379	-0.135
MV15	0.895	0.909	1.361	0.137
MV16	0.977	1.054	1.344	-0.003
MV17	0.810	0.956	1.424	0.298
MV18	0.840	0.936	1.197	0.254
MV19	0.922	0.994	1.380	0.421
MV20	0.835	1.222	1.396	0.245
MV21	0.894	1.051	1.320	0.497
MV22	0.923	1.071	1.486	0.47
MV23	0.813	0.883	1.235	0.750
MV24	0.818	0.803	1.443	0.796
MV25	0.673	0.738	1.336	1.094
ANNUAL SIZE PREMIUM	**10.27**	**12.24**	**19.06**	**-10.26**
T-statistics (MV1-MV25)	**2.02**	**1.56**	**3.59**	**1.44**

Figures 1 to 4 shows the monthly small minus big market value portfolio difference, for the 1956-66, 1967-77, 1978-88, and 1989-96 period. An overall comparison of figure 1 and 2, shows that the size effect is more pronounced in the 1967-77 period compared to 1956-66 period. During the 1967-77 period, in 1975 we notice a strong under-performance of smaller companies, while in 1972 and 1977 we observe a strong out-performance of small companies. However amongst our predefined sub-periods, the 1978-88 period, is the period where the size effect is most pronounced in magnitude. In particular figure 3 shows a strong out-performance of small companies in 1987, and also in 1978. Within the 1978-88 sub-period, in 1980, small companies under-performed. Figure 4 (1989-96), shows that small companies exhibit under-performance, especially in 1989-90 period, and in 1992. Although small companies get a little better in 1993-94 period, they continue to under-perform in 1995.

FIGURE 4.1: Small minus big (1956-66)

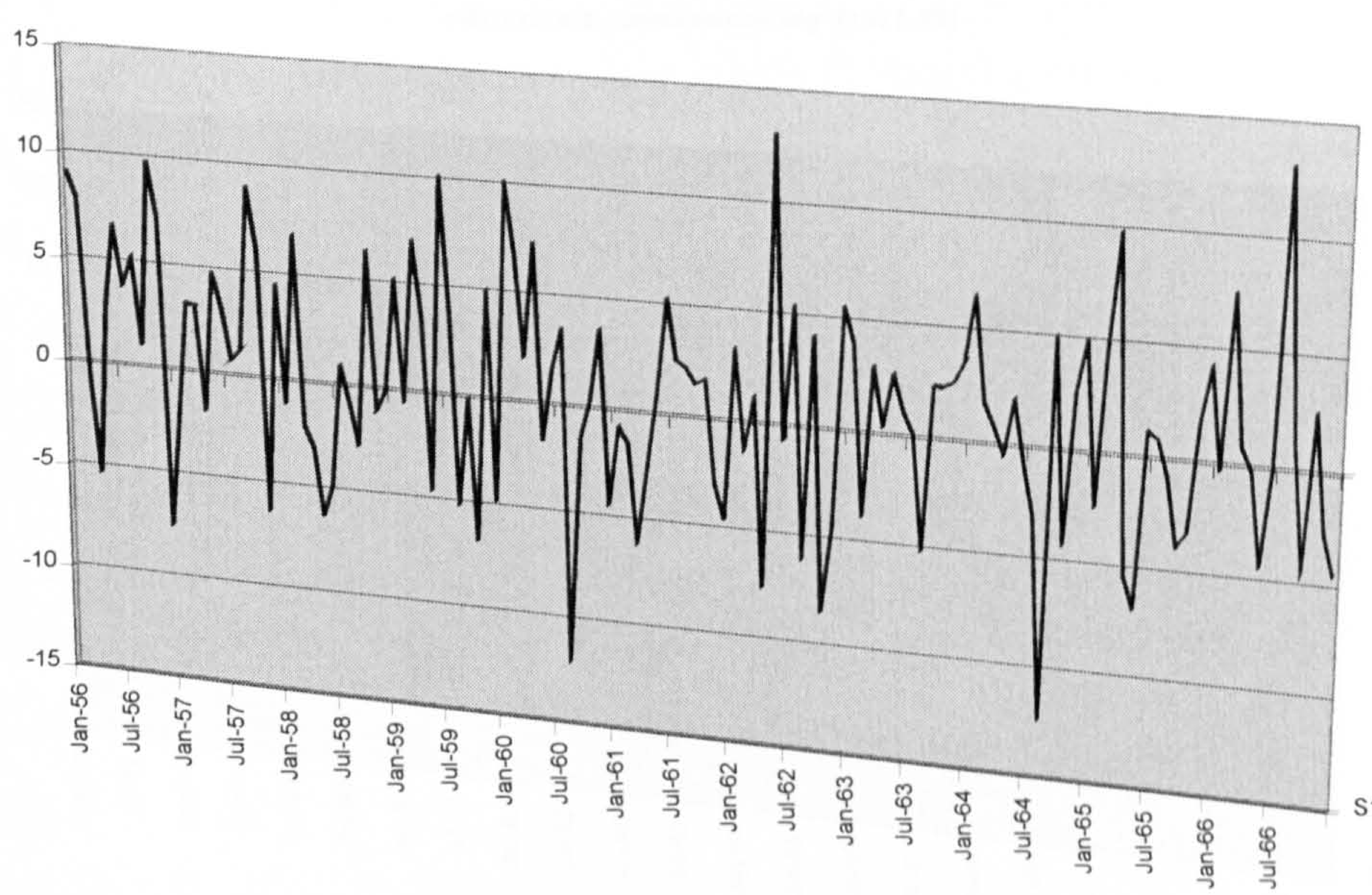


FIGURE 4.2: Small minus big (1967-77)

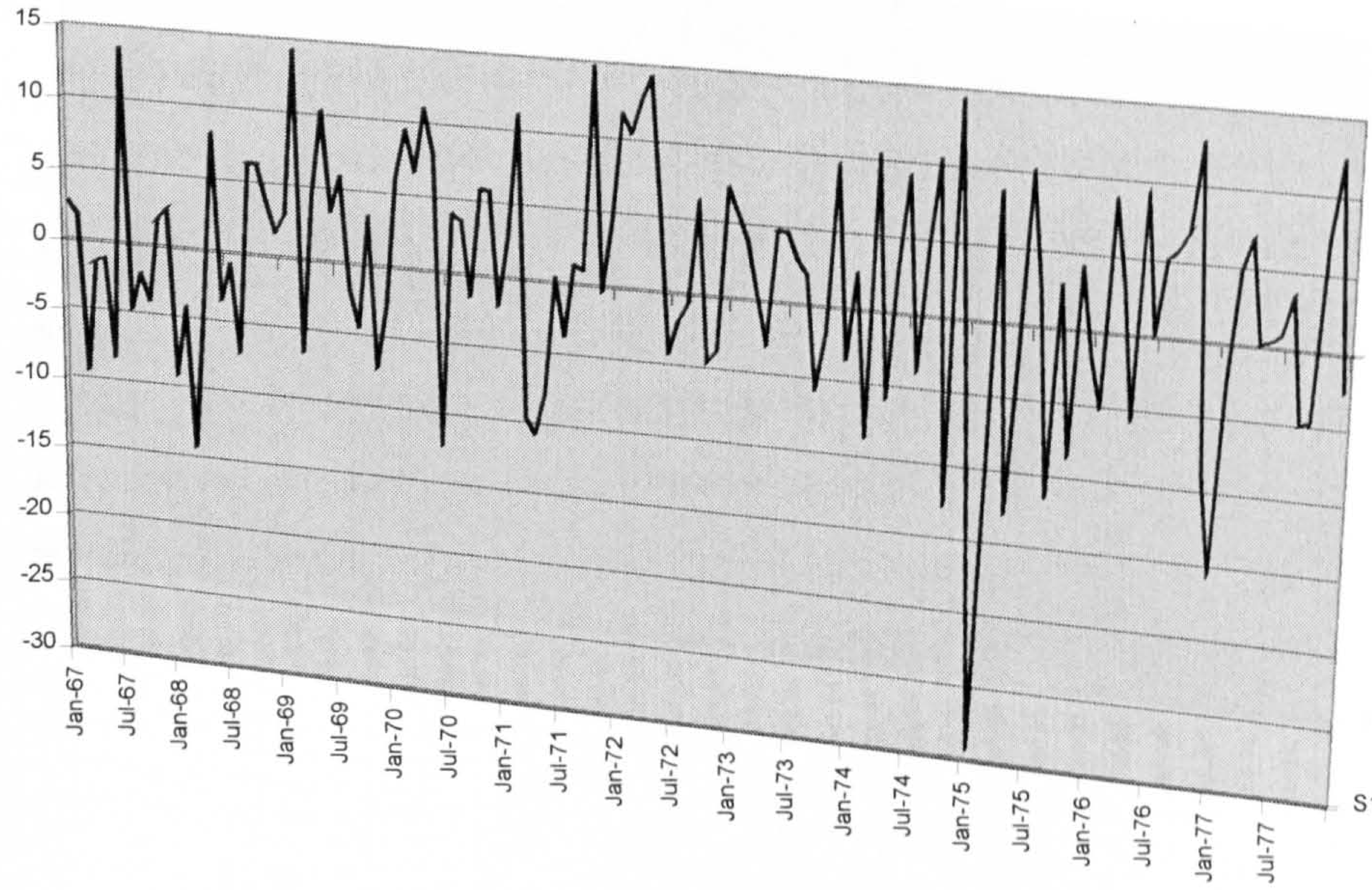


FIGURE 4.3: Small minus big (1978-88)

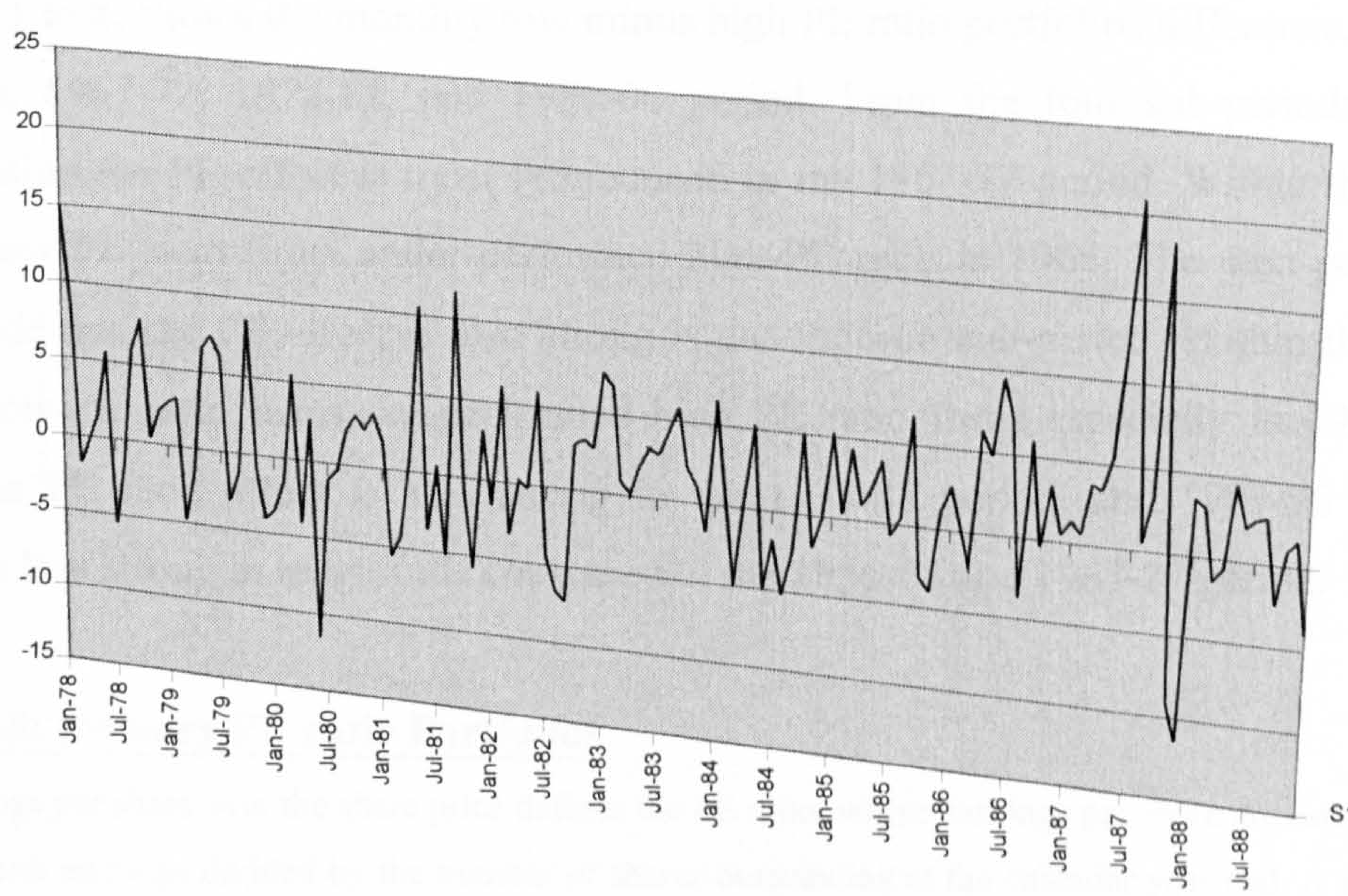


FIGURE 4.4: Small minus big (1989-96)

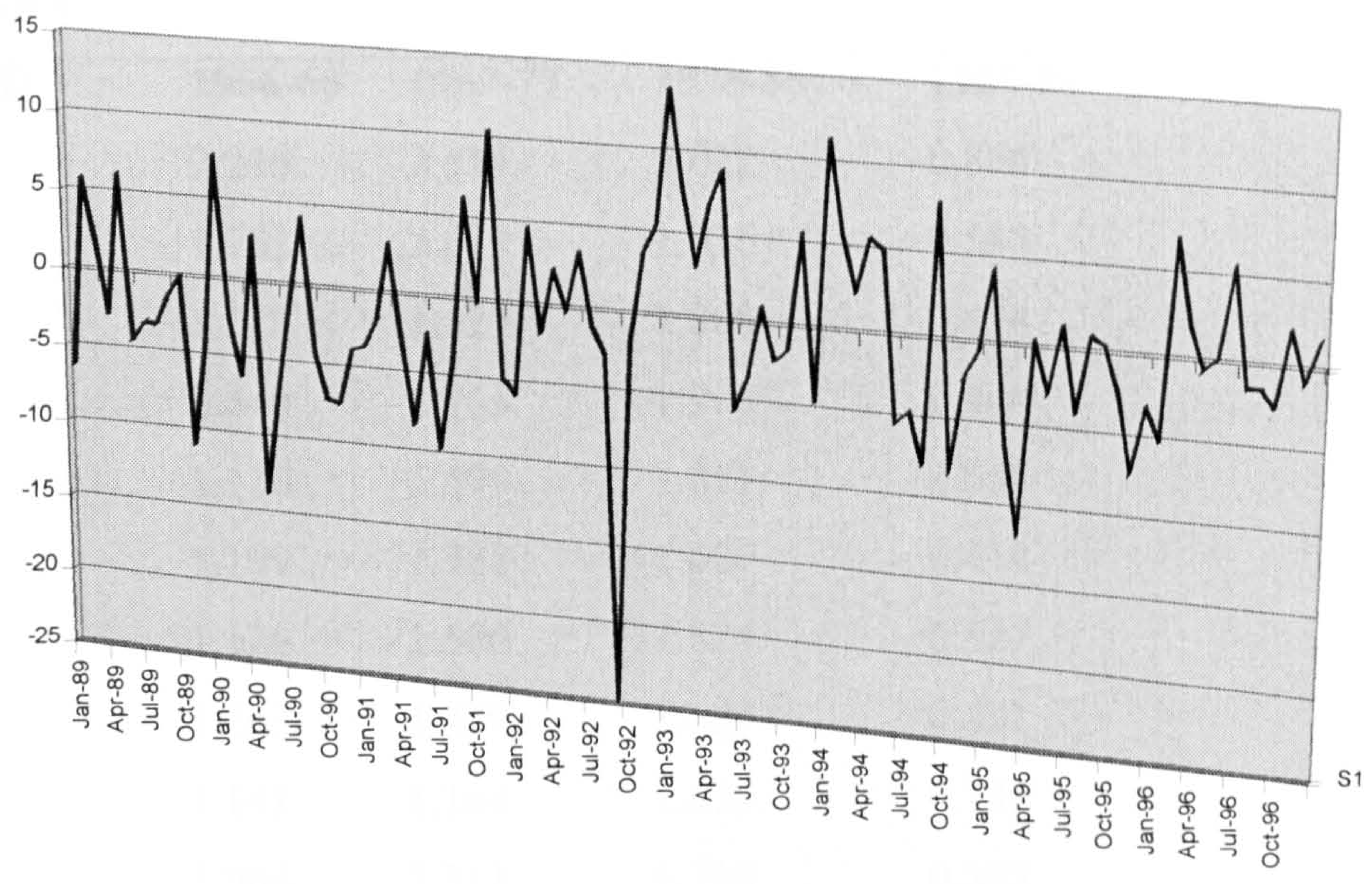


Table 4.8 reports that the average annual PE premium for the 1956-66, 1967-77, 1978-88 and 1989-96 period is 20.36%, 24.63%, 10.94%, and 9.72% respectively. Figures 5 to 8, shows the monthly low minus high PE ratio portfolios difference, for the 1956-66, 1967-77, 1978-88, and 1989-96 period. From the four sub-periods under examination the PE effect is most pronounced in the 1967-77 period. Within this sub-period low-PE ratio firms under-performed high-PE ratio in 1968. The next period in magnitude that the PE effect is also strong is the 1956-66 sub-period. Within this sub-period low-PE ratio firms out-performed high PE ratio firms especially in 1963 and 1964.The PE ratio effect is also strong in the 1978-88 period, and 1989-96 period, although less strong in magnitude compared to the 1956-66 and 1967-77 period.

Table 4.8: Primary PE ratio Portfolios

The earnings per share over the share price defines the PE ratio, where earnings per share are estimated as the 12 month earnings divided by the number of shares outstanding at the calendar year end. A firm was dropped from the sample in any year in which had negative earnings. The portfolios are formed in such a way so that portfolio 1 [PE ratio 1 (PE1)] contains the low PE ratio companies and portfolio 25 [PE ratio 25 (PE25)] contains the high PE ratio companies.

Table 4.8 *-Continued-*

PRIMARY				
PERIOD	**1956-66**	**1967-77**	**1978-88**	**1989-96**
PE1	2.216	2.514	2.022	0.894
PE2	1.732	2.039	1.936	0.548
PE3	1.513	1.627	1.888	0.414
PE4	1.540	1.765	1.906	0.446
PE5	1.110	1.599	1.811	0.658
PE6	1.199	1.788	1.627	0.414
PE7	1.126	1.500	1.824	0.527
PE8	1.263	1.479	1.587	0.421
PE9	1.141	1.164	1.619	0.148
PE10	1.004	1.311	1.738	0.302
PE11	0.884	1.211	1.553	0.083
PE12	0.935	1.117	1.727	0.326
PE13	1.019	1.176	1.643	0.308
PE14	0.878	1.046	1.711	0.369
PE15	0.809	0.819	1.498	0.219
PE16	0.903	0.949	1.583	0.308
PE17	0.771	0.789	1.436	-0.069
PE18	0.834	0.924	1.626	0.448
PE19	0.832	0.417	1.490	0.425
PE20	0.704	0.642	1.546	0.362
PE21	0.861	1.160	1.517	0.189
PE22	0.544	0.894	1.269	0.392
PE23	0.69	0.818	1.205	0.247
PE24	0.772	0.907	1.219	0.276
PE25	0.519	0.461	1.109	0.084
ANNUAL PE PREMIUM	**20.36**	**24.63**	**10.94**	**9.72**
T-statistics (PE1-PE25)	**6.03**	**5.0**	**3.64**	**3.0**

FIGURE 4.5: Low minus high PE ratio (1956-66)

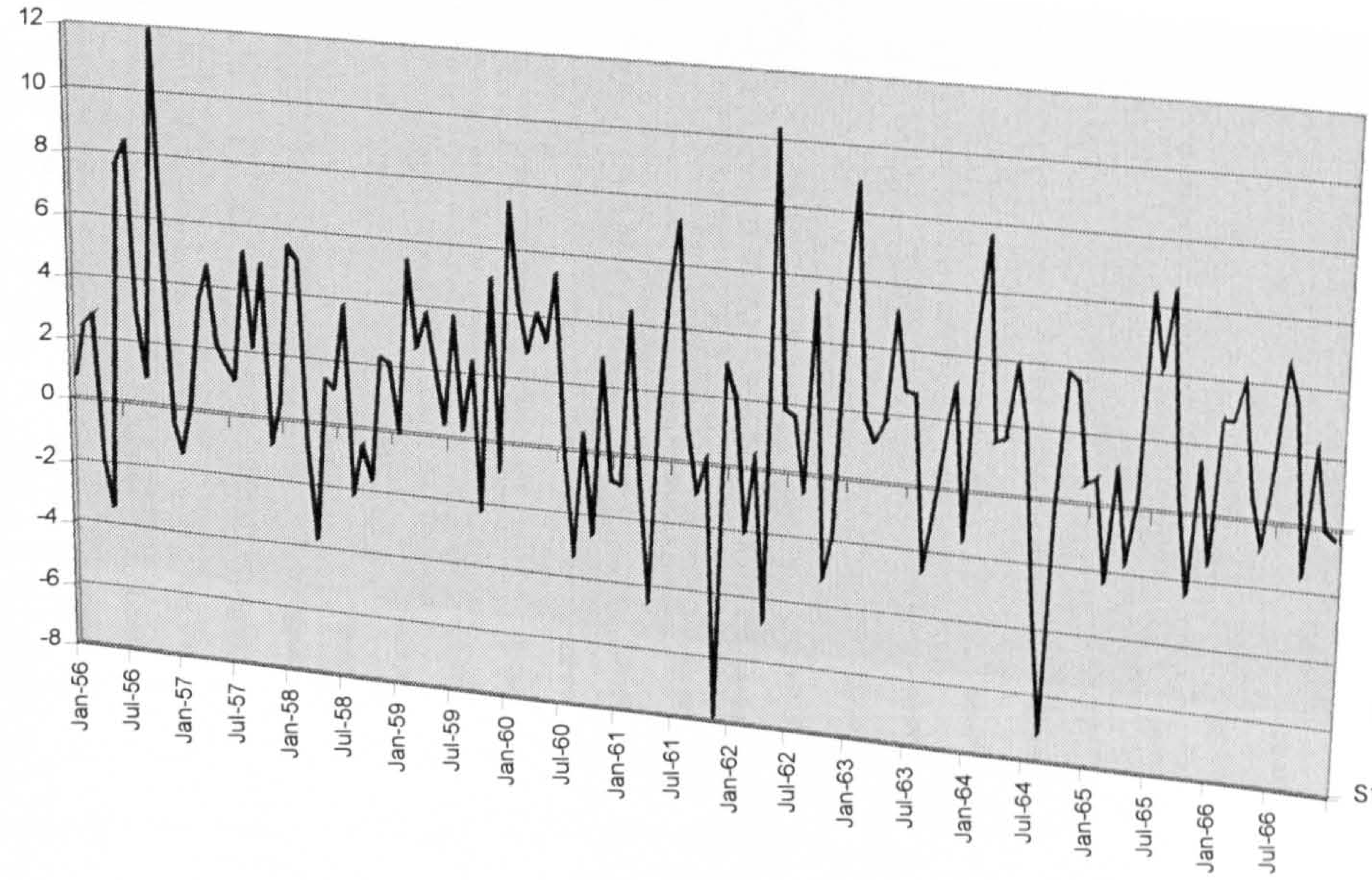


FIGURE 4.6: Low minus high PE ratio (1967-77)

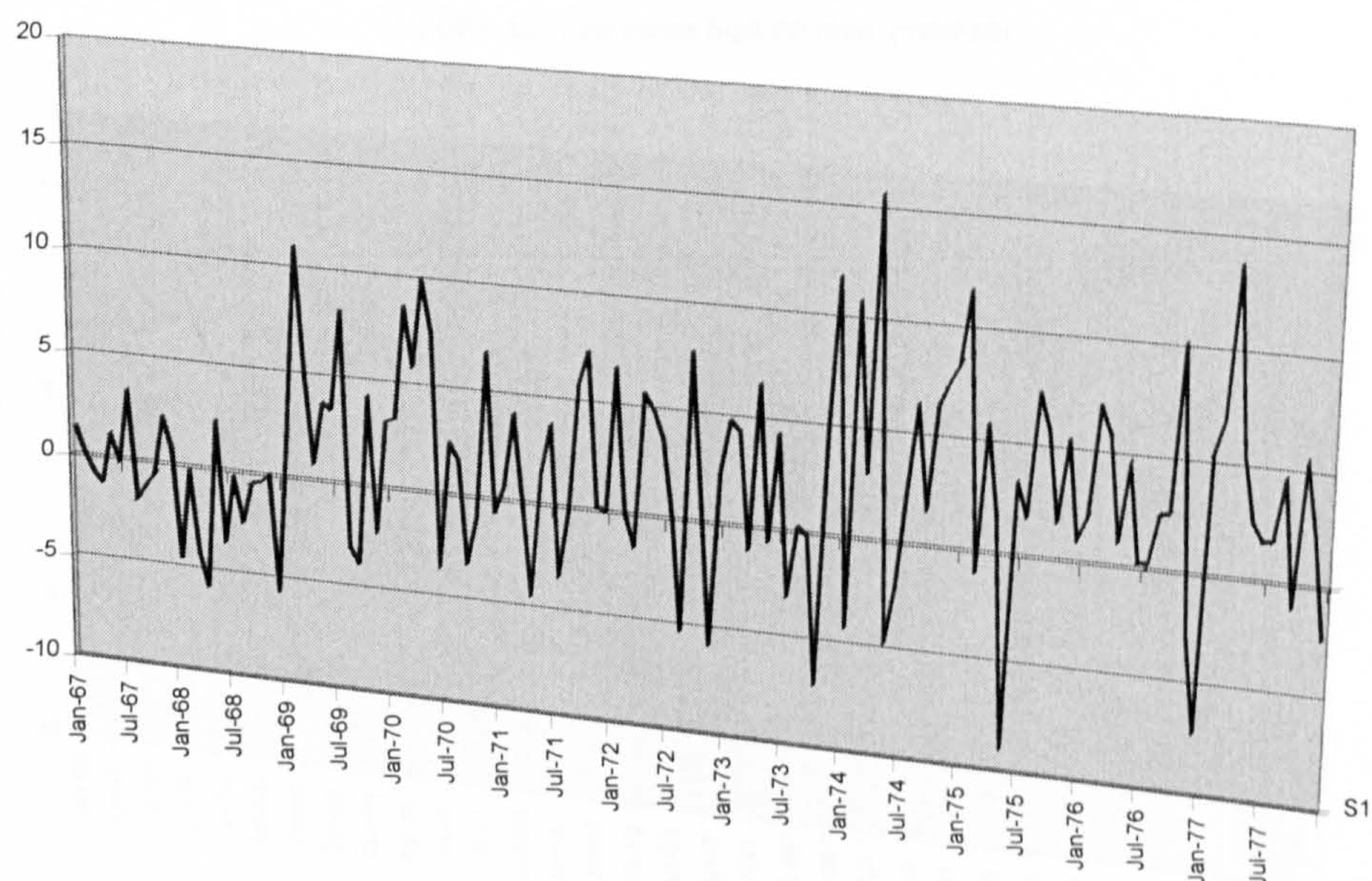


FIGURE 4.7: Low minus high PE ratio (1978-88)

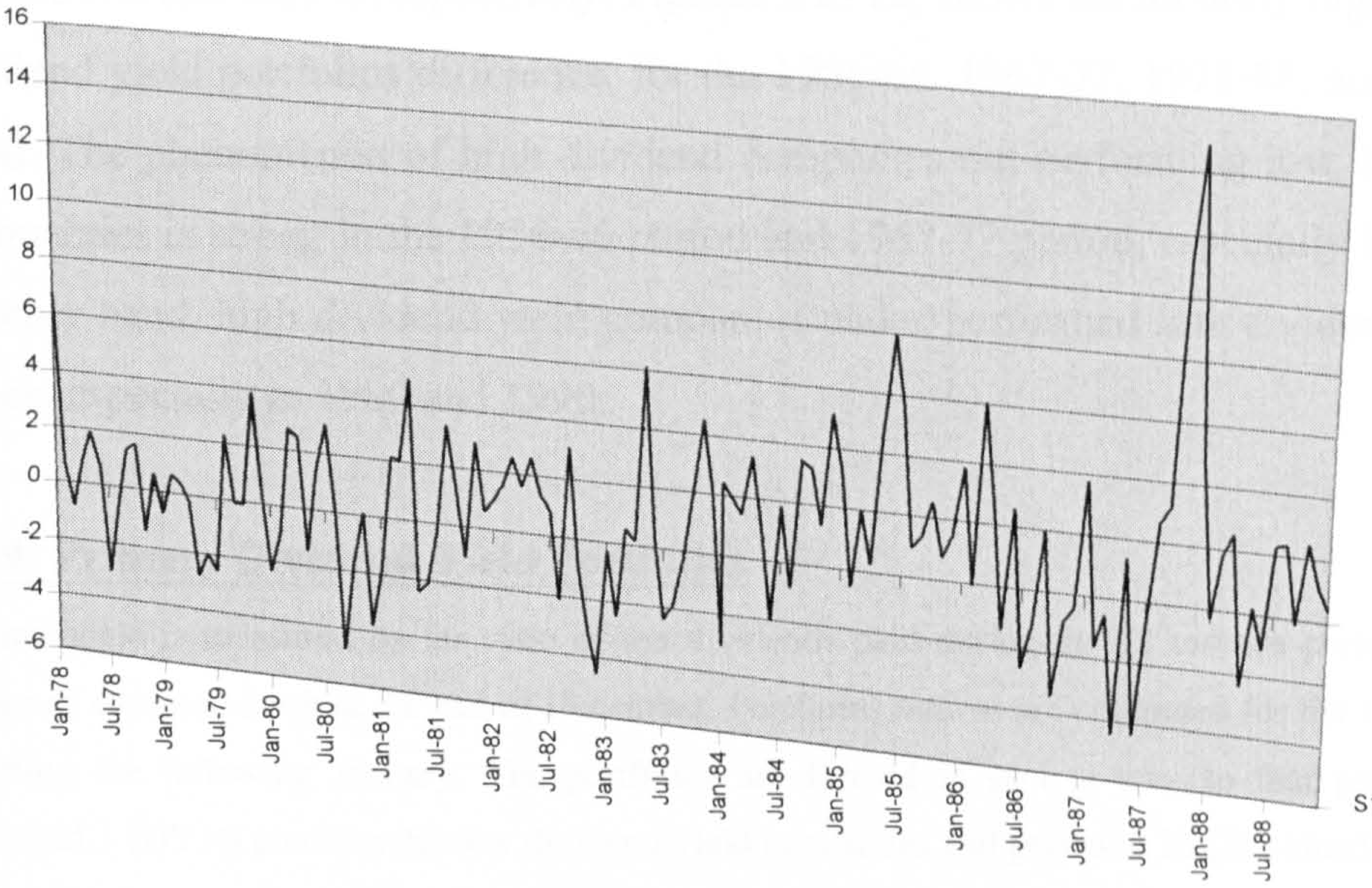


FIGURE 4.8: Low minus high PE ratio (1989-96)

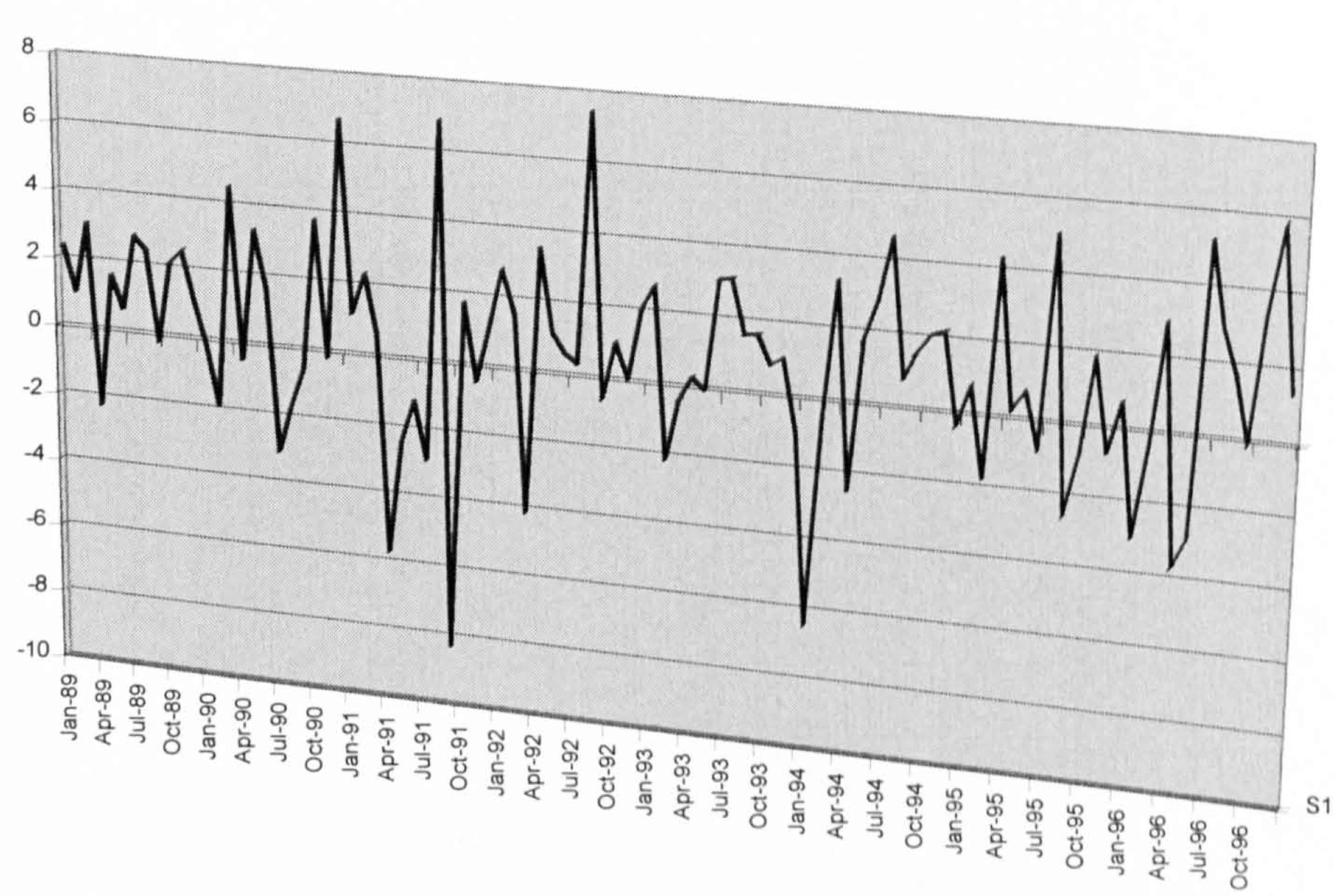


Table 4.9 shows that the average annual dividend yield premium (high minus low dividend yield) for the 1956-66, 1967-77, 1978-88 and 1989-96 period is 9.89%, 12.26%, 2.33%, and 0.20% respectively. Figures 9 to 12, shows the monthly high minus low dividend yield portfolios difference, for the 1956-66, 1967-77, 1978-88, and 1989-96 period. The phenomenon of high dividend companies out-performing low dividend yield companies is strong in the 1956-66 period and 1967-77 period, especially in 1975. On the other hand, high dividend yield companies under-performed low dividend yield companies, especially in 1980 and 1990.

Table 4.9: Primary Dividend Yield Portfolios

The dividend yield is measured by the ratio of the dividends paid during the 12 months period to the market price of common stock at the end of December. Portfolios returns are computed for the 12-month period starting the following January. The portfolios are formed in such a way so that portfolio 1 [Dividend yield 1 (DY1)] contains the low dividend yield companies and portfolio 25 [Dividend yield 25 (DY25)] contains the higher dividend yield companies.

Table 4.9-*Continued*

PRIMARY				
PERIOD	**1956-66**	**1967-77**	**1978-88**	**1989-96**
DY1	0.781	0.670	1.399	-0.045
DY2	0.716	0.690	1.389	-0.580
DY3	0.740	0.808	1.631	-0.921
DY4	0.908	0.685	1.446	-0.432
DY5	0.916	0.825	1.087	0.061
DY6	0.868	0.706	1.283	0.046
DY7	0.819	0.922	0.928	0.297
DY8	0.951	0.979	1.211	0.290
DY9	0.893	1.086	1.121	0.572
DY10	0.840	0.701	1.357	0.260
DY11	0.946	0.912	1.236	0.392
DY12	0.792	1.267	1.541	0.421
DY13	0.960	1.102	1.539	0.475
DY14	1.054	1.121	1.649	0.268
DY15	0.865	1.238	1.633	0.380
DY16	1.006	1.325	1.750	0.461
DY17	1.143	1.251	1.555	0.396
DY18	0.84	1.230	1.850	0.357
DY19	0.994	1.268	1.878	0.163
DY20	1.017	1.529	1.749	0.369
DY21	1.169	1.318	1.848	0.237
DY22	1.244	1.512	1.756	0.069
DY23	1.324	1.612	1.642	0.049
DY24	1.390	1.791	1.787	-0.204
DY25	1.605	1.693	1.593	-0.028
ANNUAL D.YIELD				
PREMIUM	**9.89**	**12.26**	**2.33**	**0.203**
T-statistics	**2.73**	**2.55**	**0.73**	**0.02**
(DY25-DY1)				

FIGURE 4.9: High minus low DY (1956-66)

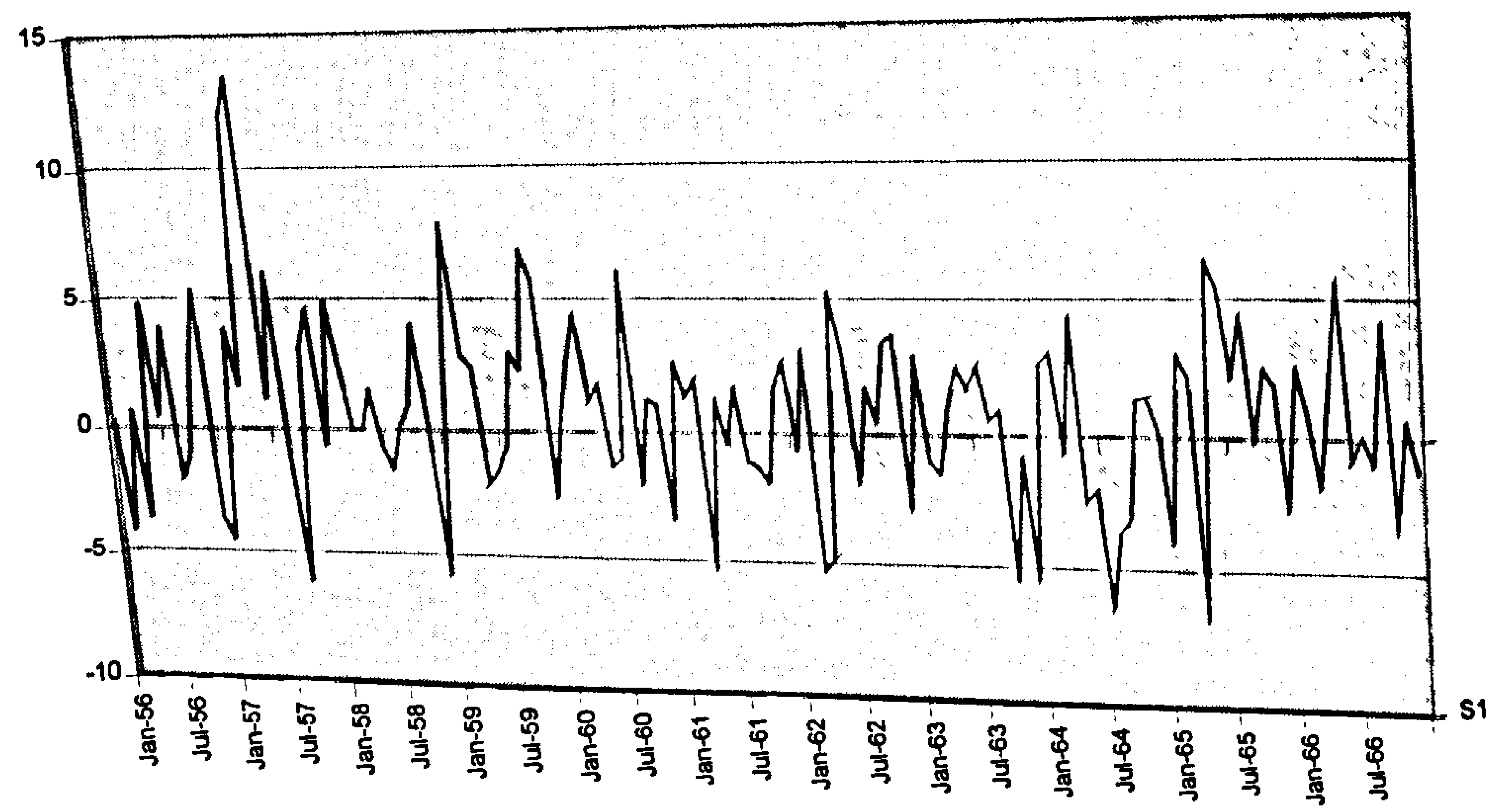


FIGURE 4.10: High minus low DY (1967-77)

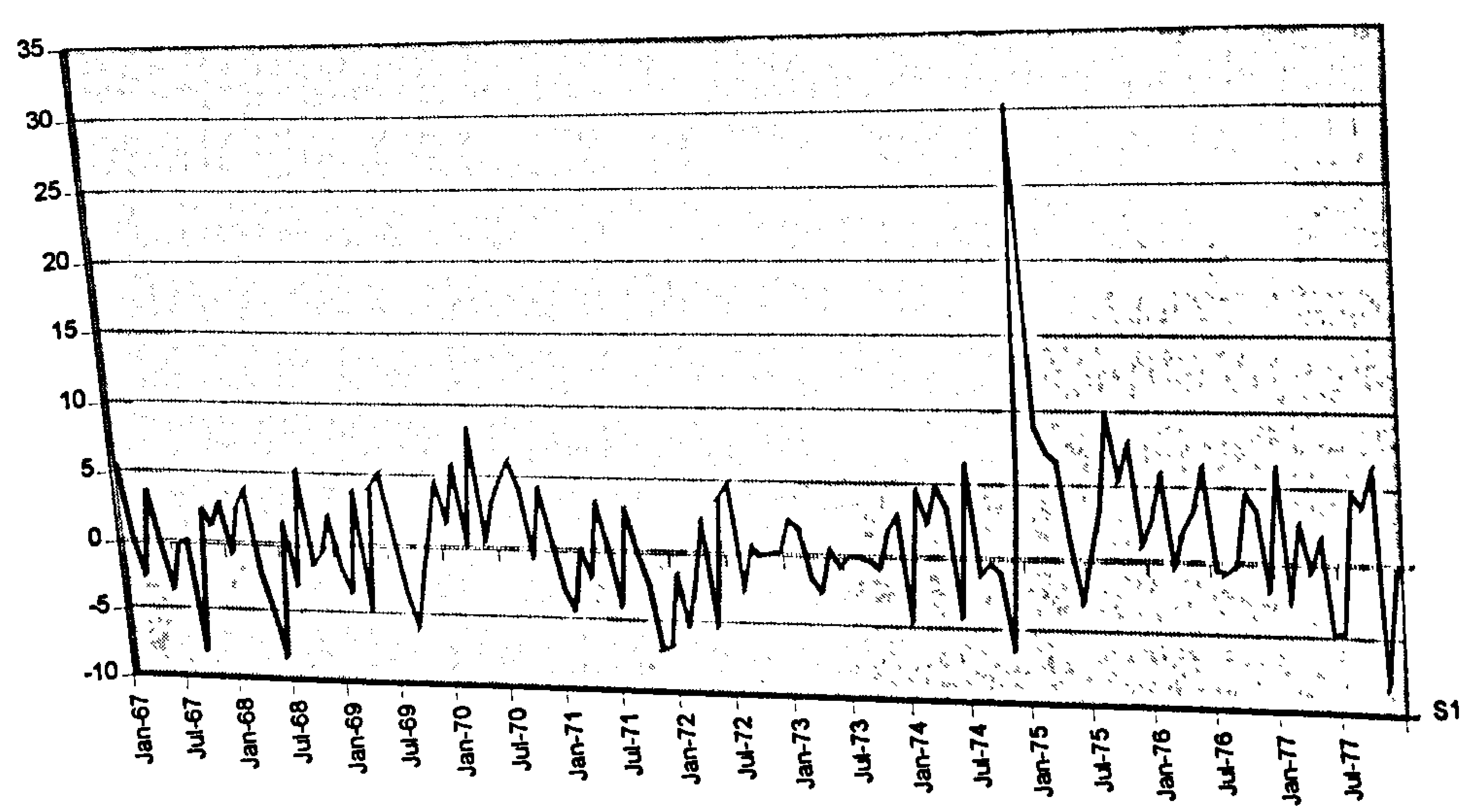


FIGURE 4.11: High minus low DY (1978-88)

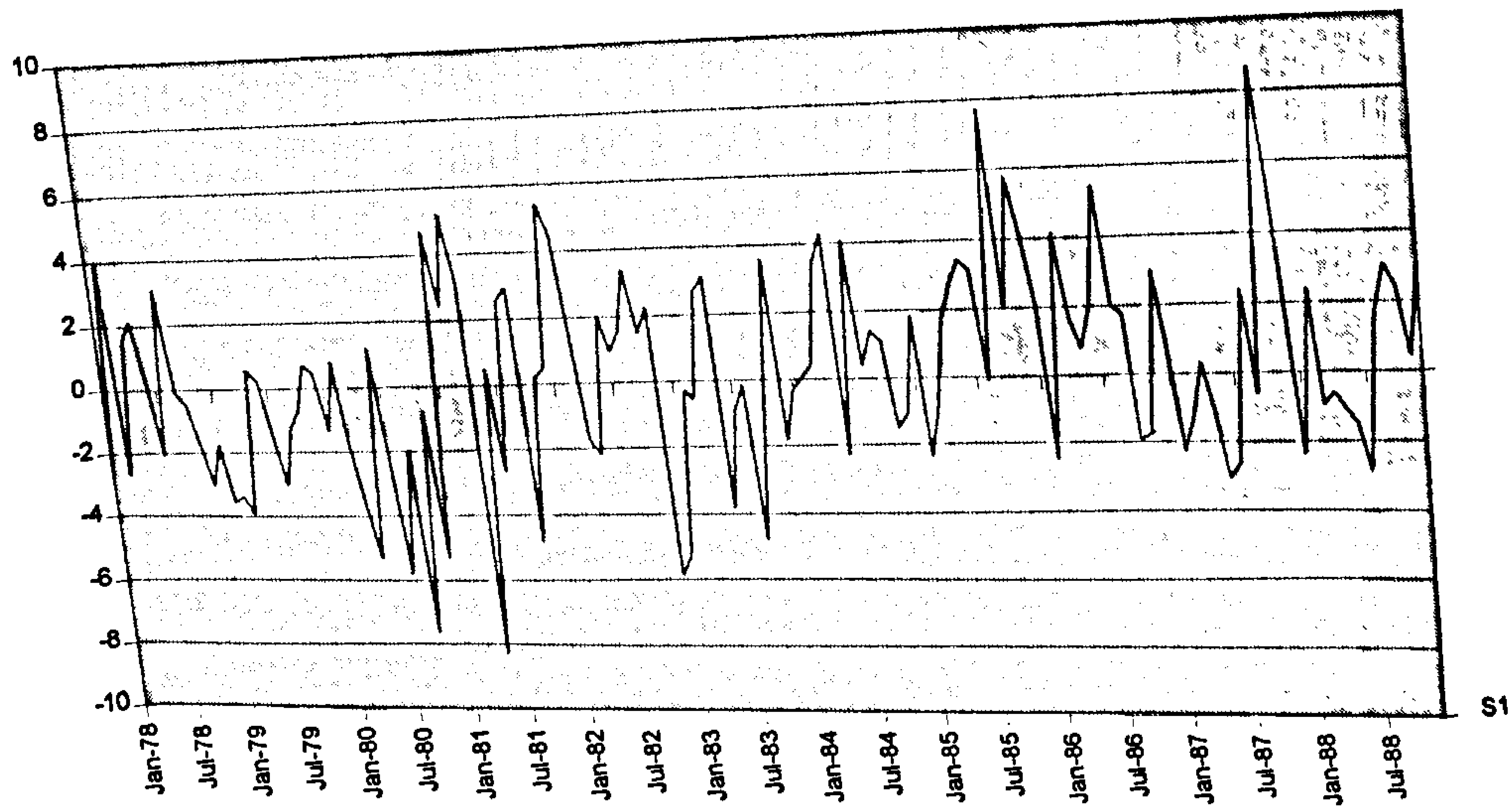
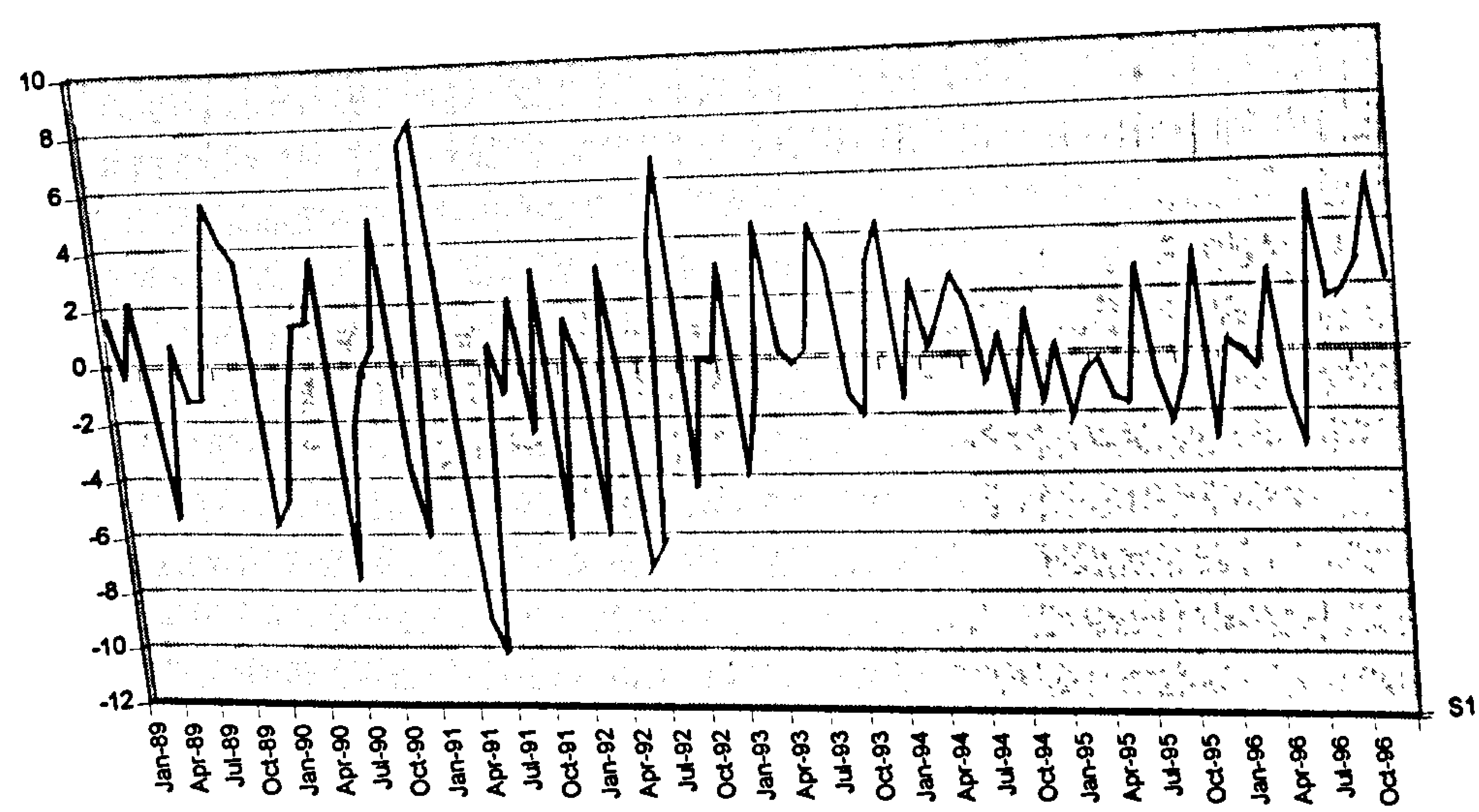


FIGURE 4.12: High minus low DY (1989-96)



4.5.2 SECONDARY PORTFOLIO FORMATION

This section explains the procedure employed to form the secondary portfolios in order to examine the interaction effects amongst the size, price earnings ratio and dividend yield for the testing period of the thesis (1976-1996). The reason we form combined portfolios is to examine whether the size, price earnings ratio and dividend yield effects are interrelated or independent of each other. The data utilised in the thesis is obtained from the London Share Price Database, (LSPD), monthly returns file and source file, which provides a wide coverage of firms traded on the London Stock Exchange. The source file of LSPD provides the data required to estimate market value, PE and dividend yields, and contains data for approximately 6000 companies. From January 1956 to December 1974, there is a random sample of 33% companies of LSE and samples of the largest companies. Since 1975, there is a complete history for all UK companies in LSE inclusive on Unlisted Securities market. The monthly returns file contains monthly rates of return, inclusive of dividends and capital gains. The return is calculated as: $R_t = \log [(p_t+d_t))/p_{t-1}]$; where R_t is the log-return in month t; p_t is the last traded price in month t; d_t is the dividend declared in month t; p_{t-1} is the last traded price in month t-1.

Market value of the firm is defined as the market price at the calendar year-end T (T= 1956, 1957, ..., 1996), times the number of shares outstanding. The dividend yield is measured by the ratio of the dividends paid during the twelve-month period of a calendar year to the market price of common stock at the end of this year. Earnings per share are estimated as the twelve months earnings divided by the number of shares outstanding at the calendar year-end; this estimate over the share price at the end of the same year determines the PE ratio.

At the end of each calendar year T firms are ranked separately in ascending order according to market value, dividend yield and PE ratio. Portfolio returns are then computed for the 12-month period commencing the following January, using equal weights. A firm needs data for market value at the end of the year and a valid rate of return for January next year to enter the sample. Firms enter or leave the sample due to new listings/mergers/ bankruptcies. A firm was dropped from the sample in any year in which it had negative earnings. Ball (1978) posits that the earnings-price ratio is a catch-all for omitted risk factors in expected returns. If current earnings proxy for expected future earnings, high-risk stocks with high-expected return will have low prices relative to their earnings. Thus, E/P should be related to expected returns whatever the omitted sources of risk. This agreement only makes sense, however, for firms with positive earnings. When current earnings are negative, they are not a proxy for the earnings forecasts embedded in the stock price, and E/P is not a proxy for expected returns. Following this argument, also Fama and French' (1992) slope of E/P in their regression is based only on positive earnings. Both Reinaganum (1981) and Basu (1983) excluded stocks in any year in which it had negative earnings. Studies by Basu (1977), Cook and Rozeff (1984), and Dowen and Baumen (1986) have found that the effects of portfolio return ranking are essentially the same, whether stocks with negative EPS are included or exclude from portfolio groups. Given the ambivalent interpretation of negative earnings and following the practice of previous studies, Levis (1989) excludes from his sample in any year firms that they had negative earnings. Levis and Liodakis (1999) also do not use stocks with negative M/B, CF/P or E/P when forming portfolios. Thus a firm was dropped from the sample in any year in which had negative earnings.

We form both primary and secondary (combined) portfolios. The primary portfolios are also used in the following chapters of this thesis, to test inferences in asset prising. The combined portfolios help us reveal information about the interaction effects between these attributes. According to the secondary portfolio groupings all firms were ranked first by a chosen criterion and quintiles are formed. Then within each quintile firms are re-ranked on a second variable and quintiles are formed within each of the original quintiles; twenty-five portfolios are formed for each combination of two attributes.

The combined portfolios give us more information regarding to what extent the individual effects depends on the particular quintile of the portfolio formation procedure in operation. For instance, if the dividend yield and the firm size effect are independent of each other we would expect the abnormal return to be enhanced by adhering to a high dividend yield small size investment strategy. Whereas, if the two effects are highly inter-related, then an additive return possibility would merely not exist, since one effect would serve as a proxy for the other.

First we report monthly averages of combined return portfolios. Table 4.10, reports the monthly average market value portfolios being randomised with respect to dividend yield from 1976 to 1996. For example MV1*DV portfolio includes securities of the first market size quintile but is drawn from the entire set of dividend yield classes; so it can be seen as being randomised with respect to dividend yield. Table 4.10 shows that there is a dividend yield effect at the first, second and third small market value portfolios, which declines as one moves to the third (MV3) largest market value portfolio. The dividend yield premium (the difference between the highest and lowest dividend yield quintile) within the market value portfolio 1 (MV1) is 0.84 per cent per month. While within the market value portfolio 2 (MV2) and market value portfolio 3 (MV3), it is 0.46 and 0.39 per cent per month respectively. More information about the interaction effects can be obtained from the Wald test. Table 4.10 show results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of DY1 to DY5 are jointly equal to zero across portfolios. This is examined at each market value level portfolio (MV1, MV2, MV3, MV4, MV5). To implement this, the following models are formed; these are estimated 5 times, for MV1, MV2, MV3, MV4 and MV5.

$$R_{DY1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$

$$R_{DY2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$

$$R_{DY3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$

$$R_{DY4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$

$$R_{DY5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

Where R_p is the return for portfolio p, R_m is the return on FTSE and R_f is the risk-free rate (one-month Treasury bill). Under the Sharpe-Lintner CAPM, the α_p is an estimate of the risk-adjusted abnormal return for portfolio p, the value of which is zero if the model holds. The Wald test tests the hypothesis that $\alpha_1 = ... = \alpha_5 = 0$. Table 4.10 indicates that the hypothesis that the abnormal returns of DY1 to DY5 are jointly equal to zero across portfolios is rejected at MV1, MV2, MV3, with p-values 0.00017, 0.013, and 0.02 respectively. At MV4, the hypothesis is accepted, with a p-value of 0.679. Whereas at MV5 it is rejected with a p-value of 0.003.

Table 4.10: Market Value-Dividend Yield Combined Portfolios

Period: 1976-1996

Average monthly return for the market value portfolios being randomised with respect to dividend yield. Table 4.10 shows results of the Wald test and the corresponding p-values of the hypothesis that the abnormal return of DY1 to DY5 at each market value portfolio (MV1, MV2, MV3, MV4, MV5) is zero. α_p is an estimate of the risk-adjusted abnormal return for portfolio p, the value of which is zero if the model holds. The Wald test tests the hypothesis that $\alpha_1 = ... = \alpha_5 = 0$.

$$R_{DY1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$
$$R_{DY2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$
$$R_{DY3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$
$$R_{DY4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$
$$R_{DY5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

	DY1	DY2	DY3	DY4	DY5	SIZE
MV1	0.70	1.24	1.37	1.55	1.54	1.28
MV2	0.61	0.91	1.28	1.27	1.07	1.03
MV3	0.58	0.99	1.14	1.15	0.97	0.97
MV4	0.84	0.92	1.17	1.29	0.93	1.03
MV5	0.83	1.14	1.22	1.26	1.32	1.15
D.YIELD	0.71	1.04	1.24	1.30	1.16	

	Wald	P-value
MV1	14.16	0.00017
MV2	6.11	0.01348
MV3	5.03	0.02491
MV4	0.17	0.67915
MV5	8.79	0.00303

Table 4.11, presents the monthly average market value portfolios being randomised with respect to PE ratio from 1976 to 1996. MV1*PE portfolio includes securities of the first market size quintile but is drawn from the entire set of PE ratio classes; so it can be seen as being randomised with respect to PE ratio. Table 4.11 reports that there is a PE effect especially at each level of the market value, which is

particularly strong in the first (MV1) and second small market value (MV2). The PE premium (the difference between the lowest and the highest PE quintile) within each market value portfolio is never lower than 0.5 per cent per month. The PE premium is 0.82 per cent per month within market value portfolio 1 (MV1) and 0.62 per cent per month within market value portfolio 2 (MV2); it decreases within the larger market value portfolios. Within market value portfolio 3 (MV3) the PE premium is 0.43 per cent per month, while within market value portfolio 4 (MV4) and market value portfolio 5 (MV5), it is 0.32 and 0.5 per cent per month, respectively. The Wald test provides further evidence of whether the abnormal returns are significant. Table 4.11 shows results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of PE1 to PE5 are jointly equal to zero across portfolios ($\alpha_1 = ... = \alpha_5 = 0$). This is examined at each market value portfolio (MV1, MV2, MV3, MV4, MV5). Thus the following models are formed; these are estimated 5 times, for MV1, MV2, MV3, MV4 and MV5.

$$R_{PE1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$

$$R_{PE2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$

$$R_{PE3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$

$$R_{PE4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$

$$R_{PE5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

Table 4.11 reports that the price earnings ratio effect is statistically significant at each level of the market value. The hypothesis that the abnormal returns (PE1 to PE5) are jointly equal to zero across portfolios is easily rejected, at each level (MV1, MV2, MV3, MV4, MV5). This further reinforces the prevailing effect of PE.

Table 4.11: Market Value-PE ratio Combined Portfolios

Period: 1976-1996

Average monthly return for the market value portfolios being randomised with respect to price earnings ratio. Table 4.11 shows results of the Wald test and the corresponding p-values of the hypothesis that the abnormal return of PE1 to PE5 at each market value portfolio (MV1, MV2, MV3, MV4, MV5) is zero. α_p is an estimate of the risk-adjusted abnormal return for portfolio p, the value of which is zero if the model holds. The Wald test tests the hypothesis that $\alpha_1 = ... = \alpha_5 = 0$.

$$R_{PE1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$
$$R_{PE2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$
$$R_{PE3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$
$$R_{PE4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$
$$R_{PE5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

	PE1	PE2	PE3	PE4	PE5	SIZE
MV1	2.02	1.59	1.51	1.55	1.20	1.58
MV2	1.41	1.16	1.23	1.02	0.79	1.12
MV3	1.33	1.38	1.11	0.93	0.90	1.13
MV4	1.28	1.03	1.03	1.15	0.96	1.09
MV5	1.49	1.25	1.11	1.08	0.99	1.19
PE	1.51	1.28	1.20	1.15	0.97	

	Wald	**P-value**
MV1	16.36	0.00005
MV2	15.69	0.00007
MV3	8.19	0.00421
MV4	5.06	0.02449
MV5	9.54	0.00201

Table 4.12, reports the monthly average dividend yield portfolios being randomised with respect to market value. For example portfolio DY1*MV contains firms of the lowest dividend yield but includes firms from all market size classes, i.e. randomised with respect to firm size. Table 4.12 indicates that there is a size effect at the lowest dividend yield portfolio (DY1), whereas this is not the case for the other levels of the dividend yield, i.e., there is not a size effect at DY2, DY3, DY4, DY5. The size premium (the difference between the smallest and largest market value quintile) within the dividend yield portfolio 1 (DY1) is 0.73 per cent per month. The Wald test provides further evidence related to the significance of abnormal returns, if any within each dividend yield portfolio. Table 4.12 show results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of MV1 to MV5 are jointly equal to zero across portfolios. This is examined at each dividend yield portfolio (DY1, DY2, DY3, DY4, DY5). Hence the following models are formed; these are estimated 5 times, for DY1, DY2, DY3, DY4, DY5.

$$R_{MV1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$

$$R_{MV2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$

$$R_{MV3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$

$$R_{MV4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$

$$R_{MV5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

The hypothesis that the abnormal returns (MV1 to MV5) are equal across portfolios and zero is rejected at the lowest dividend yield (DY1) with a p-value of 0.01. However the hypothesis that the abnormal returns (MV1 to MV5) are equal across portfolios and zero is accepted for the DY2, DY3, DY4, DY5, with p-values 0.54, 0.36, 0.32 and 0.10 respectively.

Table 4.12: Dividend Yield-Market Value Combined Portfolios

Period: 1976-1996

Average monthly return for the dividend yield portfolios being randomised with respect to market value. Table 4.12 shows results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of MV1 to MV5 at each dividend yield portfolio (DY1, DY2, DY3, DY4, DY5) is zero. α_p is an estimate of the risk-adjusted abnormal return for portfolio p, the value of which is zero if the model holds. The Wald test tests the hypothesis that $\alpha_1 = ... = \alpha_5 = 0$. The following models are formed:

$$R_{MV1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$
$$R_{MV2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$
$$R_{MV3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$
$$R_{MV4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$
$$R_{MV5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

	MV1	MV2	MV3	MV4	MV5	**D.YIELD**
DY1	1.46	0.54	0.65	0.46	0.73	0.77
DY2	1.16	0.83	0.89	0.92	1.01	0.96
DY3	1.46	1.12	1.05	1.20	1.24	1.21
DY4	1.56	1.12	1.23	1.29	1.32	1.30
DY5	1.62	1.16	1.03	0.95	1.25	1.20
SIZE	1.45	0.95	0.97	0.96	1.11	

	Wald	**P-value**
DY1	5.67	0.017
DY2	0.37	0.546
DY3	0.82	0.365
DY4	0.97	0.324
DY5	2.59	0.108

Table 4.13, shows the average monthly return for dividend yield portfolios randomised with respect to PE ratio. For example portfolio DY1*PE contains firms of the lowest dividend yield but includes firms from all PE ratio classes, i.e. randomised with respect to PE ratio. Table 4.13 indicates that there is a price earnings ratio effect at each level of the dividend yield. The PE premium (the difference between the lowest and highest PE quintile) within dividend yield 1 (DY1) is 0.77 per cent per month. The PE premium is lower but also quite high within dividend yield 2 (DY2), it is 0.59 per cent per month. Within the dividend yield 3 (DY3), (DY4) and (DY5), it is 0.4, 0.53 and 0.49 per cent per month respectively. The prevailing effect of the PE effect can further be seen from the results of the Wald test. Table 4.13 reports results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of PE1 to PE5 are equal across portfolios and zero. This is repeated for each dividend yield portfolio (DY1, DY2, DY3, DY4, DY5). The following models are formed; these are estimated 5 times, for DY1, DY2, DY3, DY4 and DY5.

$$R_{PE1} - R_f = \alpha_1 + \beta_1 (R_m - R_f) + e$$

$$R_{PE2} - R_f = \alpha_2 + \beta_2 (R_m - R_f) + e$$

$$R_{PE3} - R_f = \alpha_3 + \beta_3 (R_m - R_f) + e$$

$$R_{PE4} - R_f = \alpha_4 + \beta_4 (R_m - R_f) + e$$

$$R_{PE5} - R_f = \alpha_5 + \beta_5 (R_m - R_f) + e$$

The hypothesis that the abnormal returns (PE1 to PE5) are equal across portfolios and zero is easily rejected, at each level (DY1, DY2, DY3, DY4, DY5). The associated p-values for DY1, DY2, DY3, DY4, DY5 are 0.00007, 0.00024, 0.00605, 0.0053 and 0.00249 respectively.

Table 4.13: Dividend Yield-PE ratio Combined Portfolios

Period: 1976-1996

Average monthly return for dividend yield portfolios randomised with respect to PE ratio. Table 4.13 shows results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of PE1 to PE5 at each dividend yield portfolio (DY1, DY2, DY3, DY4, DY5) is zero. α_p is an estimate of the risk-adjusted abnormal return for portfolio p, the value of which is zero if the model holds. The Wald test tests the hypothesis that $\alpha_1 = ... = \alpha_5 = 0$. The following models are formed:

$$R_{PE1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$
$$R_{PE2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$
$$R_{PE3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$
$$R_{PE4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$
$$R_{PE5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

	PE1	PE2	PE3	PE4	PE5	**D.YIELD**
DY1	1.59	0.98	1.09	1.03	0.82	1.10
DY2	1.28	1.17	1.11	0.97	0.74	1.05
DY3	1.58	1.28	1.18	1.24	1.18	1.29
DY4	1.62	1.43	1.31	1.24	1.09	1.34
DY5	1.56	1.40	1.24	1.18	1.07	1.29
PE	1.52	1.25	1.19	1.13	0.98	

	Wald	**P-value**
DY1	15.89	0.00007
DY2	13.53	0.00024
DY3	7.54	0.00605
DY4	12.02	0.00053
DY5	9.15	0.00249

Table 4.14, shows the average monthly return for PE ratio portfolios randomised with respect to market value. For example portfolio PE1*MV contains firms of the lowest PE ratio but includes firms from all market value classes, i.e. randomised with respect to market value. In order to assess whether there is a significant market value premium at each PE portfolios we carry out the following Wald test. Table 4.14 reports results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of MV1 to MV5 are jointly equal to zero. This hypothesis is tested at each price earnings portfolio (PE1, PE2, PE3, PE4, PE5). The following models are formed; these are estimated 5 times, for PE1, PE2, PE3, PE4 and PE5.

$$R_{MV1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$

$$R_{MV2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$

$$R_{MV3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$

$$R_{MV4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$

$$R_{MV5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

Table 4.14 indicates that the hypothesis that the abnormal returns (MV1 to MV5) are jointly equal to zero across portfolios is accepted, at each level (PE1, PE2, PE3, PE4, PE5). The associated p-values for PE1, PE2, PE3, PE4, PE5 portfolios are, 0.145, 0.234, 0.053, 0.232 and 0.111 respectively. The evidence that the abnormal returns (MV1 to MV5) are jointly equal to zero across portfolios is accepted, at each level of the PE portfolio further indicates that the PE effect is prevailing and subsumes the size effect. Since Table 4.11 also show that the hypothesis that the abnormal returns (PE1 to PE5) are jointly equal to zero across market value portfolios is easily rejected, at each level (MV1, MV2, MV3, MV4, MV5).

Table 4.14: PE ratio-Market Value Combined Portfolios

Period: 1976-1996

Average monthly return for the PE ratio portfolios being randomised with respect to market value. Table 4.14 shows results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of MV1 to MV5 at each PE portfolio (PE1,PE2,PE3,PE4,PE5) is zero. α_p is an estimate of the risk-adjusted abnormal return for portfolio p, the value of which is zero if the model holds. The Wald test tests the hypothesis that $\alpha_1 = ... = \alpha_5 = 0$. The following models are formed:

$$R_{MV1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$
$$R_{MV2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$
$$R_{MV3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$
$$R_{MV4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$
$$R_{MV5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

	MV1	MV2	MV3	MV4	MV5	**PE**
PE1	1.98	1.47	1.31	1.52	1.57	1.57
PE2	1.57	1.21	1.30	1.20	1.28	1.31
PE3	1.48	1.16	1.03	1.11	1.00	1.16
PE4	1.43	1.06	0.98	1.07	1.14	1.14
PE5	1.27	0.81	0.74	0.96	0.86	0.93
SIZE	1.55	1.14	1.07	1.17	1.17	

	Wald	**P-value**
PE1	2.13	0.145
PE2	1.42	0.234
PE3	3.75	0.053
PE4	1.43	0.232
PE5	2.54	0.111

Table 4.15, reports the average monthly return for the PE ratio portfolios being randomised with respect to dividend yield. For example portfolio PE1*DY contains firms of the lowest PE ratio but includes firms from all dividend yield classes, i.e. randomised with respect to dividend yield. In order to assess whether there is a significant dividend yield premium at each PE portfolios we carry out the following Wald test. Table 4.15 reports results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of DY1 to DY5 are equal across portfolio and zero. This is examined at each price earnings portfolio level (PE1, PE2, PE3, PE4, PE5). The following models are formed; these are estimated 5 times, for PE1, PE2, PE3, PE4 and PE5.

$$R_{DY1} - R_f = \alpha_1 + \beta_1 (R_m - R_f) + e$$

$$R_{DY2} - R_f = \alpha_2 + \beta_2 (R_m - R_f) + e$$

$$R_{DY3} - R_f = \alpha_3 + \beta_3 (R_m - R_f) + e$$

$$R_{DY4} - R_f = \alpha_4 + \beta_4 (R_m - R_f) + e$$

$$R_{DY5} - R_f = \alpha_5 + \beta_5 (R_m - R_f) + e$$

The hypothesis that the abnormal returns (DY1 to DY5) are equal across portfolios and zero is accepted, at each level (PE1, PE2, PE3, PE4, PE5). Table 4.14 indicate that the hypothesis that the abnormal returns (MV1 to MV5) are jointly equal to zero across portfolios is accepted, at each level of the PE portfolios. Table 4.15 also show that when we consider the PE ratio portfolios that are randomised with respect to dividend yield, the hypothesis that the abnormal returns (DY1 to DY5) are equal across portfolios and zero is accepted at each level of the PE portfolios. The associated p-values for PE1, PE2, PE3, PE4, PE5, are 0.163, 0.396, 0.270, 0.052 and 0.725. The finding that the hypothesis that the abnormal returns (DY1 to DY5) are jointly equal to zero across PE portfolios is accepted, at each level of the PE portfolio indicates that the PE effect is prevailing and subsumes the dividend yield effect. Since Table 4.13 also show that the hypothesis that the abnormal returns (PE1 to PE5) are equal across dividend yield portfolios and zero is easily rejected, at each level (DY1, DY2, DY3, DY4, DY5). The issue investigated at this section is to what extent the individual effects depended on the particular quintile of the portfolio formation procedure in operation.

The evidence discussed above reveal that for 1976 to 1996 the dividend yield and PE effect subsume the size effect. However the findings suggest that the PE effect subsumes the dividend yield effect and it is the PE effect that is the most dominant.

Table 4.15: PE ratio-Dividend Yield Combined Portfolios

Period: 1976-1996

Average monthly return for the PE ratio portfolios being randomised with respect to dividend yield. Table 4.15 shows results of the Wald test and the corresponding p-values of the hypothesis that the abnormal returns of DY1 to DY5 at each PE portfolio (PE1,PE2,PE3,PE4,PE5) is zero. α_p is an estimate of the risk-adjusted abnormal return for portfolio p, the value of which is zero if the model holds. The Wald test tests the hypothesis that $\alpha_1 = ... = \alpha_5 = 0$. The following models are formed:

$$R_{DY1} - R_f = \alpha_1 + \beta_1(R_m - R_f) + e$$
$$R_{DY2} - R_f = \alpha_2 + \beta_2(R_m - R_f) + e$$
$$R_{DY3} - R_f = \alpha_3 + \beta_3(R_m - R_f) + e$$
$$R_{DY4} - R_f = \alpha_4 + \beta_4(R_m - R_f) + e$$
$$R_{DY5} - R_f = \alpha_5 + \beta_5(R_m - R_f) + e$$

	DY1	DY2	DY3	DY4	DY5	PE
PE1	1.66	1.49	1.76	1.49	1.41	1.56
PE2	1.21	1.18	1.40	1.35	1.35	1.30
PE3	0.96	1.31	1.22	1.23	1.14	1.17
PE4	0.94	1.18	1.12	1.12	1.27	1.13
PE5	1.00	0.84	0.81	1.00	0.95	0.92
DY	0.92	0.90	0.92	0.96	0.68	

	Wald	**P-value**
PE1	1.95	0.163
PE2	0.72	0.396
PE3	1.22	0.270
PE4	3.78	0.052
PE5	0.12	0.725

4.6 CONCLUSION

This chapter introduced the primary portfolio returns, which are used in the following chapters to test asset-pricing inferences. We examine the size, price earnings ratio and dividend yield effect from 1956 to 1996, a large time period that provide results more robust, in a attempt to examine whether these effects still exist, and on what extent, or direction.

We also examine the interaction amongst these effects by forming secondary portfolios. In order to test the hypothesis that the abnormal returns for example MV1 to MV5 (or PE1 to PE5 or DY1 to DY5) are jointly equal to zero across PE portfolios (or DY portfolios) we carry out Wald test and present the corresponding p-values. We find evidence that the hypothesis that abnormal returns (MV1 to MV5) are jointly equal to zero across portfolios is accepted, at each level of the PE portfolio. This indicates that the PE effect is prevailing and subsumes the size effect. Since the hypothesis that the abnormal returns (PE1 to PE5) are jointly equal to zero across market value portfolios is easily rejected, at each level (MV1, MV2, MV3, MV4, MV5). Furthermore the hypothesis that the abnormal returns (DY1 to DY5) are jointly equal to zero across PE portfolios is accepted, at each level of the PE portfolio, indicates that the PE effect is prevailing and subsumes the dividend yield effect. Since the hypothesis that the abnormal returns (PE1 to PE5) are equal across dividend yield portfolios and zero is easily rejected, at each level (DY1, DY2, DY3, DY4, DY5). The evidence reveals that for the 1976-1996 period, that the dividend yield and PE effect subsume the size effect. However the PE effect subsumes the dividend yield effect and it is the PE effect that is the most dominant. Evidence presented in this chapter reveal that the best documented of all stock market effects, the small-firm premium went into reverse for the 1989 to 1996 sub-period. The size effect lives on, but for the latest decade, it is the largest firms that outperform the smallest ones by 10.26% per annum. The level of long-term small-firm out-performance has been substantial but however stops in 1988. Another empirical finding, is that the dividend yield premium (high minus low) cease to exist for the 1989 to 1996 sub-period, it is only 0.20% per annum.

CHAPTER 5

UNCONDITIONAL MODELS

THE FAMA-MACBETH METHODOLOGY VERSUS THE NON-LINEAR SEEMINGLY UNRELATED REGRESSION AND DIFFERENT PORTFOLIO FORMATION CRITERIA

The Arbitrage Pricing Theory (APT) has been the subject of considerable empirical analysis, particularly in the United States. However many fundamental issues regarding the APT especially in the United Kingdom, have remained unresolved. These fundamental issues briefly consist of the adequacy of competitive methodologies to estimate the APT; the sensitivity of results to different portfolio formation; and the identification of significant factors in UK, over a long time-period, for a data-set, consisting of all companies in the LSE inclusive on Unlisted Securities market.

The purpose of this study is to shed light into the following key issues regarding the APT in the UK market. These issues can be categorised as follows. The first issue under investigation refers to the methodology employed in the estimation process of the APT. The Fama-MacBeth (FMB) and the Non-linear Seemingly Unrelated Regression methodology (NLSUR) have been employed to estimate APT models, [Chen, Roll, and Ross, (CRR), (1986) use FMB, McElroy and Burmeister (1988) use NLSUR], in the US. The NLSUR has the advantage of avoiding the Error-in-variables problem, inherent in the FMB methodology, because it simultaneously estimates the sensitivities and the prices of risk, also it allows the APT's principle that the price of risk is equal across assets to be tested. However the comparative ability of these alternative methodologies to detect a pricing relation has not been examined.

The motivation for such investigation stems from empirical evidence in the UK market, and in particular from the finding of Poon and Taylor (1991), who used the FMB methodology with the CRR factors. They find none factor to be priced and claim:

It could be......... that the FMB methodology is inadequate for detecting such pricing relationships. (Page 620)

Further, Claire and Thomas (1994) claim that an important next step is to compare their results obtained form the two-step procedure with those obtained from non-linear least squares method. (Page 326)

Therefore the first objective in this study is to answer the above stated empirical questions and examine the FMB methodology versus the NLSUR.

The second issue under empirical examination refers to the portfolio formation procedures. The urging of such examination stems from the study of CRR, (1986) which is the first study that specific macroeconomic factors are employed as proxies for the undefined state variables in the APT. CRR (1986), grouped securities into portfolios according to: a) their betas on a market index, b) the standard deviation of their return in a market model regression (i.e., residual variability), c) level of a stock price, and d) size. CRR (1986) comment that their efforts were not successful. The first two techniques did not provide a spread of returns and were discarded. Sorting on stock price, spread returns, but the state variables were individually only marginally significant, and the market indices were of no significance.

Chen, Roll and Ross, (1986), claim that the sensitivity of results to different grouping techniques is an important area for research. (page395)

Thus, the second objective of this study aims to explore the sensitivity of results to different grouping procedures of size; PE ratio and dividend yield portfolio groupings.

The third issue refers to the identification of macroeconomic factors that are priced in the UK market over a long-time period (1976-1996) and for a data-set, that represents the complete history of firms traded on the London Stock exchange, inclusive of Unlisted securities market. Poon and Taylor (1991), suggest that probably other macroeconomic factors except from the CRR (1986) are at work, in the UK market.

It could be that other macroeconomic factors are at work or the FMB methodology is inadequate for detecting such pricing relationships or possibly both explanations apply. (Page 620)

Other APT studies in the UK include Beenstock and Chan (1988), Claire and Thomas (1994), Antoniou, Garrett, and Priestley (1998). However the results of these studies represent either a rather short time period or a small data set or both. Beenstock and Chan (1988) study cover the 1977-1983 period, and 760 securities of data set. Claire and Thomas (1994) time period consist of eight years (1983-1990) and a sample of 840 stocks. Antoniou, Garrett, and Priestley (1998) study cover the January 1980 to August 1993 period and their data set include 69 securities.

Hence, the third objective, entails the identification of priced factors in the UK market, over a twenty year of period, (1976-1996), and for a data-set, which provides a complete history of firms traded on the London Stock exchange, inclusive of Unlisted securities market. The data set consist of approximately 6000 companies. This objective pursue the identification of priced macroeconomic factors in the UK market, free from data limitations and short-testing periods, which is an empirical question that we seek to answer.

Chapter 5 is organised as follows. Section 5.1 discusses the factors that could proxy for the state variables in the APT model. Section 5.1.1 defines the macroeconomic factors and indexes utilised in this study. Section 5.1.2 discuses the derivation of the unanticipated components of the factors. Section 5.2. test whether the CRR factors estimated by FMB are significant for the size return portfolios, then examines whether the CRR factors estimated by FMB are priced for the PE ratio and dividend yield return portfolios respectively. Next the same section employs other macroeconomic factors, and investigates whether these are significant by using the FMB methodology; furthermore explores the sensitivity of these results to different ranking procedures of size, PE ratio, and dividend yield. Section 5.3. examines whether the CRR factors estimated by NLSUR are significant for the size return portfolios, next tests whether the CRR factors estimated by NLSUR are priced for the PE ratio and dividend yield portfolios respectively, the same section employs other macroeconomic factors, and investigates whether these are significant by using the NLSUR methodology; furthermore explores the sensitivity of these results to different ranking procedures of size, PE ratio, and dividend yield. Section 5.4 discuses the FMB versus the NLSUR. Section 5.5 concludes.

5.1. MACROECONOMIC FACTORS

At the heart of APT is the recognition that only a few systematic factors affect the long-term average returns of financial assets. The APT acknowledges that a number of factors affect the daily price variability of individual stocks, but however focuses on the major forces that move aggregates of assets in large portfolios. If we can identify these forces we can therefore understand their influence on portfolio returns.

CRR (1986) utilise the following formula, as a rationale for identifying possible factors that proxy for the state variables in the APT. Stock prices (P_0) can be expressed as the discounted sum of expected future dividend flows.

$$P_o = \sum_{t=1}^{\infty} \frac{E(D_t)}{(1+R)^t}$$

where: E is the expectations operator, R is the appropriate discount rate, and D_t is the dividend paid at the end of period t. The above model determines prices, so any macroeconomic variable that affect the model, will affect prices. So it follows that the variables that influence returns are those that change the discount rate, and the expected cash flows. Although the selection of the macroeconomic variables is arbitrary, to the extent that the formula does not identify the important variables, however it provides the theoretical framework from which the analyst can pre-specify likely candidates.

Chen, Roll and Ross (1986) use the following factors. The monthly percentage change in industrial production. A measure of unexpected inflation. The change in expected inflation. The difference in returns on low grade (Baa and under) corporate bonds and long term government bonds (Risk premium) (Default); the difference in returns on long-term government bonds and short-tern Treasury bills (Term structure). They claim that the discount rate is an average of rates over time, and it changes with both the level of rates and the term structure across different maturities. Unanticipated changes in the risk-less interest rate will influence pricing, and, through their influence on the time value of future cash flows, they will influence returns. The discount rate also depends on the risk premium; thus, unanticipated changes in the premium will influence returns. Expected cash flows change because of both real and nominal forces. Changes in the expected rate of inflation would influence nominal expected cash flows as well as the nominal rate of interest. In terms of the pricing being done in real terms, unanticipated price-level changes will have a systematic effect, and to the extent that relative prices change along with general inflation, there can be a change in the asset valuation associated with changes in the average inflation rate. Changes in the expected level of real production would affect the current real value of cash flow. They also include market indices due to the fact that the characteristics of most macroeconomic time-series, in short holding periods, such as a single month, cannot be expected to capture all the information available in the market in the same period.

Apart from the CRR (1986) factors the following factors are possible candidates in the APT model. We describe how these can affect stock returns. Money supply is a possible candidate. Surprises in the money supply alter the outlook of interest rates, and hence the discount rate, which influences stock prices. The term money refers to a monetary aggregate that is broader than currency. People reduce their holdings of cash only by incurring more costs. These costs, called transaction costs, include the expenses of carrying out trades and the costs of making financial decisions. Therefore given the total of financial assets, a lower average cash balance means a higher average stock of bonds. Hence by economising on money, people earn more interest, or pay less when they are borrowing. The demand for money reflects this trade off between transaction costs and interest earnings.

If people put more effort into transacting and financial planning, they lower their average holding of money. A lower money balance means, a greater amount of interest earned. Therefore a higher interest rate motivates people to incur more costs of making financial decisions, in order to economise on money; hence a higher interest rate reduces the demand for money.

Geske and Roll (1983), closely relate stock returns with the money supply process and the inflation. They attribute the fact that stock market returns signal changes in the inflationary process, due to the following chain of macroeconomic events. First, the government's principal revenues are personal and corporate taxes. When stock prices decrease or increase as a consequence to changes in anticipated economic conditions, personal and corporate incomes move in the same direction, and therefore provide a similar change in government revenue. So stock market movements are closely related to fluctuations in government revenue. Second, if changes in government expenditure do not follow changes in revenue, this will reflected in deficits. Changes in economic conditions should be followed by opposite changes in the deficit. Third, when there is a deficit, the Treasury is obliged to borrow. This debt could be repaid by during later surplus periods, given that direct tax revenues increase or expenditures decrease enough to generate such a surplus. However, the typical way of dealing with this dept is to have the Federal Reserve System "monetize" this dept by printing currency or expanding bank reserves. This, in turn, generates the required surplus by indirect taxation through the inflation caused by an increase rate of monetary growth.

Another possible candidate is imports, which represents the goods and services bought from abroad. One of the components of the Gross National Product (GNP), which represents the gross output of goods and services, is government purchase of goods and services. Some of the goods and services produced in an economy are exported to foreign users. Exports must be added to domestic purchases to compute the economy's total production (GNP). Additionally to buying goods and services that are produced domestically, foreigners also produce goods and services that are imported to domestic country. Imports therefore must be subtracted from domestic purchases to calculate GNP. When the GNP falls toward a low point or trough, the economy is in a recession, or an economic contraction, when it expands towards a high point or peak, the economy is in a boom, or an economic expansion. Thus imports, being a component of the GNP, subtracted from the economy's total production, can also affect returns. Imports are related to exchange rates, and inflation. For example a stronger pound means cheaper imported commodities and lower inflation rates.

Another possible candidate to proxy for a state variable in the APT includes a proxy for the US market index. We use the S&P 500. The reason this factor is considered is the fact that the UK stock market can be influenced by the direction of the US stock market. In order to examine this possibility we comprise the S&P 500, in the list of macroeconomic factors under consideration. Furthermore another possible factor that can proxy for the state variable in the APT, consist of the UK stock exchange turnover. The UK stock exchange turnover can also have an influence on expected future cash flows, and thus has a subsequent effect on stock returns.

5.1.1. DISCUSION AND DEFINITION OF THE FINAL SET OF MACROECONOMIC FACTORS

Table 5.1 presents a list of macroeconomic factors and indexes that could proxy for the state variables in the APT model.

Table 5.1: Macroeconomic factors & Indexes

Table 5.1 provides a list of the macroeconomic factors and indexes that could proxy for the state variables in the APT model and their symbol. The Risk Premium (or Default), a measure for investors' required return for accepting risk is determined by CRR (1986) as the difference between high-grade and low-grade bond returns. Unfortunately, there is not a reliable time-series data on corporate bond grading and returns in UK. Thus, we use the difference between the monthly logarithmic returns of the Financial Times Fixed Interest securities Price index and the Financial Times Government Securities Price index. The Term Structure is measured by the difference between long-term and short-term Government interest rates. The long-term is approximated by the yield on 20-year gilts, and the short-term interest rate is approximated by the one-month Treasury bill rate.

SYMBOL	MACROECONOMIC FACTORS & INDEXES
RSRFT	Return on Financial Times All Share Index
RSRSP	Return on Standard & Poors 500 Price Index
RSRTU	Unanticipated UK Stock Exchange Turnover
RSRMO	Unanticipated Change in Money Supply (MO)
RSIMP	Unanticipated Change in Imports
RSINF	Unanticipated Change in Inflation
RSPR	Unanticipated Growth rate of Industrial production
RSTS	Unanticipated Term structure: Difference between the yield on 20-year gilts and the one-month Treasury bill rate
RSDE	Unanticipated Risk premium (or Default): Difference between the Financial Times Fixed Interest securities Price index and the Financial Times Government Securities Price index

The Default and term structure in table 5.1 are defined as follows. The Risk Premium (Default), a measure for investors' required return for accepting risk is determined by

CRR (1986) as the difference between high-grade and low-grade bond returns. Unfortunately, there is not a reliable time-series data on corporate bond grading and returns in UK. Thus, we use the difference between the monthly logarithmic returns of the Financial Times Fixed Interest securities Price index and the Financial Times Government Securities Price index.[1] The Term Structure is measured by the difference between long-term and short-term Government interest rates. The long-term is approximated by the yield on 20-year gilts, and the short-term interest rate is approximated by the one-month Treasury bill rate. In contrast to CRR we do not include two inflation variables, in order to avoid correlations between them.

We also incorporate some lags in our macroeconomic factors, since the announcement of some macroeconomic variables are subject to publication lags. For example inflation is announced to the public with a month's lag, i.e. inflation figures are announced in February. Therefore agents react to the shock in the announcement of January's inflation figures a month later, that is February and revise stock prices accordingly in February. So we introduce lags in order to produce results that are consistent to the concept that agents are responding to the shocks in the announcements of the macroeconomic variables.

It should also be mentioned that a number of other factors were considered and estimated in the original first set of factors. For example the unemployment factor, Current account balance, exchange rate, oil prices. However these factors were found totally insignificant and were discarded in the final set of factors, which consist of the factors illustrated in Table 5.1. The fact that we find the oil factor insignificant is also consistent with US data; Chen Roll and Ross (1986) find the changes in oil prices factor unpriced. Additionally Claire and Thomas (1994) also find the oil factor insignificant in the UK. In order to conclude on the final set of factors extensive investigation was carried out. The APT model was estimated several times with all the variables included and or with a reduced number of different combinations of different factors. Furthermore this extensive investigation was carried out for the different portfolio formation criteria of size, price-earnings ratio and dividend yield. Thus in order to identify significant factors, we started by doing both

[1] See Poon and Taylor (1991)

the following. By using every factor and testing the statistical significance of its price of risk and by dropping out the insignificant and then by re-estimating the model again with only the significant premia included. However be concerned about possible multicollinearity by utilising this way of identifying the significant factors, we extensively employed another technique to come up with the significant factors. We formed various APT models with different combinations of different factors and tested their statistical significance. In section 5.2 and 5.3 we show that a six-factor model consisting of the following factors: the return on FTSE, return on S&P 500, the unexpected components of the UK stock exchange turnover, change in money supply, change in imports, change in inflation, are priced for a sample of 6000 companies from 1976 to 1996. The number of factors (six-factor model) that we have identified is consistent with Roll and Ross (1980) tests for the appropriate number of factors.

Furthermore the way we outline our empirical tests in section 5.1 and 5.2, is carried out in such a way so as the empirical question of Poon and Taylor (1991) to be answered and to fill this gap in the literature. Poon and Taylor (1991), suggest that probably other macroeconomic factors except from the CRR (1986) are at work, in the UK market. It could be that other macroeconomic factors are at work or the FMB methodology is inadequate for detecting such pricing relationships or possibly both explanations apply.

5.1.2. UNANTICIPATED COMPONENTS

The reason we use the unanticipated components (innovation) is that, we are interested in the unanticipated changes of a certain factor-s. Anticipated changes are expected and have already incorporated into expected returns. In order to derive the innovations of the series we used the Arima Box-Jenkins methodology. The models chosen to derive the innovations of the series, were selected so as the minimum mean square errors to be obtained and the residual series to be white noise (i.e., serially uncorrelated errors).

Table 5.2 display the Autocorrelation of the residuals. We examine the residuals (errors), in order to check that the errors are random, which means that that the fitted model has eliminated pattern from the data and what remains is random errors. Since the autocorelation of the residuals can tell us how successive values of the residuals relate to each other, if they are random, then no autocorelation should be significantly different from zero. We can see that the Arima models provide random residuals, since no autocorelation is significantly different from zero.

Table 5.2: Autocorrelations of residuals

	RSRFT	RSRSP	RSRTU	RSRMO	RSIMP	RSINF
1	0.010584	0.007661	0.02237	-0.06884	0.0195	0.028791
2	-0.00121	0.000426	0.016657	0.087272	0.028447	-0.01376
3	0.005466	0.001029	0.014706	-0.02191	-0.04622	-0.00809
4	-0.00898	0.007177	0.02297	0.050832	0.013694	0.013461
5	-0.00783	-0.01877	0.004565	-0.01715	0.023215	0.024963
6	0.001042	-0.05081	-0.00745	0.040678	-0.03518	0.020798
7	0.001405	-0.01383	-0.00967	-0.00254	0.003635	0.020606
8	0.008171	-0.02936	-0.05104	-0.05293	0.024139	0.043558
9	0.017482	-0.07875	-0.03789	-0.00817	-0.07532	0.026302
10	-0.03675	0.087273	-0.01633	0.01919	0.058651	-0.03185
11	-0.08659	-0.02	-0.04014	0.019376	0.023617	-0.01499
12	-0.11744	-0.06988	-0.08207	-0.16283	-0.0072	-0.03773
13	-0.04408	0.038633	-0.03357	-0.08099	-0.09525	0.11392
14	-0.0362	-0.07966	0.017474	0.064665	-0.09939	-0.09854
15	-0.03779	-0.03958	-0.01514	0.040199	-0.08243	-0.02401
16	0.020947	0.001719	-0.07979	-0.02068	0.005168	-0.0285
17	-0.0218	-0.03466	0.077276	0.072307	-0.01341	0.036521
18	0.031447	-0.04618	-0.00347	0.099067	0.058257	0.041693
19	0.026074	-0.10144	-0.00816	0.025403	-0.00584	0.017519
20	-0.03149	-0.0033	-0.04712	-0.00737	0.014168	0.080436

Furthermore we include another diagnostic test, in order to see whether the residuals are white noise (uncorellated random process with constant mean and variance), using the Ljung-Box Q statistic, which is distributed as x^2 with m degrees of freedom, where m denotes the lag length. The hypothesis testing is, H_O: the residuals are white noise.

Table 5.3 displays the Ljung-Box Q statistic and the respective critical values. We can see that for every case the calculated value of Ljung-Box Q statistic < critical value, we therefore accept the hypothesis that the residuals are white noise.

Table 5.3: Ljung-Box Q statistic and critical values

	Q-stat	Q-stat	Q-stat	Q-stat	Q-stat	Q-stat	CRITICAL
Lag	RSRFT	RSRSP	RSRTU	RSRMO	RSIMP	RSINF	VALUE 5%
1	0.028342	0.014851	0.12661	1.19893	0.096206	0.20972	3.84
2	0.028715	0.014897	0.19709	3.13376	0.30178	0.25779	5.99
3	0.036335	0.015167	0.25226	3.25625	0.8466	0.27446	7.81
4	0.056968	0.028358	0.38738	3.91799	0.89462	0.32087	9.49
5	0.072721	0.11891	0.39274	3.99364	1.03321	0.4811	11.1
6	0.073002	0.78539	0.40705	4.42087	1.35268	0.59278	12.6
7	0.073514	0.83498	0.43128	4.42254	1.3561	0.70286	14.1
8	0.090896	1.05939	1.10948	5.15191	1.5078	1.19678	15.5
9	0.17078	2.68047	1.48484	5.16937	2.99088	1.37762	16.9
10	0.52528	4.67984	1.55484	5.26604	3.89385	1.64385	18.3
11	2.50176	4.78531	1.9796	5.365	4.04088	1.70303	19.7
12	6.15283	6.07786	3.76247	12.38313	4.05461	2.07987	21
13	6.66926	6.47459	4.06211	14.12695	6.46605	5.52946	22.4
14	7.01916	8.16868	4.14362	15.24322	9.10308	8.12146	23.7
15	7.40207	8.58855	4.20507	15.67645	10.9248	8.27601	25
16	7.5202	8.58934	5.91897	15.79155	10.93199	8.49466	26
17	7.64868	8.91422	7.53361	17.2052	10.98062	8.85529	27.6
18	7.91721	9.49342	7.53689	19.87031	11.90224	9.32733	28.9
19	8.10263	12.30002	7.55504	20.0463	11.91153	9.41103	30.1
20	8.37431	12.303	8.16307	20.06119	11.96652	11.18324	31.4

5.2. THE FAMA-MACBETH METHODOLOGY (FMB)

This section examines whether the CRR (1986) factors are significant with the FMB methodology, for return portfolios sorted on size. At the first step, the market value portfolios' exposure to the macroeconomic factors and the market index are estimated by regressing the market value portfolio returns on the unanticipated components of the macroeconomic factors and the market indexes, using time series regressions over an estimation period of 5 years, i.e., (60 months rolling). The slope coefficients in the time-series regressions provide estimates of the betas.

$$R_{MVit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSPR} RSPR_t + \beta_{RSINF} RSINF_t + \beta_{RSTS} RSTS_t + \beta_{RSDE} RSDE_t + e_{it}$$

where: R_{MVit} is the return for market value portfolio i at time t, $i = 1,...,25$; α_i is a constant term; $\beta_{RSRFT}, \beta_{RSPR}, \beta_{RSINF}\ \beta_{RSTS}, \beta_{RSDE}$ are the betas; $RSRFT_t, RSPR_t$, $RSINF_t, RSTS_t, RSDE_t$ are the return on FTSE, unexpected components of growth rate of industrial production, change in inflation, the term structure, and the default; e_{it} is the zero mean idiosyncratic term.

Thus the betas used as independent variables in the cross-sectional regressions for a given month are estimated from prior data. We use the five-year period ending in December of the previous calendar year and update the estimates annually. The market value portfolio returns are the dependent variable. So at the second step, for each of the 12 months, the following cross-sectional regression is run. Since the time series start in 1976, the cross-sectional start in 1981 and end in 1996.

$$R_{MVi} = \lambda_0 + \lambda_{RSRFT} \hat{\beta}_{RSRFT} + \lambda_{RSPR} \hat{\beta}_{RSPR} + \lambda_{RSINF} \hat{\beta}_{RSINF} + \lambda_{RSTS} \hat{\beta}_{RSTS} + \lambda_{RSDE} \hat{\beta}_{RSDE} + e_i$$

Where $\lambda_{RSRFT}, \lambda_{RSPR}, \lambda_{RSINF}, \lambda_{RSTS}, \lambda_{RSDE}$, are the estimates of the prices of risk for the return on FTSE, the unexpected components of growth rate of industrial production, change in inflation, the term structure, and the default; e_i is the zero mean idiosyncratic term. The result of the cross-sectional regressions; are the estimated time-series of the prices of risk associated with each of the factors. Significant average cross-sectional regression coefficient would suggest that an economic factor is priced. In order to see whether the APT has explanatory power in the cross-sectional regression we test the null hypothesis that $\lambda_{RSRFT} = 0, \lambda_{RSPR} = 0, \lambda_{RSINF} = 0, \lambda_{RSTS} = 0, \lambda_{RSDE} = 0$.

Table 5.4, panel A, shows the results of the cross-sectional regression with market value portfolio ranking.

Table 5.4: Cross-sectional regressions

The result of the cross-sectional regressions; are the estimated time-series of the prices of risk associated with each of the factors. Significant average cross-sectional regression coefficient would suggest that an economic factor is priced. Where: $\hat{\beta}_{RSRFT}, \hat{\beta}_{RSPR}, \hat{\beta}_{RSINF}, \hat{\beta}_{RSTS}, \hat{\beta}_{RSDE}$ are the betas used as independent variables in the cross-sectional regressions for a given month, which are estimated from prior data (Time-series). We use the five-year period ending in December of the previous calendar year and update the estimates annually. Where: $\lambda_{RSRFT}, \lambda_{RSPR}, \lambda_{RSINF}, \lambda_{RSTS}, \lambda_{RSDE}$ are the estimates of the prices of risk for the return on FTSE, the unexpected components of growth rate of industrial production, change in inflation, the term structure, and the default; e_t is the zero mean idiosyncratic term. Since the time series start in 1976, the cross-sectional start in 1981 and end in 1996.

Panel A: Market value portfolio ranking procedure

$$R_{MVi} = \lambda_0 + \lambda_{RSRFT}\hat{\beta}_{RSRFT} + \lambda_{RSPR}\hat{\beta}_{RSPR} + \lambda_{RSINF}\hat{\beta}_{RSINF} + \lambda_{RSTS}\hat{\beta}_{RSTS} + \lambda_{RSDE}\hat{\beta}_{RSDE} + e_i$$

R_{MVi} is the return for market value portfolio i, for $i = 1,...,25$

Price of risk λ	Estimate	T-statistics
λRSRFT	-0.0003	-0.878
λRSPR	0.1331	0.9430
λRSINF	0.0023	0.7440
λRSTS	-0.008	-0.848
λRSDE	-0.0026	-0.862

We can see that none of the CRR factors is significant. Our findings are consistent with the Poon and Taylor (1991). They sort portfolios on size, and employ the FMB methodology to test whether the CRR factors are priced, but find no significant relationship to be detected. Table 5.2, panel A, shows that the sign of the unexpected return on the FTSE is negative, a finding inconsistent with the CAPM. We know that if the market has a negative sign (in the *ex-post* model), under the CAPM the empirical security market line will slope downwards. The theoretical CAPM requires the *ex-ante* expected return on the market to be higher than the risk-free rate of return, this is because prices must be established in such a way that riskier assets have higher expected rates of return. CRR (1986) also find in some of their tests a negative relationship between the market index and returns. When they use the return on the value weighted index, along with the rest of their factors, [Table 4, panel D, page 396, CRR, (1986)], the sign of the market index is negative for the 1958-84 period. Poon and Taylor (1991), also find a negative relationship between the market index and expected returns. In an attempt to cast some light on this negative relationship, they compute rank correlations between average market betas, mean returns and firm size. They find, as expected, a negative relationship between size and mean returns. Then they find the ("puzzling" fact of a negative) and statistically significant relationship between returns and market betas. Another finding is the high significant positive relationship between size and market betas, this means that small size firms have smaller market betas or systematic risk. This implies that the size premium will increase on a risk-adjusted basis, [Levis, (1985)]. Therefore a possible explanation of this negative returns-betas relationship is that it could be induced by the positive size-betas relationship and negative size returns relationship.

We have found evidence that the CRR (1986) factors are insignificant when we sort the return portfolios on the basis of size. Next we examine the sensitivity of these results when we sort the return portfolios on the basis of PE ratio and dividend yield. At the first step, the PE ratio and dividend yield portfolios' exposure to the macroeconomic factors and the market indexes are estimated by regressing the PE ratio and dividend yield portfolio returns respectively on the unanticipated components of the macroeconomic factors and the market indexes, using time series regressions over an estimation period of 5 years.

$$R_{PEit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSPR} RSPR_t + \beta_{RSINF} RSINF_t + \beta_{RSTS} RSTS_t + \beta_{RSDE} RSDE_t + e_{it}$$

$$R_{DYit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSPR} RSPR_t + \beta_{RSINF} RSINF_t + \beta_{RSTS} RSTS_t + \beta_{RSDE} RSDE_t + e_{it}$$

where: R_{PEit} is the return for PE ratio portfolio i, R_{DYit} is the return for dividend yield portfolio i, $i = 1,...,25$; α_i is a constant term; $\beta_{RSRFT}, \beta_{RSPR}, \beta_{RSINF}, \beta_{RSTS}, \beta_{RSDE}$ are the betas; $RSRFT_t, RSPR_t, RSINF_t, RSTS_t, RSDE_t$, are the return on FTSE, the unexpected components of growth rate of industrial production, change in inflation, the term structure, and the default; e_{it} is the zero mean idiosyncratic term.

In the second step, the betas are the independent variables. The PE ratio and dividend yield portfolio returns are respectively the dependent variable. So at the second step, for each of the 12 months, the following cross-sectional regression is run. The time series start in 1976, the cross-sectional start in 1981 and end in 1996.

$$R_{PEi} = \lambda_0 + \lambda_{RSRFT}\hat{\beta}_{RSRFT} + \lambda_{RSPR}\hat{\beta}_{RSPR} + \lambda_{RSINF}\hat{\beta}_{RSINF} + \lambda_{RSTS}\hat{\beta}_{RSTS} + \lambda_{RSDE}\hat{\beta}_{RSDE} + e_i$$

$$R_{DYi} = \lambda_0 + \lambda_{RSRFT}\hat{\beta}_{RSRFT} + \lambda_{RSPR}\hat{\beta}_{RSPR} + \lambda_{RSINF}\hat{\beta}_{RSINF} + \lambda_{RSTS}\hat{\beta}_{RSTS} + \lambda_{RSDE}\hat{\beta}_{RSDE} + e_i$$

Where $\lambda_{RSRFT}, \lambda_{RSPR}, \lambda_{RSINF}, \lambda_{RSTS}, \lambda_{RSDE}$, are the estimates of the prices of risk for the return on FTSE, the unexpected components of growth rate of industrial production, change in inflation, the term structure, and the default; e_i is the zero mean idiosyncratic term. In order to see whether the APT has explanatory power in the cross-sectional regression for the PE ratio and dividend yield portfolio returns respectively, we test the null hypothesis that

$\lambda_{RSRFT} = 0, \lambda_{RSPR} = 0, \lambda_{RSINF} = 0, \lambda_{RSTS} = 0, \lambda_{RSDE} = 0$.

Table 5.4, panel B, and panel C, indicate that none significant relationship is detected, when we employ different portfolio ranking procedures, by sorting return portfolios on PE ratio and dividend yield.

Table 5.4: Cross-sectional regressions

The result of the cross-sectional regressions; are the estimated time-series of the prices of risk associated with each of the factors. Significant average cross-sectional regression coefficient would suggest that an economic factor is priced. Where: $\hat{\beta}_{RSRFT}, \hat{\beta}_{RSPR}, \hat{\beta}_{RSINF}, \hat{\beta}_{RSTS}, \hat{\beta}_{RSDE}$ are the betas used as independent variables in the cross-sectional regressions for a given month, which are estimated from prior data (Time-series). We use the five-year period ending in December of the previous calendar year and update the estimates annually. Where: $\lambda_{RSRFT}, \lambda_{RSPR}, \lambda_{RSINF}, \lambda_{RSTS}, \lambda_{RSDE}$ are the estimates of the prices of risk for the unexpected components of the return on FTSE, growth rate of industrial production, change in inflation, the term structure, and the default; e_t is the zero mean idiosyncratic term. Since the time series start in 1976, the cross-sectional start in 1981 and end in 1996.

Panel B: PE ratio portfolio ranking procedure

$$R_{PEi} = \lambda_0 + \lambda_{RSRFT}\hat{\beta}_{RSRFT} + \lambda_{RSPR}\hat{\beta}_{RSPR} + \lambda_{RSINF}\hat{\beta}_{RSINF} + \lambda_{RSTS}\hat{\beta}_{RSTS} + \lambda_{RSDE}\hat{\beta}_{RSDE} + e_i$$

R_{PEi} is the return for PE ratio portfolio i, for $i = 1,...,25$

Price of risk λ	Estimate	T-statistics
λ_{RSRFT}	-0.00053	-0.885
λ_{RSPR}	0.0301	0.899
λ_{RSINF}	0.0275	0.784
λ_{RSTS}	-0.031	-0.877
λ_{RSDE}	0.0017	0.822

Panel C: Dividend yield portfolio ranking procedure

$$R_{DYi} = \lambda_0 + \lambda_{RSRFT}\hat{\beta}_{RSRFT} + \lambda_{RSPR}\hat{\beta}_{RSPR} + \lambda_{RSINF}\hat{\beta}_{RSINF} + \lambda_{RSTS}\hat{\beta}_{RSTS} + \lambda_{RSDE}\hat{\beta}_{RSDE} + e_i$$

R_{DYi} is the return for dividend yield portfolio i, for $i = 1,...,25$

Price of risk λ	Estimate	T-statistics
λ_{RSRFT}	0.00021	0.812
λ_{RSPR}	0.1952	0.807
λ_{RSINF}	-0.0032	-0.795
λ_{RSTS}	0.158	0.957
λ_{RSDE}	0.00059	0.902

None of the CRR factors is significant. CRR (1986), claim that an interesting area for future research is the examination of the sensitivity of results to different portfolio formation procedures. In answer to that, with the FMB methodology we find that the factors are insignificant, irrelevant of the portfolio procedure employed. However, we notice some differences in the signs of the factors. With the market value and PE ratio portfolio procedure, the sign of the market is negative. On the other hand sorting on dividend yield the sign of the market is positive. Inflation has a positive sign for the market value and PE ratio portfolios, which implies that the more sensitive a portfolio is to inflation the more the expected return for this [stocks with higher inflation betas (exposures) require a higher expected return]. Sorting on dividend yield, the sign for inflation is negative, which implies that there is a lower expected rate of return associated with stocks that are more heavily exposed (higher betas/exposures) to inflation shocks. A negative sign implies that if expected inflation rises from the end of one month to the next, this will make the stock price change smaller than otherwise, or *ceteris paribus* reduce price. The term structure has a negative sign for the market value and PE ratio rankings, and a positive sign for the dividend yield portfolio procedure. Hence we notice a consistency of the signs among size and PE ratio ranking procedures (small size and low PE ratio return portfolios have higher return), while we notice the opposite signs for the dividend yield ranking (low dividend yield have lower return).

We have shown that the CRR (1986) are insignificant with the FMB methodology, and with the different portfolio formation procedures, of size, PE, and dividend yield. Next we examine whether other macroeconomic factors are significant with the FMB methodology. Furthermore we examine the sensitivity of our results to different portfolio procedures, of size, PE ratio and dividend yield. At the first step, the market value, PE ratio and dividend yield portfolios' exposure to the macroeconomic factors and the market index are estimated.

$$R_{MVit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSRSP} RSRSP_t + \beta_{RSRTU} RSRTU_t + \beta_{SRMO} RSRMO_t + \beta_{RSIMP} RSIMP_t$$
$$\beta_{RSINF} RSINF_t + e_{it}$$

$$R_{PEit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSRSP} RSRSP_t + \beta_{RSRTU} RSRTU_t + \beta_{SRMO} RSRMO_t + \beta_{RSIMP} RSIMP_t$$
$$\beta_{RSINF} RSINF_t + e_{it}$$

$R_{DYit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSRSP} RSRSP_t + \beta_{RSRTU} RSRTU_t + \beta_{SRMO} RSRMO_t + \beta_{RSIMP} RSIMP_t$
$\beta_{RSINF} RSINF_t + e_{it}$

where: R_{MVit} is the return for market value portfolio i, R_{PEit} is the return for PE ratio portfolio i, R_{DYit} is the return for dividend yield portfolio i, $i = 1,...,25$, at time t; α_i is a constant term; $\beta_{RSRFT} \beta_{RSRSP}, \beta_{RSRTU}, \beta_{SRMO}, \beta_{RSIMP}, \beta_{RSINF}$ are the betas; $RSRFT_t, RSRSP_t, RSRTU_t$ $RSRMO_t, RSIMP_t, RSINF_t$ are the return on FTSE, return on S&P 500, the unexpected components of the UK stock exchange turnover, change in money supply, change in imports, change in inflation; e_{it} is the zero mean idiosyncratic term.

In the second step, the betas are the independent variables. The market value, PE ratio and dividend yield portfolio returns are respectively the dependent variable. So at the second step, for each of the 12 months, the following cross-sectional regression is run. The time series start in 1976, the cross-sectional start in 1981 and end in 1996.

$R_{MVi} = \lambda_0 + \lambda_{RSRFT} \hat{\beta}_{RSRFT} + \lambda_{RSRSP} \hat{\beta}_{RSRSP} + \lambda_{RSRTU} \hat{\beta}_{RSRTU} + \lambda_{RSRMO} \hat{\beta}_{RSRMO} + \lambda_{RSIMP} \hat{\beta}_{RSIMP} +$
$\lambda_{RSINF} \hat{\beta}_{RSINF} + e_i$

$R_{PEi} = \lambda_0 + \lambda_{RSRFT} \hat{\beta}_{RSRFT} + \lambda_{RSRSP} \hat{\beta}_{RSRSP} + \lambda_{RSRTU} \hat{\beta}_{RSRTU} + \lambda_{RSRMO} \hat{\beta}_{RSRMO} + \lambda_{RSIMP} \hat{\beta}_{RSIMP} +$
$\lambda_{RSINF} \hat{\beta}_{RSINF} + e_i$

$R_{DYi} = \lambda_0 + \lambda_{RSRFT} \hat{\beta}_{RSRFT} + \lambda_{RSRSP} \hat{\beta}_{RSRSP} + \lambda_{RSRTU} \hat{\beta}_{RSRTU} + \lambda_{RSRMO} \hat{\beta}_{RSRMO} + \lambda_{RSIMP} \hat{\beta}_{RSIMP} +$
$\lambda_{RSINF} \hat{\beta}_{RSINF} + e_i$

Where: $\lambda_{RSRFT}, \lambda_{RSRSP}, _{RSRTU}, \lambda_{RSRMO}, \lambda_{RSIMP}, \lambda_{RSINF}$, are the estimates of the prices of risk for the return on FTSE, return on S&P 500, the unexpected components of the UK stock exchange turnover, change in money supply, imports, inflation; e_i is the zero mean idiosyncratic term. In order to see whether the APT has explanatory power in the cross-sectional regression for the market value, PE ratio and dividend yield portfolio returns respectively, we test the null hypothesis that $\lambda_{RSRFT} = 0, \lambda_{RSRSP} = 0, _{RSRTU} = 0, \lambda_{RSRMO} = 0,$ $\lambda_{RSIMP} = 0, \lambda_{RSINF} = 0$.

Table 5.5, panel A, reports that none of the other macroeconomic factors are significant when these are estimated by FMB for the size portfolios. Table 5.5, panel B and C, shows similar results for the PE ratio and dividend yield portfolios.

Table 5.5: Cross-sectional regressions

The result of the cross-sectional regressions; are the estimated time-series of the prices of risk associated with each of the factors. Significant average cross-sectional regression coefficient would suggest that an economic factor is priced. Where: $\hat{\beta}_{RSRFT} \hat{\beta}_{RSRSP}, \hat{\beta}_{RSRTU}, \hat{\beta}_{SRMO}, \hat{\beta}_{RSIMP}, \hat{\beta}_{RSINF}$ are the betas used as independent variables in the cross-sectional regressions for a given month, which are estimated from prior data (Time-series). We use the five-year period ending in December of the previous calendar year and update the estimates annually. Where: $\lambda_{RSRFT}, \lambda_{RSRSP}, \lambda_{RSRTU}, \lambda_{RSRMO}$ $\lambda_{RSIMP}, \lambda_{RSINF}$ are the estimates of the prices of risk for the return on FTSE, S&P 500, the unexpected components of the UK stock exchange turnover, changes in money supply, imports, inflation; e_t is the zero mean idiosyncratic term. Since the time series start in 1976, the cross-sectional start in 1981 and end in 1996.

Panel A: Market Value portfolio ranking procedure

$$R_{MVi} = \lambda_0 + \lambda_{RSRFT}\hat{\beta}_{RSRFT} + \lambda_{RSRSP}\hat{\beta}_{RSRSP} + \lambda_{RSRTU}\hat{\beta}_{RSRTU} + \lambda_{RSRMO}\hat{\beta}_{RSRMO} + \lambda_{RSIMP}\hat{\beta}_{RSIMP} + \lambda_{RSINF}\hat{\beta}_{RSINF} + e_i$$

R_{MVi} is the return for market value portfolio i, for $i = 1,...,25$

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	-0.0025	-0.853
λ_{RSRSP}	-0.0002	-0.967
λ_{RSRTU}	0.0370	0.883
λ_{RSRMO}	0.0041	0.864
λ_{RSIMP}	-0.005	-0.866
λ_{RSINF}	0.011	0.913

Panel B: PE ratio portfolio ranking procedure

$$R_{PEi} = \lambda_0 + \lambda_{RSRFT}\hat{\beta}_{RSRFT} + \lambda_{RSRSP}\hat{\beta}_{RSRSP} + \lambda_{RSRTU}\hat{\beta}_{RSRTU} + \lambda_{RSRMO}\hat{\beta}_{RSRMO} + \lambda_{RSIMP}\hat{\beta}_{RSIMP} + \lambda_{RSINF}\hat{\beta}_{RSINF} + e_i$$

R_{PEi} is the return for PE ratio portfolio i, for $i = 1,...,25$

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	-0.009	-0.916
λ_{RSRSP}	-0.014	-0.787
λ_{RSRTU}	0.005	1.047
λ_{RSRMO}	0.005	0.876
λ_{RSIMP}	0.119	1.030
λ_{RSINF}	0.008	0.825

Panel C: Dividend Yield portfolio ranking procedure

$$R_{DYi} = \lambda_0 + \lambda_{RSRFT}\hat{\beta}_{RSRFT} + \lambda_{RSRSP}\hat{\beta}_{RSRSP} + \lambda_{RSRTU}\hat{\beta}_{RSRTU} + \lambda_{RSRMO}\hat{\beta}_{RSRMO} + \lambda_{RSIMP}\hat{\beta}_{RSIMP} + \lambda_{RSINF}\hat{\beta}_{RSINF} + e_i$$

R_{DYi} is the return for dividend yield portfolio i, for $i = 1,...,25$

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	0.0089	0.819
λ_{RSRSP}	-0.011	-0.879
λ_{RSRTU}	-0.011	-0.840
λ_{RSRMO}	0.0033	0.882
λ_{RSIMP}	-0.047	-0.805
λ_{RSINF}	-0.025	-0.846

None of the other macroeconomic factors are priced with the FMB methodology, no matter what criterion we use to sort return portfolios, size, PE ratio, or dividend yield. However we notice differences among these different portfolio formation procedures with respect to the signs of the factors. The market (FTSE) has a negative sign for the size and PE ratio portfolio rankings whereas the same factor appear with a positive sign for the dividend yield portfolios. The stock exchange turnover has a positive sign for the size and PE ratio portfolio rankings. On the other hand the same factor has a negative sign for the dividend yield ranking. The inflation has a positive sign for the size and PE ratio rankings and appear with the opposite sign for the dividend yield portfolios. Therefore we observe a consistency of the signs among size and PE ratio ranking procedures (small size and low PE ratio return portfolios have higher return), while we observe the opposite signs for the dividend yield ranking (low dividend yield have lower return). Concluding our analysis based on the two-step methodology we should also mention, although it has been discussed in Chapter 2 that we control for the EIV problem by forming portfolios on the basis of size, price earnings ratio and dividend yield, following Chen, Roll and Ross (1986) and Chan, Chen and Hsieh (1985). Using portfolios mitigates the EIV problem since estimation error in asset betas is reduced.

5.3. THE NON-LINEAR SEEMINGLY UNRELATED REGRESSION (NLSUR)

Sections 5.2. provides evidence that the CRR (1986) factors are insignificant when estimated by FMB methodology. This finding is common to the different return portfolio ranking procedures of size, PE ratio and dividend yield portfolios. This section the NLSUR methodology is employed to test the APT.

It is assumed that in a world of n assets the differences between actual and expected returns on the ith asset and the jth time period are generated by a linear factor model with k factors.

$$R_{it} = E_t\left[R_{it}\right] + \sum_{J=1}^{K} \beta_{ij} F_{jt} + \varepsilon_{it} \qquad (4.1)$$

Where Et is the expectation operator that conditions on information available at the beginning of the period and where R_{it} = the total return on the ith asset in period t; F_{ij} = the jth factor in period t; β_{ij} = the sensitivity of asset i to factor j; and ε_{it} = a random error specific to the ith firm/portfolio or the idiosyncratic disturbance, which satisfies

$$E_t[\varepsilon_{it}] = 0 \quad E_t\left[\varepsilon_{it}\varepsilon_{jt}'\right] = \sigma_{ij} \qquad t = t' \qquad (4.2)$$

$$E_t\left[\varepsilon_{it}\varepsilon_{jt}'\right] = 0 \qquad t \neq t'$$

The APT originated with Ross (1976,1977), the APT takes the form of (4.1) and its basic postulate is that, because of competition in asset markets, it is impossible for an investor to earn a positive expected rate of return on any combination of assets without undertaking some risk and without making some net investment. The common fundamental theorem of APT is that for each time period there exists k+1 constants λ_{0t} and $\lambda_t=(\lambda_{1t}\ldots\lambda_{Kt})'$, not all zero, such that expected return is approximately given by

$$E_t[R_{it}] = \lambda_{0t} + \sum_{J=1}^{K} \beta_{ij}\lambda_{jt} \qquad (4.3)$$

To write the APT as a multivariate regression model for a sample of N<n assets, we retain the error assumptions (4.2) and substitute (4.3) into (4.1) to obtain a system of N non-linear regressions over T time periods

$$R_{it} = \lambda_{0t} + \sum_{J=1}^{K} \beta_{ij}\lambda_{jt} + \sum_{J=1}^{K} \beta_{ij}F_{jt} + \varepsilon_{it} \qquad (4.4)$$

$i = 1,\ldots,N \quad t = 1,\ldots,T$

Equation (4.4) is a multivariate non-linear regression model with cross-equations restrictions, for which McElroy, Burmeister and Wall (1985), showed that with the NLSUR, we can obtain joint estimation of the sensitivities (β_{ij}'s) and the prices of risk (λ_j's).

The essential feature of simultaneous equation models is that two or more endogenous variables are determined jointly within the model, as a function of exogenous variables or predetermined variables and error terms. Multivariate regression models arise in many circumstances, now if the same parameters appeared in more than one of the regression function, the system would be said to subject to cross-equation restrictions. In the presence of such restriction, it is obvious that one would want to estimate all equations as a system rather than individually, in order to obtain efficient estimates.

The Non-linear Seemingly unrelated regression (NLSUR) model consists of a series of equations linked because the error terms across equations are correlated, the NLSUR model involves generalised least squares estimation and achieves an improvement in efficiency by taking into account the fact that cross-equation error correlation may not be zero.

Since we do not know the price of risk for the j factors, the model is non-linear, if the λ_j were known then the model would be linear. Also the price of risk (λ_j) is the same for each jth factor for each portfolio.

We employ the NLSUR methodology to estimate the CRR factors for the size portfolio ranking. Equation (4.4) can be expressed as follows for the CRR (1986) factors.

$$R_{MVit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \\ \beta_{i1}RSRFT_t + \beta_{i2}RSPR_t + \beta_{i3}RSINF_t + \beta_{i4}RSTS_t + \beta_{i5}RSDE_t + e_{it}$$

for market value portfolio $i = 1,...,25$

Where: R_{MVit} = the return on market value portfolio i in month t

β_{ij} = The sensitivity of market value portfolio i to factor j

λ_j = The price of risk for the factor j

Where: $RSRFT_t, RSPR_t, RSINF_t, RSTS_t, RSDE_t$, are the return on FTSE, the unexpected components of growth rate of industrial production, change in inflation, the term structure, and the default; e_{it} is the zero mean idiosyncratic term.

Table 5.6, panel A, shows that the market (FTSE) is priced and has a negative sign, for the market value portfolios.

Table 5.6: NLSUR

Equation is a multivariate non-linear regression model with cross-equations restrictions. With NLSUR we obtain joint estimation of the sensitivities (β_{ij}'s) and prices of risk (λ_j's). Where β_{ij} the sensitivity of portfolio i to factor j; λ_j is the price of risk of factor j; F_j is the jth factor; ε_{it} a random error. Where: $RSRFT_t, RSPR_t, RSINF_t, RSTS_t, RSDE_t$, are the return on FTSE, the unexpected components of growth rate of industrial production, change in inflation, the term structure, and the default; e_{it} is the zero mean idiosyncratic term. The data cover the 1976 to 1996 period

$$R_{it} = \lambda_0 + \sum_{J=1}^{K} \beta_{ij}\lambda_j + \sum_{J=1}^{K} \beta_{ij}F_j + \varepsilon_{it}$$

Panel A: Market value portfolio ranking procedure

$$R_{MVit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSPR_t + \beta_{i3}RSINF_t + \beta_{i4}RSTS_t + \beta_{i5}RSDE_t + e_{it}$$

R_{MVit} is the return for market value portfolio i, for, $i = 1,...,25$

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	-0.056	-3.166***
λ_{RSPR}	0.014	1.200
λ_{RSINF}	0.167	3.1540***
λ_{RSTS}	0.809	-1.123
λ_{RSDE}	0.917	-1.346

***: Denotes significant at 1%

Negative signs for the market factors, has been found apart from CRR (1986), and Poon and Taylor (1991), by Chan, Chen, and Hsieh (1985) [Table 5, page 467]. Chan, Chen, and Hsieh (1985) claim that the negative sign of the estimated market premium is disturbing, because it suggests that if we have two firms of roughly the same size, the one with the higher market beta would have lower expected return, which is contrary to our prior belief. Table 5.6, Panel A, also indicates that inflation is priced and has a positive sign for the size portfolios. The same panel shows that the growth of industrial production, the term structure and default, are insignificant, for the market value portfolios.

We have shown that from the CRR factors estimated by NLSUR, only the return on the FTSE and the change in inflation are significant, for the size portfolio ranking. In this section we examine the sensitivity of these results when we employ different portfolio procedures of PE ratio and dividend yield.

$$R_{PEit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSPR_t + \beta_{i3}RSINF_t + \beta_{i4}RSTS_t + \beta_{i5}RSDE_t + e_{it}$$

for PE ratio portfolio $i = 1,...,25$

$$R_{DYit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSPR_t + \beta_{i3}RSINF_t + \beta_{i4}RSTS_t + \beta_{i5}RSDE_t + e_{it}$$

for dividend yield portfolio $i = 1,...,25$

Where: R_{PEit} = the return on PE ratio portfolio i in month t

R_{DYit} = The return on dividend yield portfolio i in month t

β_{ij} = The sensitivity of PE ratio portfolio i to factor j

λ_j = The price of risk for the factor j

Where: $RSRFT_t, RSPR_t, RSINF_t, RSTS_t, RSDE_t$, are the return on FTSE, the unexpected components of growth rate of industrial production, change in inflation, the term structure, and the default; e_t is the zero mean idiosyncratic term.

Table 5.6, panel B, indicates that the return on the FTSE is priced and has a negative sign, for the PE ratio portfolios. Table 5.6, Panel B, also indicates that the change in inflation is priced and has a positive sign for the PE ratio portfolios. Panel C of the same table shows that the return the FTSE is not priced for the dividend yield portfolios, and appears with positive sign.

Table 5.6: NLSUR

Equation is a multivariate non-linear regression model with cross-equations restrictions. With NLSUR we obtain joint estimation of the sensitivities (β_{ij}'s) and prices of risk (λ_j's). Where β_{ij} the sensitivity of portfolio i to factor j; λ_j is the price of risk of factor j; F_j is the jth factor; ε_t a random error. Where: $RSRFT, RSPR, RSINF, RSTS, RSDE$, are the return on FTSE, the unexpected components of growth rate of industrial production, change in inflation, the term structure, and the default; e_t is the zero mean idiosyncratic term. The data cover the 1976 to 1996 period

$$R_{it} = \lambda_0 + \sum_{J=1}^{K} \beta_{ij}\lambda_j + \sum_{J=1}^{K} \beta_{ij}F_j + \varepsilon_{it}$$

Panel B: PE ratio portfolio ranking procedure

$$R_{PEit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSPR_t + \beta_{i3}RSINF_t + \beta_{i4}RSTS_t + \beta_{i5}RSDE_t + e_{it}$$

R_{PEit} is the return for PE ratio portfolio i, for, $i = 1,...,25$

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	-0.128	-3.383***
λ_{RSPR}	0.009	1.314
λ_{RSINF}	0.108	2.188**
λ_{RSTS}	0.783	1.504
λ_{RSDE}	-0.915	-1.375

***: Denotes significant at 1%.
**: Denotes significant at 5%.

Panel C: Dividend yield portfolio ranking procedure

$$R_{DYit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSPR_t + \beta_{i3}RSINF_t + \beta_{i4}RSTS_t + \beta_{i5}RSDE_t + e_{it}$$

R_{DYit} is the return for dividend yield portfolio i, for , $i = 1,...,25$

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	0.0405	1.160
λ_{RSPR}	0.00005	0.0054
λ_{RSINF}	-0.069	-1.832*
λ_{RSTS}	-0.976	-1.441
λ_{RSDE}	0.6160	0.508

*: Denotes significant at 10 %.

Panel C also displays that the change in inflation is significant for the dividend yield portfolios. Table 5.6, Panel B and C present evidence that the growth rate of industrial production, the term structure and default, are all insignificant, for both the PE ratio and dividend yield portfolios.

We have found that the return on FTSE and the change in inflation are significant for the market value and PE ratio portfolio ranking, and the change in inflation is significant for the dividend yield portfolio ranking, estimated with the NLSUR. Based on these evidence we create an APT model that includes the return on the FTSE and the change in inflation, that we find to be priced, along with other factors that may affect returns.

$$R_{MVit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} + \\ \beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

$$R_{PEit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} + \\ \beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

$$R_{DYit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} + \\ \beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

For portfolio $i = 1,...,25$

Where: R_{MVit} = the return on market value portfolio i in month t

R_{PEit} = The return on PE ratio portfolio i in month t

R_{DYit} = The return on dividend yield portfolio i in month t

β_{ij} = The sensitivity of market value portfolio i to factor j

λ_j = The price of risk for the factor j

$RSRFT_t, RSRSP_t, RSRTU_t, RSRMO_t, RSIMP_t, RSINF_t$ are the return on FTSE, S&P 500, the unexpected components of UK stock exchange turnover, change in money supply, imports, inflation; e_{it} is the zero mean idiosyncratic term.

Table 5.7, panel A reports that the return on the FTSE is significant and has a negative sign.

Table 5.7: NLSUR

Equation is a multivariate non-linear regression model with cross-equations restrictions. With NLSUR we obtain joint estimation of the sensitivities (β_{ij}'s) and prices of risk (λ_j's). Where β_{ij} the sensitivity of portfolio i to factor j; λ_j is the price of risk of factor j; F_j is the jth factor; ε_t a random error. Where $RSRFT_t, RSRSP_t, RSRTU_t, RSRMO_t, RSIMP_t, RSINF_t$ are the return on FTSE, S&P 500, the unexpected components of UK stock exchange turnover, change in money supply, imports, inflation. The data cover the 1976 to 1996 period

$$R_{it} = \lambda_0 + \sum_{J=1}^{K} \beta_{ij}\lambda_j + \sum_{J=1}^{K} \beta_{ij}F_j + \varepsilon_{it}$$

Panel A: Market value portfolio ranking procedure

$$R_{MVit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

R_{MVit} is the return for market value portfolio i, for, $i = 1,...,25$

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	-.0220	-4.160***
λ_{RSRSP}	-.0410	-4.232***
λ_{RSRTU}	.3535	3.308***
λ_{RSRMO}	-.0209	-2.203**
λ_{RSIMP}	-1.540	-3.187***
λ_{RSINF}	.0919	2.3683***

***: Denotes significant at 1%.
**: Denotes significant at 5%.
*: Denotes significant at 10%.

Also the return on the S&P 500 is significant and has a negative sign for the market value return portfolios. Table 5.7, panel B indicates that the return on the FTSE is significant and has a negative sign for the PE ratio portfolios. Table 5.7, panel C, displays that the return on the S&P 500 is significant and has a negative sign for the dividend yield portfolios. Therefore we can a consistency of a negative sign on the market index (either on the FTSE or on the S&P 500), across the size, PE ratio and dividend yield portfolio returns.

Panel B: PE ratio portfolio ranking procedure

$$R_{PEit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} + \beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

R_{PEit} is the return for PE ratio portfolio i, for , $i = 1,...,25$

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	-.0848	-3.153***
λ_{RSRSP}	.0269	.1595
λ_{RSRTU}	.5423	2.507***
λ_{RSRMO}	-.0513	-2.320***
λ_{RSIMP}	.1908	.2531
λ_{RSINF}	.10289	1.802*

***: Denotes significant at 1%.
**: Denotes significant at 5%.
*: Denotes significant at 10%.

Panel C: Dividend yield portfolio ranking procedure

$$R_{DYit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} + \beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

R_{DYit} is the return for dividend yield portfolio i, for , $i = 1,...,25$

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	.0115	.748
λ_{RSRSP}	-.0506	-4.654***
λ_{RSRTU}	-.186	-1.920**
λ_{RSRMO}	.0303	1.816*
λ_{RSIMP}	-.642	-1.265
λ_{RSINF}	-.129	-3.177***

***: Denotes significant at 1%.
**: Denotes significant at 5%.
*: Denotes significant at 10%.

Relative to the negative sign of the market price of risk, Boudoukh, Richardson and Smith (1993), find that, for the US market, negative risk premia are associated with periods of high expected inflation and downward sloping term structures. Santis and Gerard (1998), who test the conditional CAPM for the worlds eight largest equity markets (US, UK, Japan, Canada, Germany, France, Italy, Switzerland) find between the end of the seventies and the early Eighties the price of market risk consistently negative. They claim that during those years, interest rates and inflation were unusually high and the slope of the yield curve was often negative. So they conclude that the findings of Boudoukh, Richardson and Smith (1993), hold also in an international setting. Furthermore they claim that for advocates of the traditional CAPM as a model of international asset pricing; the one-factor model which imposes non-negativity constrain on the market risk premium cannot fully explain the dynamics of international expected returns.

Table 5.7, panel A, indicates that the return on FTSE, S&P 500, stock exchange turnover, change in money supply, imports, and inflation, all are significant for the size portfolio ranking. Panel B, shows that the return on FTSE, stock exchange turnover, change in money supply, and change in inflation are significant for the PE ratio portfolios. Panel C, shows the return on S&P 500, stock exchange turnover, change in money supply, and inflation are priced for the dividend yield portfolios. Panel D, shows the betas of the market indexes and macroeconomic factors for the size, PE ratio and dividend yield groupings.

We notice some differences in the signs of these different portfolio strategies. The significant factors for the market value and the PE ratio return portfolios (small size and low PE ratio return portfolios have higher return) have the same signs. While factors which are priced for dividend yield portfolios (high dividend yield have higher return) have exactly the opposite signs compared to the market value and the PE ratio return portfolios.

For instance for the dividend yield strategy, the return on the stock exchange turnover, and the change in inflation have a negative sign. A negative sign can be seen as a hedge against the adverse influence on this factor. The negative sign for the change in inflation means that that there is a lower expected rate of return associated with stocks that are more heavily exposed (higher betas/exposures) to inflation shocks. A negative sign implies that if expected inflation rises from the end of one month to the next, this will make the stock price change smaller than otherwise, or *ceteris paribus* reduce price. Since changes in inflation have the general effect of shifting wealth among investors, there is not a priory assumption of the sign of inflation.

On the other hand, with both the market value and PE ratio portfolios the return on the stock exchange turnover, and the change in inflation have a positive sign. A positive risk price for inflation means individuals would want to hedge against unexpected increases in inflation occasioned by an increase in uncertainty. A positive sign is an indication that the more sensitive a portfolio is to a particular factor the more the expected return for this stock (stocks with e.g., higher inflation betas (exposures) require a higher expected return).

The change in money supply has a negative sign for the size and PE ratio portfolios. This could also mean that the adverse influence of the state variable to other assets that are presumably, relatively more fixed in nominal terms, can make these assets to be considered as more preferable investment choice. So a negative price of risk means people are paid positive returns for bearing this risk. On the other hand for the dividend yield portfolios, change in money supply has a positive sign. Apart from the change in imports, which is priced only with the size portfolios, and has a negative sign, implying that there is a lower expected rate of return associated with stocks that are more heavily exposed to shocks in imports, we observe the following. There is a consistency of the signs between size and PE ratio portfolios, and on the other hand we have the opposite signs for the dividend yield portfolios.

Panel D: Betas for Size, PE and Dividend yield portfolio ranking procedure

$$R_{MVit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

R_{MVit} is the return for market value portfolio i, for , $i = 1,...,25$

$$R_{PEit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

R_{PEit} is the return for PE ratio portfolio i, for, $i = 1,...,25$

$$R_{DYit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

R_{DYit} is the return for dividend yield portfolio i, for, $i = 1,...,25$

B11= the sensitivity of portfolio 1 to factor 1,i.e., the return on FTSE
B12= the sensitivity of portfolio 1 to factor 2, i.e., the return on S&P 500
B13= the sensitivity of portfolio 1 to factor 3, i.e., the unexpected UK stock exchange turnover
B14= the sensitivity of portfolio 1 to factor 4, i.e., the unexpected change in money supply
B15= the sensitivity of portfolio 1 to factor 5, i.e., the unexpected change in imports
B16= the sensitivity of portfolio 1 to factor 6, i.e., the unexpected change in inflation, etc

	SIZE	SIZE	PE	PE	DIVIDEND YIELD	DIVIDEND YIELD
	Estimate	T-statistic	Estimate	T-statistic	Estimate	T-statistic
B11	.9483	3.574***	.9716	5.815***	1.070	5.189***
B12	.2224	3.66***	.1530	1.932**	.2163	2.412**
B13	-.0256	-.0754	.9871	3.277***	.1706	.5009
B14	-.2683	-2.106**	-.6514	-2.608***	-.7067	-2.883***
B15	.2496	4.064***	-.0184	-.2940	.1838	2.948***
B16	.7005	2.908***	-.7579	-2.988***	.6542	2.920***
B21	.9566	4.244***	.97298	6.322***	1.00	5.954***
B22	.3117	2.195**	.2321	2.415**	93253	2.093**
B23	.3909	2.121**	.1836	1.674*	-.6139	-1.796*
B24	-.7099	-2.816***	-.8733	-3.520***	-91495	-6.064***
B25	-.0440	-.762	.0680	1.082	-.0549	-.8806
B26	-.1076	-1.438	-.0228	-.0300	-.4966	-.6857
B31	.95635	4.261***	.97621	6.518***	1.004	6.264***
B32	.2754	2.175**	.2306	2.406**	.3398	2.166**
B33	-.6295	-2.021**	.2931	2.105**	-.7255	-2.117**
B34	-.1351	-5.369***	-.1322	-5.323***	-.1056	-4.265***
B35	-.0837	-1.510	.0625	.9954	.2588	4.140***
B36	-.2254	-3.068***	-.2636	-2.837***	-.7459	-2.1016**
B41	.9633	4.779***	.9752	6.209***	.9870	6.436***
B42	.2630	2.166**	.1910	2.164**	.2933	1.947**
B43	-.7417	-2.361**	-.2288	-2.778**	-.1529	-4.507***
B44	-.9550	-3.792***	-.1705	-6.839***	-.1178	-4.841***
B45	.2118	3.781***	.1267	2.017**	.1046	1.681*
B46	.6182	2.837***	-.6180	-2.808***	.2048	2.952**
B51	.96357	4.808***	.97446	6.383***	.9799 .	5.904***
B52	.3050	2.194**	.2175	2.326**	.2445	2.615**
B53	-.1271	-4.084***	.0406	.1469	-.0762	-.2243
B54	-.1852	-2.736**	-.1243	-5.005***	-.1010	-4.143***
B55	-.0685	-1.235	.1364	2.172**	.0270	.4335
B56	-.8712	-2.118**	-.3827	-.5035	.2370	3.394***
B61	.9627	4.704***	.9756	6.386***	.9774	5.730***
B62	.2897	1.818*	.1793	2.092**	.2748	1.849*
B63	-.9479	-2.938***	.7292	2.573**	-.5211	-2.540**
B64	-.6464	-2.565**	-.8332	-3.350***	-.6701	-2.768**
B65	-.1558	-2.695**	.0579	.9220	.0449	.7223
B66	.1284	1.715*	-.2266	-2.975***	.1509	2.217**
B71	.9668	5.094***	.97348	6.331***	.97498	5.539***
B72	.2442	2.157**	.1876	2.143**	.2650	1.744*
B73	-.1872	-2.618**	.4769	1.736*	.9358	2.752**
B74	-.1043	-4.148***	-.5415	-2.181**	-.5837	-.2.389**
B75	.1455	2.717**	.0333	.5308	.0172	.2773
B76	.9032	2.124**	-.1015	-.1336	.1179	1.680*
B81	.9681	5.129***	.97681	6.327***	.9766	5.673**
B82	.2824	2.178**	.1147	1.992**	.2366	1.618*
B83	.0731	.2301	.3255	1.105	-.0309	-.0918
B84	-.1070	-4.250***	-.1110	-4.455***	-.1052	-4.378***
B85	.0737	1.297	-.0638	-1.016	.1126	1.815*
B86	-.3286	-4.424***	-.5887	-.7.699***	.3142	.4725
B91	.9677	5.115***	.97618	6.568***	.9732	5.417***
B92	2309	2.146**	.1797	1.995**	.2347	2.576**
B93	-.9359	-2.981***	-.0612	-.2231	.2711	.8013
B94	-1314	-5.220***	-.1164	-4.692***	-.3002	-2.123**
B95	.0183	.3275	.0774	1.233	.0832	1.338
B96	-.2143	-2.905**	-.9658	-2.271**	.1079	1.881*
B101	.9666	5.029***	.97547	6.141***	.97894	5.834***
B102	.2722	2.172**	.1961	2.195**	.1989	2.131**
B103	-.1373	-4.377***	-.5931	-1.977**	.2196	.6473
B104	-.1053	-4.182***	-.1235	-4.947***	-.4656	-1.912*
B105	.2984	5.332***	-.0742	-1.981**	.0278	.4481
B106	.7752	2.105**	.2191	2.860***	.3025	4.357***
B111	.97204	5.500***	.97713	6.756***	.97890	5.838***

B112	.27140	2.175**	.1953	2.190**	.2434	2.651**
B113	-.2717	-.9086	.0328	.1229	.1906	.5648
B114	-.1170	-4.656***	-.1040	-4.199***	-.5357	-2.221**
B115	.0446	.8447	-.0406	-.6476	.0235	.3783
B116	-.1236	-2.171**	-.3921	-2.517**	.1117	1.661*
B121	.9725	5.507***	.97545	6.557**	.97742	5.724***
B122	.2704	2.173**	.2473	2.508**	.1678	2.112**
B123	-.8000	-2.605**	.0338	.1249	-.2786	-.8223
B124	-.1001	-3.980***	-.1011	-4.077***	-.9657	-3.97***
B125	.0108	.1993	-.0442	-.7050	.1271	2.043**
B126	.1425	1.955**	.1046	2.137**	.1667	2.424**
B131	.9753	5.717***	.97342	6.243***	.9758	5.608***
B132	.2497	2.159**	.2530	2.542**	.2270	2.151**
B133	.3585	1.011	-.9188	-.0327	-.2997	-.8840
B134	-.1118	-4.444***	-.5136	-2.066**	-.4678	-1.923**
B135	.2614	4.779***	.1001	1.594	.1375	2.210**
B136	.1259	1.725*	.2163	.2842	.4033	.5830
B141	.9753	5.738***	.97456	6.556***	.7484	5.540***
B142	.2457	1.582	.2407	1467	.2191	2.150**
B143	.0810	.2682	.0570	.2147	.0152	.0452
B144	-.9284	-3.691***	-.8685	-3.506***	-.9386	-3.907***
B145	.1222	2.282**	.0341	.5430	.0308	.4964
B146	-.1022	-2.141	-.9006	-2.118**	-.6330	-.9545
B151	.7607	5.799***	.97597	6.436***	.97750	5.733***
B152	.2738	2.176**	.1938	1.881*	.2187	2.147**
B153	-.2956	-2.981***	-.0305	-.1082	-.8364	-2.475**
B154	-.1264	-5.027***	-.9983	-4.015***	-.1419	-5.874***
B155	-.5971	-.011	-.1067	-1.699*	.0172	.2771
B156	.0448	.0621	-.9332	-1.225	-.0387	-.0572
B161	.7878	5.996***	7617	6.454***	.9778	5.758***
B162	.2765	1.778*	.2222	2.354**	.1910	2.126**
B163	.3386	2.111**	-.6903	-2.447**	-.4486	-1.929**
B164	-.9374	-3.72***	-1623	-6.529***	-.1108	-4.595***
B165	.0798	1.486	-.0122	-.1947	.0989	1.593
B166	-.0523	-.0722	.4107	.5394	-.1707	-.2538
B171	.9850	6.423***	.97835	6.724***	.9787	5.824***
B172	.2807	1.782*	92320	1.914**	.2211	2.494**
B173	.6615	2.111**	.0342	.1238	-.6020	-1.781*
B174	-.1333	-5.294***	-.99594	-3.863***	-9413	-3.895***
B175	.1101	1.970**	.1263	2.011**	-.0340	-5.479***
B176	.9286	2.126**	-.9462	-2.124**	.1022	2.510**
B181	.98401	6.371***	.97983	6.628***	.97364	5.447***
B182	.28970	1.851*	.2319	1.913**	.1744	1.8174*
B183	.31655	2.102**	-.0230	-.0793	-.2405	-1.711*
B184	-.1099	-4.371***	-.1357	-5.447***	-.1246	-5.150***
B185	.0327	.5981	-.9653	-.1536	-.4130	-.0664
B186	.1918	2.262**	.1479	1.936**	-.2718	-2.399**
B191	.98889	6.684***	.97807	6.653***	.97886	5.830***
B192	.2016	2.127**	92951	1.799*	.1880	2.1254**
B193	-.5824	-1.826*	.3579	1.280	.2059	1.6077*
B194	-.1810	-2.718**	-.6162	-2.479**	-.8566	-3.526***
B195	.0236	.4145	.0967	.840	.0412	.6626
B196	.1114	2.149**	.4870	2.6402**	.0747	.1085
B201	.9931	2.709**	.97702	6.755***	.97480	5.531***
B202	.1734	2.111**	.2504	2.527**	.2110	2.141**
B203	.2307	.765	.2091	.7835	.6691	1.976**
B204	-.4801	-1.909**	-.6126	-2.472**	-.8875	-3.661***
B205	.0178	.335	.1042	1.660*	.0453	.7286
B206	.1194	1.165	.1027	1.355	-.1892	-2.765***
B211	.99437	7.188***	.97697	6.545***	.97608	5.626***
B212	.1664	2.071**	.2508	1.929**	.2235	1.896*
B213	.4359	2.144*	.5929	2.114**	-.8607	-2.542**
B214	-.2900	-2.115**	-.4921	-1.980**	-1247	-5.143***
B215	.0675	1.261	.7651	.1218	.0318	.5114
B216	.1319	1.824*	-.9567	-2.125**	-.6495	-.9477
B221	.9968	7.365***	.97918	6.794***	.97670	5.671***
B222	.1298	8.334***	.2864	1.746*	.2459	1.642*
B223	.7416	2.432**	-.0275	-.0997	.0409	.1207
B224	-.4049	-1.609*	-.1005	-4.048***	-.1289	-5.312***
B225	.1441	2.665**	.0588	.9365	.1156	1.858*
B226	.5734	2.789**	.295	2.388**	-.2779	-4.039***
B231	1.043	7.920***	1.0769	6.593***	.97485	5.540***
B232	.1183	7.580***	.2588	2.577**	2070	2.412**
B233	.3794	2.123**	-.3884	-2.401**	.3023	1.896*
B234	.1501	.5965	-.7103	-2.860**	-.1187	-4.934***

B235	-.4546	-.0834	.0798	1.270	.0722	1.164
B236	.1221	1.676*	.5612	1.7383*	-.8415	-2.1261**
B241	1.027	7.765***	.1076	6.562***	.97399	5.471***
B242	.5769	3.670***	.2604	1.587	.1949	1.305
B243	.6465	2.072**	-.2281	-.8248	.1940	.5729
B244	.3597	2.142**	-.5421	-2.183**	-.1200	-4.950***
B245	.0799	1.437	.0911	1.451	.1672	2.689**
B246	.3904	.5311	.6971	.9172	-.4353	-.6351
B251	1.009	7.617***	1.083	6.436***	.96585	4.861***
B252	.5279	3.348***	.2318	1.712*	.2002	1.797*
B253	.5097	2.162**	.1778	.5499	1913	5.608***
B254	.5643	2.240**	-.6268	-2.495**	-.7508	-3.053***
B255	.0477	.8511	.2488	3.960***	.0460	.7385
B256	1049	2.422**	.2492	3.224***	-.2267	-3.159***

***: Denotes significant at 1%.
**: Denotes significant at 5%.
*: Denotes significant at 10%.

5.4. FMB VERSUS NLSUR

In section 5.2 and 5.3, we find that none of the CRR factors is priced for the size, PE ratio and dividend yield return portfolios, when these are estimated by FMB methodology. However when the CRR factors are estimated by NLSUR, we find the return on the market, and the changes in inflation to be priced for both the size, and PE ratio portfolios; the change in inflation is priced for the dividend yield portfolios. The growth rate of industrial production, the term structure, and the default are not found to be priced with both FMB and NLSUR. Poon and Taylor (1991) claim that it could be that other macroeconomic factors are at work or the FMB methodology is inadequate for detecting such pricing relationships or possibly both explanations apply. We find that indeed both explanations apply. The term structure, the default and the growth rate of industrial production are not priced independent of the methodology employed, and the FMB methodology fails to detect a pricing relation for the return on the market and the change in inflation; whereas these factors seem are priced when estimated by NLSUR. The FMB methodology also fails to detect a pricing relation for the return on the S&P 500, UK stock exchange turnover, changes in money supply and imports; whereas these factors are significant when estimated by NLSUR.

The failure of the FMB methodology may be attributed to the fact that there may be a non-linear relationship in UK that the FMB methodology cannot capture, because it assumes a linear relationship between returns and risk. Furthermore, the FMB assumes normality, but the sensitivity of FMB from departures of normality makes standard hypothesis testing not valid. McElroy and Burmeister (1988) also claim that if the errors are not jointly normal, the properties of the estimators for the factor loadings obtained from FMB are unknown. On the other hand the NLSUR deliver, even in the absence of normally distributed errors, joint estimation of sensitivities and prices of risk that are strongly consistent and asymptotically normally distributed and to which standard hypothesis applies.

Inherent in FMB are also the following problems, that makes the "t-ratios" for testing the hypothesis that the average price of risk is zero be interpreted with caution. According to the FMB methodology, in the first stage we obtain estimates of the sensitivities, and then at the second stage obtain estimated of the prices of risk, from the cross-sectional regressions in which the betas are treated as "data". The fact, however that the cross-sectional regressions use estimates of betas instead of the true value, has the result of the independent variable in the cross-sectional regression being measured with error, so the second stage estimator is subject to an errors-in-variables (EIV) problem. EIV problem arises due to the estimation of betas in one period and the subsequent use of these betas as independent variables in another period. Fama-MacBeth proposed the construction of portfolios to minimise the measurement error.

However, Ferson and Harvey (1991), claim that even if the "true" betas are known, the second step, i.e., the cross-sectional regressions are complicated because returns are correlated and heteroskedastic. Conclusions based on the usual standard errors for these regressions are unreliable, since the betas are estimated with error; the regressions involve errors in the variables. The Fama-MacBeth "t-ratios" for testing the hypothesis that the average price of risk is zero should be interpreted with caution, given the possibility of correlated measurement errors in the beta and observations that may not be independent over time.

The NLSUR allows for heteroskedasticity across cross-sectional units. The existence of contemporaneous correlation means that allowance is made for non-zero covariances between the disturbances for different cross-sectional units. Therefore the NLSUR has the advantage of the ability to do joint hypothesis testing since heteroskedasticity across equations and contemporaneous dependence of the disturbances are explicitly incorporated into the joint hypothesis test. The NLSUR also avoids the EIV problem, since it estimates betas and prices of risk simultaneously.

Thus the NLSUR achieves more efficient estimates using Generalised Least squares (GLS), because it estimates all equations jointly rather than each one separately using Ordinary Least Squares (OLS). Thus obviously a gain in efficiency is achieved by joint estimation of a number of equations, whose disturbances are correlated (contemporaneous correlation). In our case the NLSUR adjusts for cross-portfolio correlations.

The NLSUR apart from eliminating the problems of the FMB including nonrobstuness of the estimators with respect departures from normality and efficiency losses allows for the basic principle of APT, that the price of risk is equal across assets/portfolios, to be tested. This is because; the price of risk for each factor is the same for the 25 portfolios. On the other hand the FMB by taking a time series average of the estimated prices of risk from the cross-sectional regressions, fails by all means to test the APT predictions that the price of risk is equal across all assets/ portfolios. Based on this, McElroy and Burmeister (1988) claim that the prices of risk obtain from FMB does not have any straightforward economic interpretation.

Finally it is worth noting the DW statistic of the time-series of the prices of risk. The time-series of the prices of risk (estimated from the FMB cross-sectional regressions) have DW statistics above 2, indicating a negative lag 1 autocorrelation in the underlying series. This finding, also reported by Poon and Taylor (1991), suggest that the risk premia are unstable. A higher than average premium estimate is followed by a lower average estimate. Theoretically, the risk premium should be fairly stable, therefore this very strong fluctuation of the risk premia estimates, is not very convincing as a model of returns expectations. The fact that the premia have this negative autocorrelation will bias the t-statistic towards zero, as the variance of the sample mean is overstated.

5.5. CONCLUSION

This chapter provides first an examination of the FMB methodology versus the NLSUR; Second an investigation to the sensitivity of results, when different portfolio ranking procedures, of size, PE ratio and dividend yield are employed. Third the identification of significant macroeconomic factors over the 1976 to 1996 period for all UK companies in the London Stock Exchange (LSE) inclusive on Unlisted Securities market.

We find that when the FMB methodology is employed to estimate the APT consisting of the CRR factors, these are insignificant, for all portfolio-ranking procedures. Then when we create an APT model consisting of some other factors, such as, the S&P 500, the UK stock exchange turnover, the change in money supply, imports along with the market factor, and the inflation factor, these are insignificant, for the size, PE ratio and dividend yield portfolio, estimated by FMB

On the other hand, when the NLSUR is employed to estimate the APT consisting of the CRR factors, we find the market factor and the inflation factor to be priced for the size and PE ratio portfolios, and the inflation factor to be priced for the dividend yield portfolios. Then when we test an APT model consisting of the S&P 500, the UK stock exchange turnover, the change in money supply, imports along with the market factor, and the inflation factor, these factors are found significant when estimated by NLSUR. In particular; the market (FTSE), S&P 500, stock exchange turnover, change in money supply, imports, and inflation, all are significant for the size portfolio ranking. The market (FTSE), stock exchange turnover, change in money supply, and change in inflation are significant for the PE ratio portfolios. The S&P 500, stock exchange turnover, change in money supply, and inflation are priced for the dividend yield portfolios.

The evidence from this study point out that the FMB methodology is inadequate for detecting a pricing relation in UK. This may be due to the fact that it fails to capture a non-linear relationship, since the FMB assumes a linear relationship between returns and risk. Another interesting point relating the FMB methodology, is that if the relationship between returns and macroeconomic factors holds in a manner described by CRR, why did it fail to produce positive results for their stock price portfolios? On the contrary, when we employ the NLSUR we find a pricing relationship between portfolio returns and certain factors, that gives positive results (in terms of significant factors) for alternative portfolio formation procedures, of size, PE ratio, and dividend yield.

CHAPTER 6

CONDITIONAL MODELS AND FORECASTS OF THE SIGN, MAGNITUDE OF PRICE OF RISK AND PORTFOLIO RETURNS

Asset Pricing Models have been the cornerstone of both theoretical and empirical finance. The main topic addressed in this study is Asset Pricing Models that are Conditioned on a set of ex-ante information variables. Ferson and Harvey (1991), (1993), (1999), Ferson and Korajczyk (1995), He, Kan and Zuang (1996), Jaganathan and Wang (1996), provide studies of Conditional Asset Pricing Models. In these studies researchers focus on the use of different models or estimation procedures in order estimate the conditional models, and one limitation is that they do not provide practical tests in order to assess the performance of Conditional Asset Pricing Models. This study contributes to the Conditional Asset Pricing Literature by providing practical tests and testing the performance of Conditional Asset Pricing Models. These practical tests focus on forecasts of (i) the sign of the price of risk using the probit model, (ii) the magnitude of the price of risk, and (iii) portfolio returns for the size, PE ratio and dividend yield portfolios. Chapter 5 shows the sign and the magnitude of the price of risk. However these estimates of the sign and magnitude of the price of risk are drawn from unconditional models and methodologies. Whereas the objective and contribution of this Chapter is to assess Conditional models and methodologies.[1] We therefore examine how good the Instrumental-Conditional variables predict variation of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, inflation and forecast portfolio returns under different sorting procedures.

This chapter sheds light into the underlying macroeconomic risks of the size, PE ratio and dividend yield portfolios using a model that conditions on the latest information investor use to update their expectation in the market place. Therefore this chapter tests how good Conditional models predict the sign, the price and

[1] The term ' Conditional methodology /model ' used in the thesis has been established in papers by Ferson and Harvey (1991), (1993).

portfolio returns. Furthermore by using different portfolio formation criteria of size, PE ratio and dividend yield we examine whether there are differences in the forecasting ability of the Conditional models, when these different sorting techniques are employed.

In this Chapter we model the dynamic behaviour of portfolio returns using a Conditional Asset Pricing Model and examine the behaviour of macroeconomic risk premiums over time. We utilize the Conditional methodology of Ferson and Harvey (1991), to estimate the conditional model, according to which first we estimate the unconditional model using the two-stage methodology and then regress each of the individual price of risk to a set of instrumental variables. However Ferson and Harvey (1991), mention that errors in variables affect their inferences when the fitted premiums are used as dependent variables in the time-series regressions to assess predictability. In order to address this issue, we extend the Non-linear Seemingly Unrelated Regression (NLSUR) [McElroy and Burmeister (1988)], into Conditional NLSUR. The Conditional NLSUR theoretically avoids the Errors In Variables (EIV) problem of the Ferson and Harvey (1991) methodology. The Conditional NLSUR achieves that because the price of risk, which is regressed on a set of instrumental variables, is obtained from the NLSUR, which simultaneously estimates the price of risk and betas, without having to run cross-sectional regressions as in the two-step methodology.

This study is organised as follows: Section 6.1 provides empirical results by utilising the Ferson and Harvey (1991) conditional methodology for the size; PE ratio and dividend yield portfolios. Section 6.2 discusses the Conditional non-linear seemingly unrelated regression estimates methodology and provides empirical results for the size, PE ratio and dividend yield portfolios. Section 6.3.1 describes the out-of-sample procedure that we utilise to forecast the sign of price of risk by using Probit, and summarises the empirical findings. Section 6.3.2 describes the out-of-sample procedure that we utilise to forecast the magnitude of price of risk, explains how we forecast portfolio returns, estimate the errors of the Conditional model and test the statistical significance of the errors; it also provides the empirical results. Section 6.4 concludes.

6.1 TESTS OF FERSON AND HARVEY (1991) METHODOLOGY

This section provides the analysis of the predictable components of monthly portfolio returns; it explains how we carry out tests of the Ferson and Harvey (1991) methodology and discusses the results for the size, PE ratio and dividend yield portfolios. Table 6.1, Panel A shows the price of risk of factors estimated from the unconditional macroeconomic APT model. Each of these prices of risk is regressed on a set of instrumental variables. The results of the unconditional model estimated both with the Fama Mac-Beth and the Non-linear seemingly unrelated regression estimates methodology are discussed in chapter 5.

Table 6.1

Table 6.1, Panel A shows the price of risk of the factors of the unconditional macroeconomic APT model

Panel A: The price of risk of Macroeconomic factors and Indexes

SYMBOL	PRICE OF RISK OF MACROECONOMIC FACTORS & INDEXES
λ_{RSRFT}	Price of risk of the Return on FTSE
λ_{RSRSP}	Price of risk of the Return on Standard & Poors 500
λ_{RSRTU}	Price of risk of Unanticipated UK Stock Exchange Turnover
λ_{RSRMO}	Price of risk of Unanticipated Change in Money Supply (MO)
λ_{RSIMP}	Price of risk of Unanticipated Change in Imports
λ_{RSINF}	Price of risk of Unanticipated Change in Inflation

Table 6.1, Panel B shows the instrumental variables and their symbol.

Table 6.1

Table 6.1, Panel B shows the instrumental variables.

Panel B: Instrumental Variables

SYMBOL	INSTRUMENTAL VARIABLES
CTB1	One month Treasury bill rate, lagged one month,
CDIV	Dividend yield on FTA all share price index, lagged one month
TS1	Term structure of interest rates, lagged one month,
RFT	Return on FTA all share price index, lagged one month,
RSP	Return on S&P 500 index, lagged one month,

The choice of the instrumental variables follows two basic rules, first the variables must be able to summarise expectations in the economy that are related to the prospects for stock returns, that is they should have the ability to forecast asset returns. The following variables have been found to forecast returns; short-term interest rates have been prominent instruments in several studies, their importance as instruments in tests of asset pricing models stems from their relation with consumption, production and returns. The dividend yield has also been examined and found to have predictive ability; the dividend yield is measured as the price level of a stock index divided into the previous year's dividend payments for the index.

The second basic rule deals with the number of instruments, which should be kept small because the parameter space gets larger when the cross-equation restrictions are tested. Following these criteria and also guided by the evidence provided in previous studies, we use the following set of instrumental variables: one-month Treasury bill rate; dividend yield on FTA all share price index; term structure of interest rates; the return on FTA all share price index, the return on S&P 500 index. These variables are lagged one month.

We use the Ferson and Harvey (1991) methodology to examine the predictive ability of the instrumental variables to predict variation of the individual risk premia associated with the macroeconomic variables. Having obtained the price of risk estimates λ_j from the cross-sectional regressions of FamaMacBeth for each month t, we perform time-series regressions of each of the risk premiums on the instrumental variables.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRSP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRTU} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRMO} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSIMP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSINF} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

Where λ_{RSRFT} is the Price of risk of the Return on FTSE; λ_{RSRSP} is the Price of risk of the Return on Standard & Poors 500; λ_{RSRTU} is the Price of risk of Unanticipated UK Stock Exchange Turnover; λ_{RSRMO} is the Price of risk of Unanticipated Change in Money Supply (MO); λ_{RSIMP} is the Price of risk of Unanticipated Change in Imports; λ_{RSINF} is the Price of risk of Unanticipated Change in Inflation; δ_0 is a constant; e_t is the residual.

In chapter 5 we find that the Return on FTSE, Standard & Poors 500, the Unanticipated UK Stock Exchange Turnover, Change in Money Supply, in Imports, and inflation, are not priced, when these are estimated with the Fama-MacBeth methodology. Our aim is to examine whether these are priced at certain times, depending on economic conditions tracked by the instrumental variables. So we examine whether these factors' expected compensation is larger at certain times and smaller at other, depending on economic conditions tracked by the instrumental variables. We also look at the relationship, positive or negative that each macroeconomic factor (its price of risk) has with the instrumental variables.

Table 6.2, Panel A summarises time-series regressions of the fitted premiums on the predetermined information variables for the market value portfolios. It shows the predictive ability of the instrumental variables to predict variation of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, and inflation.

The instrumental variables manage to explain a lot of variation of the price of risk of FTSE. The one-month Treasury bill rate, dividend yield and the S&P 500 are significant when we regress the price of risk of FTSE on the information variables. The price of risk of FTSE has a negative relation with the one-month Treasury bill rate, and a positive relation with the dividend yield and the S&P 500. The adjusted value of the R^2 in the predictive regressions is 10%, suggesting that the expected compensation for stock market risk (FTSE) is larger at certain times and smaller at other, depending on economic conditions tracked by the instrumental variables.

Similarly a lot of variation of the price of risk of S&P 500 is explained by the information variables. When we regress the price of risk of S&P 500 on the instrumental variables both the one-month treasury-bill rate and the dividend yield are found to be significant. The price of risk of S&P 500 has a negative relationship with the one-month treasury-bill rate, and a positive relationship with the dividend yield. The adjusted value of the R^2 in the predictive regressions is also 10%, suggesting that the US stock market risk (S&P 500) is priced at different stages of the business cycle.

Table 6.2: Tests of Ferson & Harvey methodology (1991)

We examine the predictive ability of the instrumental variables to predict variation of the individual price of risk associated with the macroeconomic variables. Having obtained the price of risk estimates λ_j from the cross-sectional regressions of the two-step methodology (Chapter 5) for each month t, we perform time-series regressions of each of the prices of risk on the instrumental variables. Where λ_{RSRFT} is the Price of risk of the Return on FTSE; λ_{RSRSP} is the Price of risk of the Return on Standard & Poors 500; λ_{RSRTU} is the Price of risk of Unanticipated UK Stock Exchange Turnover; λ_{RSRMO} is the Price of risk of Unanticipated Change in Money Supply (MO); λ_{RSIMP} is the Price of risk of Unanticipated Change in Imports; λ_{RSINF} is the Price of risk of Unanticipated Change in Inflation.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRSP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRTU} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRMO} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSIMP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSINF} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

Panel A: Market value portfolios

	λ_{RSRFT}	λ_{RSRSP}	λ_{RSRTU}	λ_{RSRMO}	λ_{RSIMP}	λ_{RSINF}
δ_0	-.015547	.827354	.049928	-.692607	-.010507	.010432
	(-.745928)	(.031356)	(.420610)	(-.624861)	(-.018727)	(.279363)
$\delta_{1\ CTB1}$	-.582702	-.422302	-2.62194	.185064	6.88579	.647829
	(-1.95246)	(-1.76270)	(-1.74816)	(1.41741)	(1.21726)	(2.05129)
$\delta_{2\ CDIV}$	1.14753	2.12447	6.11311	.103292	4.34886	1.82099
	(1.74212)	(2.80713)	(2.14932)	(.425375)	(.263169)	(2.33559)
$\delta_{3\ TS1}$	.334405	-.210879	.261106	.554187	-.043953	-.335522
	(.369833)	(-.288120)	(.481410)	(.014252)	(-.223512)	(-.304788)
$\delta_{4\ RFT}$	-.039491	.600965	.354363	.330727	.951832	-.100029
	(-.080259)	(.833165)	(.097231)	(1.56543)	(.058364)	(-.125552)
$\delta_{5\ RSP}$	1.94707	-.847036	-.961646	.959888	-2.07885	-2.80266
	(4.57093)	(-.965506)	(-.474035)	(3.61122)	(-.209265)	(-2.35436)
Adjust R^2	0.101532	0.1050	0.03359	0.087627	0.0167	0.089487

The predetermined variables predict variation in the UK stock exchange premium. In the predictive regression, both the one-month treasury-bill rate and the dividend yield are significant among the instrumental variables. The UK stock exchange premium is negatively related to the one-month treasury-bill rate; positively to the dividend yield and the adjusted value of the R^2 in the predictive regressions is 3%. Furthermore the information variables explain some variation in the money supply price of risk, since the adjusted value of the R^2 in the predictive regressions is nearly 9%. When we regress the price of risk of inflation on the information variables the one-month treasury-bill rate dividend yield and the S&P 500 are found to be significant. The expected compensation for inflation risk also seem to be larger at certain times and smaller at other, depending on economic conditions tracked by the instrumental variables, since the adjusted value of the R^2 in the predictive regressions is nearly 9%.

Table 6.2, Panel B summarises time-series regressions of the fitted premiums on the predetermined information variables for the PE ratio portfolios.

Table 6.2: Tests of Ferson & Harvey methodology (1991)

Panel B: PE ratio portfolios

	λ_{RSRFT}	λ_{RSRSP}	λ_{RSRTU}	λ_{RSRMO}	λ_{RSIMP}	λ_{RSINF}
δ_0	.015065	-.023197	.128276	.892052	-.134474	-.015266
	(.862708)	(-1.99186)	(1.09833)	(.523659)	(-.283044)	(-.428222)
$\delta_{1\,CTB1}$	-.085152	.109847	-2.72002	-.065989	3.50023	-.261556
	(-.356009)	(.759055)	(-3.00681)	(-.510693)	(.704970)	(-.745864)
$\delta_{2\,CDIV}$	.356789	-.364257	6.73234	.356944	8.30099	-.323126
	(.820358)	(-1.31387)	(3.22287)	(.936326)	(.695839)	(-.422698)
$\delta_{3\,TS1}$	.362180	-.818580	-.932850	.310396	.104099	.439898
	(.059759)	(-.165933)	(-.222426)	(.613208)	(.596179)	(.318498)
$\delta_{4\,RFT}$	1.54629	.464457	6.96042	-.101148	5.61633	2.57860
	(3.46021)	(1.80453)	(2.31099)	(-.241833)	(.777384)	(3.51770)
$\delta_{5\,RSP}$	.961565	.516049	8.64873	-.207849	-2.83643	-.601426
	(2.28055)	(2.18251)	(2.45773)	(-.522767)	(-.266457)	(-.646594)
Adjust R^2	0.13206	0.03306	0.186808	0.01645	0.01298	0.070804

The information variables manage to explain a lot of variation of the price of risk of FTSE. The FTA, S&P 500 are the instrumental variables found to be significant in the predictive regression. The fact that the adjusted value of the R^2 in the predictive regressions is 13% suggests that the stock market risk (FTSE) is priced at different stages of the business cycle. The predetermined variables manage to explain variation of the price of risk of S&P 500. In the regression of the price of risk of S&P 500 on the information variables, two instrumental variables are significant, the FTA, and S&P 500. The adjusted value of the R^2 in the predictive regressions is 3%.

The information variables predict a large amount of variation in the UK stock exchange premium. In the predictive regression, the one-month Treasury bill rate, the dividend yield, the FTA, and the S&P 500 are all significant among the instrumental variables. The adjusted value of the R^2 in the predictive regressions is nearly 19%, suggesting that the expected compensation for UK stock exchange risk is larger at certain times and smaller at other, depending on economic conditions tracked by the instrumental variables.

Variation in the inflation premium is also explained by the predetermined variables. When we regress the price of risk of inflation on the information variables, the FTA information variable is found to be significant, and the adjusted value of the R^2 in the predictive regressions is 7%, suggesting that the inflation premium is priced at different stages of the business cycle.

Table 6.2, Panel C summarises time-series regressions of the fitted premiums on the predetermined information variables for the dividend yield portfolios. In the regression of the price of risk of S&P 500 on the predetermined variables, the FTA is the information variable found to be significant, whereas the adjusted value of the R^2 in the predictive regressions is 2%. When we regress the price of risk on the instrumental variables, the S&P 500, is found to be significant, and the adjusted value of the R^2 in the predictive regressions is also 2%. So there is evidence that both the S&P 500 price of risk and the UK stock exchange turnover price of risk are significant at different stages of the economy.

Table 6.2: Tests of Ferson & Harvey methodology (1991)

Panel C: Dividend yield portfolios

	λ_{RSRFT}	λ_{RSRSP}	λ_{RSRTU}	λ_{RSRMO}	λ_{RSIMP}	λ_{RSINF}
δ_0	.461016	.767262	-.055668	.256852	-.039888	-.024753
	(.281149)	(.053727)	(-.717969)	(.204591)	(-.074085)	(-.596939)
$\delta_{1\ CTB1}$	.030691	.061294	-.377574	.102790	-12.8276	-.607195
	(.165077)	(.424257)	(-.514349)	(.659047)	(-3.13615)	(-1.85700)
$\delta_{2\ CDIV}$	-.213567	.138635	-2.59624	-.025558	12.7295	1.42235
	(-.521641)	(.440081)	(-1.28683)	(-.096747)	(1.03454)	(1.83429)
$\delta_{3\ TS1}$	.391065	-.878305	.984331	.407051	-.057453	-.014681
	(.088992)	(-.166382)	(.386613)	(1.01888)	(-.311570)	(-.866266)
$\delta_{4\ RFT}$	.147396	.725816	.963175	-.086126	19.3037	.881941
	(.297940)	(2.64253)	(.680910)	(-.371203)	(1.94897)	(1.20926)
$\delta_{5\ RSP}$	.413914	-.181271	4.65169	.197006	-14.0641	-1.37836
	(1.08165)	(-.481853)	(2.01685)	(.556176)	(-.907949)	(-1.29608)
Adjust R^2	0.01385	0.020305	0.024499	0.01704	0.03452	0.034571

The information variables predict variation in the change in imports premium. In the predictive regression, among the instrumental variables, the one-month treasury-bill rate, and the FTA, are found to be significant, the adjusted value of the R^2 in the predictive regressions is 3%. So the expected compensation for imports risk is larger at certain times and smaller at other, depending on economic conditions tracked by the instrumental variables.

In the predictive regression of the price of risk of inflation on the instrumental variables, both the one-month treasury-bill rate and the dividend yield are significant; also the adjusted value of the R^2 in the predictive regressions is 3%, suggesting that the inflation premium is priced at different stages of the economy.

Table 6.2, Panel A, B & C show that there are some differences among the size, PE ratio, and dividend yield portfolios. The adjusted value of the R^2 in the predictive regressions range from 10% for the UK and US stock market premium, nearly 9% for the imports and inflation premium to 3% for the UK stock exchange turnover premium for the market value portfolios. While for the PE portfolios the adjusted value of the R^2 in the predictive regressions range from nearly 19% for the UK stock exchange premium, 13% for the UK stock market premium, 7% for the inflation premium. For the dividend yield portfolios the adjusted value of the R^2 are generally lower (relative to the other portfolio formation strategies).

To conclude, the results from the Conditional Asset Pricing model for the size, PE ratio and dividend yield portfolios provides evidence that the following factors: the return on FTSE; S&P 500; unexpected UK stock exchange turnover; change in money supply; imports; and inflation, are priced at different stages of the business cycle.

6.2 DEVELOPMENT AND TESTS OF THE CONDITIONAL NONLINEAR SEEMINGLY UNRELATED REGRESSION METHODOLOGY

This section discusses how we develop another alternative conditional methodology, the Conditional NLSUR, with the intention to avoid some of the econometric problems that Ferson and Harvey (1991) mention about their methodology. Ferson and Harvey (1991), mention that Errors in Variables affects their inferences when the fitted premiums are used as dependent variables in the time-series regressions to assess predictability. They claim that a bias that shrinks the cross-sectional coefficients towards zero would create a tendency to understate the predictable variation captured by the model. If the biases are correlated with the predetermined information variables, the error could work in either direction, and even if the premium estimates were unbiased, estimation error in the premiums would distort the standard errors.

Therefore in order to overcome this problem, we regress the price of risk obtained from the NLSUR on a set of instrumental variables. So the difference between the Ferson and Harvey (1991) methodology and the Conditional NLSUR is that the price of risk of a certain factor is not obtained form the two-step, cross-sectional regression, but from the NLSUR, originally developed by McElroy and Burmeister (1988). The Conditional NLSUR methodology, avoids the Error in Variables problem, inherent in the Ferson and Harvey methodology, because, the price of risk of the factors is obtained from NLSUR, which simultaneously estimates betas and prices of risk. So according to the Ferson and Harvey (1991) methodology, first they run time-series regressions, to obtain the betas, then they run cross-sectional regressions with the betas used as independent variables to obtain the price of risk of certain factors. Then they use the price of risk of their factors and regress it to a set of instrumental variables. While according to the Conditional NLSUR, with just one step with obtain both betas and prices of risk for certain factors. Then we regress each price of risk to a set of instrumental variables. In that way we avoid the Error in Variables problem.

We examine the ability of the instrumental variables to predict variation of the individual price of risk associated with the macroeconomic variables. In order to do this we regress the price of risk on the instrumental variables. Having obtained the price of risk estimates λ_j from the NLSUR for each month t, we perform time-series regressions of each of the price of risk on the instrumental variables.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRSP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRTU} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRMO} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSIMP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSINF} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

Where λ_{RSRFT} is the Price of risk of the Return on FTSE; λ_{RSRSP} is the Price of risk of Return on Standard & Poors 500; λ_{RSRTU} is the Price of risk of the Unanticipated UK Stock Exchange Turnover; λ_{RSRMO} is the Price of risk of Unanticipated Change in Money Supply (MO); λ_{RSIMP} is the Price of risk of Unanticipated Change in Imports; λ_{RSINF} is the Price of risk of Unanticipated Change in Inflation; δ_0 is a constant; e_t is the residual.

Table 6.3, Panel A summarises time-series regressions of the fitted premiums on the predetermined information variables for the market value portfolios. It shows the predictive ability of the instrumental variables to predict variation of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, and inflation.

The information variables explain a lot of variation of the price of risk of FTSE. The one-month treasury bill rate, dividend yield, the term structure of interest rates, the FTA, and the S&P 500 are all significant in the regression of the price of risk of FTSE on these instrumental variables. The price of risk of FTSE is negatively related to the one-month Treasury bill rate, the term structure of interest rates and positively related to the dividend yield.

In the regression of the price of risk of S&P 500 on the predetermined variables, the one-month Treasury bill rate, and the term structure of interest rates are significant. These two information variables are negatively related to the price of risk of S&P 500. When we regress the price of risk of the UK stock exchange turnover on the instrumental variables, the term structure of interest rates is significant, and negatively related to the price of risk of the UK stock exchange turnover.

Table 6.3: Conditional NLSUR

We examine the predictive ability of the instrumental variables to predict variation of the individual price of risk associated with the macroeconomic variables. Having obtained the price of risk estimates λ_j from the Non-linear Seemingly Unrelated Regression Estimates (NLSUR) methodology (Chapter 5) for each month t, we perform time-series regressions of each of the prices of risk on the instrumental variables. Where λ_{RSRFT} is the Price of risk of the Return on FTSE; λ_{RSRSP} is the Price of risk of Return on Standard & Poors 500; λ_{RSRTU} is the Price of risk of Unanticipated UK Stock Exchange Turnover; λ_{RSRMO} is the Price of risk of Unanticipated Change in Money Supply (MO); λ_{RSIMP} is the Price of risk of Unanticipated Change in Imports; λ_{RSINF} is the Price of risk of Unanticipated Change in Inflation.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRSP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRTU} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRMO} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSIMP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSINF} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

Panel A: Market value portfolios

	λ_{RSRFT}	λ_{RSRSP}	λ_{RSRTU}	λ_{RSRMO}	λ_{RSIMP}	λ_{RSINF}
δ_0	-.022060	.483340	-.041028	.222425	.353501	-.025644
	(-.614006)	(107005)	(-.924202)	(.225568)	(.458875)	(-.532600)
$\delta_{1\,CTB1}$	-.161960	-.134964	.511805	.176541	-.322969	.560149
	(-6.2968)	(-2.06924)	(.720469)	(.148974)	(-.348847)	(.096805)
$\delta_{2\,CDIV}$	.454426	.306482	-.367342	-.257077	.576857	.229793
	(6.49469)	(.279141)	(-.331162)	(-.122386)	(.351517)	(.022404)
$\delta_{3\,TS1}$	-.138806	-.976147	-.112215	-.556472	.139495	.270411
	(-3.4511)	(-4.26210)	(-4.85516)	(-.147497)	(.473267)	(1.46789)
$\delta_{4\,RFT}$	.630649	.404543	.377712	.893372	.170550	.110945
	(3.24842)	(.418987)	(.384048)	(.048904)	(.119502)	(.124380)
$\delta_{5\,RSP}$	.240814	.255067	-.156979	.294137	.413937	-.918766
	(4.3755)	(.021277)	(-.128194)	(.123979)	(.223328)	(-.079311)
Adjust R^2	0.02	0.02	0.02	0.02	0.02	0.02

Table 6.3, Panel B summarises time-series regressions of the fitted premiums on the predetermined information variables for the PE ratio portfolios. It shows the predictive ability of the instrumental variables to predict variation of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, and inflation.

In the regression of the price of risk of the UK market on the predetermined variables, the term structure of interest rates is found to be significant, and negatively related the price of risk of the UK market. Similarly, when we regress the price of risk of the S&P 500 on the information variables, the term structure of interest rates is found to be significant, and negatively related the price of risk of the S&P 500. In the regression of the price of risk of the UK stock exchange turnover on the information variables, also the term structure of interest rates is found to be significant, and negatively related to the price of risk of the UK stock exchange turnover.

Table 6.3: Conditional NLSUR

Panel B: PE ratio portfolios

	λ_{RSRFT}	λ_{RSRSP}	λ_{RSRTU}	λ_{RSRMO}	λ_{RSIMP}	λ_{RSINF}
δ_0	-.084859	.716562	.269089	.153015	.542302	.987126
	(-.905018)	(.726686)	(.403806)	(.159842)	(.900389)	(.128137)
δ_{1CTBI}	-.130776	-.338947	-.112274	.443858	-.626703	-.249871
	(-1.00490)	(-.286019)	(-.160935)	(.374168)	(-.753717)	(-.269891)
$\delta_{2\,CDIV}$	.530617	.150407	.432352	-.163528	.485242	-.218742
	(.249102)	(.071604)	(.032789)	(-.078136)	(.778933)	(-.133294)
$\delta_{3\,TSI}$	-.159680	-.587533	-.584392	-.372690	.826303	-.120999
	(-3.48933)	(-1.65729)	(-2.35412)	(-.986670)	(.656439)	(-.410517)
$\delta_{4\,RFT}$	.290238	.702752	.349221	.928729	-.921544	.118002
	(.156285)	(.384694)	(.301299)	(.050802)	(-.932227)	(.082682)
$\delta_{5\,RSP}$	.783463	.137974	.274085	.322842	.774158	-.132585
	(.321111)	(.581565)	(.180995)	(.013660)	(.644655)	(-.071532)
Adjust R^2	0.02	0.02	0.02	0.02	0.02	0.02

Table 6.3, Panel C summarises time-series regressions of the fitted premiums on the predetermined information variables for the dividend yield portfolios. The information variables explain some variation of the price of risk of FTSE. The term structure of interest rates is significant, and has a negative relationship with the UK stock market premium. The instrumental variables also explain some variation of the price of risk of S&P 500. In the predictive regression of the price of risk of S&P 500 on the predetermined variables, the term structure of interest rated is found to be significant and negatively related with the US stock market premium. When we regress the price of risk of the UK stock exchange turnover on the instrumental variables, the term structure of interest rates is found to be significant, and to have a negative relationship with the UK stock exchange turnover.

Table 6.3: Conditional NLSUR

Panel C: Dividend yield portfolios

	λ_{RSRFT}	λ_{RSRSP}	λ_{RSRTU}	λ_{RSRMO}	λ_{RSIMP}	λ_{RSINF}
δ_0	.011579	.702729	-.050667	.216369	-.186684	.170643
	(.450967)	(.356329)	(-.210464)	(.877704)	(-.484663)	(.886034)
$\delta_{1\ CTB1}$	-.136102	-.101279	-.252455	-.236415	-.100379	.986442
	(-.488316)	(-.427321)	(-.087259)	(-.797993)	(-.216844)	(.426192)
$\delta_{2\ CDIV}$	.720040	.343988	-.649026	-.503855	-.171665	-.268149
	(.139198)	(.818805)	(-.012656)	(-.095948)	(-.209213)	(-.653602)
$\delta_{3\ TS1}$	-.219923	-.110673	-.200444	-.172125	.616327	.259684
	(-2.31802)	(-1.66672)	(-2.72020)	(-.182491)	(.418205)	(.028193)
$\delta_{4\ RFT}$	.322945	.382302	.356597	.749797	.173395	.274090
	(.716447)	(.104638)	(.799561)	(.164179)	(.024299)	(.768205)
$\delta_{5\ RSP}$	.197239	.508761	.606407	.150808	-.396692	.249678
	(.333847)	(.107222)	(.104694)	(.254263)	(-.042805)	(.538827)
Adjust R^2	0.02	0.02	0.02	0.02	0.02	0.02

6.3 FORECASTS OF SIGN, MAGNITUDE OF PRICE OF RISK & PORTFOLIO RETURNS

The objective of this section is to assess the performance of Conditional models. Therefore we carry out practical tests and test how good Conditional models are in predicting the sign, magnitude of the price of risk and forecast portfolio returns under different sorting procedures.

Chapter 5 shows the sign and the magnitude of the price of risk. However these estimates of the sign and magnitude of the price of risk are drawn from unconditional models and methodologies. Whereas the objective and contribution of this Chapter is to assess Conditional models and methodologies. We therefore examine how good the Instrumental-Conditional variables predict variation of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, inflation and forecast portfolio returns under different sorting procedures.

This section sheds light into how good Conditional models predict the sign, the price and portfolio returns. Furthermore by using different portfolio formation criteria of size, PE ratio and dividend yield we examine whether there are differences in the forecasting ability of the Conditional models, when these different sorting techniques are employed.

6.3.1 FORECASTS OF SIGN OF PRICE OF RISK USING PROBIT

In order to forecast the sign of the price of risk we use a probit model. Probit is used for analysing the determinants of a choice between two discrete alternatives; common are the cases where in which the dependent variable can take only two values. For example a person may be studying/not studying, working/not working, e.t.c. If we want to explain these variables, in an econometric model, we must acknowledge their discrete nature. These models are generally called qualitative response models, and are usually estimated by maximum likelihood. The dependent variable in these models represents two alternatives. These are coded as 0 or 1, and often called binary response models/ binary choice models.

The probit model can be derived from a model involving an unobserved or latent, variable Y_t*.

Latent = $Y_t^* = X_t b + e_t$, $e_t \sim NID(0,1)$[2]

We observe only the sign of Y_t^*, which determines the value of the observed binary variable Y_t. The dependent variable may be treated as an indicator of the sign of a latent dependent variable Y_t^*. That is,

$Y_t = 1$ if Latent $Y_t^* > 0$ (equation 1)

$Y_t = 0$ if Latent $Y_t^* \leq 0$ (equation 2)

This latent variable has a meaningful interpretation, such as the net value of being in choice 1 versus choice 0. Since the numerical scale of the latent variable is unobservable, the model is identified by normalising the standard deviation of the disturbance (e) to one.

In econometric applications the probit and the logit models have been used. The logistic distribution is similar to the normal except in the tails, which are considerably heavier. Therefore for intermediate values of $X_t b$ the two distributions tend to give similar probabilities. The logistic distribution tends to give larger probabilities to $Y_t=0$ when $X_t b$ is extremely small (and smaller probabilities to $Y_t=0$ when $X_t b$ is very large) than the normal distribution. Amemiya (1981) discusses a number of related issues, but as a general proposition and in most application Greene (1997) claims that the choice of the model seems not to make much difference. Original experiments indicated that this is indeed the case for our data.

We classify each month as choice 1 or zero based on the sign of the price of risk, that is, if in particular month the price of risk is positive we classify this month as 1, (equation 1). On the other hand if in particular month the price of risk is negative we classify this month as 0, (equation 2).

Let P_t denote the conditional probability that the price of risk is positive (equation 1), the binary response model is trying to model P_t (conditional) on certain information set, say Ω_t, that consists of exogenous and predetermined variables Specifying Y_t so that it is either 0 or1 is very convenient, because P_t is the expectation of Y_t conditional on Ω_t:

$P_t \equiv Pr(Y_t=1 \mid \Omega_t) = E(Y_t \mid \Omega_t)$

[2] X_t denotes a row vector of length k variables that belong to the information set Ω_t.

The probit model is trying to model P_t conditional on the following predetermined variables that belong to the information set Ω_t. So we fit a model with the following independent variables plus a constant, in order to predict the sign of the price of risk; One-month Treasury bill rate, dividend yield on FTA all share price index, term structure of interest rates, return on FTA all share price index, return on S&P 500 index. These predetermined variables are lagged one month. Table 6.1, Panel B shows these variables and their symbol.

We use the Probit model and run regressions with the price of risk being the dependent variable, and the predetermined variables, being the independent variables. For example we use the Probit model and run regressions of the price of risk of the FTSE on the information variables. First we run this regression using data from 1981-1985, this generate probabilities (we keep the fitted probabilities) for the next twelve months, 1986. Then the previous twelve months are added to the estimation period for the re-estimation of the model, which generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk of FTSE.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRSP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRTU} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRMO} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSIMP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSINF} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

Where λ_{RSRFT} is the Price of risk of the Return on FTSE; λ_{RSRSP} is the Price of risk of Return on Standard & Poors 500; λ_{RSRTU} is the Price of risk of Unanticipated UK Stock Exchange Turnover; λ_{RSRMO} is the Price of risk of Unanticipated Change in Money Supply (MO); λ_{RSIMP} is the Price of risk of Unanticipated Change in Imports; λ_{RSINF} is the Price of risk of Unanticipated Change in Inflation; δ_0 is a constant; e_t is the residual.

So we use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

If the probit probability is above 0.5, the set of characteristics X_t predicts that $Y_t = 1$ then the price of risk is positive.

If the probit probability is below 0.5, the set of characteristics X_t predicts that $Y_t = 0$ then the price of risk is negative.

Figures 6.1 to 6.18 provide a graphical illustration of the probabilities generated by the probit model of the sign of the price of risk of the return on FTSE, S&P 500, unexpected stock exchange turnover, changes in money supply, imports, and inflation, for the size PE ratio and dividend yield portfolios throughout the 1986-96 period. The errors that can occur in our forecast procedure is that the model may incorrectly predict a positive sign of risk when the actual sign of that month is negative or the model may incorrectly predict a negative sign of risk when the actual sign of that month is positive. In order to evaluate how our probit model predicts we report the % of correct predictions in each probit regression, and the average % of correct predictions for all (11) probit regressions for each price of risk we attempt to predict. Table 6.4, 6.5, 6.6, 6.7, 6.8 and 6.9 reports results of the probit regression model for the sign of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, changes in money supply, imports, and inflation for the market value portfolios. Table 6.4 shows the results of the probit regression model for the sign of risk of the return on FTSE. The average % of correct prediction for all the probit regressions is 58%. The probit regression model reaches the highest % of correct prediction of 65% during the 1984-1988, and 1985-1989 period. Table 6.5 reports the results of the probit regression model for the sign of risk of the return on S&P 500. The average % of correct prediction for all the probit regressions is 66%.

The probit regression model reaches the highest % of correct prediction of 75% during the 1986-1990, and 1987-1991 period. Table 6.6 reports the results of the probit regression model for the sign of risk of the unexpected UK stock exchange turnover. The average % of correct prediction for all the probit regressions is 64%. The probit regression model reaches the highest % of correct prediction of 71% during the 1987-1991, and 1988-1992 periods. Table 6.7 shows the results of the probit regression model for the sign of risk of the unexpected changes in money supply. The average % of correct prediction for all the probit regressions is 61%. The probit regression model reaches the highest % of correct prediction of 71% during the 1981-1985 period that generate probabilities for 1986. Table 6.8 reports the results of the probit regression model for the sign of risk of the unexpected changes in imports. The average % of correct prediction for all the probit regressions is 60%. The probit regression model reaches the highest % of correct prediction of 65% during the 1988-1992 period. Table 6.9 reports the results of the probit regression model for the sign of risk of the unexpected changes in inflation. The average % of correct prediction for all the probit regressions is 66%. The probit regression model reaches the highest % of correct prediction of 70% during the 1982-1986 period that generates probabilities for 1987.

Table 6.4: Probit model/ Price of risk of FTSE-Size portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the return on FTSE is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

MARKET	VALUE				
DEPENDENT	**VARIABLE λ_{RSRFT}**				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.134262	0.585968	δ_0	0.037848	0.177008
$\delta_{1\ RFT}$	-4.65308	-1.43528	$\delta_{1\ RFT}$	-1.60139	-0.502443
$\delta_{2\ RSP}$	3.0219	0.607405	$\delta_{2\ RSP}$	5.44691	1.13484
$\delta_{3\ CTB1}$	-2.27675	-1.35334	$\delta_{3\ CTB1}$	-3.28799	-1.90604
$\delta_{4\ CDIV}$	5.18362	1.39555	$\delta_{4\ CDIV}$	7.02644	1.79222
$\delta_{5\ TS1}$	0.062085	0.952099	$\delta_{5\ TS1}$	0.062884	0.939978
R-squared		0.115457	R-squared		0.125715
% Correct	Predictions	0.627119	% Correct	Predictions	0.616667
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.097971	-0.503621	δ_0	-0.131194	-0.660377
$\delta_{1\ RFT}$	-0.150407	-0.043575	$\delta_{1\ RFT}$	-2.69937	-0.771693
$\delta_{2\ RSP}$	4.82597	1.09413	$\delta_{2\ RSP}$	15.0377	2.63372
$\delta_{3\ CTB1}$	-4.58754	-1.78059	$\delta_{3\ CTB1}$	-3.62074	-1.20473
$\delta_{4\ CDIV}$	3.90738	0.926393	$\delta_{4\ CDIV}$	1.97392	0.442463
$\delta_{5\ TS1}$	0.147144	1.70443	$\delta_{5\ TS1}$	0.169603	1.17461
R-squared		0.0922	R-squared		0.14201
% Correct	Predictions	0.616667	% Correct	Predictions	0.65
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.295977	-1.3225	δ_0	-0.165903	-0.818032
$\delta_{1\ RFT}$	0.379879	0.09667	$\delta_{1\ RFT}$	3.81402	0.973964
$\delta_{2\ RSP}$	15.3202	2.68479	$\delta_{2\ RSP}$	4.35784	0.904905
$\delta_{3\ CTB1}$	-1.29054	-0.480164	$\delta_{3\ CTB1}$	-1.81582	-0.853756
$\delta_{4\ CDIV}$	0.923486	0.180907	$\delta_{4\ CDIV}$	1.03835	0.210292
$\delta_{5\ TS1}$	0.196694	1.36224	$\delta_{5\ TS1}$	0.050169	0.383242
R-squared		0.140066	R-squared		0.0377
% Correct	Predictions	0.65	% Correct	Predictions	0.6

Table 6.4–*Continued*

SAMPLE	**1987-1991**		**SAMPLE**	**1988-1992**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.098284	-0.491892	δ_0	-0.088266	-0.463209
$\delta_{1\,RFT}$	6.11183	1.33163	$\delta_{1\,RFT}$	5.58725	1.5752
$\delta_{2\,RSP}$	1.63034	0.356043	$\delta_{2\,RSP}$	5.06885	1.17124
$\delta_{3\,CTB1}$	-0.313934	-0.129724	$\delta_{3\,CTB1}$	0.495368	0.207323
$\delta_{4\,CDIV}$	11.5388	1.95054	$\delta_{4\,CDIV}$	4.19624	1.05694
$\delta_{5\,TS1}$	0.015272	0.114621	$\delta_{5\,TS1}$	-1.44E-03	-0.010818
R-squared		0.0812	R-squared		0.0788
% Correct	Predictions	0.583333	% Correct	Predictions	0.5
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter		t-statistic
δ_0	-0.186343	-1.02675	δ_0	-0.061086	-0.285166
$\delta_{1\,RFT}$	4.3648	1.37149	$\delta_{1\,RFT}$	2.5065	0.871292
$\delta_{2\,RSP}$	2.97355	0.795717	$\delta_{2\,RSP}$	2.17321	0.639135
$\delta_{3\,CTB1}$	0.026268	0.013109	$\delta_{3\,CTB1}$	-0.821005	-0.364758
$\delta_{4\,CDIV}$	2.49817	0.724874	$\delta_{4\,CDIV}$	1.02736	0.330771
$\delta_{5\,TS1}$	-0.042314	-0.351455	$\delta_{5\,TS1}$	-9.42E-03	-0.097562
R-squared		0.0529	R-squared	of	0.0233
% Correct	Predictions	0.533333	% Correct	Predictions	0.483333
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	-0.023017	-0.098597			
$\delta_{1\,RFT}$	2.74098	0.975172			
$\delta_{2\,RSP}$	5.61672	1.55871			
$\delta_{3\,CTB1}$	0.554193	0.202962			
$\delta_{4\,CDIV}$	0.480073	0.15791			
$\delta_{5\,TS1}$	0.030887	0.350533			
R-squared		0.0628			
% Correct	Predictions	0.633333			

Table 6.5: Probit model/ Price of risk of SP 500-Size portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the return on SP500 is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRSP} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

MARKET	**VALUE**				
DEPENDENT	**VARIABLE** λ_{RSRSP}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.109438	-0.449071	δ_0	-8.70E-04	-3.90E-03
$\delta_{1\,RFT}$	4.06382	1.25177	$\delta_{1\,RFT}$	-0.959866	-0.296953
$\delta_{2\,RSP}$	12.8979	2.27537	$\delta_{2\,RSP}$	13.61	2.53299
$\delta_{3\,CTB1}$	-0.226823	-0.140809	$\delta_{3\,CTB1}$	-1.44591	-0.938
$\delta_{4\,CDIV}$	0.26689	0.077741	$\delta_{4\,CDIV}$	2.79354	0.763219
$\delta_{5\,TS1}$	0.03639	0.53327	$\delta_{5\,TS1}$	0.042219	0.608396
R-squared		0.129395	R-squared		0.142149
% Correct	Predictions	0.627119	% Correct	Predictions	0.633333
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.053906	0.259389	δ_0	-0.042368	-0.203146
$\delta_{1\,RFT}$	-1.4251	-0.39256	$\delta_{1\,RFT}$	0.760414	0.204894
$\delta_{2\,RSP}$	14.1629	2.68041	$\delta_{2\,RSP}$	9.65566	1.75617
$\delta_{3\,CTB1}$	-4.91821	-1.79425	$\delta_{3\,CTB1}$	-8.84698	-2.60358
$\delta_{4\,CDIV}$	5.33448	1.20232	$\delta_{4\,CDIV}$	13.9573	2.52095
$\delta_{5\,TS1}$	0.089702	1.01718	$\delta_{5\,TS1}$	0.246201	1.59533
R-squared		0.230808	R-squared		0.249223
% Correct	Predictions	0.733333	% Correct	Predictions	0.683333
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	5.15E-04	2.30E-03	δ_0	5.87E-03	0.027116
$\delta_{1\,RFT}$	5.40636	1.33986	$\delta_{1\,RFT}$	3.07166	0.743424
$\delta_{2\,RSP}$	4.44451	0.859513	$\delta_{2\,RSP}$	0.789769	0.154731
$\delta_{3\,CTB1}$	-6.40753	-2.1276	$\delta_{3\,CTB1}$	-7.31809	-2.57992
$\delta_{4\,CDIV}$	17.8213	2.93881	$\delta_{4\,CDIV}$	19.2679	3.05668
$\delta_{5\,TS1}$	0.21616	1.43587	$\delta_{5\,TS1}$	0.233673	1.61267
R-squared		0.219444	R-squared		0.24671
% Correct	Predictions	0.666667	% Correct	Predictions	0.75

Table 6.5- *Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.231619	1.04535	δ_0	0.154891	0.774583
$\delta_{1\,RFT}$	4.35854	0.855318	$\delta_{1\,RFT}$	4.78001	1.51172
$\delta_{2\,RSP}$	-3.32673	-0.652233	$\delta_{2\,RSP}$	-7.49405	-1.70605
$\delta_{3\,CTB1}$	-6.6646	-1.91952	$\delta_{3\,CTB1}$	-3.12234	-1.04926
$\delta_{4\,CDIV}$	30.6042	3.76976	$\delta_{4\,CDIV}$	19.8553	3.29684
$\delta_{5\,TS1}$	0.295705	1.82188	$\delta_{5\,TS1}$	0.03055	0.211707
R-squared		0.327864	R-squared		0.285296
% Correct	Predictions	0.75	% Correct	Predictions	0.716667
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.033411	0.180424	δ_0	0.136524	0.61911
$\delta_{1\,RFT}$	4.06065	1.39669	$\delta_{1\,RFT}$	0.190442	0.072212
$\delta_{2\,RSP}$	-2.64738	-0.769459	$\delta_{2\,RSP}$	-2.82153	-0.800335
$\delta_{3\,CTB1}$	-1.70564	-0.781127	$\delta_{3\,CTB1}$	-2.09302	-0.905633
$\delta_{4\,CDIV}$	11.7953	2.29191	$\delta_{4\,CDIV}$	4.81191	1.32698
$\delta_{5\,TS1}$	0.132479	1.04678	$\delta_{5\,TS1}$	0.091061	0.925961
R-squared		0.15962	R-squared		0.0635
% Correct	Predictions	0.65	% Correct	Predictions	0.583333
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	0.254629	1.11204			
$\delta_{1\,RFT}$	-2.40993	-0.983997			
$\delta_{2\,RSP}$	-2.63378	-0.793358			
$\delta_{3\,CTB1}$	-0.062188	-0.02242			
$\delta_{4\,CDIV}$	1.27299	0.430018			
$\delta_{5\,TS1}$	0.081477	0.920798			
R-squared		0.0538			
% Correct	Predictions	0.566667			

Table 6.6 Probit model/ Price of risk of UK Stock Exchange Turnover -Size portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of unanticipated UK stock exchange turnover is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRTU} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

MARKET	VALUE				
DEPENDENT	VARIABLE λ_{RSRTU}				
SAMPLE	1981-1985		SAMPLE	1982-1986	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.246332	1.00565	δ_0	0.288012	1.23355
$\delta_{1\,RFT}$	-1.65591	-0.498344	$\delta_{1\,RFT}$	-2.87254	-0.783565
$\delta_{2\,RSP}$	-4.09765	-0.749518	$\delta_{2\,RSP}$	-8.7572	-1.60616
$\delta_{3\,CTB1}$	-3.89514	-1.8927	$\delta_{3\,CTB1}$	-4.37585	-2.09661
$\delta_{4\,CDIV}$	7.73774	2.01204	$\delta_{4\,CDIV}$	4.61549	1.16699
$\delta_{5\,TS1}$	0.014842	0.216551	$\delta_{5\,TS1}$	-0.011617	-0.160329
R-squared		0.203727	R-squared		0.207061
% Correct	Predictions	0.694915	% Correct	Predictions	0.7
SAMPLE	1983-1987		SAMPLE	1984-1988	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.090137	0.444032	δ_0	0.167046	0.860187
$\delta_{1\,RFT}$	-2.50373	-0.657646	$\delta_{1\,RFT}$	-3.15436	-0.85747
$\delta_{2\,RSP}$	-4.97652	-1.10628	$\delta_{2\,RSP}$	-0.910909	-0.194396
$\delta_{3\,CTB1}$	-5.71214	-2.06823	$\delta_{3\,CTB1}$	-3.95165	-1.35138
$\delta_{4\,CDIV}$	2.94915	0.704595	$\delta_{4\,CDIV}$	3.56681	0.823258
$\delta_{5\,TS1}$	0.060129	0.684617	$\delta_{5\,TS1}$	-0.011806	-0.08698
R-squared		0.121074	R-squared		0.0652
% Correct	Predictions	0.666667	% Correct	Predictions	0.616667
SAMPLE	1985-1989		SAMPLE	1986-1990	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.148131	0.709626	δ_0	0.117155	0.583291
$\delta_{1\,RFT}$	-2.55499	-0.67962	$\delta_{1\,RFT}$	1.30208	0.356445
$\delta_{2\,RSP}$	-0.938304	-0.202045	$\delta_{2\,RSP}$	0.347928	0.075001
$\delta_{3\,CTB1}$	2.18841	0.850135	$\delta_{3\,CTB1}$	2.34245	1.05633
$\delta_{4\,CDIV}$	3.81024	0.782522	$\delta_{4\,CDIV}$	2.37945	0.478349
$\delta_{5\,TS1}$	-0.121873	-0.901182	$\delta_{5\,TS1}$	-0.101625	-0.760857
R-squared		0.0297	R-squared		0.0308
% Correct	Predictions	0.533333	% Correct	Predictions	0.6

Table 6.6- *Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.136754	-0.652406	δ_0	0.029487	0.152656
$\delta_{1\,RFT}$	10.7026	2.19231	$\delta_{1\,RFT}$	6.5427	1.69571
$\delta_{2\,RSP}$	4.02161	0.848656	$\delta_{2\,RSP}$	-3.05811	-0.916315
$\delta_{3\,CTB1}$	5.88774	1.70635	$\delta_{3\,CTB1}$	5.3191	1.72751
$\delta_{4\,CDIV}$	7.25403	1.19685	$\delta_{4\,CDIV}$	6.22231	1.41342
$\delta_{5\,TS1}$	-0.097334	-0.708406	$\delta_{5\,TS1}$	-0.217304	-1.56499
R-squared		0.191228	R-squared		0.189942
% Correct	Predictions	0.716667	% Correct	Predictions	0.716667
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.031242	-0.171044	δ_0	0.156828	0.717223
$\delta_{1\,RFT}$	4.02702	1.24596	$\delta_{1\,RFT}$	2.83401	0.963246
$\delta_{2\,RSP}$	-2.62273	-0.795209	$\delta_{2\,RSP}$	-0.176422	-0.054948
$\delta_{3\,CTB1}$	0.684557	0.343032	$\delta_{3\,CTB1}$	-2.57274	-1.15355
$\delta_{4\,CDIV}$	7.03364	1.64498	$\delta_{4\,CDIV}$	4.29711	1.34322
$\delta_{5\,TS1}$	-0.057669	-0.482057	$\delta_{5\,TS1}$	0.051903	0.531768
R-squared		0.0905	R-squared		0.0653
% Correct	Predictions	0.65	% Correct	Predictions	0.633333
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	0.060493	0.253784			
$\delta_{1\,RFT}$	3.05058	1.05368			
$\delta_{2\,RSP}$	-0.34615	-0.111955			
$\delta_{3\,CTB1}$	-6.02266	-1.81574			
$\delta_{4\,CDIV}$	4.08489	1.31536			
$\delta_{5\,TS1}$	0.015896	0.176458			
R-squared		0.0941			
% Correct	Predictions	0.633333			

Table 6.7: Probit model/ Price of risk of Money Supply-Size portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the unanticipated change in money supply is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRMO} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

MARKET	VALUE				
DEPENDENT	VARIABLE	λ_{RSRMO}			
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.27502	-1.14029	δ_0	-0.307235	-1.36839
$\delta_{1\ RFT}$	1.9661	0.612606	$\delta_{1\ RFT}$	-3.20351	-0.961869
$\delta_{2\ RSP}$	8.30889	1.48748	$\delta_{2\ RSP}$	10.2241	1.86412
$\delta_{3\ CTB1}$	3.27799	1.65918	$\delta_{3\ CTB1}$	2.30225	1.27179
$\delta_{4\ CDIV}$	4.43174	1.21749	$\delta_{4\ CDIV}$	5.93342	1.52797
$\delta_{5\ TS1}$	9.17E-04	0.013589	$\delta_{5\ TS1}$	0.036484	0.520459
R-squared		0.177542	R-squared		0.154806
% Correct	Predictions	0.711864	% Correct	Predictions	0.633333
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.143745	-0.733719	δ_0	-0.130706	-0.700632
$\delta_{1\ RFT}$	-3.41309	-0.952993	$\delta_{1\ RFT}$	-0.131742	-0.038464
$\delta_{2\ RSP}$	5.51007	1.23246	$\delta_{2\ RSP}$	-1.10604	-0.23686
$\delta_{3\ CTB1}$	1.65621	0.671242	$\delta_{3\ CTB1}$	2.70331	0.988161
$\delta_{4\ CDIV}$	5.2692	1.28932	$\delta_{4\ CDIV}$	4.43396	1.0436
$\delta_{5\ TS1}$	-8.20E-03	-0.099241	$\delta_{5\ TS1}$	-0.034889	-0.262049
R-squared		0.0615	R-squared		0.0345
% Correct	Predictions	0.583333	% Correct	Predictions	0.583333
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.039671	0.192344	δ_0	-0.089893	-0.412193
$\delta_{1\ RFT}$	-4.03313	-1.04339	$\delta_{1\ RFT}$	-7.1609	-1.65126
$\delta_{2\ RSP}$	-1.11279	-0.235039	$\delta_{2\ RSP}$	-0.519226	-0.105157
$\delta_{3\ CTB1}$	1.48389	0.566396	$\delta_{3\ CTB1}$	-0.71776	-0.334089
$\delta_{4\ CDIV}$	5.55381	1.14268	$\delta_{4\ CDIV}$	9.66716	1.88257
$\delta_{5\ TS1}$	-0.025382	-0.190874	$\delta_{5\ TS1}$	0.106249	0.738885
R-squared		0.0408	R-squared		0.119906
% Correct	Predictions	0.5	% Correct	Predictions	0.616667

Table 6.7– ***Continued***

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.060349	-0.304134	δ_0	-0.267581	-1.39043
$\delta_{1\,RFT}$	-5.38237	-1.21728	$\delta_{1\,RFT}$	2.21724	0.704418
$\delta_{2\,RSP}$	0.360974	0.078097	$\delta_{2\,RSP}$	9.10264	1.9243
$\delta_{3\,CTB1}$	-1.57336	-0.675173	$\delta_{3\,CTB1}$	-2.84867	-1.21806
$\delta_{4\,CDIV}$	6.07447	1.05573	$\delta_{4\,CDIV}$	0.838626	0.236216
$\delta_{5\,TS1}$	0.081328	0.610335	$\delta_{5\,TS1}$	0.139614	1.03602
R-squared		0.0667	R-squared		0.0846
% Correct	Predictions	0.683333	% Correct	Predictions	0.583333
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.189971	-0.99305	δ_0	-0.322477	-1.35498
$\delta_{1\,RFT}$	2.43376	0.804503	$\delta_{1\,RFT}$	2.66261	0.848388
$\delta_{2\,RSP}$	13.7567	2.55733	$\delta_{2\,RSP}$	10.8421	2.26964
$\delta_{3\,CTB1}$	-1.04034	-0.506273	$\delta_{3\,CTB1}$	-0.8175	-0.363315
$\delta_{4\,CDIV}$	6.16244	1.32035	$\delta_{4\,CDIV}$	2.92703	0.818766
$\delta_{5\,TS1}$	0.033726	0.266941	$\delta_{5\,TS1}$	-0.040002	-0.402177
R-squared		0.150036	R-squared		0.123144
% Correct	Predictions	0.616667	% Correct	Predictions	0.666667
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	-0.221724	-0.914469			
$\delta_{1\,RFT}$	3.54412	1.20367			
$\delta_{2\,RSP}$	7.55149	1.93532			
$\delta_{3\,CTB1}$	0.65046	0.230704			
$\delta_{4\,CDIV}$	2.72891	0.827025			
$\delta_{5\,TS1}$	-0.038797	-0.428067			
R-squared		0.116594			
% Correct	Predictions	0.65			

Table 6.8: Probit model/ Price of risk of Imports-Size portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the unanticipated change in imports is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSIMP} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

MARKET	VALUE				
DEPENDENT	VARIABLE	λ_{RSIMP}			
SAMPLE	1981-1985		SAMPLE	1982-1986	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-1.34E-03	-5.98E-03	δ_0	0.077254	0.361751
$\delta_{1\,RFT}$	-1.01041	-0.330726	$\delta_{1\,RFT}$	-4.95937	-1.5048
$\delta_{2\,RSP}$	5.46225	1.11222	$\delta_{2\,RSP}$	3.82544	0.830208
$\delta_{3\,CTB1}$	1.35692	0.82127	$\delta_{3\,CTB1}$	1.41251	0.917608
$\delta_{4\,CDIV}$	-1.85658	-0.566131	$\delta_{4\,CDIV}$	-4.14966	-1.13574
$\delta_{5\,TS1}$	-9.66E-04	-0.015374	$\delta_{5\,TS1}$	-0.046799	-0.715295
R-squared		0.0420	R-squared		0.0824
% Correct	Predictions	0.59322	% Correct	Predictions	0.6
SAMPLE	1983-1987		SAMPLE	1984-1988	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.139965	0.695214	δ_0	0.129137	0.638917
$\delta_{1\,RFT}$	-6.19766	-1.63883	$\delta_{1\,RFT}$	-8.78517	-2.15883
$\delta_{2\,RSP}$	3.56893	0.826602	$\delta_{2\,RSP}$	-2.70101	-0.570416
$\delta_{3\,CTB1}$	-0.225396	-0.093278	$\delta_{3\,CTB1}$	-1.4963	-0.545376
$\delta_{4\,CDIV}$	-7.73083	-1.74325	$\delta_{4\,CDIV}$	-4.68898	-1.02524
$\delta_{5\,TS1}$	-0.070759	-0.824883	$\delta_{5\,TS1}$	-0.063245	-0.459153
R-squared		0.110715	R-squared		0.132753
% Correct	Predictions	0.616667	% Correct	Predictions	0.6
SAMPLE	1985-1989		SAMPLE	1986-1990	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.213733	1.00238	δ_0	0.030163	0.146743
$\delta_{1\,RFT}$	-5.54065	-1.39422	$\delta_{1\,RFT}$	-4.40214	-1.10768
$\delta_{2\,RSP}$	-3.56563	-0.75909	$\delta_{2\,RSP}$	-3.87727	-0.829314
$\delta_{3\,CTB1}$	2.57466	0.994698	$\delta_{3\,CTB1}$	0.218115	0.105587
$\delta_{4\,CDIV}$	7.29E-03	1.50E-03	$\delta_{4\,CDIV}$	3.92333	0.791781
$\delta_{5\,TS1}$	-0.1475	-1.09628	$\delta_{5\,TS1}$	-5.39E-04	-4.12E-03
R-squared		0.0536	R-squared		0.0462
% Correct	Predictions	0.55	% Correct	Predictions	0.616667

Table 6.8- ***Continued***

SAMPLE	**1987-1991**		**SAMPLE**	**1988-1992**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.133308	-0.686273	δ_0	-0.252824	-1.45258
$\delta_{1\,RFT}$	0.497725	0.113885	$\delta_{1\,RFT}$	-1.92515	-0.688627
$\delta_{2\,RSP}$	-0.563608	-0.126536	$\delta_{2\,RSP}$	0.691483	0.203656
$\delta_{3\,CTB1}$	0.445798	0.195154	$\delta_{3\,CTB1}$	2.85915	1.26236
$\delta_{4\,CDIV}$	5.13927	0.911121	$\delta_{4\,CDIV}$	-1.969	-0.53148
$\delta_{5\,TS1}$	-0.063928	-0.493563	$\delta_{5\,TS1}$	-0.140332	-1.06695
R-squared		0.0192	R-squared		0.0445
% Correct	Predictions	0.616667	% Correct	Predictions	0.65
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.185293	-1.06749	δ_0	-0.2899	-1.33311
$\delta_{1\,RFT}$	0.83565	0.328433	$\delta_{1\,RFT}$	0.397223	0.152918
$\delta_{2\,RSP}$	0.764211	0.229356	$\delta_{2\,RSP}$	3.18878	0.910699
$\delta_{3\,CTB1}$	1.31831	0.675514	$\delta_{3\,CTB1}$	-0.767691	-0.329848
$\delta_{4\,CDIV}$	-2.37971	-0.685959	$\delta_{4\,CDIV}$	-0.967222	-0.311208
$\delta_{5\,TS1}$	-0.091719	-0.772437	$\delta_{5\,TS1}$	-0.128538	-1.30847
R-squared		0.0272	R-squared		0.0541
% Correct	Predictions	0.583333	% Correct	Predictions	0.616667
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	-0.353791	-1.52305			
$\delta_{1\,RFT}$	2.4933	1.01265			
$\delta_{2\,RSP}$	3.88158	1.11259			
$\delta_{3\,CTB1}$	0.11457	0.040873			
$\delta_{4\,CDIV}$	0.379933	0.131573			
$\delta_{5\,TS1}$	-0.099871	-1.12144			
R-squared		0.0729			
% Correct	Predictions	0.666667			

Table 6.9: Probit model/ Price of risk of Inflation-Size portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the unanticipated change in inflation is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSINF} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

MARKET	VALUE				
DEPENDENT	**VARIABLE** λ_{RSINF}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.09806	0.413628	δ_0	0.051186	0.224083
$\delta_{1\,RFT}$	4.3345	1.31597	$\delta_{1\,RFT}$	0.627939	0.187929
$\delta_{2\,RSP}$	-6.61672	-1.25991	$\delta_{2\,RSP}$	-6.57039	-1.29649
$\delta_{3\,CTB1}$	4.86444	2.30576	$\delta_{3\,CTB1}$	3.54502	1.8685
$\delta_{4\,CDIV}$	-5.25736	-1.46708	$\delta_{4\,CDIV}$	-10.3124	-2.56658
$\delta_{5\,TS1}$	-6.35E-04	-9.73E-03	$\delta_{5\,TS1}$	-0.017375	-0.252705
R-squared		0.132067	R-squared		0.19585
% Correct	Predictions	0.661017	% Correct	Predictions	0.7
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.023846	0.115852	δ_0	0.138291	0.675913
$\delta_{1\,RFT}$	0.186021	0.050531	$\delta_{1\,RFT}$	-2.20223	-0.583035
$\delta_{2\,RSP}$	-8.70857	-1.8917	$\delta_{2\,RSP}$	-9.41928	-1.89388
$\delta_{3\,CTB1}$	1.99131	0.775457	$\delta_{3\,CTB1}$	0.316749	0.108271
$\delta_{4\,CDIV}$	-9.34162	-2.02242	$\delta_{4\,CDIV}$	-9.87426	-1.99337
$\delta_{5\,TS1}$	0.012847	0.151155	$\delta_{5\,TS1}$	0.017919	0.122909
R-squared		0.170622	R-squared		0.179144
% Correct	Predictions	0.666667	% Correct	Predictions	0.666667
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.12324	0.529605	δ_0	0.134781	0.633787
$\delta_{1\,RFT}$	-7.31715	-1.60876	$\delta_{1\,RFT}$	-9.2244	-1.9467
$\delta_{2\,RSP}$	-11.1557	-2.15812	$\delta_{2\,RSP}$	-8.25605	-1.6231
$\delta_{3\,CTB1}$	-0.768949	-0.263125	$\delta_{3\,CTB1}$	0.183469	0.083632
$\delta_{4\,CDIV}$	-4.29054	-0.812761	$\delta_{4\,CDIV}$	-1.98573	-0.376514
$\delta_{5\,TS1}$	5.48E-03	0.03767	$\delta_{5\,TS1}$	0.034717	0.255824
R-squared		0.202136	R-squared		0.124684
% Correct	Predictions	0.683333	% Correct	Predictions	0.683333

Table 6.9–*Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.217177	1.06469	δ_0	0.224612	1.00169
$\delta_{1\ RFT}$	-6.8046	-1.48396	$\delta_{1\ RFT}$	-9.0868	-1.9324
$\delta_{2\ RSP}$	-8.13242	-1.65254	$\delta_{2\ RSP}$	-12.3131	-2.20675
$\delta_{3\ CTB1}$	-0.556663	-0.244309	$\delta_{3\ CTB1}$	1.3019	0.54571
$\delta_{4\ CDIV}$	10.4201	1.76008	$\delta_{4\ CDIV}$	2.79365	0.826502
$\delta_{5\ TS1}$	0.073505	0.518868	$\delta_{5\ TS1}$	0.097768	0.675319
R-squared		0.143315	R-squared		0.190407
% Correct	Predictions	0.7	% Correct	Predictions	0.666667
SAMPLE	1989-1993		SAMPLE	1990-1994	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.117695	-0.601733	δ_0	-0.267072	-1.16312
$\delta_{1\ RFT}$	-5.03803	-1.46258	$\delta_{1\ RFT}$	-0.782881	-0.281998
$\delta_{2\ RSP}$	-10.0527	-2.09349	$\delta_{2\ RSP}$	-5.57006	-1.54902
$\delta_{3\ CTB1}$	2.67295	1.31989	$\delta_{3\ CTB1}$	3.84556	1.64145
$\delta_{4\ CDIV}$	4.26279	1.30068	$\delta_{4\ CDIV}$	6.088	2.02194
$\delta_{5\ TS1}$	-0.125684	-0.999801	$\delta_{5\ TS1}$	-0.084196	-0.829578
R-squared		0.145635	R-squared		0.123899
% Correct	Predictions	0.65	% Correct	Predictions	0.633333
SAMPLE	1991-1995				
Parameter	Estimate	t-statistic			
δ_0	-0.470363	-1.84757			
$\delta_{1\ RFT}$	-0.650816	-0.248709			
$\delta_{2\ RSP}$	-4.95143	-1.53728			
$\delta_{3\ CTB1}$	3.84593	1.33732			
$\delta_{4\ CDIV}$	7.54035	2.51003			
$\delta_{5\ TS1}$	-0.084386	-0.899901			
R-squared		0.143138			
% Correct	Predictions	0.65			

FIGURE 6.1: The sign of price of risk for FTSE (Market value portofolios)

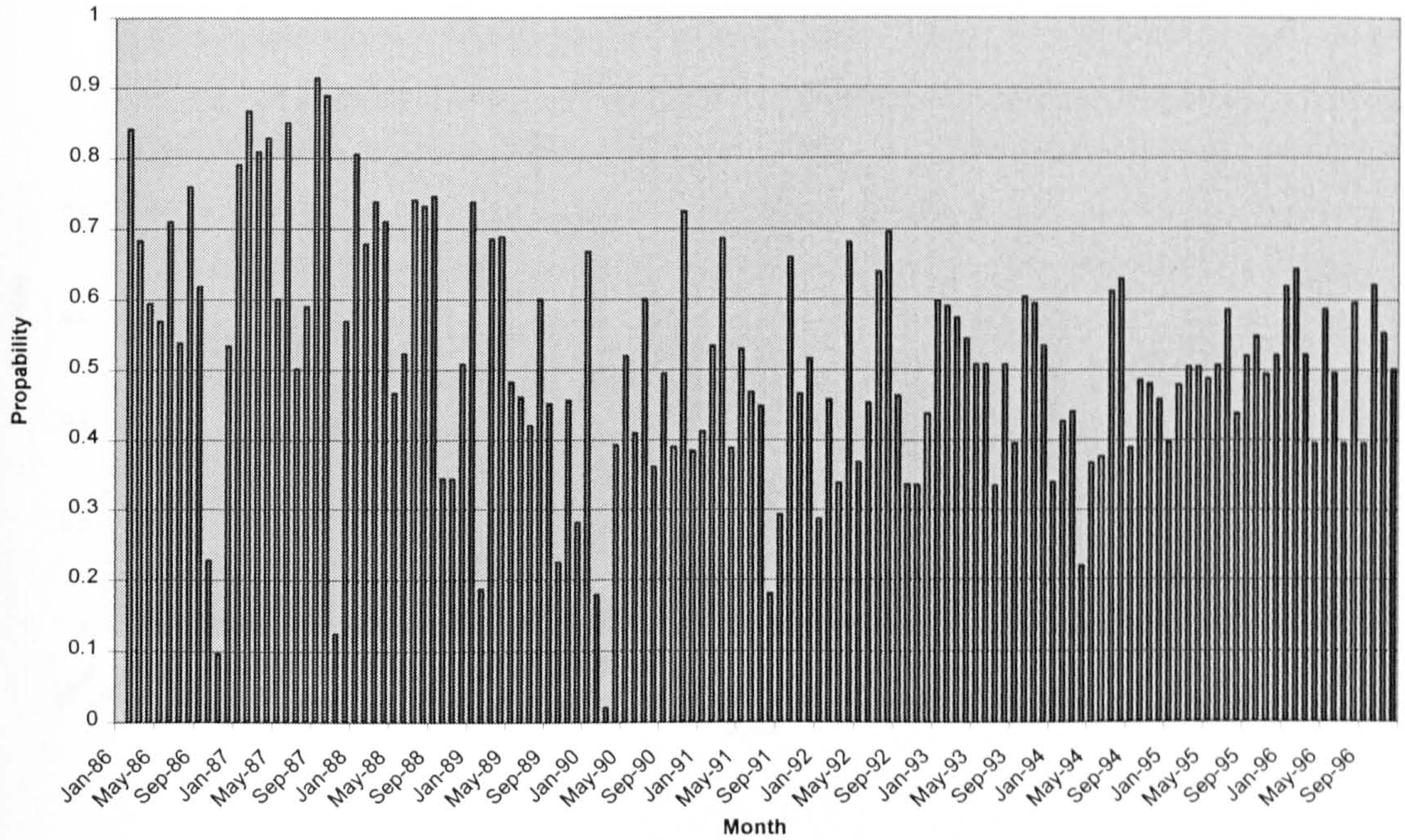


FIGURE 6.2: The sign for the price of risk for SP500 (Market value portfolios)

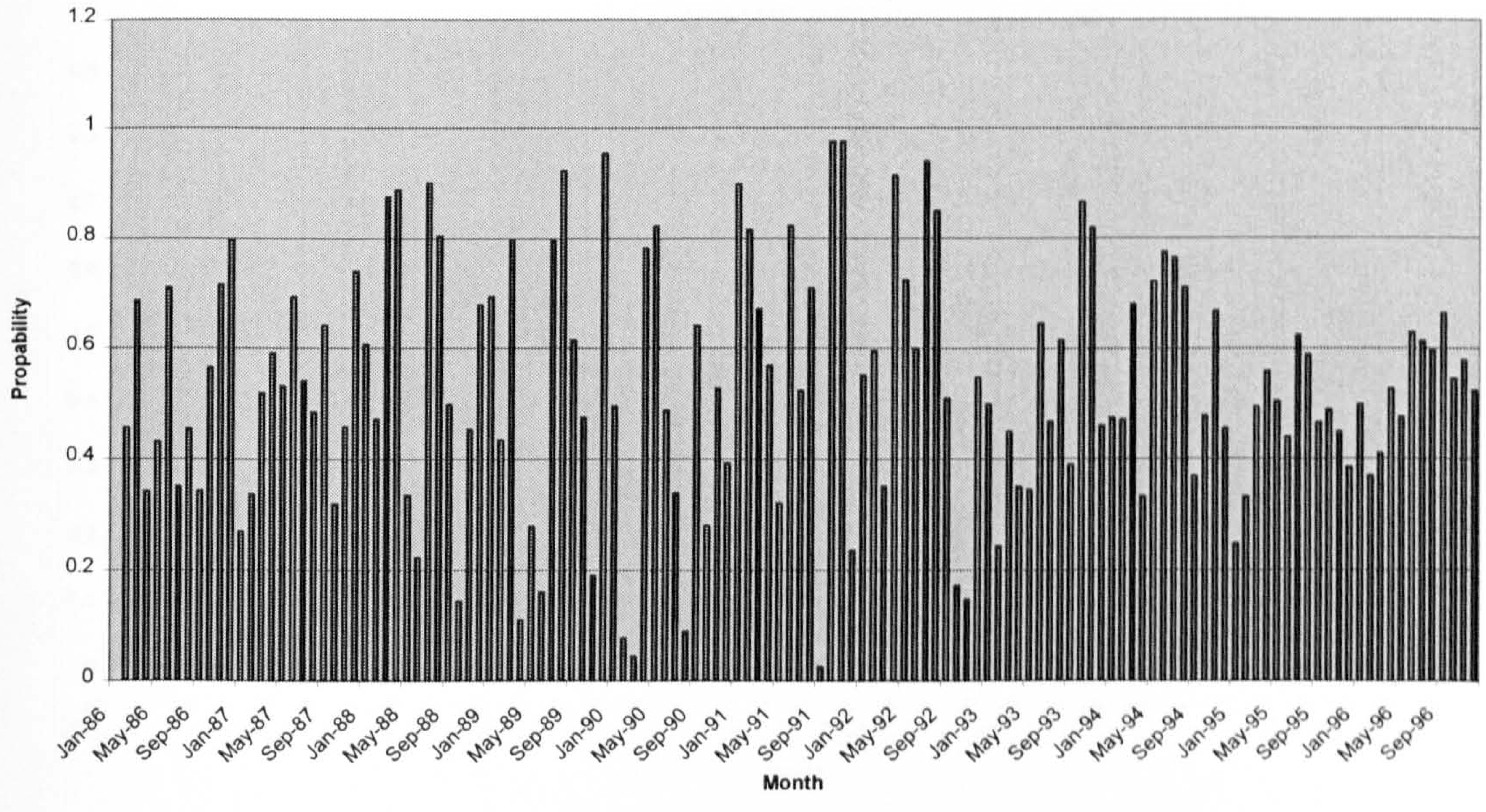


FIGURE 6.3: The sign for the price of risk for the Stock exchange Turnover (Market value portfolios)

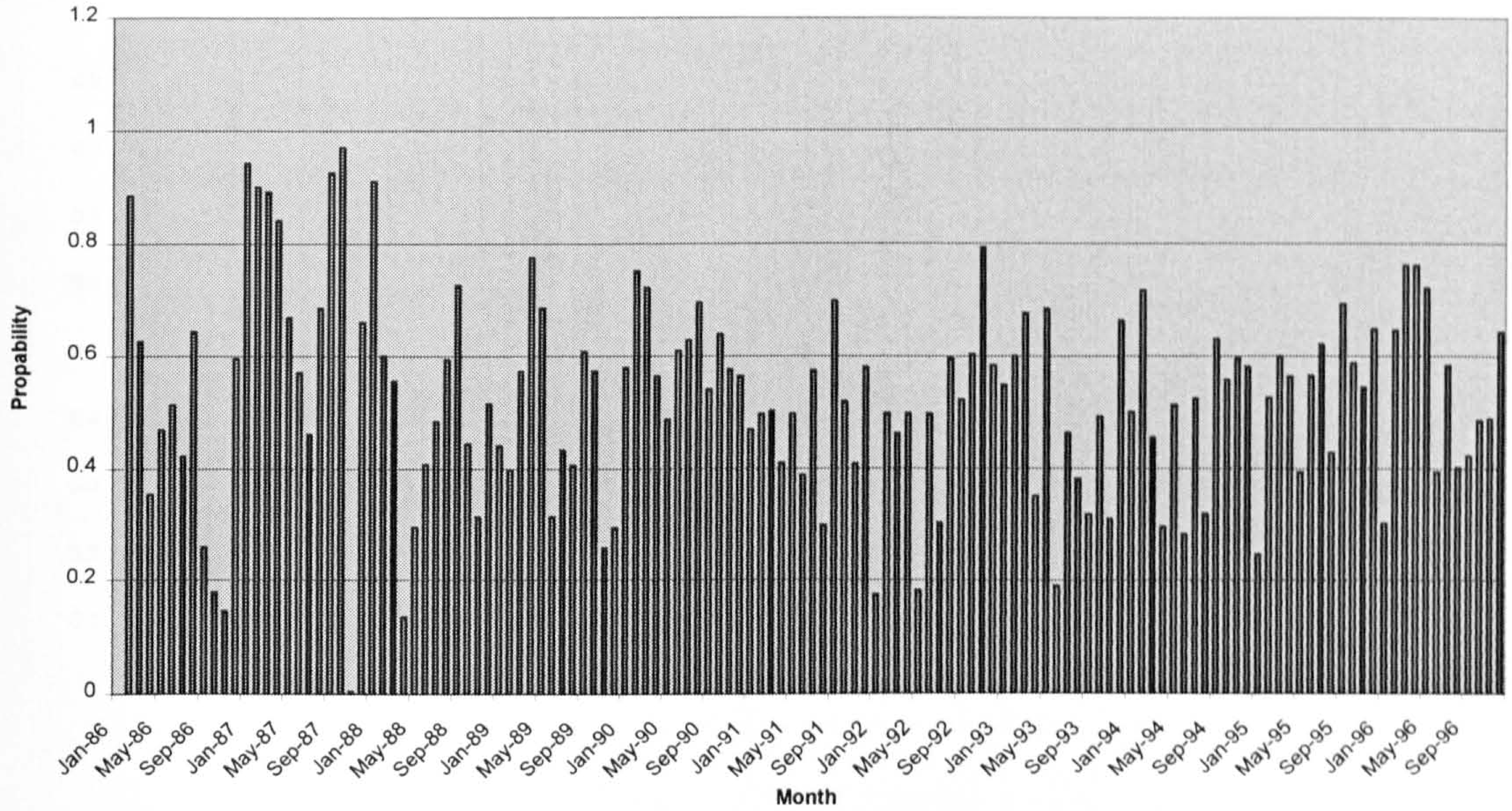


FIGURE 6.4: The sign for the price of risk for Money supply (Market value portfolios)

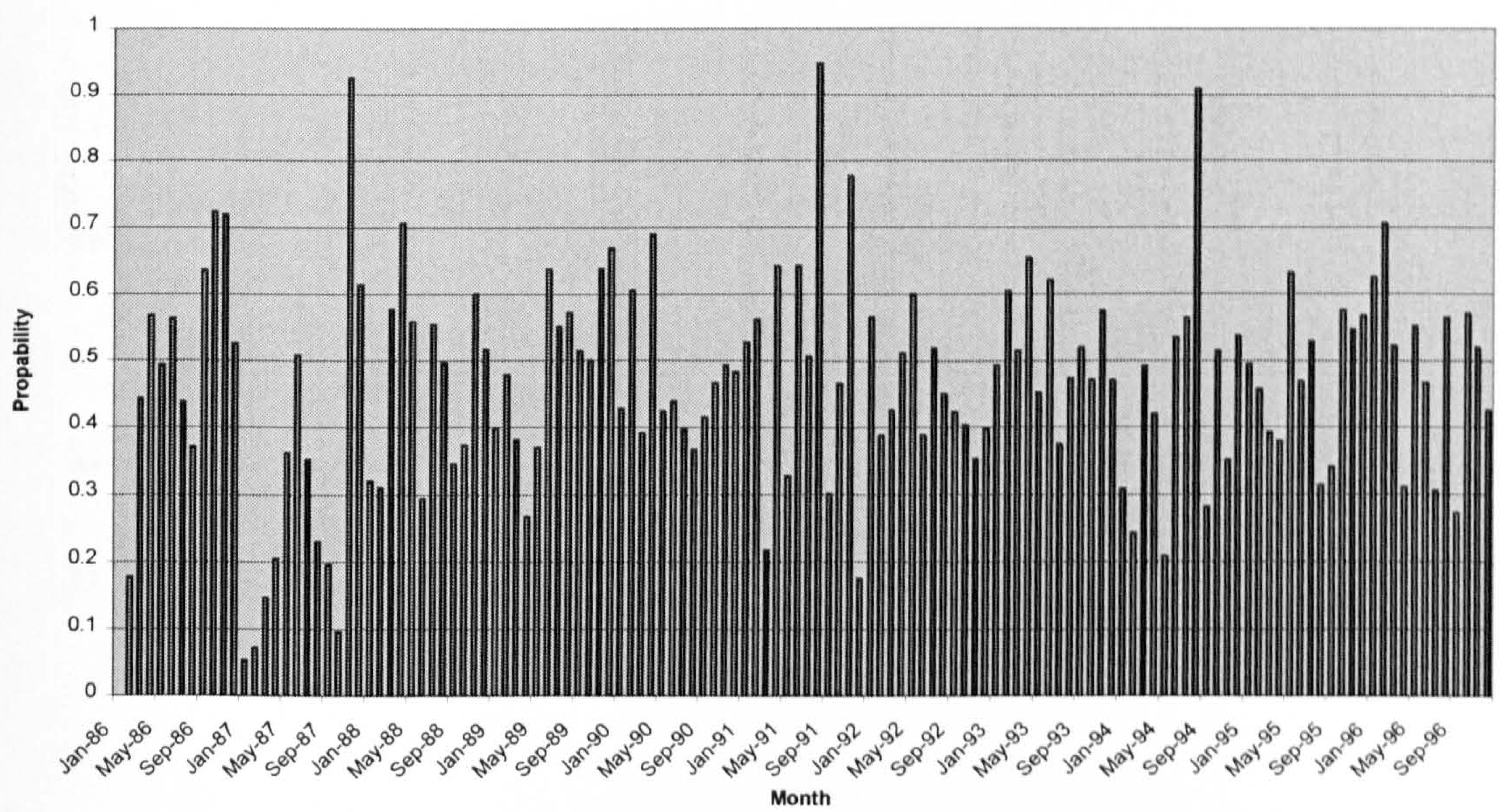


FIGURE 6.5: The sign for the price of risk for Imports (Market value portfolios)

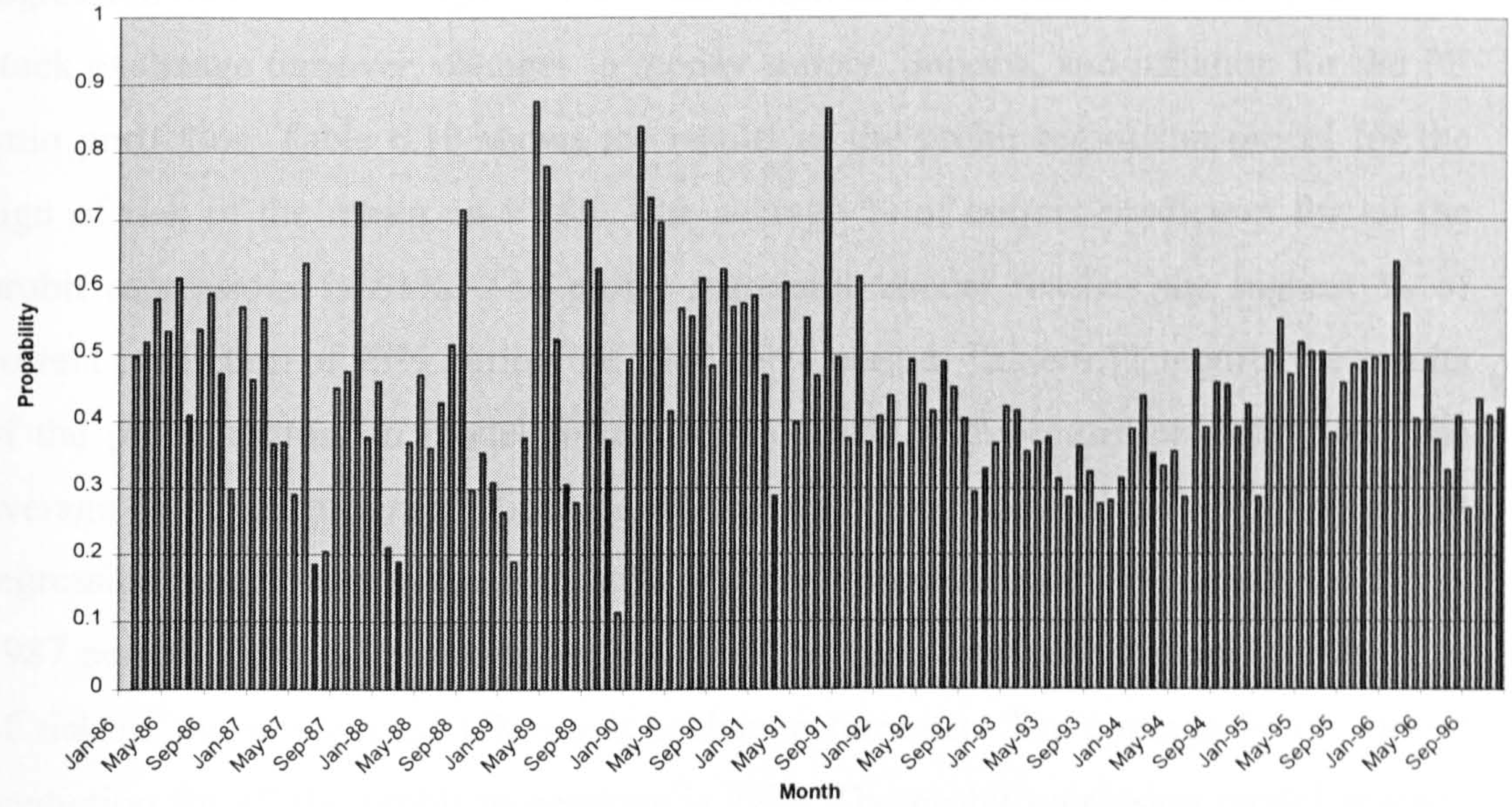


FIGURE 6.6: The sign for the price of risk for Inflation (Market value portfolios)

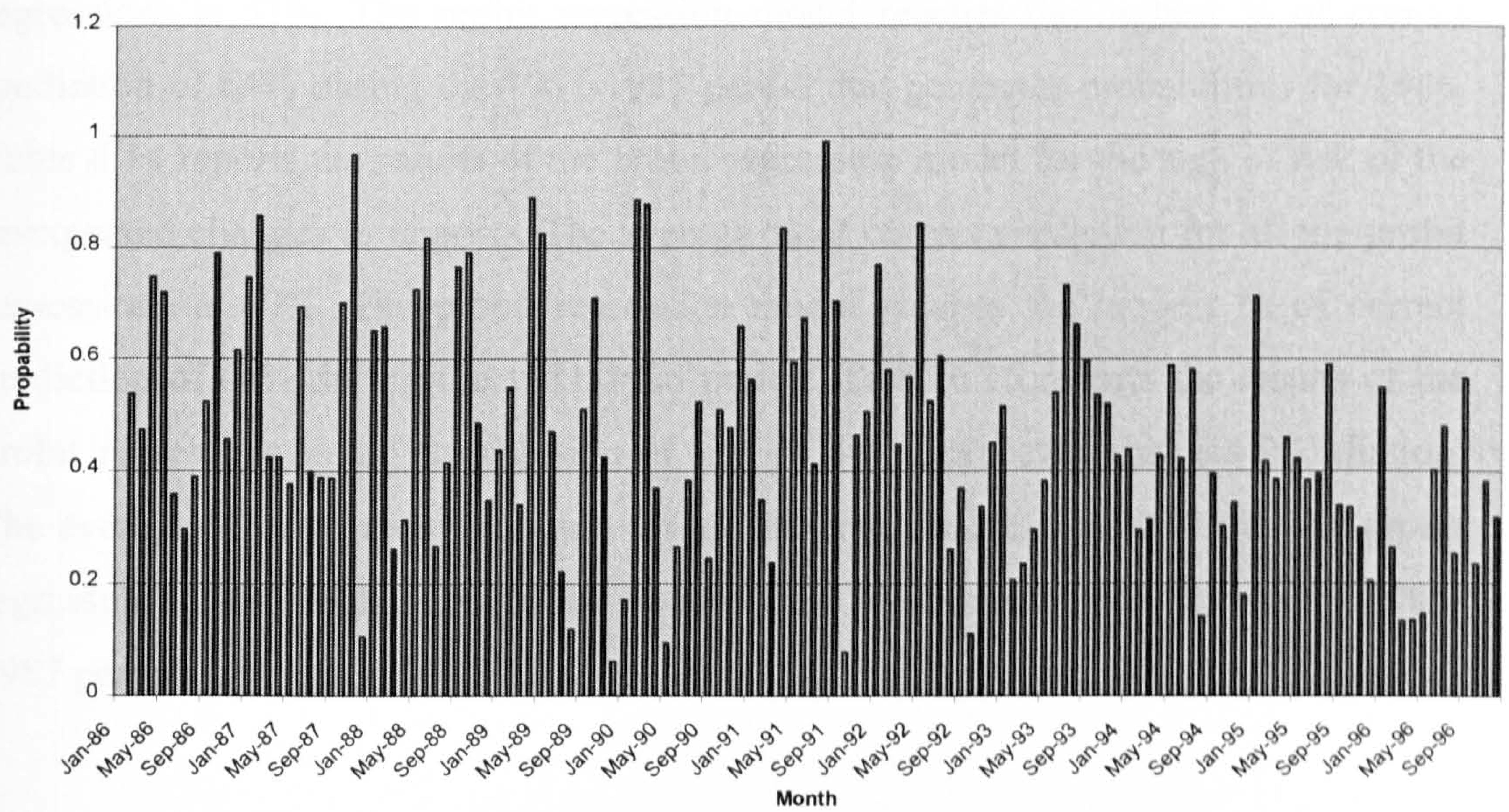


Table 6.10, 6.11, 6.12, 6.13, 6.14 and 6.15 reports results of the probit regression model for the sign of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, changes in money supply, imports, and inflation for the PE ratio portfolios. Table 6.10 shows the results of the probit regression model for the sign of risk of the return on FTSE. The average % of correct prediction for all the probit regressions is 61%. The probit regression model reaches the highest % of correct prediction of 73% during the 1990-1994 period. Table 6.11 reports the results of the probit regression model for the sign of risk of the return on S&P 500. The average % of correct prediction for all the probit regressions is 64%. The probit regression model reaches the highest % of correct prediction of 73% during the 1983-1987 period. Table 6.12 reports the results of the probit regression model for the sign of risk of the unexpected UK stock exchange turnover. The average % of correct prediction for all the probit regressions is 72%. The probit regression model reaches the highest % of correct prediction of 80% during the 1989-1993 period. Table 6.13 shows the results of the probit regression model for the sign of risk of the unexpected changes in money supply. The average % of correct prediction for all the probit regressions is 53%. The probit regression model reaches the highest % of correct prediction of 64% during the 1981-1985 period that generates probabilities for 1986. Table 6.14 reports the results of the probit regression model for the sign of risk of the unexpected changes in imports. The average % of correct prediction for all the probit regressions is 60%. The probit regression model reaches the highest % of correct prediction of 66% during the 1981-1985 period. Table 6.15 reports the results of the probit regression model for the sign of risk of the unexpected changes in inflation. The average % of correct prediction for all the probit regressions is 62%. The probit regression model reaches the highest % of correct prediction of 70% during the 1983-1987 period.

Table 6.10: Probit model/ Price of risk of FTSE-PE portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the return on FTSE is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

PE RATIO					
DEPENDENT	VARIABLE λ_{RSRFT}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.29135	-1.25409	δ_0	-0.287043	-1.33876
$\delta_{1\,RFT}$	3.85375	1.22217	$\delta_{1\,RFT}$	3.1197	0.977986
$\delta_{2\,RSP}$	6.49692	1.23885	$\delta_{2\,RSP}$	6.54349	1.34743
$\delta_{3\,CTB1}$	-1.56412	-1.0362	$\delta_{3\,CTB1}$	-0.633809	-0.423099
$\delta_{4\,CDIV}$	4.43844	1.28998	$\delta_{4\,CDIV}$	0.762266	0.208456
$\delta_{5\,TS1}$	0.043576	0.67762	$\delta_{5\,TS1}$	0.046695	0.712044
R-squared		0.0785	R-squared		0.0425
% Correct	Predictions	0.694915	% Correct	Predictions	0.6
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.244713	-1.26289	δ_0	-0.239601	-1.27108
$\delta_{1\,RFT}$	0.057647	0.016681	$\delta_{1\,RFT}$	0.232215	0.067935
$\delta_{2\,RSP}$	0.746639	0.175129	$\delta_{2\,RSP}$	2.78078	0.602216
$\delta_{3\,CTB1}$	-2.00459	-0.800849	$\delta_{3\,CTB1}$	-1.06381	-0.386487
$\delta_{4\,CDIV}$	0.292798	0.073101	$\delta_{4\,CDIV}$	0.709197	0.171131
$\delta_{5\,TS1}$	0.041223	0.502002	$\delta_{5\,TS1}$	0.096731	0.725718
R-squared		0.0108	R-squared		0.0132
% Correct	Predictions	0.566667	% Correct	Predictions	0.55
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.15741	-0.760659	δ_0	-0.048806	-0.243928
$\delta_{1\,RFT}$	2.84251	0.78191	$\delta_{1\,RFT}$	4.06121	1.11595
$\delta_{2\,RSP}$	1.20004	0.256231	$\delta_{2\,RSP}$	1.30573	0.283695
$\delta_{3\,CTB1}$	-1.22486	-0.465052	$\delta_{3\,CTB1}$	-1.08308	-0.516346
$\delta_{4\,CDIV}$	0.071848	0.01468	$\delta_{4\,CDIV}$	4.11701	0.813457
$\delta_{5\,TS1}$	0.169118	1.23982	$\delta_{5\,TS1}$	0.121718	0.901949
R-squared		0.0509	R-squared		0.0594
% Correct	Predictions	0.583333	% Correct	Predictions	0.683333

Table 6.10–*Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.143642	0.723309	δ_0	0.111661	0.539875
$\delta_{1\,RFT}$	8.45944	1.82881	$\delta_{1\,RFT}$	8.15216	1.89061
$\delta_{2\,RSP}$	7.62089	1.61925	$\delta_{2\,RSP}$	5.84315	1.24758
$\delta_{3\,CTB1}$	-1.363	-0.585292	$\delta_{3\,CTB1}$	-0.990541	-0.411836
$\delta_{4\,CDIV}$	2.27522	0.388419	$\delta_{4\,CDIV}$	-2.06707	-0.560283
$\delta_{5\,TS1}$	0.03526	0.257354	$\delta_{5\,TS1}$	0.088468	0.638666
R-squared		0.105865	R-squared		0.116056
% Correct	Predictions	0.666667	% Correct	Predictions	0.65
SAMPLE	1989-1993		SAMPLE	1990-1994	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.203776	0.981818	δ_0	-0.050307	-0.200378
$\delta_{1\,RFT}$	8.96747	2.12295	$\delta_{1\,RFT}$	6.92945	1.78099
$\delta_{2\,RSP}$	14.2561	2.68163	$\delta_{2\,RSP}$	11.9433	2.40501
$\delta_{3\,CTB1}$	0.738645	0.351252	$\delta_{3\,CTB1}$	3.11888	1.33585
$\delta_{4\,CDIV}$	-1.24306	-0.310064	$\delta_{4\,CDIV}$	0.024372	6.85E-03
$\delta_{5\,TS1}$	-0.146873	-1.14214	$\delta_{5\,TS1}$	-0.148307	-1.42234
R-squared		0.189489	R-squared		0.187557
% Correct	Predictions	0.683333	% Correct	Predictions	0.733333
SAMPLE	1991-1995				
Parameter	Estimate	t-statistic			
δ_0	-0.075507	-0.304504			
$\delta_{1\,RFT}$	3.33975	1.14226			
$\delta_{2\,RSP}$	9.6324	2.35997			
$\delta_{3\,CTB1}$	2.46319	0.868098			
$\delta_{4\,CDIV}$	-0.117854	-0.036601			
$\delta_{5\,TS1}$	-0.076165	-0.827436			
R-squared		0.149082			
% Correct	Predictions	0.65			

Table 6.11: Probit model/ Price of risk of SP 500-PE portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the return on SP500 is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

PE RATIO					
DEPENDENT	**VARIABLE**	λ_{RSRSP}			
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.176799	-0.772406	δ_0	-0.128622	-0.58925
$\delta_{1\,RFT}$	3.23776	1.02535	$\delta_{1\,RFT}$	5.11136	1.48288
$\delta_{2\,RSP}$	5.75719	1.17492	$\delta_{2\,RSP}$	7.82121	1.66072
$\delta_{3\,CTB1}$	-0.754326	-0.486422	$\delta_{3\,CTB1}$	-0.127993	-0.083321
$\delta_{4\,CDIV}$	-5.81549	-1.67936	$\delta_{4\,CDIV}$	-6.44417	-1.73947
$\delta_{5\,TS1}$	0.047932	0.767799	$\delta_{5\,TS1}$	0.035113	0.550374
R-squared		0.0829	R-squared		0.123241
% Correct	Predictions	0.644068	% Correct	Predictions	0.683333
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.106577	-0.529757	δ_0	-0.093825	-0.480445
$\delta_{1\,RFT}$	9.18678	2.27808	$\delta_{1\,RFT}$	8.98698	2.22916
$\delta_{2\,RSP}$	4.83811	1.14514	$\delta_{2\,RSP}$	3.09917	0.672632
$\delta_{3\,CTB1}$	-0.054776	-0.021808	$\delta_{3\,CTB1}$	4.17073	1.43535
$\delta_{4\,CDIV}$	-6.57732	-1.58905	$\delta_{4\,CDIV}$	-5.23867	-1.20988
$\delta_{5\,TS1}$	4.55E-03	0.054798	$\delta_{5\,TS1}$	-0.071719	-0.524246
R-squared		0.157518	R-squared		0.137539
% Correct	Predictions	0.716667	% Correct	Predictions	0.633333
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.302538	1.23348	δ_0	-0.02366	-0.113775
$\delta_{1\,RFT}$	5.77936	1.28586	$\delta_{1\,RFT}$	6.55553	1.48089
$\delta_{2\,RSP}$	3.69503	0.748616	$\delta_{2\,RSP}$	1.99941	0.421659
$\delta_{3\,CTB1}$	11.87	2.55159	$\delta_{3\,CTB1}$	3.05582	1.37694
$\delta_{4\,CDIV}$	6.73039	1.22005	$\delta_{4\,CDIV}$	5.83265	1.10769
$\delta_{5\,TS1}$	-0.182678	-1.29411	$\delta_{5\,TS1}$	-0.023312	-0.17346
R-squared		0.21338	R-squared		0.0950
% Correct	Predictions	0.633333	% Correct	Predictions	0.616667

Table 6.11 – *Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.015712	0.07913	δ_0	-0.166549	-0.8371
$\delta_{1\,RFT}$	5.86725	1.23775	$\delta_{1\,RFT}$	5.72946	1.48929
$\delta_{2\,RSP}$	5.67149	1.22327	$\delta_{2\,RSP}$	8.12859	1.65452
$\delta_{3\,CTB1}$	1.1113	0.460652	$\delta_{3\,CTB1}$	1.15578	0.480671
$\delta_{4\,CDIV}$	11.0302	1.82761	$\delta_{4\,CDIV}$	4.80799	1.14533
$\delta_{5\,TS1}$	-0.068173	-0.509339	$\delta_{5\,TS1}$	-0.130876	-0.945103
R-squared		0.0985	R-squared		0.13421
% Correct	Predictions	0.6	% Correct	Predictions	0.616667

SAMPLE	1989-1993		SAMPLE	1990-1994	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.141257	-0.697503	δ_0	-0.248811	-0.971669
$\delta_{1\,RFT}$	7.77713	1.84261	$\delta_{1\,RFT}$	8.80286	1.94049
$\delta_{2\,RSP}$	13.882	2.45468	$\delta_{2\,RSP}$	10.9638	2.17659
$\delta_{3\,CTB1}$	0.97299	0.453013	$\delta_{3\,CTB1}$	-0.53841	-0.237792
$\delta_{4\,CDIV}$	10.5134	2.05017	$\delta_{4\,CDIV}$	4.29484	1.06782
$\delta_{5\,TS1}$	-0.124346	-0.935305	$\delta_{5\,TS1}$	-0.024046	-0.230578
R-squared		0.229426	R-squared		0.158804
% Correct	Predictions	0.7	% Correct	Predictions	0.666667

SAMPLE	1991-1995	
Parameter	Estimate	t-statistic
δ_0	-0.151513	-0.628734
$\delta_{1\,RFT}$	6.03163	1.81692
$\delta_{2\,RSP}$	3.36452	0.971049
$\delta_{3\,CTB1}$	0.943273	0.338265
$\delta_{4\,CDIV}$	0.998112	0.32455
$\delta_{5\,TS1}$	-0.03442	-0.383384
R-squared		0.0898
% Correct	Predictions	0.6

Table 6.12: Probit model/ Price of risk of UK Stock Exchange Turnover -PE portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of unanticipated UK stock exchange turnover is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRTU} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

PE RATIO					
DEPENDENT	VARIABLE λ_{RSRTU}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.322124	1.36863	δ_0	0.349904	1.54674
$\delta_{1\,RFT}$	2.35803	0.734432	$\delta_{1\,RFT}$	6.83632	1.95132
$\delta_{2\,RSP}$	6.56671	1.26868	$\delta_{2\,RSP}$	4.9043	0.981725
$\delta_{3\,CTB1}$	-5.63372	-2.5729	$\delta_{3\,CTB1}$	-6.52911	-2.73778
$\delta_{4\,CDIV}$	1.99349	0.574807	$\delta_{4\,CDIV}$	-0.444623	-0.121823
$\delta_{5\,TS1}$	-0.084318	-1.29799	$\delta_{5\,TS1}$	-0.080148	-1.17842
R-squared		0.171745	R-squared		0.219748
% Correct	Predictions	0.677966	% Correct	Predictions	0.7
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.249753	1.19967	δ_0	0.306006	1.51358
$\delta_{1\,RFT}$	10.4227	2.54371	$\delta_{1\,RFT}$	11.0194	2.63836
$\delta_{2\,RSP}$	5.47726	1.19275	$\delta_{2\,RSP}$	4.94135	1.0275
$\delta_{3\,CTB1}$	-6.16883	-2.09382	$\delta_{3\,CTB1}$	-1.88822	-0.619649
$\delta_{4\,CDIV}$	7.36715	1.71364	$\delta_{4\,CDIV}$	6.40553	1.44791
$\delta_{5\,TS1}$	-0.078939	-0.930884	$\delta_{5\,TS1}$	0.064948	0.471446
R-squared		0.250925	R-squared		0.195682
% Correct	Predictions	0.733333	% Correct	Predictions	0.65
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.149513	0.694348	δ_0	0.41061	1.68177
$\delta_{1\,RFT}$	7.38456	1.71703	$\delta_{1\,RFT}$	12.8487	2.40502
$\delta_{2\,RSP}$	5.62833	1.17121	$\delta_{2\,RSP}$	5.47564	1.03944
$\delta_{3\,CTB1}$	-0.99908	-0.368149	$\delta_{3\,CTB1}$	-2.09883	-0.872944
$\delta_{4\,CDIV}$	8.55994	1.64226	$\delta_{4\,CDIV}$	15.6808	2.72145
$\delta_{5\,TS1}$	0.142498	1.04698	$\delta_{5\,TS1}$	0.064971	0.433962
R-squared		0.162391	R-squared		0.269688
% Correct	Predictions	0.65	% Correct	Predictions	0.75

Table 6.12 - *Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.609678	2.31685	δ_0	0.771208	2.46803
$\delta_{1\,RFT}$	15.1614	2.45522	$\delta_{1\,RFT}$	16.9146	2.56429
$\delta_{2\,RSP}$	9.00455	1.57421	$\delta_{2\,RSP}$	12.0535	1.74739
$\delta_{3\,CTB1}$	-1.42217	-0.524467	$\delta_{3\,CTB1}$	-2.60998	-0.85577
$\delta_{4\,CDIV}$	29.0655	3.76795	$\delta_{4\,CDIV}$	23.3397	3.24767
$\delta_{5\,TS1}$	0.070712	0.415803	$\delta_{5\,TS1}$	0.126036	0.724514
R-squared		0.399522	R-squared		0.455447
% Correct	Predictions	0.75	% Correct	Predictions	0.783333
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.289667	1.14392	δ_0	0.189761	0.63306
$\delta_{1\,RFT}$	9.69699	1.85105	$\delta_{1\,RFT}$	10.1419	2.09365
$\delta_{2\,RSP}$	7.72964	1.36877	$\delta_{2\,RSP}$	10.3079	1.79141
$\delta_{3\,CTB1}$	-5.20287	-1.65579	$\delta_{3\,CTB1}$	-4.82433	-1.67586
$\delta_{4\,CDIV}$	32.5103	3.62767	$\delta_{4\,CDIV}$	19.4211	3.15249
$\delta_{5\,TS1}$	0.088036	0.538134	$\delta_{5\,TS1}$	-0.063607	-0.556279
R-squared		0.48982	R-squared		0.381442
% Correct	Predictions	0.8	% Correct	Predictions	0.733333
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	-0.152124	-0.51819			
$\delta_{1\,RFT}$	8.44291	2.07245			
$\delta_{2\,RSP}$	5.79386	1.4755			
$\delta_{3\,CTB1}$	-7.32795	-1.93425			
$\delta_{4\,CDIV}$	15.4522	3.00534			
$\delta_{5\,TS1}$	-0.082062	-0.783804			
R-squared		0.327822			
% Correct	Predictions	0.716667			

Table 6.13: Probit model/ Price of risk of Money Supply-PE portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the unanticipated change in money supply is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRMO} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

PE RATIO					
DEPENDENT	**VARIABLE** λ_{RSRMO}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.100472	-0.431387	δ_0	-0.153434	-0.698859
$\delta_{1\ RFT}$	2.90976	0.900603	$\delta_{1\ RFT}$	7.36512	2.07548
$\delta_{2\ RSP}$	4.13046	0.789305	$\delta_{2\ RSP}$	4.95965	1.01484
$\delta_{3\ CTB1}$	-2.24937	-1.37904	$\delta_{3\ CTB1}$	-3.18313	-1.87657
$\delta_{4\ CDIV}$	4.5917	1.30671	$\delta_{4\ CDIV}$	-0.653969	-0.177859
$\delta_{5\ TS1}$	0.102198	1.53248	$\delta_{5\ TS1}$	0.060427	0.898669
R-squared		0.0976	R-squared		0.144391
% Correct	Predictions	0.644068	% Correct	Predictions	0.616667
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.177208	-0.88021	δ_0	-0.135069	-0.694039
$\delta_{1\ RFT}$	8.63167	2.16134	$\delta_{1\ RFT}$	8.73317	2.22329
$\delta_{2\ RSP}$	4.01608	0.901013	$\delta_{2\ RSP}$	1.66462	0.356573
$\delta_{3\ CTB1}$	-2.79049	-1.12948	$\delta_{3\ CTB1}$	-3.09098	-1.1117
$\delta_{4\ CDIV}$	-3.00524	-0.724662	$\delta_{4\ CDIV}$	-3.30914	-0.775495
$\delta_{5\ TS1}$	0.114712	1.32775	$\delta_{5\ TS1}$	0.076396	0.570082
R-squared		0.127524	R-squared		0.112673
% Correct	Predictions	0.633333	% Correct	Predictions	0.616667
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.195168	-0.868768	δ_0	-0.122068	-0.57969
$\delta_{1\ RFT}$	10.6367	2.28333	$\delta_{1\ RFT}$	8.42299	1.9109
$\delta_{2\ RSP}$	2.75194	0.571968	$\delta_{2\ RSP}$	4.75501	0.989042
$\delta_{3\ CTB1}$	-2.55233	-0.952739	$\delta_{3\ CTB1}$	-0.500775	-0.236022
$\delta_{4\ CDIV}$	2.34922	0.460566	$\delta_{4\ CDIV}$	-1.42734	-0.276571
$\delta_{5\ TS1}$	0.07919	0.57896	$\delta_{5\ TS1}$	0.058707	0.442448
R-squared		0.114945	R-squared		0.0842
% Correct	Predictions	0.633333	% Correct	Predictions	0.633333

Table 6.13- *Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.165579	-0.826721	δ_0	0.102246	0.598615
$\delta_{1\,RFT}$	8.1404	1.78205	$\delta_{1\,RFT}$	0.18766	0.068524
$\delta_{2\,RSP}$	6.50453	1.38577	$\delta_{2\,RSP}$	-1.11383	-0.340707
$\delta_{3\,CTB1}$	1.81735	0.709249	$\delta_{3\,CTB1}$	1.39761	0.570743
$\delta_{4\,CDIV}$	-8.36776	-1.43155	$\delta_{4\,CDIV}$	3.02045	0.871974
$\delta_{5\,TS1}$	0.061157	0.451398	$\delta_{5\,TS1}$	3.05E-03	0.023717
R-squared		0.119282	R-squared		0.0204
% Correct	Predictions	0.633333	% Correct	Predictions	0.483333
SAMPLE	1989-1993		SAMPLE	1990-1994	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.012016	0.069396	δ_0	0.041359	0.189473
$\delta_{1\,RFT}$	-1.31239	-0.478038	$\delta_{1\,RFT}$	-3.98579	-1.26784
$\delta_{2\,RSP}$	-1.01677	-0.309992	$\delta_{2\,RSP}$	-0.280415	-0.083893
$\delta_{3\,CTB1}$	-0.568862	-0.292144	$\delta_{3\,CTB1}$	-1.28337	-0.583927
$\delta_{4\,CDIV}$	2.59961	0.773624	$\delta_{4\,CDIV}$	1.83046	0.587841
$\delta_{5\,TS1}$	0.07512	0.636861	$\delta_{5\,TS1}$	0.082805	0.836568
R-squared		0.0266	R-squared		0.0485
% Correct	Predictions	0.483333	% Correct	Predictions	0.583333
SAMPLE	1991-1995				
Parameter	Estimate	t-statistic			
δ_0	0.059012	0.247544			
$\delta_{1\,RFT}$	-5.5877	-1.71901			
$\delta_{2\,RSP}$	-0.591384	-0.178186			
$\delta_{3\,CTB1}$	-3.62483	-1.24112			
$\delta_{4\,CDIV}$	1.62313	0.530137			
$\delta_{5\,TS1}$	0.100455	1.09657			
R-squared		0.0954			
% Correct	Predictions	0.616667			

Table 6.14: Probit model/ Price of risk of Imports-PE portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the unanticipated change in imports is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSIMP} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

PE RATIO					
DEPENDENT	VARIABLE λ_{RSIMP}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.022939	-0.101336	δ_0	-0.042027	-0.198509
$\delta_{1\,RFT}$	0.750464	0.237905	$\delta_{1\,RFT}$	4.10773	1.26594
$\delta_{2\,RSP}$	-5.76674	-1.17727	$\delta_{2\,RSP}$	-2.02846	-0.445407
$\delta_{3\,CTB1}$	0.232666	0.149343	$\delta_{3\,CTB1}$	-1.05001	-0.680473
$\delta_{4\,CDIV}$	5.51995	1.62154	$\delta_{4\,CDIV}$	2.86699	0.789748
$\delta_{5\,TS1}$	-0.013882	-0.220155	$\delta_{5\,TS1}$	-0.01658	-0.257595
R-squared		0.0641	R-squared		0.0510
% Correct	Predictions	0.661017	% Correct	Predictions	0.633333
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.071016	-0.361315	δ_0	-0.148384	-0.779639
$\delta_{1\,RFT}$	3.19801	0.896655	$\delta_{1\,RFT}$	3.81975	1.0598
$\delta_{2\,RSP}$	2.54754	0.605268	$\delta_{2\,RSP}$	5.447	1.16011
$\delta_{3\,CTB1}$	-1.38385	-0.583011	$\delta_{3\,CTB1}$	-0.080144	-0.029725
$\delta_{4\,CDIV}$	5.86732	1.36987	$\delta_{4\,CDIV}$	1.22997	0.288038
$\delta_{5\,TS1}$	-8.04E-03	-0.097563	$\delta_{5\,TS1}$	0.013365	0.09975
R-squared		0.0852	R-squared		0.0610
% Correct	Predictions	0.666667	% Correct	Predictions	0.633333
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.01358	-0.064414	δ_0	-0.154175	-0.73936
$\delta_{1\,RFT}$	0.710376	0.186493	$\delta_{1\,RFT}$	5.82343	1.43432
$\delta_{2\,RSP}$	8.93107	1.79663	$\delta_{2\,RSP}$	4.82358	0.985806
$\delta_{3\,CTB1}$	1.48205	0.560256	$\delta_{3\,CTB1}$	-1.92561	-0.908965
$\delta_{4\,CDIV}$	-0.847212	-0.169612	$\delta_{4\,CDIV}$	-1.67061	-0.332321
$\delta_{5\,TS1}$	-0.028336	-0.211464	$\delta_{5\,TS1}$	0.041055	0.308868
R-squared		0.0684	R-squared		0.0604
% Correct	Predictions	0.566667	% Correct	Predictions	0.55

Table 6.14– *Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.096356	-0.494256	δ_0	-0.014647	-0.080977
$\delta_{1\,RFT}$	0.75724	0.174532	$\delta_{1\,RFT}$	0.188099	0.065233
$\delta_{2\,RSP}$	-0.107878	-0.023907	$\delta_{2\,RSP}$	-7.07405	-1.72113
$\delta_{3\,CTB1}$	-2.44797	-1.02528	$\delta_{3\,CTB1}$	-0.403897	-0.172357
$\delta_{4\,CDIV}$	3.23717	0.566419	$\delta_{4\,CDIV}$	-2.33199	-0.652816
$\delta_{5\,TS1}$	0.140769	1.06199	$\delta_{5\,TS1}$	0.126389	0.940641
R-squared		0.0284	R-squared		0.0860
% Correct	Predictions	0.55	% Correct	Predictions	0.583333
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	9.22E-04	5.12E-03	δ_0	0.148515	0.635423
$\delta_{1\,RFT}$	-0.189794	-0.068141	$\delta_{1\,RFT}$	-1.16179	-0.41176
$\delta_{2\,RSP}$	-6.36668	-1.59142	$\delta_{2\,RSP}$	-10.2571	-2.16072
$\delta_{3\,CTB1}$	-1.86154	-0.91578	$\delta_{3\,CTB1}$	-1.97877	-0.821873
$\delta_{4\,CDIV}$	-2.05908	-0.601399	$\delta_{4\,CDIV}$	-2.42683	-0.70522
$\delta_{5\,TS1}$	0.220808	1.75943	$\delta_{5\,TS1}$	0.152482	1.47479
R-squared		0.110839	R-squared		0.151325
% Correct	Predictions	0.616667	% Correct	Predictions	0.616667
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	0.102342	0.445574			
$\delta_{1\,RFT}$	-1.44969	-0.580091			
$\delta_{2\,RSP}$	-2.90049	-0.895159			
$\delta_{3\,CTB1}$	0.067358	0.025044			
$\delta_{4\,CDIV}$	-1.31254	-0.437217			
$\delta_{5\,TS1}$	0.112039	1.25984			
R-squared		0.0539			
% Correct	Predictions	0.633333			

Table 6.15 Probit model/ Price of risk of Inflation-PE portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the unanticipated change in inflation is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSINF} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

PE RATIO

DEPENDENT VARIABLE λ_{RSINF}

SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-9.33E-03	-0.03967	δ_0	-0.161747	-0.745585
$\delta_{1\,RFT}$	7.84947	2.21962	$\delta_{1\,RFT}$	6.22994	1.80499
$\delta_{2\,RSP}$	1.25618	0.248928	$\delta_{2\,RSP}$	1.33388	0.285732
$\delta_{3\,CTB1}$	-2.87523	-1.66156	$\delta_{3\,CTB1}$	-2.91412	-1.76848
$\delta_{4\,CDIV}$	6.36013	1.64322	$\delta_{4\,CDIV}$	4.56095	1.21976
$\delta_{5\,TS1}$	0.040917	0.629702	$\delta_{5\,TS1}$	0.058815	0.885284
R-squared		0.187003	R-squared		0.144762
% Correct	Predictions	0.694915	% Correct	Predictions	0.683333

SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.217705	-1.10163	δ_0	-0.21582	-1.12072
$\delta_{1\,RFT}$	5.85136	1.60035	$\delta_{1\,RFT}$	7.24073	1.93509
$\delta_{2\,RSP}$	0.078978	0.018711	$\delta_{2\,RSP}$	0.711514	0.155843
$\delta_{3\,CTB1}$	-3.30747	-1.32376	$\delta_{3\,CTB1}$	-1.02968	-0.370797
$\delta_{4\,CDIV}$	4.7988	1.13209	$\delta_{4\,CDIV}$	0.052093	0.012308
$\delta_{5\,TS1}$	0.121776	1.40348	$\delta_{5\,TS1}$	0.033662	0.255854
R-squared		0.118678	R-squared		0.0737
% Correct	Predictions	0.733333	% Correct	Predictions	0.616667

SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.198458	-0.94671	δ_0	-0.134608	-0.610412
$\delta_{1\,RFT}$	3.08695	0.773386	$\delta_{1\,RFT}$	7.58349	1.59872
$\delta_{2\,RSP}$	2.42888	0.517265	$\delta_{2\,RSP}$	-3.91958	-0.782254
$\delta_{3\,CTB1}$	3.48767	1.25222	$\delta_{3\,CTB1}$	4.2696	1.72163
$\delta_{4\,CDIV}$	-7.73221	-1.57186	$\delta_{4\,CDIV}$	-8.39225	-1.62598
$\delta_{5\,TS1}$	-0.044398	-0.34109	$\delta_{5\,TS1}$	-0.142255	-1.03047
R-squared		0.0882	R-squared		0.164793
% Correct	Predictions	0.633333	% Correct	Predictions	0.683333

Table 6.15- *Continued*

SAMPLE 1987-1991			SAMPLE 1988-1992		
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.106258	-0.53449	δ_0	-3.19E-04	-1.79E-03
$\delta_{1\,RFT}$	1.80303	0.399862	$\delta_{1\,RFT}$	1.36876	0.465737
$\delta_{2\,RSP}$	-3.28586	-0.6907	$\delta_{2\,RSP}$	-4.03999	-1.17212
$\delta_{3\,CTB1}$	5.24337	1.85723	$\delta_{3\,CTB1}$	4.60498	1.65926
$\delta_{4\,CDIV}$	-7.85115	-1.32911	$\delta_{4\,CDIV}$	-4.96484	-1.19471
$\delta_{5\,TS1}$	-0.138158	-1.03043	$\delta_{5\,TS1}$	-0.124864	-0.935437
R-squared		0.0969	R-squared		0.0909
% Correct	Predictions	0.6	% Correct	Predictions	0.583333
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.029439	-0.16686	δ_0	0.122925	0.56799
$\delta_{1\,RFT}$	-1.28658	-0.49033	$\delta_{1\,RFT}$	-1.0643	-0.407914
$\delta_{2\,RSP}$	-3.15878	-0.92953	$\delta_{2\,RSP}$	-3.14609	-0.926527
$\delta_{3\,CTB1}$	4.09553	1.81373	$\delta_{3\,CTB1}$	2.51698	1.04381
$\delta_{4\,CDIV}$	-4.71988	-1.16797	$\delta_{4\,CDIV}$	-3.48349	-1.02135
$\delta_{5\,TS1}$	-0.105102	-0.86199	$\delta_{5\,TS1}$	6.15E-03	0.062356
R-squared		0.0832	R-squared		0.0504
% Correct	Predictions	0.583333	% Correct	Predictions	0.583333
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	0.091686	0.402095			
$\delta_{1\,RFT}$	-1.47399	-0.59451			
$\delta_{2\,RSP}$	-1.51412	-0.49368			
$\delta_{3\,CTB1}$	2.10639	0.733778			
$\delta_{4\,CDIV}$	-2.32093	-0.75224			
$\delta_{5\,TS1}$	0.064964	0.731967			
R-squared		0.0418			
% Correct	Predictions	0.566667			

FIGURE 6.7: The sign of the price of risk for FTSE (PE portfolios)

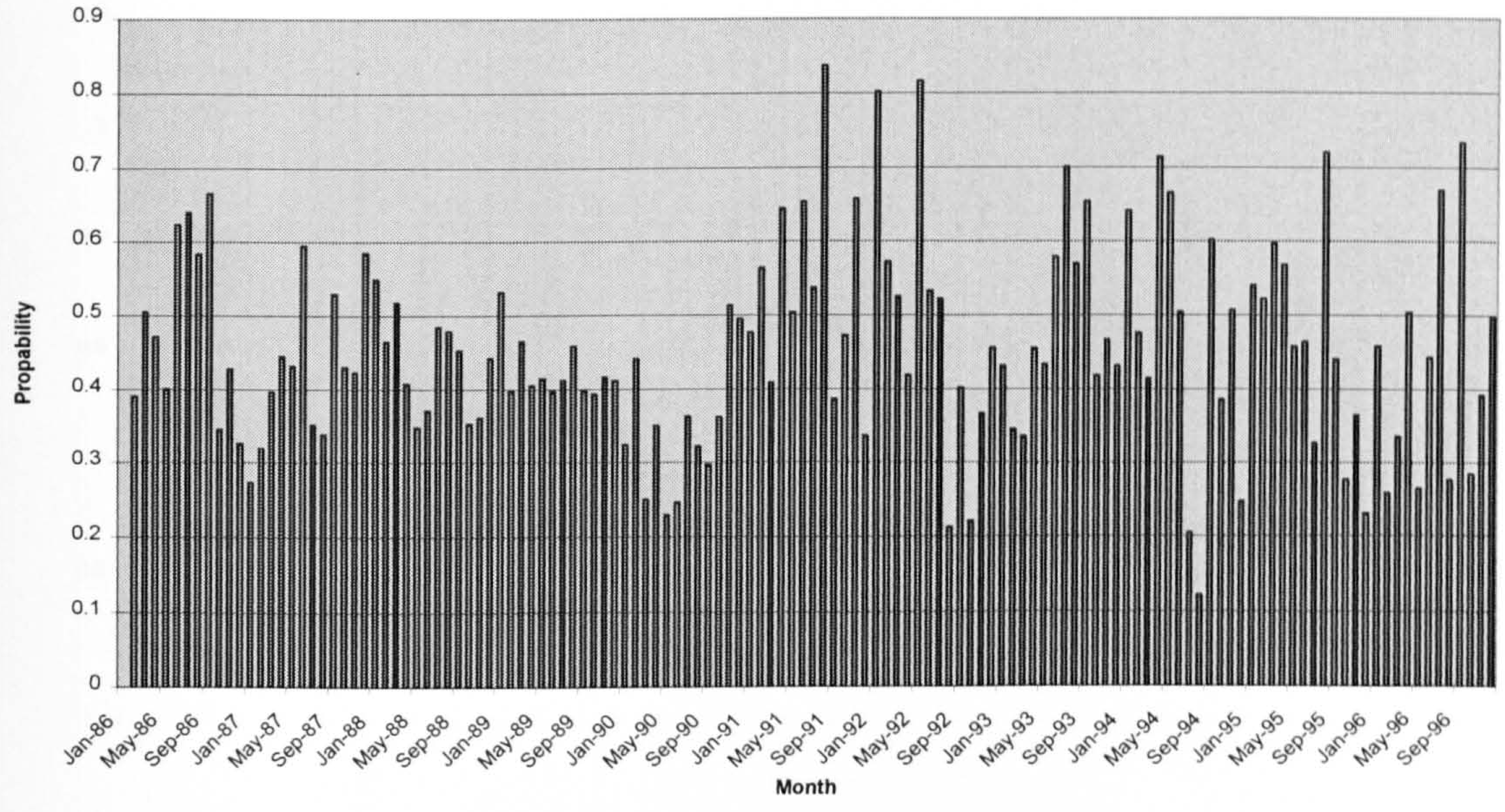


FIGURE 6.8: The sign for the price of risk for SP500 (PE portfolios)

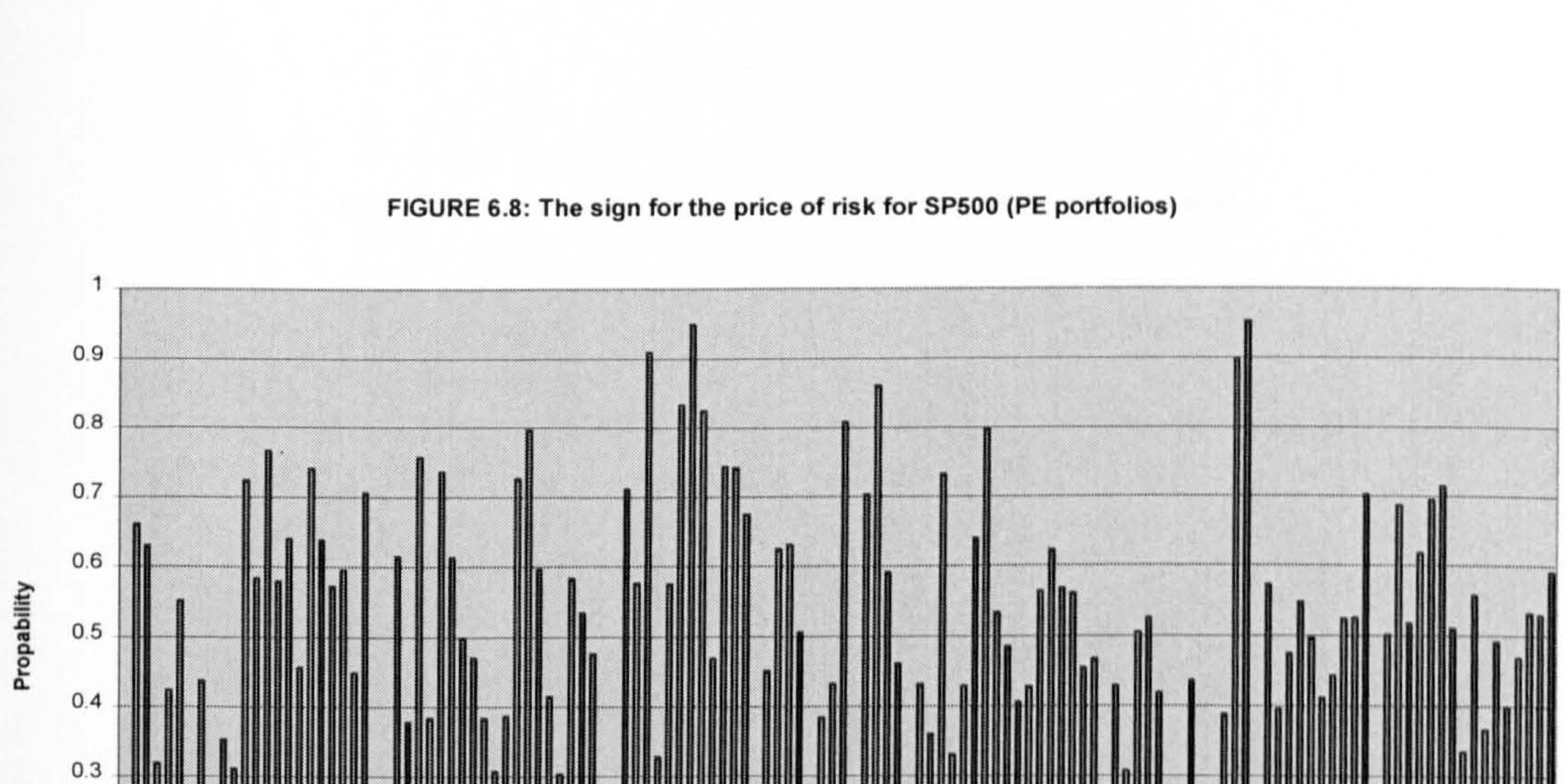


FIGURE 6.9: The sign for the price of risk for the Stock exchange Turnover (PE portfolios)

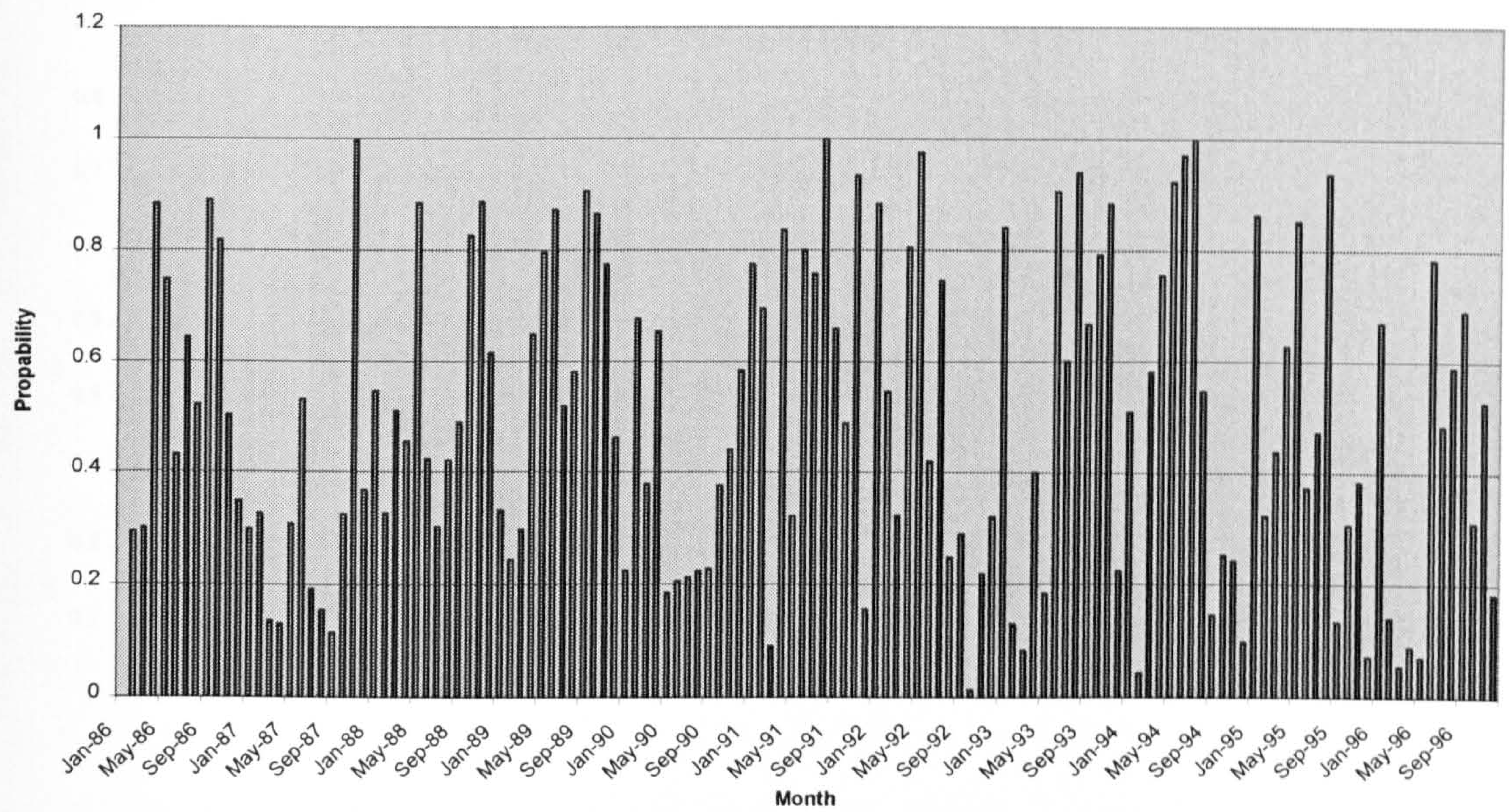


FIGURE 6.10: The sign for the price of risk for Money supply (PE portfolios)

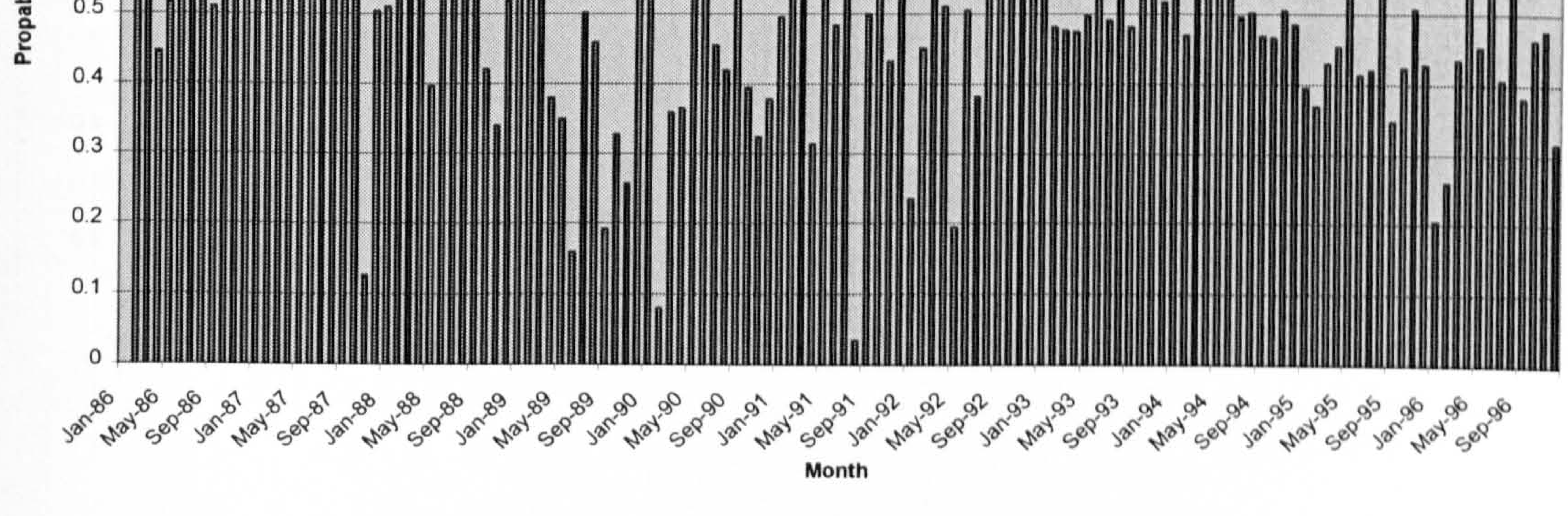


FIGURE 6.11: The sign for the price of risk for Imports (PE portfolios)

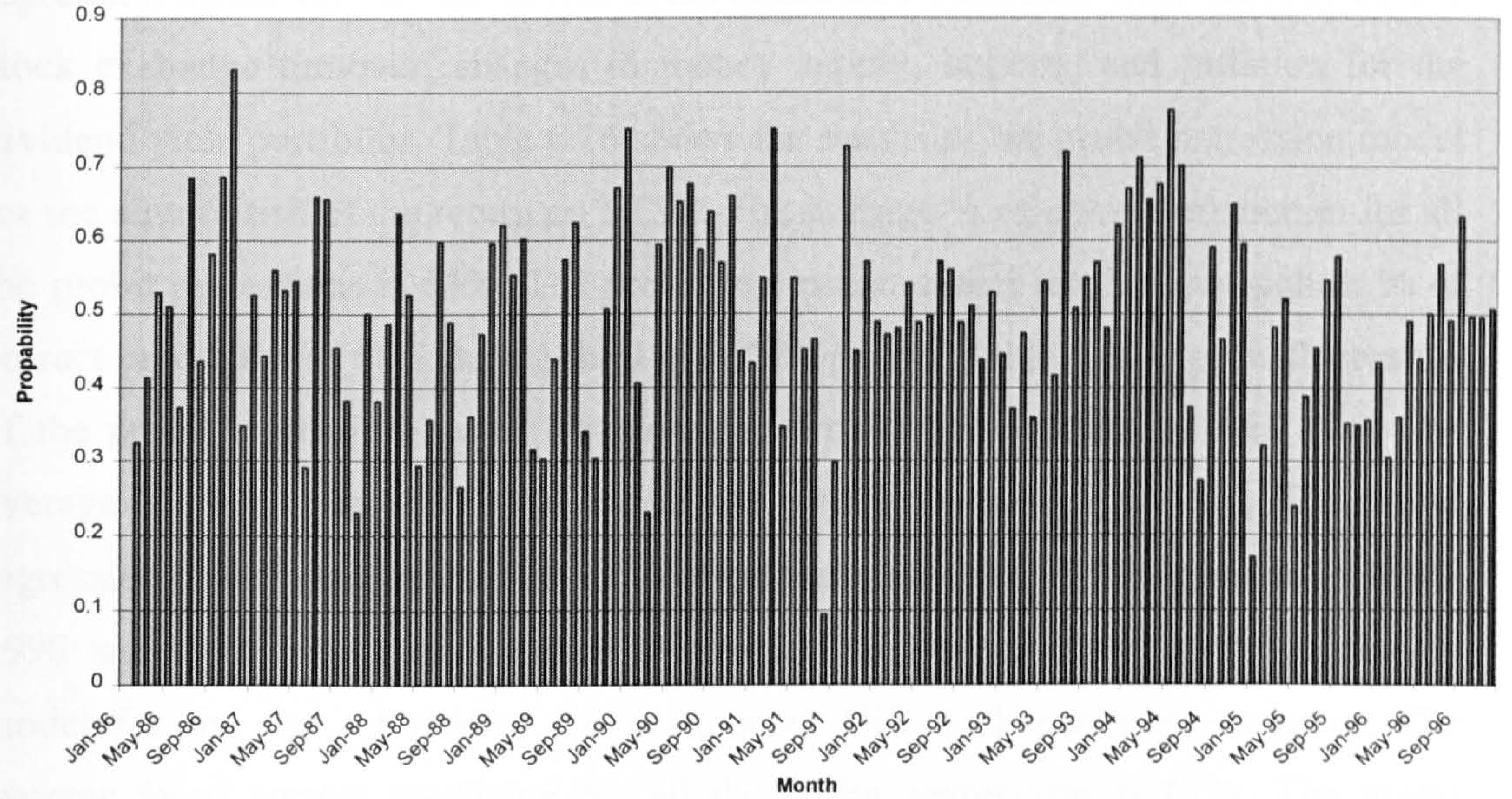


FIGURE 6.12: The sign for the price of risk for Inflation (PE portfolios)

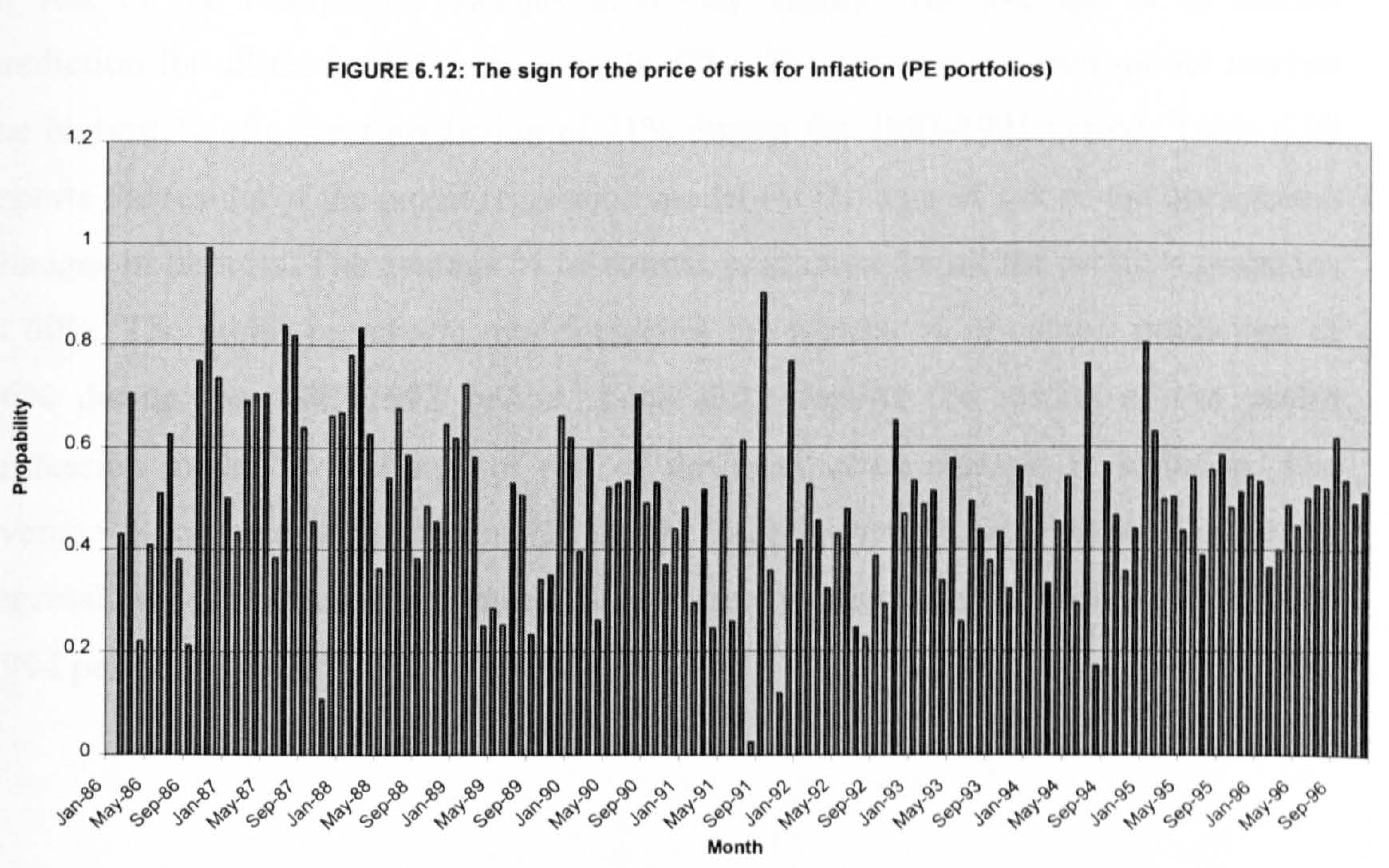


Table 6.16, 6.17, 6.18, 6.19, 6.20 and 6.21 reports results of the probit regression model for the sign of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, changes in money supply, imports, and inflation for the dividend yield portfolios. Table 6.16 shows the results of the probit regression model for the sign of risk of the return on FTSE. The average % of correct prediction for all the probit regressions is 63%. The probit regression model reaches the highest % of correct prediction of 68% during the 1984-1988 period. Table 6.17 reports the results of the probit regression model for the sign of risk of the return on S&P 500. The average % of correct prediction for all the probit regressions is 63%. The probit regression model reaches the highest % of correct prediction of 70% during the 1986-1990 and 1991-1995 period. Table 6.18 reports the results of the probit regression model for the sign of risk of the unexpected UK stock exchange turnover. The average % of correct prediction for all the probit regressions is 61%. The probit regression model reaches the highest % of correct prediction of 68% during the 1990-1994 period. Table 6.19 shows the results of the probit regression model for the sign of risk of the unexpected changes in money supply. The average % of correct prediction for all the probit regressions is 62%. The probit regression model reaches the highest % of correct prediction of 71% during the 1987-1991 period. Table 6.20 reports the results of the probit regression model for the sign of risk of the unexpected changes in imports. The average % of correct prediction for all the probit regressions is 60%. The probit regression model reaches the highest % of correct prediction of 66% during the 1982-1992 period. Table 6.21 reports the results of the probit regression model for the sign of risk of the unexpected changes in inflation. The average % of correct prediction for all the probit regressions is 61%. The probit regression model reaches the highest % of correct prediction of 68% during the 1990-1994 period.

Table 6.16 Probit model/ Price of risk of FTSE -Dividend yield portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the return on FTSE is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

DIVIDEND	YIELD				
DEPENDENT	VARIABLE λ_{RSRFT}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.312088	1.32543	δ_0	0.169612	0.806646
$\delta_{1\,RFT}$	-0.873472	-0.272478	$\delta_{1\,RFT}$	2.25359	0.701073
$\delta_{2\,RSP}$	-2.7883	-0.543135	$\delta_{2\,RSP}$	-0.913015	-0.196945
$\delta_{3\,CTB1}$	0.16238	0.104093	$\delta_{3\,CTB1}$	0.108646	0.073904
$\delta_{4\,CDIV}$	-5.71707	-1.60066	$\delta_{4\,CDIV}$	-0.840719	-0.235826
$\delta_{5\,TS1}$	-0.013443	-0.206961	$\delta_{5\,TS1}$	-0.035663	-0.554092
R-squared		0.0585	R-squared		0.0140
% Correct	Predictions	0.576271	% Correct	Predictions	0.55
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.05636	0.293284	δ_0	0.141332	0.7562
$\delta_{1\,RFT}$	1.27362	0.369406	$\delta_{1\,RFT}$	1.57547	0.450125
$\delta_{2\,RSP}$	0.404524	0.095703	$\delta_{2\,RSP}$	1.28239	0.282888
$\delta_{3\,CTB1}$	-2.56893	-1.03448	$\delta_{3\,CTB1}$	0.88438	0.326709
$\delta_{4\,CDIV}$	4.71386	1.17741	$\delta_{4\,CDIV}$	2.31428	0.560991
$\delta_{5\,TS1}$	-5.34E-03	-0.064849	$\delta_{5\,TS1}$	-0.098182	-0.738772
R-squared		0.0591	R-squared		0.0369
% Correct	Predictions	0.633333	% Correct	Predictions	0.683333
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.190948	0.880036	δ_0	0.046277	0.213871
$\delta_{1\,RFT}$	3.40604	0.832627	$\delta_{1\,RFT}$	8.57075	1.74564
$\delta_{2\,RSP}$	-0.024243	-5.23E-03	$\delta_{2\,RSP}$	1.24422	0.26241
$\delta_{3\,CTB1}$	4.10179	1.3915	$\delta_{3\,CTB1}$	2.19267	0.989778
$\delta_{4\,CDIV}$	7.32413	1.39167	$\delta_{4\,CDIV}$	8.41358	1.54369
$\delta_{5\,TS1}$	-0.203955	-1.49034	$\delta_{5\,TS1}$	-0.181793	-1.30006
R-squared		0.11299	R-squared		0.144265
% Correct	Predictions	0.65	% Correct	Predictions	0.633333

Table 6.16– *Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.014492	0.072317	δ_0	0.134969	0.781345
$\delta_{1\,RFT}$	8.11889	1.76344	$\delta_{1\,RFT}$	1.90324	0.732124
$\delta_{2\,RSP}$	-0.773645	-0.16963	$\delta_{2\,RSP}$	-0.392916	-0.118089
$\delta_{3\,CTB1}$	2.04172	0.863616	$\delta_{3\,CTB1}$	3.4043	1.44881
$\delta_{4\,CDIV}$	0.469941	0.081437	$\delta_{4\,CDIV}$	-4.59308	-1.2059
$\delta_{5\,TS1}$	-0.054821	-0.416424	$\delta_{5\,TS1}$	-0.10963	-0.826756
R-squared		0.0757	R-squared		0.0928
% Correct	Predictions	0.616667	% Correct	Predictions	0.683333
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.013367	-0.076083	δ_0	-0.025251	-0.116476
$\delta_{1\,RFT}$	1.88724	0.741108	$\delta_{1\,RFT}$	2.97908	1.17501
$\delta_{2\,RSP}$	2.3508	0.675382	$\delta_{2\,RSP}$	2.89598	0.82437
$\delta_{3\,CTB1}$	1.38336	0.703637	$\delta_{3\,CTB1}$	-1.51416	-0.638626
$\delta_{4\,CDIV}$	-4.70563	-1.2572	$\delta_{4\,CDIV}$	-4.71521	-1.4
$\delta_{5\,TS1}$	-0.140613	-1.14993	$\delta_{5\,TS1}$	-0.085173	-0.859448
R-squared		0.0858	R-squared		0.112109
% Correct	Predictions	0.616667	% Correct	Predictions	0.65
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	-0.054204	-0.233698			
$\delta_{1\,RFT}$	4.6409	1.90608			
$\delta_{2\,RSP}$	2.71287	0.797427			
$\delta_{3\,CTB1}$	0.123113	0.043783			
$\delta_{4\,CDIV}$	-4.37178	-1.37063			
$\delta_{5\,TS1}$	-0.06922	-0.772362			
R-squared		0.153179			
% Correct	Predictions	0.7			

Table 6.17: Probit model/ Price of risk of SP 500

-Dividend yield portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the return on SP500 is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRSP} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

DIVIDEND YIELD

DEPENDENT VARIABLE λ_{RSRSP}

SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.081636	0.358487	δ_0	9.41E-03	0.044916
$\delta_{1\,RFT}$	1.42621	0.449472	$\delta_{1\,RFT}$	2.08039	0.64921
$\delta_{2\,RSP}$	-5.6456	-1.15415	$\delta_{2\,RSP}$	-1.23979	-0.272908
$\delta_{3\,CTB1}$	0.854873	0.564601	$\delta_{3\,CTB1}$	0.0497	0.033547
$\delta_{4\,CDIV}$	4.21199	1.24054	$\delta_{4\,CDIV}$	0.672067	0.189738
$\delta_{5\,TS1}$	3.19E-03	0.050993	$\delta_{5\,TS1}$	-0.011508	-0.180941
R-squared		0.0532	R-squared		0.00947
% Correct	Predictions	0.576271	% Correct	Predictions	0.483333

SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.025986	0.134048	δ_0	0.094254	0.470572
$\delta_{1\,RFT}$	2.57248	0.730191	$\delta_{1\,RFT}$	5.85507	1.51086
$\delta_{2\,RSP}$	-3.25636	-0.771313	$\delta_{2\,RSP}$	-8.76692	-1.76422
$\delta_{3\,CTB1}$	1.21286	0.512133	$\delta_{3\,CTB1}$	-2.36646	-0.813283
$\delta_{4\,CDIV}$	-0.659552	-0.164936	$\delta_{4\,CDIV}$	-1.2379	-0.287211
$\delta_{5\,TS1}$	-0.062661	-0.773921	$\delta_{5\,TS1}$	-0.177347	-1.24688
R-squared		0.0344	R-squared		0.135318
% Correct	Predictions	0.55	% Correct	Predictions	0.633333

SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.159588	-0.686564	δ_0	-0.255178	-1.09018
$\delta_{1\,RFT}$	3.17566	0.794104	$\delta_{1\,RFT}$	5.63542	1.22405
$\delta_{2\,RSP}$	-7.61984	-1.54269	$\delta_{2\,RSP}$	-6.17126	-1.20771
$\delta_{3\,CTB1}$	-8.84529	-1.95047	$\delta_{3\,CTB1}$	-10.7788	-2.34501
$\delta_{4\,CDIV}$	-1.0632	-0.206311	$\delta_{4\,CDIV}$	0.86187	0.15742
$\delta_{5\,TS1}$	-0.096195	-0.701247	$\delta_{5\,TS1}$	0.036133	0.258154
R-squared		0.144492	R-squared		0.178879
% Correct	Predictions	0.616667	% Correct	Predictions	0.7

Table 6.17- ***Continued***

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.25417	-1.12747	δ_0	-0.354944	-1.70808
$\delta_{1\ RFT}$	8.37706	1.7349	$\delta_{1\ RFT}$	6.80373	1.95228
$\delta_{2\ RSP}$	-9.06535	-1.7246	$\delta_{2\ RSP}$	4.2806	1.2095
$\delta_{3\ CTB1}$	-14.9761	-2.79834	$\delta_{3\ CTB1}$	-11.528	-2.40044
$\delta_{4\ CDIV}$	12.5718	1.82585	$\delta_{4\ CDIV}$	-2.75664	-0.772571
$\delta_{5\ TS1}$	3.75E-03	0.026155	$\delta_{5\ TS1}$	0.105215	0.756265
R-squared		0.291033	R-squared		0.194342
% Correct	Predictions	0.783333	% Correct	Predictions	0.666667
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.214791	-1.19402	δ_0	-0.357892	-1.56728
$\delta_{1\ RFT}$	4.68975	1.54293	$\delta_{1\ RFT}$	5.71459	1.76286
$\delta_{2\ RSP}$	3.14006	0.930887	$\delta_{2\ RSP}$	3.85756	1.09478
$\delta_{3\ CTB1}$	-2.30263	-1.04202	$\delta_{3\ CTB1}$	-0.45797	-0.200873
$\delta_{4\ CDIV}$	-0.397053	-0.120117	$\delta_{4\ CDIV}$	-0.302741	-0.093468
$\delta_{5\ TS1}$	-0.122127	-1.01515	$\delta_{5\ TS1}$	-0.186173	-1.82114
R-squared		0.103112	R-squared		0.121975
% Correct	Predictions	0.666667	% Correct	Predictions	0.65
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	-0.4097	-1.55965			
$\delta_{1\ RFT}$	7.64415	2.29401			
$\delta_{2\ RSP}$	6.26402	1.72286			
$\delta_{3\ CTB1}$	1.89596	0.65241			
$\delta_{4\ CDIV}$	-4.63647	-1.1654			
$\delta_{5\ TS1}$	-0.151301	-1.55061			
R-squared		0.191637			
% Correct	Predictions	0.7			

Table 6.18: Probit model/ Price of risk of UK Stock Exchange Turnover -Dividend yield portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of unanticipated UK stock exchange turnover is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRTU} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

DIVIDEND	YIELD				
DEPENDENT	VARIABLE λ_{RSRTU}				
SAMPLE	1981-1985		SAMPLE	1982-1986	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.196468	-0.849514	δ_0	-0.179884	-0.82449
$\delta_{1\ RFT}$	2.71699	0.832234	$\delta_{1\ RFT}$	1.67652	0.520238
$\delta_{2\ RSP}$	0.16427	0.031977	$\delta_{2\ RSP}$	3.46588	0.694756
$\delta_{3\ CTB1}$	-5.24663	-2.41088	$\delta_{3\ CTB1}$	-6.33708	-2.76172
$\delta_{4\ CDIV}$	1.92884	0.550464	$\delta_{4\ CDIV}$	2.76353	0.761835
$\delta_{5\ TS1}$	0.015226	0.235222	$\delta_{5\ TS1}$	0.029139	0.432478
R-squared		0.139736	R-squared		0.161393
% Correct	Predictions	0.610169	% Correct	Predictions	0.65
SAMPLE	1983-1987		SAMPLE	1984-1988	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.112591	-0.572353	δ_0	-0.051535	-0.274307
$\delta_{1\ RFT}$	0.662994	0.186444	$\delta_{1\ RFT}$	1.25463	0.364591
$\delta_{2\ RSP}$	-1.91638	-0.442595	$\delta_{2\ RSP}$	-0.63881	-0.141045
$\delta_{3\ CTB1}$	-5.06738	-1.83946	$\delta_{3\ CTB1}$	-3.41783	-1.19732
$\delta_{4\ CDIV}$	6.50002	1.57608	$\delta_{4\ CDIV}$	4.1261	0.991603
$\delta_{5\ TS1}$	0.057565	0.665157	$\delta_{5\ TS1}$	0.091125	0.694697
R-squared		0.0992	R-squared		0.0394
% Correct	Predictions	0.666667	% Correct	Predictions	0.6
SAMPLE	1985-1989		SAMPLE	1986-1990	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.147485	0.714349	δ_0	6.54E-03	0.032401
$\delta_{1\ RFT}$	-2.59193	-0.684151	$\delta_{1\ RFT}$	1.56466	0.416755
$\delta_{2\ RSP}$	-1.85578	-0.40138	$\delta_{2\ RSP}$	-3.7408	-0.802802
$\delta_{3\ CTB1}$	0.958985	0.366687	$\delta_{3\ CTB1}$	-1.26811	-0.585468
$\delta_{4\ CDIV}$	6.00486	1.2221	$\delta_{4\ CDIV}$	4.98362	0.994303
$\delta_{5\ TS1}$	-0.015577	-0.119045	$\delta_{5\ TS1}$	0.033033	0.249427
R-squared		0.0347	R-squared		0.0322
% Correct	Predictions	0.55	% Correct	Predictions	0.583333

Table 6.18- *Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.042971	-0.215083	δ_0	-0.014759	-0.084313
$\delta_{1\,RFT}$	3.89153	0.862449	$\delta_{1\,RFT}$	1.08291	0.414232
$\delta_{2\,RSP}$	-5.52796	-1.21101	$\delta_{2\,RSP}$	2.49602	0.709401
$\delta_{3\,CTB1}$	-1.37518	-0.571264	$\delta_{3\,CTB1}$	-1.98061	-0.861903
$\delta_{4\,CDIV}$	-4.81463	-0.84095	$\delta_{4\,CDIV}$	-8.67819	-1.95066
$\delta_{5\,TS1}$	1.68E-03	0.012812	$\delta_{5\,TS1}$	0.129488	0.979823
R-squared		0.0628	R-squared		0.105334
% Correct	Predictions	0.583333	% Correct	Predictions	0.65

SAMPLE	1989-1993		SAMPLE	1990-1994	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.03181	0.180351	δ_0	0.150435	0.657113
$\delta_{1\,RFT}$	1.9582	0.776658	$\delta_{1\,RFT}$	0.815973	0.310822
$\delta_{2\,RSP}$	2.84301	0.820759	$\delta_{2\,RSP}$	4.63184	1.31689
$\delta_{3\,CTB1}$	-1.43561	-0.726635	$\delta_{3\,CTB1}$	-3.15717	-1.34935
$\delta_{4\,CDIV}$	-6.63316	-1.72394	$\delta_{4\,CDIV}$	-8.38208	-2.12217
$\delta_{5\,TS1}$	0.1036	0.859161	$\delta_{5\,TS1}$	0.073397	0.713572
R-squared		0.0857	R-squared		0.137327
% Correct	Predictions	0.6	% Correct	Predictions	0.683333

SAMPLE	1991-1995	
Parameter	Estimate	t-statistic
δ_0	0.177594	0.730891
$\delta_{1\,RFT}$	0.912944	0.36069
$\delta_{2\,RSP}$	6.23032	1.79793
$\delta_{3\,CTB1}$	-1.46241	-0.5096
$\delta_{4\,CDIV}$	-6.22331	-1.85186
$\delta_{5\,TS1}$	0.065536	0.711634
R-squared		0.125484
% Correct	Predictions	0.633333

Table 6.19 Probit model/ Price of risk of Money Supply

-Dividend yield portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the unanticipated change in money supply is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSRMO} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

DIVIDEND	YIELD				
DEPENDENT	VARIABLE λ_{RSRMO}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.019654	0.087038	δ_0	0.064258	0.307107
$\delta_{1\,RFT}$	0.223193	0.072314	$\delta_{1\,RFT}$	2.2996	0.715172
$\delta_{2\,RSP}$	4.47646	0.885413	$\delta_{2\,RSP}$	0.959042	0.208278
$\delta_{3\,CTB1}$	0.091236	0.061439	$\delta_{3\,CTB1}$	-0.293564	-0.200392
$\delta_{4\,CDIV}$	-2.76057	-0.831921	$\delta_{4\,CDIV}$	-3.13875	-0.879173
$\delta_{5\,TS1}$	0.049013	0.767439	$\delta_{5\,TS1}$	0.015226	0.236549
R-squared		0.0290	R-squared		0.0192
% Correct	Predictions	0.59322	% Correct	Predictions	0.566667
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.11699	-0.591771	δ_0	-0.14029	-0.715728
$\delta_{1\,RFT}$	4.46439	1.18739	$\delta_{1\,RFT}$	7.86357	1.99272
$\delta_{2\,RSP}$	1.92774	0.445125	$\delta_{2\,RSP}$	-0.987339	-0.215727
$\delta_{3\,CTB1}$	3.58441	1.41166	$\delta_{3\,CTB1}$	2.91407	1.04216
$\delta_{4\,CDIV}$	-3.31444	-0.825549	$\delta_{4\,CDIV}$	-2.6471	-0.627748
$\delta_{5\,TS1}$	0.015439	0.184073	$\delta_{5\,TS1}$	-0.030728	-0.232508
R-squared		0.0807	R-squared		0.0924
% Correct	Predictions	0.633333	% Correct	Predictions	0.666667
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.182784	-0.878628	δ_0	-0.214448	-1.02424
$\delta_{1\,RFT}$	4.54329	1.13529	$\delta_{1\,RFT}$	4.6232	1.12528
$\delta_{2\,RSP}$	-0.419067	-0.090986	$\delta_{2\,RSP}$	-2.67606	-0.554624
$\delta_{3\,CTB1}$	1.21304	0.473357	$\delta_{3\,CTB1}$	0.918289	0.427015
$\delta_{4\,CDIV}$	-5.95778	-1.23795	$\delta_{4\,CDIV}$	-11.3789	-2.21501
$\delta_{5\,TS1}$	-4.70E-03	-0.036054	$\delta_{5\,TS1}$	-0.033934	-0.248961
R-squared		0.0591	R-squared		0.137157
% Correct	Predictions	0.55	% Correct	Predictions	0.7

Table 6.19– *Continued*

SAMPLE 1987-1991			SAMPLE 1988-1992		
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.260833	-1.32216	δ_0	-0.088069	-0.517279
$\delta_{1\ RFT}$	1.77817	0.408689	$\delta_{1\ RFT}$	-0.900763	-0.336461
$\delta_{2\ RSP}$	1.27134	0.270852	$\delta_{2\ RSP}$	1.36015	0.413925
$\delta_{3\ CTB1}$	0.985319	0.422188	$\delta_{3\ CTB1}$	0.34675	0.153263
$\delta_{4\ CDIV}$	-13.4261	-2.27315	$\delta_{4\ CDIV}$	-2.70545	-0.803165
$\delta_{5\ TS1}$	0.039793	0.298881	$\delta_{5\ TS1}$	0.05729	0.443413
R-squared		0.0992	R-squared		0.0191
% Correct	Predictions	0.716667	% Correct	Predictions	0.55

SAMPLE 1989-1993			SAMPLE 1990-1994		
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.132144	-0.764292	δ_0	-0.147605	-0.686628
$\delta_{1\ RFT}$	-1.74461	-0.648682	$\delta_{1\ RFT}$	-0.439363	-0.163795
$\delta_{2\ RSP}$	2.36811	0.72737	$\delta_{2\ RSP}$	4.13558	1.19686
$\delta_{3\ CTB1}$	-1.35187	-0.661847	$\delta_{3\ CTB1}$	-1.7524	-0.762176
$\delta_{4\ CDIV}$	-2.59297	-0.787819	$\delta_{4\ CDIV}$	0.067788	0.023477
$\delta_{5\ TS1}$	0.094006	0.786651	$\delta_{5\ TS1}$	8.50E-03	0.087616
R-squared		0.0402	R-squared		0.0338
% Correct	Predictions	0.616667	% Correct	Predictions	0.65

SAMPLE 1991-1995		
Parameter	Estimate	t-statistic
δ_0	-0.101689	-0.449574
$\delta_{1\ RFT}$	0.323589	0.127464
$\delta_{2\ RSP}$	2.40815	0.765351
$\delta_{3\ CTB1}$	-1.12205	-0.405015
$\delta_{4\ CDIV}$	2.93906	1.06414
$\delta_{5\ TS1}$	-0.039477	-0.449557
R-squared		0.0434
% Correct	Predictions	0.616667

Table 6.20: Probit model/ Price of risk of Imports -Dividend yield portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the unanticipated change in imports is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSIMP} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

DIVIDEND	YIELD				
DEPENDENT	**VARIABLE** λ_{RSIMP}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.103538	-0.442787	δ_0	-0.148729	-0.697529
$\delta_{1\,RFT}$	1.5272	0.463246	$\delta_{1\,RFT}$	3.98639	1.21323
$\delta_{2\,RSP}$	4.46191	0.856555	$\delta_{2\,RSP}$	0.65282	0.140705
$\delta_{3\,CTB1}$	-5.1828	-2.52096	$\delta_{3\,CTB1}$	-2.14291	-1.33883
$\delta_{4\,CDIV}$	5.50751	1.48789	$\delta_{4\,CDIV}$	-0.015475	-4.33E-03
$\delta_{5\,TS1}$	0.033841	0.515822	$\delta_{5\,TS1}$	0.014373	0.221015
R-squared		0.161619	R-squared		0.0552
% Correct	Predictions	0.644068	% Correct	Predictions	0.65
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.237684	-1.20946	δ_0	-0.112738	-0.592894
$\delta_{1\,RFT}$	4.23468	1.16578	$\delta_{1\,RFT}$	5.0508	1.38069
$\delta_{2\,RSP}$	-0.295937	-0.070661	$\delta_{2\,RSP}$	-1.41236	-0.314261
$\delta_{3\,CTB1}$	-1.30104	-0.545079	$\delta_{3\,CTB1}$	0.309455	0.11402
$\delta_{4\,CDIV}$	-2.28651	-0.568326	$\delta_{4\,CDIV}$	-2.50088	-0.601834
$\delta_{5\,TS1}$	0.029996	0.367443	$\delta_{5\,TS1}$	0.013708	0.10414
R-squared		0.0269	R-squared		0.0335
% Correct	Predictions	0.516667	% Correct	Predictions	0.483333
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.204145	-0.945114	δ_0	-0.110898	-0.549439
$\delta_{1\,RFT}$	7.26991	1.77698	$\delta_{1\,RFT}$	1.70442	0.460172
$\delta_{2\,RSP}$	-2.29543	-0.49981	$\delta_{2\,RSP}$	-0.599183	-0.130652
$\delta_{3\,CTB1}$	-3.44723	-1.30374	$\delta_{3\,CTB1}$	-2.58149	-1.14969
$\delta_{4\,CDIV}$	-0.776388	-0.158571	$\delta_{4\,CDIV}$	-3.32995	-0.667355
$\delta_{5\,TS1}$	0.137156	1.00844	$\delta_{5\,TS1}$	0.118317	0.882572
R-squared		0.0632	R-squared		0.0381
% Correct	Predictions	0.566667	% Correct	Predictions	0.6

Table 6.20- ***Continued***

SAMPLE	**1987-1991**		**SAMPLE**	**1988-1992**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-7.20E-03	-0.036397	δ_0	0.200109	1.07297
$\delta_{1\ RFT}$	3.33311	0.767384	$\delta_{1\ RFT}$	6.19576	1.85602
$\delta_{2\ RSP}$	1.38574	0.308279	$\delta_{2\ RSP}$	-0.194637	-0.057117
$\delta_{3\ CTB1}$	-3.9061	-1.52921	$\delta_{3\ CTB1}$	-6.25302	-2.09115
$\delta_{4\ CDIV}$	8.06909	1.37264	$\delta_{4\ CDIV}$	8.39382	1.57243
$\delta_{5\ TS1}$	0.202556	1.47492	$\delta_{5\ TS1}$	0.217502	1.5679
R-squared		0.0718	R-squared		0.153277
% Correct	Predictions	0.583333	% Correct	Predictions	0.65

SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.249859	1.27848	δ_0	0.239379	1.00332
$\delta_{1\ RFT}$	6.09427	1.87236	$\delta_{1\ RFT}$	5.91766	1.83277
$\delta_{2\ RSP}$	-0.376855	-0.108605	$\delta_{2\ RSP}$	-0.029323	-8.77E-03
$\delta_{3\ CTB1}$	-7.88478	-2.7662	$\delta_{3\ CTB1}$	-5.19332	-1.90316
$\delta_{4\ CDIV}$	5.66661	1.13856	$\delta_{4\ CDIV}$	7.69137	1.6766
$\delta_{5\ TS1}$	0.180964	1.40557	$\delta_{5\ TS1}$	0.074357	0.687617
R-squared		0.212584	R-squared		0.163069
% Correct	Predictions	0.7	% Correct	Predictions	0.65

SAMPLE	**1991-1995**	
Parameter	Estimate	t-statistic
δ_0	0.249299	0.959852
$\delta_{1\ RFT}$	6.13793	1.95064
$\delta_{2\ RSP}$	-0.329221	-0.10288
$\delta_{3\ CTB1}$	-6.75321	-2.02229
$\delta_{4\ CDIV}$	5.56048	1.35202
$\delta_{5\ TS1}$	0.048464	0.491914
R-squared		0.165759
% Correct	Predictions	0.633333

Table 6.21: Probit model/ Price of risk of Inflation -Dividend yield portfolio formation

The probit model is used to model the conditional probability (P_t) that the price of risk of the unanticipated change in inflation is positive or negative, conditional on the following instrumental variables CTB1(-1), CDIV(-1), TS1(-1), RFT(-1), RSP(-1), that belong to the information set Ω_t plus a constant. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place. Using an initial estimation period of 60 months from 1981-1985, we generate probabilities for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, that generate probabilities for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of probit probabilities in a monthly frequency for the sign of the price of risk.

$$\lambda_{RSINF} = \delta_0 + \delta_1 RFT_{t-1} + \delta_2 RSP_{t-1} + \delta_3 CTB1_{t-1} + \delta_4 CDIV_{t-1} + \delta_5 TS1_{t-1} + e_t$$

DIVIDEND	YIELD				
DEPENDENT	VARIABLE λ_{RSINF}				
SAMPLE	**1981-1985**		**SAMPLE**	**1982-1986**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.154015	-0.669394	δ_0	-0.126359	-0.594293
$\delta_{1\,RFT}$	1.42358	0.430168	$\delta_{1\,RFT}$	-1.1968	-0.363188
$\delta_{2\,RSP}$	-1.2511	-0.254843	$\delta_{2\,RSP}$	-0.984061	-0.211174
$\delta_{3\,CTB1}$	-3.78558	-1.92851	$\delta_{3\,CTB1}$	-2.92479	-1.66664
$\delta_{4\,CDIV}$	7.05497	1.92518	$\delta_{4\,CDIV}$	6.01187	1.63452
$\delta_{5\,TS1}$	0.022363	0.34963	$\delta_{5\,TS1}$	0.06758	1.0144
R-squared		0.125185	R-squared		0.0902
% Correct	Predictions	0.677966	% Correct	Predictions	0.633333
SAMPLE	**1983-1987**		**SAMPLE**	**1984-1988**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.073821	-0.384533	δ_0	4.71E-04	2.50E-03
$\delta_{1\,RFT}$	0.456544	0.131412	$\delta_{1\,RFT}$	-1.05048	-0.300807
$\delta_{2\,RSP}$	-2.14468	-0.514944	$\delta_{2\,RSP}$	-1.12984	-0.246018
$\delta_{3\,CTB1}$	-1.75875	-0.719399	$\delta_{3\,CTB1}$	-0.064845	-0.02414
$\delta_{4\,CDIV}$	2.69369	0.676057	$\delta_{4\,CDIV}$	5.64825	1.36634
$\delta_{5\,TS1}$	0.04982	0.600685	$\delta_{5\,TS1}$	0.084024	0.627857
R-squared		0.0212	R-squared		0.0373
% Correct	Predictions	0.566667	% Correct	Predictions	0.583333
SAMPLE	**1985-1989**		**SAMPLE**	**1986-1990**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.051796	0.248583	δ_0	0.017215	0.085514
$\delta_{1\,RFT}$	-1.05939	-0.285069	$\delta_{1\,RFT}$	-0.611507	-0.162007
$\delta_{2\,RSP}$	1.10739	0.23652	$\delta_{2\,RSP}$	-2.63065	-0.556976
$\delta_{3\,CTB1}$	1.65711	0.611835	$\delta_{3\,CTB1}$	-0.385738	-0.181243
$\delta_{4\,CDIV}$	6.9545	1.41998	$\delta_{4\,CDIV}$	7.52182	1.5109
$\delta_{5\,TS1}$	0.020631	0.154448	$\delta_{5\,TS1}$	3.86E-03	0.029208
R-squared		0.0453	R-squared		0.0447
% Correct	Predictions	0.566667	% Correct	Predictions	0.633333

Table 6.21- *Continued*

SAMPLE	1987-1991		SAMPLE	1988-1992	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	0.069141	0.354364	δ_0	-0.080794	-0.452707
$\delta_{1\,RFT}$	-2.57508	-0.598815	$\delta_{1\,RFT}$	1.93717	0.690683
$\delta_{2\,RSP}$	-0.592	-0.129164	$\delta_{2\,RSP}$	-0.92432	-0.272412
$\delta_{3\,CTB1}$	-0.035666	-0.015479	$\delta_{3\,CTB1}$	-1.04704	-0.409459
$\delta_{4\,CDIV}$	9.24899	1.61593	$\delta_{4\,CDIV}$	15.0859	2.74944
$\delta_{5\,TS1}$	-0.0463	-0.354465	$\delta_{5\,TS1}$	-0.048314	-0.359542
R-squared		0.0537	R-squared		0.156295
% Correct	Predictions	0.6	% Correct	Predictions	0.6
SAMPLE	**1989-1993**		**SAMPLE**	**1990-1994**	
Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
δ_0	-0.171418	-0.930082	δ_0	-0.39616	-1.64754
$\delta_{1\,RFT}$	0.794732	0.291765	$\delta_{1\,RFT}$	1.10848	0.389055
$\delta_{2\,RSP}$	-3.70283	-1.05399	$\delta_{2\,RSP}$	-5.86426	-1.62669
$\delta_{3\,CTB1}$	0.545673	0.25383	$\delta_{3\,CTB1}$	-0.015576	-5.82E-03
$\delta_{4\,CDIV}$	11.1592	2.25697	$\delta_{4\,CDIV}$	8.88152	2.15891
$\delta_{5\,TS1}$	-0.238831	-1.8699	$\delta_{5\,TS1}$	-0.282057	-2.48425
R-squared		0.160301	R-squared		0.204982
% Correct	Predictions	0.633333	% Correct	Predictions	0.683333
SAMPLE	**1991-1995**				
Parameter	Estimate	t-statistic			
δ_0	-0.398176	-1.6221			
$\delta_{1\,RFT}$	1.85571	0.662922			
$\delta_{2\,RSP}$	-4.23495	-1.34832			
$\delta_{3\,CTB1}$	0.738993	0.253115			
$\delta_{4\,CDIV}$	5.08327	1.58546			
$\delta_{5\,TS1}$	-0.194349	-2.04749			
R-squared		0.141283			
% Correct	Predictions	0.65			

FIGURE 6.13: The sign for the price of risk for FTSE (Dividend yield portfolios)

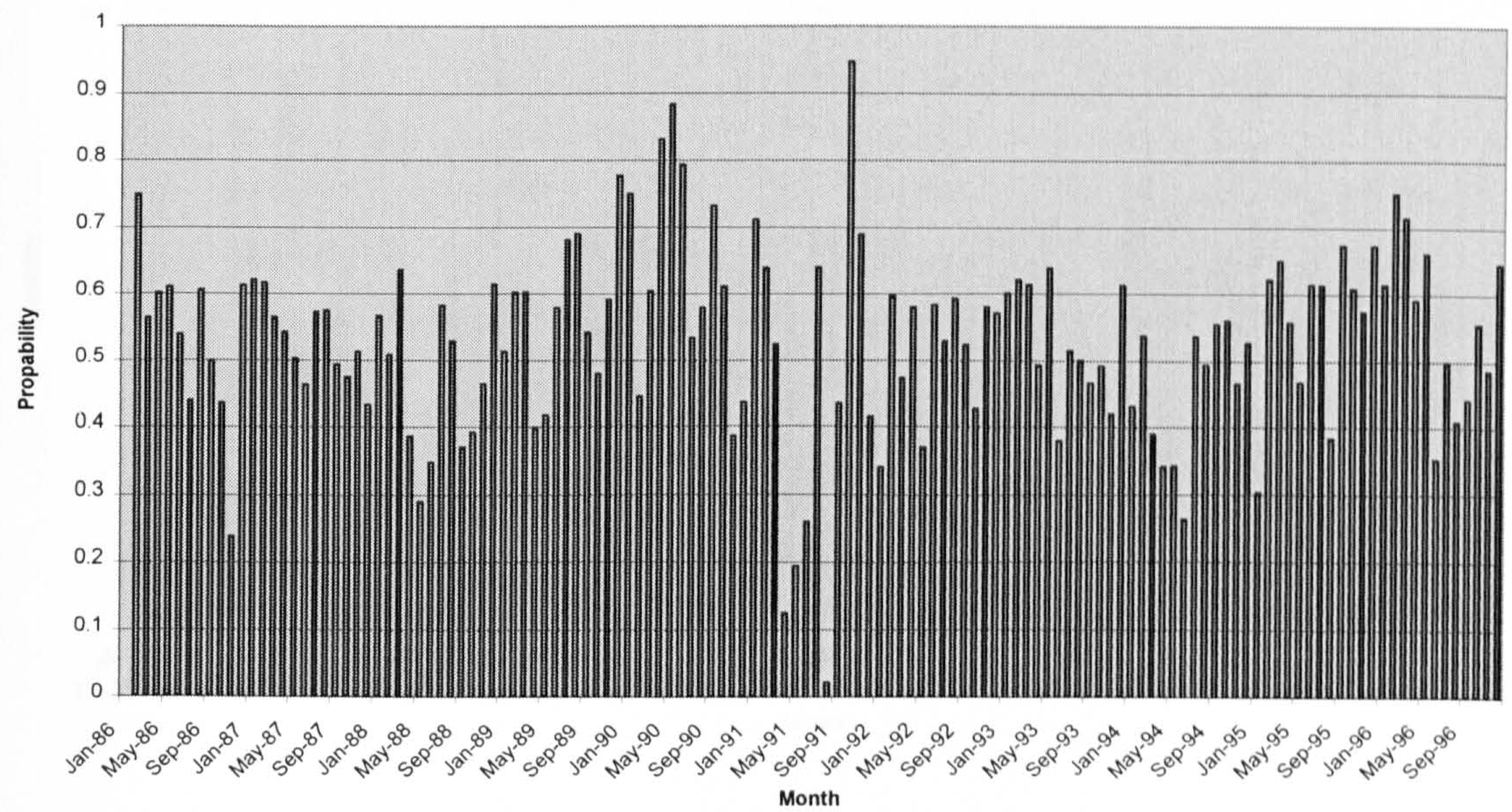


FIGURE 6.14: The sign for the price of risk for SP500 (Dividend yield portfolios)

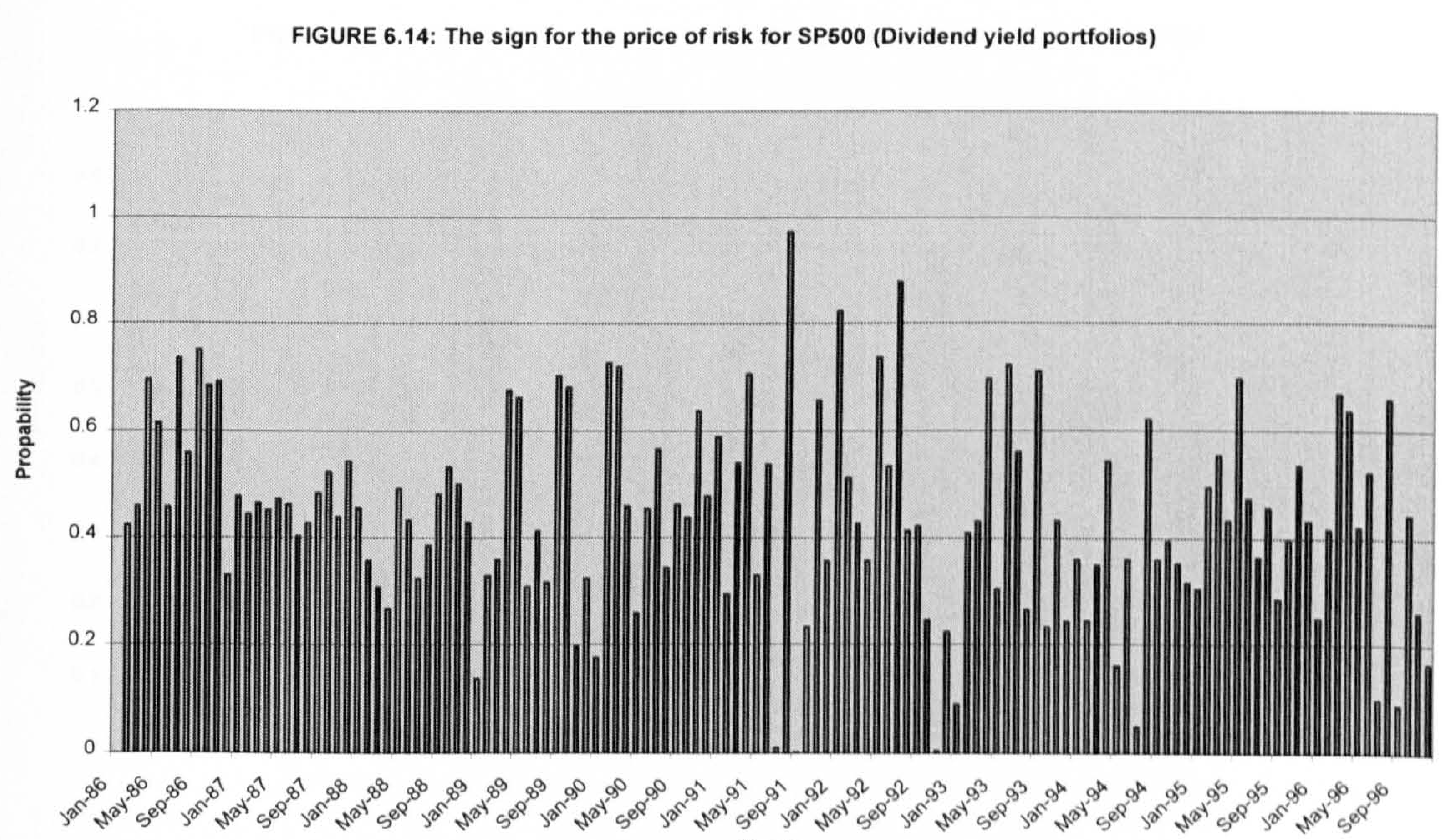


FIGURE 6.15: The sign for the price of risk for the Stock exchange Turnover (Dividend yield portfolios)

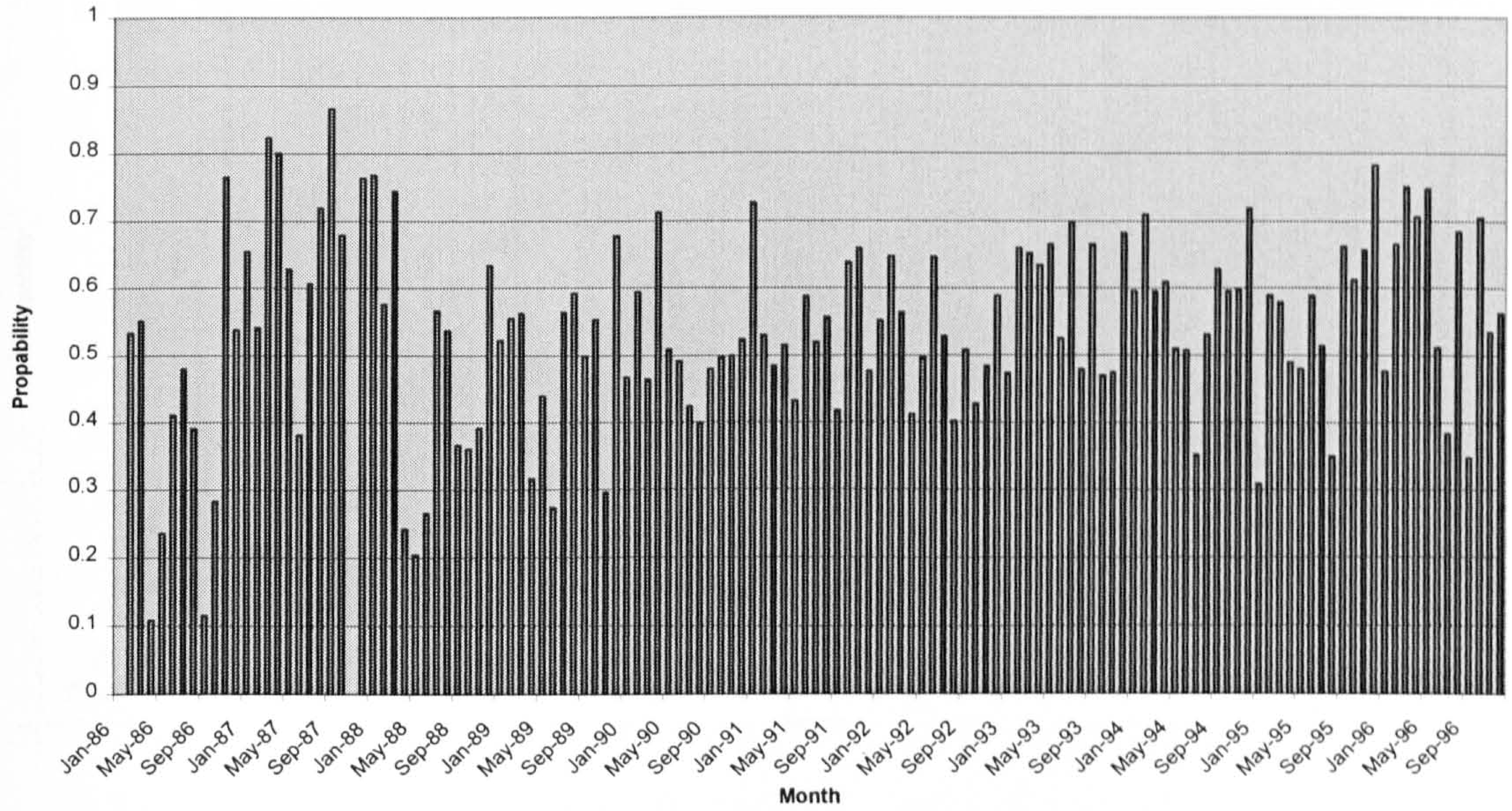


FIGURE 6.16: The sign for the price of risk for Money supply (Dividend yield portfolios)

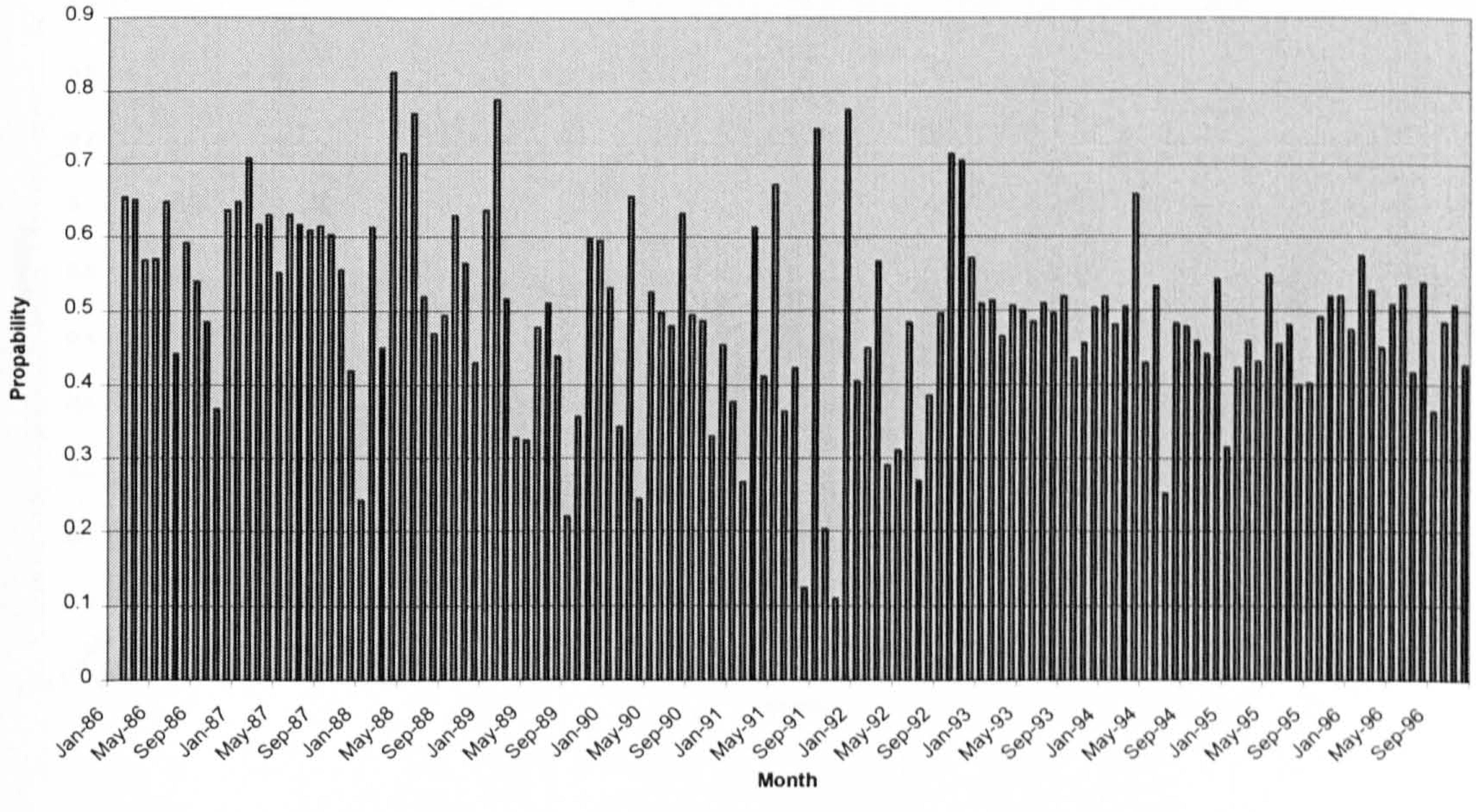


FIGURE 6.17: The sign for the price of risk for Imports (Dividend yield portfolios)

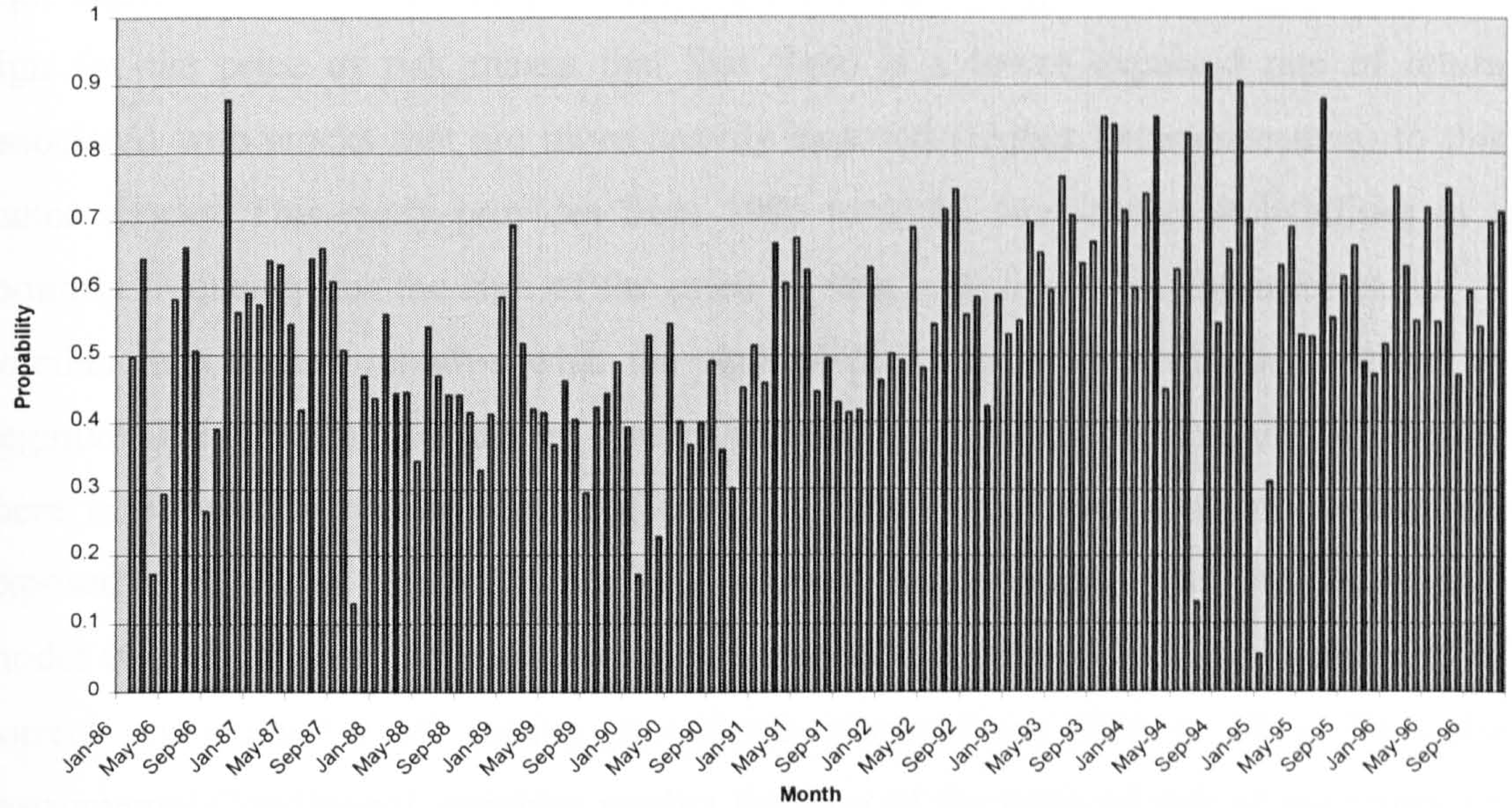
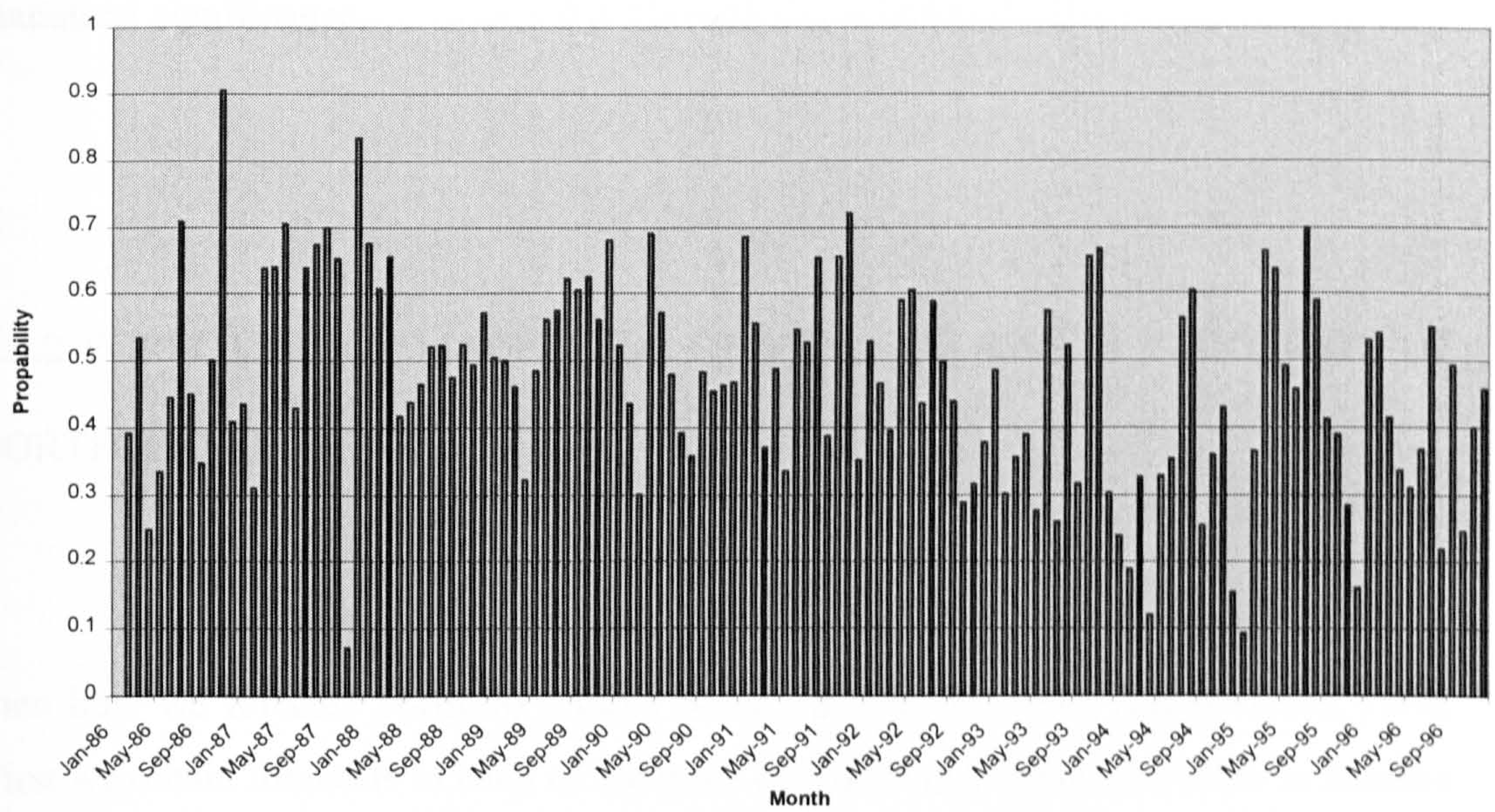


FIGURE 6.18: The sign for the price of risk for Inflation (Dividend yield portfolios)



A positive sign for the price of risk is an indication that the more sensitive a portfolio is to a particular factor the more the expected return for this stock (stocks with e.g., higher inflation betas (exposures) require a higher expected return). A negative sign for the price of risk means that that there is a lower expected rate of return associated with stocks that are more heavily exposed (higher betas/exposures) to this factor shocks. This study provides from 1985 to 1996, time-series probabilities in a monthly frequency for the sign of the price of risk, which provide the information of whether in a certain month-s what the sign of the price of risk will be, positive or negative. This information can be used to indicate in a certain month-s the of whether there is a lower or higher degree of expected return associated with stocks that are exposed to shocks of certain factors, i.e., inflation, money supply etc. The Conditional model is doing a good job in predicting the sign of the price of risk, the average % of correct prediction for all sorting procedures ranges from 50% to 80%. Thus the Instrumental-Conditional variables predict the sign of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, inflation quite well. The following section further examines the errors that arise when portfolio returns are forecasted using the Conditional variables and concludes on the assessment of the Conditional model by estimating these errors and testing for their statistical significance.

6.3.2 FORECASTS OF MAGNITUDE OF PRICE OF RISK & FORECASTS OF PORTFOLIO RETURNS

This section first discuss how we forecast the magnitude of the price of risk, then how we forecast portfolio returns based on size, PE ratio, and dividend yield. First we obtain forecasts of each of the price of risk of our factors. In order to achieve this, we use OLS and run regressions with the price of risk being the dependent variable, and the predetermined variables (shown in Table 6.1, Panel B) being the independent variables.

We use a holdout sample of 132 months where the out-of-sample evaluation is taking place, in order to forecast the magnitude of the price of risk. Using an initial estimation period of 60 months from 1981-1985, we forecast the magnitude of the price of risk for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, this forecast the magnitude of the price of risk for the following twelve months, 1987. This forecasting procedure is taking place 11 times, and the outcome of this is a time-series of forecasts in a monthly frequency for the magnitude of the price of risk. So we obtain time-series forecasts of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, changes in money supply, imports, and inflation for the 1986-1996 period.

$$\lambda_{RSRFT} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRSP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRTU} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSRMO} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSIMP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\lambda_{RSINF} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

Where λ_{RSRFT} is the Price of risk of the Return on FTSE; λ_{RSRSP} is the Price of risk of Return on Standard & Poors 500; λ_{RSRTU} is the Price of risk of Unanticipated UK Stock Exchange Turnover; λ_{RSRMO} is the Price of risk of Unanticipated Change in Money Supply (MO); λ_{RSIMP} is the Price of risk of Unanticipated Change in Imports; λ_{RSINF} is the Price of risk of Unanticipated Change in Inflation; δ_0 is a constant; e_t is the residual.

In order to forecast portfolio returns based on size, PE ratio, and dividend yield, we need estimates of the prices of risk for each of our factors, the sensitivities (betas) for each of these factors, plus the risk-free rate (the constant). We obtain forecasts of the prices of risk, as discussed earlier. So we have time-series of forecasts of the prices of risk from 1986-1996. The betas are obtained from rolling regressions, (see chapter 5). The betas are obtained by regressing portfolio returns on the factors, using time series regressions over an estimation period of 5 years. The slope coefficients in the time-series regressions provide estimates of the betas. The time series start in 1981, and we obtain estimates of betas for 1986, etc. To forecast portfolio returns (FR_i) we simply add the estimate of the risk-free rate to the sum of the products of the β_j's and forecasts of λ_j's ($f\lambda_j$) of our factors.

$$FR_{MVi} = \lambda_0 + f\lambda_{RSRFT} * \beta_{RSRFT} + f\lambda_{RSRSP} * \beta_{RSRSP} + f\lambda_{RSRTU} * \beta_{RSRTU} + f\lambda_{RSRMO} * \beta_{RSRMO} + f\lambda_{RSIMP} * \beta_{RSIMP} + f\lambda_{RSINF} * \beta_{RSINF} + e_t$$

To obtain forecasts of market value portfolio i, $i = 1,...,25$;

$$FR_{PEi} = \lambda_0 + f\lambda_{RSRFT} * \beta_{RSRFT} + f\lambda_{RSRSP} * \beta_{RSRSP} + f\lambda_{RSRTU} * \beta_{RSRTU} + f\lambda_{RSRMO} * \beta_{RSRMO} + f\lambda_{RSIMP} * \beta_{RSIMP} + f\lambda_{RSINF} * \beta_{RSINF} + e_t$$

To obtain forecasts of PE ratio portfolio i, $i = 1,...,25$;

$$FR_{DYi} = \lambda_0 + f\lambda_{RSRFT} * \beta_{RSRFT} + f\lambda_{RSRSP} * \beta_{RSRSP} + f\lambda_{RSRTU} * \beta_{RSRTU} + f\lambda_{RSRMO} * \beta_{RSRMO} + f\lambda_{RSIMP} * \beta_{RSIMP} + f\lambda_{RSINF} * \beta_{RSINF} + e_t$$

To obtain forecasts of dividend yield portfolio i, $i = 1,...,25$;

In order to evaluate the forecasts of portfolio returns (for the size, PE ratio and dividend yield portfolios) we need to compare the forecasts with the actual portfolio returns. To do that we use a summary measure, which gives us the ability to summarise errors and to make judgement about what the average error has been. So we estimate the Root Mean Square Error (RMSE). Table 6.22 shows the Root Mean Square Error for the market value, PE ratio, and dividend yield portfolios.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} e_t^{2}}{n}}$$

Where e_t is the difference between the portfolio forecasts and the actual portfolio returns, and n is the number of observations. Table 6.22 indicate that the RMSE for the market value portfolios range from the lowest RMSE of 0.078 for the market value portfolio 16 (MV16) to the highest RMSE of 0.471 for the market value portfolio 1 (MV1). For the PE ratio sorting procedure the RMSE range from the lowest RMSE of 0.318 for the PE ratio portfolio 1 (PE1) to the highest RMSE of 0.397 for the PE ratio portfolio 22 (PE22). For the dividend yield ranking the RMSE range from the lowest RMSE of 0.365 for the dividend yield portfolio 15 (DY15) to the highest RMSE of 0.549 for the dividend yield portfolio 2 (DY2).

Furthermore we perform another analysis so as to test the statistical significance of the errors that the Conditional model leaves. We run Monte Carlo simulations, having obtained a large number of simulations, we estimate the cross-sectional average of the number of simulations we have run. Then given this average we test the statistical significance of the errors of the Conditional model. Table 6.23 show the statistical significance of the errors of Conditional Model for each of the size, price earnings ratio and dividend yield portfolios We find these errors to be statistically insignificant for all sorting procedures. Based on this evidence we conclude that the Instrumental-Conditional variables predict the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, inflation and forecast portfolio returns quite well, since the errors that the Conditional model leaves are statistically insignificant.

Table 6.22

Table 6.22 shows the Root Mean Square Error for the market value, PE ratio, and dividend yield portfolios. Where e_t is the difference between the portfolio forecasts and the actual portfolio returns, and n is the number of observations.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} e_t^2}{n}}$$

ROOT	MEAN	SQUARE	ERROR		
SIZE	**RMSE**	**PE RATIO**	**RMSE**	**DIVIDEND**	**RMSE**
SAMPLE	**1986-1996**	**SAMPLE**	**1986-1996**	**SAMPLE**	**1986-1996**
MV1	0.471104	**PE1**	0.318808	**DY1**	0.38845
MV2	0.45702	**PE2**	0.393399	**DY2**	0.549838
MV3	0.347013	**PE3**	0.370788	**DY3**	0.532264
MV4	0.435286	**PE4**	0.360735	**DY4**	0.491645
MV5	0.333746	**PE5**	0.330346	**DY5**	0.404377
MV6	0.336063	**PE6**	0.339504	**DY6**	0.386576
MV7	0.191595	**PE7**	0.3484	**DY7**	0.373868
MV8	0.264268	**PE8**	0.32177	**DY8**	0.404477
MV9	0.236842	**PE9**	0.376982	**DY9**	0.374972
MV10	0.181708	**PE10**	0.343015	**DY10**	0.390861
MV11	0.394536	**PE11**	0.356092	**DY11**	0.378339
MV12	0.343818	**PE12**	0.374316	**DY12**	0.376621
MV13	0.416035	**PE13**	0.368581	**DY13**	0.371588
MV14	0.323015	**PE14**	0.361901	**DY14**	0.380827
MV15	0.386725	**PE15**	0.339646	**DY15**	0.365927
MV16	0.078085	**PE16**	0.351844	**DY16**	0.385343
MV17	0.104209	**PE17**	0.353323	**DY17**	0.407461
MV18	0.2539	**PE18**	0.381476	**DY18**	0.388471
MV19	0.172919	**PE19**	0.368253	**DY19**	0.431186
MV20	0.351185	**PE20**	0.380119	**DY20**	0.413844
MV21	0.277867	**PE21**	0.38533	**DY21**	0.423372
MV22	0.385865	**PE22**	0.397937	**DY22**	0.430872
MV23	0.373467	**PE23**	0.345584	**DY23**	0.440089
MV24	0.426754	**PE24**	0.333199	**DY24**	0.466824
MV25	0.381876	**PE25**	0.37435	**DY25**	0.431417

Table 6.23: Monte Carlo Simulations

Statistical Significance of the Errors of the Conditional Model

We run Monte Carlo simulations, having obtained a large number of simulations, we estimate the cross-sectional average of the number of simulations we have run. Then given this average we test the statistical significance of the errors of the Conditional model. Table 6.23 show the statistical significance of the errors of the Conditional Model. The errors are statistically insignificant.

STATISTICAL SIGNIFICANCE OF ERRORS

SIZE	t-statistic	PE	t-statistic	D.YIELD	t-statistic
MV1	0.777	PE1	0.558	DY1	0.297
MV2	0.735	PE2	0.387	DY2	0.165
MV3	0.725	PE3	0.395	DY3	0.332
MV4	0.296	PE4	0.403	DY4	0.184
MV5	0.232	PE5	0.463	DY5	0.237
MV6	0.220	PE6	0.258	DY6	0.318
MV7	0.238	PE7	0.383	DY7	0.543
MV8	0.285	PE8	0.381	DY8	0.255
MV9	0.281	PE9	0.271	DY9	0.619
MV10	0.299	PE10	0.377	DY10	0.529
MV11	0.254	PE11	0.244	DY11	0.514
MV12	0.219	PE12	0.372	DY12	0.639
MV13	0.236	PE13	0.382	DY13	0.740
MV14	0.207	PE14	0.415	DY14	0.724
MV15	0.268	PE15	0.284	DY15	0.279
MV16	0.319	PE16	0.255	DY16	0.784
MV17	0.321	PE17	0.162	DY17	0.662
MV18	0.308	PE18	0.376	DY18	0.752
MV19	0.213	PE19	0.331	DY19	0.484
MV20	0.226	PE20	0.269	DY20	0.865
MV21	0.254	PE21	0.264	DY21	0.682
MV22	0.219	PE22	0.307	DY22	0.573
MV23	0.556	PE23	0.222	DY23	0.408
MV24	0.520	PE24	0.236	DY24	0.359
MV25	0.671	PE25	0.299	DY25	0.660

6.4 CONCLUSION

In this chapter we model the dynamic behaviour of portfolio returns using a Conditional Asset Pricing Model and examine the behaviour of macroeconomic risk premiums over time. In order to do this we provide tests of the Ferson and Harvey (1991) methodology, for the size, PE ratio and dividend yield portfolios, and also develop an alternative Conditional Methodology, the Conditional Non Linear Seemingly Unrelated Regression (NLSUR), in an attempt to avoid the Errors in Variables problem inherent in the Ferson and Harvey (1991) methodology. We find that under the Ferson and Harvey (1991) methodology, that the following factors: the return on FTSE; S&P 500; unexpected UK stock exchange turnover; change in money supply; imports; and inflation, are priced at different stages of the business cycle. Under the Conditional NLSUR, the instrumental variables also show predictive ability to predict variation of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, and inflation.

Furthermore unlike existing conditional asset-pricing studies that just focus on the methodology employed, we test the performance of Conditional models by carrying out practical tests. These practical tests focus on forecasts of (i) the Sign of the Price of Risk using the Probit model, (ii) the Magnitude of the Price of Risk, and (iii) Portfolio Returns for the size, PE ratio and dividend yield portfolios.

We utilise the Probit model and an out-of-sample evaluation in order to obtain-forecast time-series probabilities in a monthly frequency for the sign of the price of risk, which provide the information of whether in a certain month-s what the sign of the price of risk will be, positive or negative. This information can be used to indicate in a certain month-s of whether there is a lower or higher degree of expected return associated with stocks that are exposed to shocks of certain factors, i.e., inflation, money supply e.t.c. The errors that can occur in our forecast procedure is that the model may incorrectly predict a positive sign of risk when the actual sign of that month is negative or the model may incorrectly predict a negative sign of risk when the actual sign of that month is positive. In order to evaluate how our probit model predicts, we report the % of correct predictions in each probit regression, and the average % of correct predictions for all (11) probit regressions for each price of risk we attempt to predict. We find, for example, that the probit regression model for the sign of risk of the return on S&P 500 (for the size portfolio ranking) has an average % of correct prediction for all the probit regressions of 66%. The probit regression model reaches the highest % of correct prediction of 75% during the 1986-1990, and 1987-1991 period. Another example, the probit regression model for the sign of risk of the unexpected UK stock exchange turnover (for the PE portfolio ranking) has an average % of correct prediction for all the probit regressions of 72%. The probit regression model reaches the highest % of correct prediction of 80% during the 1989-1993 period. The Conditional model is doing a good job in predicting the sign of the price of risk, the average % of correct prediction for all sorting procedures ranges from 50% to 80%. Thus the Instrumental-Conditional variables predict the sign of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, inflation quite well.

We also forecast the magnitude of the Price of Risk -with an out-of-sample evaluation-, and carry on to forecast portfolio returns for our size, PE ratio and dividend yield portfolios. In order to evaluate how well our model forecasts portfolio returns for the size, PE ratio and dividend yield portfolios, we estimate the Root Mean Square Error (RMSE). Furthermore we run Monte Carlo simulations and test the statistical significance of the errors of the Conditional model. We find these errors to be statistically insignificant for all sorting procedures. This chapter provides empirical evidence that show that the Conditional model employed in the thesis is doing a good job in predicting the price of risk and portfolio returns, since the errors that the model leaves are statistically insignificant.

CHAPTER 7

ESTIMATION OF THE UK INDUSTRY COST OF CAPITAL USING NLSUR AND UNCONDITIONAL & CONDITIONAL BETAS

The estimation of the cost of capital is one of the most important tasks that a company has to deal with, and the key factor that affects the allocation of resources within the economy. The cost of capital determines the selected projects by a company.

Both the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Models (APM) have been used to estimate the cost of capital (D.Bower, R.Bower and Loque (1984), Goldenberg and Robin (1991), Pettway and Jordan (1987), Elton, Gruber and Mei (1994), Schink and Bower (1994), Fama and French (1997)). Fama and French (1997) estimate the industry cost of capital for US, whereas the other mentioned researchers focus on the utilities sector.

The purpose of this paper is to compare different competitive models in order to identify which provide the best estimates of the UK Industry Cost of Capital. We first compare the Unconditional-constant and Conditional beta estimates of the UK Industry Cost of Capital and second the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Model (APM) estimates of the UK Industry Cost of Capital.

This study is the first to provide estimates of the industry cost of capital for the UK market. In order to estimate the cost of capital our first task is to identify the model that is a good description of the UK returns; Which are the relevant factors, that is to identify which factors affect returns in the UK. In answer to that we find that the APM consisting of the following factors explain returns in the UK: the return on the FTSE, S&P 500 share price index, unexpected UK stock exchange turnover, change in money supply, imports, and inflation.

The estimation of the cost of capital requires estimates of betas. Given the evidence of time-varying conditional betas for portfolio returns (Ferson and Harvey (1991), (1993), etc, we allow betas to depend on instruments, that is we model betas as linear functions of predetermined instruments. Ferson and Harvey (1999) find that conditional versions of models with time-varying betas provides some improvement, and that their results carry implications for risk analysis, performance measurement, cost of capital calculations and other applications. However given other evidence by Ghysels and Cirano (1997) who find that the some times errors with the constant traditional beta models are smaller than with conditional beta models, we also estimate constant betas. Therefore we estimate an unconditional-constant beta model and conditional (time-varying & conditioned on a set of instrumental variables) beta model to examine and provide practical evidence of which beta model provides more accurate estimation of the industry cost of capital.

For the estimation of the cost of capital we also need estimates of the prices of risk. The literature on the estimation of the cost of capital (Schink and Bower (1994), Fama and French (1997)) use historic averages for the estimation of the factor premiums. Schink and Bower (1994), actually claim that estimates of expected factor premiums can be improved by considering data beyond historic averages and that the historical averages for the factors provide a simple but not the best estimate for the expected premiums.

Therefore we estimate the prices of risk using the non-linear seemingly unrelated regression estimates (NLSUR). Elton, Gruber and Mei (1994) actually claim that an estimation procedure worthwhile exploring in the future involves estimating the prices of risk via seemingly unrelated regression. This technique allows us to impose the constraint that the prices of risk are constant across all industries.

We also estimate the cost of capital using the Capital Asset Pricing Model (CAPM), in order to compare the CAPM estimates of cost of capital to the Arbitrage Pricing Model (APM) estimates of cost of capital and conclude on which model provide more accurate estimates of the cost of capital.

This chapter is organised as follows: Section 7.1 provides a summary of the theory and review of the literature. Section 7.2 outlines the industry indices and briefly describes the competitive models that are estimated for the cost of capital calculation. Section 7.3 explains the estimation of the unconditional-constant and conditional betas. Section 7.4 explains the estimation of the prices of risk. Section 7.5 discuses the APM estimates of the cost of capital and compares the APM cost of capital estimates with the Capital Asset Pricing Model estimates of the cost of capital. Section 7.6 concludes.

7.1 THEORY AND LITERATURE REVIEW

Elton and Gruber (1994), mention essentially five techniques that have been used to estimate the cost of capital. These are the comparable earnings; the valuation models; risk premium; the CAPM and the APT. Comparable earnings involve setting the cost of capital by calculating the earnings on book equity for "comparable companies". They claim that his technique is rarely discussed in texts but is used in practise by regulatory agencies. The deficiency of this technique is that it leaves the researcher with the problem of determining, which are the " comparable companies". The other deficiency is that it bases the estimate on book figures when cost of capital is a market concept.[1] Valuation models define the cost of capital as the discount rate that equates expected future cash flows to the current price. If D_t is the dividend expected at time t, then the cost of capital is k in the following equation.

$$Price = \frac{D_1}{(1+k)^1} + \frac{D_2}{(1+k)^2} + \frac{D_3}{(1+k)^3} \qquad (7.1)$$

For a valuation model to be manageable in practise more structure has to be imposed, this involves specifying a growth path for dividends. If we assume that dividends grow at a constant rate forever, and if g is the constant growth rate, then equation (a) reduces to: $Price = \frac{D_1}{k-g}$ (7.2).

The assumption of a constant growth rate is only one of many assumptions that can be made about growth. Elton and Gruber (1994), claim that what matter is not what the analysts believe but rather the growth path assumption embodied in current prices. In the last decade growth expectations have been systematically collected from analysts (IBESS and ZACKS). Even though the availability of expectational data eliminates the exclusive reliance on past growth to predict future growth, the expectational data which is usually provided by analysts' services is relatively short term so that an individual employing a growth model must exercise considerable judgement in estimating the growth for long-term.

[1] For instance, if interest rates increase then the cost of capital should also increase, however a measure based on book values would remain unchanged.

According to the risk premium approach, an estimate of the extra return required on equity over and above the yield on some long-term bond is made. This premium plus the current yield to maturity on long-term bond is then used as an estimate of the average cost of equity for all firms. A risk adjustment to recognise that the firm in question may have different risk than the average firm if done at all is done on an ad hoc basis. However many proponents of this technique argue that more accurate estimates can be obtained for an average firm than any particular firm and that introducing firm risk adjustment, creates more inaccuracies than information.

The CAPM and APT techniques are related to the risk premium approach, but differ in that they use a set of theories to make differential risk adjustment for alternative firms. Although empirical studies combine cross sectional and time series data, it is common to classify them as cross-sectional or time-series on the basis of the approach used in the final, testing stage of the analysis. Time-series tests, assume that we observe $\lambda_{0,t-1}$ and $\lambda_{t-1}+f_t = F_t$, which represent the return on a zero-beta asset and the vector of excess return (i.e., returns in excess of the zero-beta return), we can consider the time-series system of regressions: $R_t = a + BF_t + \varepsilon_t$ (7.3)

Where a is a n*1 vector of intercept coefficient. A testable restriction implied by the pricing model is that a=0. This approach to testing the specification of asset pricing models is used by Black, Jensen & Scholes (1972) to test the CAPM where F_t represents the excess return on the market portfolio proxy (the equal weighted NYSE portfolio in their case).

A variant of this approach applies when the risk-less or zero-beta return is not observed. Let $F_t^* = \lambda_{0,t-1} + F_t$, the "raw" returns (i.e., not in excess of the zero-beta return), and consider the time-series regression: $R_t^* = a + BF_t^* + \varepsilon_t$ (7.4)

The CAPM can be used for applications requiring a measure of expected stock returns. Some of these applications include the cost of capital estimation. The cost of equity capital is required for use in capital budgeting decisions and the determination of a fair rate of return for regulated utilities. Implementation of the model, in a manner such as the BJS (72) approach, requires three inputs: the stock's beta, the market risk premium, and the risk-free return. The usual estimate of beta of equity is the estimator of the slope coefficient in the excess-return market model, that is, the beta in the regression equation

$P_{it} = a_{im} + \beta_{im} P_{mt} + \varepsilon_{it}$

Where i denotes the asset and t denotes the time period, t=1,T. P_{it} and P_{mt} are the realised excess returns in time period t for asset i and the market portfolio respectively. For the US market, the standard and Poor's 500 index serves a proxy for the market portfolio, and the US Treasury bill rate proxies for the risk-free return. This equation is most commonly estimated using 5 years of monthly data (T=60). Then given an estimate of beta, the cost of capital is calculated using a historical average for the excess return on the S&P 500 over treasury bills. However this sort of application is justified if the CAPM provides a good description of the data. In a multi-factor framework, also the regression slopes and the historical average premiums for the factors can be used to estimate the expected return on a firm's securities, for the purpose of judging its cost of capital.

In asset pricing some authors have specified, ex-ante certain macroeconomic series as being the pervasive factors (CRR, (1986)), other authors have specified, ex-ante, sets of portfolios whose returns are assumed to be maximally correlated with the pervasive factors. When macroeconomic series are used, a second step is required to form factor-mimicking portfolios (generally through cross-sectional regressions of asset returns on estimated betas). When ex-ante specified portfolios are used, one can avoid the second step since the factors are asset returns which contain the appropriate risk premia. The time-series regressions use excess returns (monthly stock or bond returns minus the one-month Treasury bill rate) as dependent variables and either excess returns or returns on zero-investment portfolios as explanatory variables. The average returns on the explanatory portfolios are the average premiums per unit of risk (regression) slope for the candidate common risk factor in returns. So in the time-series regression approach to asset-pricing tests the average risk premiums for the common factor in returns are just the average values of the explanatory variables. In such regressions, a well-specified asset-pricing model produces intercepts indistinquisable from zero.

Fama and French (1993) specify the factors to be five portfolio excess returns: (1) the return on a value weighted market portfolio (in excess of the one-month treasury bill return); (2) the difference in returns on a small-firm portfolio and a large portfolio; (3) the difference in returns on a portfolio of firms with high book-to-market equity and a portfolio of firms with low book-to-market equity; (4) the difference in returns on a long-term government portfolio and the return on one-month treasury bill; (5) the difference in the return on a long-term corporate bond portfolio and the return on a long-term government bond portfolio. Methodologically, in the time-series regression variation through time in the expected premiums $E(R_m-R_f)$, E(SMB), E(HML), etc, is embedded in the explanatory returns R_m-R_f, SMB, HML. In the time-series regression if the factor model describes expected returns, the regression intercepts should be close to zero. Fama & French find that the multifactor models do a much better job in explaining asset returns (i.e., values of a close to zero) than do standard single index models.

D.Bower, R Bower, and D. Loque (1984), present evidence that the APT may lead to different and better estimates of expected return than the CAPM in their attempt to estimate the cost of capital for utility stock returns. They estimate the CAPM and APT as follows. For the CAPM: $r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it}$, where r_{it} is the return on asset i in period t, r_{mt} is the return on the market portfolio in the same period, β_i is the estimate of systematic risk, a_i is the expected to be $(1\text{-}b)R_f$, and ε_{it} is the error tem. For the APT: $r_{it} = b_{i0} + \lambda_1 b_{i1} + +\lambda_2 b_{i2} + ... + \lambda_{j1} b_{ij} + u_{it}$. They used the CAPM β_is and the APT b_{ij}s estimated in each portfolio in the time-series work and run cross-sectional regressions for each month with these risk coefficient as independent variables and returns as dependent variable, to estimate the prices of risk. Bower, Bower, and Loque (1984) compare CAPM and APT cost-of-capital estimates for non-combination electric utilities and natural gas distribution companies. Using monthly data, they obtain estimates opposite in rank to CAPM estimates for the two industries. They conclude in favor of the APT estimates because the four APT factors explain more in-sample variation (average adjusted $R^2 = 0.869$) than the market index (average adjusted $R^2 = 0.605$; Also the APT measures of risk provide more precise forecasts of returns of holdout stocks than do the market model betas.

Goldenberg and Robin (1991), use the CAPM and the APT to estimate the cost of capital for sample of electric utilities. They find that the statistical factors APT method is found to produce significantly different estimates depending on the number of factors specified and the set of firms' factors analyzed. The macroeconomic factors APT is found to have advantages over the statistical factors APT and the market model. They find that APT estimates using statistical factors are therefore not robust. Prior studies (e.g.. Roll and Ross (1983)) show that market model estimates are underestimates and that the statistical factors APT estimates are closer to the true cost of capital.

Pettway and Jordan (1987) extent Bower, Bower, and Loque (1984) by comparing the relative efficiency of the CAPM and APT in the true forecasting sense of predicting future equity returns. Using weekly data on electric utilities, they find that in addition to explaining a greater degree of in-sample returns, the APT provides better forecasts of future returns than the CAPM. They also find that the market model forecast errors are partially explained by the APT factors. Finally, they find evidence consistent with Roll and Ross (1983) that the APT cost-of-capital estimates are greater than the market model estimates. However Goldenberg and Robin (1991), find that statistical APT can bee higher or lower than the market model estimates depending on the number of factors employed and the firms used to extract the factors.

Goldenberg and Robin (1991), use McElroy and Burmeister's (1988) data set of macroeconomic factors to generate cost-of equity estimates for 1983. McElroy and Burmeister's (1988) provide the authors with a data set of monthly observations on four macroeconomic factors for 1972-1982. The first macroeconomic factor is a measure of bond-default premiums and is the difference between monthly returns on 20-year corporate and government bond portfolios. The second factor is a measure of bond-maturity premiums and is the difference between the monthly returns on a 20-year government bond portfolio and monthly returns on T-bills. The third factor is an unexpected inflation series measured as the difference between expected inflation and the actual inflation rate. The fourth factor is unexpected growth in sales measured as the difference between current and future expectations of the growth rate in sales.

Goldenberg and Robin (1991), find that the macroeconomic factor cost-of-capital estimates are higher than those arising from the statistical factor implementation of the APT. For the utility portfolio, the ten-and five-factor statistical implementation lead to cost-of-capital estimates of 11.31% and 8.66%, while the macro variables leads to 16.26 %. They conclude that the cost-of-equity estimates using the macroeconomic APT method appear more reasonable than those using statistical factors as well as the market model because: (1) in most cases they are greater than the benchmark of average yields on Aaa public utility bonds; (2) in most cases they are greater than the estimates provided by the market model that have been criticized as underestimates of the true cost by the prior literature; and (3) they are less likely to be abnormally low for individual firms.

Elton, Gruber and Mei (1994), describe an Arbitrage Pricing Model that can be used to determine the cost of equity for any company. They find that the required return on common stock depends on its sensitivity to a set of indexes which include the return on the market but also include unexpected changes in the level of interest rates, the shape of the yield curve, exchange rates, production and inflation.

The CAPM was the first theoretical model that allow to estimate how the return of a specific company should differ from a benchmark rate. However as soon as the CAPM was developed, authors began to find obvious mispriced securities and to question the generality of the theory. Questions led to an alternative and potentially more complete explanation, the APT.

The CAPM is written as: $E(R_i) = R_f + \beta_i [E(R_m) - R_f]$; where $E(R_i)$ is the expected return on stock i; $E(R_m)$ the expected return on the market; R_f the riskless rate of interest usually interpreted as the return on 30-day treasury bills. Although there are a number of papers with theoretical and empirical criticism of the CAPM, there is a basic criticism. The CAPM model does not describe accurately the expected return for groups of stocks with particular characteristics, such as small stocks. Many academics believe that the CAPM fails because due to the fact that there are additional systematic or pervasive influences that the CAPM fails to capture.

Elton, Gruber and Mei (1994), for each of their 100 randomly selected firms regress monthly returns against the monthly value of the unexpected change in each of the economic variábles affecting stock returns. This produces a set of betas for each of the 100 firms. The second step involves regressing for each month, the monthly return for each of the 100 firms against the six sensitivities. This produces for each month an estimate of the market price of risk. The cost of equity capital (on a monthly basis) for any utility can be estimated by simply adding an estimate of the risk free rate to the sum of the products of the b_j's and λ_i's. For example Elton, Gruber and Mei (1994), find that for Mohawk data the monthly cost of capital is ($R_i = R_f + .72$). This implies that the monthly cost of capital should be .72% above the monthly risk-free rate. By using the average 30-day treasury-bill rate for the year 1991 (.455%) as the risk free rate, the monthly cost of capital is 1.175%. If instead the rate on the one-year treasury bill as of January 1, 1991 (converted into monthly rate), the monthly cost of capital is 1.27%. The annual estimates are obtained by multiplying the two estimates by 12, 14.1 % and 15.24 % respectively.

Elton, Gruber and Mei (1994), made the assumption that the intercept of the cost of capital equation is the risk-less rate of interest in preparing the estimates of the cost of capital. The APT theory states that the intercept should be the risk-less rate, and it did not differ from the risk-less rate. They based their cost of capital estimates on four alternatives: (1) the actual average Treasury bill rate over the year of the estimate. They claim that while the treasury bill rate over the year could not have been known at the time of the estimate, they consider this the estimate that would have been made on average from an unbiased forecast. (2): the yield to maturity on a one-year Treasury bill at the time of the estimate. One year yields reflect the market expectations about the average of one-month to 12-month treasury bills at the time the yield is observed if the expectations theory of the term structure holds. (3): The yield to maturity on a one-year treasury bill minus an estimate of the amount by which one-year rates have exceeded the return from holding a series of twelve one-month bills. (4): the yield to maturity on a five-year treasury bond minus an estimate of the amount by which five-year rates have exceeded the return from holding a series of 600 one-month bills. Techniques 3 and 4 are similar in concept and except in times when the shape of the yield curve is behaving in an atypical way should lead to similar estimates of the risk free-rate. They find that the cost of equity capital is higher in the early years and declines to 1991, this primarily reflects the lowering of the T-bill rates over this period.

Schink and Bower (1994), test the FF multi-factor model's ability to measure the cost of equity for New York electric utilities. They develop returns for these utilities based on the model and compare them with returns allowed by the New York Public Service Commission in the past. They also claim that the CAPM has been criticized on both theoretical and empirical grounds. An empirical problem of particular interest in utility regulation is that the CAPM model underpredicts the cost of common equity for stocks. The CAPM fails to explain return on equity differences among stocks of companies that vary in size, leverage, earnings-price ratios and book-to-market ratios.

Schink and Bower (1994) test the FF multi-factor consisting of the following factors: the market factor (RM-RF), the size or vulnerability factor, which is a portfolio that proxies the common risk factor in returns related to size by the difference between returns on portfolios of small stocks and portfolios of big stocks that have approximately the same weighted-average-average book-to-market equity ratio. The book-to-market or stress factor, which is a portfolio that proxies the common risk factor in returns related to book-to-market equity by the difference between returns on high and low book-to-market ratio portfolios of stocks that approximately the same weighted average size. The term factor, which is a return series that proxies thee common risk factor associated with movements in interest rates by the difference between returns for long-term government bonds and for one-month treasury bills.

In order to estimate the sensitivity of an asset to these factors, Schink and Bower (1994), regress monthly returns from the assets on the five risk factor proxies. The estimated equation is:

$$(R-R_F)_t = b_0 + b_1(R_M - R_F) + b_2 SMB_t + b_3 HML_t + b_4 TERM_t + b_5 DEF_t + \varepsilon_t$$

b_1 to b_5 are regression coefficients that estimate sensitivity to each risk factor; and b_0, the regression intercept, should approach zero or quite properly, should be forced to zero, because the five risk factors reflect all systematic elements of risk that cause the portfolio, stock, or bond return to exceed the risk-free rate. The historical averages for the factors provide a simple, if not the best, estimate for the expected premium. To turn the expected excess return for an asset calculated from the asset's sensitivity and factor premiums into the asset's cost of equity capital require a final step, the addition of the risk-free rate to the expected excess return.

They initially applied the FF model to a single portfolio of 69 electric and combination electric/gas utility stocks (hereafter described simply as electric). Using the average monthly excess returns for the 69 electric utility companies for each month for the period January 1964 through December 1991, they estimated the sensitivities, and found the intercept not significantly different from. To calculate the cost of equity capital or required return implied by the risk sensitivities of this electric utility portfolio, the average 1964-1991 average monthly premium on each risk factor is multiplied by the corresponding estimated factor sensitivity and summed. The resulting sum is the return above the risk free rate or excess return that is required to compensate for the portfolio's risk sensitivity. The excess return is 0.45, to convert the monthly figure to an annual return; it is raised to the 12^{th} power, for annual return of 5.5%. Schink and Bower (1994), calculate the expected risk-free rate as the yield on long-term government bonds, 7.3% in December 1991, less the historic 1926-1991 difference off 1.3% in total return on long-term government bonds and US treasury bills as reported by Ibbotson Associates. Adding the risk-free rate (6%) to the annual excess return for the 69-ccompany electric portfolio (5.5%) produces an estimated cost of equity capital for the average electric utility in the US at the end of 1991 of 11%.

Next, in order to focus their analysis on a single jurisdiction, New York, they estimate the FF regression for each of the seven New York electric utilities, using monthly data from January 1964 through December 1991. They find the R-squareds for individual company equations substantially lower as a group because the individual company data are noisier. They find the average cost of equity capital across the seven individual estimates is 12.5%, 1% point above the 11.5% for the 69-stock electric utility portfolio. They also estimate the FF regression for size/book-to-market portfolios of US electric/combination stocks. They divide the 69 US electric utilities into four size/book-to-market portfolios: big ME/low BE/ME, the portfolio that should have the least risk; small ME/low BE/ME; big/ME/high BE/ME; and small ME/high BE/ME, the portfolio that should have the most risk. They estimate the FF regression for each of the four size/book-to-market utility stock portfolios using monthly data for the period of January 1964 through December 1991. The R-squareds are higher than those for the noisier individual New York utilities. The cost of equity capital rises from the 10% for the lowest risk big/low portfolio to 12.3% for the highest risk small/high portfolio.

To test their cost of equity calculations, Schink and Bower (1994), compare for 1980 to 1992, the bare-bone returns actually allowed by the New York Commission and the returns they would have provided. They make this comparison for each New York electric utility case and for the annual average of New York electric utility cases. For the twelve years in their sample, the returns actually allowed by the New York Commission and the returns they would have estimated have almost identical mean values. The mean allowed return for cases is 13.99%, and the mean of their estimates is 13.97%. The means for annual averages (which vary from the means for cases because some years include more cases than others) are 13.88% allowed and 13.96% estimated. Although the average allowed return and the estimated cost of equity are almost identical over the 1980-1991, the allowed return figures have a wider dispersion by case and by year. For example, they mention, the standard deviation of allowed return by year is 1.67%, while that for estimated cost of equity is 0.93%.

However a more difficult comparative test for the FF model-based cost of equity estimates involves individual cases and individual years. Of the 56 cases, allowed return and estimated return differ by 2% points or more in 12, by more than 1% points but less than 2% points in 20, and by less than 1 % point in 24. The mean absolute deviation is 1.29%. For the 12 annual average figures, only two have a difference between allowed and estimated above 2%, and 8 have a difference of less than 1%. The mean absolute deviation for the years is 0.89%. Schink and Bower (1994), comment that these results do not make a very good case for of individual electric utility estimates, but do support the use of averages for the New York electric utilities.

Having reviewed the literature on the estimation of cost of capital, we believe that the following issues related to the cost of capital estimation are worth explored. First to provide estimates of the UK industry cost of capital. Second to explore whether traditional-unconditional betas or conditional time-varying betas provide more accurate estimates of the cost of capital estimation and which have smaller errors. Third to obtain estimates of expected factor premiums beyond historic averages and estimate the prices of risk using the non-linear seemingly unrelated regression estimates (NLSUR), suggested by Elton, Gruber and Mei (1994). Fourth we also estimate the cost of capital using the Capital Asset Pricing model (CAPM) and compare the Arbitrage Pricing Model (APM) estimates of cost of capital with the CAPM estimates of cost of capital in order to examine which model provide more accurate estimates of the cost of capital.

7.2 INDUSTRY INDICES AND MODEL DESCRIPTION

The industry indices are obtained from Datastream (Datastream classification), for the period 1976 to 1996. Table 7.1 shows the industries, the number of companies in each index and reports the mean monthly return. The indices are value weighted, with capital gains included without dividend adjustment. Table 7.1 indicates that over the 1976 to 1996 period the sectors that provide the highest return are the banking sector, the life assurance, the media, pharmaceuticals, retail and the support services sector.

Since the aim of the chapter is to compare different competitive models in order to identify which provide the best estimates of the UK Industry Cost of Capital, we proceed with the estimation of the parameters of these models. The competitive models that are going to be estimated are the following:

1. The Unconditional-constant APT model
2. The Conditional APT model
3. The CAPM model

The Unconditional-constant APT model is a macroeconomic factor model consisting of the following factors: the return on the FTSE, S&P 500 share price index, unexpected UK stock exchange turnover, change in money supply, imports, and inflation. The particular characteristic of the Unconditional APT model is the betas of the factors are constant throughout the 1976-1996 time period.

The Conditional APT model is also a macroeconomic factor model consisting of the same following factors: the return on the FTSE, S&P 500 share price index, unexpected UK stock exchange turnover, change in money supply, imports, and inflation. However the betas are time-varying and conditioned on the following set of instrumental variables. These consist of one-month Treasury bill rate, lagged one month, the dividend yield on FTA all share price index, lagged one month, the term structure of interest rates, lagged one month, the return on FTA all share price index, lagged one month and the return on S&P 500 index, lagged one month.

Both the Unconditional-constant APT model and the Conditional APT estimates of the cost of capital use estimates of the prices of risk obtained from Non-linear Seemingly unrelated regression (NLSUR). The CAPM cost of capital estimated in this paper, uses estimate of the price of risk for the market factor obtained also via Non-linear Seemingly unrelated regression (NLSUR). The market beta of the CAPM model remains constant.

Table 7.1: Industry Indices

The Industry Indices are obtained from Datastream, for the period 1976 to 1996. These are value weighted with capital gains included without dividend adjustment. Table 7.1 shows the industries, the number of companies in each index and reports the mean monthly return.

Period: 1976-1996	**No of**	**Mean Return**
Industry	**Companies**	**Monthly**
Banks	13	0.011153
Building mats & Merchants	23	0.007069
Breweries Pubs & Restaurant	22	0.010815
Chemicals	20	0.006569
Construction	38	0.0067
Distributors	11	0.010708
Diversified Materials	2	0.008855
Engineering	26	0.008986
Engineering Vehicles	7	0.005668
Extractive Industries	5	0.009939
Food Producers	18	0.009104
Health Care	8	0.011306
Household Goods & Texts	8	0.009462
Insurance	10	0.007038
Leisure & Hotels	11	0.010224
Life Assurance	7	0.012089
Media	25	0.013472
Oil Exploration & Production	10	0.00844
Oil Integrated	2	0.010927
Paper, packaging, printing	10	0.007163
Pharmaceuticals	12	0.015632
Property	24	0.00842
Retail general	25	0.010969
Support Services	32	0.011474

7.3. ESTIMATION OF UNCONDITIONAL AND CONDITIONAL BETAS

A manager that utilises an asset pricing model in order to measure the discount rate for a project faces the problem of estimating as accurate as possible the project's sensitivities (betas) to the model's risk factors. Section 7.3 explains how we estimate the unconditional-constant betas and the conditional sensitivities. Thus in order to estimate the cost of capital as precise as possible we need precise estimates of risk loading for the factors. Estimates of the Arbitrage Pricing Model (APM) would be precise, provided that the betas are constant over time; however there is evidence that betas vary over time. However we do not know whether they change rapidly or vary slowly through time. In order to examine this issue, we estimate full-period constant unconditional betas and conditional betas.

7.3.1 UNCONDITIONAL BETAS

The constant unconditional betas are the slopes $\beta_{RSRFT}, \beta_{RSRSP}$ $\beta_{RSRTU}, \beta_{RSRMO}$ $\beta_{RSIMP}, \beta_{RSINF}$ in the regression of the industry return on the factors.

$$R_{INDUSTRYit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSRSP} RSRSP_t + \beta_{RSRTU} RSRTU_t + \beta_{RSRMO} RSRMO_t$$
$$+ \beta_{RSIMP} RSIMP_t + \beta_{RSINF} RSINF_t + e_{it}$$

Where: $R_{INDUSTRYit}$ is the industry return in month t; α_i a constant term; $\beta_{RSRFT} \beta_{RSRSP}, \beta_{RSRTU}, \beta_{SRMO}, \beta_{RSIMP}, \beta_{RSINF}$ are the constant betas of the return on FTSE, return on S&P 500, unexpected components of the UK stock exchange turnover, change in money supply, change in imports, change in inflation; e_t is the zero mean idiosyncratic term. Table 7.2 shows the full-period Unconditional betas for each factor.

The betas measure the average response of the industry to unanticipated changes in the respective economic factors. For example an industry with an S&P 500 beta of one will tend to move up or down by 1% in response to 1% rate of S&P 500. If the industry's beta is less than one, then the S&P 500 has less than proportional impact on the industry's return. An industry with a beta of 0.3, will show a 0.3% increase, in return for every 1% return of the S&P 500. However many industries have negative betas and tend to do worse than expected when a factor is greater than expected. For example an industry with an inflation beta of (-0.4), loses 0.4% for each 1% unanticipated inflation.

Table 7.2: Unconditional Betas

The full-period unconditional betas are the slopes $\beta_{RSRFT}\beta_{RSRSP}$ $\beta_{RSRTU}, \beta_{SRMO}, \beta_{RSIMP}, \beta_{RSINF}$ of the return on FTSE, S&P 500, the unexpected components of the UK stock exchange turnover, change in money supply, imports, and inflation, in the regression of the industry return on the factors.

$$R_{INDUSTRYit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSRSP} RSRSP_t + \beta_{RSRTU} RSRTU_t + \beta_{RSRMO} RSRMO_t$$
$$+ \beta_{RSIMP} RSIMP_t + \beta_{RSINF} RSINF_t + e_{it}$$

Where: $R_{INDUSTRYit}$ is the industry return in month t; α_i a constant term; e_t is the zero mean idiosyncratic term.

UNCONDITIONAL BETAS						
INDUSTRY	RSRFT	RSRSP	RSRTU	RSRMO	RSIMP	RSINF
Banks	0.870438	-0.01103	0.017487	-0.05832	6.24E-03	-1.25E-03
Build mats & merch.	0.822451	8.44E-03	-0.02046	-0.29227	-2.45E-03	-0.03449
Brew pubs & rest.	0.604671	-0.14945	7.38E-03	0.066888	-2.23E-03	-0.04812
Chemicals	0.882503	0.046312	-0.01645	-0.2423	6.43E-03	2.04E-03
Construction	0.773715	0.053361	-0.05377	-0.50733	2.52E-04	-0.08193
Distributors	0.850144	5.47E-04	-0.0273	-0.1577	3.04E-03	-0.07083
Diversif. materials	0.809165	0.044976	-0.01678	-0.22139	6.02E-03	-0.01499
Enginnering	0.82988	0.027996	-0.03265	-0.35071	4.70E-06	2.67E-03
Engineer. vehicles	0.910855	-0.01297	-0.04815	-0.37355	-6.12E-04	-0.0268
Extractive indust	1.00486	0.049458	-0.02235	-0.15141	4.37E-03	5.47E-03
Food producers	0.709825	-3.47E-03	-3.32E-03	-0.12988	3.87E-03	-0.03481
Health care	0.740038	-0.04162	-0.0108	0.048912	3.86E-03	-0.04699
Household goods	0.843878	0.048429	-7.22E-03	-0.22154	4.15E-03	-0.08532
Insurance	0.793301	0.082735	-0.0152	-0.15998	4.40E-03	-0.02066
Leisure & hotels	0.74571	0.057517	-0.04245	-0.2742	3.05E-03	-0.0622
Life assurance	0.845776	-0.02595	-0.01482	-0.03881	3.58E-03	-0.06403
Media	0.917829	-0.03966	-0.0207	-0.29816	3.57E-03	-0.01569
Oil expl & product.	0.977058	-0.11162	-0.02099	-0.42107	1.82E-03	0.135874
Oil integrated	0.732222	0.011691	-0.0184	-0.11125	-1.21E-03	0.035523
Paper, pack, print.	0.792876	0.054252	-0.02469	-0.17654	4.07E-03	-0.03673
Pharmaceuticals	0.846398	0.095242	-8.07E-03	-0.16215	4.78E-03	-0.06797
Property	0.642367	0.056987	-3.81E-03	-0.09358	-3.81E-03	-0.03367
Retail	0.678997	7.62E-03	-0.01091	-0.11391	-2.26E-03	-0.05532
Support services	0.72215	0.017358	-0.01622	-0.14183	7.34E-04	-0.04138

7.3.2. CONDITIONAL BETAS

Conditional beta models assume that market prices fully reflect readily available information, and one of the hypotheses involved is that managers use this information to determine their portfolio strategies. So conditional betas, defined in this paper, incorporate not only time variation as a property, but also these betas are conditioned to a set of information-instrumental variables, which reflect information in the market that investors use.

Conditional beta estimation involves the following steps. Step 1 involves estimation of rolling betas. Step 2 involves use of these rolling betas as dependent variable regressed on a set of instrumental variables. The fitted values from this regression (the beta regressed on the instrumental variables) is defined as the conditional beta. Thus in the first step we incorporate the time variation property in the estimation of the conditional betas. The second step incorporates the conditional property, since the time-varying betas are conditioned on a set of instrumental variables that convey publicly available information.

Step 1: In order to document temporal variation in risk loadings, we estimate rolling regressions using five years of past returns, i.e., using a rolling window of 60 prior monthly returns. Thus the industry's exposure to the macroeconomic factors and the market index are estimated by regressing the industry return on the unanticipated components of the macroeconomic factors and the market indexes, using time series regressions over an estimation period of 5 years, i.e., (60 months rolling). The slope coefficients in the time-series regressions provide estimates of the betas. We use the five-year period and update the estimates annually. For example we run the following regression with the industry return being the dependent variable on the factors, from 1976-1980 in order to obtain betas for 1981.

$$R_{INDUSTRYit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSRSP} RSRSP_t + \beta_{RSRTU} RSRTU_t + \beta_{RSRMO} RSRMO_t + \beta_{RSIMP} RSIMP_t + \beta_{RSINF} RSINF_t + e_{it}$$

Where: $R_{INDUSTRYit}$ = the industry return in month t

The rolling betas are the slopes $\beta_{RSRFT}, \beta_{RSRSP}, \beta_{RSRTU}, \beta_{RSRMO}$ $\beta_{RSIMP}, \beta_{RSINF}$ of the rolling regression of the industry return on the factors.

Thus the outcome of step 1 is a time-series (from 1981 to 1996) of rolling betas for each factor. Step 2: Then each beta is used as dependent variable regressed on a constant and a set of instrumental variables. The fitted values from this regression is defined as the conditional beta. A conditional beta is defined as the beta conditioned on a set of instrumental variables.

Hence having obtained a time series of rolling betas from 1981 to 1996 for the FTSE, S&P 500, UK stock exchange turnover, changes in money supply, imports and inflation, we run the following regressions.

$$\beta_{RSRFT} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\beta_{RSRSP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\beta_{RSRTU} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\beta_{RSRMO} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\beta_{RSIMP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

$$\beta_{RSINF} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

Where $\beta_{RSRFT}, \beta_{RSRSP}, \beta_{RSRTU}, \beta_{RSIMP}$ β_{RSRMO} β_{RSINF} are the betas of the return on FTSE; Standard & Poors 500, unanticipated UK Stock Exchange Turnover, change in money supply, imports and inflation; δ_0 is a constant; e_t is the residual. Where $CTB1_{t-1}, CDIV_{t-1}, TS1_{t-1}, RFT_{t-1}, RSP_{t-1}$, are the instrumental variables; the One month Treasury bill rate, lagged one month, the dividend yield on FTA all share price index, lagged one month, the term structure of interest rates, lagged one month, the return on FTA all share price index, lagged one month and the return on S&P 500 index, lagged one month. These instrumental variables are chosen because, the summarise expectations in the economy that are related to the prospects for stock returns, that is they have the ability to forecast asset returns. For example short-term interest rates have been prominent instruments in several studies, their importance as instruments in tests of asset pricing models stems from their relation with consumption, production and returns. The dividend yield has also been examined and found to have predictive ability.

We estimate conditional betas with an out-of-sample evaluation. We fit a model in which the rolling beta is used as dependent variable regressed on a constant and a set of instrumental variables. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place, in order to forecast the conditional betas. Using an initial estimation period of 60 months from 1981-1985, we forecast the conditional betas for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, this forecast the conditional betas for the following twelve months, 1987. [2] Table 7.3 shows the Conditional betas for each of the factors for December 1996. These are used in the following section for the estimation of the Conditional cost of capital for December 1996.

The betas express the response of each industry to unanticipated changes in the respective economic factors. A beta of a factor greater than one means that the industry's return is magnified by that respective factor. For example Table 3 shows that the banking, the construction and the media industry sectors have a FTSE December 96 conditional beta of 1.128, 1.146 and 1.31 respectively. This implies that a 1% increase in the FTSE will lead to 1.128 % additional return to the banking sector, 1.146 % additional return to the construction sector and 1.31 % additional return to the media industry sector, or the other way around if there is a 1% fall in the FTSE. This reflects the fact that media companies are normally marked down by investors during slowdown. The reason is that advertising normally falls quicker than the economy as a whole slows, also holdings in the banking sector. Regarding to the construction sector, during recession periods both residential and commercial

[2] Campbell (1986) examines whether variables that have been used to predict excess returns in the term structure also predict excess stock returns in the US. His data consist of monthly time-series returns on five asset returns and four instrumental variables. First he runs regressions of the excess return on a constant and four instruments, and keeps the fitted values. Then he uses the fitted values as the dependent variable and regress on a constant and the four instruments.

construction are weak. On the other hand some industries have a FTSE beta less than one, which expresses the fact that the FTSE has less than proportional impact on the industry's return. Table 3 show that this is the case for the food industry and the health care industry sectors; they have a December 96 conditional beta of 0.90 and 0.93. The fact that these industries have a FTSE beta less than one reflects the fact that they are more traditionally defensive sectors, given the argument that food and healthcare products will always be in demand.

Table 7.3: Conditional Betas

Conditional beta estimation involves the following steps. Step 1 involves estimation of rolling betas. Step 2 involves use of these rolling betas as dependent variable regressed on a set of instrumental variables. The fitted values from this regression (the beta regressed on the instrumental variables) is defined as the conditional beta.

Step 1: In order to document temporal variation in risk loadings, we estimate rolling regressions using five years of past returns, i.e., using a rolling window of 60 prior monthly returns. Thus the industry's exposure to the macroeconomic factors and the market index are estimated by regressing the industry return on the unanticipated components of the macroeconomic factors and the market indexes, using time series regressions over an estimation period of 5 years, i.e., (60 months rolling). The slope coefficients in the time-series regressions provide estimates of the betas. We use the five-year period and update the estimates annually. For example we run the following regression with the industry return being the dependent variable on the factors, from 1976-1980 in order to obtain betas for 1981.

$$R_{INDUSTRYit} = \alpha_i + \beta_{RSRFT} RSRFT_t + \beta_{RSRSP} RSRSP_t + \beta_{RSRTU} RSRTU_t + \beta_{RSRMO} RSRMO_t$$
$$+ \beta_{RSIMP} RSIMP_t + \beta_{RSINF} RSINF_t + e_{it}$$

Where: $R_{INDUSTRYit}$ the industry return in month t

The rolling betas are the slopes $\beta_{RSRFT}, \beta_{RSRSP}, \beta_{RSRTU}, \beta_{RSRMO}$ $\beta_{RSIMP}, \beta_{RSINF}$ of the rolling regression of the industry return on the factors.

Thus the outcome of step 1 is a time-series (from 1981 to 1996) of rolling betas for each factor. Step 2: Then each beta is used as dependent variable regressed on a constant and a set of instrumental variables. The fitted values from this regression is defined as the conditional beta. A conditional beta is defined as the beta conditioned on a set of instrumental variables.

Hence having obtained a time series of rolling betas from 1981 to 1996 for the FTSE, S&P 500, UK stock exchange turnover, changes in money supply, imports and inflation, we run the following regressions.

$$\beta_{RSRFT} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$
$$\beta_{RSRSP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$
$$\beta_{RSRTU} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$
$$\beta_{RSRMO} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$
$$\beta_{RSIMP} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$
$$\beta_{RSINF} = \delta_0 + \delta_1 CTB1_{t-1} + \delta_2 CDIV_{t-1} + \delta_3 TS1_{t-1} + \delta_4 RFT_{t-1} + \delta_5 RSP_{t-1} + e_t$$

Where $\beta_{RSRFT}, \beta_{RSRSP}, \beta_{RSRTU}, \beta_{RSIMP}$ β_{RSRMO} β_{RSINF} are the betas of the return on FTSE; Standard & Poors 500, unanticipated UK Stock Exchange Turnover, change in money supply, imports and inflation; δ_0 is a constant; e_t is the residual. Where $CTB1_{t-1}, CDIV_{t-1}, TS1_{t-1}, RFT_{t-1}, RSP_{t-1}$, are the instrumental variables; the One month Treasury bill rate, lagged one month, the dividend yield on FTA all share price index, lagged one month, the term structure of interest rates, lagged one month, the return on FTA all share price index, lagged one month and the return on S&P 500 index, lagged one month.

We estimate conditional betas with an out-of-sample evaluation. We fit a model in which the rolling beta is used as dependent variable regressed on a constant and a set of instrumental variables. We use a holdout sample of 132 months where the out-of-sample evaluation is taking place, in order to forecast the conditional betas. Using an initial estimation period of 60 months from 1981-1985, we forecast the conditional betas for twelve next twelve months, 1986. Then the previous twelve months are added to estimation period for the re-estimation of the model, this forecast the conditional betas for the following twelve months, 1987.

Table 7.3: -*Continued*- Conditional Betas

DECEMBER 96 CONDITIONAL BETAS						
INDUSTRY	RSRFT	RSRSP	RSRTU	RSRMO	RSIMP	RSINF
Banks	1.128735	-0.09056	-0.00892	-0.00269	0.005159	-0.14669
Build mats & merch.	1.19462	0.053929	-0.04097	-0.56588	-0.00604	-0.11028
Brew pubs & rest.	0.732091	-0.10558	0.041651	0.121268	-0.01091	-0.10749
Chemicals	1.224109	0.162927	-0.03042	-0.2611	0.00723	-0.0653
Construction	1.146125	0.031236	-0.09398	-0.70223	-0.0043	-0.10351
Distributors	1.123977	-0.01528	-0.0373	-0.20051	0.00038	-0.11158
Diversif. materials	1.175976	0.031506	-0.02887	0.074107	0.00504	-0.04988
Engineering	1.125724	0.024777	-0.03612	-0.56034	-0.00162	-0.03638
Engineer. vehicles	1.388711	-0.03624	-0.05021	-0.49408	0.003086	-0.19611
Extractive indust	1.294828	0.010996	-0.02357	0.083491	-0.00081	-0.00061
Food producers	0.901047	0.001462	-0.006	-0.23763	-0.0015	-0.10658
Health care	0.936605	-0.03818	-0.02283	0.042515	0.002846	-0.12477
Household goods	0.965619	0.124644	-0.0081	-0.19183	0.003648	-0.14724
Insurance	1.09141	0.073457	-0.03408	-0.19956	0.006194	-0.0762
Leisure & hotels	1.087028	0.057359	-0.02813	-0.12685	-0.00125	-0.12027
Life assurance	1.053786	-0.0781	-0.01344	-0.02993	0.001684	-0.10845
Media	1.317991	0.017919	-0.02098	-0.26277	0.005802	-0.05251
Oil expl & product.	0.948496	0.068624	-0.06818	-0.67622	-0.0016	0.341957
Oil integrated	0.722724	0.013879	-0.04862	-0.26799	-0.0007	0.058794
Paper, pack, print.	1.092118	0.002152	-0.0371	-0.24071	-0.00232	-0.1268
Pharmaceuticals	1.089225	0.126997	-0.00746	-0.29641	0.009398	0.013424
Property	0.914895	0.017845	-0.01388	0.135403	-0.00831	-0.04204
Retail	0.94948	-0.13464	0.005206	-0.23088	-0.00629	-0.15462
Support services	0.971913	-0.05144	-0.00213	-0.16659	-0.00145	-0.10776

7.4. ESTIMATION OF ARBITRAGE PRICING MODEL PRICES OF RISK

The estimation of the Industry Cost of Capital requires apart from the estimation of the sensitivities (betas) the estimation of the prices of risk. We estimate the prices of risk using Non-linear Seemingly unrelated regression (NLSUR). We decide to estimate the prices of risk using this approach because since the same parameters appeared in more than one of the regression function, the system would be said to subject to cross-equation restrictions. In the presence of such restriction, it is obvious that we would want to estimate all equations as a system rather than individually, in order to obtain efficient estimates. The essential feature of simultaneous equation models is that two or more endogenous variables are determined jointly within the model, as a function of exogenous variables or predetèrmined variables and error terms.

The Non-linear Seemingly unrelated regression (NLSUR) model consists of a series of equations linked because the error terms across equations are correlated, the NLSUR model involves generalised least squares estimation and achieves an improvement in efficiency by taking into account the fact that cross-equation error correlation may not be zero. Elton, Gruber and Mei (1994) actually claim that an estimation procedure worthwhile exploring in the future involves estimating the prices of risk via seemingly unrelated regression. This technique allows us to impose the constraint that the prices of risk are constant across all industries. An advantage of using NLSUR is that it allows the APT's principle, that the price of risk is equal across every industry to be tested.

$$R_{INDUSTRYit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

For industry return $i = 1,\ldots,24$

Where: $R_{INDUSTRYit}$ = the industry return in month t

λ_j = the price of risk for the factor j

Where: $RSRFT_t, RSRSP_t, RSRTU_t, RSRMO_t, RSIMP_t, RSINF_t$, the return on FTSE, S&P 500, unexpected components of UK stock exchange turnover, change in money supply, imports, inflation; e_{it} is the zero mean idiosyncratic term. Also the price of risk (λ_j) is the same for each jth factor for each industry.

Table 7.4, Panel B, shows the estimates and t-statistics of the prices of risk for the return on FTSE, S&P 500, unexpected stock exchange turnover, change in money supply, imports and inflation. Table 7.4, Panel B, shows that the return on FTSE, S&P 500, unexpected stock exchange turnover, change in money supply, imports and inflation are all significant for the industry sectors under consideration in this paper. It is possible to find companies that are relatively more sensitive to certain non-unique factors (in the sense that they carry different premia for different sub-samples of assets). The fact that we identified factors that have significant prices of risk for all of the industry sectors examined shows that we have obtained uniqueness in the return generating process.

Table 7.4

The Non-linear Seemingly unrelated regression (NLSUR) model consists of a series of equations linked because the error terms across equations are correlated, the NLSUR model involves generalised least squares estimation and achieves an improvement in efficiency by taking into account the fact that cross-equation error correlation may not be zero.

$$R_{INDUSTRYit} = \lambda_0 + \lambda_1\beta_{i1} + \lambda_2\beta_{i2} + \lambda_3\beta_{i3} + \lambda_4\beta_{i4} + \lambda_5\beta_{i5} + \lambda_6\beta_{i6} +$$
$$\beta_{i1}RSRFT_t + \beta_{i2}RSRSP_t + \beta_{i3}RSRTU_t + \beta_{i4}RSRMO_t + \beta_{i5}RSIMP_t + \beta_{i6}RSINF_t + e_{it}$$

For industry return $i = 1,\ldots,24$

Where: $R_{INDUSTRYit}$ = the industry return in month t; λ_j = the price of risk for the factor j; e_t is the zero mean idiosyncratic term.

Panel A

SYMBOL	MACROECONOMIC FACTORS & INDEXES
RSRFT	Return on Financial Times All Share Index
RSRSP	Return on Standard & Poors 500 Price Index
RSRTU	Unanticipated UK Stock Exchange Turnover
RSRMO	Unanticipated Change in Money Supply (MO)
RSIMP	Unanticipated Change in Imports
RSINF	Unanticipated Change in Inflation

Panel B

Price of risk λ	Estimate	T-statistic
λ_{RSRFT}	0.30201	3.9964***
λ_{RSRSP}	-0.06837	-1.7460*
λ_{RSRTU}	0.350781	5.9111***
λ_{RSRMO}	-0.77503	-5.0962***
λ_{RSIMP}	-0.27437	-2.0360**
λ_{RSINF}	0.13595	4.9503***

***: Denotes significant at 1%.
**: Denotes significant at 5%.
*: Denotes significant at 10%.

7.5. THE INDUSTRY COST OF CAPITAL

Section 7.3 and 7.4 described the estimation of the unconditional-constant betas, the conditional betas and the estimation of the prices of risk of the return on FTSE, S&P 500, unexpected components of UK stock exchange turnover, change in money supply, imports, inflation via Non-linear Seemingly unrelated regression. Section 5 estimates the cost of capital using these parameters.

Table 7.5 reports estimates of the cost of capital for the constant-unconditional and conditional betas. We notice differences, between unconditional betas and conditional betas cost of capital. Table 7.5 shows that for certain industries the conditional cost of capital is higher than the constant cost of capital. This is the case for the following industries: banks, building materials and merchants, breweries pubs & restaurant, chemicals, construction, distributors, engineering, engineering vehicles, food producers, health care, insurance, life assurance, media, oil exploration and production, oil integrated, paper, packaging, printing, pharmaceuticals, retail, and the support services industry. These differences in unconditional betas capital and conditional betas capital are driven by differences in the estimates of constant betas and conditional betas. Table 7.2 and 7.3 report the full period-constant Unconditional betas and the Conditional betas for December 1996 respectively. The conditional betas for December 1996 are above the estimates from the full-period constant betas. As a result the conditional betas capital is above the constant beta capital for these industries.

Table 7.5: Cost of Capital-APT Model

The first estimate of cost of capital in table 7.5 use slopes from the full-period constant-unconditional beta APT model. The second estimate of cost of capital use estimates of betas from the conditional regressions for December 1996. These figures of cost of capital in table 7.5 have been multiplied by 12 (annual rate), since annual data is often supplied for capital budgeting purposes. [3]

COST OF CAPITAL	FULL PERIOD	DECEMBER 96
INDUSTRY	UNCONDITIONAL	CONDITIONAL
Banks	13.91	14.64
Build mats & merch.	15.70	19.00
Brew pubs & rest.	11.81	12.50
Chemicals	15.48	15.57
Construction	17.26	20.03
Distributors	14.46	15.86
Diversif. materials	14.99	13.29
Engineering	16.25	19.03
Engineer. vehicles	16.68	19.48
Extractive indust	15.06	13.89
Food producers	13.86	15.42
Health care	12.29	13.13
Household goods	15.05	14.26
Insurance	14.34	15.14
Leisure & hotels	15.07	14.55
Life assurance	13.43	14.58
Media	16.14	17.03
Oil expl & product.	17.79	19.60
Oil integrated	13.82	15.05
Paper, pack, print.	14.45	15.97
Pharmaceuticals	14.50	15.88
Property	13.26	12.00
Retail	13.55	16.50
Support services	13.94	15.42

On the other hand, for certain industries the conditional cost of capital is lower than the constant cost of capital. This is the case for the following industries:

[3] See Fama and French (1997).

diversified materials, extractive industries, household goods, leisure and hotels and the property industry. These differences in unconditional betas capital and conditional betas capital are attributed to the differences in the estimates of constant betas and conditional betas.

In order to evaluate which betas, the unconditional, or the conditional provide the best forecasts of the cost of capital we estimate the Mean Square Error (MSE). The MSE is summary measures, which gives us the ability to summarise errors to make judgement about what the average error has been.

$$MSE = \sum_{t=1}^{n} \frac{e_t^2}{n}$$

Where e_t is the difference between the Arbitrage Pricing Model (APM) estimates and the actual industry returns, and n is the number of observations.

Table 7.6 shows the MSE for each industry and the average MSE. The average MSE for the unconditional and conditional betas is 0.310 and 0.298 respectively. The conditional beta cost of capital gives less mean square error for nineteen out of twenty four industries, banks, building materials and merchants, chemicals, construction, distributors, engineering, engineering vehicles, food producers, health care, household goods, insurance, leisure and hotels, life assurance, media, paper, packaging, printing, pharmaceuticals, retail, and the support services industry. On the other hand the unconditional cost of capital gives less mean square error for five out of the twenty four indices; breweries pubs & restaurant, extractive industries, oil exploration and production, oil integrated, paper, packaging, printing. This evidence implies the following explanations. Maybe the industry's beta is mean reverting for the industries that the unconditional cost of capital gives less errors, so deviations from the long-term mean are temporary, and estimates from the full-period constant unconditional-slope regressions provide better estimates. A possible explanation is that betas change through time very slowly, and for the breweries pubs & restaurant, extractive industries, oil exploration and production, oil integrated, paper, packaging, printing the conditional betas may have a tendency to overstate the time-variation and as a result produce beta that is too volatile and changing too rapidly.

Table 7.6: Mean Square Error -APT Model

Table 7.6 shows the Mean Square Error. Where e_t is the difference between the APM estimates and the actual industry returns, and n is the number of observations.

$$MSE = \sum_{t=1}^{n} \frac{e_t^2}{n}$$

MEAN SQUARE ERROR		
INDUSTRY	UNCONDITIONAL	CONDITIONAL
Banks	0.230	0.196
Build mats & merch.	0.395	0.329
Brew pubs & rest.	0.092	0.329
Chemicals	0.371	0.274
Construction	0.528	0.449
Distributors	0.276	0.208
Diversif. materials	0.324	0.283
Engineering	0.455	0.417
Engineer. vehicles	0.503	0.392
Extractive indust	0.330	0.473
Food producers	0.226	0.167
Health care	0.118	0.092
Household goods	0.330	0.227
Insurance	0.265	0.259
Leisure & hotels	0.332	0.213
Life assurance	0.192	0.117
Media	0.442	0.299
Oil expl & product.	0.642	1.113
Oil integrated	0.222	0.423
Paper, pack, print.	0.275	0.238
Pharmaceuticals	0.279	0.229
Property	0.180	0.145
Retail	0.201	0.085
Support services	0.232	0.189
AVERAGE	0.310	0.298

The empirical evidence show that the average MSE of the Arbitrage Pricing Model (APM) with the conditional betas are smaller compared to the constant-unconditional betas. Table 7.7 reports the full-period constant betas of the CAPM model for each industry. We find for example, the banking sector to have a beta of 1.02, the building materials & merchants has a beta of 1.16, the construction sector has a beta of 1.39, the food producers have a beta of 0.85, the household goods have a beta of 0.93, the insurance sector has a beta of 1.21, the pharmaceuticals 0.76, and the retail 1.11. Fama and French (1997) find more or less similar betas for the US market. For example they report the following betas: for the banking sector 1.09, for the building materials & merchant sector 1.13, for the construction 1.28, for the food producers 0.87, for the household goods 0.97, for the pharmaceuticals 0.92 and for the retail 1.11.

In order to compare the APM estimates of cost of capital with the CAPM, we also estimate the industry cost of capital based on the market model, using NLSUR with constant betas. Table 7.8 shows the industry cost of capital based on the CAPM model. Table 7.9 shows the Mean Square Error of the CAPM.

$$MSE = \sum_{t=1}^{n} \frac{e_t^2}{n}$$

Where e_t is the difference between the CAPM estimates and the actual industry returns, and n is the number of observations.

Consistent with evidence from the US [Roll and Ross (1983), Pettway and Jordan (1987)] we find that the CAPM underestimates the cost of capital. Roll and Ross (1983) show that market model estimates are underestimates and that the statistical factors APT estimates are closer to the true cost of capital. Pettway and Jordan (1987) also find evidence consistent with Roll and Ross (1983) that the APT cost-of-capital estimates are greater than the market model estimates.

Table 7.9 summarizes the Mean Square Error of the CAPM estimates of the cost of capital. Table 7.9 shows that the CAPM has larger MSE than the APT model. The average MSE of the CAPM is 0.761. This is consistent with US evidence. Pettway and Jordan (1987) compare the relative efficiency of the CAPM and APT in the true forecasting sense of predicting future equity returns. Using weekly data on electric utilities, they find that in addition to explaining a greater degree of in-sample returns, the APT provides better forecasts of future returns than the CAPM. In fact we find that the CAPM has larger MSE not only compared to the APT model with conditional betas, but with APT model with unconditional betas. Thus our empirical evidence suggests that there are more errors involved between the CAPM and APM than between Unconditional and Conditional Beta Models. This is because there are priced factors which the CAPM miss out and does not provide a good description of the Industry returns.

Table 7.7: Market Beta

Table 7.7 reports the market beta of industries based on the market model. The market beta is constant.

CAPM	MARKET
INDUSTRY	BETA
Banks	1.02
Build mats & merch.	1.16
Brew pubs & rest.	1.03
Chemicals	0.98
Construction	1.39
Distributors	1.27
Diversif. materials	1.14
Engineering	0.91
Engineer. vehicles	1.29
Extractive indust	0.98
Food producers	0.85
Health care	0.81
Household goods	0.93
Insurance	1.21
Leisure & hotels	1.02
Life assurance	1.03
Media	1.09
Oil expl & product.	0.87
Oil integrated	0.96
Paper, pack, print.	0.86
Pharmaceuticals	0.76
Property	1.08
Retail	1.00
Support services	0.91

Table 7.8: Cost of Capital-CAPM Model

Table 7.8 show the industry cost of capital estimates based on the market model with constant market beta. The CAPM cost of capital estimated in this paper uses estimate of the price of risk for the market factor obtained also via Non-linear Seemingly unrelated regression (NLSUR). The market beta of the CAPM model is constant.

CAPM	COST OF CAPITAL
INDUSTRY	
Banks	10.48
Build mats & merch.	11.12
Brew pubs & rest.	10.52
Chemicals	10.29
Construction	12.17
Distributors	11.62
Diversif. materials	11.03
Engineering	9.97
Engineer. vehicles	11.71
Extractive indust.	10.29
Food producers	9.69
Health care	9.52
Household goods	10.06
Insurance	11.35
Leisure & hotels	10.48
Life assurance	10.52
Media	10.80
Oil expl & product.	9.77
Oil integrated	10.21
Paper, pack, print.	9.74
Pharmaceuticals	9.30
Property	10.75
Retail	10.37
Support services	9.97

Table 7.9: CAPM Model-Mean Square Error

Table 7.9 shows the Mean Square Error. Where e_t is the difference between the CAPM estimates and the actual industry returns, and n is the number of observations.

$$MSE = \sum_{t=1}^{n} \frac{e_t^2}{n}$$

CAPM	MSE
INDUSTRY	
Banks	0.756
Build mats & merch.	0.851
Brew pubs & rest.	0.762
Chemicals	0.729
Construction	1.021
Distributors	0.931
Diversif. materials	0.837
Engineering	0.684
Engineer. vehicles	0.945
Extractive indust	0.729
Food producers	0.647
Health care	0.623
Household goods	0.697
Insurance	0.887
Leisure & hotels	0.755
Life assurance	0.762
Media	0.803
Oil expl & product.	0.655
Oil integrated	0.718
Paper, pack, print.	0.653
Pharmaceuticals	0.595
Property	0.796
Retail	0.740
Support services	0.685
AVERAGE	0.761

In order to evaluate which beta model, the unconditional, the conditional or the CAPM model provide the best forecasts of the cost of capital we have estimated the Mean Square Error (MSE). We have found that the average MSE for the conditional betas are smaller compared to constant betas and that the CAPM has larger MSE not only compared to the APT model with conditional betas, but with APT with unconditional betas. The results show that the Conditional beta model has the least errors. Furthermore we perform another analysis so as to test the statistical significance of the errors that the Conditional beta model leave. We run Monte Carlo simulations, having obtained a large number of simulations, we estimate the cross-sectional average of the number of simulations we have run. Then given this average we test the statistical significance of the errors of the Conditional beta model. Table 7.10 show that the errors of the Conditional beta model are statistically insignificant. This additional evidence further indicates that the Conditional beta model is doing a good job in estimating the UK industry cost of capital, since the errors that the model leave are statistically insignificant.

Table 7.10: Monte Carlo Simulations

Statistical Significance of the Errors of the Conditional Beta Model

We run Monte Carlo simulations, having obtained a large number of simulations, we estimate the cross-sectional average of the number of simulations we have run. Then given this average we test the statistical significance of the errors of the Conditional beta model. Table 7.10 show the statistical significance of the errors of Conditional beta Model. The errors are statistically insignificant.

STATISTICAL SIGNIFICANCE OF ERRORS

INDUSTRY	T-STATISTIC
Banks	0.4230
Build mats & merch.	0.1576
Brew pubs & rest.	0.3601
Chemicals	0.5617
Construction	0.1953
Distributors	0.4297
Diversif. materials	0.8370
Engineering	0.3829
Engineer. vehicles	0.3793
Extractive indust	0.1579
Food producers	0.6738
Health care	0.6074
Household goods	0.5845
Insurance	0.4029
Leisure & hotels	0.2680
Life assurance	0.1711
Media	0.5823
Oil expl & product.	0.8858
Oil integrated	0.1037
Paper, pack, print.	0.2863
Pharmaceuticals	0.2011
Property	0.4342
Retail	1.1294
Support services	0.1414

7. 6 CONCLUSION

In this Chapter we estimate the UK industry cost of capital. We identify the model that is a good description of the UK returns, this is an APT model comprised of the following factors: the return on the FT all share price index, the S&P 500 share price index, the unexpected UK stock exchange turnover, change in money supply, imports, and inflation.

Literature on the estimation of the cost of capital (Schink and Bower (1994), Fama and French (1997)) use historic averages for the estimation of the factor premiums, and Schink and Bower (1994), actually claim that estimates of expected factor premiums can be improved by considering data beyond historic averages. In this study we use another method of estimating the price of risk, the non-linear seemingly unrelated regression estimates (NLSUR) suggested by Elton, Gruber, and Mei (1994). This technique allows us to impose the constrain that lamdas are constant across all companies. We also estimate unconditional-constant and conditional (time-varying & conditioned on a set of instrumental variables) betas in order to identify which provide better estimates of the cost of capital.

We find differences, between constant-unconditional betas and conditional betas cost of capital. For certain industries the conditional cost of capital is higher than the constant cost of capital. These differences in constant betas capital and conditional betas capital are driven by differences in the estimates of constant betas and conditional betas. The conditional betas for December 1996 are above the estimates from the full-period constant betas. As a result the conditional betas capital is above the constant beta capital for these industries.

On the other hand, for certain industries the conditional cost of capital is lower than the constant cost of capital. These differences in constant betas capital and conditional betas capital are attributed to the differences in the estimates of constant betas and conditional betas.

In order to evaluate which betas, the unconditional or the conditional provide the best forecasts of the cost of capital we estimate the Mean Square Error (MSE). The average MSE for the unconditional and conditional betas is 0.310 and 0.298 respectively. The average MSE for the conditional betas are smaller compared to constant betas.

We also estimate the CAPM with constant betas. Consistent with evidence from the US [Roll and Ross (1983), Pettway and Jordan (1987)] we find that the CAPM underestimates the cost of capital. In fact we find that the CAPM has larger MSE not only compared to the APT model with conditional betas, but with APT with unconditional betas. Furthermore we run Monte Carlo simulations and test the statistical significance of the errors of the Conditional beta model. We find these errors to be statistically insignificant. This additional evidence further indicates that the APT model with Conditional betas is doing a good job in estimating the UK industry cost of capital, since the errors that the model leave are statistically insignificant.

CHAPTER 8

CONCLUSION

This thesis empirically examines equilibrium factor models in the UK. It mainly focuses on the arbitrage pricing model, but also estimates and examines the capital asset pricing model and provides empirical evidence that the arbitrage-pricing model have less error (mean square error), i.e., provides a better description of UK returns. In particular it contributes to the body of literature by extending our knowledge on unconditional (constant) and conditional (time-varying & conditioned on a set of instrumental variables) models and their comparative performance. At the same time the thesis extends our knowledge on the sensitivity of utilising different portfolio formation criteria, while testing both unconditional and conditional asset pricing inferences. We sort both primary and combined portfolios on the basis of market capitalisation, price earnings ratio and dividend yield. We examine the behaviour and interaction amongst these effects for a large time period (1956-1996) and a data-set consisting of all companies listed on the London Stock Exchange that provide results more robust. Both the issue of the methodology employed and the sensitivity of the results to different portfolio formation criteria are critical when asset-pricing inferences are tested. We examine the empirical differences of different methodologies [two-step methodology, Non Linear Seemingly Unrelated Regression Estimates (NLSUR)] employed to estimate asset-pricing models. This thesis indicates that the choice of one methodology over another has important implications. Another important contribution of the thesis is the empirical estimation and examination of both unconditional and conditional models. The thesis provides an empirical examination of conditional asset-pricing models and adds to the body of literature by exploring the sensitivity of different portfolio formations when conditional asset pricing inferences are tested. Furthermore the thesis contributes to the literature by providing the empirical framework of carrying out practical tests in order to test the performance of conditional asset pricing models, by forecasting the sign, magnitude of price of risk and portfolio returns. Another important contribution to the body of literature is the fact that this thesis empirically compares unconditional and conditional beta models and estimates which model contain less errors.

To conclude the thesis contributes to the literature in the following ways:

First it contributes to the body of literature by extending our knowledge on the predictive ability of alternative Unconditional (FMB, NLSUR) methodologies.

Second it adds to the body of literature by providing practical tests of Conditional models, so as to assess their performance.

Third the thesis extends our knowledge on the sensitivity of utilising different portfolio formation criteria, while testing both Unconditional and Conditional asset pricing inferences.

Fourth it contributes to the body of literature by extending our knowledge on Unconditional and Conditional beta models and their comparative performance. The thesis provides empirical evidence of whether Unconditional or Conditional beta models have less error (mean square error), i.e., which provides a better description of UK returns.

Fifth the thesis adds to the existing literature by estimating the Industry cost of capital, using the following different models, Unconditional, Conditional, the Arbitrage Pricing Model and the Capital Asset Pricing model. Thus provides empirical evidence using a practical application of which model provides a better description of UK returns.

The empirical chapters of the thesis conclude the following:

Chapter 4: This chapter introduces the primary portfolio returns, which are used in the following chapters to test asset-pricing inferences. The size, price earnings ratio and dividend yield effect are examined from 1956 to 1996, a large time period that provide results more robust, in order to examine and learn whether these effects still exist, and on what extent, or direction. The interaction amongst these effects is also examined so as to identify whether these effects are independent or interrelated. We find evidence that the hypothesis that abnormal returns (MV1 to MV5) are jointly equal to zero across portfolios is accepted, at each level of the PE portfolio. This indicates that the PE effect is prevailing and subsumes the size effect. Since the hypothesis that the abnormal returns (PE1 to PE5) are jointly equal to zero across market value portfolios is easily rejected, at each level (MV1, MV2, MV3, MV4, MV5). Furthermore the hypothesis that the abnormal returns (DY1 to DY5) are jointly equal to zero across PE portfolios is accepted, at each level of the PE portfolio, indicates that the PE effect is prevailing and subsumes the dividend yield effect. Since the hypothesis that the abnormal returns (PE1 to PE5) are equal across dividend yield portfolios and zero is easily rejected, at each level (DY1, DY2, DY3, DY4, DY5). The evidence reveals that for the 1976-1996 period, the dividend yield and PE effect subsume the size effect. However the PE effect subsumes the dividend yield effect and it is the PE effect that is the most dominant. The best documented of all stock market effects, the small-firm premium went into reverse for the 1989 to 1996 sub-period. The size effect lives on, but for the latest decade, it is the largest firms that outperform the smallest ones by 10.26% per annum. The level of long-term small-firm out-performance has been substantial but however stops in 1988. Furthermore the dividend yield premium (high minus low) cease to exist for the 1989 to 1996 sub-period, it is only 0.20% per annum.

Chapter 5: This chapter first examines the predictive ability of alternative methodologies, it examines the two-step methodology versus the NLSUR; Second it explores the sensitivity of results when different portfolio ranking procedures, of size, PE ratio and dividend yield are employed. Third it identifies significant macroeconomic factors over the 1976 to 1996 period for all UK companies in the London Stock Exchange (LSE) inclusive on Unlisted Securities market. We find that when the two-step methodology is employed to estimate the arbitrage pricing model (APM) consisting of the Chen, Roll and Ross (1986) factors, these are insignificant, for all portfolio ranking procedures. Then when we create an APM model consisting of some other factors, such as, the S&P 500, the UK stock exchange turnover, the change in money supply, imports along with the market factor, and the inflation factor, these are insignificant, for the size, PE ratio and dividend yield portfolio, estimated by the two-step methodology. On the other hand, when the NLSUR is employed to estimate the APT consisting of the CRR factors, we find the market factor and the inflation factor to be priced for the size and PE ratio portfolios, and the inflation factor to be priced for the dividend yield portfolios. Then when we test an APM model consisting of the S&P 500, the UK stock exchange turnover, the change in money supply, imports along with the market factor, and the inflation factor, these factors are found significant when estimated by NLSUR. In particular; the market (FTSE), S&P 500, stock exchange turnover, change in money supply, imports, and inflation, all are significant for the size portfolio ranking. The market (FTSE), stock exchange turnover, change in money supply, and change in inflation are significant for the PE ratio portfolios. The S&P 500, stock exchange turnover, change in money supply, and inflation are priced for the dividend yield portfolios. Thus the evidence point out that the two-step methodology is inadequate for detecting a pricing relation in UK. This may be due to the fact that it fails to capture a non-linear relationship, since the two-step methodology assumes a linear relationship between returns and risk. Another interesting point relating the FMB methodology, is that if the relationship between returns and macroeconomic factors holds in a manner described by CRR, why did it fail to produce positive results for their stock price portfolios? On the contrary, when we employ the NLSUR we find a pricing relationship between portfolio returns and certain factors, that gives positive results (in terms of significant factors) for alternative portfolio formation procedures, of size, PE ratio, and dividend yield.

Chapter 6: This chapter models the dynamic behaviour of portfolio returns using a Conditional Asset Pricing Model and examine the behaviour of macroeconomic risk premiums over time. In order to implement this we provide tests of the Ferson and Harvey (1991) methodology, for the size, PE ratio and dividend yield portfolios, and also develop an alternative Conditional Methodology, the Conditional NLSUR, in an attempt to avoid the Errors in Variables problem inherent in the Ferson and Harvey (1991) methodology. Furthermore unlike existing conditional asset-pricing studies that just focus on the methodology employed, we provide practical tests to test the performance of Conditional Asset Pricing Models. These practical tests consist of forecasts of (i) the Sign of the Price of Risk using the Probit model, (ii) the Magnitude of the Price of Risk, and (iii) Portfolio Returns for the size, PE ratio and dividend yield portfolios. We use the Probit model and an out-of-sample evaluation in order to obtain-forecast time-series probabilities in a monthly frequency for the sign of the price of risk, which provide the information of whether in a certain month-s what the sign of the price of risk will be, positive or negative. This information can be used to indicate in a certain month-s the of whether there is a lower or higher degree of expected return associated with stocks that are exposed to shocks of certain factors, i.e., inflation, money supply e.t.c. We also forecast the magnitude of the Price of Risk -with an out-of-sample evaluation-, and carry on to forecast portfolio returns for out size, PE ratio and dividend yield portfolios. In order to evaluate how well our model forecasts portfolio returns for the size, PE ratio and dividend yield portfolios, we estimate the Root Mean Square Error (RMSE). Furthermore we run Monte Carlo simulations and test the statistical significance of the errors of the Conditional model. We find these errors to be statistically insignificant for all sorting procedures. We find under the Ferson and Harvey (1991) methodology, that the following factors: the return on FTSE, S&P 500, the unexpected UK stock exchange turnover, change in money supply, imports and inflation, are priced at different stages of the business cycle. Under the Conditional NLSUR, the instrumental variables also show predictive ability to predict variation of the price of risk of the return on FTSE, S&P 500, unexpected UK stock exchange turnover, change in money supply, imports, and inflation. In order to evaluate how our probit model predicts the sign of risk we report the % of correct predictions in each probit regression, and the average % of correct predictions for all (11) probit regressions for each price of risk we attempt to predict. We find, for example, that the probit regression model for the sign of risk of the return on S&P 500 (for the size portfolio ranking) has an average % of correct prediction for all the probit regressions of 66%. The probit regression model reaches the highest % of correct prediction of 75% during the 1986-1990, and 1987-1991 period. This chapter provides empirical evidence that show that the Conditional model employed in the thesis is doing a good job in forecasting the price of risk and portfolio returns, since the errors that the Conditional model leave are statistically insignificant.

Chapter 7: This chapter estimates the UK industry cost of capital, compares unconditional (constant) and conditional (time-varying & conditioned on a set of instrumental variables) beta models and the capital asset pricing model estimates of cost of capital with the arbitrage pricing model. We find differences, between constant-unconditional betas and conditional betas cost of capital. For certain industries the conditional cost of capital is higher than the constant cost of capital. These differences in constant betas capital and conditional betas capital are driven by differences in the estimates of constant betas and conditional betas. The conditional betas for December 1996 are above the estimates from the full-period constant betas. As a result the conditional betas capital is above the constant beta capital for these industries. On the other hand, for certain industries the conditional cost of capital is lower than the constant cost of capital. These differences in constant betas capital and conditional betas capital are attributed to the differences in the estimates of constant betas and conditional betas. To evaluate which betas, the constant-unconditional or the conditional provide the best forecasts of the cost of capital we estimate the Mean Square Error (MSE). We find that the average MSE for the conditional betas are smaller compared to unconditional betas. We also estimate the CAPM with constant betas. Consistent with evidence from the US [Roll and Ross (1983), Pettway and Jordan (1987)] we find that the CAPM underestimates the cost of capital. In fact we find that the CAPM has larger MSE not only compared to the APT model with conditional betas, but with the APT model with unconditional betas. Furthermore we perform another analysis so as to test the statistical significance of the errors that the Conditional beta model leave. We run Monte Carlo simulations and test the statistical significance of the errors of the APT model with Conditional betas. We find these errors to be statistically insignificant. This additional evidence further indicates that the Conditional beta model is doing a good job in estimating the UK industry cost of capital, since the errors that the model leave are statistically insignificant.

REFERENCES

Aggarwal R., T. Hiraki and R. Rao, 1988, Earnings price ratios, size and seasonal anomalies in the Japanese securities market, Working paper, John Carroll University, University Heights, Ohio.

Amemiya T., 1981, Qualitative response models: A survey, *Journal of Economic Literature* 19, 481-536.

Amihud Y., and H. Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223-250.

Antoniou A., I. Garrett and R. Priestley, 1998, Calculating the equity cost of capital using the APT: The impact of the ERM, *Journal of International Money and Finance* 17, 949-965.

Antoniou A., I. Garrett and R. Priestley, 1998, Macroeconomic variables as common pervasive risk factors and the empirical content of the arbitrage pricing theory, *Journal of Empirical Finance* 5, 221-240.

Ball R, 1978, Anomalies in relationships between securities' yields and yield-surrogates, *Journal of Financial Economics* 6, 103-26.

Banz R., 1981, The relationship between returns and market value of common stocks, Journal *of Financial Economics* 9, 3-18.

Basu S., 1978, Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis, *The Journal of Finance* 32, 663-680.

Basu S., 1983, The relationship between earnings yield, market value, and return for NYSE common stocks: Further evidence, *Journal of Financial Economics* 12, 129-156.

Bauman S., and R. Dowen, 1994, Security analyst forecasts and the earnings yield anomaly, *Journal of Business Finance and Accounting* 21, 374-400

Beck J.B, 1998, Sorting out sorts, *Journal of Finance* 53, 663-680

Blume M.E., 1980, Stock returns and dividend yields: Some more evidence, *Review of Economics and Statistics* 62, 567-577.

Blume M.E. and R.F. Stambaugh, 1983, Biases in computed returns: An application to the size effect, *Journal of Financial Economics* 12, 387-404.

Boudoukh J., M. Richardson and T. Smith, 1993, Is the *ex ante* risk premium always positive?, *Journal of Finance Economics* 34, 387-408.

Bower D.H., R.S. Bower and D.E Logue, 1984, Arbitrage pricing theory and utility stock returns, *Journal of Finance* 39, 1041-1054.

Calvet A., and J., Lefoll, 1989, Risk and return on Canadian capital markets: seasonality and size effect, *Journal of Finance* 10, 21-39.

Campbell J.Y., 1986, Stock returns and the term structure, *Journal of Financial Economics* 18, 374-400.

Campbell J.Y., and Y. Hamao, 1992, Predictable stock returns in the U.S., and Japan: A study of long-term capital market integration, Journal *of Finance* 47, 43-72.

Chan K.F, and N.F Chen, 1991, Structural and return characteristics of small and large Firms, *Journal of Finance* 46, 1467 – 1483.

Chan K.C., Chen and D. Hsieh, 1985, An explanatory investigation of the firm size Effect, *Journal of Financial Economics* 14, 451-471.

Chan L.K., Y. Hamao and J Lakonishok, 1991, Fundamentals and stock returns in Japan, *Journal of Finance* 46, 1739-1765.

Chen N.F., 1991, Financial investment opportunities and the macroeconomy, *Journal of Finance* 46, 529-555.

Chen N.F., Roll R. and S.A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383-403.

Chou S. R., and K. Johnson, 1990, An empirical analysis of stock market anomalies: Evidence from the Republic of China in Taiwan, S.G. Rhee and R.P. Chang (eds), *Pacific-Basin Capital Markets Research* 1, North Holland, Amsterdam.

Claire A.D, S.H. Thomas, 1994, Macroeconomic factors, the APT and the UK stockmarket, *Journal of Business Finance & Accounting* 21, 309-330.

Claire A., R. Priestley and S. Thomas, 1997, The robustness of the APT to alternative estimators, *Journal of Business Finance & Accounting* 24, 645-655.

Claire A.D, P. N. Smith and S.H. Thomas, 1997, UK stock returns and robust tests of mean variance efficiency, *Journal of Banking and Finance* 21, 201-218.

Claire A.D., R. Priestley and S.H. Thomas, 1998, Reports of beta's death are premature: Evidence from the UK, *Journal of Banking and Finance* 22, 1207-1229.

Cook T. L., and M.S. Rozeff, 1984, The size and earnings price anomalies: One effect or two ?, *Journal of Finance. Quant. Anal.* 13, 449-66.

Corad J. and G. Kaul, 1988, Time variation in expected returns, Journal *of Business* 61, 409-25.

Corhay A., G. Hawawini and P.Mitchel, 1987, The pricing of equity on the London Stock Exchange: Seasonality and size premium, E. Dimson (ed), *Stock Market Anomalies*, Cambridge University Press, Cambridge.

De Santis G. and B. Gerald, 1998, International asset pricing and portfolio diversification with time-varying risk, *Journal of Finance* 53, 557-574

Dimson E., 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197-226.

Dimson E. and P. Marsh, 1986, Event study methodologies and the size effect, *Journal of Financial Economics* 17, 113-142.

Dimson E. and P. Marsh, 1999, Murphy's law and market anomalies, *Journal of Portfolio Management,* 53-69.

Elton E.J., M.J. Gruber and J. Rentzer, 1983, A simple examination of the empirical relationship between dividend yields and deviations from the CAPM, *Journal of Banking and Finance* 7, 135-146.

Elton E.J., M.J. Gruber and J. Mei, 1994, Cost of capital using arbitrage pricing theory: A case study of nine New York utilities, Financial *Markets Institutions & Instruments* 3, 45-64.

Fama E. F, 1965, The behaviour of stock market prices, *Journal of Business* 38, 84-105.

Fama E. F, 1984, The information in the term structure, *Journal of Financial Economics* 13, 509-528.

Fama E. F. and K. R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23-49.

Fama E. F, 1990, Stock returns, expected returns, and real activity, *Journal of Finance* 45, 1089-1109.

Fama E.F, 1990, Term-structure forecasts of interest rates, inflation, and real returns, *Journal of Monetary Economics* 25, 59-76.

Fama E. F, 1991, Efficient capital markets: II, *Journal of Finance* 46, 1575-1616.

Fama E. F. and K. R. French, 1992a, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama E. F. and K. R. French, 1992b, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 36, 1-55.

Fama E. F. and K. R. French, 1999, Industry costs of equity, *Journal of Financial Economics* 43, 153-193.

Fama E. F and J. D. MacBeth, 1971, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 71, 607-635.

Ferson, W. E., and C. R. Harvey, 1991, The variation of economic risk premiums, *Journal of Political Economy* 99, 385-415.

Ferson, W.E., and C. R. Harvey, 1991, Sources of predictability in portfolio returns, *Financial Analysts Journal* 47, 49-56.

Ferson, W.E., and C. R. Harvey, 1993, The risk and predictability of international equity markets, *Review of Financial Studies* 6, 527-566.

Ferson, W.E., and C. R. Harvey, 1996, Evaluating fund performance in a dynamic market, *Financial Analysts Journal* 52, 20-28.

Ferson, W. E. and R.A. Korajczyk, 1995, Do arbitrage pricing models explain the predictability of stock returns, *Journal of Business* 68, 131-156

Ferson, W. E., and R. W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 50, 425-461.

Ferson, W.E, C. Harvey, 1999, Conditioning variables and the cross-section of stock returns, *The Journal of Finance* 53, 407-432.

Foerster, S. R., 1987, Asset pricing models with changing expectations: An empirical study, unpublished Ph.D. dissertation, The Wharton School, University of Pennsylvania, Philadelphia, PA.

French, K., and R. Roll, 1986, Stock return variances: The arrival of information and the reaction of traders, *Journal of Financial Economics* 17, 5-26.

Geske R. and R. Roll, 1983, The fiscal and monetary linkage between stock returns and inflation, *Journal of Finance* 38, 1-31.

Ghysels E. and Cirano, 1997, On stable factor structures in the pricing of risk: Do time varying betas help or hurt?, *Journal of Finance* 51, 549-574.

Goldenberg D.H. and A. Robin, 1991, The arbitrage pricing theory and cost of capital estimation: The case of electric utilities, *The Journal of Financial Research* 45, 181-196.

Gordon R. H. and D.F. Bradford, 1980, Taxation and the stock market valuation of capital gains and dividends: Theory and empirical results, *Journal of Public Economics* 14, 109-136.

Greene H., 1997, Econometric analysis, Third Edition.

Harvey C.R., 1989, Time-varying conditional covariances in tests of asset pricing models, *Journal of Financial Economics* 24, 290-317.

Hawawini G., P. Mitchell and A. Corhay, 1989, A look at the validity of the capital asset pricing model in light of equity market anomalies: The case of Belgium common stocks, S.Taylor (ed), *A Reapraisal of the efficiency of financial markets*, NATO ASI Series, Springer-Verlang.

He J. and L.K. Ng, 1994, Economic forces, fundamental variables, and equity returns, *Journal of Business* 67, 599-609.

He J., R. Kan, L. Ng, and C. Zuang, 1996, Tests of the relations among marketwide factors, firm-specific variables and stock returns using a conditional asset pricing model, *Journal of Finance* 50, 1891-1909.

Jaganathan R. and Z. Wang, 1996, The conditional CAPM and the cross-section of expected returns, *Journal of Finance* 50, 3-54.

Jarrow R. A, V. Maksimovic, and W. T. Ziemba, 1995, *Handbooks in operational Research and Management Science* 9.

Kan R, and C. Zhang, 1997, Two-pass tests of asset pricing models with useless factors, *Journal of Finance* 51, 203-235.

Keim D.B. and R.F. Stambaugh, 1984, A further investigation of the weekend effect in stock returns, Journal *of Finance* 39, 819-35.

Keim D.B., 1985, Dividend yields and stock returns: Implications for abnormal January returns, *Journal of Financial Economics* 14, 473-490.

Levis M, 1985, Are small firms big performers?, *The Investment Analysts Journal* 76, 21-27.

Levis M, 1989, Stock market anomalies: A re-assessment based on the UK evidence, *Journal of Business and Finance* 13, 675-696.

Levis M, 1999, The record on small companies: A review of the evidence, Working Paper, City University Business School.

Levis M. and M. Liodakis, Investors' expectations and the performance of value and growth portfolios: The UK evidence, Working Paper, City University Business School.

Litzenberger R.H and K. Ramaswamy, 1979, The effects of personal taxes and dividends on capital asset prices: Theory and market equilibrium, *Journal of financial economics* 7, 163-195.

Lo A. W. and A. C. MacKinlay, 1988, Stock market prices do not follow random walks: Evidence from simple specification test, *Review of Financial Studies* 1, 41-66.

Lo A. W. and A. C. MacKinlay, 1990, Data-snooping biases in tests of financial asset pricing models, *Review of Financial Studies* 3, 431-466.

Ma T. and T.Y. Shaw, 1990, The relationship between market value, pe ratio, trading volume and the stock return of Taiwan stock exchange, S.G. Rhee and R.P. Chang (eds), *Pacific-Basin Capital Markets Research* 1, North Holland, Amsterdam.

McElroy M. B. and E. Burmeister and K.D. Wall, 1985, Two estimators for the APT model when factors are measured, *Economic Letters* 19, 271-275.

McElroy M. B. and E. Burmeister, 1988, Arbitrage pricing theory as a restricted non-linear multivariate regression model, *Journal of Business & Economic Statistics* 6, 29-42.

Miller M.H and M.S. Scholes, 1982, Dividend and taxes: Some empirical evidence, *Journal of Political Economy* 90, 1118-1141.

Morgan G. and S. Thomas, 1998, Taxes, dividend yields and returns in the UK equity market, *Journal of Banking and Finance* 22, 405-423.

Parvez A. and L. J. Lockwood, 1995, Changes in multi-factor risk premia over varying market conditions, Working Paper, Texas University.

Pettway R.H. and B.D. Jordan, 1987, APT vs. CAPM estimates of the return generating function parameters for regulated public utilities, *Journal of Financial Research* 10, 227-238.

Poon S. and S.J. Taylor, 1991, Macroeconomic factors and the UK stock market, *Journal of Business Finance and Accounting* 18, 619-636.

Queen M. and R. Roll, 1987, Firm mortality: using market indicators to predict survival, *Financial Analyst Journal* 43, 9-26.

Reinganum M.R, 1981, A misspecification of capital asset pricing: Empirical based on earnings yields and market values, *Journal of Financial Economics* 9, 19-46.

Reinganum M.R, 1990, Market microstructure and asset pricing: An empirical investigation of NYSE and NASDAQ securities, *Journal of Financial Economics* 28, 127-148.

Roll R. and S. A. Ross, 1995, The Arbitrage pricing theory approach to strategic portfolio planning, *Financial Analysts Journal* 51, 122-131.

Rozeff M., 1984, Dividend yields are equity risk premiums, *Journal of Portfolio Management* 11, 68-75.

Rubio G., 1988, Further international evidence on asset pricing: The case of the Spanish capital market, *Journal of Banking Finance* 12, 221-242.

Schink G.R and R.S. Bower, 1994, Application of the Fama-French model to utility stocks, *Financial Markets, Institutions & Instruments* 3, 56-78.

Scholes M and J. Williams, 1977, Estimating betas from non-synchronous data, *Journal of Financial Economics* 5, 309-328.

Schwert G. W., 1990, Stock returns and real activity: A century of evidence, *Journal of Finance* 45, 1227-1257.

Shanken J. and M. Weinstein, 1990, Macroeconomic variables and asset pricing: Further results, 1990, Working paper, Rochester University.

Shiller R.J., 1984, Stock prices and social dynamics, *Brookings Pap. Econ Act.* 2, 457-510.

Siegel Jeremy J, 1991, Does it pay stock investors to forecast the business cycle?, *The Journal of Portfolio* Management, 27- 33.

Stoll H, and R. Whaley, 1983, Transaction costs and the small firm effect, *Journal of Financial Economics* 12, 57-80.