540829

School of Economics and Finance

A Dynamic Investigation into the Predictability of Australian Industry Stock Returns

Juan Yao

This thesis is presented for the Degree of Doctor of Philosophy
of
Curtin University of Technology

May 2004

Declaration

This thesis contains no material that has been accepted for the award of any other degree or diploma in any university.

To the best of my knowledge and belief, this thesis contains no material previously published by any other person except where due acknowledgment has been made.

Signature:

Date: ....

Acknowledgments

This thesis is a result of many people's help. I would like to thank my principal supervisor Associate Professor Lakshman Alles. He led me into one of the most challenging and exciting areas of finance and continuously provided valuable suggestions and guidelines. Very special thanks go to my co-supervisor Dr Jiti Gao at the University of Western Australia. In the most difficult time of my study, Dr Gao generously agreed to join the thesis committee. He has always given me excellent academic support and warm encouragement. I have benefited greatly from his help in both the PhD study and my academic career.

I would also like to thank the School of Economics and Finance at Curtin University of Technology for providing me with a three-year PhD scholarship. I am especially indebted to the Head of School, Associate Professor Ian Kerr, and to other staff in the school: Professor Harry Block, Associate Professor Sandra Hopkins, Associate Professor Jeff Pope and Associate Professor Michael Thorpe for their friendly support and encouragement. My colleagues in the Finance Discipline of University of Sydney have also offered me their support. I specially thank Professor Alex Frino, Dr Maxwell Stevenson and Associate Professor Graham Partington. Finally, I would like to thank my parents and best friends Shao-ling Sun and Maria Mangano for their love, patience, understanding and support.

Abstract

This thesis involved an empirical investigation of the predictability of Australian industrial stock returns using a dynamic state-space framework.

The systematic risks of industrial portfolios were examined in a stochastic market-model. The systematic risks of industry portfolios are found to be stochastic processes. Most of the industry groups have time-varying systematic risks that are mean-reverting to their stable or moving long-term mean. However, the investment and financial services, alcohol and tobacco, gold, insurance and media industry groups have rather random systematic risks. The time-varying market model provides a better explanation of the portfolio returns than the single-index model since it captures the stochastic properties of market risk.

Further, a Bayesian dynamic-forecasting model was employed to examine the explanatory power of a set of economic and financial variables. The unanticipated components of the term-structure variable, the interest-rate variable and the aggregate-dividend-yield variable were shown to be significant in explaining the industry portfolio excess returns. The comparison between multivariate analysis and univariate analysis strongly indicates that the correlations within industries are critical in the investigation of the predictability of returns.

In the out-of-sample analysis, a maximally predicted portfolio (MPP) was constructed based on the updated economic and financial information; however, the predictability of the MPP did not exceed that of a naive forecast. Furthermore, the market timing ability associated with the predictability of the MPP was insignificant. The industry-group-rotation strategy is able to enhance the industry portfolio performance, but the predictability only contributes a small proportion of the profits. The results indicate that the industry returns contain predictive components; however, investors are less likely to exploit the existing predictability to gain excess profit. The level of predictability discovered here does not contradict market-efficiency theory.

Table of contents

List of tables

List of figures

Abbreviations

ADF	Augmented Dickey–Fuller tests
AIC	Akaike information criterion
APT	Arbitrage Pricing Theory
ARCH	Autoregressive conditional heteroskedastic model
ARMA(1,1)	Autoregressive moving average model
ASX	Australian Stock Exchange
BDLM	Bayesian dynamic linear model
BPP	Best performing portfolio
CAPM	Capital Asset Pricing Model
C-P test	Cumulated periodogram test
DDY	First difference of dividend yield
DLM	Dynamic linear model
D-W	Durbin–Watson statistics
GICS	Global Industry Classification Standard
G-Q test	Goldfeld–Quandt test
MAE	Mean absolute error
MMM	Moving mean model
MPP	Maximally predicted portfolio
MRM	Mean-reverting model
MSE	Mean squared error
OLS	Ordinary least square
RCM	Random-coefficient model
R-SQ	R-square statistics
RWM	Random-walk model
UGCB	Unexpected change in current account balance
UCB	Unexpected change in commercial bill spread
UEI	Unexpected inflation rate
UEX	Unexpected change in exchange rate
UIP	Unexpected change in industrial production
UM3	Unexpected change in money supply
UTS	Unexpected change in the term structure
UUM	Unexpected change in unemployment

Chapter 1 Introduction

1.1 The efficient-market hypothesis and the predictability of returns

The predictable components of stock returns have always been of great interest to both financial practitioners and academics. In recent decades, an extensive empirical literature on the predictability of returns has arisen, together with debates about the implications for orthodox market-efficiency theory. Both the discovery of predictability in stock returns and the dominance of market efficiency have survived empirical testing and theoretical rationalising however.

Samulson (1965) first introduced the idea of an efficient-market hypothesis. He pointed out that in an efficient market, price changes fully incorporate the expectations and information of all market participants. Price changes must, therefore, be unforecastable if they are properly anticipated. Several years later, Fama (1970) summarised the efficient-market hypothesis in three different forms: the weak form, the semi-strong form and the strong form.

The three versions of the hypothesis differ in what is meant by the phrase "all available information." The weak form states that stock prices already reflect all information that can be derived by examining market-trading data such as the history of past prices, trading volume or short interest. Therefore, the weak-form efficiency implies that trend analysis is fruitless. If any past stock-price data that was publicly available conveyed a reliable signal about future performance, all investors would have learned to exploit the signals. The semi-strong form asserts that, in addition to past prices, all publicly available information regarding the prospects of a firm such as the fundamental data on the firm's production and business environment, are already reflected in the stock price. Thus, the semi-strong form efficiency predicts that most fundamental analysis is doomed to fail. The strong form of the hypothesis states that stock prices reflect all information relevant to the firm, even information available only to company insiders. Theoretically, no insider trading would be profitable in a highly efficient market.

In summary, the efficient-market hypothesis states that security prices fully reflect all available information. The more efficient the market, the quicker the stock prices respond to the newly arrived information.

The essence of the hypothesis is associated with the idea of a "random walk"; that is, in a highly efficient market, all subsequent price changes represent random departures from previous prices. Stock prices will immediately reflect the news, and the news is — by definition — unpredictable and random; therefore, the price changes are random and unpredictable too. Successive stock returns should be independent and identically distributed. In practice, technical and fundamental analyses are carried out to find the "uncovered" information that could make profit possible. However, once the information is made publicly available, investors will trade on this information, so the opportunity for trade to profit will quickly die away.

If stock prices follow a random walk, price changes are random and unpredictable. Strictly speaking, though, stock price follows a *submartingale* process. This means that the expected change in the price can be positive as compensation for the time value of money and systematic risk. Market efficiency suggests that all that is known and knowable by investors is incorporated into the price of a stock, bond or other asset (Fama, 1991). For many, predictability is synonymous with market inefficiency. The market-efficiency hypothesis indicates the absence of predictability of returns because, if returns are predictable, profit opportunities will exist so that investors will exploit them until the predictability disappears. In the presence of transaction costs, not all predictability is exploitable.

Fama (1991) claims, though, that market efficiency must be tested jointly with an equilibrium-pricing model. As a result, when academics find anomalous evidence on the behaviour of returns, it is hard to say if it is due to market inefficiency or a bad model of market equilibrium. Further, Fama states that even asset-pricing theory does not place itself in the realm of tests of market efficiency. This just means that efficiency is a maintained hypothesis. Depending on the emphasis desired, the efficiency must be tested, conditional upon an asset-pricing model, or the asset-pricing model must be tested conditional on efficiency. Such tests are always joint evidence regarding efficiency and an asset-pricing model.

Numerous works in the equity market have supported the predictability of stock returns (see Fama, 1976; Fama, 1984; Shiller, 1984; Fama, 1986; Keim and Stambaugh, 1986; Campbell, 1987; Fama and Bliss, 1987). The most important works showing that stock returns are predictable are those of Fama and French (1988a; 1988b; 1989). They find that stock prices have a slowly decaying stationary component. The negative autocorrelation of returns generated by a slowly decaying component of prices is weak at the short return, but stronger as the return horizon increases; therefore, long-run stock returns are indeed predictable. Fama and French (1989) report that dividend yields, term spreads and default spreads predict excess returns on stocks and on corporate bonds. The predictor variables are interpreted as correlated with changes in investors' required returns.

The evidence of predictability is specified at three levels. First, the predictability is reflected by the autoregressive and dividend-yield models. These include the work of Fuller and Kling (1990), Fama and French (1988b, 1988a) and Jegadeesh (1990). At this level, the future excess returns are shown to be correlated with the historical returns. Additionally, as the dividend yield reflects the expected returns from securities investment, the dividend-yield model is found to have predictive power.

Second, as the excess returns are associated with economic activities, macro-factors are able to tame the change of investors' required returns. Mounting evidence has shown that stock returns are predictable as future excess returns are related to measures of economic conditions. This is shown in the work of Bodie (1976); Jaffe and Mandelker (1976); Nelson (1976); Fama and Schwert (1977); Fama (1981); Campbell (1987); French et al. (1987). This stream of work also yields international applications in different equity markets. The findings of Campbell and Hamao (1992), Black and Fraser (1995) and Groenewold and Fraser (1997) demonstrate the relationship between macroeconomic factors and stock returns in the Japanese, UK and Australian stock markets respectively.

Third, predictability is detected by some trading strategies. Pesaran and Timmermann (1995) examine predictability in excess of a buy-and-hold strategy. They find that the extent to which this predictability could be exploited was very low; however, when Rosenberg et al. (1985) investigated a book–price strategy and a "specific return reversal" strategy, their results indicated the large potential profits to be made. That is, the predicted excess returns could be exploited by investors to earn profits by some "successful" trading strategies.

The economic interpretation of predictability results is controversial in the finance literature. If the expected returns are taken as constant, the predictability of stock returns is evidence of market inefficiency; however, it has been pointed out that the results supporting predictability do not necessarily contradict the idea of rational pricing in an efficient market. Rather, the predictor variables are interpreted as being correlated with changes in investors' required returns (Balvers, Cosimano and McDonald, 1990).

Campbell (1991) shows that small but persistent variations in expected returns can have a dramatic impact on a security's stock price. It is possible that the predictable components in stock returns reflect time-varying expected returns, in which case predictability of stock returns is — in principle — consistent with market efficiency. The predictability of excess returns, on its own, thus does not imply stock market inefficiency.

Predictability does not guarantee that an investor can earn profits from a trading strategy based on forecasts (see Pesaran and Timmermann, 1995). Jensen (1978) states that "A market is efficient with respect to information set ***K*** if it is impossible to make economic profits by trading on the basis of information set ***K***." He points out that the predictability of the dividend-yield model or other models does not contradict market efficiency. Given the erratic results of various predicting models, it is not clear that investors would have been able to identify its predictive ability and then capitalise on it to earn abnormal returns (Fuller and Kling, 1990). When trading costs are considered, the inconsistency of results across return horizons and default ratings shows that market timers would have had difficulty in identifying models (Fuller and Kling, 1994).

Predictability thus does not directly imply profitability or market inefficiency. Lo (2000) argues that whether or not predictability in security prices is inefficient can only be answered by weighing it against the risks inherent in exploiting such predictabilities. This is because of the existence of a trade-off between risk and expected returns. He states that:

If a security's price changes are predictable to some degree, then this may be just the reward needed to attract investors to hold the asset and bear the associated risks (see, e.g., Lucas, 1978). Indeed, if an investor is sufficiently risk averse, then he might gladly pay to avoid holding a security that has unforecastable returns (Lo, 2000, p.631).

To evaluate the economic significance of stock market predictability, we need to test whether the evidence of predictability could have been exploited successfully in the investment strategies. Pesaran and Timmermann (1995) point out that one way to do this is to investigate whether some portfolios systematically generate excess returns by checking the performance of the portfolios. Another way is to simulate investors' decisions in real time using publicly available information on a set of factors. The first approach does not give information about the predictive factors, though, and it does not guarantee that the information used by the portfolio managers is publicly available. The second approach, which is testing predictability based on a set of predictor variables, thus becomes the most common and fruitful method.

1.2 Motivation of the study

This research is motivated by several factors. First, the evidence of stock return predictability has been well researched in the US market at both the macroeconomic level and the market microstructure level. Few Australian studies, however, have directly addressed the predictable components of Australian stock returns.

The efficiency of the Australian share market has been tested by Hogan et al. (1982) and Groenewold and Kang (1992). Hogan et al. examined the relationship between equity returns, interest rates and monetary aggregates. They found that there was a strong relationship between medium-term government-security yields and equity returns. They found a weaker relationship between short-term commercial-bill yields and equity returns. They argued that the observed relationship between lagged fixed interest and returns suggested the inefficiency of the Australian stock market.

When Groenewold and Kang (1992) used the aggregate share-price indices and macroeconomic data to test the weak and semi-strong forms of the efficient-markets hypothesis, however, they didn't find a significant explanatory power for either lagged returns or lagged explanatory variables for share returns. Their results thus generally supported market efficiency.

The mixed findings of market efficiency in Australia have resulted in an interest in whether some predictability in the Australian stock market exists and, further, what the implications are of the predictability for the efficiency-testing literature in Australia. The Australian market is relatively small compare to the US market. The set of stocks in Australia is spread across a range of industries, with a division popularly recognised between resources stocks and industrial stocks. Furthermore, the Australian market is generally concentrated. Ball and Brown (1980) suggested that the Australian resources and industrial sectors were fundamentally different in terms of risk and return. The Australian setting presents an ideal opportunity to verify the existence of predictability using a different dataset. A close look at the Australian industrial sector returns will thus enhance understanding of the market.

The second factor motivating this study is the importance of the industry analysis in the investment practice. The first stage of investment is to allocate total capital globally to broad asset classes on the basis of forecasts of the overall economic and market environment; however, in the second stage, the group-rotation stage, managers attempt to identify economic sectors and industries that stand to gain or lose relative to the overall market (Beller, Kling and Levinson, 1998). The early work of King (1966) presented evidence that the movement of a group of security price changes could be decomposed into market and industry components. King's work inspired a group of researchers to investigate the industry factors or risks in security returns.

Most of the empirical works in this area focus on industry differences or industry factors to explain the variance of asset returns. The general empirical result is that there is a substantial divergence in relative performance among industries. Those works include Fama and French (1988a); Reilly and Drzycimski (1974); Rosenberg (1974); Breeden et al. (1989); Kale et al. (1991); and Boudoukh et al. (1994). Technically, they use industry groups as a form of classification; however, there were few studies with a focus on industry-sector predictability, despite a recent resurgence in industry momentum (see Moskowitz and Grinblatt, 1999 and Grundy and Martin, 2001). Wei and Wong (1992) and Boudoukh et al. (1994) both indicate the different sensitivities of various industrial groups to inflation. Jensen et al. (1997) have identified the different expected returns across industries as different responses of monetary policy. Faff and Chan (1998) apply a three-factor model to the returns of gold stocks in the Australian equity market. They have found that the market and gold-price factors could explain the gold-stock returns. Cooper et al. (2002) have uncovered that the individual bank fundamental variables are able to predict the bank stock returns. An investigation of predictability with concentrating on industry sectors will thus contribute to the industry-analysis field and the predictability literature as a whole.

A third motivation for this study is that, despite mounting empirical work on predictability of stock markets, most previous studies assume the existence of a time-invariant forecasting model. That is, the prediction is based on a set of "static" parameters. Some recent studies have questioned the efficiency of the tests of return predictability based on the standard regression techniques (see, for example, Pesaran and Timmermann 1995, 2000; Stambaugh, 1999; Campbell and Yogo, 2003; Ang and Bekaer, 2003). These critics argue that, in real time, no investor could have obtained parameter estimates based on the whole sample period; therefore, the forecasting from the normal regression model has been made with the benefit of hindsight.

The finance literature has recently begun to address questions of model instability and parameter uncertainty (see, for example, Pesaran and Timmermann, 2002; Lewellen and Shanken, 2002). An interesting on-going issue is to re-examine the evidence of predictability with incorporation of the investor's learning process. Lewellen and Shanken argue that returns might appear predictable to an econometrician, but investors can neither perceive nor exploit this predictability. They further suggest that the parameter uncertainty is a potential source of predictability. To assess market efficiency, the researcher should mimic the Bayesian-updating process of rational investors to determine whether the patterns observed in the data could have been exploited. The current study is in line with this direction.

1.3 Objectives and significance

It is both interesting and puzzling to financial economists that after decades of research and hundreds of journal articles, there is still no definite conclusion on whether the financial markets are efficient. For many, predictability is synonymous with market inefficiency; however, as Fama (1991) argued, tests of market efficiency can only be carried out jointly with an asset-pricing model. The judgments on stock return predictability are much more controversial. This thesis aims to present an empirical work using an Australian dataset to investigate the relationship between market efficiency and the predictability of stock returns. By using a technique that incorporates time-varying properties of risk premium and investor's learning processes, this study will offer a new set of evidence and a new perspective on the this topic.

In particular, the major objectives of the study are to:

- Provide a comprehensive literature review on the predictability of stock returns and the relationship between the traditional market-efficiency theory and they evidence of predictability.
- Investigate the time-varying properties of industry-sector returns, within the Australian market in particular. The systematic risks of Australian industry-sector returns are investigated with a focus on their stochastic properties. The best estimation of industrial beta is obtained through this investigation.
- Test the relationship between economic change and the Australian stock market to examine the predictability of stock returns. That is, to what extent can currently available economic and financial information be used to predict industry-sector returns? Furthermore, are there commonalities or differences in the predictability of industry sectors?
- If evidence of predictability is found, a further aim is to investigate whether the existence of predictability is economically significant and exploitable to investors. If investors are able to exercise the predicability for profit, the efficiency of the Australian stock market will be questioned.

The issue of predictability of industry stock returns has important implications to both portfolio managers and individual investors. At the macro level, the policy makers would be able to allocate resources according to market signals that convey investors' expectations regarding current and expected aggregate business conditions. At the micro level, the market participants would be able to effectively hedge or raise capital by exercising market-timing or asset-allocation strategies based on the predictability of future stock returns. Stock market predictability has thus always been of great interest to both market participants and academics.

Empirically, most previous work used the classical regression method to evaluate the returns-generating process. The analysis using classical regression was concerned with static models. The forecast was made through one set of parameters whose values were fixed across the sample period. The concern of this research was to forecast the return time series within a state-space framework. Although the state-space methodology has been generally used in scientific empirical work, it is an emerging method within the finance literature.

State-space models, introduced into economics by Harvey (1981; 1989), deal with dynamic time-series models in which an observed variable is the sum of a linear function of the state variable plus an error. In the state-space framework, the path of the state variable through time, the parameters describing the dynamics of the state variables and the covariance structure of the stochastic disturbances are thus inferred from the data.

The dynamic model is based upon analysis of the historical development of the return series and the utilisation of information relevant to the return's likely future development. The assumption that the quantified relationship between the economy and stock market remains the same across the time horizon is not required. Unlike previous studies, this research also employs a multivariate setting to test predictability. The multivariate setting is able to incorporate the correlations among the industry groups that are usually ignored by the univariate framework. The forecasts of a multivariate dynamic model in this study are thus expected to be more accurate and reliable.

In Australia, especially, there is an absence of research into the predictability of industry stock returns. The Australian market is a relatively small market with a small number of listed companies compared to the US market. At the end of 2001, the number of listed companies in the Australian stock market was 1,410, and the total market capitalisation was $1.1 trillion (ASX Fact book, 2002). The Australian market is also a very concentrated market with the top-fifty largest domestic securities accounting for over 76 per cent of the total market capitalisation at 31 December 2001. The most actively traded fifty stocks contributed over 35 per cent of the trading volume of the domestic share markets (ASX Fact book, 2002). The Australian market used to be heavily influenced by resource-based stocks; however, in recent years, the industrial stocks (such as banks, finance and media) have grown substantially. The Australian market has thus offered a unique dataset for a market with small size, concentrated trading and a variety of industry groups. A test of the predictability of industry groups in the Australian market in this study will fill a void in the Australian literature and will also contribute to the empirical predictability research in general.

1.4 Thesis structure

The remainder of this thesis is organised as follows. Chapter 2 presents a review of the relevant literature on the topic of predictability in financial markets, with particular reference to the predictability of returns in equity markets. The major empirical works on testing predictability and related methodology are reviewed and evaluated. In particular, some Australian empirical studies are presented to provide the background literature in the Australian context.

Chapter 3 presents detailed information on the data and the overall research methodology adopted in this study. The sources and construction of data employed in the study are presented. The methodologies employed by previous studies when testing for predictability in equity markets are reviewed and evaluated. The adoption of a new technique, the state-space framework in the current study is motivated by the weakness of previous methods in testing predictability. A comprehensive description of the state-space model and the Kalman-filter technique are introduced. In particular, their advantages and usefulness in comparison to the standard econometric methods are presented.

Chapter 4 presents a study on the time-varying properties of systematic risk of Australia industry stocks. The different time-varying characteristics of systematic risk of each industry group are identified and discussed. A comparison of the single-index market model with the stochastic-parameter model provides strong results that the industry-systematic risks are stochastic processes. The evidence in this chapter shows that each industry beta contains different stochastic properties. This result further indicates that the test of predictability of industry-sector returns should take into account the time-varying risk premiums of the Australia market.

In Chapter 5, the single-index model is extended to a multi-factor model in a multivariate-state-space setting to investigate whether the national economic and financial information conveys the predictability of industrial returns. A brief review of literature regarding the relationship between various economic variables and equity returns is included. Following the previous studies, a set of economic and financial variables is selected to test whether the unexpected changes of economy contain predictive power over industry-sector returns. The state-space setting of the model incorporates the time-varying properties of risk premiums by allowing the model parameters to be updated each month. The existence of explanatory power of economic and financial information indicates the potential for predictability of Australian industry-sector returns.

The economic significance of the predictability is tested in Chapter 6. While the predictability of stock returns is only meaningful when investors can actually exercise it in their trading strategies, a test of the economic significance of the predictability is both necessary and interesting. By adopting a set of out-of-sample tests, the potential profitability is examined to discover whether investors can actually achieve a profit by following a market-time strategy or an industry-rotation strategy. If the achieved profits are persistent, the predictability discovered here might be a result of market inefficiency. The results here will have significant implications for the Australian asset-pricing literature and equity-market industries.

Finally, the discussion and conclusions of the current study are presented in Chapter 7. A summary of the previous chapters is presented along with the findings of each chapter. The significance of this study is presented, along with a discussion of the implications of the results. The limitations of the current study are also discussed. Future research is directed towards overcoming those limitations.

Chapter 2 A literature review of the stock market predictability

2.1 Introduction

In financial literature, the efficient-market hypothesis indicates that a well-functioning, or efficient market will fully reflect "all available information" (Fama 1970, 1991). "*Competition among investors leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future*" *(Fama, 1995, p. 76).*

Thus, the stock price will only increase or decrease in response to new information. Any information that could be used to predict stock performance should already be reflected in stock prices. The new information, by definition, is not predictable, so stock prices that change in response to new (unpredictable) information must move unpredictably. The change in stock prices thus follows a random walk; that is, the price changes are random and unpredictable.

Since the establishment of the market efficiency theory, though, there has also been a resurgence of research on testing the predictability of stock returns. The topic of predictability has attracted a lot of attention from academics and financial practitioners as predictability generally possesses obvious implications of investment profits. Therefore, in this chapter, a thorough literature review of tests on predictability of stock returns will be presented in next section, the Section 2.2. Section 2.3 presents a discussion on interpretation of the evidence of predictability and its implication to market efficiency theory. Some empirical work which has been done in the Australian market is discussed in Section 2.4, and a summary of the chapter is given in Section 2.5.

2.2 Are returns predictable?

The early tests of market efficiency rest on the tests for a random walk of stock prices. For many, any rejection of the random-walk model seems to be the evidence of market inefficiency; therefore, the existence of predictable patterns in stock returns is indication of the invalidity of the market efficiency theory.

Strictly speaking, however, the stock prices follow a submartingale process: the expected change in the price can be positive as compensation for the time value of money and systematic risk (Granger, 1992). One of the central tenets of modern financial theory is the necessity of a trade-off between risk and expected returns. The expected return may change over time as risk factors change. Many financial economists therefore have argued that whether predictability in security prices is inefficient or not can only be answered by weighing it against the risks inherent in exploring such predictabilities (for example, Pesaran and Timmermann, 1995 and Lo, 2000). In the presence of transaction costs, not all the predictabilities are exploitable.

Market efficiency theory implies that returns are unpredictable as stock prices follow a random walk or martingale process; however, contrary to the random-walk hypothesis, recent literature has presented strong support for the predictability of stock returns. Empirically, predictability can be defined as predictability of "excess" or "abnormal" returns or the predictable variation in expected returns.

Fuller and Kling (1994) argue that the alternative to predictability is that the forecasting models may be used to actually "time" the market; i.e. to predict periods when excess returns are negative allowing investors to earn abnormal profits. Kaul (1996) defines predictability in terms of the predictability of returns. That is, let the return on a stock R_t, follow a stationary and ergodic stochastic process with finite expectation $E(R_t) = \mu$ and finite autocovariances $E[(R_t-\mu)(R_{t-k}-\mu)] = \gamma_k$. Let Ω_{t-1} denote the information set that exists at time $t-1$, of which X_{t-1} (an $M \times 1$ vector) is the subset of information that is available. Predictability is defined as specific restrictions on the parameters of the linear projection of R_t on X_{t-1}:

$$R_t = \mu + \beta \cdot X_{t-1} + \varepsilon_t ,$$

where $\beta_{(1\times M)} \neq 0_{(1\times M)}$.

Early evidence of predictability in returns was the discovery of the mean reversion property of stock prices. The mean-reversion hypothesis states that the stock price contains a temporary component that is mean-reverting; i.e. the market value of stock deviates from its fundamental values from time to time but will revert to their mean. As early as 1971, Blume (1971) had revealed that asset betas have a regression tendency; that is, the estimated betas tend to regress toward the mean. Blume (1975) suggested that the source of this mean reversion of betas related to the idea that initially a company could choose relatively high risk projects but, over time, the risk of these projects declines thus leading to a decline in the company's equity beta. His finding was supported by Brenner and Smidt (1977) and Francis (1979).

Numerous work on the equity market has documented that stock prices contain predictable components (see Fama, 1976; Fama, 1984; Shiller, 1984; Fama, 1986; Keim and Stambaugh, 1986; Campbell, 1987; Fama and Bliss, 1987). Studies of mean reversion and the associated predictable component of stock prices normally adopt two testing methodologies: the test of auto-regression on multi-period returns (Fama and French 1988a, 1988b, 1989) and the variance-ratio test (Lo and MacKinlay 1988, 1989).

The regression-based test, such as that applied by Fama and French (1988a), finds that stock prices have a slowly decaying stationary component. The return is positively correlated for short horizons and negatively correlated for longer horizons. Their results show that the predictable variation due to mean reversion is about 35 per cent. The negative autocorrelation of returns generated by a slowly decaying component of prices is weak at the short return, but stronger as the return horizon increases. The first-order autocorrelations of industry and decile portfolio returns for the 1926–85 periods form a U-shaped pattern across increasing return horizons. Between 25 and 45 per cent of the variation of three-to-five-year US stock returns thus appears to be predictable from past returns.

Conrad and Kaul (1989) have confirmed the evidence of mean reversion in short-horizon expected returns. They find that the rapid mean reversion in short-horizon expected returns implies much greater variation through time in monthly expected returns. More specifically, during the period 1962 to 1985, over 25 per cent of the return variance of small firms can be explained by time variation in expected returns. The mean reversion phenomenon of stock prices suggests that the stock prices may contain a predictable component. A number of models of stock market behaviour thus yield the prediction that stock returns, far from being unpredictable, exhibit negative autocorrelation over long time horizons.

Jegadeesh (1990) documents strong evidence that predictability exists in individual stock returns. The negative first-order serial correlation in monthly stock returns is highly significant. Further, the twelve-month serial correlation is particularly strong, and there is also a significant positive serial correlation existing at long lags. By using the discovered systematic behaviour of stock returns, the extreme decile portfolios formed from the forecast over the period 1934–87 have abnormal returns of around 2.49 per cent per month.

The variance-ratio test, however, concentrates on the relative variability of returns over different horizons. The variance ratio at lag K is defined as the ratio of the variance of the K-period return to the variance of the one-period return divided by K. If the ratio of the return variance for a K-period to a 1-period is equal to K then the random-walk hypothesis cannot thus be rejected.

Lo and MacKinlay (1988) tested the random-walk hypothesis for weekly stock market returns by comparing variance estimators derived from data sampled at different frequencies. Their results strongly rejected the random-walk model. In contrast to Fama and French (1988), though, they found significant positive serial correlations for both weekly and monthly returns. Their rejection of the random walk for weekly returns does not support a mean-reverting model of asset pricing. Poterba and Summers (1988) investigated the mean reversion in stock prices for 18 countries. They have shown that time variation in expected stock returns accounts for substantial proportions (in excess of 30 per cent) of return variance for holding periods greater than one year.

Mills (1991) adopted the variance-ratio tests to assess the predictability of UK monthly stock returns. He found positive autocorrelation and, therefore, his results support the predictability of UK stock returns at horizons ranging from three months up to eight years. Mills (1995) employed variance-ratio tests in a multivariate framework through the incorporation of the common trend in dividends by using both monthly and annual data. His monthly results confirmed the findings of Mills (1991) that stock prices exhibit mean reversion rather than random walk behaviour. Specifically, returns are positively correlated over long horizons and are thus predictable.

Gallagher (1999) investigated the mean-reverting components in real stock prices. He used the multivariate time-series technique to identify the size and significance of the temporary (or mean-reverting) and permanent components for real stock prices for 16 stock markets. His evidence supports the mean-reversion hypothesis that stock prices are not random walk and, further, a significant temporary component in real stock prices contributes between 7 and 64 per cent of the variation of quarterly real stock price movement. His results offer broad international evidence regarding the size of the mean-reverting component and the predictability of stock prices. Other similar and related studies reporting the predictable components of stock prices are those of Cochran (1994), Ray et al. (1997) and Lee (1995).

Though the regression-based tests and the variance-ratio tests have suggested that the stock prices are, to some degree, mean-reverting, the significance of the mean-reverting component is not conclusive as other studies suggest. Fuller and Kling (1990, 1994) have re-examined the Fama and French study with an out-of-sample analysis. Their study shows that though the dividend-yield model of Fama and French (1988b) could be useful in forecasting stock returns in an out-of-sample, the auto-regression model of Fama and French (1988a) does not forecast even as well as the mean of past returns.

Cochrane and DeFina (1995) employ both the regression-based test and variance-ratio tests using an international dataset of 18 countries. Their regression-based tests show that indices in some countries have a mean-reverting component; however, the variance-ratio statistics have offered little support for this. Malliaropulos (1996) has re-examined the evidence of predictability using both the univariate variance-ratio tests as well as multivariate tests. To avoid the small-sample bias and to be free from distributional assumptions, he artificially generated the history of stock returns by using a bootstrap method. His tests found no evidence of mean-reversion in stock prices.

In another study, Malliaropulos and Priestley (1999) assessed the predictable component of South-East-Asian stock markets using a similar method, and they found that the mean-reversion in their results was due to either time-variation of risk exposure and prices of risk or partial integration of the local market into world stock markets.

Cochrane (1988) and Mills (1995) estimated the variance-ratio tests for different return horizons in a multivariate context. Their findings indicated that because the standard errors of the pure random walk are considerably larger than the temporary component, the evidence of the mean-reversion hypothesis is not strongly supported.

2.2.1 Returns over short and long horizons

Much research has revealed that there is a nontrivial predictability in short-run returns. Conrad and Kaul (1988; 1989) and Lo and MacKinlay (1988) have all addressed the significant positive autocorrelation of stock returns at short horizons.

Summers (1986) demonstrates that the negative autocorrelation of returns approaches zero as the length of the return interval decreases but, alternatively, these negative autocorrelations grow larger in absolute values as the return interval lengthens. He further argues that autocorrelation of short-horizon returns might give the appearance that such mean-reverting components of prices are of no consequence; however, they account for a substantial fraction of the variation of returns. He questions the statement that the failure to reject the market-efficiency hypothesis implies that market prices represent rational assessments of fundamental valuations.

Shiller (1981, 1984) argues that the overreaction of stock prices leads to positive serial correlation over short time horizons. Subsequent correction of the overreactions leads to poor performance following good performance and vice versa. The corrections mean that a run of positive returns eventually will tend to be followed by negative returns, leading to negative serial correlation over longer horizons. The episodes of apparent overshooting followed by correction give stock prices the appearance of fluctuation around their fair values.

Early tests of market efficiency examined autocorrelations of daily and weekly stock returns. The studies of short-horizon returns have detected modest positive serial correlation in stock market prices, and tests of long-horizon returns have found negative long-term serial correlation. Fama (1970) claims that the estimated autocorrelation is usually close to zero; therefore, the evidence of predictability is claimed to be economically insignificant. Moreover, some of the observed predictability may be spuriously induced by market microstructure effects; for example, non-synchronous trading (Boudoukh et al., 1994; Muthuswamy, 1988).

Some recent work has indicated, though, that short-horizon returns can be more predictable. Chelley-Steeley (2001) follows the work of Conrad and Kaul (1989) to examine UK monthly returns. She finds that using a weighted sum of past weekly returns can predict better future monthly returns than using past monthly returns. The improvement of predictability suggests that there are rapidly decaying, mean-reverting, predictable components in UK short-horizon portfolio returns; though, the discovered magnitude of mean-reversion is less than that of Conrad and Kaul (1989).

Evidence of a large mean-reverting component indicates that the stock returns are predictable over long investment horizons, which has spawned numerous studies investigating the predictability of returns. It is usually believed that the behaviour of long-horizon returns can give a clearer impression of the importance of mean-reverting price movements. Stambaugh (1986), in a discussion of Summers (1986), argues that although the long swings away from intrinsic value will not be detectable in short-term data, long-term returns should be significantly negatively autocorrelated. Specifically, Fama and French (1988a) show that a slowly decaying component of prices induces a negative autocorrelation in returns that is weak for the daily and weekly returns but would be stronger in long-horizon returns. Fama and French (1988a) further claim, however, that the strong predictive behaviour of long-horizon returns due to slowly decaying price components is consistent with common models of an irrational market in which stock prices take long temporary swings away from fundamental values. The predictability of long-horizon returns can also be attributed to the time-varying equilibrium of expected returns generated by rational pricing in an efficient market.

Generally, the existing literature suggests that stock prices have a tendency to revert back to the mean. Returns have been found to be positively serially correlated over short periods, but negatively correlated over longer periods. Thus, short-term returns are autocorrelated and long-term returns are mean reverting. The predictive evidence discovered over the short-term horizon of returns is less controversial. Most arguments over predictability in the literature rest upon long-horizon returns. The long-horizon returns are more interesting in shedding light on the persistence of return predictability. Ferson and Korajczyk (1995) claim that the estimated predictable fraction of long-horizon return variances for multi-month returns is larger than for one-month returns. Additionally, returns measured for longer holding periods are less susceptible to the effects of thin and nonsynchronous trading, bid–ask spreads and microstructure issues.

Some recent work adopting new methods has presented new evidence of mean-reversion in long horizon returns. Balvers et al. (2000) employ a panel of stock price indices for 18 well-developed capital markets (16 OECD countries plus Hong Kong and Singapore) for the period 1969 to 1996. Benefiting from additional cross-sectional power, they find strong evidence of full mean-reversion in relative stock index prices. Their results indicate a positive speed of reversion with a half-life of three to three-and-a-half years, and the results are claimed to be robust to alternative specifications and data. Additionally, by using some parametric contrarian investment strategies from their panel parameter estimates, they have produced both statistically and economically significant excess returns.

Supplementing the work in developed markets, Chaudhuri and Wu (2003) place a test of random walk versus breaking trends analysis in 14 emerging markets. By implanting a test accounting for structure breaks in the stock prices, they have found that the null hypothesis of a random walk can be rejected at the 1 per cent or 5 per cent significance level in 10 out of 14 countries. Therefore, the stock prices of most of the emerging markets investigated can be characterized as mean-reverting processes rather than as random walk processes.

Klein (2001) has investigated long-horizon return reversal from the point of view of a capital gain lock-in effect. His results show that the effects of investors' accrued capital gains have contributed to the long-horizon return reversal.

Barberis (2000) has suggested that given the evidence that returns are predictable, long-term investors allocate their investments more to stocks because the time-variation in expected returns induces mean-reversion in the long run and lowering variances of cumulative returns over long horizons.

2.2.2 Cross-section return predictability

The majority of work reviewed so far has focussed on the time series return predictability; that is, predictability based on return autocorrelations or the forecasting power of ex-ante predictor variables. There is another stream of empirical work that places attention on the cross-section variation of returns.

According to the traditional capital-asset-pricing model (CAPM), the expected return of any asset is a linear function of the security's beta measured relative to the market portfolio. Any persistent departure from this relationship is a violation of the joint hypothesis of both the CAPM and efficient-market hypothesis. In some contexts, the evidence of cross-section predictability has also been classified as "anomalies" of the market. Hawawini and Keim (1995) provide an excellent review of cross-section return predictability.

Banz (1981) was the first to document the size effect of the stock returns. He found that the statistical association between returns and size is negative and of a greater order of magnitude than that between returns and beta that were documented in the earlier studies of CAPM. His work has inspired a great deal of international research in investigation of size effect; for example, work in the United Kingdom (Corhay et al., 1987), Belgium (Hawawini et al., 1989), Japan (Hawawini, 1991), and Spain (Rubio, 1988). A negative relationship between returns and size has been discovered in all countries except Canada (Calvet and Lefoll, 1989) and France (Hawawini and Viallet, 1987).

Nicholson (1960) discovered the earning/price (E/P) effect. Basu (1977) argued that the price/earnings (P/E) ratios may explain the violations of the CAPM. He finds that there is a significant negative relation between P/E ratios and excess returns. Reinganum (1981) has confirmed his work. Evidence of a P/E effect has also been discovered internationally by Aggarwal et al. (1988) for the Japanese market, Chou and Johnson (1990) for the Taiwanese market and Levis (1989) for the UK market. Except for the size and E/P effect, other anomalies contributable to the cross-section predictability include the price/book effect (Keim, 1988; Fama and French, 1992).

Kim (1997) re-examined the explanatory power of beta, firm size, book-to-market equity and the earnings/price ratio for average stock returns after correcting the selection bias and the errors-in-variable bias. He found that firm size was almost no longer significant in explaining monthly and quarterly stock returns. Though the book-to-market equity still has significant explanatory power, the support for beta pricing theory has been stronger than previous studies. Griffin and Lemmon (2002) discovered that the relationship between book-to-market equity and stock returns is subject to the distress risk of the firm.

Recent literature has uncovered some new "anomalies" of the market, which relate to the trading activity. For example, Diether et al. (2002) have presented evidence that stocks with higher dispersion in analysts' earnings forecasts earn lower future returns than otherwise similar stocks. The dispersion in analysts' forecasts can be interpreted as the differences in opinion about a stock. Their evidence shows that stock prices will reflect the optimistic view when investors with the lowest valuations do not trade, while the dispersion in analyst's forecast does not necessarily proxy for risk. Chordia and Swaminathan (2000) find that the lead–lag patterns observed in stock returns are caused by the trading volume. Because low-volume portfolios adjust to the information slower than high-volume portfolios, daily and weekly returns on high-volume portfolios lead returns on low-volume portfolios even after controlling for firm size.

The evidence of cross-section predictability based on the variables of size, E/P and price/book (P/B) has questioned the validity of the asset-pricing model and the market-efficiency hypothesis. Studies have discovered, however, that the "anomalies" often suffer the problem of "survival bias"[1] and "error-in-variable bias"[2] (see Kim, 1997). Many authors argue that the findings of anomalies provide support for the multi-factor model. The potential alternative sources of risk might have contributed to the predictive patterns discovered in cross-sectional returns.

2.2.3 Predictors of broad market returns

The most fruitful and recent work on predictability has focused on the use of some ex-ante observable variables. As the excess returns are associated with economic activities, the macro-factors will be able to tame the change of investors' required returns. Mounting evidence has shown that stock returns are predictable as future excess returns are related to measures of economic conditions. Such work includes Bodie (1976), Jaffe and Mandelker (1976), Nelson (1976), Fama and Schwert (1977), Fama (1981) and Campbell (1987).

Some early work implies that stock returns would vary with the business cycle (Lucas, 1978). Fama (1981) suggests that positive relations between stock returns and real variables are fundamental determinants of equity values. Keim and Stambaugh (1986) find significant predictability in stock prices by using forecasts based on certain predetermined variables. French et al. (1987) confirm the previous findings that the expected return on a stock is related to covariances between its return and:

1. the return on a market portfolio (Black et al., 1972; Fama and MacBeth, 1973);
2. factors extracted from a multivariate time series of returns (Roll and Ross, 1980);
3. macroeconomic variables such as industrial production and changes in interest rates (Chen et al., 1986); and
4. aggregate consumption (Breeden et al., 1989).

Fama and Schwert (1977) examined whether the statistically significant negative correlation between stock returns and nominal interest rates can be used to forecast

---

[1] The empirical analysis of stock returns implicitly condition on the stocks surviving into the sample; therefore, the statistical results are biased towards the rejection of the random walk hypothesis.

[2] The errors-in-variables problem results from the situation that the true betas are unobservable, and the estimated betas are thus used as a proxy for unobservable betas.

times when the expected nominal risk premium on stock is negative. They conclude that the negative slope coefficient in the regression of stock returns on Treasury bill returns is not useful in predicting times when stocks do worse than bills. Following their work, however, Breen et al. (1989) discovered that the forecasting ability of Treasury bill rates is economically significant as both the expected value and the variance of the nominal stock excess returns depend on the nominal interest rate. Campbell (1987) has also reported the predictive power of Treasury bill rates on stocks' excess returns with model's R^2 around 11 per cent.

Previous studies have examined the interest rate variable and the dividend/price ratio as the forecasting factor of stock returns, while many researchers have considered aggregate business factors. In the spirit of Arbitrage Pricing Theory (APT), numerous studies have discovered the linkage between stock returns and the change in fundamental macroeconomic information. Hung and Kracaw (1984) and Balvers et al. (1990) emphasise the relationship between economic growth, production and stock returns. Fogler et al. (1981) and French et al. (1987) focus on the inter-relationship of interest rates and stock returns. Other works — such as those by Fama and Schwert (1977), Fama (1981) and Fama and Gibbons (1982) — document the effects of inflation and money on stock returns. Those studies suggest that the innovations of the macro economy are related to asset returns. Since the aggregate economic information is serially correlated, and hence predictable, stock returns can be predicted based on forecasts of economic variables.

Chen et al. (1986) identified that the innovations in macroeconomic variables are risks that are rewarded in the stock market. Their work motivated a group of work linking the factors in the APT framework with macroeconomic variables. They argued that the systematic forces that influenced returns are those which change discount factors and expected cash flows. They thus maintained that real production variables, the interest rate, inflation and consumption variables are likely candidates for pervasive state variables to influence stock returns.

Fama and French (1989) have demonstrated that dividend yields, term spreads and default spreads predict excess returns on stocks and on corporate bonds. The predictor variables are interpreted as correlated with changes in investors' required returns. Dividend yields and default spreads are highly correlated. These two factors capture long-term movements in economic activity, predicting high excess returns when business conditions are persistently weak and low excess returns when business conditions are persistently strong. The term-spread is more closely related to the shorter-term business cycle. The term-spread and its component of the predicted excess returns are low around the peak of a measured business cycle and high around the trough. Dividend yields and default spreads thus predict long-term (three to four year) excess returns, while term-spreads predict shorter-term (one month to two year) excess returns.

Empirically, the macro-factor model has been applied to different economies. For example, Hamao (1988) showed that those changes in expected inflation, unanticipated changes in risk premium and unanticipated changes in the slope of term structure appear to have a significant effect on the Japanese stock market. Kwon (1994) found, though, that inflation and interest-rate related variables are not important to the Korean stock market. Instead, those variables that were related to real activities were significant factors. This was different from the US and Japanese security market.

Fung and Lie (1990) utilised these tests to examine the economic role of the Taiwan stock market in response to changes in economic activities such as GNP and money supply. They found that the market fails to capture economic information. Groenewold and Fraser (1997) discovered that the inflation rate has been consistently priced in the monthly Australian sectoral share-price index returns, but the significance of other factors depend on their choice of sample period and estimating model.

Additionally, Asprem (1989) found that the associations between stock prices and macroeconomic variables were strong in Europe. Similar studies were also carried out by Clare and Thomas (1994) for the UK market, Koutoulas and Kryzanowski (1996) for the Canadian market.

Recently, Bilson et al. (2001) found that local macroeconomic variables have explanatory power over stock returns in 20 emerging markets. The most common choices of state variables that can reflect economic and business conditions are industrial production, the term structure, the Treasury bill rate, the default spread, the dividend yield and some macroeconomic variables such as consumption.

Gjerde and Sættem (1999) examine the causal relationships among stock returns and macroeconomic variables in a small, open economy, the Norwegian market. They find that to be consistent with US and Japanese findings, the real interest rate changes and oil prices changes affect stock returns. However, they find that the stock market shows a delayed response to changes in domestic real activity.

Gallagher and Taylor (2000, 2002) investigate how the temporary and permanent components of stock price movements are related to aggregate macroeconomic supply and demand disturbances. They find that the aggregate demand shocks have only temporary effects on real stock prices, while supply shocks affect the level of real stock prices permanently. Their evidence supports the man-reversion hypothesis that stock prices are not pure random walk.

Generally speaking, most empirical work within this category has shown that returns are predictable, but there is an absence of consistent or reliable models for prediction. The most common and fruitful method is to track the expected excess returns based on publicly available economic information. Even the exact cause-and-effect relationships between macroeconomic variables and the stock market are not known; however, they are related. Economic activity affects corporate profits, investor attitudes and expectations, and ultimately security prices. Overall, economic activity manifests itself in the behaviour of stocks in the stock market (Fischer and Jordan, 1987).

2.2.4 Trading strategy, momentum and profitability

In addition to the time series and cross-section return variation, predictability has been detected by some trading strategies. The momentum literature has provided considerable evidence of profitability from investment strategies that challenge the efficient-market hypothesis.

Momentum refers to a predictable pattern in stock returns. Momentum literature implies that stocks with above (or below) average returns in recent months tend to outperform (or under-perform) other stocks in subsequent months. Momentum trading strategies thus involve taking advantage of this kind of anomaly by purchasing stocks that have performed well and short selling those that have under-performed a common benchmark. The contrarian trading strategy is the opposite position of momentum strategy.

Sorensen and Burke (1986) have suggested a strategy based on buying and holding the best performing industry group — a naive strategy that requires only knowledge of past information and no superior forecasting ability that may enhance portfolio returns.

Rosenberg et al. (1985) investigate a book/price strategy and a "specific return reversal" strategy. Their results indicate that there are large potential profits to be made through these two trading strategies; that is, the predicted excess returns could be exploited by investors to earn profits. They thus concluded that the prices on the New York Stock Exchange are inefficient.

Pesaran and Timmermann (1995) have examined predictability in excess of a buy-and-hold strategy; however, they found that the degree of exploitation of this predictability was very low. Jegadeesh and Titman (1993) investigated a variety of momentum strategies. The strategy of buying stocks that have performed well in the past and selling stocks that have performed poorly in the past generated significant positive returns of about 1 per cent per month over a 3- to 12-month holding period.

Moskowitz and Grinblatt (1999) find momentum profits across industry-sorted portfolios. They have discovered that buying stocks from past winning industries and selling stocks from past losing industries is highly profitable even after controlling for size, book-to-market equity, individual stock momentum, the cross-section dispersion in mean returns and potential microstructure influences.

Grundy and Martin (2001) claim that momentum strategies have been consistently profitable in the US. They find that industry momentum strategies earn significant returns of about 0.55 per cent (value-weighted) and 0.89 per cent (equal-weighted), but this level of profit only partially explains average total returns of 1.59 per cent from the momentum strategies they have examined.

Some non-US studies have provided evidence of profitability of momentum strategies. Rouwenhorst (1998) documents average monthly excess returns of about 0.96 per cent from stocks in twelve European countries. Rouwenhorst (1999) examined the momentum premium for twenty emerging markets and found that excess returns to the zero-cost portfolio averaged 0.39 per cent per month when stocks were equally weighted and 0.58 per cent per month when countries were equally weighted.

Darling (2000) investigated Australian equities. He found that momentum returns in Australian stocks are more pronounced than in US stocks, with average monthly returns of 1.56 per cent for the "six-month estimation and holding period" strategy. Demir et al. (2002) investigated the returns to short-term and intermediate-horizon momentum strategies in the Australian equities market. They found that not only is momentum prevalent in the Australian market but also the returns have greater magnitude than previously found in overseas markets. Additionally, the momentum strategy returns are robust to risk adjustment and prevail over time. The profits to these investment strategies are not explained by size or liquidity differences among the stocks.

The interpretation of momentum strategies usually involves the overreaction and persistence of returns (Jegadeesh, 1990). The recent literature suggests that momentum profits are to be explained by some behavioural models (Jegadeesh and Titman, 2001). Chordia and Shivakumar (2002) show that profits to momentum strategies can be explained by a set of lagged macroeconomic variables. They point out that the payoffs to momentum strategies disappear once stock returns are adjusted for their predictability, based on these macroeconomic variables relating to business cycles. They thus argue that time-varying expected returns are a plausible explanation for stock momentum. The predictability of stock returns by macroeconomic variables is due to the ability of these variables to capture time-varying returns.

2.2.5 The predictability of industrial sector returns

In the practice of international equity management, the first stage of investment by the manager usually is to allocate the funds globally to broad asset classes on the basis of forecasts of the overall economic and market environment. In the second stage, the group-rotation stage, managers attempt to identify economic sectors and industries that stand to gain or lose relative to the overall market. Lastly, the manager uses industry analysts to select the most attractive stocks from those sectors. This process of international investments highlights the importance of predictability of industrial sector returns.

The early work of King (1966) provides evidence that the movement of a group of security price changes can be broken down into market and industry components. He used a factor analysis to break down the variance of security prices into two parts. One part was attributable to common factors only. Another part, the residual part, was unique to the securities. King's work inspired a group of researchers to investigate the industry factor or risks in security returns.

Sorensen and Burke (1986) found significant abnormal returns relative to the market index for their ranked industry groups. Their study indicated that active industry group rotation would enhance the portfolio returns. Their results support industry predictability. Significant abnormal returns have also been found in the industrial portfolios constructed and rebalanced through multiple periods by Grauer et al. (1990).

Boyle and Young (1988) identified situations where variation in hedging-benefits may exist across different equities, consistent with industry differences in the relationship between nominal equity returns and inflation. Their model explains variation in expected inflation/equity return correlation across industries where the industry classification is based on product or commodity.

According to Boudoukh et al. (1994), industry variation in the relationship between inflation and nominal equity returns is a function of expected real dividend growth and possibly the expected value of the ratio of real price to real dividends. In the case of dividend growth, they argued that the industry inflation beta coefficient varies with the extent to which dividend growth is correlated with the aggregate economy.

Most empirical work in this area focuses on industry differences or industry factors to explain the variance of asset returns. The empirical results are generally consistent regarding the issue of substantial divergence in relative performance of industries. Those studies include Fama and French (1988a), Reilly and Drzycimski (1974), Rosenberg (1974), Breeden et al. (1989), Kale et al. (1991) and Boudoukh et al. (1994). Technically, they use industry groups as a form of classification. The industry factor or risks are reflected as different variances relative to the market; however, there is an absence of work that concentrates on the industrial predictability of returns.

Wei and Wong (1992) and Boudoukh et al. (1994) both indicate the different sensitivities of various industrial groups to inflation. Jensen, Johnson and Bauman (1997) identify the different expected returns across industries as different responses of monetary policy. Another study by Boyle and Yong (1988) also confirmed the findings of industry differences in the relationship between nominal equity returns and inflation.

Faff and Chan (1998) applied a three-factor model to the returns of gold stocks in the Australia equity market. They found that the market and gold price factors could explain the gold stock returns. Faff and Heaney (1999) investigated the relationship between inflation and Australian industry returns. Their results implied a variation observed in the relationship between expected inflation and equity returns.

A more recent study by Cooper, Jackson III and Patterson (2002) found that bank-stock returns can be predicted by variables related to non-interest income, loan–loss reserves, earnings, leverage and standby letters of credit.

Krishnamoorthy (2001) discovered that the industrial structure is an important determinant of exchange-rate exposure of industry portfolio returns. His results showed that industries identified as competitive (airlines, automotive, banking etc.) are more sensitive to exchange-rate changes than those classified as oligopolistic (tobacco, construction manufacturing etc.). Furthermore, industries that primarily serve the consumer sector of the economy (airlines, tobacco, banking and household appliances etc.) are more sensitive to exchange-rate exposure than those that serve the institutional sector; for example aerospace, construction manufacturing and industrial chemicals.

Recently, some empirical evidence has shown that market effects have become less important in the management of equity funds, and industry effects have become more important (Black et al., 2001; Campbell et al., 2001). Cavaglia et al. (2000)

have shown that diversification across global industries has provided greater risk reduction than diversification by countries; therefore, industry allocation is an increasingly important consideration for active managers of global equity portfolios.

There has been a rising interest in testing industry momentum; for example, Moskowitz and Grinblatt (1999) and Grundy and Martin (2001). Moskowitz and Grinblatt (1999) found strong evidence that persistence in industry return components generates significant profits that may account for much of the profitability of individual stock momentum strategies. Industry momentum is strongest in the short-term and tends to dissipate after 12 months, eventually reversing at long horizons. They further argue that industry momentum strategies are more profitable than individual stock momentum strategies and are robust to various specifications and methodologies. The existence of industries as a key source of momentum profits may support the viability of behavioural models that have been offered for the individual stock momentum anomaly.

Additionally, some recent evidence has suggested the benefits of using an industry portfolio in the asset pricing literature. Groenewold and Fraser (2002) have shown that the asset pricing tests using the Australian industry portfolio are not sensitive to the assumption that returns are identically, independently, and normally distributed (iid-normal).

2.3 Australian literature on return predictability

Since this thesis focuses on the Australia market, it is necessary to conduct a review of the Australian background literature on return predictability. Early Australian research relating to the efficiency of the stock market includes studies of serial dependence in share prices by Officer (1975) and Praetz et al. (1975). Officer (1975) discovered the seasonal pattern of stock indices, and argued that the presence of a seasonal pattern does not contradict market efficiency as the opportunity cost of capital varies at different times of the year. Praetz et al. (1975) compared the returns from various filters with those from buy-and-hold strategies but failed to reject the market-efficiency hypothesis.

Ball et al. (1977) and Sharpe and Walker (1975) have all suggested that market returns quickly reflect the announcement of bonus issues and asset re-evaluations of individual companies after accounting announcements. Therefore, their results suggest that the Australian market is generally efficient.

Hogan et al. (1982) examined the efficiency with which the Australian share market incorporated new information relating to interest rates and the monetary aggregates. They found a strong relationship between medium-term government security yields and equity returns, although little relationship was found between unanticipated changes in the monetary aggregates and share returns. Furthermore, the interest rate relationship was found to involve long lags, which suggests inefficiency in stock market pricing in Australia.

Sharpe (1983) investigated the relationship between weekly Australian equity returns and a group of domestic and external financial variables. He tested the joint hypothesis of market efficiency and of the assumed equity market equilibrium pricing relationship. He discovered that about 10 per cent of the unanticipated rate of growth of the monetary base was associated with a 2–2.5 per cent upward revision in stock prices. The stock price was also related to the rate of change of the exchange rate; however, the joint hypothesis of market efficiency and constancy of equilibrium expected equity returns was strongly rejected, which suggested that the Australian market was inefficient.

Groenewold and Kang (1992) used the monthly aggregate-share-price indices and macroeconomic data to test the weak and semi-strong form of the efficient-markets hypothesis; however, they didn't find a significant explanatory power from either lagged returns or lagged explanatory variables for share returns. Their results thus generally supported market efficiency. Groenewold (1997) reported efficiency testing results using daily data. He found that the autocorrelation of returns provided evidence of return predictability.

Brailsford and Faff (1996) examined the relative ability of various models to forecast Australian monthly stock market volatility. The models that they tested were:

- a random-walk model;
- a historical-mean model;
- a moving-average model;

- an exponential-smoothing model,
- an exponentially-weighted moving-average model;
- a simple-regression model;
- two standard GARCH models; and
- two Glosten–Jagannathan–Runkle (GJR) asymmetric GARCH models.

They found no superior forecasting ability in any of the models to predict stock volatility as the rankings of the various model forecasts are sensitive to the choice of error statistics.

Kearns and Pagan (1993) point out that the Australian market does not have similar features of asymmetry in responses and sensitivity to economic conditions to the US market because the Australian market is relatively dependent on commodity prices while the US market is more diversified.

Halliwell et al. (1999) indicated that the abnormal returns in the Australian share market can be explained by the size and book-to-market effects; therefore, the market risk premium was not the sole explanatory variable for Australian equity returns over 1981–91.

Hewarathna and Silvapulle (1999) pointed out that the real, monetary and financial variables of Australia were related to each other, and that this relationship was not subject to the structural change of market deregulation in 1983 and the stock market crash in 1987.

Faff and Heaney (1999) investigated the relationship between the expected inflation and nominal equity returns. They decomposed the observed inflation rate into two components: the expected inflation rate (the signal) and the forecasting error (the noise); however, they did not discover a significant relationship between expected inflation and nominal equity returns.

Recently, Trivedi and Brooks (1999) used the power transformations of Ding, Granger and Engle (1993) and Hentschel (1995) to explore the predictable autocorrelation structure in Australian stock indices data. They revealed that for a larger number of different market indices there exists an autocorrelation structure in the power transformations of returns that could be exploited in forecasting.

From the macroeconomic point of view, Black, Fraser and Groenewold (2003a) investigated the speculative component in Australian share prices. They found that observed share prices deviate substantially and significantly from their fundamental values for about four years and at the end of their sample period, mid of 2000, the share prices were overvalued by approximately 10 per cent.

In the trading strategy literature, in an earlier work by Brailsford (1992), no winner–loser anomaly was found in Australia. This denied mean-reversion return behaviour. However, both Darling (2000) and Demir et al. (2002) confirmed that the momentum strategies are in fact profitable in Australian equities market.

2.4 The economic significance of predictability

The economic interpretation of predictability results is controversial in the finance literature. Fama (1991) stressed that any attempts at interpretation of excess-return predictability will be model dependent and, hence, inconclusive. For many who take expected returns as constant, the predictability of stock returns is evidence of market inefficiency; however, it is possible that the predictable components in stock returns reflect time-varying expected returns, in which case predictability of stock returns, in principle, is consistent with an efficient stock market (Pesaran and Timmermann, 1995).

It has been pointed out that the results supporting predictability do not necessarily contradict the idea of rational pricing in an efficient market (for example, Balvers, Cosimano and McDonald, 1990; Pesararan and Timmermann, 1995). Rather, the predictor variables are interpreted as being correlated with changes in investors' required returns.

The evidence of mean reversion needs to be interpreted carefully. On the one hand, it may imply that stock returns can be predicted, which indicates market inefficiency. Another interpretation is that the market risk premium actually varies over time. The presence of mean reversion might just be an indication of the stock prices reacting to variation in the risk premium. The impression of overreaction and correction of the market price is, maybe no more than a rational response of market prices to changes in discount rates. In the aggregate market level, the predictor variables are proxying for variation in the market risk premium. The predictability of market returns is indeed due to the predictability of risk premium, not risk-adjusted abnormal returns.

Balvers Cosimano and McDonald (1990) present two explanations for the predictability of returns. One possible explanation for predictability is some form of general or limited irrationality such as fads and speculative bubbles as documented in Summers (1986) and Poterba and Summers (1988). Another possible attribute of predictability is some form of general equilibrium model that provides for variation in real rates of return over time. They further present a general equilibrium theory relating returns on financial assets to macroeconomic fluctuations in a context that is consistent with efficient markets in that no excess-profit opportunities are available. They show that within an efficient market framework, stock prices do not need to follow a random walk. The changes in the equilibrium return on stocks can be predicted to the extent that there is predictability in aggregate output.

Reichenstein and Rich (1993) estimate the market risk premium based on value-line forecasts of dividends and capital gains. Their tests show that the measured risk premium predicts long-horizon stock returns as it moves with the unobservable market risk premium; therefore, the predictability of long-term stock returns reflects time-varying expected returns in a rational market.

To evaluate the economic significance of stock market predictability, it is necessary to test whether the evidence of predictability could have been exploited successfully in investment strategies. Pesaran and Timmermann (1995) point out that one way to do this is to investigate whether some portfolios systematically generate excess returns by checking the performance of portfolios. Another way is to simulate investors' decisions in real time using publicly available information on a set of factors. The first approach does not give information about the predictive factors, though, and it does not guarantee that the information used by the portfolio managers is publicly available. The second approach — testing the predictability on the basis of a set of predictable variables — thus becomes the most common and fruitful way.

Ferson and Harvey (1991a) have discovered that changes in the risk premiums are far more important than changes in the betas in explaining the variation of the returns. The predictor variables they chose are past excess returns of the market index, the excess return on the three-month Treasury bill, the past dividend yield, the yield spread between Baa and Aaa class of corporate bonds, the one-month Treasury bill rate and a dummy variable for the month of January.

Ferson and Harvey (1991b) provide evidence that most of the predictability of monthly common stock is associated with sensitivity to economic variables in a rational asset-pricing model with multiple betas. Time variation in the premium for beta risk is more important than changes in the betas. More sophisticated methods that incorporate the time-varying risk premium are thus necessary for research into the predictability of industrial returns.

Schmitz (1996) presents a theory to link market premiums to the current and future health of the economy. This allows for the modelling of market risk premium expectations as a function of financial state variables if the state variables can be shown to predict output growth. His results also revealed that predictability, specifically the predictability of market risk premiums, is profitable. He claimed, though, that as the proposed model permitted time-varying market risk premiums, the evidence of predictability does not violate market efficiency.

Ferson and Korajczyk (1995) point out that rational expectation implies that security returns should be predictable only to the extent that expected returns are related to the predictor variables. While in the traditional asset-pricing models, the expected returns of securities are determined by their "beta coefficients" or factor loadings and by the associated market-wide risk premiums, any predictability of returns should thus be driven by changes in the betas and changes in the expected risk premiums. They further find that a large fraction of the predictability in returns can be explained by their arbitrage-pricing model for all investment horizons from one month to two years. Their tests also imply that the beta is not constant for the shorter-horizon returns but is more stable for long-horizon returns, and the multi-beta models perform better than the single-beta model.

Recently, Kirby (1998) drew attention to the restrictions on predictability implied by the rational asset-pricing model. He argued that the asset-pricing model implies that the parameters of the prediction regression must take on certain values. His results showed that with these restrictions returns are too predictable to be consistent with consumption-based specification, CAPM and the three-factor model of Fama and French (1993). His results do suggest, though, that the cross-sectional differences in predictability are reasonably consistent with normal expectations under circumstances where predictability is rational.

Ferson and Harvey (1998) provide a global, conditional, asset-pricing perspective on the fundamental determinates of 21 national equity markets. They find that the relation of the fundamental attributes to expected stock returns and to risk is different across countries. Fletcher (2001) employs the conditional asset-pricing model of Ferson and Harvey (1999) and Kirby (1998) to examine the predictability of UK stock returns. He finds that the domestic APT tends to capture most of the time-series predictability in UK stock returns and performs better than the CAPM.

Recent developments in behavioural finance have offered some new interesting explanations to the predictability of returns from an investor-behaviour point of view. Daniel et al. (1998) proposed a theory of securities market under- and overreactions. They show that there are two psychological biases within investors: overconfidence in private information and biased self-attribution. Investors overestimate the precision of private information, which causes stock prices to overreact to private information signals, and they under react to public signals. This overreaction-correction pattern is attributed to long-run negative autocorrelation in stock returns with unconditional excess volatility.

Another bias within investors is that investors update their confidence in their own ability in a biased manner according to the outcomes of their previous actions. This biased self-attribution causes short-run momentum and long-term reversals in security prices; however, Fama (1998) interprets the predictabilities as chance deviations to be expected under market efficiency. He argues that the discovered anomalies split randomly between under reaction and overreaction, and the apparent overreaction to information is as common as under reaction, which is consistent with market efficiency.

2.5 Summary

Overall, a large number of empirical studies have shown that stock returns can be predicted by means of publicly available information. The evidence for predictability of short-horizon returns is inconclusive; however, the time-series data on financial and macroeconomic variables can partially explain the returns. As noted by Fama and French (1989), the business-cycle pattern of real output has a direct influence on the equity yields and, therefore, the movements in these yields can explain the observed predictability in excess returns.

The evidence of predictability in the short- and long-terms is inconsistent due to the different correlation structure among returns. From a macroeconomic point of view, some academics claim that long-run and short-run stock prices respond to different economic shocks; thus, the predictability of stock returns is a result of supply and demand effects (see Gjerde and Sætten, 1999; Gallager and Taylor, 2000; Black, Fraser and Groenewold, 2003b). Lee (1998) identified various components of stock prices and examined the response of stock prices to different types of shocks. These included permanent and temporary changes in earnings and dividends, changes in discount factors, and non-fundamental factors. He found that the long-term trend in stock prices is due to permanent changes in fundamentals. Short-term volatility is due to discount-factor changes reflected in excess stock return changes and, partly, due to non-fundamental factors. The deviation of stock prices from fundamentals declines as the time horizon increases. His results suggest that the over-reaction of the stock market and the mean reversion in stock returns are in response to the excess return changes and, partially, in response to non-fundamental factors.

The economic interpretation of the predictability results is contentious and inconclusive. It should be noted that predictability itself does not necessarily imply market inefficiency. One explanation for time-series predictability is the time-varying property of expected returns. The interpretation of cross-section returns rests on the potential alternative of risk sources in a multi-factor model. The predictability of stock returns in the context of time-varying expected returns is consistent with rational pricing behaviour in an efficient market. Further tests on predictability should thus incorporate the time-varying behaviour of expected returns in a multi-factor model framework.

Chapter 3 Data and methodology

3.1 Introduction

This chapter focuses on the data and methodology of the study. Section 3.2 introduces the data. Section 3.3 reviews methodologies adopted by previous studies and discusses the empirical difficulties and problems in testing the predictability of stock returns. Section 3.4 presents the empirical design of the current research with Section 3.5 summarising and concluding the chapter.

3.2 Data

The stock price data used in this study are the monthly Australian All Ordinaries price index and Australian Stock Exchange industrial stock indices from December 1979 to March 2000. The data is sourced from the DataStream, an existing database. The Australian market is broken into two main sectors and 24 industry groups. The market capitalisations of each industry group and its proportion to the All Ordinaries Index at the end of 2000 are provided in Table 3.1. The banking sector has become the largest industry group in ASX, which is followed by the media industry, the diversified resources industry and the telecommunications industry.

Industry sectors were introduced to Australia in 1980 to coincide with the commencement of the national All Ordinaries index. Since then, new industry sectors have been created to reflect the changing nature of companies listed on Australian Stock Exchanges. In general, the way new sectors were created was purely a function of whether there were enough companies within an industry group to warrant an independent sector.

Table 3.1: ASX industry groups

Group	% of All Ords	Group	% of All Ords	Group	% of All Ords
Gold	1.09	Building Materials	1.44	Retail	4.31
Other Metals	1.12	Alcohol & Tobacco	2.33	Transport	2.34
Diversified Resources	8.86	Food & Household	1.44	Media	11.75
Energy	3.02	Chemicals	0.43	Banks and Fins.	22.75
Infrastructure & Utilities	2.36	Engineering	0.16	Insurance	5.59
Developers & Contractors	2.78	Paper & Packaging	0.85	Telecommunications	9.59
Investment & Fin. Services	2.67	Property Trust	5.76	Healthcare & Biotech.	3.08
Misc. Industrials	2.2	Diversified industrial	2.4	Tourism & Leisure	1.7

Source: ASX Fact Book 2001.

Two main sectors are the resources sector, which consists of the gold, other metals, energy and diversified resources industry groups and the industrial sector, which consists of all other industry groups. However, five of these industrial indices started in 1990s and thus do not have complete sample periods; therefore they are excluded from this study. These five industry groups are Healthcare and Biotechnology, Infrastructure and Utilities, Miscellaneous Industries, Telecommunications, and Tourism and Leisure Industry.

In June 2001, ASX introduced the global sector indices, derived from the GICS (Global Industry Classification Standard) structure. The GICS system has four levels of detail: 10 sectors, 23 industry groupings, 59 industries and 122 sub-industries. The GICS global sector indices have run in parallel to the ASX sector indices since June 2001. The old ASX sectors are mapped into GICS sectors (see Appendix A. for more details).

The stock returns are calculated using the first difference of stock price index as:

$$R_t = \ln(P_t) - \ln(P_{t-1}),$$

where R_t is the index return and P_t is the index price at time of t. The excess return is obtained by subtracting the return from the monthly yield of Treasury-bill as the Treasury-bill rate is usually considered as the proxy for the risk-free rate.

The economic data needed for this research were the national economic statistics for Australia compiled from the DataStream and the bulletin of Australian Bureau of Statistics. The previous studies of Chen, Roll and Ross (1986) and Groenewold and Fraser (1997) suggested that some economic variables were significant in explaining the stock market returns. These variables are measurements of the real domestic activity, nominal domestic influences and foreign influences. Therefore, a set of economic statistics are selected with consideration of the availability of the monthly series.

The economic series used are monthly series of industrial production index, money supply in the level of M3, the unemployment rate and the aggregate dividend yield on index. Since there is no monthly statistics of inflation in Australia, the monthly Reserve Bank of Australian Commodity Price Index is adopted to compute the inflation rate. The interest rate statistics include yield of 10-year government bond, the 90-day commercial bill rate and 3-month Treasury bill rate. For measurement of international trade and foreign influences, the current account balance and the Australian dollar exchange rate to the US dollar are adopted. Each variable is constructed as the following:

- Industrial Production (IP):

$$IP_t = \ln(IPI_t) - \ln(IPI_{t-1}),$$

where IPI_t is the monthly industrial production index at time of t.

- Inflation (EI):

$$EI_t = \ln(CPI_t) - \ln(CPI_{t-1}),$$

where CPI_t is the Commodity Price index. While the Consumer Price Index is usually used to compute the inflation, however, the monthly data of Australian Consumer Price Index is not available. Therefore, the Reserve Bank of Australian Commodity Price Index is adopted here.

- The Term Structure (TS):

$$TS_t = \ln(LTB_t) - \ln(TB_{t-1}),$$

where LTB_t is the monthly yield of 10-year government bond at time t and TB_{t-1} is the monthly yield of Treasury bill at time of $t-1$.

- The Commercial Bill Spread (CBS):

$$CBS_t = \ln(CB_t) - \ln(LTB_t),$$

where CB_t is the monthly yield on Commercial Bill rate and LTB_t is the monthly yield on government bond.

- The Dividend Yield (DDY):

$$DDY_t = \ln(DY_t) - \ln(DY_{t-1}),$$

where DY_t is the aggregate dividend yield of time t.

- The Money Supply (M3):

$$M3_t = \ln(MS_t) - \ln(MS_{t-1}),$$

where MS_t is the money supply at level of $M3$ at time of t.

- The Unemployment (UM):

$$UM_t = \ln(UML_t) - \ln(UML_{t-1}),$$

where UML_t is the monthly unemployment level at time of t.

- The Exchange Rate (EX):

$$EX_t = \ln(EXU_t) - \ln(EXU_{t-1}),$$

where EXU_t is the exchange rate of Australian dollars to US dollars at time of t.

- The Current Account Balance (GCB):

$$GCB_t = (CAB_t - CAB_{t-1}) / CAB_{t-1},$$

where CAB_t is the current account balance at time of t.

3.3 Review of testing methodology for predictability

The efficient-market hypothesis proposes that in an efficiency market, the successive price changes in individual securities are independent, by definition; the stock price changes follow a random walk. The early tests for predictability concentrate on the random walk model to test whether the successive price changes are independent. This approach for testing the dependence relies primarily on common statistical tools such as serial correlation coefficient.

Under the random-walk hypothesis, all changes in prices are permanent; therefore, stock returns are unpredictable. There will be no transitory component in return series. If returns were predictable then "there would be a transitory, but serially correlated component to prices that allows them to diverge from their 'fundamental' values, possibly, for a considerable period of time" (Mills, 1995, p.1). Thus another focus of research into predictability of stock returns is closely related to the problem of estimating the permanent component of stock prices.

The majority of the previous studies testing predictability adopted a regression-based approach — e.g. Fama and French (1988a, 1988b) — or variance-ratio tests; e.g. Lo and MacKinlay (1988, 1989). Kaul (1996) and Granger (1992) provide reviews of the methods of and results from work on predictability.

The regression-based tests of predictability focus on the pattern of the return autocorrelation function over increasing horizons. The pattern possessing predictability is a positive autocorrelation for short-return horizons and negative autocorrelation for longer horizons. The regression-based work on testing predictability of stock returns has two categories. The first category includes using information from past stock prices alone. The second category applies the test using the public information.

Fama and French (1988), Poterba and Summers (1986) and Cutler et al. (1991) use univariate studies to test the patterns in return autocorrelation. Mills (1995) argues that a problem with univariate methods of examining returns is that the test tends to have low power in detecting departures from the random-walk hypothesis due to lack of non-overlapping long-time-series data.

Clare, Tomas and Wickens (1994), Shah and Wadhwani (1990), Fama and French (1988a, 1988b) and Campbell (1987) employ the multivariate single-equation method. Though these studies have confirmed that some economic variable, such as the dividend-price ratio, the yield spread, those variables are often interpreted as determinants of the expected return.

The variance-ratio test, however, compares the relative variability of returns over different horizons. If the stock prices follow a random walk process, the ratio of the return variance for a *T*-period return horizon to a *1*-period return horizon should equal *T*. French and Roll (1986) use the variance-ratio test to compare the behaviour of stock return volatility during trading and non-trading days. Lo and MacKinlay (1988, 1989) have been the most formal usage of the variance-ratio test to examine the random-walk hypothesis. Other studies employing the variance-ratio statistics also include Cochrane (1988), Poterba and Summers (1988) and Mills (1991).

The reliability of inferences drawn from individual point-estimates of long-horizon autocorrelations and variance ratios has been questioned, though, by Jegadeesh (1990), Kim et al. (1991), Mankiw et al. (1991) and Richardson (1993). These critics argue that the long-horizon t statistics tend to overstate the degree of mean-reversion. They claim that as only a relatively few non-overlapping long time series exist, the tests of autocorrelations and variance ratios lack high quality data. The results from regression-based tests and variance-ratio tests thus appear to be data-dependent and suffer from a small-sample problem.

Kim et al. (1991) challenged the evidence for mean reversion by using measures of statistical significance that are independent of normality assumptions of stock returns. They found that mean reversion was primarily a phenomenon in the volatile markets of 1926–46.

Recently, some new techniques have appeared in the literature to increase the efficiency of tests for predictability. A recursive modelling approach to predicting returns has been proposed by Timmermann (1993) and Pesaran and Timmermann (1994, 1995, 2000). There is also a resurgence in using time-varying beta and the dynamic-linear models; for example by Huang (2001) and Campagnoli et al. (2001). The nonlinear approach was adopted by Qi and Maddala (1999) and Racine (2001), and the nonparametric method was used by Chung and Zhou (1996). More recently, Stambaugh (1999) and Avramov (2002) have adopted the Bayesian approach.

Despite mounting evidence of predictable components of returns, the literature on predictability of stock returns almost uniformly assumes a time-invariant relationship between state variables and returns. Pesaran and Timmermann (1995) described this assumption as being inappropriate because, in real time, no investor could have obtained parameter estimates based on the entire sample. Any forecasting model over the whole sample period could be criticised for ignoring the problem of model uncertainty. When the same forecasting model is used over the whole sample period, it increases the possibility that the choice of the model could have been made with the benefit of hindsight. Forecasting from this category of static models thus cannot be regarded as reliable and accurate.

Empirically, one problem that arises is the choice of predictable variables. It seems that there is no satisfactory financial theory addressing what the predictable variables are. Financial theory suggests, though, that markets would vary with the state of the business cycle; therefore, a common study of predictability of stock returns would usually be based on variables related to the business cycle (see Lucas, 1978 and Balvers et al., 1990). In the spirit of Arbitrage Pricing Theory, one of the classical methods is to derive factors by factor analysis, as in the work of Roll and Ross (1980); however, the variables extracted through this method were found to be short of economic meaning.

Some other works have been done by choosing macroeconomic variables arbitrarily because those variables have economic implications. These include the work of Chen et al. (1986), Hamao (1988), Clare and Thomas (1994), and Groenewold and Fraser (1997); however, most of these "models" are subject to different violations of classical econometric assumptions. The choices of the classical specification were always found to be sensitive to the initial specification investigated, the order in which tests were taken, type I and II errors, and the innumerable prior beliefs of researchers concerning the parameters, which subtly influenced decisions taken throughout the specification process (see Kennedy, 1998).

Even if it is believed that different possible specifications should lead to the same conclusion with respect to the purpose for which the study was taken, the empirical works have not been giving consistent results. Fama (1991) points out that any research focus on testing for predictability has to be associated with some kind of joint hypothesis regarding the asset-pricing model.

Campbell (1991) points out that the impact of revision in expectations about future returns on current stock prices depends not only on the degree of return predictability but also on the time-series properties of expected returns. In particular, even if return predictability is low, the news about expected returns still can have a powerful effect on stock prices provided that expected returns are "persistent"; i.e. a shock to the current expected return has a permanent effect on expectations of all future returns.

At the industry-group level, most researchers consider that industry returns focus on industry "factors" or risks in security returns (Beller et al., 1998). There is an absence of work with the primary purpose of investigating industry returns' predictability. It is less likely to know to what extent the available information could explain the different industry groups' expected returns. In fact, the issue of industry stock returns' predictability has important implications to both portfolio management and security pricing theories.

Many of the earlier studies used their whole sample for tests of predictability without an out-of-sample analysis. However, for a forecasting model to be accepted, it has to show that it actually forecasts. It is not sufficient to produce a regression model evaluated only in sample. Nelson and Kim (1990) have argued that there is always the possibility of small-sample in-sample biases of coefficients which give overly encouraging results. Therefore, the out-of-sample evaluation is important and is able to avoid those problems to some degree.

Other problems in testing predictability arise from data limitations such as long-run time series, industry classification and portfolio selection. Since there are always limited reliable long-time series, normal statistical testing suffers from the problem of small samples. The standard econometric procedures lack the power to reject the null hypothesis of a random walk in stock prices against the alternative of mean-reversion.

Overall, a desirable further test for predictability of returns requires a capability to handle some of the problems discussed above, especially to release the assumption of a time-invariant relationship. The state-space framework allows the model parameters to be updated with newly arrived information; therefore it is expected to have advantages in investigating the predictabilities of the stock market. Additionally, an out-of-sample test should be conducted to evaluate the power of the in-sample test.

3.4 Empirical design

A forecast is a statement about an uncertain future. The conventional methods of developing forecasts for time series are unreliable as they do not give probabilistic treatment to the uncertainty arising from inexact knowledge of the true "model specification" (Doan et al., 1984). Generally speaking, there are only two sources of information we could use for forecasting. These are historical information and knowledge about the structure of the system generating the data. Especially with time-series forecasting, the passage of time always brings changed circumstances, new situations and fresh considerations.

Most early literature on predictability is concerned with static models: models with one set of parameters whose values are fixed across all sample periods. Those kinds of static model formulations imply that the quantified relationship remains the same across the design space of the data, while the stock prices or returns are a time series (a series of observations taken sequentially over time). A dynamic system is thus a more suitable framework for modelling the time series as it is able to incorporate the changed situation brought by the passage of time.

Pankratz (1991) explains that in forecasting with dynamic-regression models, "dynamic" means that the attention is paid to the time structure of the input–output relationship and the time structure of the disturbance series. West and Harrison (1997) define the dynamic models as "sequences of sets of models", one for each possible value of the model's parameter with a probability description of parameter distribution. The dynamic model thus defines a qualitative form for the underlying structure of a series. Dynamic models are explicitly formulated to allow for changes in parameter values as time passes. The passage of time, with additional observations becoming available sequentially, is usually associated with increasing knowledge, thereby adding to the information store.

3.4.1 The state-space model and the Kalman-filter technique

The state-space model has been highly popular and productive recently in modelling dynamic systems, especially when an observed or state variable is involved in the system. Kim and Nelson (1999) describe the state-space model as follows:

> *A state-space model is one in which an observed variable is the sum of a linear function of the state variable plus an error. The state variable, in turn, evolves according to a stochastic difference equation that depends on parameters that in economic applications are generally unknown. Thus, both the path of the state variable, its relationship to the data, and the covariance structure of stochastic disturbances – are to be inferred from the data (p. 2).*

The state-space representation of a system is a fundamental concept in modern control theory, which has been widely used for expressing dynamic systems (Anderson and Moore, 1979). A state-space system consists of two equations: a transition equation (or state equation) and a measurement equation. The measurement equation describes the relation between observed variables (data) and unobserved state variables. The transition equation describes the dynamics of the state variables, which is defined as a minimum set of information from the present and past such that the future behaviour of the system can be completely described by the knowledge of the present state and the future input.

A state-space framework has been adopted in the econometric and statistics field in various applications; for example, Harvey's (1981, 1989) pioneering work to introduce the state-space model into econometrics. Harvey (1989) gives a comprehensive state-space treatment of structural time-series models. Other recent literature on application of the state-space framework includes Kim and Nelson (1999) and Durbin and Koopman (2001).

The state-space model is a non-stationary stochastic model. The state-space form of varying-parameter regression as developed by Engle and Watson (1981) has two benefits. First, the extra observations available for the regression give added power. Second, use of all the data makes it unnecessary to specify either the event data or a period containing the event date.

A general linear Gaussian state-space model has the following form:

The measurement equation:

$$Y_t = X_t B_t + v_t, \quad v_t \sim N(0, H_t), \tag{3.1}$$

The transition equation:

$$B_t = \Phi_t B_{t-1} + w_t, \; w_t \sim N(0, Q_t), \; t = 1, \ldots n, \tag{3.2}$$

where Y_t is a vector of observations and B_t is an unobserved vector called the state vector. The idea underlying the model is that the development of the system over time is determined by B_t according to the transition equation.

Equations 3.1 and 3.2 are also named the observation equation and state equation respectively in some contexts. The matrices X_t, Φ_t, H_t and Q_t are initially assumed to be known, and the error terms v_t and w_t are assumed to be serially independent and independent of each other.

State-space models typically deal with dynamic time-series models that involve unobserved variables. The basic tool used to deal with the standard state-space model is the Kalman filter. The Kalman filter is based on the early work of Kalman (1960, 1963) and is an algorithm to deal with simple dynamic models in engineering control. The Kalman filter recursive procedure is the tool to compute the optimal estimate of the unobserved state vector B_t, $t=1, 2, \ldots, T$, in equation 3.2. The computation of the estimator of the observed component or the state vector at time t is based on the available information at time t. It provides a minimum mean-square-error estimate of B_t, given the appropriate information set. When the shocks to the model and the initial unobserved variables are normally distributed, the Kalman filter enables the likelihood function to be calculated via the prediction error decomposition. For a linear state-space model, the Kalman filter enables the state-space estimation to be both intuitively appealing and computationally efficient.

Based on the information set used, the Kalman filter consists of two procedures, the basic filter and smoothing. If the estimate of B_t is based on information available up to time t, the filter is referred to as the basic filter. If the estimate of B_t is based on all the available information in the sample through time T, the filter is referred to as smoothing. There are several derivations of the filter available in the literature. Harvey derives it from the properties of the multivariate normal distribution (Harvey, 1989, pp. 109–10). Kalman himself used the ideal of orthogonal projection (Kalman, 1960).

The Kalman filter (basic filter) consists of two steps (prediction and updating) in which B is the state vector, while $\sum$ is its covariance.

Prediction

Treating period $t\text{-}1$ as the initial period, the estimate of the state and its covariance at time t, conditional on information available at $t\text{-}1$, is:

$$B_{t|t-1} = \Phi\, B_{t-1|t-1}, \tag{3.3}$$

$$\textstyle\sum_{|t-1} = \Phi \sum_{t-1|t-1} \Phi^{T} + \Xi. \tag{3.4}$$

When the new observation and corresponding X_t are available, the one-step-ahead prediction error, v_t, and its variance, f_t, can be obtained by:

$$v_{t|t-1} = R_t - R_{t|t-1} = R_t - X_t\, B_{t|t-1}, \tag{3.5}$$

$$f_{t|t-1} = X_t \textstyle\sum_{|t-1} X_t^T + \sigma^2 \tag{3.6}$$

Updating

The prediction error contains new information about B_t beyond that contained in $B_{t|t-1}$; thus, after observing R_t, a more accurate inference can be made of B_t. $B_{t|t}$, an inference of B_t based on information up to time t, would be of the following form:

$$B_{t|t} = B_{t|t-1} + K_t v_{t|t-1}, \tag{3.7}$$

where K_t is the weight assigned to new information about B_t contained in the prediction error. The covariance of time t can be obtained:

$$\textstyle\sum_{|t} = \sum_{|t-1} - K_t X_t \sum_{|t-1}, \tag{3.8}$$

where $K_t = \Sigma_{t|t-1}X_t^T f_{t|t-1}^{-1}$ is the Kalman gain, which determines the weight assigned to information about B_t contained in the prediction error.

When the shocks to the model and the initial unobserved variables are normally distributed, the Kalman filter enables the likelihood function to be calculated via prediction-error decomposition. The unknown hyperparameters of the system, such as elements of Φ and variances of the error terms, are estimated by numerical optimisation over the likelihood function (see Harvey, 1989, chapter 3). This is given by:

$$L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(|f_{t\,|\,t-1}|) - \frac{1}{2}\sum_{t=1}^{T}\frac{v_{t|t-1}^2}{f_{t\,|\,t-1}}, \tag{3.9}$$

where T is the number of observations.

Using the Kalman filter to estimate the time-varying parameters has two benefits. First, the calculations are recursive, so that although the current estimates are based on the entire past history of measurement, there is no need for expanding memory and the extra observations available for the regression give added power. Second, the Kalman filter converges quickly, no matter whether the underlying model is a constant or evolving through time.

Meinhold and Singpurwalla (1983) state that the Kalman filter can actually be viewed as an updating procedure that consists of forming a preliminary guess about the development of the state variable interested and then adding a correction to this guess, the correction being determined by how well the guess has performed in predicting the next observation. Due to the ease of implementation of the algorithm, the Kalman filter has now become well known and widely used in the state-space form of varying-parameter regression, especially by some financial researchers to explore the dynamics of financial series (see Wells, 1996).

3.4.2 Classical approach versus Bayesian framework

The classical econometric method has special difficulties in estimating the state-space model because of the potentially very large number of evaluations of the likelihood function required. Two shortcomings of the classical approach has motivated interest in the Bayesian alternative.

First, Kim and Nelson (1999) have argued that when the classical framework is used to estimate the state variables it is necessary to obtain a computationally feasible algorithm for estimation and to treat parameter estimates as fixed. The degree of approximation in any particular case is unknown.

Second, in the classical approach, estimation of state variables is conditional on the maximum likelihood estimation of the parameter. In contrast, treatment of state variables, parameters and regimes as jointly distributed random variables means that, with the Bayesian approach, estimates of each appropriately reflect uncertainty about the others (see Kim and Nelson, 1999, chapter 7).

The Bayesian forecast allows for changes in parameter values as time passes. Thus it enables us to incorporate both past information and newly discovered information to make probabilistic statements about the parameters. It is more flexible, logical and consistent. The Kalman filter introduced in the previous section was originally an application of the Bayesian sequential updating process in the field of engineering control.

Kennedy (1998) introduced the idea that the main output of the Bayesian analysis is a density function instead of a point estimate as in classical analysis. The algebra of Bayesian analysis is more difficult than that of classical analysis, especially in multidimensional problems. For example, the classical analysis of a multiple regression with normally distributed errors in the Bayesian context requires a multivariate normal-gamma prior which, when combined with a multivariate normal likelihood function, produces a multivariate normal-gamma posterior from which the posterior marginal distribution (marginal with respect to the unknown variance of the error term) of the vector of slope coefficients can be derived as a multivariate t distribution (see Press, 1972). Recent developments in computer techniques have eased the difficulty in numerical integration when the mean of the posterior distribution must be found.

In practice, the Bayesian model has two characteristics. The first is that it requires the researcher to select a prior probability function. The second characteristic is that the Bayesian approach encourages more careful formulation of the model space.

Griffith et al. (1993, Chapter 24) summarises the differences between the classical approach and Bayesian approach. The classical approach is usually used to describe inference with at least the following characteristics:

- Estimators and test procedures are evaluated in terms of their properties in repeated samples.
- The probability of an event is defined in terms of the limit of the relative frequency of that event.
- There is no provision for the formal inclusion of non-sample and loss information.

In the Bayesian approach, probability statements are used, not only for sample outcomes, but also for fixed, unknown parameters. The probability density functions of different types are used to:

- express uncertainty about a parameter before a sample is taken (a prior probability density function);
- describe the likelihood of particular sample outcomes; and
- express uncertainty about a parameter after a sample is taken (a post-sample probability density function).

Also, within this framework, it is possible to include non-sample information about a parameter and to take into account any losses that might occur from making incorrect decisions (Griffiths et al., 1993, p. 764). The procedure that combines a prior distribution with sample information to form a posterior distribution is known as *Bayes' theorem*:

$$\textit{Posterior information} \propto \textit{sample information} \times \textit{prior information} \qquad (3.10)$$

Let θ be a vector of parameters in which we are interested, and let y be a vector of sample observations from the joint density function $f(y|\theta)$. The function $f(y|\theta)$ is algebraically identical to the likelihood function for θ and contains all the sample information about θ. In the Bayesian framework, where a subjective probability distribution is placed on θ — and, in this sense, θ is a random vector — $f(y|\theta)$ is regarded as the conditional density function for y, given θ. Furthermore, we can write

$$h(\theta, y) = f(y|\theta)g(\theta) = g(\theta|y)\, f(y) \tag{3.11}$$

Here h is the joint density function for θ and y; g denotes a density function for θ, and f denotes a density function for y; therefore, Bayes' theorem states:

$$g(\theta|y) = \frac{f(y|\theta)g(\theta)}{f(y)} \tag{3.12}$$

The posterior density function for θ is $g(\theta|y)$ since it summarises all the information about θ after the sample y has been observed; $g(\theta)$ is the prior density for θ, summarising the non-sample information about θ. If we recognise that, with respect to θ, $f(y)$ can be regarded as a constant and that $f(y|\theta)$ can be written as the likelihood function $l(\theta, y)$ then we have

$$g(\theta \mid y) \propto l(\theta, y)g(\theta). \tag{3.13}$$

The posterior distribution is proportional to the likelihood and the prior.

The Bayesian approach has distinct advantages in forecasting. Litterman (1986) applies the Bayesian approach in his vector-regression techniques. He has argued that by using the Bayesian approach, the forecasting method could be evaluated on its own, without reference to the forecaster running the model. This method generates not only a forecast but also a complete, multivariate probability distribution for future outcomes of the economy that appear to be more realistic than those generated by other competing approaches. Additionally, it does not require judgmental adjustment.

Another advantage of the Bayesian forecast is that the external information could be incorporate by directly adjusting the prior specification. The information is not only from historical data and other related factors, but it also extends to forthcoming events that affect the environment of the series; that is, the so called *feed-forward* information (West and Harrison, 1997). The intervention can also be *feedback*, which is corrective, responding to events that had not been foreseen or adequately allowed for. Such information will be used retrospectively in order to adjust the model appropriately to the current, local conditions (West and Harrison, 1997).

West and Harrison (1997) present a Bayesian treatment of the state-space model with an emphasis on forecasting. The framework they have proposed is termed the Dynamic Linear Model (DLM). The standard assumptions for the DLM are that all stochastic terms are normally distributed, and basic theory shows that linear combinations of normal variables are also normally distributed; therefore, all the defining distributions of the DLM are normal.

Concentrating on moments rather than full distributions forms the analysis of the DLM; however, DLM applies much more generally than just the normal models. In normal DLMs with known variances, the recurrence relationships for sequential updating of posterior distributions are essentially equivalent to the Kalman filter equations. West and Harrison (1997) argue that under "weak probability modelling" the derived means and variances from normal distribution assumptions may be used with other distributional forms. Additionally, in a decision-theoretic setting where decision rules are functions of moments (regardless of underlying distribution), the moment definitions from the normal analysis are again sufficient. They further presented the information discounting as a practicable solution to capture both the essence of the evolution mechanism and the spirit of Bayesian thinking.

The Bayesian treatment of state-space models is best illustrated by a simple univariate DLM setting introduced by West and Harrison (1997). The proof is available in West and Harrison (1997, pp. 35-36).

For example, the observation series Y_t is represented as

$$Y_t = \mu_t + v_t, \; v_t \sim N[0, V_t] \tag{3.14}$$

Here μ_t is the level of the series at time t and v_t is the observational error. The time evolution of the level is then modelled as a simple random walk:

$$\mu_t = \mu_{t-1} + \omega_t, \quad \omega_t \sim N[0, W_t], \tag{3.15}$$

with evolution error ω_t.

The observational and evolution error sequences comprise internally and mutually independent normal random variables. So for all t and all s with $t \neq s$, v_t and v_s are independent, ω_t and ω_s are independent, and v_t and ω_s are independent.

To begin, it is also assumed that the variance V_t and W_t are known for each time t. The foregoing observational and evolution equations may also be expressed for each $t = 1, 2, \ldots$, as

$$(Y_t / \mu_t) \sim N[\mu_t, V_t], \tag{3.16}$$

$$(\mu_t / \mu_{t-1}) \sim N[\mu_{t-1}, W_t]. \tag{3.17}$$

For each t, the DLM $\{1, 1, V_t, W_t\}$ is defined by

Observation equation: $\quad Y_t = \mu_t + v_t, \quad v_t \sim N[0, V_t]$, (3.18)

System equation: $\quad \mu_t = \mu_{t-1} + \omega_t, \quad \omega_t \sim N[0, W_t]$, (3.19)

Initial information: $\quad (\mu_0 / D_0) \sim N[m_0, C_0]$. (3.20)

Here the error sequences v_t and ω_t are internally independent and mutually independent. In addition, they are independent of (μ_0 / D_0).

Initial information is the probabilistic representation of the forecaster's beliefs about the level μ_0 at time $t = 0$. The mean, m_0, is a point estimate of this level, and the variance, C_0, measures the associated uncertainty. Each information set, D_v, comprises all the information available at time v, including D_0, the values of the variances $\{V_t, W_t: t > 0\}$, and the values of the observations Y_v, $Y_{v-1}, \ldots, Y_1$. The only new information becoming available at any time, t, is thus the observed value Y_t, so that $D_t = \{Y_t, D_{t-1}\}$.

The one-step forecast and level posterior distributions for any time $t > 0$ can be obtained sequentially as follows:

Assume the conditional distribution of μ_{t-1} on the information set D_{t-1} is:

$$\text{(a) } \textit{Posterior for } \mu_{t-1}\text{:} \quad (\mu_{t-1} / D_{t-1}) \sim N[m_{t-1}, C_{t-1}]. \tag{3.21}$$

Then μ_t is the sum of two independent normal random quantities μ_{t-1} and ω_t as indicated by (3.19), and is therefore also normal. The mean and variance are obtained by adding means and variances of the summands, leading to:

$$\text{(b) } \textit{Prior for } \mu_t\text{:} \quad (\mu_t / D_{t-1}) \sim N[m_{t-1}, R_t]. \tag{3.22}$$

Here $R_t = C_{t-1} + W_t$.

Similarly, conditional up D_{t-1}, Y_t is the sum of the independent normal quantities μ_t and v_t according to (3.18), and is also normal, leading to:

$$\text{(c) } \textit{1-step forecast:} \quad (Y_t / D_{t-1}) \sim N[f_t, Q_t], \tag{3.23}$$

where $f_t = m_{t-1}$ *and* $Q_t = R_t + V_t$.

By either Bayes' theorem or standard normal theory, the posterior distribution of μ_t is:[3]

$$\textit{(d) Posterior for } \mu_t\text{:} \quad (\mu_t / D_t) \sim N[m_t, C_t], \tag{3.24}$$

with $m_t = m_{t-1} + A_t e_t$ and $C_t = A_t V_t$, where $A_t = R_t / Q_t$, and $e_t = Y_t - f_t$.

Here, e_t is the one step ahead forecast error, the difference between the observed value and its expectation. A_t is the prior regression coefficient of μ_t upon Y_t and, in this particular case, is the square of their correlation coefficient. The alternative representation for m_t is:

$$m_t = A_t Y_t + (1 - A_t)\, m_{t-1}, \tag{3.25}$$

where m_t is a weighted average of the prior level estimate m_{t-1} and the observation Y_t. The adaptive coefficient A_t, or weight, lies between 0 and 1, being closer to 0 when $R_t < V_t$ so that the prior distribution is more concentrated than the likelihood, and

---

3 The derivation is shown in Western and Harrison (1997), chapter 2, pages 36–7.

being closer to 1 when the prior is more diffuse, or less informative, than the likelihood.

The DLM $\{1, 1, V_t, W_t\}$ depends on choosing appropriate vales for the variances V_t and W_t. The choice of W_t is given by a discount factor δ, typically between 0.8 and 1 as the following:

$$W_t = C_{t-1} (1 - \delta) / \delta \tag{3.26}$$

With an unknown but constant variance V, the inverse of V, $\phi=1/V$ follows a gamma distribution conditional on D_t.

Denote S_t as the estimate of the variance V at time t, and it can be obtained through the conjugate analysis,

$$(\phi / D_t) \sim G[n_t/2, n_t S_t/2] \tag{3.27}$$

with $n_t = n_{t-1} + 1$ and $S_t = S_{t-1} + \frac{S_{t-1}}{n_t}(\frac{e_t^2}{Q_t} - 1)$.

The simple, first-order polynomial model here serves as the introduction to the Bayesian approach to sequential learning and forecasting. It can be easily extended to the comprehensive state-space models in both univariate and multivariate settings, which will be employed in later chapters.

3.5 Summary

In this chapter, the methodology issues in the literature have been reviewed. In summary, the variance-ratio and the regression-based tests suggest that stock prices are to some degree mean reverting. The significance of the mean-reverting component has been questioned due to the limitation of standard econometric techniques. Previous testing for predictability suffers from "model/parameter uncertainty" and "small sample" problems. Additionally, the testing for predictability has always been associated with some asset-pricing model.

The future research has been directed to improve the tests of stock return predictability in a few perspectives. First of all, a dynamic framework is able to release the assumption of time-invariant relationship between returns and forecast variables imposed by most of previous studies. Secondly, the multivariate setting has some advantages over univariate setting as the univariate methods tend to have low power due to the small sample problem. Additionally, the tests for predictability are only sufficient when accompanied by an out-of-sample test. As the stock return is said to be predictable, most often the researchers mean that returns are correlated with some observable variables; this does not indicate that investors are able to predict returns and make their profit out of it. The studies in the following chapters of this thesis are designed to incorporate these issues.

Chapter 4 Time-varying systematic risk of Australian industrial stock returns: a Kalman-filter approach[4]

4.1 Introduction

While the empirical literature has presented mounting evidence that returns are partially predictable, the interpretation of this predictability is controversial. For those who look to time-varying equilibrium-expected returns, the predictability is indeed the predictability of risk premium, which is consistent with rational pricing in an efficient market.

The chapter focuses on the time-varying systematic risk of Australian industrial sector returns. Beta represents the systematic risk of a stock as beta measures the extent to which returns on the stock and the market move together. Beta is usually defined as

$$\beta_i = \frac{Cov(r_i, r_m)}{\sigma_m^2}.$$

Here r_i is the return of a stock or portfolio, r_m is the return of market portfolio and σ_m^2 is the variance of the market portfolio.

The traditional asset-pricing models imply that the expected returns of securities are determined by their measure of systematic risk, beta or the factor loadings of the associated risk premiums. In a rational model, any predictability of returns should thus be driven by changes in the betas and changes in the expected risk premiums (Ferson and Korajczyk, 1995). Since predictability is possibly linked with time-varying expected returns, it is sensible to draw attention to properties of time-varying

[4] A paper derived from this chapter has been accepted for publication in the *Australian Journal of Management* in June 2004. The content of this chapter has benefited from the comments of anonymous referees.

returns through a conditional asset-pricing model. In fact, in recent decades many academics and practitioners of investment community have been interested in studying the time-varying betas.

In this chapter, a state-space framework will be employed to model the measurement for time-varying systematic risk; i.e. beta. The research will investigate the stochastic properties of betas of Australian industrial portfolios. Four stochastic state-space models are examined using the Kalman filter approach:

- the random-walk model (RWM);
- the random-coefficient model (RCM);
- the autoregressive moving average model, ARMA(1,1); and
- mean reverting (or moving mean) models (MRM or MMM).

By comparing these models' performance with the ordinary-least-square model (OLS), the best-fitting time-series of industrial betas are therefore obtained. The time variations of returns are shown to be well explained by the time varying beta of the industry portfolios.

The chapter is organised as follows. In the following section, the background literature on time varying beta is provided. Section 4.3 introduces the methodology of the time-varying beta model and the Kalman filter approach employed by this paper. The empirical design is provided in Section 4.4. Information regarding data and testing results is given in Section 4.5. The final section provides the discussion and conclusion.

4.2 Background

The systematic risk of an asset in financial markets is normally estimated by using the market model (or the single index model), in which the return of an asset is regressed against the market return and the regression-coefficient beta thus offers an estimate of systematic risk. More recent literature, though, has widely recognised that the systematic risk of asset change over time is due to both the microeconomic factors in the level of the firm and macroeconomic factors (Fabozzi and Francis, 1978; Bos and Newbold, 1984).

Blume (1971) was one of the first to consider the time-varying betas of the market model. Blume (1971) revealed that asset betas had a regression tendency; that is, the estimated betas tended to regress toward the mean. Blume (1975) suggested that the source of this mean-reversion of betas related to the idea that initially a company could choose relatively high-risk projects, but over time the risk of these projects declines. This would lead to a decline in the company's equity beta. His finding was supported by Brenner and Smidt (1977) and Francis (1979).

Other studies have attempted to describe the stochastic behaviour of betas. For example, Fabozzi and Francis (1978) applied the Hildreth-Houck random-coefficient model to beta, and their results were in favour of the random-coefficient model for individual stocks over a six-year period. Alternatively, Sunder (1980) and Simonds et al. (1986) suggested that a random-walk coefficient model is most suitable for modelling the US data over a longer time period. Ohlson and Rosenberg (1982) proposed an ARMA(1,1) model for the beta coefficient, which was supported by Collins et al. (1987).

Empirically, considerable evidence has suggested that the beta-stability assumption is invalid. Evidence of beta's time-varying property can be found internationally; for example, Bos and Ferson (1992) for the Korean market; Black et al. (1992) and Buckland and Fraser (2001) for UK market; Cheng (1997) for the Hong Kong market; Brook, Faff and Ariff (1998) for the Singaporean market; Wells (1994) for the Finnish market; and Grieb and Reyes (2001) for the Brazilian market.

In Australia, Brooks, Faff and Lee (1992) and Faff, Lee and Fry (1992) were among the first to investigate the time-varying properties of beta. Faff, Lee and Fry (1992) employed a locally-best invariant test to study the hypothesis of stationary beta. They found evidence of nonstationarity across all of their analyses. Brooks, Faff and Lee (1994) further suggested that the random-coefficient model was the preferred model to best describe the systematic risk of both individual shares and portfolios. Pope and Warrington (1996), however, re-estimated the market model by using a modified random-coefficients model[5] on 191 individual companies. They found that

---

[5] They allowed the intercept to vary too.

the random-coefficient model was appropriate for only about 23 per cent of these stocks.

Faff and Brooks (1998) investigated the possibility of directly modelling time-varying beta models for Australian industry portfolios. Specifically, industry betas were modelled in terms of:

- regimes related to periods of regulation, deregulation and imputation;
- the level of market returns; and
- a measure of volatility on the risk-free rate of interest.

Their univariate and multivariate tests provided mixed evidence, though, concerning the applicability of a time-varying beta CAPM that could incorporate those variables.

Brooks et al. (1998) considered three techniques by which one may estimate conditional time-dependent betas:

- the multivariate, generalised ARCH approach;
- a time-varying beta market-model approach suggested by Schwert and Seguin (1990); and
- the Kalman filter technique.

Their evidence overwhelmingly supported the Kalman filter approach.

Though most of these previous studies explored the stochastic behaviour of betas against stationarity using individual stocks, very few of them have focused on industrial portfolios. It is generally believed that an individual stock beta is time-varying and that the beta of a portfolio is more stable; however, the stationarity of portfolio beta is less well researched.

Ferson and Harvey (1991, p. 52) suggested that portfolio betas are more stable than individual common-stock betas because, as more assets are combined into portfolios, the extent of instability in individual firm's betas will tend to offset each other. Brooks et al. (1992) argued, though, that while increasing portfolio size is likely to reduce actual beta instability, it also reduces background noise; thus, making beta instability easier to detect. When this reduction of background noise more than offsets the diversification effect, greater beta instability would be expected. Collins et al. (1987) argued that as the portfolio becomes larger, the background noise decreases at a faster rate than the variability in beta, and leads to more powerful tests of the stationarity hypothesis.

One prominent problem associated with beta estimation is the "errors in variable" problem when an individual asset is used. The estimation of individual company beta normally contains a large sampling error; therefore, over- or under-estimation of beta is unavoidable. Collins et al. (1987) conducted tests on portfolios. They argued that the analysis of beta instability at the portfolio level was particularly important since, empirically, the risk-return examination has been conducted at the portfolio level. It would be interesting to see how aggregation affects the nature of beta variation through time. Additionally, levels of background noise could be reduced to some degree, which would enable a better detection of sequential versus random variation in equity betas.

Ohlson and Rosenberg (1982) argued that it was virtually impossible to derive the stochastic behaviour of beta at the portfolio level as a function of the stochastic behaviour of individual security betas; therefore, a thorough investigation of time-varying portfolio betas is needed.

Practically, beta estimates for portfolios are more valuable for the investors especially at the industry level. In the process of securities-analysis, the macroeconomic and industry analysis are two major aspects. The macroeconomic condition is translated to the security market through the impacts on corporate profits. The investment advice is usually tied to macroeconomic forecasts. Portfolio managers will recommend special industries when the macroeconomic condition changes according to the sensitivity of the industry. For example, the portfolio manager might recommend investment into financial stocks in a low-rate environment. However, not all industries are equally sensitive to the business cycle. Firms in the sensitive industries will have high-beta stocks and are therefore riskier. Once a financial analyst has forecast for the state of the macroeconomy, it is necessary to determine the implication of the forecast to specific industries by using information about the industry beta.

Industry groups usually show more dispersion in their stock market performance. Industry beta is especially useful to fund managers as many of the mutual funds focus on industry sectors. For example, Fidelity offers about 40 Select Funds, each of which is invested in a particular industry (O'Neal, 2000). In Australia, typical industry-sector funds include Challenger Gold Trust, Lowell Australian Resources, Colonial First State Technology and Commerce funds, and many more. One prominent feature of sector funds is the high volatility of funds' returns relative to the broad market. Even small investors can easily take positions in industry performance using mutual funds with an industry focus. Morningstar offers investors an online education course on investing sector funds using analysis of R-square and beta (Teresa, 2000).

The results of this chapter have important implications to portfolio management and securities-analysis practice. Industry betas normally serve as the "prior" to individual beta estimation (Vasicek, 1973, p. 1237). The identification of industry beta stability and the identified best stochastic model will help to determine whether the forecasting method for beta is optimal since the industry adopts different estimation methods.

Another interesting issue is whether (and how) the time-varying properties of industrial betas differ from each other. The earlier work of Ball and Brown (1980) discovered that Australian resources and industry sectors have different characteristics in risk and return. Faff, Lee and Fry (1992) investigated the links between beta's nonstationarity and three characteristics of firms: riskiness, size and industrial sector. They did not find a strong pattern between size or industry sector and nonstationarity.

Groenewold and Fraser (1999) argued that the industrial sectors could be divided into two groups: one with volatile and non-stationary betas and the other group with relatively constant and generally stationary betas.

Other recent studies include Trivedi and Brooks (1999), Brooks et al. (2000), Gangemi, Brooks, and Faff (2001), Josev, Brooks, and Faff (2001) and others. Since beta's variability is due to the changes of micro- or macroeconomic factors, which influence assets' risk, it is natural to suspect that industries with unique characteristics might have different stochastic properties of betas. The different behaviour of industry betas might be contributed to by industry life-cycles, industry structure and performance.

Overall, the findings on the stochastic property of industrial-portfolio betas are not conclusive. The form of beta variations and estimates of time series of industrial betas are yet to be provided. While industrial betas summarise the systematic risks of an industry portfolio, industry betas are now widely used by finance practitioners and industry analysts in many applications. A clear understanding of the time-varying properties of industry betas is important. By exploring different stochastic processes of betas and by revealing the most accurate time path of betas, this present chapter will serve as a reference for both asset-pricing theory and industrial analysis practice.

4.3 The time-varying market model

The empirical evidence has shown that it is inappropriate to assume beta to be constant. The point estimates of beta obtained by regression of the asset returns over the market portfolio are therefore not justified. More sophisticated estimation techniques are required in this issue. State-space models typically deal with dynamic time-series models that involve unobserved variables. The state-space framework fits nicely for estimating the time-varying parameters.

The state-space representation of a system is a fundamental concept in modern control theory and has been widely used for expressing dynamic systems (Anderson and Moore, 1979). A state-space system consists of two equations: a transition equation (or state equation) and a measurement equation. The measurement equation describes the relation between observed variables (data) and unobserved state variables. The transition equation describes the dynamics of the state variables. This is defined to be a minimum set of information from the present and past such that the future behaviour of the system can be completely described by knowledge of the present state and the future input.

To incorporate the stochastic process of beta to the market model, the time-varying market model would be expressed as:

$$R_t = \alpha_t + \beta_t R_{m,t} + \nu_t \quad \nu_t \sim N(0, \sigma^2). \tag{4.1}$$

Here R_t is the industry index portfolio return. $R_{m,t}$ is the market portfolio return. α_t and β_t are time-varying parameters, and $\{\nu_t\}$is a sequence of normal distributed random errors with variance σ^2. If the risk-free rate α and the regression coefficient β are assumed to be constant, the model can be estimated by ordinary least squares.

The state-space form of the time-varying market model above can be rewritten as

$$\textit{Measurement equation:} \quad R_t = X_t B_t + \nu_t \quad \nu_t \sim N(0, \sigma^2), \tag{4.2}$$

$$\textit{Transition equation:} \quad B_t = \Phi B_{t-1} + \omega_t \quad \omega_t \sim N(0, \Xi), \tag{4.3}$$

Here X_t is a 1×2 vector, with elements ($1\ R_{mt}$). R_t is the asset return and R_{mt} is the market portfolio return at time t. B_t is a 2×1 state vector, with elements $(\alpha_t\ \beta_t)^T$. Φ is the coefficient matrix of the state vector B_t. Normally ν_t and ω_t are assumed to be white noises and be independent of each other. ν_t has zero mean and constant variance σ^2 and ω_t has zero mean and a constant covariance matrix Ξ. The sequences of B_t, ν_t and ω_t are jointly Gaussian. The covariance matrix Ξ and any estimated elements of the transition matrix Φ are thus known as the *hyperparameters* of the system. By setting different values to Φ, the state coefficients could develop as random walk, random coefficient or mean reverting processes.

Though a sequence of generalised least-squares regression models can achieve inferences about state vectors conditional on information available up to time t, it is extremely inefficient in terms of computational burden (Kim and Nelson, 1999, p.20). The Kalman filter method was originally developed by Kalman (1960) within the context of linear systems. The method now serves as the basic tool to deal with the standard state-space model. Due to the ease of implementation of the algorithm on computers, the Kalman filter has now become well known and widely used in the state-space form of varying-parameter regression, especially by some financial researchers to explore the dynamics of financial series (see Wells, 1996).

Brooks, Faff and McKenzie (1998) investigated three techniques for the time-varying beta risk of Australian industry portfolios. They compared a multivariate generalized ARCH model and a time-varying beta approach suggested by Schwert and Seguin (1990). They found that the Kalman filter approach performed better in both in-sample and out-of-sample forecasts.

Wells (1994) employed the Kalman filter approach to estimate betas for a small sample of the Swedish stocks. Black, Fraser and Power (1992) used a similar method to estimate random walk betas for a sample of UK unit trusts.

Groenewold and Fraser (1999) estimated time-varying betas using the Kalman filter approach as well as the rolling regression and recursive regression method. They found that the Kalman filter betas were not totally consistent with betas obtained by the other two approaches, though much of the variability of betas could be explained by a time trend.

4.4 Empirical design

The CAPM suggests that the beta of any asset will have a tendency to revert towards the grand mean of unity, which is the grand mean of all betas. Previous empirical work has presented various models for modelling the systematic-risk-measure beta. Such work includes the random-coefficient model, the AR(1) model and the ARMA(1,1) model. All of the models are desirable as they possess a mean-reverting property; therefore, in the state-space framework, all of the models of systematic risk may be expressed by restricting some of the parameters of the model and by changing the dimension of the state vector. Wells (1996, chapter 5) argued that all of the models are actually nested and collapse to the simple OLS estimation of the market model.

In this section, the four most popular models initiated by previous literature are brought together, and a preliminary investigation on the time varying property of Australian industrial betas is presented. The method here is indeed a "data driven" method. The purpose is to empirically test how the stochastic process describes each industrial index beta.

The models chosen here are the random-walk model, the random-coefficient model, the mean-reverting model (moving-mean model) and the ARMA(1,1) model. The models that have appeared in previous literature seem mostly to fall into these four categories. The description for each model is provided below.

4.4.1 The random-walk model

Setting the transition matrix Φ of equation 4.3 equal to 1, the following random-walk model is obtained. The state-space representation of the model is as follows:

$$R_t = \alpha_t + R_{m,t}\,\beta_t + \nu_t \quad \nu_t \sim N(0, \sigma^2) \tag{4.5}$$

$$\begin{pmatrix} \alpha_t \\ \beta_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} \alpha_{t-1} \\ \beta_{t-1} \end{pmatrix} + \begin{pmatrix} w_{1t} \\ w_{2t} \end{pmatrix}, \tag{4.6}$$

$$\begin{pmatrix} w_{1t} \\ w_{2t} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_a^2 & 0 \\ 0 & \sigma_b^2 \end{pmatrix}\right). \tag{4.7}$$

Here R_t is the asset return and R_{mt} is the market index portfolio return at time t. The error term of measurement equation $\{\nu_t\}$ is assumed to be normally distributed with mean zero and variance σ^2. The state noise vector $(w_{1t}, w_{2t})^{\tau}$ is also assumed to be normally distributed with zero mean and a constant covariance matrix Ξ. Thus, $w_{1t} \sim N(0, \sigma_a^2)$ and $w_{2t} \sim N(0, \sigma_b^2)$. w_{1t}, and w_{2t} are assumed to be serially uncorrelated. This implies that Ξ has just the diagonal elements σ_a^2 and σ_b^2. The hyperparameters that must be estimated are three parameters: σ_a^2, σ_b^2 and σ^2.

The random-walk model seems to be the first to be used in modelling the time-varying beta initiated by the hypothesis that asset prices follow a random walk. The earliest literature can be traced to Fisher (1971) and Kantor (1971). The random-walk model explains that the current period's beta is equal to the last period's beta. The resulting estimation error is a random variable. The random-walk model is consistent with the hypothesis that the market reacts to industry dependent developments and not just to noise. One may use the path traced by beta as a random walk to examine events within the industry that have been reflected in the market's evaluation of the risks involved in holding the assets in the industry.

4.4.2 The random-coefficient model

Setting the transition matrix Φ equal to zero, a random-coefficient model is derived. The excess-return-version model is given by:[6]

$$R_{et} = R_{emt}\beta_t + v_t, \qquad v_t \sim N(0, \sigma^2), \tag{4.8}$$

$$\beta_t = \overline{\beta} + n_t, \qquad n_t \sim N(0, \sigma_n^2). \tag{4.9}$$

Here R_{et} and R_{emt} are excess returns of individual industry and the market index portfolio respectively. $\overline{\beta}$ is the mean value of β_t.

The error series v_t and n_t[7] are assumed to be normally distributed with zero mean and a constant variance of σ^2 and σ_n^2 ; so, in this model, three parameters need to be estimated: $\overline{\beta}$, σ^2 and σ_n^2.

Hildreth and Houck (1968) and Schaefer et al. (1975) have presented the earliest studies using the random-coefficient model in the stock market. The random-coefficient model defines that there is a "long-term" mean about which there is random variation each period. The "true" or "long-term" risk is associated with a given stock or portfolio even if temporary disturbances may tend to increase or decrease this risk. The random-coefficient model is in fact a special case of the mean-reverting model presented below. Since the random-coefficient model was favoured by previous Australian literature such as Brooks, Faff and Lee (1994), the model will be estimated independently here.

4.4.3 The autoregressive moving average ARMA (1,1) model

Ohlson and Rosenberg (1982) proposed an ARMA(1,1) model for beta coefficients. The model states that the current value of a beta series depends linearly on its own

---

6 The reason for using the excess-return-version model is to reduce the dimension of the state vector.

7 For the simplicity of producing tables in this chapter, v_t is used to denote the measurement equation noise with σ^2 as its variance. n_t is used to denote the error process of the transition equation, with σ_n^2 as it is variance for the three models: the random coefficient, ARMA(1,1) and mean-reverting models.

previous values plus a combination of current and previous values of a white-noise error term. They have summarised the behaviour of beta as attributed to two distinct stochastic factors. First, there is a tendency for beta to converge rather slowly toward a norm (the stationary mean), which requires a "memory" for beta to be modelled by a stationary first-order, autoregressive process. Second, at the same time, in each period there is a purely random (serially independent) perturbation in beta.

Ohlson and Rosenberg (1982) argue that whatever the economic determinants of the stochastic behaviour of the parameters are, the effects on the parameters should be captured by a few stochastic variables; therefore, the proposed model for beta should allow for a memory that admits regression toward the norm as a special case. Moreover the tendency for stochastic drift in beta does not exhaust the possible form of stochastic variation; therefore, not all factors that impart a change to beta must also have a "carry forward" effect. Collins et al. (1987) argue that the Ohlson and Rosenberg model is more general than the random coefficients or the pure first-order autoregressive models. Their results are also in favour of Ohlson and Rosenberg's model.

To model the ARMA(1,1) process of β, the excess version of the market model is also adopted here. Therefore, the model is set up as:

$$R_{et} = R_{emt}\beta_t + v_t, \qquad v_t \sim N(0,\sigma^2), \tag{4.10}$$

$$\beta_t = \phi\beta_{t-1} + n_t - \theta n_{t-1}, \qquad n_t \sim N(0,\sigma_n^2), \tag{4.11}$$

Here R_{et} and R_{emt} are excess returns of individual industry and market index portfolio. The error series v_t and n_t are assumed to be normally distributed with zero mean and the constant variance σ^2 and σ_n^2. The parameter ϕ and θ are chosen to ensure that $\{\beta_t\}$ is stationary. The parameters need to be estimated are thus ϕ, θ, σ_n^2 and σ^2.

4.4.4 The mean-reverting model and moving-mean model

The mean-reverting model was first mentioned by Rosenberg (1973). It was tested later by Sunder (1980) and Bos and Newbold (1984). In comparison to other models, this AR(1) process is a more general specification. The autoregressive process claims that the difference between the current beta and the long-term mean is a function of the difference between the immediate past value of beta and the long-term mean. Other models except for the ARMA(1,1) are indeed special cases of the mean-reverting model, for example, by setting the coefficient ϕ to be zero, the resulting transition equation will be in the form of the random-coefficient model discussed above; and by setting the coefficient ϕ to be 1, the resulting beta process will be the random-walk form.

The mean-reverting model using excess returns is as follows:

$$R_{et} = R_{emt}\beta_t + v_t, \qquad v_t \sim N(0,\sigma^2), \tag{4.12}$$

$$\beta_t - \overline{\beta} = \phi(\beta_{t-1} - \overline{\beta}) + n_t, \qquad n_t \sim N(0,\sigma_n^2), \tag{4.13}$$

Here R_{et} and R_{emt} are excess returns of individual industry and market index portfolio. The error series v_t and n_t are assumed to be normally distributed with a zero mean and the constant variance σ^2 and σ_n^2. $\overline{\beta}$ is the mean value of β_t. The parameters which need to be estimated are σ^2, $\overline{\beta}$, σ_n^2 and ϕ.

The mean-reverting model states that the systematic risk of the stock or portfolio develops according to its "long term" steady mean. It is quite restrictive in that this long-term state of the risk is constant over time, while the economic environment and market or industry condition changes periodically.

Wells (1994) further developed the mean-reverting model to allow for $\overline{\beta}$ varying; that is, β_t is mean reverting but it reverts to a mean that itself develops as a random walk. The suggested moving mean model is as follows:

$$\alpha_t = \phi_{11}\alpha_{t-1} + \delta_t, \qquad \delta_t \sim N(0,\sigma_\delta^2), \tag{4.14}$$

$$\beta_t - \overline{\beta_t} = \phi_{22}(\beta_{t-1} - \overline{\beta}_{t-1}) + u_t, \quad u_t \sim N(0,\sigma_u^2), \tag{4.15}$$

$$\overline{\beta_t} = \overline{\beta}_{t-1} + \gamma_t, \qquad \gamma_t \sim N(0,\sigma_\gamma^2). \tag{4.16}$$

The state-space form of the model is therefore:

$$R_t = \alpha_t + R_{m,t}\,\beta_t + v_t, \qquad v_t \sim N(0,\sigma^2), \tag{4.17}$$

$$\begin{pmatrix} \alpha_t \\ \beta_t - \overline{\beta}_t \\ \overline{\beta}_t \end{pmatrix} = \begin{pmatrix} \phi_{11} & 0 & 0 \\ 0 & \phi_{22} & 0 \\ 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} \alpha_{t-1} \\ \beta_{t-1} - \overline{\beta}_{t-1} \\ \overline{\beta}_{t-1} \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} \delta_t \\ \mu_t \\ \gamma_t \end{pmatrix}, \tag{4.18}$$

where R_t is the asset return, and R_{mt} is the market index portfolio return. v_t, δ_t, u_t and γ_t are all normally distributed and mutually independent residual series; therefore, the parameters to be estimated are their variances $\sigma^2, \sigma_\delta^2$, σ_u^2, σ_γ^2, and the coefficients ϕ_{11}, and ϕ_{22}. In the tests of section 4.5 below, each industry β will be estimated using both the moving-mean model and the mean-reverting model. If the variance of γ_t closes to zero then the results for the mean-reverting model will be shown and suggest that $\{\overline{\beta}_t\}$ behaves like a constant.

To apply the Kalman filter to the above models, two different sets of initial values need to be set. The first set of the initial values is for the state vector and its covariance in the Kalman filter. Wells (1996) has suggested that for the mean-reverting model and random-coefficient model, the initial states are set to be zero and the initial covariance is set to be a large number. For the random-walk model, the initial states are set equal to the OLS estimates obtained from the first ten observations, and the initial covariance of the states is the covariance matrix of these OLS estimates.

The second set of the initial values is for the hyper parameters to be estimated by maximising the likelihood function. The means in the mean-reverting model and the random-coefficient model are simply set by using the OLS estimates from the entire sample. The choice of the variance of the measurement equation is no problem because it is concentrated out of the likelihood function. The coefficients ϕ involved in both the ARMA(1,1) and the mean-reverting model, and ϕ_{11} and ϕ_{22} involved in the moving-mean model, are set to be 0.5 as the experiment has shown that the final estimates are not at all sensitive to this value.

4.5 Data and results

4.5.1 Summary statistics

The data used in this study are nineteen monthly ASX industrial stock return indices from December 1979 to March 2000. Using the industry index can minimise the estimation error for beta. Also, because the industry index is highly correlated with the independent variable, the residual variance will be low to ensure the background noise is low.

The risk-free rate of return is computed from the Australian three-month Treasury bill rate.[8] The data are sourced from DataStream. The summary statistics of the stock returns data are provided in Table 4.1. The means are monthly proportional rates of return and vary from 2 per cent for the media sector to 0.1 per cent for the gold sector. The gold sector has the highest variance, while the property trusts sector has the lowest variance.

Skewness, kurtosis and Jarque-Bera are the tests of normality on returns. The null of normality has been widely rejected. Most of the return series are left skewed and leptokurtic; however, when the observation of October 1987 is excluded, skewness, kurtosis and Jarque-Bera statistics are highly improved.

The ADF column shows the results for the augmented Dicky–Fuller unit-root test. All returns series are shown to be stationary. The last column presents the ARCH test, and 6 industries out of 19 have shown evidence of heteroskedasticity, which implies the possible non-stationarity of betas.[9]

---

8 The formula to convert the three-month interest rate to monthly is taken from Knox, Zima and Brown (1996); that is, $r_m=(1+r_q)^{1/3}-1$ where r_m is the monthly rate and r_q is the quarterly rate.

9 If the coefficients of the regression are time varying but are estimated as constant, the resulted residual series will be heteroskedastic.

Table 4.1: Summary data

ASX Index group	Mean	Var	Skew	Kurt	Jarque-Bera	Skew (ex. Oct 87)	Kurt (ex. Oct87)	Jarque-Bera (ex. Oct 87)	ADF	ARCH (6)
Alcohol and Tobacco	0.01413	0.00326	-2.2306	17.979	3474.26	-0.1666	2.4789	63.0806	-3.6766	2.956
Banks and Finance	0.01292	0.00344	-0.9276	6.3555	443.82	0.1371	0.1791	1.0819	-3.9140	12.80*
Building Mats	0.00764	0.00339	-1.6128	10.318	1183.34	-0.2009	0.3511	2.8711	-4.4036	16.78*
Chemicals	0.00814	0.00405	-0.8534	5.671	355.12	0.04861	0.8063	6.6514	-3.2693	5.277
Devl. Contractor	0.01227	0.00500	-3.6709	34.673	12697.32	-0.0689	0.5655	3.4167	-3.5473	6.249
Divs. Industrial	0.0103	0.00454	-2.6704	21.036	4716.22	-0.2587	0.1797	3.0247	-4.5936	6.025
Divs. Resources	0.00741	0.00617	-1.0665	7.0169	544.60	0.0092	0.6530	4.3026	-3.9016	28.64*
Energy	0.00251	0.00782	-0.9042	5.946	391.12	-0.1866	2.5728	68.1483	-4.3303	8.046
Engineering	0.00547	0.00389	-0.8625	4.001	192.24	-0.1918	0.4157	3.2267	-4.0251	5.444
Food and Household	0.00893	0.00358	-4.4112	7.528	654.42	-0.5288	2.2064	60.3643	-3.5678	12.427
Gold	0.00094	0.01658	-0.2438	3.876	154.51	0.4688	0.9099	17.2102	-4.5588	10.399
Insurance	0.01102	0.00472	-1.7369	13.734	2032.02	0.1161	0.5164	3.2334	-2.9757	13.63*
Inv and Fin Servs.	0.00911	0.00300	-3.8226	37.257	14646.12	0.0490	0.3814	1.5636	-3.6325	11.010
Media	0.01767	0.00797	-1.3155	6.960	560.54	-0.5902	3.0614	108.5533	-3.1279	33.88*
Other Metals	0.00250	0.00908	-1.8509	14.882	2381.18	0.05661	1.2355	15.5207	-4.3489	5.613
Paper and Packaging	0.00621	0.00329	-1.0381	5.072	304.07	-0.3848	1.6621	33.8280	-3.8413	19.04*
Property Trusts	0.00797	0.00136	-1.5050	11.860	1515.98	0.2302	-0.124	2.2906	-2.9365	9.104
Retail	0.01002	0.00362	-2.0813	18.413	3608.04	0.3243	0.1625	4.5082	-4.2307	5.796
Transport	0.01095	0.00530	-2.4975	20.044	4320.61	-0.1227	0.2901	1.4562	-4.1263	6.680
ASX Market Index	0.00835	0.00363	-3.3504	29.765	9425.11	-0.2189	0.8705	9.5732	-3.5788	

Notes: Significance levels (5%): Skewness and Kurtosis 1.96, Normality 5.99, ARCH(6) 12.59, ADF -3.4297.

4.5.2 Empirical comparison result

Tables 4.2 to 4.19 provide a summary of the results for the nineteen industry portfolios. The left panel of each table shows the estimated parameters of the models: the moving-mean model (MMM) or the mean-reverting model (MRM), the ARMA(1,1) model (ARMA), the random-coefficient model (RCM), the random-walk model (RWM) and the ordinary-least-square model (OLS), respectively.

The right panel of each table provides the diagnostic test results and the four criteria used to measure the model's performances. The diagnostic tests of the models are Box-Ljung statistics for higher-order serial correlation, the Goldfeld-Quandt test (G-Q) test for heteroskedasticity, and the classical ARCH test. The cumulated periodogram test (C-P test) reports the maximum gap between the distribution function of residual series and white noises. If the residual series are white noise, the cumulated periodogram should differ only slightly from the theoretical spectral distribution function of the white noise.

4.5.2.1 Criterion for comparison

To compare the models' performances, four criteria are used for estimation of each industrial index beta to find out the best possible model that describes the particular industrial beta. Apart from the normal R-square, which measures the proportion of the variability of industrial returns that is explained by the model, the Akaike information criterion (AIC) was used to weigh the reduction in the likelihood function against the increase in the number of parameters necessary to achieve this reduction. Harvey (1989, p.245) and Wells (1996, p.100) expressed the AIC as follows:

$$AIC = \sigma^2 \, exp(\frac{2(k+s)}{T}).$$

Here σ^2 is the estimated residual variance of the model; s is the dimension of the state vector; k is the number of the hyper-parameters, and both are to be estimated. The "best" possible models should have the lowest AIC values.

The other two criteria used here are the mean-absolute error (MAE) and the mean-square error (MSE) of the estimates. The mean-absolute error and the mean-square error of the estimates are defined like so:

$$\text{MAE}_i = \frac{1}{T}\sum_{t=1}^{T}\frac{|\hat{R}_{it} - R_{it}|}{T}$$

$$\text{MSE}_i = \frac{1}{T}\sum_{t=1}^{T}\frac{(\hat{R}_{it} - R_{it})^2}{T}.$$

Here $\hat{R}_{it}$ represents the estimated return of industry i; R_{it} is i^{th} industry return, and T is the number of observations. The best possible models should have the lowest errors of the estimates.

One problem here is the identification of the "best" model for each industry group. Neither theory nor econometric procedures provide guidance in terms of how to estimate the betas for industry portfolio groups, although the empirical work has provided more consistent evidence on individual stock's beta. For example, it is more widely accepted that an individual beta process is a mean reverting process; however, the results of industry portfolios are mixing.

The approach adopted here is a "data driven" approach. The previous literature has supported the non-stability of beta, thus the stochastic parameter approach is both feasible and practical. It is thus expected that the statistical identification and estimation of different models will uncover the real pattern of the stochastic process of industry beta. Though the different criteria adopted might give different rankings of the models, and there might not be a "perfect" stochastic model for each industry, the purpose here is to identify the most suitable model by using a balance of the four criteria, especially considering the R-square and the forecasting errors of the estimation.

4.5.2.2 Best model for each industry portfolio

Across all the industries shown from Table 4.2 to 4.19, there is at least one time-varying parameter model that performs better than the ordinary-least-square model in either R-square value, low predication error or better diagnostic results; thus the efforts spent on the estimation of time-varying beta models are quite worthwhile.

Although there is no perfect model for every industry, one can certainly select the most appropriate time-varying beta model balanced by the four criteria. One problem here is that the different criteria give different rankings of the models. Here the most suitable model will be found by first considering the R-square and then forecasting errors and AIC.

For the alcohol and tobacco industry shown in Table 4.2, five models have close values of R-square statistics, but the random-coefficient model (RCM) has both the lowest MAE and MSE errors. It strongly suggests that the beta for the alcohol and tobacco industry is close to a random process. This implies that there is little predictability in the beta of this industry.

For the banks and finance industry shown in Table 4.3, the moving-mean model (MMM) has much higher R-square numbers; however, the random-coefficient model (RCM) predicts better despite a low R-square. It is also noted that OLS almost has similar performance as the time-varying beta model. The results of the MMM and the OLS both suggest that the beta of this industry in relatively stable.

For the building materials industry shown in Table 4.4, the ARMA model and the RCM provide mixed results on the stochastic behaviour of beta as the ARMA model has higher R-square but the RCM has lower prediction error. The result here indicates that the mean-reverting property of this industry beta is not obvious and the ARMA(1,1) process looks to be the better description of beta.

In the chemicals industry shown in Table 4.5, the MMM is convinced as the best description for beta due to its lower prediction errors than other models. The chemical industry beta is more likely a mean-reverting process, but the long-term state of the beta is not constant over time.

In the developers and contractors industry shown in Table 4.6, the MRM and the RCM actually provide the mixed results as their R-square and prediction errors are all similar; however, the MRM could be identified as the slightly better one.

For the diversified industrial, diversified resources and energy industries shown in Table 4.7, 4.8 and 4.9, it is convincing that the MMM dominates the other models as the R-square statistics are higher than other models, and the prediction errors are also lower than other models. The results strongly imply that the betas of these industry portfolios are reverting to an unstable long-term mean.

In the engineering industry shown in Table 4.10, the MRM outperforms the RCM slightly in the R-square statistics; however, it is less convincing that the beta process of engineering industry is mean-reverting rather than being random.

For the food and household industry shown in Table 4.11, the RCM has much lower prediction errors than the MMM and the ARMA model; however, the R-square of RCM is also low. Thus, the ARMA model has been identified as the better model for food and household industry beta, which might indicate that the food and household industry beta is close to an ARMA(1,1) process.

The gold industry shown in Table 4.12 is a special case among all the industry groups as all models tested have relatively high prediction errors including the OLS model. Interestingly, the RWM appears to be the better one as it has much higher R-square and relatively lower prediction error.

For the same reason, the RWM is identified as the best model for insurance industry beta in Table 4.13. The results here show that in both gold and insurance industries, the betas are more like the random walk processes. The random walk process simply implies that no predictability exists in their betas.

In the investment and financial services industry shown in Table 4.14, the MRM and the RCM have very similar R-squares, but the RCM has slightly lower forecasting errors, which suggests that the investment and financial services beta is better described as a random process.

For the media industry in Table 4.15, the RWM has a much higher R-square statistic despite the prediction errors being slightly higher than the other three stochastic models; thus, the media beta is identified to be close to a random walk process.

In the paper and packaging industry shown in Table 4.16, the result is mixed. The ARMA model performs slightly better than the OLS; however, it is less clear that the ARMA outperforms other time-varying models.

On the contrary, in the property trusts industry shown in Table 4.17, the ARMA model has a much higher R-square statistics than other time-varying models despite all models including the OLS have similar prediction errors. It might thus be appropriate to describe the property trust beta as an ARMA(1,1) process.

Table 4.18 shows that for the retail industry, the MMM has highest R-square; however, the AIC number is large. It should be kept in mind that the extra parameter of this model has largely reduced the degrees of freedom. The RCM shows both a lower prediction error and lower R-square statistics; therefore, it is not clear that the retail industry beta is either random or mean reverting.

For the transport industry shown in Table 4.19, the MRM outperforms the RCM in terms of a higher R-square value despite a similar level of prediction errors; therefore, the MRM has been chosen for this industry. The results here imply that the beta of this industry has the mean-reverting property.

Lastly, for the other metals industry shown in Table 4.20, the ARMA model achieved the highest R-square value, though the prediction errors are similar to other stochastic models. The results here indicate that the other metals industry beta might follow an ARMA(1,1) process.

4.5.2.3 Summary of model performances

In summary, the most popular model for the industrial indexes is the moving mean model (MMM), which shows the convincing performance in chemicals, diversified industrial, diversified resources and energy industries and relatively better performance in the banks and finance and retail industries.

The second most popular model is the ARMA(1,1) model which well describes the stochastic behaviour of beta for the building materials, food and household, paper and packaging, property trusts and other metals industries.

The random-walk model (RWM) best fits the gold industry, insurance and media industry betas.

Additionally, the mean reverting model (MRM) has been chosen as the best to model the developer contractors, engineering and transport industry betas.

Surprisingly, the random-coefficient model (RCM) — which was favoured by Brooks, Faff and Lee (1992) and Wells (1994) — only performs well in two of the nineteen industries: the alcohol and tobacco and the investment and financial services industries.

Overall, it is obvious that the industry portfolio beta is also best described as a time-varying stochastic process; however, the evidence on what type of stochastic evolution each industry portfolio beta follows is inconclusive. Based on the diagnostics and the current analysis, the question that can be answered is what kind of stochastic process each industry portfolio beta is "most likely" to follow.

The present results are consistent with previous findings that the industry portfolio betas have either random or sequential stochastic variations, just like individual asset betas. The industries that possess the mean-reverting type[6] of betas are banks and finance, chemicals, developers and contractors, diversified industrial, diversified resources, energy, engineering, retail, and transport industries.

It has also been identified that the building materials, food and household, paper and packaging, property trust and other metals industries have an ARMA beta process, which indicates that the current value of a beta series depends linearly on its own previous values plus a combination of current and previous values of a white noise error term.

Other industries are believed to have random process betas. They are alcohol and tobacco, gold, insurance, investment and financial services and media industries.

The identification of a mean-reverting or random property of beta has important implications for portfolio-performance evaluation, asset valuation, capital budgeting decision and tests of asset pricing models. If beta is close to a random coefficient or a random walk process, the beta would not be predictable as the fluctuations in beta are purely random. The transitory shocks to the systematic risk of portfolio do not carry over from period to period. However, a mean-reverting process or an ARMA process of beta implies that deviations in beta from its mean is serially correlated or the current beta is partially related to previous beta and thus would be at least partially predictable.

---

[6] The mean-reverting process discussed here includes the moving-mean model because the moving-mean model is also a mean-reverting process, but the mean of beta is time-varying too.

4.5.2.4 Time-varying industry beta and fitted returns

Figures 4.1 to 4.38 show the plots of time-series betas and the corresponding fitted returns. Figure 4.1 depicts the time-varying beta for banks and finance industry modelled by moving-mean model. The beta of this industry has been relatively stable in 1980s but experienced a rapid increase since late 80s. The time-variation of the long-term mean is quite obvious. However, in Figure 4.3, chemical industry beta only experienced a mild increase in early 90s.

The long-term means of betas for the diversified industrial and diversified resources industries are relatively more stable shown in Figure 4.5 and Figure 4.7; moreover, the diversified industrial beta shows a decreasing tendency recently.

On the contrary, Figure 4.9 show that the energy industry has a more volatile mean of the beta, which increases suddenly just before 1983, and decreases continuously till the end of 1980s. The energy beta eventually recovers to its original level in recent time. Figure 4.9 clearly depicts the mean-reversion property of energy industry beta.

In Figure 4.12, the beta of retail industry oscillates seemingly randomly about its long-term moving mean value. Collins et al. (1987) pointed out that the oscillation of beta is due to the estimated negative parameter ϕ. This point has been confirmed by the results given in Table 4.18.

Figures 4.13, 4.15 and 4.17 depict the random-walk beta models for the media, insurance and gold industries. The series of the media industry beta clearly shows that the media industry has a volatile beta over time. Two jumps in the beta have happened in the mid-80s and early 90s. Especially, the media beta climbed to its peak in late 80s and after short period dived back to its mean level in early 90s. There seems to be a long-term increasing trend of insurance beta shown in Figure 4.15. The insurance beta has increased continually from mid 80s to late 80s. The insurance beta had a dive in early 90s, but it sustained its high level through 90s. Figure 4.17 shows that though the beta goes up and down from time to time in the gold industry, the long-term trends seem to be stable. The gold industry beta had its peak period in early 80s and the recent years.

Figures 4.19-4.27 are for ARMA(1,1) models of the building-material industry, the food-and-household industry, and the paper and packaging industry. The figures show that the systematic risk in those industries has increased dramatically since 1996. While the building-material industry and the food-and-household industry went through a relatively stable period before 1996, the paper-and-packaging industry experienced a continuously long-term increase.

The beta series for the property-trusts industry and the other metals industry are both relatively stable after the Kalman filter is converged as they are shown in Figure 4.25 and 4.27. The beta series for the other metals industry is more volatile than the property trust industry and also at a higher level.

Figures 4.29-4.31 show the behaviour of the beta series for the investment-and-financial-services and the alcohol-and-tobacco industries. In these two industries, each beta series varies randomly around its long-term constant mean and is more volatile for some periods; e.g. 1986–89 for the investment and financial services industry and 1991–95 for the alcohol and tobacco industry.

Figures 4.33, 4.35 and 4.37 provide the time-varying beta for the developers-and-contractors, engineering and transport industries. These figures show that each beta fluctuates unevenly around its steady long-term state when each index is modelled by a mean-reverting model. The developers-and–contractors industry has peak betas around late 80s, early 90s and recent years. The engineering industry has high betas in the mid 80s and whole period of 90s. The engineering industry has a very low beta period between 1986 and 1990, which is surprising given that the stock market crashed in October 1987. The transport industry beta is relatively stable after the filter is converged in the sample period but to show a declining trend in recent years.

When comparing the actual returns with their corresponding fitted values in each industry, fitting figures show that the time variances of the returns have been well captured by the corresponding stochastic beta model, however, the random coefficients modelling of investment and finance services industry and alcohol and tobacco industry betas are not as good as others. It also should be noted that, given the beta at time of t, $B_{t|t}$, the effect of the observed market return X_t has a lag effect on the predicted return $R_{t+1|t}$. Therefore, in the case of a market crash, the effect of such a crash can only be fitted afterwards; i.e. one month later.[10]

Overall, the stochastic parameter models fit reasonably well in modelling the time-varying systematic risk of the industry portfolios. Moreover, the results of different stochastic models discovered for each industry have presented some more accurate description of the time paths of beta series, which provides a good understanding of the risk characteristics in different industries.

Over the full sample period, the industries with an increasing systematic risk are banks and finance, chemicals, paper and packaging, and insurance industries. The diversified industrial, diversified resources, developer–contractor, engineering, gold and transport industries have a generally stable long-term risk. While the systematic risk of investment and financial services and alcohol and tobacco industries are very close to being random with little predictabilities.

Some of the industries seem to have higher risks in particular time periods, such as the media industry from 1990 to 1992; and the building materials, food and household, and paper and packaging industries in recent years.

4.5.3 Explanation for beta variability

The results of this chapter have revealed that industry portfolios don't have stable betas. Similar to the individual asset beta, the variation of an industry portfolio beta is either a mean-reverting or a random process. Additionally, for some industry groups, the long-term mean of beta is also time-varying. However, the question of why the industrial betas have different stochastic properties is less clear. As defined at the beginning of this chapter, beta, or the systematic risk, is the covariance of security or portfolio returns with the market returns, divided by the variance of returns for the market. It is possible that some industry related characteristics have caused different covariance structure with the market which resolves the different stochastic behaviour of industry betas.

10 $R_{t+1|t} = X_t B_{t+1;t}$, where the predicted return at time t for t+1 is a product of observed market return X_t and the updated state B_{t+1} at time t. I thank an anonymous referee of Australian Journal of Management for pointing out this.

Blume (1975) finds that the discovered "mean-reversion" property of beta is in part due to the estimation error, termed the "order bias". The mean-reversion tendency of beta is explained by the fact that companies of extreme risk (either high or low) tend to have less extreme risk characteristics over time.

Elgers et al. (1979) argue, though, that after correction of beta estimates for order bias in Blume (1975), the remaining regressions are attributed to real causes such as capital restructure or asset changes. Further the authors point out that the "real" cause of beta regression tendencies reflects the fact that true betas are imperfectly correlated over time.

Hamada (1972) has addressed the effect of firms' capital structure on the systematic risk of common stocks. He discovered that the observed systematic risk of common stocks can be explained by corporate leverage, when a firm takes extra financial risk by using debt and preferred stock.

DeJong and Collins (1985) employed a joint option pricing and Capital Asset Pricing Model to explain the instability of equity beta using risk-free rate changes and leverage effects. They found that highly leveraged firms exhibit greater equity beta instability than firms with lower leverage. Furthermore, the individual equity beta exhibit greater instability during periods of large expected changes in the risk-free rate when compared to period with small unexpected changes in the risk-free rate.

Castagna and Matolcsy (1978) explained the source of the systematic risk of beta by using accounting variables. Specifically, they found that there was a positive relationship between systematic risk and the accounting variables of debt-to-equity, debt-to-total assets, EBIT-to-total assets, return on shareholders' funds, and growth in EPS. They also found that there was a negative relationship between systematic risk and liquid ratio, current ratio, payout ratio and interest coverage. Trading volume has also been found by the authors to positively affect the systematic risk of the security, which suggests that the more frequently traded securities have a higher price volatility than the market.

Contrary to US findings, Castagna and Matolcsy also found that there is a positive relationship between asset size and systematic risk in the Australian market. They suggest that the Australian market is a concentrated market, in which the concentration in key industries has promoted the sensitivity of large companies to anticipated and actual changes in the economic climate. Additionally, large companies in the Australian market undertake more risky projects than small companies.

The literature reviewed above has provided the explanation for beta instability and variation for individual companies. Overall, the previous work has indicated that the difference in variability of beta is related to the specific characteristics of a firm; for example, the size, leverage, capital structure and accounting variables. However, it is difficult to investigate the source of beta variability of the portfolios as it is not clear how the individual company's information can be "averaged" into the portfolio.

Empirically, the literature on the variable-beta model has provided explanations for sources of beta risk from the economic point of view. Shanken (1990) modelled beta as a function of three state variables: TB (the monthly T-bill rate), TBV (a measure of T-bill volatility) and a January dummy variable. Abell and Krueger (1989) examined the influence of macroeconomic variables on the beta. They found that interest rate, budget deficit, trade deficits, inflation, and oil prices are important factors that influence changes in betas. Furthermore, the prediction of future betas using macroeconomic variables is more accurate than historical betas obtained by the single-index market model.

Following Abell and Krueger's study, Krueger and Rahbar (1995) discovered that the reporting-period-lagged macroeconomic variables in their lagged variable beta model have stronger power in explaining industry returns.

Rosenberg and Guy (1995) argue that the beta is the consequence of underlying economic events. They find that the level of beta is determined by the degree of uncertainty attached to various categories of economic events and the response of the security returns to these events. The answer to whether the beta will change over time and how the beta will change depends on the degree of uncertainty attached to various categories of economic events and the response of the security returns to these events. The degree of predictability of beta depends on the predictability of economic events changes.

Brooks, Faff and Josev (2001) investigated cross-industry variation in the mean-reversion of Australian stock betas using a set of their own composed industry portfolios instead of industrial indexes. They found the mean-reversion tendency exists for the gold, energy, finance and consumer industry groups; however, the mean-reversion of beta is different across industries. The maximum mean-reversion appears in the gold industry, while the minimum mean-reversion appears in the miscellaneous and consumer industry groups.

In this present work, though, the discovered differences in variability of industry betas are possibly related to the industry-specific characteristics and different sensitivities to the macroeconomic events and conditions. The Australian market is usually seen as a market with an under-performing resources sector compared to the industrial sector. Also the Australian market is considered a concentrated market. The dominance of large companies might also have contributed to the different stochastic properties of industry betas.

Wong and Lakshman (2001) have provided some evidence that the different industry groups react to different economic variables after they examined the stability of Australian industry betas in relation to the variation of key macroeconomic factors. They found that betas of some industries are sensitive to at least one or two macroeconomic factors. The most influential variables were the exchange rate factor, followed by the current account balance, trade balance, interest rates and unemployment.

In next chapter, the sensitivities of Australian industrial returns to economic and financial factors will be examined in detail.

4.6 Discussion and conclusion

For similar industrial stock returns, Brooks, Faff and McKenzie (1998) considered using the GARCH, Schwert and Seguin, and Kalman approaches for estimating time-varying beta models. Their research overwhelmingly supported the Kalman filter approach. The present study further considered the use of the Kalman filter approach to the estimation of time-varying beta models.

The results presented in this chapter indicate that industry portfolios do not have stable betas. Similar to the individual asset beta, the variation of an industry portfolio beta is either a mean-reverting or random process. Additionally, for some industry groups, the long-term mean of beta is also time-varying. This chapter has suggested the best time-varying beta model for each industrial index.

From the detailed studies, the time-varying market model performed better than the ordinary-least-squares in explaining industrial returns. The industrial betas for six industries (banks and finance, chemicals, diversified industrial, diversified resources, energy and retail) are best modelled as moving-mean processes.

The industrial betas for the developers and contractors, engineering and transport industries are best modelled as mean reverting processes. These results clearly show that the industrial betas vary according to their long-term moving or stable state. These facts have confirmed the mean-reversion findings by Blume (1971), Brenner and Smidt (1977) and Francis (1979).

Two industries (the investment and financial services and alcohol and tobacco industries modelled by random coefficients models) have random betas, which wander randomly around their zero means. The results of these two industries suggest that the systematic risks of these two industries are not predictable.

The betas in the gold, insurance and media industries are best described by random-walk processes, while the building materials, food and household, paper and packaging, property trusts and other metals industries are best described by ARMA(1,1) models.

The different stochastic behaviours of industrial betas have both theoretical and practical implications. On the one hand, as previous studies have suggested, the different industrial characteristics as well as different sensitivities have contributed the time varying properties of betas. On the other hand, the betas of industry portfolios with the mean-reverting process can be predicted to some degree, while betas of random walk or random processes are not predictable.

However, caution needs to be taken in the use of "best fitted" or "best possible" models, as the "best" model is just chosen according to one or two of the different criteria. It should also be noted that the diagnostic statistics and forecasting change as the model changes, so does the time path of each beta.

It may be true that no one model will adequately describe the stochastic behaviour of betas. Beta is the covariance of the asset return with the market portfolio divided by the variance of the market portfolio return; therefore, the time-varying property of beta could be due to the time-varying covariance and/or variance of the returns. See, for example, Schwert and Seguin (1990), Episcopos (1996), and Grieb and Reyes (2001).

This chapter has provided an empirical and practical comparison procedure for the selection of a best-possible model for each industrial stock return. The general conclusion here is that the industrial risk, which is summarised by the beta, varies around its steady or moving-mean state. The common stochastic properties of industry betas are either mean reverting or random; however, each industrial index has to be studied individually to understand the factors driving the stochastic behaviour of beta.

4.7 Notes for the tables and figures:

Tables 4.2-4.20 provide the detailed estimation and testing properties of the models used for the industrial stock returns.

- MRM stands for mean reverting model; ARMA stands for ARMA(1,1) model; RCM stands for random-coefficient model; RWM stands for random-walk model and OLS stands for ordinary least square model.
- σ^2 σ^2_a,σ^2_δ σ^2_b, σ^2_n, σ^2_u σ^2_γ $\overline{\beta}$ $\Phi_{11}(\phi)$ Φ_{22} θ are estimated hyper-parameters for each model respectively.
- Q(12) is Box-Ljung statistics for serial correlation.
- C-P test is the cumulated periodogram test for residual series to be white noise.
- G-Q tests is the Goldfeld-Quandt test for heteroskedasticity.
- ARCH(6) is the classic ARCH test.

- Four criteria here to measure the model performance are R-square, Akaike information criterion (AIC), mean absolute error (MAE) and mean square error (MSE) of the estimates.
- ** means 5% level significance, and * means 10%level significance.

The best performing models are highlighted in bold.

Plots of the estimated industrial beta series and the fitted industrial returns are given in Figures 4.2-4.38.

In the figures for the banks and finance, chemicals industry, diversified industrial industry, diversified resources industry, energy industry, and retail industry, the broken lines marked with "betam" denote the estimated values of $\overline{\beta_t}$ while the real lines denote the estimated values of β_t.

In the figures for the alcohol and tobacco, and the investment and financial services industry, the broken lines marked with "betam" denote the estimated values of $\overline{\beta}$ while the real lines denote the estimated values of β_t.

In the figures for the developer and contractor, engineering industry, and the transport industry, the broken lines marked with "betam" denote the estimated values of $\overline{\beta}$ while the real lines denote the estimated values of β_t.

Table 4.2: Alcohol and tobacco

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2\ \sigma_\gamma^2$	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MRM	0.0014		0.0002	0.7773	1.001			21.1632**	0.1491**	3.8037	0.8881	0.5573	0.0015	0.1465	0.0065
ARMA	0.0014		0.0099		0.6977		1.0000	19.7413	0.1440**	2.7307	1.3620	0.5080	0.0015	0.1670	0.0068
RCM	**0.0057**		**3.0659**	**0.2865**				**10.8919**	**0.0769**	**7.8299**	**1.232**	**0.5586**	**0.0059**	**0.0964**	**0.0029**
RWM	0.0047	0.0000	0.0059					20.6294*	0.1642**	4.3746	0.839	0.591	0.0049	0.2025	0.0094
OLS				0.6233				29.6916**	0.1662**	3.6209	0.7616	0.5369	0.0015	0.219	0.0122

Table 4.3: Banks and finances

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2\ \sigma_\gamma^2$	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	**0.187**	**0.0183**	**4.9603** **0.0281**		**0.7622**	**0.000**		**27.0701****	**0.1537****	**5.9698**	**0.8833**	**0.677**	**0.2013**	**0.2122**	**0.0116**
ARMA	0.0014		0.0122		0.8889		1.0000	7.2988	0.0601	4.8481	1.6227*	0.5521	0.0015	0.2425	0.0165
RCM	0.0063		3.0244	0.3086				11.6752	0.0983	3.6647	1.1767	0.4923	0.0066	0.1148	0.0039
RWM	0.0129	0.0000	0.0065					37.1076**	0.1659**	6.8459	0.9005	0.5466	0.0134	0.1991	0.0101
OLS				0.7666				16.2831	0.0922	8.0448	0.632	0.5681	0.0015	0.1741	0.0091

Notes: See the notes after Table 4.20.

Table 4.4: Building materials

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	8.2319	0.0034	105.9004	0.3625		0.9883	0.000		19.9922*	0.0541	19.5093**	2.465**	0.7161	8.864	0.1551	0.0056
ARMA	**0.0009**		**0.0064**			**0.8188**		**1.0000**	**21.3917****	**0.0568**	**22.2025****	**1.0282**	**0.7621**	**0.0009**	**0.1670**	**0.0078**
RCM	0.0034		2.2723		0.7942				16.3174	0.0793	26.7311**	3.3211**	0.6371	0.0035	0.0866	0.0022
RWM	0.0566	0.0001	0.1283						20.9564*	0.1528**	6.854	0.7773	0.5311	0.0590	0.2336	0.0137
OLS					0.8608				16.0027	0.0465	15.5403**	2.31291**	0.7204	0.0010	0.1735	0.0073

Table 4.5: Chemicals

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	**0.2351**	**0.8048**	**16.1616**	**0.0311**		**-1.9E-07**	**1E-06**		**17.7563**	**0.0713**	**6.0149**	**0.9830**	**0.8204**	**0.2532**	**0.0450**	**0.0005**
ARMA	0.0018		0.0020			0.9038		1.0118	20.8695*	0.0762	6.5948	0.8510	0.5737	0.0019	0.2607	0.0176
RCM	0.0054		2.2569		0.7397				14.8742	0.1315**	5.2993	1.4543*	0.4540	0.0056	0.1505	0.0068
RWM	0.0068	0.0000	0.001						55.0927**	0.1998**	5.1782	0.8640	0.8879	0.0019	0.2218	0.0124
OLS					0.8079				18.9747*	0.0662	5.3965	0.8984	0.5300	0.0019	0.2223	0.0133

Notes: See the notes after Table 4.20.

Table 4.6: Developer–contractor

	σ^2	$\sigma_a^2,\sigma_\delta^2$	$\sigma_b^2,\sigma_n^2,\sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MRM	**0.0011**		**0.0020**		**0.9240**	**1.0001**			**7.6446**	**0.0534**	**6.3253**	**0.867**	**0.7640**	**0.0012**	**0.1371**	**0.0061**
ARMA	0.0011		0.0225			0.7959		1.0000	6.5304	0.0530	2.1331	0.8281	0.7209	0.0012	0.2117	0.0123
RCM	0.0036		2.9930		0.4364				15.6733	0.0473	7.0467	2.2208**	0.7183	0.0038	0.1051	0.0032
RWM	0.0081	0.0000	0.0077						10.8835	0.1179*	2.4426	0.6994	0.6353	0.0085	0.2635	0.0179
OLS					0.8994				6.9501	0.0397	9.1219	0.6392	0.7453	0.0013	0.2229	0.012

Table 4.7: Diversified industrial

	σ^2	$\sigma_a^2,\sigma_\delta^2$	$\sigma_b^2,\sigma_n^2,\sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	**2.932**	**5.7287**	**158.3832**	**0.1038**		**0.0600**	**8E-06**		**16.5715**	**0.0569**	**5.6981**	**1.1323**	**0.8585**	**3.1572**	**0.0709**	**0.0013**
ARMA	0.0012		0.0001			0.8903		1.0000	13.8364	0.0548	12.3197*	1.3428	0.6892	0.1167	0.1379	0.0054
RCM	0.0040		2.2616		0.9285				13.444	0.0576	12.1652*	2.2129**	0.6281	0.0042	0.095	0.0028
RWM	0.0089	0.0000	0.0028						16.6512	0.1336*	7.8648	0.8189	0.6333	0.0093	0.2457	0.0152
OLS					0.9011				16.5542	0.0667	6.683	1.0039	0.7160	0.0013	0.2534	0.017

Notes: See the notes after Table 4.20.

Table 4.8: Diversified resources

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	**0.049**	**0.1006**	**5.1883**	**0.0017**		**0.3093**	**0.023**		**11.275**	**0.0423**	**21.4309****	**2.3674****	**0.8585**	**0.0528**	**0.0466**	**0.0006**
ARMA	0.0016		0.0294			0.6587		1.0000	12.1166	0.0955	37.0483**	0.6073	0.7015	0.0017	0.2745	0.0205
RCM	0.0043		2.2751		1.0576				18.0685	0.074	42.9727**	3.2636**	0.5660	0.0045	0.1599	0.0059
RWM	0.0026	0.0000	0.009						29.5625**	0.1688**	7.5516	0.5523	0.6372	0.0027	0.2963	0.0211
OLS					1.2187				13.9786	0.1042	25.7572**	2.40794**	0.7250	0.0017	0.167	0.0076

Table 4.9: Energy

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	**0.0443**	**0.2393**	**17.1501**	**0.6822**		**0.3213**	**0.174**		**19.1453***	**0.0871**	**2.9625**	**0.9981**	**0.9148**	**0.0363**	**0.0359**	**0.0004**
ARMA	0.0026		0.1002			0.7639		1.0000	13.9942	0.1496**	5.9862	0.5895	0.6885	0.0027	0.3460	0.0325
RCM	0.0052		2.2609		1.0873				18.5492	0.1573**	9.2276	0.9204	0.5540	0.0054	0.254	0.0208
RWM	0.0012	0.0000	0.0098						42.6317**	0.2439**	11.28070*	0.2082	0.5887	0.0013	0.3843	0.0384
OLS					1.2402				23.0530**	0.1820**	11.4358*	0.5252	0.5898	0.0032	0.3316	0.0349

Notes: See the notes after Table 4.20.

Table 4.10: Engineering

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MRM	**0.0014**		**0.0042**		**0.9570**		**0.9988**		**30.5992****	**0.1329****	**9.1591**	**1.7540****	**0.6766**	**0.0015**	**0.1421**	**0.0061**
ARMA	0.0015		0.0143				0.8668	1.0000	26.6067**	0.1331**	9.8570	1.0894**	0.6594	0.0016	0.2459	0.0181
RCM	0.0036		2.2731		0.7579				20.3047*	0.1904**	13.4883**	2.6913**	0.5895	0.0038	0.1149	0.0039
RWM	0.0037	0.0000	0.0104						20.5489*	0.1507**	6.3188	0.772	0.5655	0.0038	0.2355	0.0144
OLS					0.8553				18.1507	0.1218*	5.10477	1.39197	0.5927	0.00159	0.1901	0.0113

Table 4.11: Food and household

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	0.2683	0.0001	1.8002	0.0157		0.9880	-0.95		11.6195	0.074	7.525951	2.6125**	0.5566	0.2889	0.1403	0.0059
ARMA	**0.0015**		**0.0047**			**0.9575**		**0.4915**	**21.1994****	**0.0956**	**11.2551***	**1.8469****	**0.5859**	**0.0016**	**0.1507**	**0.0065**
RCM	0.0092		3.0157		0.2782				15.5107	0.1034**	13.2163**	3.5782**	0.4767	0.0096	0.09	0.0029
RWM	0.0014	0.0000	0.0075						18.5145	0.1320*	1.71689	1.22827	0.538	0.0015	0.2133	0.0114
OLS					0.7152				20.7441*	0.0808	12.95439**	2.8231**	0.4996	0.0018	0.2107	0.0115

Notes: See the notes after Table 4.20.

Table 4.12: Gold

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MRM	0.0096		0.0000		1.2218		1.000		16.1011	0.1440*	7.19728	0.55834	0.4520	0.0101	0.4193	0.0692
ARMA	0.0090		0.1035			0.7753		1.0000	13.9762	0.1343**	10.2558	0.5796	0. 3954	0.0090	0.6232	0.1067
RCM	0.0183		3.0385		0.7537				11.8228	0.0992**	4.4034	0.6055	0.2999	0.0191	0.4649	0.0615
RWM	**0.0088**	**0.0000**	**0.0084**						**15.7056**	**0.1224****	**7.02363**	**0.45597**	**0.8282**	**0.0091**	**0.3041**	**0.0226**
OLS					1.5085				17.407	0.1349*	11.59311*	0.49677	0.4426	0.00928	0.459	0.0653

Table 4.13: Insurance

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	2.8053	0.0608	14.59	13.0918		0.947	-0.92		7.1418	0.0599	2.07892	0.86867	0.6065	3.0207	0.2219	0.012
ARMA	0.0020		0.0009			0.9947		1.0000	14.3683	0.1099**	5.699	0.941	0.5307	2.9780	0.1534	0.0085
RCM	0.0124		2.2673		0.7519				23.6557**	0.1388**	4.9015	1.3666	0.3719	0.0129	0.1466	0.0071
RWM	**0.0017**	**0.0000**	**0.0024**						**21.6819****	**0.1158***	**3.5034**	**0.63668**	**0.6580**	**0.0017**	**0.2086**	**0.0102**
OLS					0.6624				24.3543**	0.0814	13.5834**	0.5834	0.4471	0.0026	0.3536	0.0344

Notes: See the notes after Table 4.20.

Table 4.14: Investment and financial services

	σ^2	$\sigma_a^2,\sigma_\delta^2$	$\sigma_b^2,\sigma_n^2,\sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MRM	0.0009		0.5319		0.7662	2E-04			17.5051	0.1488**	3.7686	0.809	0.6796	0.0097	0.1184	0.0039
ARMA	0.0009		0.0021			0.9400		0.7898	16.8398	0.0944	5.8254*	0.4599	0.6859	0.0009	0.1812	0.0076
RCM	**0.0052**		**3.0042**		**0.3028**				**17.5074**	**0.1489****	**3.7685**	**0.8090**	**0.6795**	**0.0054**	**0.1084**	**0.0039**
RWM	0.0056	0.0000	0.0101						23.9437**	0.1511**	2.3241	0.83463	0.4821	0.0058	0.2054	0.0097
OLS					0.5832				23.1020**	0.0881	19.00588**	0.31614	0.6232	0.0011	0.2588	0.0171

Table 4.15: Media

	σ^2	$\sigma_a^2,\sigma_\delta^2$	$\sigma_b^2,\sigma_n^2,\sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	1.1041	0.485	0.0000	3.9322		0.4480	-0.8700		7.4818	0.0437	28.5301**	2.90487**	0.5565	1.1889	0.1387	0.0053
ARMA	0.0043		0.0112			0.9489		0.4406	15.1681	0.1485*	24.1528**	5.8904**	0.4005	0.0045	0.1967	0.0126
RCM	0.0061		2.2622		0.8573				15.5596	0.1264**	25.9940**	3.1508**	0.4121	0.0064	0.1329	0.0065
RWM	**0.004**	**0.0000**	**0.0131**						**28.9840****	**0.1749****	**21.9943****	**0.83584**	**0.7386**	**0.0042**	**0.2089**	**0.0098**
OLS					0.9268				17.1685	0.1338*	35.14037**	1.69174**	0.4032	0.0048	0.3566	0.0334

Notes: See the notes after Table 4.20.

Table 4.16: Paper and packaging

	$\sigma 2$	$\sigma^2_a, \sigma^2_\delta$	$\sigma^2_b, \sigma^2_n, \sigma^2_u$	σ^2_γ	$\overline{\beta}$	Φ11(ϕ)	Φ22	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	0.0238	0.0001	0	0.0724		0.9800	0.3000		10.2503	0.0631	34.6344**	1.85356**	0.6204	0.0256	0.1674	0.0064
ARMA	**0.0013**		**0.0219**			**0.8491**		**1.0000**	**9.1054**	**0.1162***	**39.2708****	**2.0110****	**0.6434**	**0.0014**	**0.1482**	**0.0055**
RCM	0.0072		3.043		0.3075				9.4904	0.1560**	20.0986**	2.9364**	0.5266	0.0075	0.1192	0.0037
RWM	0.0001	1.2E-06	2E-05						31.5228**	0.1754**	2.3658	0.9616	0.5048	0.0001	0.2254	0.0126
OLS					0.782				11.3277	0.0954	14.86994**	2.0353**	0.5610	0.0015	0.1758	0.0073

Table 4.17: Property trusts

	$\sigma 2$	$\sigma^2_a, \sigma^2_\delta$	$\sigma^2_b, \sigma^2_n, \sigma^2_u$	σ^2_γ	$\overline{\beta}$	Φ11(ϕ)	Φ22	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	21.7738	0.0251	2.1915	0.0000		0.9907	-0.9700		13.7699	0.0818	8.0639	0.8693	0.4832	23.4462	0.1437	0.0533
ARMA	**0.0036**		**0.0000**			**0.8678**		**1.0000**	**10.8494**	**0.2021****	**17.5747****	**1.0135**	**0.7003**	**0.0038**	**0.1544**	**0.0061**
RCM	0.0121		2.9683		0.2077				23.4458**	0.3320**	5.5857	1.1471	0.5404	0.0126	0.1101	0.0037
RWM	0.0028	0.0000	0.0025						10.4695	0.0717	6.1524	0.8304	0.4795	0.003	0.1351	0.005
OLS					0.3725				10.0484	0.0688	6.6382	0.8402	0.4609	0.0007	0.1479	0.0056

Notes: See the notes after Table 4.20.

Table 4.18: Retail

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MMM	**34.0919**	**0.0000**	**155.72**	**8.7982**		**-0.1220**	**-0.9400**		**5.8607**	**0.0501**	**9.198**	**0.8549**	**0.6519**	**36.7104**	**0.1624**	**0.0074**
ARMA	0.0014		0.0004			0.9385		0.6029	5.2754	0.0606	1.4817	0.8328	0.6014	0.0813	0.1736	0.0082
RCM	0.0053		2.2606		0.6907				13.2108	0.1188**	2.6954	1.1743	0.5550	0.0055	0.1099	0.0037
RWM	0.0049	0.0000	0.0059						18.7931*	0.1404**	6.2669	0.7287	0.5916	0.0051	0.1766	0.0085
OLS					0.6637				8.9243	0.0768	7.3631	0.7816	0.5557	0.0016	0.2861	0.0207

Table 4.19: Transport

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2$	σ_γ^2	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MRM	**0.0016**		**0.0011**		**0.9431**		**0.999**		**14.1532**	**0.1114***	**5.9607**	**0.7734**	**0.6741**	**0.0018**	**0.1470**	**0.0072**
ARMA	0.0017		0.0012			0.7975		1.0000	15.0978	0.1092*	6.1264	0.8098	0.6727	0.0018	0.2545	0.0017
RCM	0.0047		2.2771		0.9724				6.0132	6.0132	21.0509**	0.8815	0.5947	0.0049	0.1236	0.0045
RWM	0.0618	0.0000	0.0053						12.9061	0.1174*	2.6254	0.4918	0.6101	0.0644	0.3008	0.0295
OLS					0.933				12.3858	0.0872	6.327	0.7371	0.6743	0.0017	0.2269	0.0132

Notes: See the notes after Table 4.20.

Table 4.20: Other metals

	σ^2	$\sigma_a^2, \sigma_\delta^2$	$\sigma_b^2, \sigma_n^2, \sigma_u^2\ \sigma_\gamma^2$	$\overline{\beta}$	$\Phi_{11}(\phi)$	Φ_{22}	θ	Q(12)	C-P Test	Arch(6)	G-Q Test	R-sq	AIC	MAE	MSE
MRM	0.0029		0.0008	0.1907		1.000		16.8012	0.1029	7.0744	1.3624	0.6964	0.0030	0.1944	0.012
ARMA	**0.0013**		**0.02185**		**0.8491**		**1.0000**	**17.6734**	**0.1102***	**4.1494**	**1.3721**	**0.7468**	**0.1208**	**0.2056**	**0.0119**
RCM	0.0049		2.2624	1.2701				13.4531	0.0579	4.4183	1.8280**	0.579	0.0051	0.1955	0.0091
RWM	0.1468	0.0000	0.0000					16.099	0.1745**	1.5046	0.4025	0.6536	0.1530	0.4118	0.044
OLS				1.3128				16.0142	0.1055	5.5914	1.2363	0.694	0.0028	0.2860	0.0192

Notes:

- MRM stands for mean reverting model; ARMA stands for ARMA(1,1) model; RCM stands for random-coefficient model; RWM stands for random-walk model and OLS stands for ordinary least square model.
- $\sigma^2\ \sigma_a^2, \sigma_\delta^2\ \sigma_b^2, \sigma_n^2, \sigma_u^2\ \sigma_\gamma^2\ \overline{\beta}\ \Phi_{11}(\phi)\ \Phi_{22}\ \theta$ are estimated hyper-parameters for each model respectively.
- Q(12) is Box-Ljung statistics for serial correlation.
- C-P test is the cumulated periodogram test for residual series to be white noise.
- G-Q tests is the Goldfeld-Quandt test for heteroskedasticity.
- ARCH(6) is the classic ARCH test.
- Four criteria here to measure the model performance are R-square, Akaike information criterion (AIC), mean absolute error (MAE) and mean square error (MSE) of the estimates.
- ** means 5% level significance, and * means 10%level significance.

The best performing models are highlighted in bold.

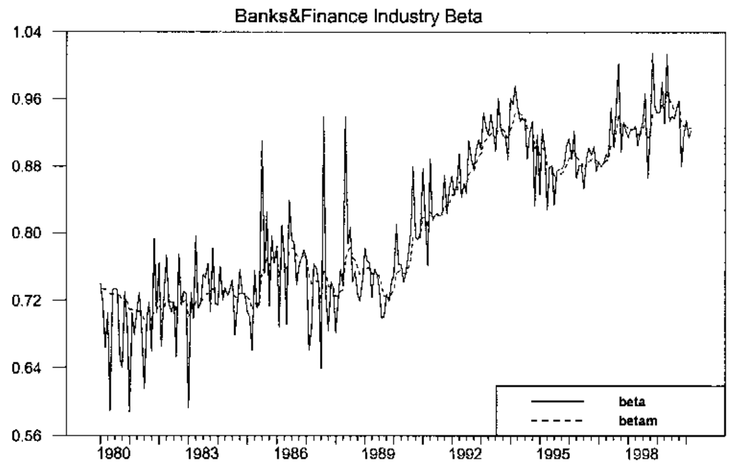


Figure 4.1: Banks & Finance industry Beta

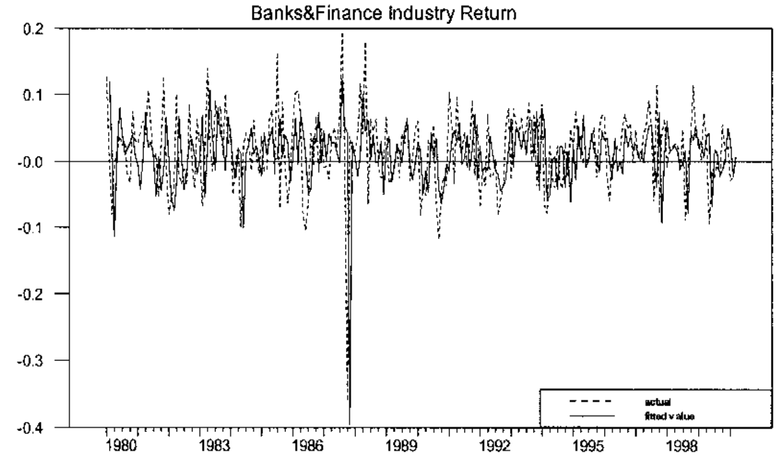


Figure 4.2: Banks & Finance Industry Return

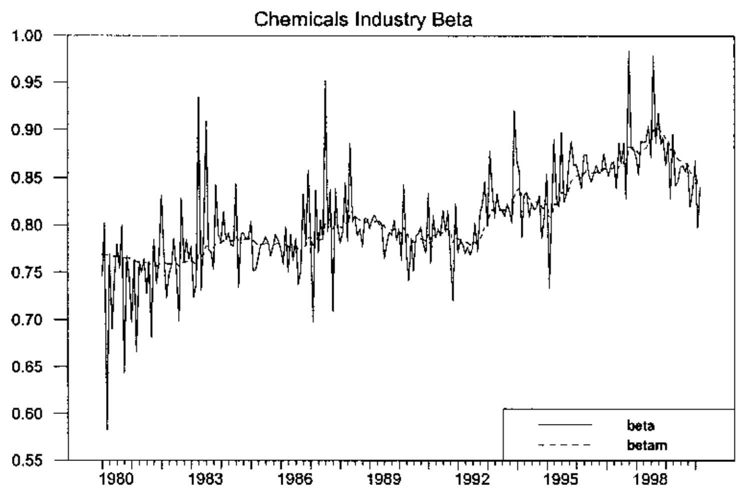


Figure 4.3: Chemicals Industry Beta

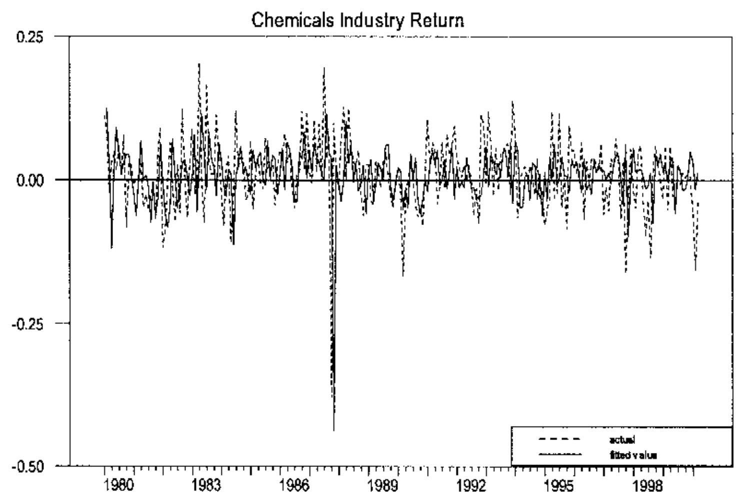


Figure 4.4: Chemicals Industry Return

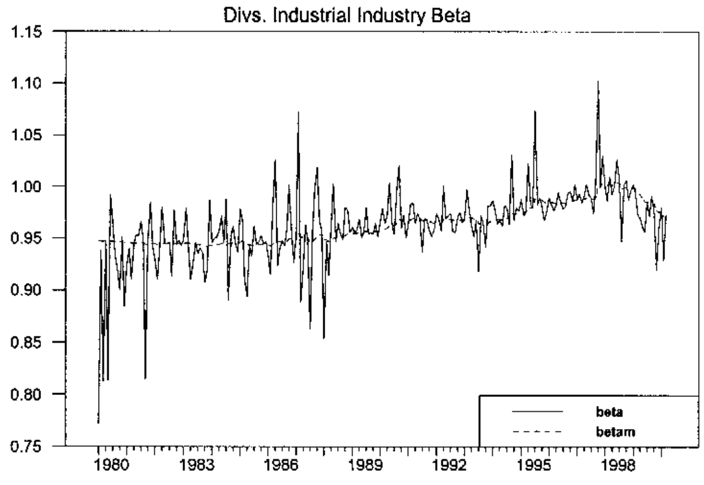


Figure 4.5: Diversified Industrial Industry Beta

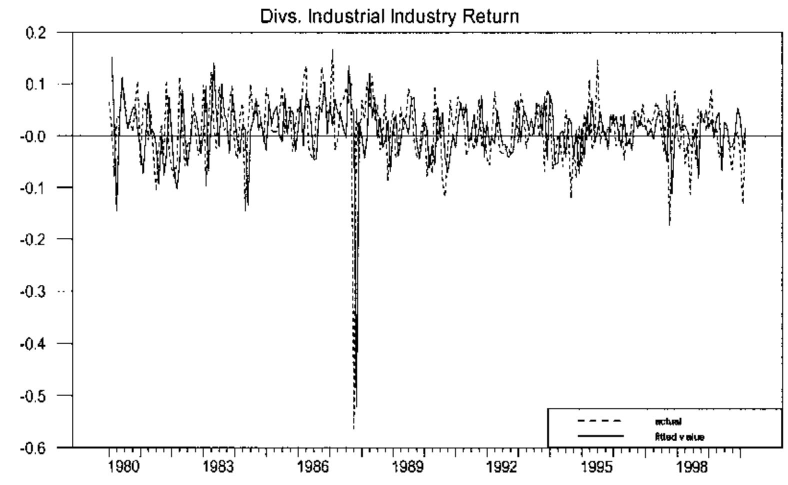


Figure 4.6: Diversified Industrial Industry Return

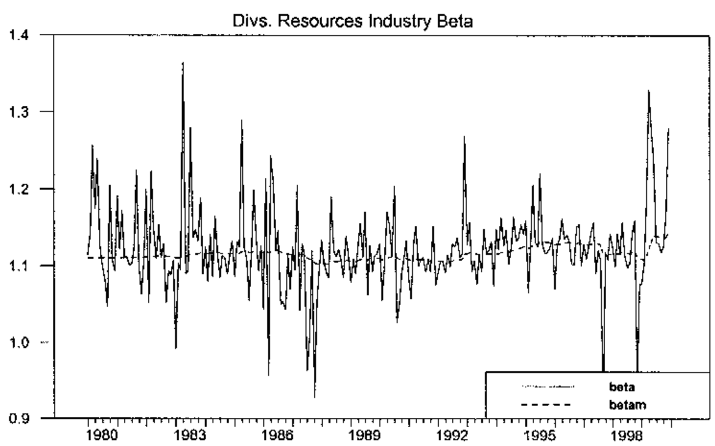


Figure 4.7: Diversified Resources Industry Beta

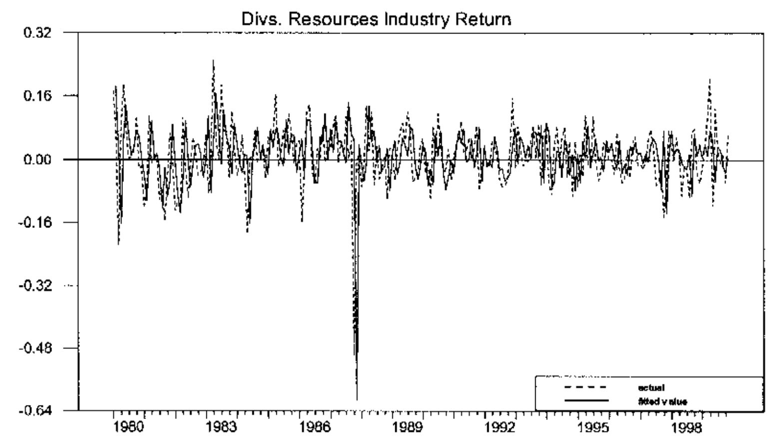


Figure 4.8: Diversified Resources Industry Return

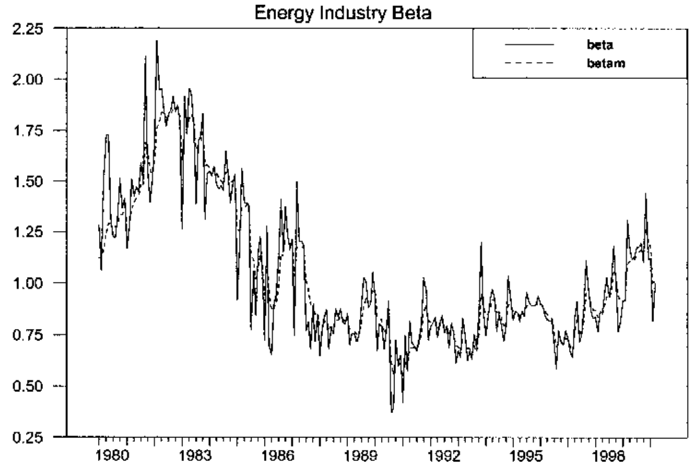


Figure 4.9: Energy Industry Beta

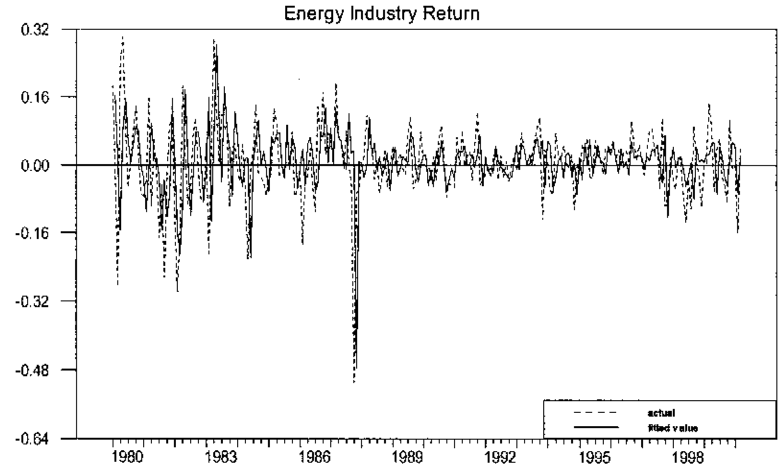


Figure 4.10: Energy Industry Return

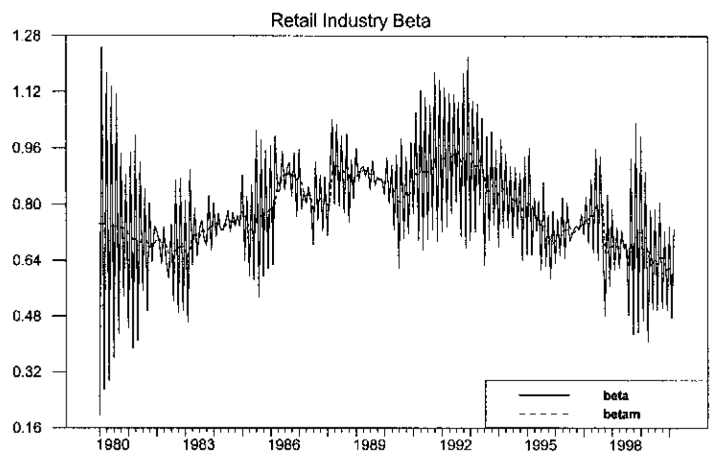


Figure 4.11: Retail Industry Beta

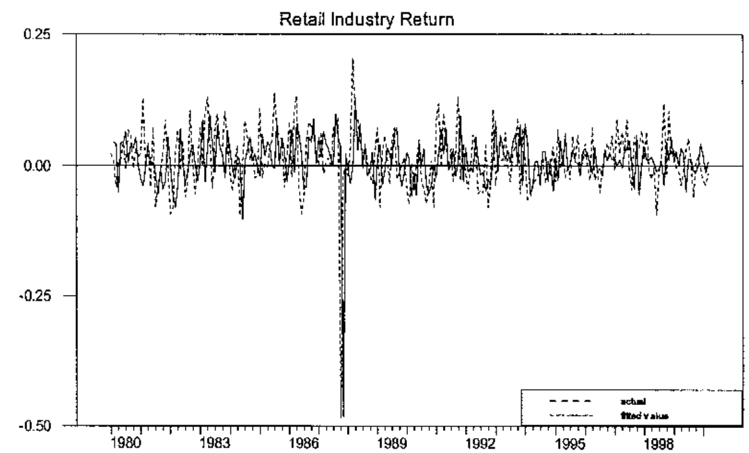


Figure 4.12: Retail Industry Beta

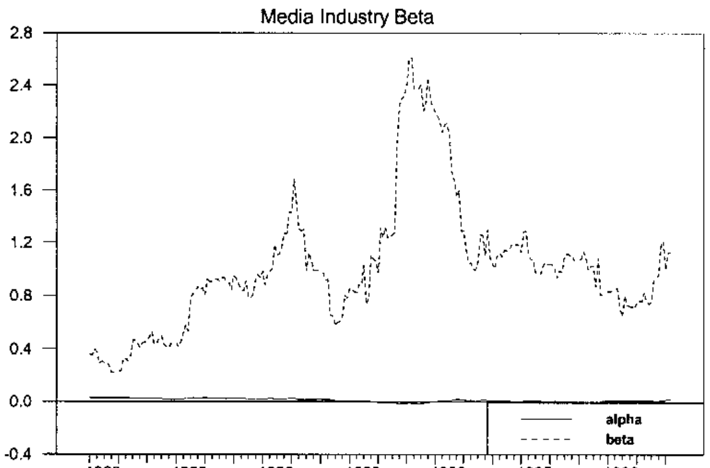


Figure 4.13: Media Industry Beta

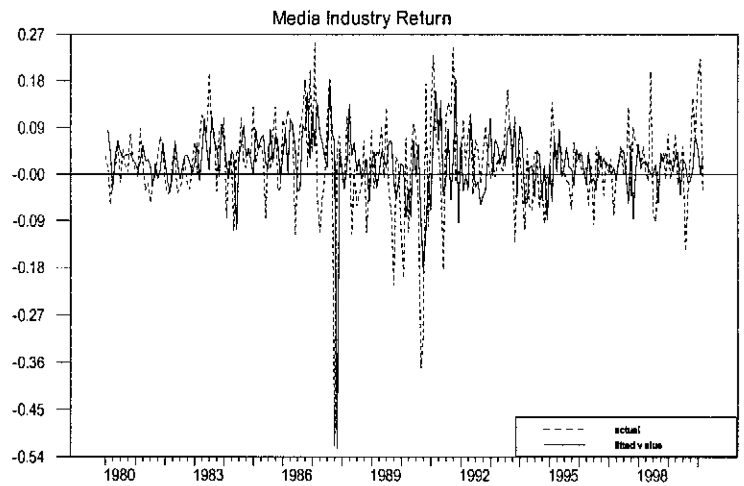


Figure 4.14: Media Industry Return

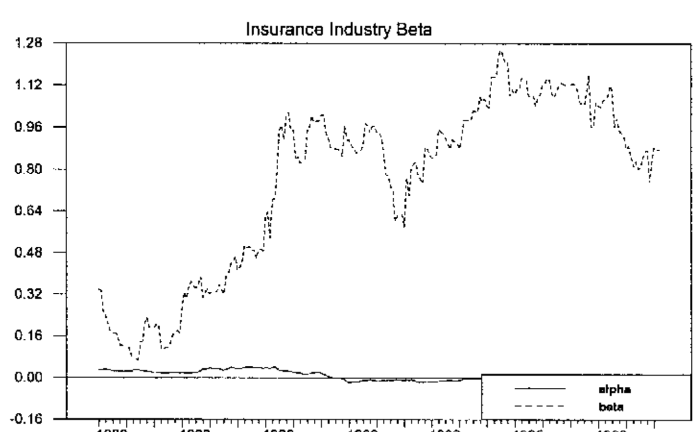


Figure 4.15: Insurance Industry Beta

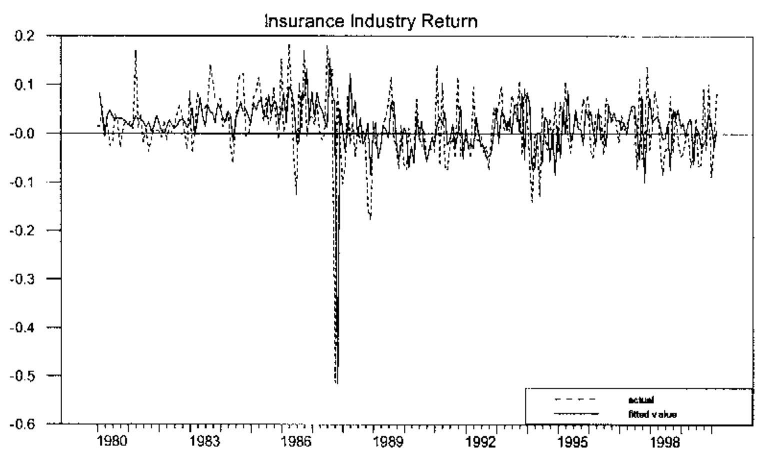


Figure 4.16: Insurance Industry Return

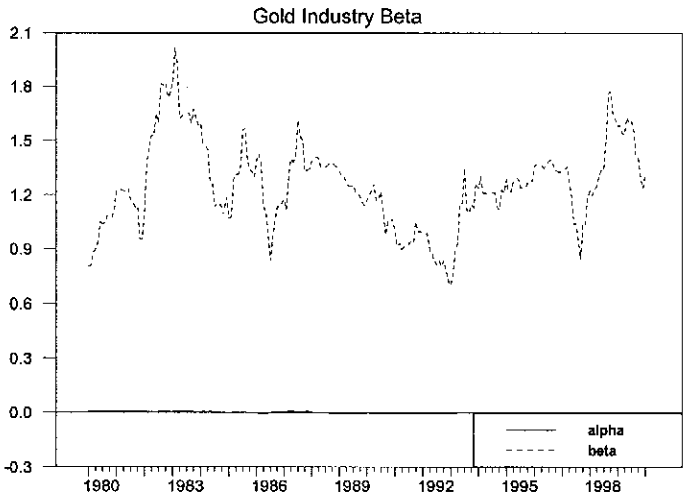


Figure 4.17: Gold Industry Beta

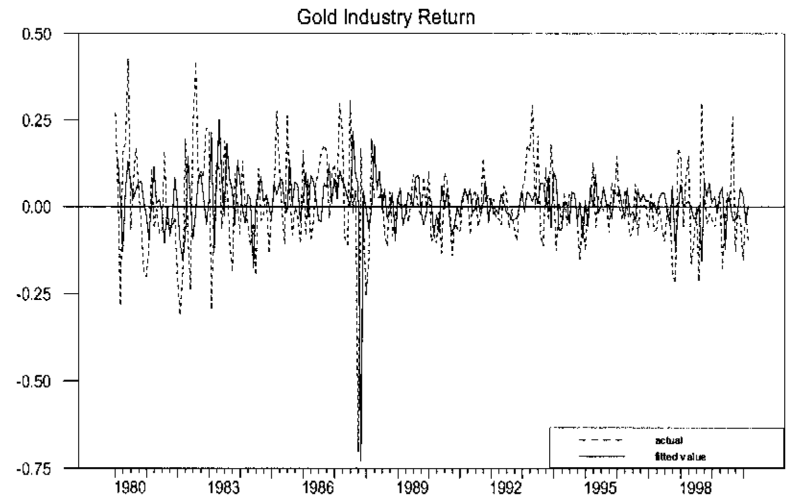


Figure 4.18: Gold Industry Return

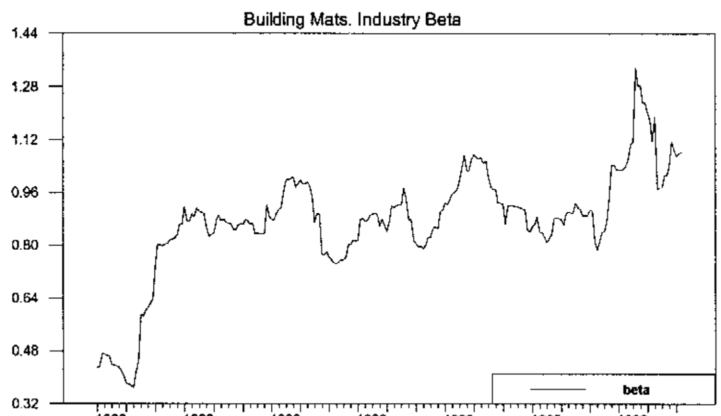


Figure 4.19: Building Materials Industry Beta

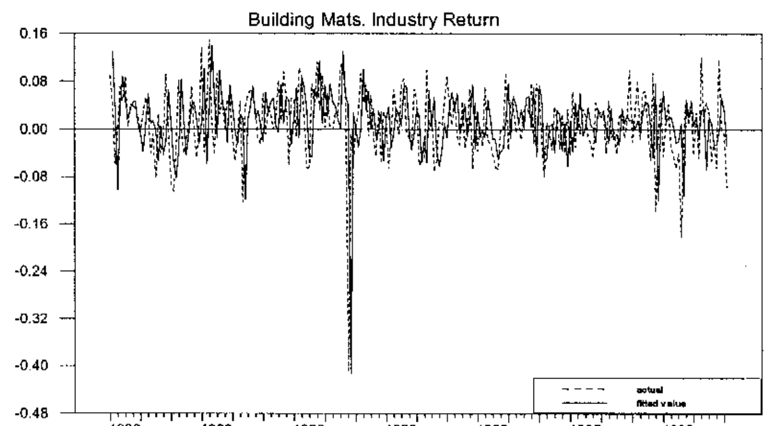


Figure 4.20: Building Materials Industry Return

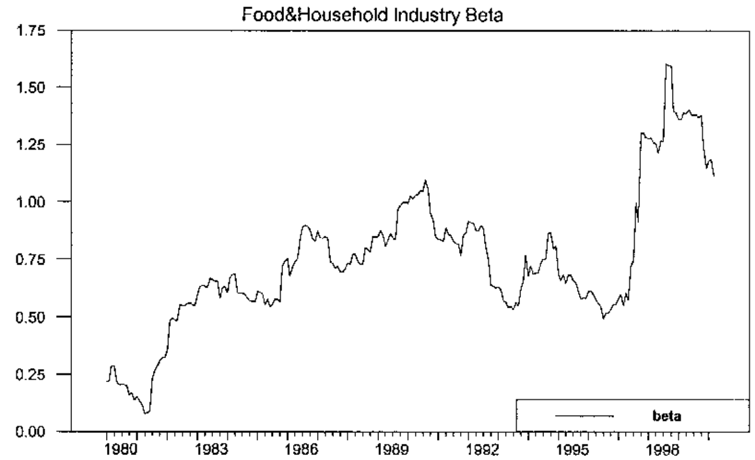


Figure 4.21: Food & Household Industry Beta

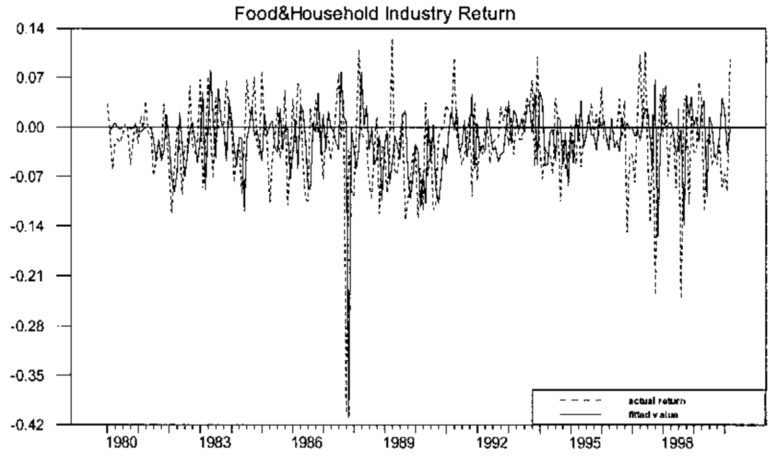


Figure 4.22: Food & Household Industry Return

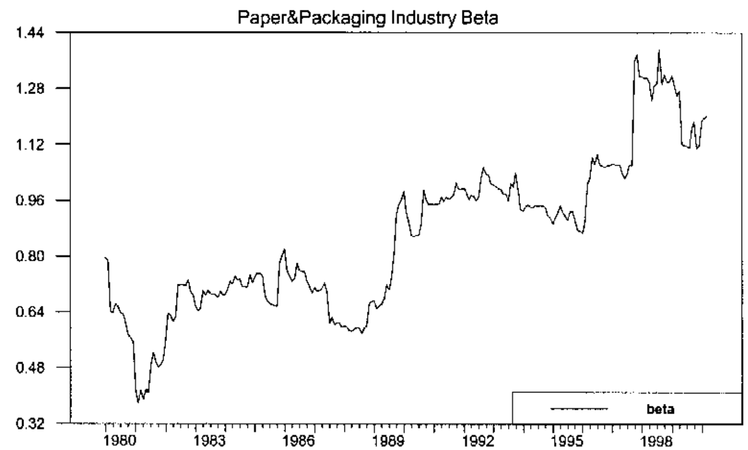


Figure 4.23: Paper & Packaging Industry Beta

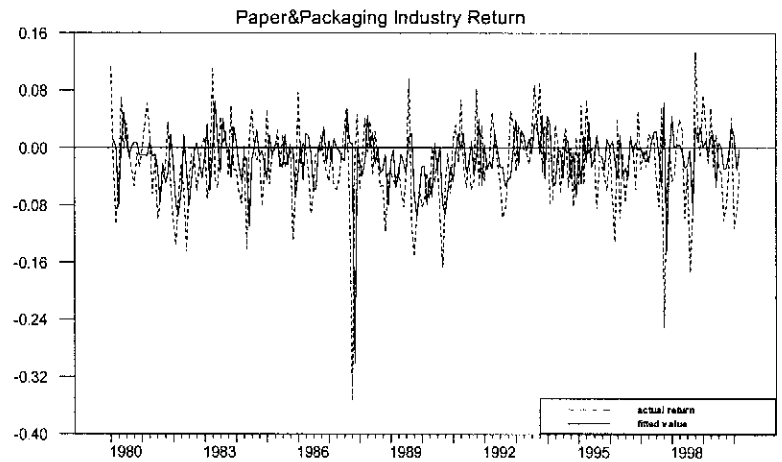


Figure 4.24: Paper & Packaging Industry Return

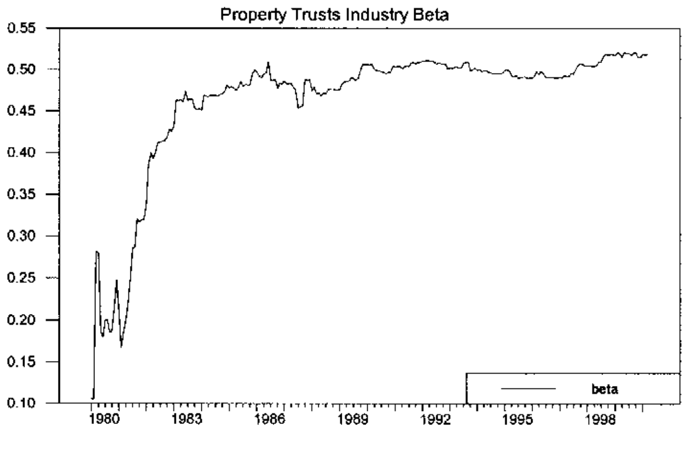


Figure 4.25: Property Trust Industry Beta

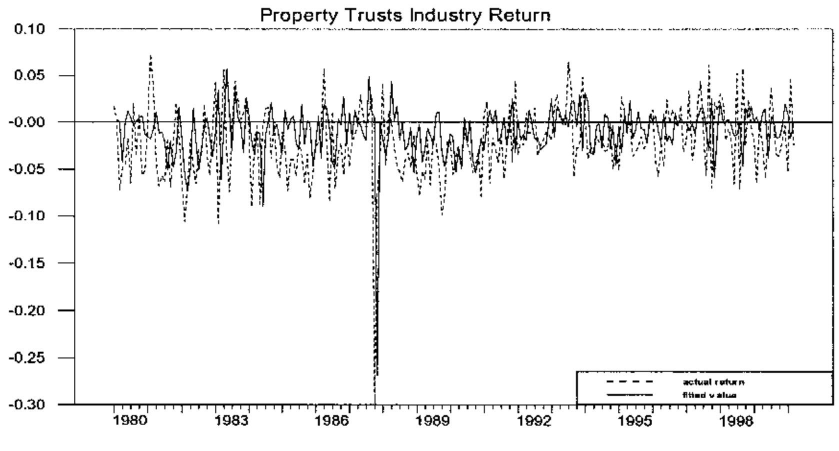


Figure 4.26: Property Trusts Industry Return

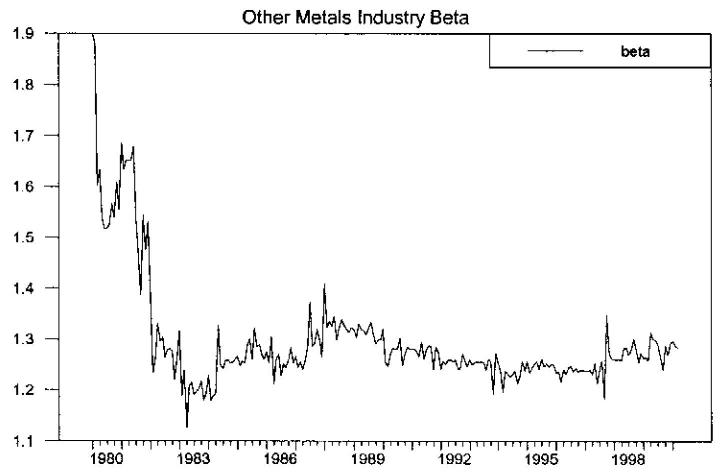


Figure 4.27: Other Metals Industry Beta

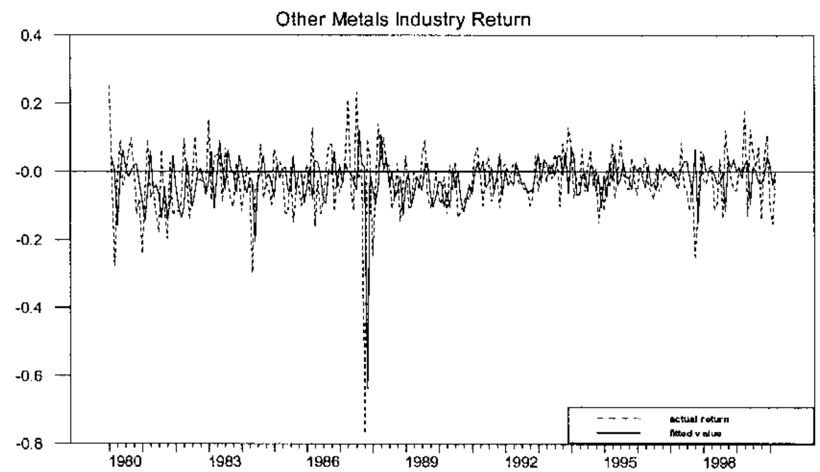


Figure 4.28: Other Metals Industry Return

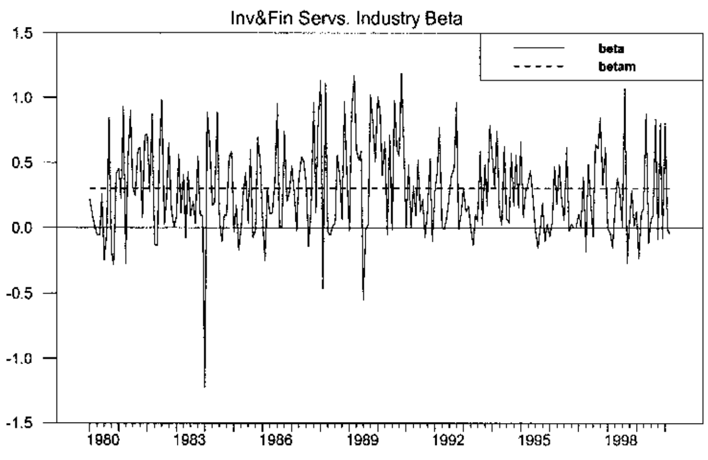


Figure 4.29: Inv & Fin Servs. Industry Beta

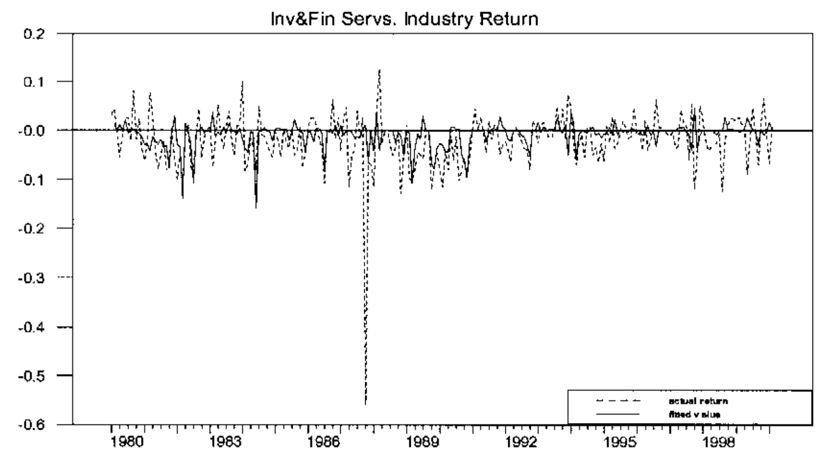


Figure 4.30: Inv & Fin Servs. Industry Return

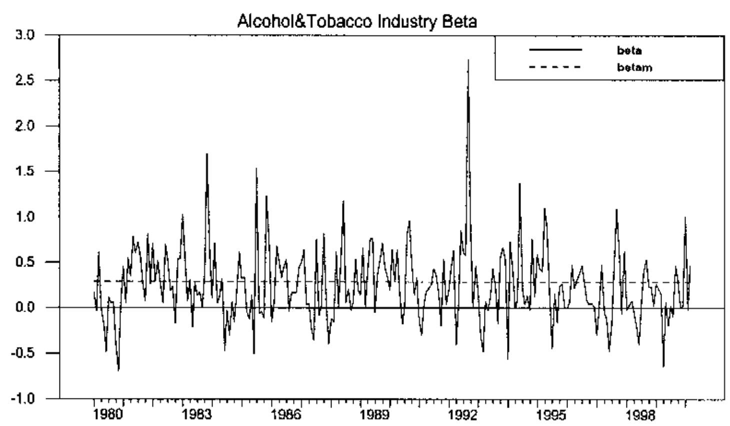


Figure 4.31: Alcohol & Tobacco Industry Beta

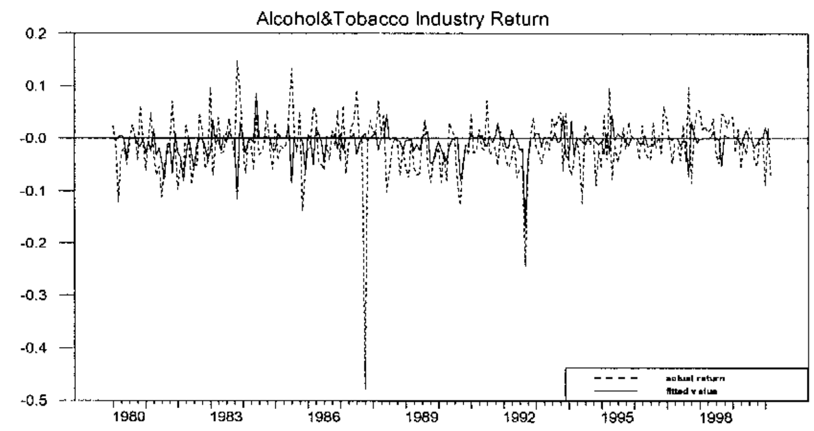


Figure 4.32: Alcohol & Tobacco Industry Return

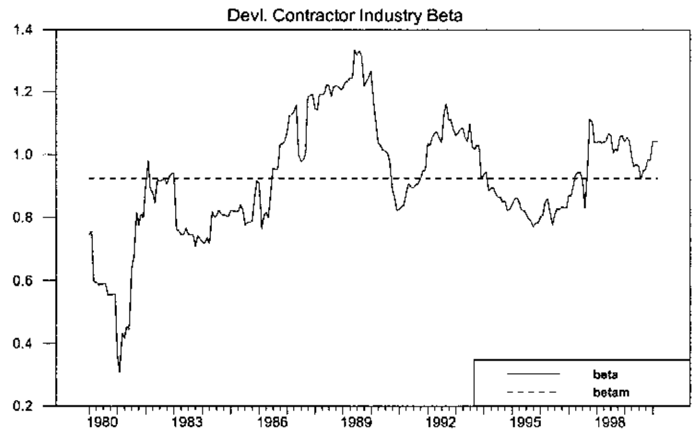


Figure 4.33: Devl. Contractor Industry Beta

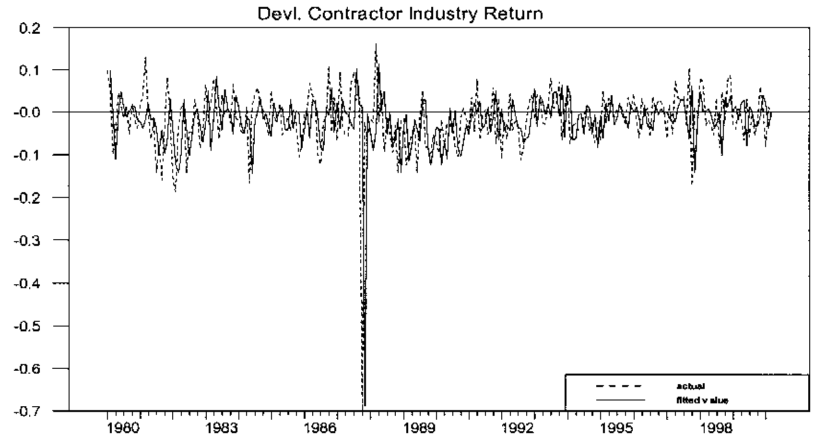


Figure 4.34: Devl. Contractor Industry Return

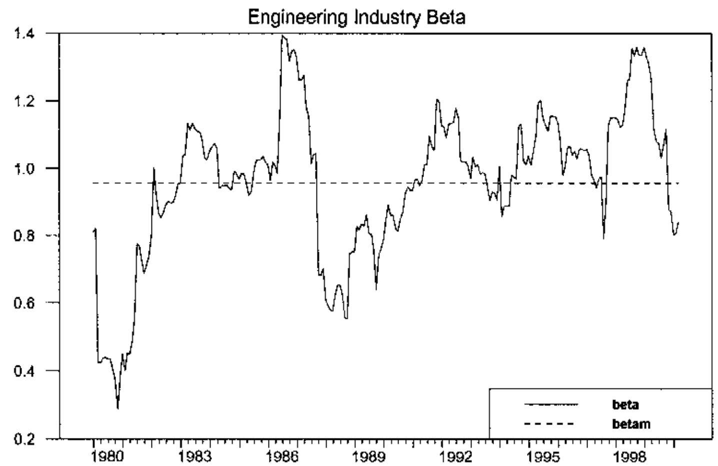


Figure 4.35: Engineering Industry Beta

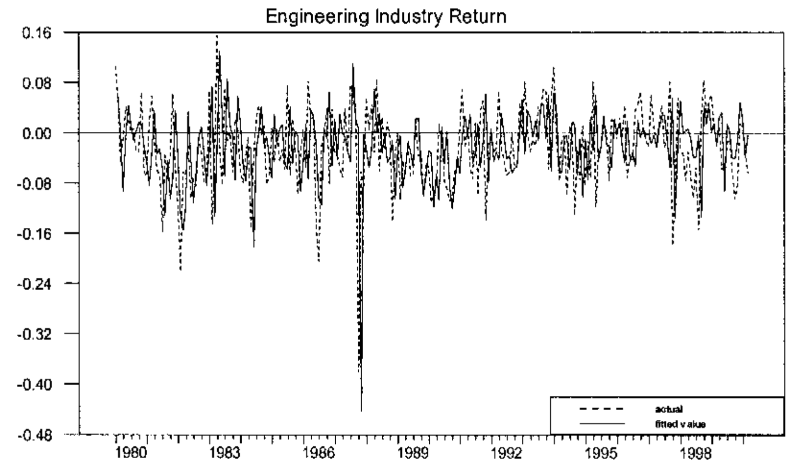


Figure 4.36: Engineering Industry Return

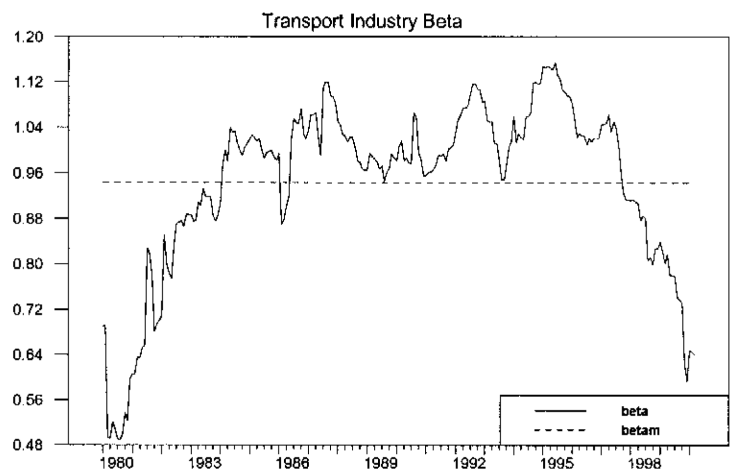


Figure 4.37: Transport Industry Beta

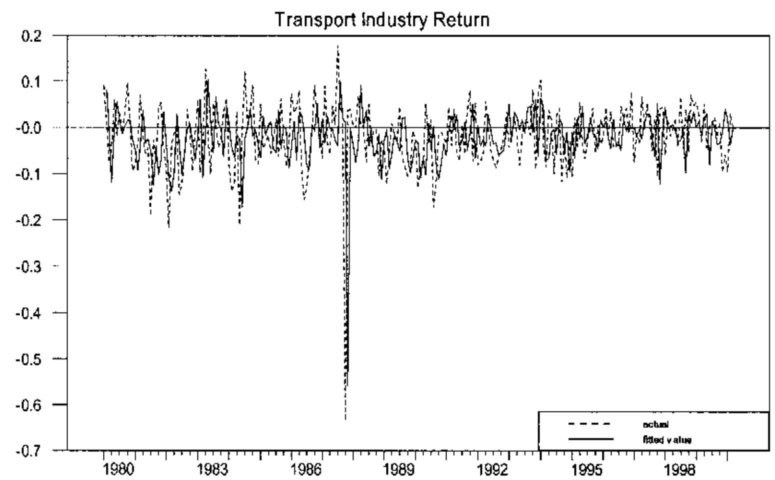


Figure 4.38: Transport Industry Return

Chapter 5 Predictability of Australian industrial stock returns using economic and financial information[11]

5.1 Introduction

Many existing studies into the equity market have supported the predictability of stock returns (see the literature review in Chapter 2). The evidence for predictability can be found either through the autocorrelation of the returns or the explanatory power of predictor variables. The previous chapter presented an investigation of the relationship between Australian industrial-portfolio returns and market-portfolio returns by using the time-varying beta model. The study suggested that the single-index model can offer a good explanation to industrial returns only when the time-varying property of systematic risk is incorporated. While it may not be appropriate to use the same time-varying beta model for all the industrial indexes, due to their individual stochastic behaviour and characteristics, the study demonstrated that it is possible to select a best available model for each industrial index for the purpose of prediction. In this chapter, the single-index model used in the previous chapter will be extended to a multi-factor model by incorporating national economic and financial information.

It is well recognised that stock returns are found to be partially predictable by publicly available information such as time-series data on financial and economic variables, especially information with an important business cycle component (see Chapter 2, Section 2.2.4). The economic interpretation of predictability results is much more controversial in the finance literature, however. If the expected returns are treated as being constant, the predictability of stock returns is evidence of market inefficiency. It has been pointed out that the results supporting predictability do not

[11] A paper derived from this chapter is in revision for the second round review by the *Pacific Basin Finance Journal*. The content of this chapter has benefited from the comments of the anonymous referees, the conference participants of the 2002 APFA/PACAP/FMA Finance Conference in Tokyo and seminar participants at the University of Technology of Sydney and University of Western Australia.

necessarily contradict the idea of rational pricing in an efficient market (Balvers, Cosimano and McDonald, 1990). Rather, Pesaran and Timmerman (1995) argue that the predictor variables are interpreted as being correlated with changes in investors' required returns. It is possible that the predictable components in stock returns reflect time-varying expected returns in which the predictability of stock returns, in principle, is consistent with market efficiency.

The most common and fruitful method is to track the expected excess returns based on publicly available economic information. Although the exact cause-and-effect relationships between macroeconomic variables and the stock market are not known, they are believed to be related. Fischer and Jordan (1987) point out that economic activity affects corporate profits, investor attitudes, expectations and, ultimately, security prices; therefore, overall economic activity manifests itself in the behaviour of stocks. Other related work includes Bodie (1976), Jaffe and Mandelker (1976), Nelson (1976), Fama and Schwert (1977), Fama (1981), Campbell (1987) and French, Schwert and Stambaugh (1987).

Following the seminal paper of Chen, Roll and Ross (1986), many researchers have devoted themselves to discovering the links between economic factors and stock market returns. This stream of work yields international applications in different equity markets. The findings of Hamao (1988), Black and Fraser (1995) and Groenewold and Fraser (1997) indicate the relationship between macroeconomic factors and stock returns in the Japanese, UK and Australian stock markets, respectively. Recently, Bilson, Brailsford and Hooper (2001) also found that local macroeconomic variables have explanatory power over stock returns in 20 emerging markets. The most common choices of state variables that can reflect economic and business conditions are industrial production, the term structure, the Treasury bill rate, the default spread, the dividend yield and some macroeconomic variables such as consumption.

Most of the work on the predictability of stock returns has been based on the regression of an entire sample of available observations. The standard regression based model is:

$$R_t = Z_{t-1}^T \beta + \epsilon_t \tag{5.1}$$

Here R_t is the continuously compounded excess stock return. $Z_{t-1}^T = (1, F_{t-1})^T$, and the $N\times 1$ vector F_{t-1} contains N "predictive" variables that are observed at the end of month $t-1$. The disturbances, ϵ_t, $t=1,2,..., T$, are assumed to be independent normal error processes with mean zero and variance σ^2.

The academic literature offers extensive empirical evidence on stock-return predictability by reporting the estimation results of linear time-series regressions of stock returns on one or more predictive variables. Those analyses, however, are concerned with static models. The forecast was made through one set of parameters whose values were fixed across the sample period. Pesaran and Timmermann (1995) argue that this is inappropriate because in real-time no investor could have obtained parameter estimates based on the entire sample, and any forecasting model taken as known with certainty over the whole sample period could be criticised for ignoring the problem of "model uncertainty". They further point out that when the same forecasting model is used over the whole sample period, it increases the possibility that the choice of the model could have been made with the benefit of hindsight; therefore, the forecasting from this model cannot be regarded as reliable and accurate.

Since forecasting is a statement about an uncertain future, there are only two sources of information we could use for forecasting. Those are historical information and knowledge about the structure of the system generating the data. Generally speaking, the Bayesian approach enables us to incorporate both past information and newly discovered information to make probabilistic statements about the parameters that we are interested in. It thus provides a rational, coherent, and formal framework for combining prior information and new information by adjusting the routine forecast model with subjective intervention. Especially for time series forecasting, the passage of time alone always brings changed circumstances, new situations, and fresh considerations. The Bayesian forecast allows for changes in parameter values as time passes; thus, it is more flexible, logical and consistent.

The main objective of this chapter is to forecast the time series of returns within a Bayesian dynamic framework. The purpose is to construct a system of dynamic models based upon analysis of the historical development of the series and utilisation of information relevant to the series' likely future development. The assumption that the quantified relationship remains the same across the time horizon is not required. The parameters used to forecast will be updated throughout the process once there is a new observation available. The detailed analysis develops both the univariate and multivariate-normal-dynamic-linear model for determining the relationship between the Australian industrial stock returns and the national economic and financial information. After some significant economic and financial variables are chosen, the relationship between the industrial stock returns and the significant variables is established, as are the market returns. The predictability of returns is assessed for both the models using updated parameters and the one-step-ahead forecasting ability.

The chapter is organised as follows: Section 5.2 provides a review of the previous literature and presents a motivation for the work. Section 5.3 introduces the empirical design of the paper. Data is given in Section 5.4. Section 5.5 presents the empirical results of the study; and, finally, the conclusion and summary are given in Section 5.6.

5.2 Previous literature and motivation

Numerous studies in the equity market have supported the predictability of stock returns; for example, Fama, 1976; Fama, 1984; Shiller, 1984; Fama, 1986; Keim and Stambaugh, 1986; Campbell, 1987; Fama and Bliss, 1987. The most important studies showing that stock returns are predictable are those of Fama and French (1988a, 1988b, 1989). They find that stock prices have a slowly decaying stationary component. The negative autocorrelation of returns generated by a slowly decaying component of prices is weak at the short return but stronger as the return horizon increases; therefore, long-run stock returns are indeed predictable. Fama and French (1989) further report that dividend yields, term spreads and default spreads predict excess returns on stocks and on corporate bonds. The predictor variables are interpreted as correlated with changes in investors' required returns.

Mounting evidence has shown that real equity-return movements can be explained by the fundamental variables; however, there is no reason to believe that this linkage between fundamental economic information and equity returns is static as described by the model of section 5.1. Rather, the risk premiums on equity returns vary according to the economic conditions. Faff and Heaney (1999) have investigated the relationship between inflation and Australian industry returns. Their results imply the variation observed in the relationship between expected inflation and equity returns.

Boudough, Richardson and Whitelaw (1994) have discovered that the industry variation in the relationship between inflation and nominal equity returns is a function of expected real dividend growth and, possibly, the expected value of the ratio of real prices and real dividends. They also suggest that the industry inflation beta coefficients will vary with the extent to which dividend growth is correlated with the aggregate economy.

Ferson and Harvey (1991a) point out that changes in risk premiums are far more important than changes in the betas in explaining the variation of the returns. The predictor variables they choose are past excess returns of the market index, the excess return on the three-month Treasury bill, the past dividend yield, the yield spread between BAA and AAA corporate bonds, the one-month Treasury bill rate and a dummy variable for the month of January. Ferson and Harvey (1991b) provide further evidence that most of the predictability of monthly common stock is associated with sensitivity to economic variables in a rational asset-pricing model with multiple betas. Time variation in the premium for beta risk is more important than changes in the betas; therefore, more sophisticated methods that incorporate the time-varying risk premium are necessary for research into predictability of industrial return.

Recently, Ferson and Harvey (1998) provided a global conditional asset-pricing perspective on the fundamental determinates of 21 national equity markets. They found that the relation of the fundamental attributes to expected stock returns and to risk is different across countries. Fletcher (2001) employs the conditional asset-pricing model of Ferson and Harvey (1999) and Kirby (1998) to examine the predictability of UK stock returns. He found that the domestic APT tends to capture most of the time-series predictability in UK stock returns and performs better than the CAPM.

As excess returns are associated with economic activities, economic factors will be able to tame the change of investors' required returns. The early work of King

(1966) has provided evidence that the movement of a group of security price changes can be broken down into market and industry components. King's work subsequently spawned a group of researchers who investigated industry factors or risks in security returns.

Sorensen and Burke (1986) have found significant abnormal returns relative to the market index for their ranked industry groups; that is, active industry-group rotation would enhance portfolio returns. Their results support industry predictability. Significant abnormal returns were also found in the industrial portfolios constructed and rebalanced through multiple periods by Grauer, Hakansson and Shen (1990).

Beller, King and Levinson (1998) argued that the first stage of investment is to allocate funds globally to broad asset classes on the basis of forecasts of the overall economic and market environment. In the second stage, however, the group-rotation stage, the fund managers attempt to identify economic sectors and industries that stand to gain or lose relative to the overall market. Most of the empirical work in this area focuses on industry differences or industry factors to explain the variances of asset returns. The empirical results are generally consistent with the issue that there is a substantial divergence in the relative performance of industries. These studies include Fama and French (1988a), Reilly and Drzycimski (1974), Rosenberg (1974), Breeden, Gibbons and Litzenberger (1989), Kale, Hakansson and Platt (1991), Boudoukh, Richardson and Whitelaw (1994). Technically, they use industry groups as a form of classification. The industry factors or risks are reflected as different variances relative to the market.

Wei and Wong (1992) and Boudoukh, Richardson and Whitelaw (1994) both indicate the different sensitivities of various industrial groups to inflation. Jensen, Johnson and Bauman (1997) identify different expected returns across industries as different responses of monetary policy. Boyle and Yong (1988) also have confirmed the findings of industry differences in the relationship between nominal equity returns and inflation. Faff and Chan (1998) apply a three-factor-model to the returns of gold stocks in Australia equity market. They suggest that the market and gold price factors could explain the gold stock returns. A study by Cooper, Jackson III, and Patterson (2002) found that the bank stock returns could be predicted by variables related to non-interest income, loan-loss reserves, earnings, leverage and standby letters of credit.

Recently, some empirical evidence has shown that market effects have become less important in the management of equity funds, and the industry effects have become more important (Black et al., 2001; Campbell et al., 2001). There has been a rising interest in testing industry momentum; for example, the work by Moskowitz and Grinblatt (1999), Grundy and Martin (2001). Additionally, some recent evidence has suggested the benefits of using an industry portfolio in the asset-pricing literature. Groenewold and Fraser (2002) have shown that the asset-pricing tests using the Australian industry portfolio are not sensitive to the assumption of being identically, independently and normally distributed (iid-normal).

The study presented in this chapter contributes to the existing literature in a number of ways. First, a general multivariate-normal-dynamic-linear model was developed for determining the relationship between Australian industrial stock returns and national economic and financial information. After some significant economic and financial variables were chosen, the relationship between industrial stock returns and market returns — as well as the significant variables — was established. The multivariate, dynamic model fits nicely when modelling the time-varying properties of returns. This indicates that the predictability of industrial returns is well explained by the time-varying risk premium of economic factors. The results replenish the existing asset-pricing evidence in the Australian market.

Second, much of the empirical literature that considers industry return concentrates on industry "factors" or risks in security returns. There is less work undertaken with the primary purpose of investigating the different predictabilities of industrial stock returns. It is thus less likely to uncover to what extent the available information could explain the different industry groups' expected returns.

The issue of predictability of industry stock returns has important implications for both portfolio management and security pricing theories. Given the importance of industry analysis in the investment process, as well as the rising interest of testing industry momentums, this research serves as a preliminary guide to both investors and academics. Especially in Australia, there is little research into the predictability of industry sector returns. This study thus makes a contribution to the Australian financial-research literature.

Additionally, the multivariate-model adopted here suggests not only that there are some correlations between the individual industrial returns but also that the multivariate method is superior to the conventional univariate method. This has been justified through an empirical comparison of the corresponding statistical measures. The main reason for the superiority of the multivariate method over the univariate method is that the multivariate method can incorporate correlations between the industrial returns, while the univariate method inevitably imposes uncorrelated assumptions on the relationship between the industrial returns. This study thus shows that correlations within the industrial returns are critical when investigating the predictability of the returns.

5.3 Theoretical framework

5.3.1 Variable decomposition

Most previous studies used the economic variables directly in a model for predicting stock returns. However, Fama (1990) states that in the standard stock valuation models the variation in stock returns are largely the result of big enough changes to generate "shocks to expected cash flows" and unexpected economic developments that lead to "shocks in discount rates". Some recent studies have suggested that in an efficient market, the stock market only reacts to the unanticipated component of the economic variables (see, for example, Gangemi, Brooks and Faff, 2000). Therefore, a more feasible method to test for predictability is to investigate how the "unanticipated" components of economic variables affect returns.

The common method to obtain the unanticipated components of economic variables is to subject each variable to time-series modelling. The error series of the time-series models are then taken as the unanticipated components; however, the obtained unanticipated components are often highly correlated with each other, which imposes the multicollinearity problem on the forecasting model.

Obtaining the unanticipated components of the economic variables involves extracting a signal from a noisy environment. Cheung (1993) introduced the Kalman filter as the signal-extraction method to extract the unobserved *ex ante* real interest rate from the observed *ex post* real interest rate. Faff and Heaney (1999) also adopted this method. Therefore, before establishing the model for forecasting stock returns in this chapter, the selected economic variables are decomposed into the unanticipated component and anticipated component by using Kalman-filter techniques through a simple state-space framework.

Similar to Faff and Heaney (1999),[12] the simplest version of the state-space form is adopted here. Assume that $\{X_t\}$ is a vector of economic variables. The signal of the system below is taken as the expected component of the variable, while the forecasting error (the noise), is the unanticipated component. The decomposition can then be defined as:

$$X_{t-1,t} = X^{e}_{t-1,t} + F_t \tag{5.2}$$

$$X^{e}_{t-1,t} = X^{e}_{t-2,t-1} + H_t, \tag{5.3}$$

Here $\{X_{t-1,t}\}$ is a vector of n economic-variable values for the period t-1 to t observed at t. $X^{e}_{t-1,t}$ is the vector of n expected economic-variable values for the period t-1 to t observed at t. $\{F_t\}$ is a vector of n unanticipated component, which will enter the regressions in both univariate and multivariate analysis below, and $\{H_t\}$ is the random and unobserved component. Through the rest of this paper, it is assumed that F_t and H_t are uncorrelated, Gaussian, white-noise errors.

5.3.2 Univariate model analysis

In the framework of state-space model, the univariate regression model is defined like so:

Observation equation: $\quad R_t = Z_t \mu_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2),$ (5.4)

System equation: $\quad \mu_t = \mu_{t-1} + \xi_t, \quad \xi_t \sim N(0, \Xi).$ (5.5)

[12] Faff and Heaney (1999) decompose the observed inflation rate into two components: the expected inflation rate: the "signal", and the forecasting error: the "noise".

Here R_t is the industrial return at time t, and $Z_t = (1, F_t)^T$, F_t is a $N \times 1$ vector of derived unanticipated components of economic and financial variables observed at the end of month t. μ_t is a vector of regression coefficients, which are assumed to follow a random walk. [13] The observation equation and the system equation residuals, ε_t and ξ_t, are both Gaussian and mutually independent.

The state-space framework here avoids the assumption that the risk premiums of returns are constant over time. The model allows the risk premium itself to be a time-varying stochastic process. Bayesian statistical analysis for the state-space model proposed above begins by first quantifying the existing knowledge on the state vector μ_t and the variance structure. These prior inputs are then combined with the information from observed data, Z_t, quantified probabilistically through the likelihood function: the joint probability of the data under the stated model assumptions. The mechanism of prior and likelihood combination is Bayes' theorem introduced in chapter 3. The resulting synthesis of prior and likelihood information is the posterior distribution or information of the state vector μ_t.

5.3.3 Multivariate model analysis

This section establishes a multivariate-normal-dynamic-linear model (MNDLM) to determine the relationship between the vector of the industrial excess returns and the vector F_t.

Denote each individual industrial return j at time t by Y_{tj} then, assume that a system (Y_{tj}, F_t) satisfies a dynamic system of the form shown below. For details of dynamic linear systems, see, Pole, West and Harrison (1994).

$$\textit{Observation equation:}\ Y_{tj} = F_t\,\theta_{tj} + v_{tj}, \qquad v_{tj} \sim N[0,\ V_t\,\sigma_j^2], \tag{5.6}$$

$$\textit{System equation:}\quad \theta_{tj} = \theta_{t-1,j} + w_{tj}, \qquad w_t \sim N[0,\ W_t\,\sigma_j^2], \tag{5.7}$$

[13] The system equation can also be set up as other forms for example, mean-reverting or ARMA process. The experiment shows that random walk form of system equation provides better fitting than other forms.

where $F_t = (F_{t1}, \ldots F_{tn})^T$ is a vector of the unanticipated economic components, and θ_{tj} is a $n \times 1$ vector of random parameters.[14] Both error sequences, v_{tj} and w_{tj}, are univariate, Gaussian, random processes and are mutually independent with each other. V_t is a known and non-random function of t, and W_t is a known n×n evolution matrix. The individual variance σ_j^2 serves as a multiplier of the known evolution matrix W_t.

The joint, cross-sectional structure across q series at time t is represented by the covariance between the observational errors of each of the series, and also between evolution errors. The covariance matrix $\sum$ is given by:

$$\sum = \begin{vmatrix} \sigma^2{}_1 & \sigma_{1,2} & \cdots & \sigma_{1,q} \\ \sigma_{1,2} & \sigma^2{}_2 & \cdots & \sigma_{2,q} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1,q} & \sigma_{2,q} & \cdots & \sigma^2{}_q \end{vmatrix}, \tag{5.8}$$

where σ_{ij} determines the covariance between series Y_{ti} and Y_{tj}, and $1 \leq i \neq j \leq q$. The cross-sectional assumptions conditional on $\sum$ are:

$$C\,[v_{ti}, v_{tj}] = V_t \sigma_{ij}$$

and:

$$C\,[w_{ti}, w_{tj}] = W_t \sigma_{ij}, \text{ for } i \neq j.$$

In this study, the matrix normal DLM is employed to investigate the dynamic relationship between industrial returns and national economic variables. These are extensions of the basic multivariate DLM in which the state parameters are naturally involved through a state matrix, rather than the usual vector. The model introduced by West and Harrison (1997) enables us to incorporate the cross-sectional structure of similar industrial returns time series.

The model can be written as the matrix normal DLMs:

$$\boldsymbol{Y}_t = \boldsymbol{F}_t\, \boldsymbol{\Theta}_t + \boldsymbol{v}_t, \qquad \boldsymbol{v}_t \sim N[\boldsymbol{0}, V_t\, \boldsymbol{\Sigma}] \tag{5.9}$$

---

[14] See footnote 11.

$$\Theta_t = \Theta_{t-1} + \Omega_t, \qquad \Omega_t \sim N[0, W_t, \Sigma], \tag{5.10}$$

where

$Y_t = (Y_{t1}, \ldots, Y_{tq})^T$, the q-vector of industry returns at time t;

$F_t = (F_{t1}, \ldots F_{tn})^T$, the vector of n predictor variables at time t;

$\Theta_t = [\theta_{t1}, \ldots \theta_{tq}]$, the $n \times q$ matrix of regression coefficients;

$v_t = (v_{t1}, \ldots, v_{tq})^T$, the q-vector of observation errors at time t.

$\Omega_t = [\omega_{t1}, \ldots \omega_{tq}]$, the $n \times q$ matrix whose columns are the evolution errors of the individual DLMs.

In the matrix form, F_t is common to each of the j univariate DLMs, and the observational error vector v_t, conditional on Σ is multivariate normal, and independent over time. The evolution error matrix Ω_t, also conditional on Σ is a matrix normal distribution with mean matrix 0, left-variance matrix W_t and right-variance matrix Σ

The joint distribution of Θ and Σ is defined as a matrix normal/inverse Wishart distribution:

$$(\Theta, \Sigma) \sim NW_n^{-1}[m, C, S]$$

The marginal distribution of the matrix Θ is a matrix-variate analogue of the multivariate T distribution (Dawid, 1981). As with the matrix normal, the component columns of Θ themselves follow p-dimensional multivariate T distributions with n degrees of freedom.

Following Dawid (1981),

$$\Theta_j \sim T_n[m_j, CS_j], \; (j = 1, \ldots, q)$$

If $n > 1$, $E[\theta_j] = m_j$. If $n > 2$, $V[\theta_j] = CS_j n/(n-2)$, and the covariance structure between the columns is given by:

$$C[\theta_j, \theta_k] = CS_{jk}\, n/(n-2), \qquad (j,k = 1, \ldots p; j \neq k).$$

The matrix T distribution of Θ is denoted by

$$\Theta \sim T_n[\boldsymbol{m}, \boldsymbol{C}, \boldsymbol{S}].$$

West and Harrison (1997) provide the updating and forecasting equations.

Suppose that the initial prior for Θ_0 and Σ is matrix normal/inverse Wishart:

$$(\boldsymbol{\Theta}_0, \ \Sigma \mid D_0) \sim NW_{n0}^{-1}[\boldsymbol{m}_0, \boldsymbol{C}_0, \boldsymbol{S}_0],$$

for some known defining parameters $\boldsymbol{m}_0$, $\boldsymbol{C}_0$, $\boldsymbol{S}_0$ and n_0. Then for all times $t>1$, the following results apply:

Posteriors at *t-1*

For some $\boldsymbol{m}_{t-1}$, $\boldsymbol{C}_{t-1}$, $\boldsymbol{S}_{t-1}$ and n_{t-1},

$$(\boldsymbol{\Theta}_{t-1}, \ \Sigma \mid D_{t-1}) \sim NW_{n,t-1}^{-1}[\boldsymbol{m}_{t-1}, \boldsymbol{C}_{t-1}, \boldsymbol{S}_{t-1}].$$

Priors at *t*

$$(\boldsymbol{\Theta}_t, \ \Sigma \mid D_{t-1}) \sim NW_{n,t-1}^{-1}[\boldsymbol{a}_t, \boldsymbol{R}_t, \boldsymbol{S}_{t-1}],$$

Here:

$$\boldsymbol{a}_t = \boldsymbol{m}_{t-1} \qquad \text{and} \qquad \boldsymbol{R}_t = \boldsymbol{C}_{t-1} + \boldsymbol{W}_t$$

One-step forecast

$$(Y_t \mid \Sigma, D_{t-1}) \sim N[\boldsymbol{f}_t, \boldsymbol{Q}_t\boldsymbol{S}_{t-1}],$$

Here:

$$\boldsymbol{f}_t^T = \boldsymbol{F}_t^T \boldsymbol{a}_t \qquad \text{and } Q_t = V_t + \boldsymbol{F}_t^T \boldsymbol{R}_t \boldsymbol{F}_t$$

Posteriors at *t*

$$(\boldsymbol{\Theta}_t, \ \Sigma \mid D_t) \sim NW_{n,t}^{-1}[\boldsymbol{m}_t, \boldsymbol{C}_t, \boldsymbol{S}_t],$$

with:

$$\boldsymbol{m}_t = \boldsymbol{a}_t + \boldsymbol{A}_t \boldsymbol{e}_t^T \quad \text{and} \quad \boldsymbol{C}_t = \boldsymbol{R}_t - \boldsymbol{A}_t \boldsymbol{A}_t^T Q_t,$$

$$n_t = n_{t-1} + 1 \qquad \text{and} \quad \boldsymbol{S}_t = n_t^{-1}[n_{t-1}\boldsymbol{S}_{t-1} + \boldsymbol{e}_t \boldsymbol{e}_t^T / Q_t],$$

Here

$$A_t = R_t F_t / Q_t \quad \text{and} \qquad e_t = Y_t - f_t$$

These models allow fully conjugate and closed-form analyses of the covariance structure when it is assumed that the scalar-component time series follow univariate DLMs with common F_t. The prior and posterior means, a_t and m_t, are both $n \times q$ matrices, so their columns provide the means of the q state vectors of the individual DLMs.

Discounting was used as a practical solution to the problem of setting evolution disturbance variances (see West and Harrison, 1997). The state prior variance at any time is computed as a function of the posterior variance at the previous time determined by a discount factor, δ, which is between 0 and 1. The discount factor represents the amount of information loss attributed to temporal advancement. Discounting variance this way is equivalent to setting the evolution variance as a proportion of the posterior variance; therefore:

$$W_t = (1/\delta - 1)\, C_{t-1}. \tag{5.11}$$

The covariance structure across the series can be explored by considering the inverse Wishart posterior for Σ at any time t.

$$(\Sigma \,|\, D_t) \sim W_{n,t}^{-1}[S_t].$$

The matrices S_t provide estimates of the variances and covariances of the series. These provide obvious estimates of the correlations between series.

The cross-sectional covariance structure Σ may vary stochastically over time. To model variation of the covariance structure Σ, Quintana and West (1987) developed the model by using the time-varying variance matrix discounting:

$$(\Sigma_t | D_t) \sim W_{n,t}^{-1}[S_t]. \tag{5.12}$$

Here

$$n_t = \beta n_{t-1} + 1 \quad \text{and} \qquad S_t = n_t^{-1}[\beta n_{t-1} S_{t-1} + e_t e_t^T / Q_t], \quad 0<\beta<1.$$

β is a discount factor to the prior quantities n_{t-1} and S_{t-1} before updating. When $\beta=1$, the model has the static Σ. Harrison and West (1986, 1987) indicate that the effects of different values of δ and β can be explored by fitting several models and assessing the performances using forecast errors. They suggest that the prior plausible values for δ are between 0.75 and 1, and for β are between 0.95 and 1.

5.3.4 Principle-component analysis

One way to explore the joint structure of the return series is to subject an estimate of the covariance matrix to the principle-components decomposition (Press, 1972, chapter 9). Quintana (1987) shows that the eigenvalues and eigenvectors of the estimate S_t are, at time t, optimal Bayesian estimates of those of Σ.

Denote the eigenvalues S_t of by λ_j, $(j=1,...,q)$, the corresponding orthonormal eigenvectors by η_j, $(j=1,...q)$, satisfying $\eta_j^T \eta_j = 1$ and $\eta_i^T \eta_j = 0$ for $i \neq j$. Then the covariation of the elements of any random vector Y having variance matrix S_t is explained through the random quantities $X_j = \eta_j^T Y$, $(j = 1,...q)$, the principal components of Y. These X variates are uncorrelated and having variances $V[X_j] = \lambda_j$, decreasing as j increases. Total variation in Y is measured by $\lambda = trace(S_t) = \sum_{j=1}^{q} \lambda_j$, so the j^{th} principle component explains a proportion λ_j / λ of this total.

The eigenvectors of the estimate S_t represent the composition of industry groups explained by the multivariate model. The eigenvector associated with the maximum eigenvalue represents the information of the weights of the maximally predicted industry portfolio. The maximally predicted industry portfolio is obviously the source of the predictability. The significance of the maximally predicted portfolio (MPP) will be examined in detail in the next chapter.

5.4 Data

The sample period of the research covers December 1979 to March 2000. The stock return data used in this study are the monthly industrial stock return indices of the Australian Stock Exchange (adjusted for dividends, stock splits, bonus issues etc). The excess returns are obtained by subtracting the monthly growth rate of return indices from the one-month yield on three-month Australian Treasury note rates.[15] The data are primarily sourced from DataStream, an existing database.

The summary statistics of the stock returns data are provided in Table 5.1. The means are monthly proportional rates of return and vary from a high of 2 per cent for the media sector to a low of 0.1 per cent for the gold sector. The gold sector also has the highest variance, while the property-trusts sector has the lowest variance.

Skewness, Kurtosis and Jarque-Bera are the tests of normality on returns. The null of normality has been widely rejected. Most return series are left skewed and leptokurtic; however, when the October 1987 observation is excluded, the normality tests are greatly improved. The ADF column shows the results for the augmented Dickey-Fuller unit-root test. All returns series are shown to be stationary.

Table 5.2 presents the autocorrelations of the excess-industrial-return series. Not surprisingly, the monthly excess-return series are not highly autocorrelated, but exceptions appear in the energy and media industries for the first lag. The results here suggest that the excess-return series itself does not contain predictability.

---

[15] The formula to convert the three-month interest rate to monthly is taken from Knox, Zima and Brown (1996), that is, $r_m=(1+r_q)^{1/3}-1$ where r_m is the monthly rate where r_q is the quarterly rate.

Table 5.1: Summary statistics of industry sector returns.

ASX Industry group	Mean	Variance	Skewness	Kurtosis	Jarque-Bera	Skewness(ex. Oct 1987)	Kurtosis(ex. Oct 1987)	Jarque-Bera (ex.Oct 1987)	ADF
Alcohol and Tobacco	0.01413	0.003260	-2.2306	17.9787	3474.2582	-0.1666	2.4789	63.0806	-3.6766
Banks and Finance	0.01292	0.003444	-0.9276	6.3555	443.8172	0.1371	0.1791	1.0819	-3.9140
Building Mats	0.00764	0.003385	-1.6128	10.3183	1183.3353	-0.2009	0.3511	2.8711	-4.4036
Chemicals	0.00814	0.004049	-0.8534	5.6710	355.1151	0.04861	0.8063	6.6514	-3.2693
Devl. Contractor	0.01227	0.005001	-3.6709	34.6733	12697.3216	-0.0689	0.5655	3.4167	-3.5473
Divs. Industrial	0.01030	0.004537	-2.6704	21.0359	4716.2155	-0.2587	0.1797	3.0247	-4.5936
Divs. Resources	0.00741	0.006170	-1.0665	7.0169	544.5896	0.0092	0.6530	4.3026	-3.9016
Energy	0.00251	0.007815	-0.9042	5.9463	391.1154	-0.1866	2.5728	68.1483	-4.3303
Engineering	0.00547	0.003885	-0.8625	4.0014	192.2401	-0.1918	0.4157	3.2267	-4.0251
Food and Household	0.00893	0.003583	-4.4112	7.5278	654.4176	-0.5288	2.2064	60.3643	-3.5678
Gold	0.00094	0.016577	-0.2438	3.8758	154.5054	0.4688	0.9099	17.2102	-4.5588
Insurance	0.01102	0.004720	-1.7369	13.7341	2032.0215	0.1161	0.5164	3.2334	-2.9757
Inv and Fin Servs.	0.00911	0.003001	-3.8226	37.2570	14646.1159	0.0490	0.3814	1.5636	-3.6325
Media	0.01767	0.007967	-1.3155	6.9599	560.5373	-0.5902	3.0614	108.5533	-3.1279
Other Metals	0.00250	0.009083	-1.8509	14.8820	2381.1833	0.05661	1.2355	15.5207	-4.3489
Paper and Packaging	0.00621	0.003291	-1.0381	5.0716	304.0717	-0.3848	1.6621	33.8280	-3.8413
Property Trusts	0.00797	0.001360	-1.5050	11.8603	1515.9808	0.2302	-0.1235	2.2906	-2.9365
Retail	0.01002	0.003615	-2.0813	18.4126	3608.0417	0.3243	0.1625	4.5082	-4.2307
Transport	0.01095	0.005301	-2.4975	20.0444	4320.6082	-0.1227	0.2901	1.4562	-4.1263
ASX Market Index	0.00835	0.003631	-3.3504	29.7653	9425.1096	-0.2189	0.8705	9.5732	-3.5788

Notes: Significance levels (5%): Skewness and Kurtosis 1.96, Normality 5.99, ADF -2.8742 for Dickey-Fuller regression include an intercept but not a trend.

Table 5.2: Autocorrelations of returns.

	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}
Alcohol and Tobacco	0.0614	0.0069	-0.0699	-0.0297	-0.0355	0.0503	0.0958	0.0261	0.1029	0.0011	0.0056	-0.0603
Banks and Finance	0.0312	-0.0515	-0.0368	-0.0279	-0.0795	0.0256	-0.0471	0.0806	-0.0046	-0.0624	-0.0563	-0.0648
Building Mats.	0.0169	-0.0234	-0.0402	-0.0308	-0.0682	0.0482	0.0452	-0.0167	0.0957	-0.0666	-0.0473	-0.0302
Chemicals	-0.0142	-0.0111	0.0586	0.0553	-0.0913	0.0236	0.1012	0.0489	0.1302	0.0096	-0.0383	0.0280
Devl. Contractor	-0.0129	0.0215	-0.1487	-0.0417	-0.0349	0.0233	0.0254	0.0140	0.0872	0.0010	-0.0099	-0.1328
Divs. Industrial	-0.0094	-0.0067	-0.0227	0.0050	-0.0871	0.0787	0.0335	-0.0474	0.0128	-0.0044	0.0463	-0.1416
Divs. Resources	0.0599	-0.1021	0.0207	0.0611	-0.0181	-0.0087	-0.0479	0.0712	0.0204	-0.0672	-0.0623	-0.0312
Energy	0.1664	-0.1363	-0.0912	0.1193	0.07162	-0.0749	-0.0393	0.0293	0.0067	-0.0740	-0.0907	-0.0549
Engineering	0.0786	-0.0302	-0.0347	0.0048	-0.0707	0.0331	0.0500	0.0776	-0.0039	-0.0321	-0.0775	-0.0543
Food and Household	-0.0006	0.0477	0.0565	-0.1201	-0.0964	0.0089	0.0239	0.0626	0.0928	0.0901	0.0213	-0.0509
Gold	0.0673	-0.0559	0.0502	0.1568	-0.0394	-0.1348	-0.0558	0.0530	0.0083	-0.1276	0.0062	-0.0218
Insurance	0.0019	0.0640	0.0472	0.0825	0.0117	0.0808	0.0289	0.0773	0.0685	0.0719	0.1070	-0.0355
Inv. and Fin. Servs.	0.0811	-0.0203	0.0281	0.0310	-0.1295	0.0692	0.0157	0.0031	0.0624	-0.0248	-0.0629	-0.1005
Media	0.1511	-0.0261	-0.0178	-0.0317	-0.0706	0.0943	0.1589	0.0371	0.0765	-0.0336	0.010	-0.0737
Other Metals	-0.0646	-0.1243	0.0309	0.0655	-0.0535	-0.1731	0.0191	0.0356	-0.0108	-0.0204	0.0824	-0.1181
Paper and Packaging	0.0850	-0.0868	0.0393	-0.0080	-0.0799	0.0003	0.0103	0.0378	0.0605	-0.0005	0.0121	-0.0534
Property Trust	-0.0108	-0.0853	-0.0727	0.0063	-0.1096	-0.0947	0.0295	0.1132	0.0473	0.0305	-0.0607	-0.0075
Retail	0.0741	-0.0412	0.0016	-0.023	-0.1454	-0.0042	0.0333	0.0299	-0.0085	0.0278	-0.0413	-0.0570
Transport	0.0069	-0.0874	-0.1244	-0.0374	-0.0980	0.0822	0.0933	-0.0274	0.0274	-0.0172	-0.0931	-0.0325
ASX Market Index	0.0006	-0.0934	-0.0313	0.0761	-0.0550	-0.0367	-0.0035	0.0280	0.0247	-0.0399	-0.0106	-0.0976

The economic data used in this research are the national economic statistics for Australia, which are also sourced from DataStream. The major categories of economic variables considered by previous studies in this area are those representing the stock market, money supply, industrial production, labour market and international trade (Cheng, 1995). These variables are assumed to influence future cash flows or the risk-adjusted discount rate when stocks are priced by the expectation of the present value of future cash flows (see Chen, Roll and Ross, 1986).

Groenewold and Fraser (1997) choose their predictable variables based on the hypothesis that returns are influenced by three classes of factors: real domestic activity, nominal domestic influences and foreign variables. They have found that the set of factors priced in Australia overlaps considerably with those found by others overseas. Their results show that the short-term interest rate, the inflation rate and the money-growth rate are most often priced. This is consistent with previous studies by Chen, Roll and Ross (1986), Clare and Thomas (1994) and Beenstock and Chan (1988). Ariff and Johnson (1990) also reveal that the trade and international payment variables are priced in stock returns.

Follow previous studies and being restricted to the availability of the monthly economic series in Australia; there is some overlap between the selection of the current study's predictor variables and the previous research. The monthly economic series of industrial production, money supply at the level of M3, the unemployment rate and the aggregate dividend-yield on index were chosen to measure domestic economic activity.

Since there are no monthly statistics of inflation in Australia, the monthly Reserve Bank of Australia's Commodity-Price Index is adopted to compute the inflation rate. The term structure and commercial bill-spread variables are computed using the yield of ten-year government bonds, the 90-day commercial bill rate and the three-month Treasury bill rate. The current-account balance and the Australian dollar's exchange rate to US dollars are adopted as the proxies of foreign variables and international trade.

After decomposing selected variables, the derived predictor variables used in the Bayesian dynamic-linear-regression analysis are as shown here:

Table 5.3: Selection of economic variables.

Variable name	Economic variable used	Definition
DDY	Dividend Yield	First Difference of Dividend yield on Australian All Ordinary Stock Index
UEI	RBA Commodity Price Index	Unexpected Inflation Rate
UTS	Term Structure	Unexpected Change in the yield spread between 10-year Treasury bond and Treasury bill rate
UCB	Commercial Bill Spread	Unexpected Change in Difference between 90-day commercial bill rate and Treasury bill rate
UTB	Treasury Bill Rate	Unexpected Change in Treasury bill return
UIP	Industrial Production Index	Unexpected Change in Industrial Production
UM3	Money supply (M3)	Unexpected Change in Money Supply
UUM	Unemployment	Unexpected Change in Unemployment
UEX	Exchange Rate to US$	Unexpected Change in Exchange Rate
UGCB	Current Account Balance	Unexpected Change in Current Account Balance

The correlation matrix of derived economic variables is provided in Table 5.4. As can be seen, there is no high correlation between any of the two derived economic variables since, in this study, the decomposed unanticipated components of variables are used. The highest correlation is –0.33, between the unexpected inflation and unexpected change in exchange rate, and –0.31 between dividend yield and unexpected change in industrial production.

Table 5.5 shows the autocorrelation of derived economic variables. Most of the variables have no significant autocorrelations but an unanticipated component of industrial production is highly autocorrelated. Furthermore, unexpected inflation and unexpected change in exchange rate have mild autocorrelations.

The correlation matrix of the industrial returns is given in Table 5.6. All industrial return series are correlated with each other, and the correlation varies from 0.5 to 0.7. However, the gold industry has low correlations with other industries except the other metals industry. Each industry return is highly correlated with the market index return. The correlations here partly motivate the use of a multivariate setting of the model as it is capable of retaining correlation between the industries.

Table 5.4: Correlation matrix of derived economic variables: Monthly data from 1980:02 to 2000:03

	UEI	UTS	UCB	UTB	DDY	UIP	UUM	UM3	UEX	UGCB
UEI	1.0000									
UTS	0.0916	1.0000								
UCB	-0.0302	0.1255	1.0000							
UTB	0.0575	-0.0615	-0.2075	1.0000						
DDY	0.1145	-0.0327	-0.0421	0.1144	1.0000					
UIP	-0.0459	0.0795	-0.0537	-0.0995	-0.3119	1.0000				
UUM	0.0557	0.0098	-0.0350	-0.0501	0.0083	-0.2029	1.0000			
UM3	0.1222	0.0325	0.0425	-0.1622	0.0278	0.1140	-0.0301	1.0000		
UEX	-0.3271	0.0222	-0.0234	-0.1198	-0.1930	0.2694	-0.0383	0.0003	1.0000	
UGCB	0.0208	-0.0650	0.0311	-0.0170	-0.0312	0.0668	0.0198	-0.0914	0.0396	1.0000

Table 5.5: Autocorrelations of variables:

	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}
UEI	0.2483	-0.1351	-0.1145	-0.1844	-0.0685	0.0655	0.0431	0.0079	0.0003	0.0435	0.0359	-0.0733
UTS	-0.0097	0.0400	0.0022	0.0110	-0.1715	0.1192	-0.0031	-0.0751	-0.0091	0.0293	-0.0618	0.0198
UCB	-0.0023	0.0641	-0.1512	-0.1759	-0.1482	-0.1710	-0.1375	-0.1002	0.1057	0.0277	0.2275	0.1438
UTB	0.1182	-0.0658	-0.0246	0.1298	-0.0493	-0.1161	0.1736	0.0594	0.0183	-0.0869	0.0553	0.2284
DDY	0.0507	-0.1310	0.0040	0.0457	0.0434	-0.0478	-0.0320	-0.0116	0.0170	0.0277	0.0195	-0.0727
UIP	0.7753	0.5448	0.3181	0.2664	0.2245	0.1802	0.1298	0.0678	0.0049	-0.0968	-0.1927	-0.3002
UUM	-0.1956	0.0515	0.0419	0.0799	0.2272	-0.0301	0.0445	0.0735	0.0185	-0.0196	0.0341	-0.1881
UM3	0.1006	-0.0045	-0.0819	-0.0161	-0.0759	0.0987	0.0483	-0.0394	-0.0866	0.0318	-0.0450	-0.0354
UEX	0.3211	0.0111	-0.0368	-0.1467	-0.0551	0.0179	0.0683	0.1439	0.0984	-0.0190	-0.0604	-0.1287
UGCB	-0.0034	0.0512	0.0168	0.0229	-0.0396	-0.0100	0.0040	-0.0211	-0.0046	0.0078	0.0458	0.0254

Table 5.6: Correlation Matrix of Industrial Returns: (Monthly Data from 1980:02 to 2000:03)

	A&T	B&F	BM	CH	DC	DI	DR	ENE	ENG	F&H	GO	IN	I&F	ME	OM	P&P	PT	RE	TR	IND
A&T	1.000																			
B&F	0.653	1.000																		
BM	0.666	0.708	1.000																	
CH	0.574	0.647	0.742	1.000																
DC	0.724	0.718	0.781	0.647	1.000															
DI	0.701	0.709	0.821	0.726	0.780	1.000														
DR	0.550	0.569	0.736	0.639	0.678	0.696	1.000													
ENE	0.454	0.510	0.647	0.548	0.616	0.599	0.784	1.000												
ENG	0.617	0.700	0.779	0.709	0.721	0.762	0.634	0.602	1.000											
F&H	0.583	0.600	0.718	0.621	0.692	0.720	0.578	0.505	0.624	1.000										
GO	0.397	0.367	0.468	0.481	0.467	0.458	0.591	0.596	0.417	0.396	1.000									
IN	0.537	0.585	0.592	0.537	0.662	0.611	0.542	0.452	0.577	0.569	0.407	1.000								
I&F	0.646	0.658	0.705	0.653	0.768	0.726	0.607	0.542	0.667	0.654	0.467	0.659	1.000							
ME	0.546	0.524	0.542	0.407	0.584	0.553	0.465	0.394	0.503	0.471	0.287	0.507	0.584	1.000						
OM	0.538	0.511	0.685	0.626	0.654	0.675	0.750	0.634	0.584	0.562	0.710	0.502	0.632	0.406	1.000					
P&P	0.626	0.691	0.763	0.670	0.711	0.723	0.659	0.544	0.697	0.658	0.403	0.553	0.636	0.540	0.601	1.000				
PT	0.587	0.656	0.597	0.528	0.723	0.613	0.496	0.502	0.592	0.547	0.398	0.529	0.608	0.493	0.487	0.543	1.000			
RE	0.662	0.692	0.706	0.599	0.744	0.736	0.550	0.512	0.672	0.624	0.345	0.631	0.667	0.547	0.533	0.618	0.646	1.000		
TR	0.692	0.689	0.761	0.657	0.802	0.803	0.626	0.549	0.739	0.666	0.404	0.599	0.697	0.552	0.625	0.681	0.636	0.721	1.000	
IND	0.740	0.767	0.854	0.740	0.869	0.848	0.855	0.777	0.780	0.714	0.663	0.678	0.799	0.649	0.832	0.759	0.697	0.755	0.826	1.000

Note: the indexes here are alcohol and tobacco, banks and finance, building materials, chemicals, development contractor, diversified industrials, diversified resources, energy, engineering, food and household, gold, insurance, investment and financial services, media, other metals, paper and packaging, property trusts, retail, transport and All Ordinary market index.

5.5 Empirical results

The empirical test in this section includes both of the Bayesian univariate and multivariate regression methods. As there are correlations among the industrial returns shown in Table 5.6, the main interest is the multivariate model; however, the superiority of the multivariate model can only be verified through comparison with the univariate model.

5.5.1 Multivariate-model results

The multivariate regression is the main interest as it incorporates the correlations among the industry returns. The multivariate model requires the specification of the observational variance factors, V_t, the evolution variances W_t and the discounting factor, δ, the variance matrix discount factor, β, and initial priors $\boldsymbol{m_0}$, $\boldsymbol{C_0}$, $\boldsymbol{S_0}$, n_0. The priors chosen here are vague specifications: $\boldsymbol{S_0} = 10^{-5}I$ and $d_0 = 10^{-3}$. The discounting values are $\delta=1$ and $\beta=1$. Those values imply that they are purely deterministic for Θ_t for a static model. Harrison and West (1986, 1987) suggest that the prior plausible value for δ is between 0.75 and 1 and for β is between 0.95 and 1. After comparing the prediction errors by setting different values of δ and β, it has been found that the static model has the smallest prediction error. The prior for $\boldsymbol{m_0}$ is a matrix with the elements of the first column chosen as 0.2 and other elements as 0. $\boldsymbol{C_0}$ is a matrix with 1 as the diagonal elements and 0.5 as the non-diagonal elements.

The first step of the tests is to allow all predetermined variables to be included in the model. Table 5.7 provides the results with all the variables considered. The first row of each industry is the updated coefficients at the end of the sample period. The bold numbers are t-statistics. Because the model is Bayesian, the coefficient estimates are actually the elements of the mean matrix of the posterior distribution for $\boldsymbol{\Theta}$ at the end of sample period. The significant coefficients show that with at least 90 per cent or 95 per cent probabilities, the coefficients are not equal to zero.

The regression shows that when all the variables used, the term-structure UTS and Treasury-bill rate UTB variables have significant influence on most of the industry excess returns. The dividend-yield variable DDY is significant for the alcohol-and-tobacco industry, the food-and-household, the paper-and-packaging and the retail industries. The engineering industry seems to be influenced by the exchange-rate variable UEX too. The derived current-account balance variable UGCB is shown to have some explanatory power over the gold and insurance-industry stock.

The finding here is consistent with Groenewold and Fraser (1997) in that they find the short-term interest rate is often priced in the stock returns; however, they also find inflation and the money-growth rate have significant influence in Australia stock returns, which is not supported by the present results. The signs of the significant estimated regression coefficients are consistent with previous studies of Chen, Roll and Ross (1986) and Groenewold and Fraser (1997). The term-structure variable and interest-rate variable have negative relationships with returns and dividend-yield variable has positive relationship with returns.

Chen, Roll and Ross (1986) claim that the term-structure variable measures a change in the long-term rate of interest. When long-term rates decline, investors place a relatively higher value on assets whose prices increase. Dividend-yield has positive risk premiums as generally investors view the high-dividend stocks more valuable. It is surprising that inflation variable does not show significant impact on industry returns here. The suspicion is that the monthly commodity price index used here is not a good proxy for inflation[16].

Table 5.7 shows that the engineering industry is also exposed to the unexpected change of the exchange-rate while gold and insurance industry stocks are also influenced by unexpected changes in current-account-balance. But interestingly, the impact of current-account-balance on gold industry is positive and impact on insurance industry is negative.

In the Bayesian regression framework, the regression coefficients are actually updated every month by using previous month's prediction errors (see section 5.3.3), the R-square statistics are therefore relatively higher. The model explains about 52–70 per cent of the variation of different industrial returns as indicated by R-squares in Table 5.7.

---

16 The monthly statistics of inflation is not available in Australia.

Since most of the economic variables were not found to be significant in the regression, it would be interesting to see whether the market return plays a more significant role here. The regression was thus modified, keeping only the term-structure variable, interest-rate variables, the aggregate dividend-yield variable and then including the market-index return.

Faff (1988) argues that comprehensive models incorporating both the CAPM beta and the APT factor loadings are not favoured for over-specification and multicollinearity reasons. However, the unanticipated component of economic variables was used here, and the multicollinearity problem is thus not serious. As to the problem of over-specification, if the market-index return captures all the innovations from the economy then it would be expected that the derived economic variables will turn out to be insignificant when the market index return is included.

The regression results with market index return included are given in Table 5.8. Not surprisingly, for most of the industries, the derived term-structure variable and the interest-rate variable seem to be insignificant. This indicates that the market index has captured all of the economic innovations; however, the gold industry is a special case in which the term-structure and interest-rate variables are still significant. This implies that the market is not the only source of risk in explaining the gold industry return. The term-structure and interest-rate are still important in explaining the gold industry return. Faff and Chan (1998) claimed that gold price is an import factor to explain the returns of gold stocks in the Australian market. However, the gold price is not considered in the current study.

Additionally, the term-structure variables are still significant in the paper and packaging industry and the property trusts industry while the dividend-yield variable is significant in the retail industry.

The diagnostic tests of the regression with market index are also provided in Table 5.8. The diagnostic tests for each industry return here include R-square measures (R-SQ), mean absolute error (MAE), the mean square error (MSE), Durbin-Watson statistics for residual serial correlation (D-W), ARCH test (ARCH-6) and Goldfeld-Quandt test for heteroskedasticity (G-Q test).

It is apparent that when market return is included, the R-square measures are improved. The market-index return with term-structure and interest-rate variables has been able to explain 60–70 per cent of the variations of the returns over most of the industrial returns. However, when accompanied with high R-square, the mean absolute errors (MAE) are also higher, which vary between around 0.2 and 0.8. The forecast errors are especially high in the diversified resources sector, the energy sector, the gold and other metal sectors as the mean squared errors (MSE) vary from 0.014 to 0.19. These prediction error measures show that the model with market index return performs poorly in forecasting. Other diagnostic tests show that the model encounters residual serial correlation and a mild heteroskedasticity problem.

Since the significant variables found in the preliminary regression are only the term-structure, short-term interest rate and aggregate-dividend variables, a plausible model for the prediction of industrial returns can be obtained by including those significant variables only. Table 5.9 provides the regression coefficients and diagnostic tests. C-P test is the cumulated-periodogram test for residual series to be white noise.

For 19 industries, the R-square results are between 0.52 and 0.75, which indicates that some high proportions of the variances on returns have been captured by the model. Though the overall R-square measurements seem to be lower than the regression with market return (see table 5.8), the prediction errors MAE and MSE are uniformly lower. MAE varies from 0.08 to 0.31 and MSE varies from 0.0022 to 0.032. This indicates that the model with three financial variables forecasts better than the model with market return.

Other diagnostic tests, though, show that the model also encounters residual serial correlation and a heteroskedasticity problem. The C-P test indicates that the residuals from the model are not white noise. It would not be surprising to see the non-Gaussianity of the residual series given the non-Gaussianity of the stock-return data shown in Table 5.1.

The performances of the models are also presented by the fitting figures of the model. For brevity, four industries are illustrated here by Figure 5.1 to Figure 5.4. The fitting figures for all other industries, shown in Figure 5.5 to Figure 5.19, are provided in Appendix B. Panel (a) of each figures provides multivariate model fitting. For most of the industries the multivariate models fit nicely in modelling the returns' time-varying path. The fitted return series coincide with the variation of the actual return series, however, it should be noted that the fitted values of returns are one month behind.[17] The results here strongly indicate that the industrial returns can be predicted by the derived financial variables in this dynamic framework.

The estimated covariance structure of industrial returns Σ can be analysed by using components decomposition. Let $S_{t|t-1}$ denote the estimated covariance structure of Σ_{t-1} given the information set at t-1. The maximum fraction of the variability in the industry portfolio explained by the multivariate model can be computed from the largest eigenvalue of the matrix $S_{t|t-1}$.

Table 5.11 provides the principle components of industry returns at the end of the sample period. According to the eighteen eigenvalues of the estimated covariance, the first four components explain over 80 per cent of the total estimated variation in Σ. The proportions of total variation contributed by the first four components are approximately 44 per cent, 14.8 per cent, 12.5 per cent and 9.33 per cent, respectively. The first component here can serve as the basis for the composition of the maximally predicted portfolio (MPP) at the end of the sample period after rescaling its standardized elements sum to unity.

The MPP is the upper bound to what the investor can achieve in the search for predictability among the portfolios. Obviously the MPP is the focus of the source of predictability. Therefore, it will be interesting to investigate the significance of the predictability of MPP. The following chapter, Chapter 6, provides a set of out-of-sample tests with focus on the MPP.

5.5.2 Univariate-model results

The multivariate-model method has the advantage of retaining the correlations between the industrial returns, while the univariate-model method does not. To see

---

[17] Given the current economic information, the fitted returns are produced using the updated regression coefficients; therefore, the effect of the observed economic series have a lag effect on the fitted returns. That is, for the case of market crash, the effect of such crash can only be fitted one month later. I thank the referees of Australian Journal of Management for pointing out this.

whether this assumption is valid, the univariate analysis was conducted as well for comparison; that is, each individual industry return was also regressed on the respective set of significant variables alone. The univariate regression results are provided in Table 5.10.

Since no significant factors were found in the model of the diversified resources and media industry returns, these two industries had to be excluded here. It can be observed from Table 5.10 that, although the diagnostic test results are better than multivariate regression, the univariate model captures low variations of individual returns. The *R*-square is as low as 0.08 for the chemicals and the other-metals industry and as high as 0.53 for the investment-and-financial services industry. Both of the forecast errors MAE and MSE are uniformly higher in univariate models than multivariate model.

The model fitting figures for the univariate models are provided in panel (b) of Figure 5.1 to Figure 5.4 for the first four industries to compare with the multivariate fitting. Univariate fitting of other industries are presented in Figure 5.5 to Figure 5.17 in Appendix B. The results are convincing. Though the univariate model also fits reasonably well in some industries (namely, the alcohol-and-tobacco industry in Figure 5.1, the banks-and-finance industry in Figure 5.2, the engineering industry in Figure 5.8, the food-and-household industry in Figure 5.9, the property trusts industry in Figure 5.15, the retail industry in Figure 5.16 and the transport industry in Figure 5.17), it certainly provides poorer fittings for other industry returns. Especially, it can hardly capture any of the return variation of the energy industry in Figure 5.7 and the other-metals industry in Figure 5.13.

It is quite obvious that across all of the industries, the multivariate model fits better than the univariate model. The comparison between the multivariate and univariate method strongly suggests that the correlations within the industrial returns are both significant and relevant. The results here highlight the importance of multivariate setting in tests for predictability.

5.5.3 Summary and discussion

The results of this section support the previous findings on predictability of stock returns. The derived variables of unanticipated economic and financial information contain the predictive power to industry sector excess returns. More specifically, those variables are unanticipated change of term-structure, short-term interest rate and aggregate dividend-yield. The unanticipated changes in exchange rate and current account balance are also important to several industries.

Other factors such as growth of money supply and inflation, which were found to be significant in the previous studies, had no explanatory power in the current study. Few factors might have caused the differences in current results. First of all, this study employed the monthly data while the monthly statistics of inflation in Australia is not available. The proxy variable used here is the Australian Reserve Bank Commodity Price Index, which could be a poor representation of the inflation. Secondly, some of the economic variables might have a lagged effect on stock returns, for example, the money supply; however, the lagged effects are not captured by the Bayesian updating process here.

It is not surprising that industrial sector returns are to be predicted by some common economic variables. As being discussed previously, the economic activity manifests itself into the stock market through affecting the corporate profits. Thus the macroeconomic variables such as interest rate and term-structure are priced in the stock returns. Therefore, the predictability discovered here is consistent with the asset pricing behaviour of the stock market.

The extent of predictability by the economic and financial variables is certainly not same across all the industries. The different sectors contain different industrial specific characteristics, for example, size, leverage, and life-cycle dynamics. These industry specific factors might result in the different risk premiums in the individual industries. For example, the results of previous section indicate that the market risk is not the only risk source for the gold industry. Faff and Chan (1995) have presented some evidence that the Australian gold industry return is also significantly affected by gold price. In a recent study on bank sector stocks, Cooper et al. (2002) found that the individual bank fundamental variables, such as income from derivative usage, previous loan commitments, loan-loss reserves, earnings, leverage, and standby letters of credit were all important in examining the predictability.

The results here highlight the interest of future research, which is to focus on each individual industry's structure and risk characteristics. With recent launch of GICS (Global Industry Classification Standard) by Australian Stock Exchange, [18] the individual company's main business operation, financial performance and analysis are better reflected by their industry classification. The specific investigation into each industry groups will be both interesting and valuable to the academics and the investment community.

The results in this chapter also overwhelmingly support the multivariate framework for modelling the time-varying properties of stock returns. The results show that the correlations among the industries are both critical and relevant in the testing of predictability. Therefore, any studies into the asset pricing behaviour and market efficiency theory shall not ignore this issue.

---

[18] The GICS global sector indices were introduced to ASX in June 2001. Each individual company is assigned to a single GICS sub-industry according to the definition of its principle business activity as determined by Standard & Poor's and MSCI. Calculation and dissemination of the ASX sectors are discontinued in July 2002. (See Appendix A. for mapping of ASX sectors to GICS sectors).

Table 5.7: Multivariate regression results using economic variables:

	const	UTS	UTB	DDY	UGCB	UCB	UEI	UIP	UUM	UM3	UEX	R-sq
Alcohol & Tobacco	-0.0079	-0.1749	-0.2263	0.1813	0.0067	-0.0391	0.0921	0.0726	0.0131	-0.0269	-0.1511	0.5197
	-0.1509	-1.9632*	-1.6454^	1.7348^	1.0261	-0.2657	0.4437	0.3432	0.0927	-0.1286	-0.9855	
Banks & Finance	0.0004	-0.2260	-0.1599	0.0507	0.0048	-0.0055	0.0298	0.1659	0.2377	-0.0158	0.1419	0.5852
	0.0065	-2.0829*	-0.9546	0.3983	0.5982	-0.0305	0.1179	0.6439	1.3808	-0.0620	0.7599	
Building Mat.	0.0842	-0.0875	-0.3133	0.2192	0.0098	0.0543	-0.0550	0.1719	0.0199	-0.0531	0.4088	0.5258
	0.9316	-0.5679	-1.7171^	1.2126	0.8669	0.2134	-0.1532	0.4698	0.0814	-0.1468	1.5416	
Chemicals	0.0398	-0.0422	-0.3318	0.0941	0.0088	-0.1097	-0.0115	0.1698	0.1208	0.0241	0.2548	0.5743
	0.5840	-0.3632	-1.8497^	0.6903	1.0231	-0.5716	-0.0425	0.6154	0.6553	0.0883	1.2742	
Devl. Contractor	0.0245	-0.2188	-0.3813	0.0974	0.0036	0.0331	0.0342	0.2142	0.1504	-0.0020	-0.0018	0.5881
	0.3253	-1.7042^	-1.9238^	0.6467	0.3841	0.1561	0.1143	0.7026	0.7384	-0.0065	-0.0083	
Divs. Industrial	0.0287	-0.0927	-0.3048	0.0497	0.0027	-0.2068	-0.0455	0.1965	0.0583	-0.0660	0.1402	0.5798
	0.4597	-0.8709	-1.8548^	0.3980	0.3500	-1.1762	-0.1835	0.7773	0.3452	-0.2640	0.7653	
Divs. Resources	0.1449	-0.1885	-0.4236	0.2823	0.0096	0.1628	-0.0162	0.0935	0.0132	-0.0277	0.1212	0.5968
	1.1265	-0.8596	-1.2513	1.0974	0.5913	0.4495	-0.0317	0.1795	0.0379	-0.0538	0.3211	
Energy	0.0630	-0.3678	-0.2606	-0.0457	0.0049	-0.1156	-0.0334	0.0274	-0.1851	-0.0643	0.1531	0.6295
	0.6590	-2.2566*	-1.0357	-0.2390	0.4071	-0.4294	-0.0880	0.0708	-0.7158	-0.1680	0.5458	
Engineering	0.0222	-0.1789	-0.3084	0.0933	0.0073	-0.1314	-0.0454	0.1544	-0.1797	-0.0271	0.3515	0.5693
	0.3644	-1.7227^	-1.9236^	0.7658	0.9547	-0.7660	-0.1876	0.6261	-1.0906	-0.1111	1.9667*	
Food & Household	0.0036	-0.4838	-0.4219	0.3485	-0.0103	-0.1519	-0.1355	0.1594	-0.1036	-0.1220	0.1641	0.5284
	0.0436	-3.4408*	-1.9436^	2.1128*	-0.9936	-0.6540	-0.4136	0.4774	-0.4644	-0.3695	0.6781	
Gold	0.1492	-0.5195	-1.1663	-0.0089	0.0328	-0.1605	-0.0916	0.0028	-0.0266	-0.1491	0.2449	0.5856
	0.9597	-1.9600*	-2.8503*	-0.0286	1.6785^	-0.3666	-0.1483	0.0045	-0.0633	-0.2396	0.5369	
Insurance	-0.0938	-0.2894	-0.3522	-0.2181	-0.0192	0.1189	-0.1111	0.0061	-0.1388	-0.1893	0.0627	0.7137
	-1.1810	-2.1373*	-1.6849^	-1.3730	-1.9233^	0.5316	-0.3522	0.0190	-0.6461	-0.5953	0.2691	

	const	UTS	UTB	DDY	UGCB	UCB	UEI	UIP	UUM	UM3	UEX	R-sq
Inv &	0.0038	-0.1233	-0.2666	-0.0462	-0.0016	-0.0800	-0.1409	0.0444	-0.0433	-0.1065	-0.0068	0.6891
Fin Servs.	**0.0590**	**-1.7191^**	**-1.6673^**	**-0.3574**	**-0.1922**	**-0.4396**	**-0.5489**	**0.1697**	**-0.2477**	**-0.4116**	**-0.0357**	
Media	0.0178	-0.1683	-0.1128	0.2737	0.0087	0.3456	-0.0222	0.0895	0.3814	0.0401	-0.2204	0.6071
	0.1420	**-0.7874**	**-0.3419**	**1.0916**	**0.5529**	**0.9790**	**-0.0446**	**0.1763**	**1.1248**	**0.0799**	**-0.5992**	
Other	0.1926	-0.1724	-0.6628	0.1399	0.0228	-0.1188	-0.0372	0.0963	0.0332	-0.0969	0.2837	0.5935
Metals	**1.5126**	**-0.7942**	**-1.9778***	**0.5494**	**1.4246**	**-0.3313**	**-0.0736**	**0.1868**	**0.0964**	**-0.1901**	**0.7594**	
Paper &	0.0434	-0.0548	-0.2961	0.3696	0.0059	0.0223	0.0405	0.2102	0.1419	-0.0337	0.4146	0.5798
Packaging	**0.4811**	**-0.3563**	**-1.2471**	**2.0486***	**0.5242**	**0.0878**	**0.1130**	**0.5755**	**0.5816**	**-0.0933**	**1.5665**	
Property	-0.0167	-0.2434	-0.2340	-0.0773	0.0009	-0.1050	-0.0699	0.0053	0.0518	-0.0744	-0.0226	0.5927
Trusts	**-0.3827**	**-3.2720***	**-2.0376***	**-0.8858**	**0.1561**	**-0.8546**	**-0.4033**	**0.0301**	**0.4389**	**-0.4259**	**-0.1765**	
Retail	-0.0336	-0.2562	-0.0027	-0.1941	-0.0007	-0.0098	0.1271	0.0968	0.0315	-0.0767	0.1444	0.6499
	-0.5723	**-2.5598***	**-0.0176**	**-1.6531^**	**-0.0972**	**-0.0592**	**0.5450**	**0.4073**	**0.1984**	**-0.3263**	**0.8383**	
Transport	0.0236	-0.1360	-0.2967	0.0088	0.0014	-0.0233	0.1173	0.1802	0.2780	-0.0004	0.1723	0.6045
	0.3331	**-1.6561^**	**-1.6913^**	**0.0621**	**0.1523**	**-0.1168**	**0.4168**	**0.6283**	**1.4508**	**-0.0015**	**0.8290**	

Note: * indicates 95% significant and ^ indicates 90% significant.

UTS, UTB, DDY, UGCB, UCB, UEI, UIP, UUM, UM3 and UEX are derived variables of terms structure, interest rate, dividend yield, current account balance, commercial bill spread, inflation, industrial production, unemployment, M3 and exchange rate with US dollars, respectively.

Table 5.8: Multivariate regression with market return:

	Const	UTS	UTB	DDY	Market Return	R-SQ	MAE	MSE	D-W	G-Q test	ARCH(6)
Alcohol &	-0.0454	-0.0884	-0.044	0.1361	0.6176	0.6348	0.2755	0.0188	2.3024	1.1075	6.3073
Tobacco	**-1.8011^**	**-0.6488**	**-0.2164**	**0.8887**	**3.5288***						
Banks &	-0.0304	-0.0087	0.0152	-0.0164	0.8858	0.6504	0.2172	0.0158	2.5134	1.2078	19.5855**
Finance	**-1.6655^**	**-0.0884**	**0.1036**	**-0.1479**	**6.9892***						
Building	-0.0217	0.1375	-0.0339	0.0287	1.0551	0.6815	0.2045	0.0142	2.5801	0.4328	24.3882**
Mat.	**-0.6241**	**0.7316**	**-0.1209**	**0.1359**	**4.3706***						
Chemicals	-0.0562	0.183	-0.1154	-0.0769	0.9350	0.6446	0.2375	0.0185	2.7023	0.7127	8.0443
	-1.7475^	**1.0527**	**-0.4449**	**-0.3936**	**4.1872***						
Devl.	0.00476	-0.0055	-0.174	0.0853	0.9736	0.5788	0.2537	0.0229	2.3495	1.0021	9.6928
Contractor	**0.2106**	**-0.0448**	**-0.9547**	**0.6212**	**6.2047***						
Divs.	-0.0257	0.1327	-0.0820	-0.1308	0.9512	0.6000	0.2579	0.0204	2.5241	1.2385	11.1650*
Industrial	**-0.7781**	**0.7432**	**-0.3078**	**-0.6877**	**4.1476***						
Divs.	0.0196	0.1619	-0.2874	-0.0835	1.3602	0.6577	0.4367	0.0753	2.2390	0.1392	30.3338**
Resources	**0.3523**	**0.5384**	**-0.6406**	**-0.2471**	**3.5216***						
Energy	-0.0278	-0.1164	-0.0824	-0.1382	0.9267	0.6945	0.6379	0.1496	2.1908	0.1511	31.6019**
	-0.5711	**-0.4424**	**-0.2099**	**-0.4673**	**2.7420**						
Engineering	-0.0348	0.0109	-0.0147	-0.0914	0.8870	0.7217	0.2244	0.0160	2.4051	0.9921	14.5688**
	-1.1776	**0.0682**	**-0.0617**	**-0.5090**	**4.3227***						
Food &	0.0294	-0.2033	-0.2570	0.2072	0.9239	0.6302	0.1585	0.0087	2.5097	1.6493	16.3673**
Household	**0.7353**	**-0.9406**	**-0.7970**	**0.8529**	**3.3280***						
Gold	-0.1122	-0.5983	-0.7752	-0.362	1.0058	0.6277	0.7842	0.1947	2.2295	0.3871	10.7935*
	-1.8441	**-1.8191**	**-1.5798**	**-0.9793**	**2.3808***						
Insurance	0.0415	0.0595	-0.2388	-0.2137	0.9121	0.5664	0.1814	0.0118	2.5544	2.2898	22.8413**
	1.0379	**0.2753**	**-0.7406**	**-0.8797**	**3.2855***						

	Const	UTS	UTB	DDY	Market Return	R-SQ	MAE	MSE	D-W	G-Q test	ARCH(6)
Inv &	0.0106	0.0041	-0.0383	-0.0550	0.8454	0.4839	0.1991	0.0119	2.3350	2.2297**	13.4172**
Fin Servs.	**0.5543**	**0.0398**	**-0.2484**	**-0.4734**	**6.3672***						
Media	0.0438	0.0438	0.4431	0.2301	1.0836	0.6939	0.2492	0.0203	2.3389	4.4451**	24.7379**
	0.8128	**0.1504**	**1.0195**	**0.7028**	**2.8959***						
Other	-0.0220	0.0718	-0.2906	-0.3341	1.4668	0.6683	0.4757	0.0777	2.4322	0.5505	15.3843**
Metals	**-0.4290**	**0.2590**	**-0.7026**	**-1.0723**	**4.1194***						
Paper &	-0.0211	0.2051	-0.1252	0.2005	1.1349	0.6250	0.2225	0.0159	2.4334	0.5073	10.9684*
Packaging	**-0.7356**	**1.3228**	**-0.5412**	**1.1505**	**5.6984***						
Property	-0.0143	-0.1926	-0.1345	-0.1127	0.4590	0.5337	0.1687	0.0096	2.4207	1.2342	24.9531**
Trusts	**-0.8226**	**-2.0496***	**-0.9594**	**-1.0670**	**3.8027***						
Retail	-0.0360	-0.0243	0.0552	-0.2202	0.5049	0.6173	0.2150	0.0140	2.3803	0.7968	2.9420
	-1.7257^	**-0.2155**	**0.3281**	**-1.7374^**	**3.4858***						
Transport	0.0052	-0.0349	-0.1122	-0.1108	0.7564	0.6330	0.2576	0.0163	2.2501	2.2246	3.2653
	0.1665	**-0.2063**	**-0.4446**	**-0.5828**	**3.4815***						

Note: * indicates 95% significant and ^ indicates 90% significant. RM stands for the return on market index, R-SQ is the R-squared statistics, MAE is the mean absolute error, MSE is the mean squared error, D-W stands for Durbin-Watson statistics for residual serial correlation, G-Q tests is the Goldfeld-Quandt test for heteroskedasticity which follows the classic ARCH test. C-P test is the cumulated periodogram test for residual series to be white noise.

Table 5.9: Multivariate regression with significant variables:

	Const	UTS	UTB	DDY	R-sq	MAE	MSE	D-W	Q(12)	C-P Test	ARCH(6)	G-Q Test
Alcohol & Tobacco	-0.0599	-0.2925	-0.2609	0.2351	0.5153	0.1234	0.0046	2.53	32.5474**	0.1805**	14.5489**	10.1026**
Banks & Finance	-0.0497	-0.2680	-0.3017	0.0685	0.5806	0.1214	0.0056	2.67	35.3800**	0.2492**	11.7020*	6.7197**
Building Mat.	-0.0447	-0.1723	-0.4081	0.1220	0.5493	0.1489	0.0065	2.63	43.3617**	0.2256**	9.5586	8.2254**
Chemicals	-0.0769	-0.1005	-0.4654	0.0358	0.5340	0.1179	0.0059	2.58	44.9932**	0.2259**	12.3541*	5.0657**
Devl. Contractor	-0.0168	-0.2900	-0.4884	0.1829	0.6071	0.1301	0.0067	2.63	42.6625**	0.2066**	16.9236**	7.3792**
Divs. Industrial	-0.0479	-0.1651	-0.4194	0.0102	0.5913	0.1300	0.0067	2.68	52.4956**	0.2448**	16.9078**	7.6842**
Divs. Resources	-0.0116	-0.2485	-0.7504	0.0128	0.5629	0.1788	0.0107	2.49	29.7813**	0.1793**	8.2183	1.9938**
Energy	-0.0496	-0.4020	-0.3939	-0.0478	0.6553	0.2517	0.0221	2.36	27.2264**	0.1622**	9.8732	0.5389
Engineering	-0.0552	-0.2590	-0.3200	0.0304	0.5610	0.1102	0.0050	2.61	45.9393**	0.2570**	2.9854	4.1428**
Food & Household	0.0101	-0.4781	-0.6031	0.2727	0.5573	0.0970	0.0049	2.72	41.2443**	0.2625**	12.0477*	13.1977**
Gold	-0.1364	-0.9253	-1.1691	-0.2271	0.5163	0.3075	0.0319	2.50	33.1689**	0.2000**	12.5317*	2.0207**
Insurance	0.0203	-0.2125	-0.5401	-0.0967	0.7236	0.0880	0.0037	2.69	38.8868**	0.2497**	10.1051	5.6021**
Inv & Fin Servs.	-0.0081	-0.2343	-0.3016	0.0166	0.7464	0.0934	0.0031	2.46	36.1887**	0.1949**	19.5389**	3.6856**
Media	0.0197	-0.2669	0.1313	0.3508	0.6213	0.1272	0.0078	2.58	37.6415**	0.1963**	20.5808**	14.3590**
Other Metals	-0.0566	-0.3874	-0.8245	-0.2064	0.5101	0.2001	0.0137	2.61	39.5677**	0.2247**	45.9886**	5.7204**
Paper & Packaging	-0.0457	-0.1298	-0.5157	0.2807	0.5922	0.1044	0.0043	2.65	42.4285**	0.2430**	25.0384**	2.7341**
Property Trusts	-0.0250	-0.3354	-0.3062	-0.0738	0.5919	0.0787	0.0022	2.66	44.4861**	0.2598**	9.4281	2.3786**
Retail	-0.0488	-0.1881	-0.1093	-0.1131	0.6865	0.1049	0.0047	2.65	41.1086**	0.2507**	29.6172**	4.4903**
Transport	-0.0122	-0.2656	-0.3673	0.0282	0.6203	0.1491	0.0084	2.65	44.5227**	0.2325**	19.5288**	6.0970**

Note: R-SQ is the R-squared statistics, MAE is the mean absolute error, MSE is the mean squared error, D-W stands for Durbin-Watson statistics for residual serial correlation, G-Q tests is the Goldfeld-Quandt test for heteroskedasticity which follows the classic ARCH test. C-P test is the cumulated periodogram test for residual series to be white noise.

Table 5.10: Univariate regression with significant variables:

	Const	UTS	UCB	UTB	DDY	UEX	R-sq	MAE	MSE	D-W	Q(12)	C-P Test	ARCH(6)	G-Q Test
Alcohol & Tobacco	-0.0061	-0.043		-0.4301	-0.2033		0.3712	0.1882	0.0101	1.797	9.0178	0.0896	2.5724	0.6372
Banks & Finance	-0.005	-0.0688		-0.4021			0.2684	0.2815	0.0214	1.9365	4.8323	0.0428	14.9563**	0.6506
Building Mat.				-0.2465			0.1622	0.2697	0.0197	1.6845	5.1908	0.1912	0.4903	0.9562
Chemicals	-0.0298			-0.443			0.0865	0.2863	0.0212	2.0958	9.5646	0.0645	4.4488	0.7792
Devl. Contractor		-0.132		-0.3197			0.4453	0.3245	0.0265	1.6075	26.5727**	0.1828	44.9502**	0.4894
Divs. Industrial				-0.7242			0.1237	0.2597	0.0211	1.8958	12.6815	0.1113	0.1679	0.6837
Divs. Resources														
Energy		-0.2393					0.1061	0.6907	0.1262	1.3985	27.5819**	0.2265	0.4139	0.2098
Engineering	-0.0198	-0.296		-0.4699		1.444	0.3711	0.2698	0.019	1.9357	7.8678	0.0513	3.8902	0.8603
Food & Household		-0.2263		-0.2741			0.4435	0.171	0.0083	1.4641	27.6925**	0.2507	3.7834	2.0155**
Gold	-0.0237	-0.6393		-1.5753			0.1839	0.787	0.1577	1.8084	13.6769	0.1039	19.8708**	0.3902
Insurance			0.816	-0.1793			0.3256	0.1788	0.0098	1.6682	31.2473**	0.179	38.6648**	1.5696**
Inv & Fin Servs.		-0.1573		-0.1666			0.5261	0.1484	0.0083	1.2726	41.4200**	0.3004	57.1877**	0.6277
Media														
Other Metals				0.0394			0.0816	0.673	0.1308	1.9262	18.6684*	0.1064	6.5482	0.5739
Paper & Packaging				-0.8685	-0.2003		0.2141	0.2016	0.0148	1.51	12.9658	0.2181	1.8177	1.6415**
Property Trusts	-0.001	-0.3247		-0.2422			0.3404	0.1517	0.0063	1.9338	15.3668	0.0639	16.2516**	0.5298
Retail	-0.0107	0.1129					0.2512	0.2026	0.0118	1.7572	21.7618**	0.1103	26.6218**	0.4994
Transport		-0.2045		-0.4919			0.3847	0.319	0.0251	1.6791	15.911	0.1811	15.5184**	0.3939

Note: R-SQ is the R-squared statistics, MAE is the mean absolute error, MSE is the mean squared error, D-W stands for Durbin-Watson statistics for residual serial correlation, G-Q tests is the Goldfeld-Quandt test for heteroskedasticity which follows the classic ARCH test. C-P test is the cumulated periodogram test for residual series to be white noise.

Table 5.11: Principle components analysis of industrial returns

(March 2000)

	λ_1	λ_2	λ_3	λ_4
Alcohol & Tobacco	-0.0135	0.1172	0.2271	-0.1625
Banks & Finance	0.0931	-0.0679	0.2439	-0.1232
Building Mat.	0.2602	0.0726	0.1182	0.3567
Chemicals	0.2462	-0.0288	0.0244	0.0267
Devl. Contractor	0.0762	0.0226	0.2231	-0.1616
Divs. Industrial	0.2447	-0.1173	0.0211	0.0681
Divs. Resources	0.5201	-0.0134	-0.0565	-0.1520
Energy	0.3651	-0.1189	-0.0389	0.4532
Engineering	0.0754	0.1311	0.1872	-0.0111
Food & Household	0.2466	-0.2108	-0.0811	0.1204
Gold	0.1182	0.7450	-0.2911	-0.2263
Insurance	0.1538	-0.2571	0.2378	-0.4259
Inv & Fin Servs.	0.0730	-0.0336	0.2622	-0.0349
Media	-0.1116	0.4073	0.6440	0.3692
Other Metals	0.4637	0.2738	-0.0831	-0.1086
Paper & Packaging	0.2287	-0.0284	0.2640	-0.1664
Property Trusts	-0.0204	0.0736	0.1758	-0.1529
Retail	0.0510	-0.1153	0.1587	-0.0110
Transport	-0.0345	-0.0522	0.1426	-0.3515
% Variation	44	14.8	12.5	9.33

Notes: $\lambda_1 \ldots \lambda_4$ are principle components of the joint structure of return series Σ.

5.6 Conclusions and future research

In this chapter, the Bayesian dynamic framework was employed to investigate the predictability of Australian industrial-stock returns. Bayesian dynamic regression models in both multivariate and univariate frameworks were established. Unlike previous studies in which the relationship between the economy and financial markets are assumed to be constant, the method here incorporates new information from the derived predictor variables into the model's parameters, which are updated at each month during the sample period.

After exploring a set of unanticipated components of the economic and financial variables, it was found that only the derived term-structure, interest-rate variable and aggregate dividend-yield variable seem to be significant in explaining the variation of most industry excess returns.

The multivariate-model method has performed better than expected in explaining the stock returns. The comparison between the multivariate and univariate method strongly suggests that the correlations among the industries are existent and critical, which indicates that any study employs industry portfolios should not ignore this issue.

The results also strongly demonstrate the explanatory power of the market-index return, which gives support to the traditional CAPM theory. It appears that for most of the industrial returns, the risk source is the market itself. However, gold industry appeared to be an exception that the gold industry stocks look to be priced not only by the derived variables and the market-index return.

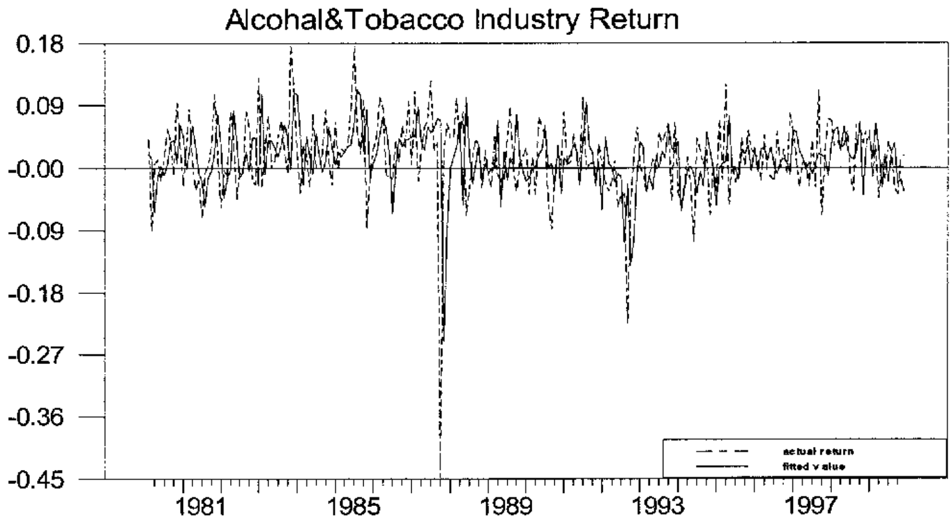
Generally, the dynamic regression model has captured some predictability of excess returns, especially in a multivariate framework. The predictability of industrial returns is consistent with the asset pricing literature suggested by previous studies. However, whether the discovered predictability is an indication of market inefficiency is an unanswered question. If the predictability is just a reflection of the time-varying expected returns in response to the risk premiums of economic and financial factors in the dynamic forecasting model, it is consistent with market efficiency theory. Thus a further investigation on the significance of the predictability will be conducted in the next chapter, Chapter 6.

The results given in this chapter can be extended in a number of directions. First, as suggested through the comparison between the multivariate and univariate method, there is some kind of autocorrelation within individual industrial returns. It is thus reasonable to assume that the observational error, v_{tj}, $j = 1,2,...n$, is serially correlated. In addition, one can also consider the case where both v_{tj} and the system error w_{tj} are serially correlated.

Second, it is interesting to consider the case where both v_{tj} and w_{tj} are non-Gaussian, as some empirical studies show that industrial returns may show some degree of skewness, which cannot be captured if the normality assumption is imposed.

Third, it would be wise to examine whether the industrial stock returns have some kind of long-memory property before modelling them as existing studies already suggest that a long-memory property is a key feature in some stock returns (see Ding, Granger and Engle, 1993; Ding and Granger, 1996; Pagan, 1996; Trivedi and Brooks, 1999; Brooks et al., 2000 and Gao, 2002). The extensions of Bayesian multivariate forecasting models are left for future research.

Figure 5.1: a. Multivariate model fitting Alcohol and Tobacco Industry.
b. Univariate model fitting Alcohol and Tobacco Industry.



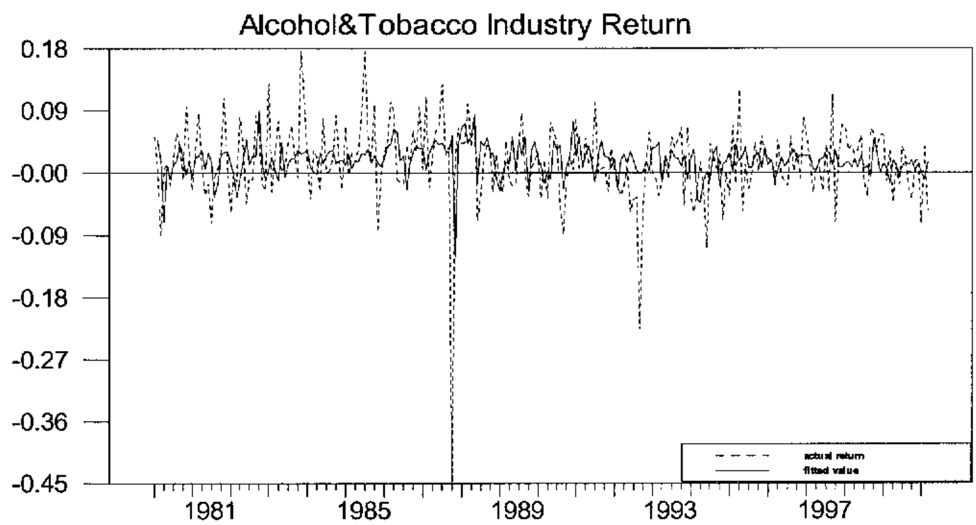
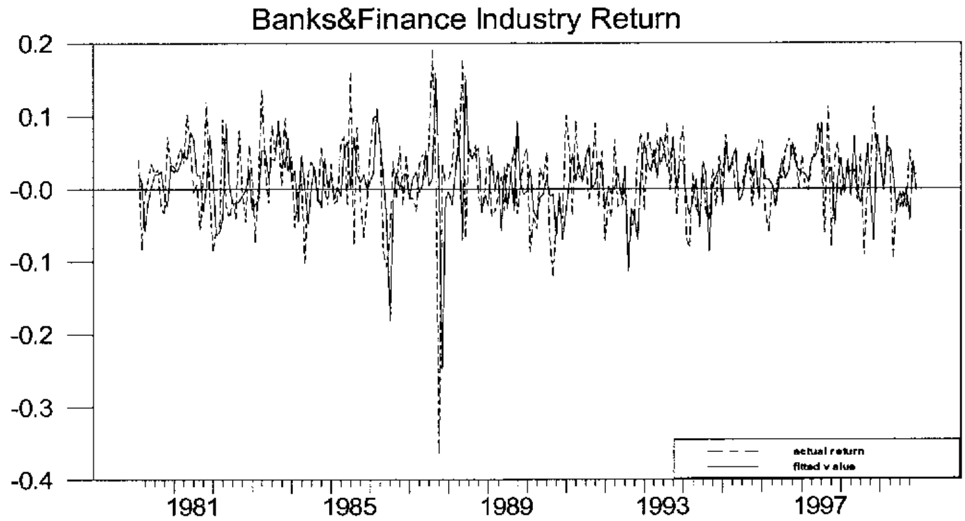


Figure 5.2: a. Multivariate model fitting Banks and Finance Industry.
b. Univariate Model fitting Banks and Finance Industry.



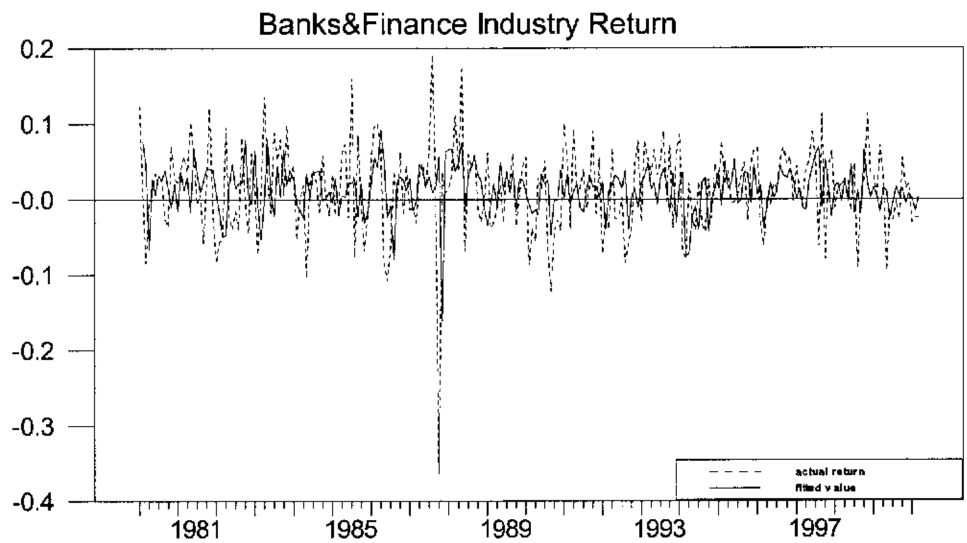
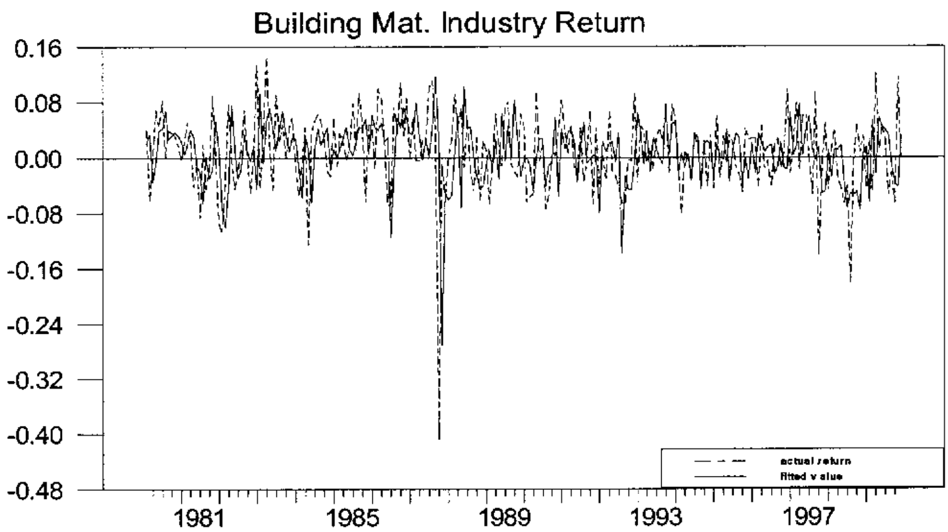


Figure 5.3 a. Multivariate model fitting Building Material Industry.
b. Univariate model fitting Building Material Industry.



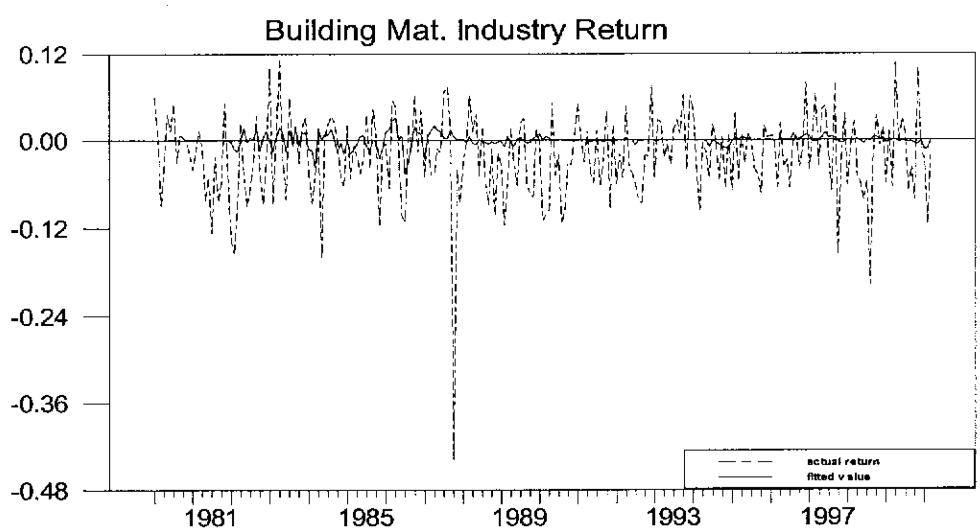
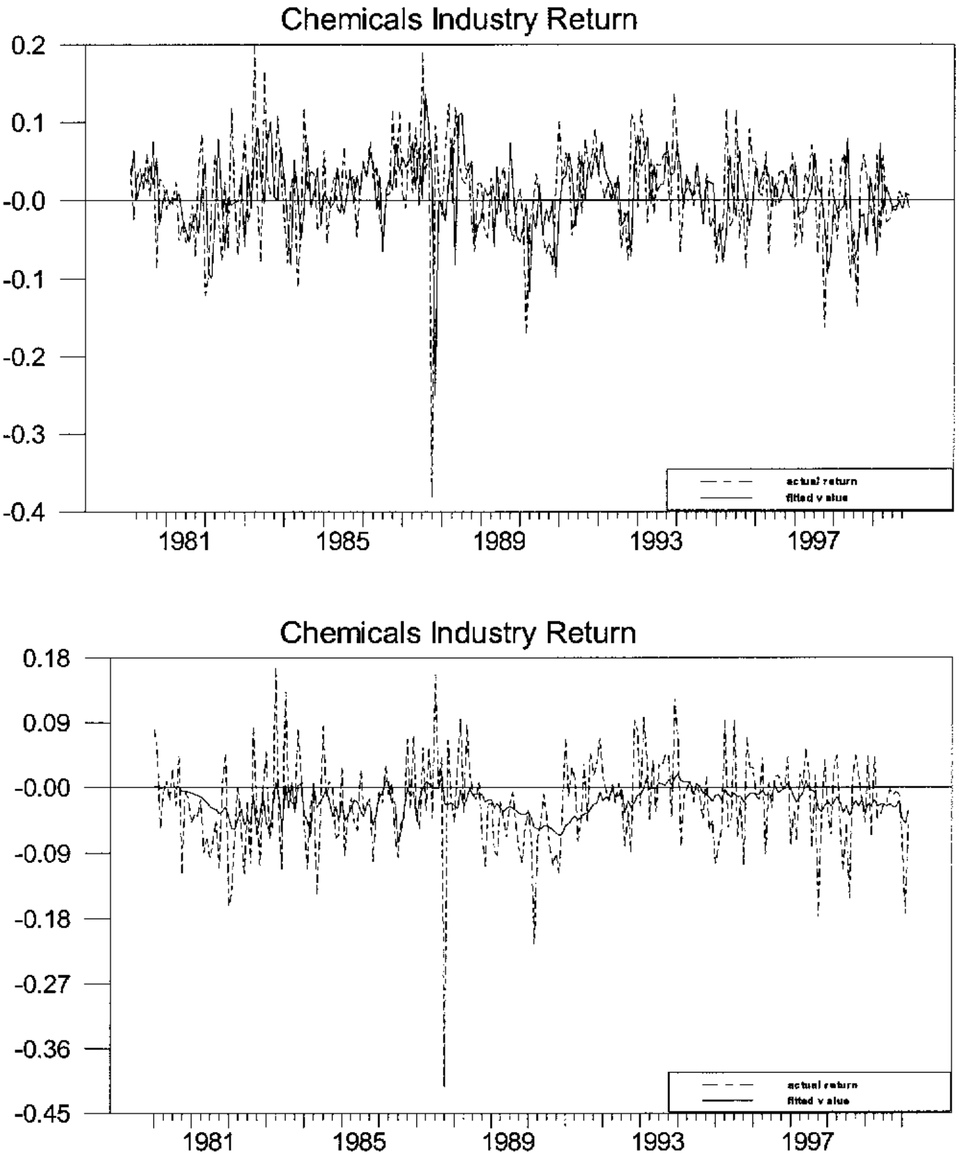


Figure 5.4: a. Multivariate model fitting Chemicals Industry.
b. Univariate model fitting Chemicals Industry.



Chapter 6 Market timing, profitability and the predictability of Industry returns[19]

6.1 Introduction

The previous chapter demonstrated that Australian industrial-stock returns can be predicted by using national and economic information. The economic variables that have significant influences on returns are the term-structure variable, the interest-rate variable and the aggregate dividend-yield; however, the time-series predictability is of little use to investors. In reality, investors are most interested in whether they could trade on so-called "predictability" to enhance their portfolio returns.

In this chapter, the economic significance of predictability implied by public information was studied. The sample period was partitioned into two for both in-sample and out-of-sample analysis. Based on the in-sample regression results, several out-of-sample tests investigated whether the predictability of the maximally predictable portfolio (MPP) is economically significant and whether the predictability can be exploited through a market-timing strategy by shifting investment in and out-of the MPP.

Additionally, a test was performed to uncover whether the predictability of industry-relative performance is beneficial to the industry-group-rotation strategy. If the predicted industry relative performance could assist investors to improve their industry portfolio returns, the predictability is of significance.

Thus, this chapter of study was to test the possibility of turning time-series industry return predictability into profitability. The results presented in this chapter are critical to both the implications of predictability and to market-efficiency theory.

[19] A paper derived from the chapter has been accepted by the 16th Australasian Finance and Banking Conference, December 2003, Sydney.

The empirical design of the tests for the significance of predictability is introduced in Section 6.2. Section 6.3 presents the results in detail, and Section 6.4 concludes the chapter.

6.2 Empirical design of the out-of-sample tests

The discovered predictive power of the public information so far cannot be viewed directly as evidence of market inefficiency. If the expected returns are time varying, the predictability could be the reflection of the rational pricing behaviour of the efficient market; therefore, it is both interesting and necessary to test whether the predictability is of significance to investors.

Lo and MacKinlay (1995) used a cross-section of assets to construct a portfolio that is "maximally predictable" by a given set of predictable variables. The maximally predictable portfolio (MPP) is the upper bound to what the investor will achieve in the search for predictability among portfolios. Since the MPP is the focus for the source of the predictability, it would be interesting to investigate the desirability of such a portfolio based on the Bayesian dynamic-updating procedure in the previous chapter.

First of all, the sample period was partitioned into two. Data from January 1980 to March 1995 was the in-sample data, and data from April 1995 to March 2000 was kept as the out-of-sample data. The primary purpose of this is to test whether the predictability discovered in the in-sample period can be realised and exploited in the out-of-sample period. A "maximally predicted portfolio" named MPP by Lo and MacKinlay (1995) was constructed based on the principle components of industrial returns starting from March 1995, the end of the in-sample period. The composition of MPP was updated throughout the out-of-sample period.

Three out-of-sample tests proposed by Lo and MacKinlay (1995) were used here to examine whether the time-series predictability can actually be exploited by some trading strategies to enhance investors' returns.

The first method introduced by Lo and MacKinlay was to compare the conditional forecasted returns of MPP formed by using past information with a naive forecast. The second test was a test of Merton's market-time ability, and the third test was to compare the total return of a passive investment in the maximally predicted portfolio with the total return of an active asset allocation strategy.

Additionally, the significance of the predictability was also be examined by using a simple industry-group-rotation trading strategy. The employment of an industry-group-rotation trading strategy was to test whether buying-and-holding the forecasted best performing portfolio (BPP) can achieve higher return, if so, it indicates that the predictability has contributed the enhanced return.

6.2.1 Forming the maximally predicted portfolio

The construction of the MPP in this study differs fundamentally from the usual two-step procedure of testing predictability in returns. The usual two-step procedure is to construct a linear factor model of returns based on cross-section explanatory power in the first step. The second step of the procedure is to analyse the predictability of those factors.

Lo and MacKinlay (1995) use a "rolling" procedure to get the conditional-factor model's parameters and weights of the MPP. In the current study, though, the MPP is formed based on the Bayesian updating procedure detailed in section 5.3. That is, investors' forecasted MPP composition is corrected each month when new economic information is available to them. The weights of the MPP are a function of time-varying economic risk premiums rather than a function of past returns only. The Bayesian updating framework offers the comprehensive routine learning for investors. The sequential updating procedure places the attention on the future development of the MPP conditional on existing information.

Following chapter 5, the multivariate Bayesian forecasting model with the same definition was used in the sample:

$$\boldsymbol{Y}_t = \boldsymbol{F}_t\, \boldsymbol{\Theta}_t + \boldsymbol{v}_t, \qquad \boldsymbol{v}_t \sim N[\boldsymbol{0}, V_t\, \Sigma],$$

$$\boldsymbol{\Theta}_t = \boldsymbol{\Theta}_{t-1} + \boldsymbol{\Omega}_t, \qquad \boldsymbol{\Omega}_t \sim N[\boldsymbol{0}, \boldsymbol{W}_t, \Sigma],$$

where

$\boldsymbol{Y}_t = (Y_{t1}, \ldots, Y_{tq})^T$, the q-vector of industry returns at time t;

$\boldsymbol{F}_t = (1, F_{t1}, ..., F_{tq})^T$ is the vector of the predictor variables at time t;

$\boldsymbol{\Theta}_t = [\boldsymbol{\theta}_{t1}, ... \boldsymbol{\theta}_{tq}]$, the $n \times q$ matrix of regression coefficients;

$\boldsymbol{v}_t = (v_{t1}, ..., v_{tq})^T$, the q-vector of observation errors at time t.

$\boldsymbol{\Omega}_t = [\omega_{t1}, ... \omega_{tq}]$, the $n \times q$ matrix whose columns are the evolution errors of the individual DLMs.

In the out-of-sample, suppose the existing information available to the investor is denoted by the information set at time t: $\boldsymbol{F}_t$. Here $\boldsymbol{F}_t$ is the information set on the national economic status available to the investor at time of t. Then the one-step-ahead forecast of returns $\boldsymbol{R}_t$ by investor will be structured from:

$$p(\boldsymbol{R}_t | \boldsymbol{\Theta}_{t|t-1}, \boldsymbol{F}_t)$$

Here, $\boldsymbol{\Theta}_{t|t-1}$ is the defining regression parameter vector at time of t, which provides the means by which information relevant to forecasting the return is summarised and used in forming forecast distribution. With every new observation available, the posterior for $\boldsymbol{\Theta}_{t|t-1}$ becomes the prior for $\boldsymbol{\Theta}_{t|t}$.

The one-step-forecasted industry return takes the form of:

$$\boldsymbol{R}_t = \boldsymbol{\Theta}_{t|t-1} \boldsymbol{F}_t \,. \tag{6.1}$$

Here:

$\boldsymbol{R}_t = (R_{t1}, ..., R_{tq})^T$, the vector of forecasted industry excess returns;

$\boldsymbol{\Theta}_{t|t-1} = [\boldsymbol{\theta}_{t|t-1,1}, ... \boldsymbol{\theta}_{t|t-1,q}]^T$, the updated matrix of regression coefficients at time t based on information of $t-1$.

In the matrix form, Σ defines the cross-sectional covariance structure of the industrial return series. Let $\boldsymbol{S}_t$ denote the estimated covariance structure of Σ given the information set at t. The largest eigenvalue of the matrix $\boldsymbol{S}_t$ represents the maximum of the fraction of the variability in the industry portfolio explained by the conditional factor model. Lo and MacKinlay (1995) verify that the eigenvector associated with the largest eigenvalue provides the estimated weights of the MPP after rescaling its standardised components sum to unity.

Assume $\lambda_{pc,t}$ is the normalised eigenvector associated with the highest eigenvalue of estimated covariance structure $\boldsymbol{S}_t$ at time t, and $\lambda_{pc,t}$ is the composition of MPP at time of t. The return of MPP is therefore:

$$R_t^* \equiv \lambda_{pc,t}^{\tau} \boldsymbol{R}_t . \tag{6.2}$$

Here R_t^* is a linear combination of industry groups, which "explains" the maximum cross-sectional variation in returns of time t, which is therefore a natural focus for the sources of predictability in excess returns.

6.2.2 Is predictability economically significant?

The first measurement of out-of-sample predictability proposed by Lo and MacKinlay (1995) is to examine the relation between the forecast error of a naive constant-expected-return model and the incremental value of the conditional forecast based on economic information beyond the naive forecast. The regression framework they have suggested is the following.

Let R_t^* denote the excess return for the MPP in month t:

$$R_t^* - \widehat{R}_t^n = \beta_0 + \beta_1 \cdot \left[\widehat{R}_t^b - \widehat{R}_t^n \right] + \varepsilon_t . \tag{6.2}$$

Here $\widehat{R}_t^n$ is the naive one-step-ahead forecast of MPP return R_t^* computed by using the previous moving average returns of MPP, which is the unconditional forecast of R_t^*. $\widehat{R}_t^b$ is the one-step-ahead forecast of MPP conditioned on the economic variables discovered from previous section. ϵ_t is the error term and subjects to the iid-normal assumption.

If $\widehat{R}_t^b$ has no forecast power beyond the naive forecast of $\widehat{R}_t^n$ then the estimated coefficient $\widehat{\beta}_1$ should not be statistically different from zero.

6.2.3 Market timing ability

If the forecasted excess return of MPP is positive, it means investment in MPP would be possibly profitable. Let θ_t denote the fraction of the portfolio invested in the MPP in month t. The naive asset allocation strategy is given by:

$$\theta_t = 1 \text{ if } \widehat{R}_t^b > 0,$$

$$\theta_t = 0 \text{ if } \widehat{R}_t^b \leq 0.$$

That is, given the predicted excess return of MPP, investors can actually make a decision on allocation of their investment either into MPP or into the risk-free assets. Lo and MacKinlay (1995) propose that if the MPP return, R_t^*, were considered the market, the asset allocation rule indicated by θ_t should exhibit positive market-timing performance.

Merton (1981) shows that the following two conditional probabilities in equation 6.3 and 6.4 are the probabilities that the forecast is correct in both "up" and "down" markets.

$$p_1 = \text{Prob}\ (\theta_t = 1 \mid R_t^* > 0) \tag{6.3}$$

$$p_2 = \text{Prob}\ (\theta_t = 0 \mid R_t^* \leq 0). \tag{6.4}$$

A test of a forecaster's market-timing ability is to determine whether or not the sum of p_1 and p_2 equals to 1. If the sum of p_1 and p_2 exceeds unity then the forecast θ_t has the value and R_t^* is predictable. If the sum of p_1 and p_2 is smaller than 1, though, it indicates that the forecasts are systematic incorrect. Furthermore, if the sum of p_1 and p_2 is 1, it shows that the forecaster's predictions have no value.

Lo and MacKinlay (1995) suggest using the following nonparametric tests to study market-timing ability. The following contingency table should be constructed:

$$\begin{array}{lcc} & R_t^* > 0 & R_t^* \leq 0 \\ \theta_t > 0 & n1 & n2 \\ \theta_t \leq 0 & N1 - n1 & N2 - n2 \end{array} \tag{6.5}$$

Here *n1* is the number of correct forecast in "up-market"; *n2* is the number of incorrect forecast in "down-markets", and *N1* and *N2* are the number of up-market and down-market periods, respectively. Henriksson and Mertion (1981) suggested that under the null hypothesis of no market-timing ability, *n1* has a hypergeometric distribution, which can be approximated by the normal distribution:

$$n1 \sim N\left(\frac{nN1}{N}, \frac{n1N1N2(N-n)}{N^2(N-1)}\right) \tag{6.6}$$

Here $N \equiv N1+N2$ and $n \equiv n1+n2$.

6.2.4 The profitability of predictability

The third measure of out-of-sample predictability is to test the profitability derived from MPP. Lo and MacKinlay (1995) suggest comparing the total return of a passive investment in MPP with the total return of the active asset-allocation strategy described in last section.

Comparison of the end-of-period value of the investment *W* distinguishes the profitability from the predictability:

$$W_T^{Passive} \equiv \prod_{t=1}^{T} (1+R_t^*) \tag{6.7}$$

$$W_T^{Active} \equiv \prod_{t=1}^{T} [\theta_t \cdot (1+R_t^*) + (1-\theta_t) \cdot (1+R_{ft})]. \tag{6.8}$$

Here R_t^* is the return of the MPP in month *t*; R_{ft} is the risk-free rate. $W_T^{Passive}$ is the end-of-period value of an investment of $1 over the entire investment period by the passive strategy, that is "buy-and-hold". W_T^{Active} is the end-of-period value of an investment of $1 over the entire investment period by the active strategy, which is allocating the investment according to the values of θ_t.

Lo and MacKinlay (1995) have also defined the "break even" transaction cost to be that percentage cost $100 \times s$ of buying or selling the MPP that equates the active strategy's total return to the passive strategy's. If the active strategy requires *k* switches into or out of the MPP, the one-way break-even transactions cost $100 \times s$ is defined by:

$$W_T^{Passive} = W_T^{Active} \cdot (1-s)^k \tag{6.9}$$

$$s = 1 - (\frac{W_T^{Passive}}{W_T^{Active}})^{1/k} \tag{6.10}$$

6.2.5 Industry-group-rotation performances

Since this study focuses on the predictability of industry returns, another interesting issue is whether investors could take advantage of the predictability indicated by the conditional factor model and implement it in their trading strategies for profit.

Sorensen and Burke (1986) have discovered that industry-specific stock price movements tend to persist for short time periods. The strategy of buying and holding the best performing industry groups can actually enhance portfolio returns even without any superior forecasting ability. Their evidence has been supported by Grauer, Hakansson and Shen (1990). Some recent work in momentum literature has also suggested the existence of industry momentums (see, for example, Moskowitz and Grinblatt, 1999).

One plausible way to explore predictability, therefore, is to conduct a group-rotation trading strategy based on forecasted industry performances. Based on public information the investor could have "forecasts" of industry relative performances by ranking the forecasted industry returns. If the forecasted relative performances can be informative to construct the true best performing industry portfolios then the predictability of public information is both significant and profitable for investors.

In the multivariate Bayesian dynamic-updating framework, the forecasted industry returns are computed simultaneously with incorporation of the correlations within the industries. Thus a best performing portfolio (BPP) can be constructed monthly based on their performances in previous month. The forecasted best-performance portfolios will be the ones holding the highest ranking industries. Therefore, starting from April 1995, the start of the out-of-sample period, all industry groups were ranked according to the forecasted returns in previous month. The ranking of each industry in every month provides information for investors to construct their "desired" industry portfolios, which could be achieved through short-selling the worst industry stocks while requisitioning the better ones.

Three kinds of forecasted BPP constructed here are those equally holding the best one, three and five industry groups. The excess returns of these forecasted BPP were compared with the naive industry portfolio as well as the actual BPP. The naive industry portfolio is constructed using the equally-weighted average of industry groups, and the actual BPP are constructed based on rankings of actual returns for the same classification.

The results of the comparison shed light on the existence of industry effects and the possible industry momentum sourced from return predictability.

6.3 Out-of-sample results

Table 6.1 presents the Bayesian regression results of the in-sample period ending at March 1995. The most significant variables are the derived term-structure and interest-rate variables. The aggregate-dividend-yield variable is significant in four industries. The exchange-rate variable is significant in explaining the banking-and-finance industry returns only. The unemployment variable is significant in the food-and-household and insurance industries. The term-structure, interest-rate, and dividend-yield variables were thus chosen as the predictor variables for out-of-sample analysis. The one-step-ahead forecast at the end of the in-sample period, March 1995, is the first set of forecasted returns for April 1995. The out-of-sample period starts at April 1995 and ends at March 2000.

Table 6.2 presents the principle components of the industry returns at March 1995. The proportions of total variation contributed by the first three components are 45 per cent, 18 per cent and 8 per cent, respectively. The first component provides the estimated weights for the MPP at March 1995 after rescaling its standardized elements sum to unity. The column $\mathbf{S}\boldsymbol{\lambda}_1$ provides the estimated weights of the MPP at March 1995. While Lo and MacKinlay (1995) restricted their estimated weights of MPP to be positive, the construction of MPP here allowed short-sale.

Three out-of-sample predictability measures are shown in Table 6.3. Panel 1 of the table shows the coefficients from the regression of deviation of the naive forecast over the deviation of the conditional forecast using the economic variables specified by equation 6.2. Neither of the estimated coefficients is significantly different from zero; therefore, the conditional forecast of $\hat{R}_t^b$ does not show significant forecast power beyond the naive forecast.

Panel 2 of the table computes the sum of estimated probabilities of the correct forecast in both the "up" and "down" market. Though the value of $\hat{p}1 + \hat{p}2$ is greater than one, the ρ-value is not significant. It indicates that the null of no-forecasting skills cannot be rejected.

Panel 3 of the table presents a comparison of the total return of a passive investment in the MPP with an active asset allocation strategy between MPP and the risk-free asset. An additional portfolio here is the simple investment in the market index in this period. The comparison shows that the MPP with a passive strategy earns an excess return of 5.6 per cent and the MPP with active strategy earns an excess return of 7.4 per cent. Both of the strategies of MPP outperform the market-index return with much higher mean excess returns. The Sharpe ratios of MPP are higher than the market-index portfolio despite the higher standard deviations of returns. When the ending values of every \$1 investment were compared, the strategies based on MPP earned \$8.278 for passive strategy and \$13.17 for active strategy. Both of these strategies achieved higher values than a simple market index investment \$1.747.

Not surprisingly, the active strategy of the MPP achieved a better return than the passive holding of the MPP. The Sharpe ratios of the active MPP is 0.2945 which is higher than 0.2303 of the passive MPP. However, for the active strategy of the MPP, the frequency of switches in and out-of the MPP is 24, which implies the break-even cost at 1.9 per cent according to the definition of Lo and MacKinlay (1995). This implies that only when the trading costs are below 1.9 per cent, the active strategy of the MPP is able to outperform the passive strategy.

Table 6.4 provides a comparison of forecasted BPP with the actual BPP, the naive industry portfolio and the market-index portfolio. Both of the forecasted BPP and actual BPP were constructed by holding the best performing one, three and five industries, respectively.

Compared to the actual BPP returns, all the forecasted BPP portfolios generated much lower excess return despite the number of industry groups in holding. The real BPP achieved excess returns from 5.9 per cent to 9.6 per cent; however, the forecasted BPP only obtained excess returns from 0.8 per cent to 1 per cent. This result shows that though the group-rotation strategy could enhance the portfolio returns in general, the captured predictability of return movements here is only a small fraction of real return's variations. When more best performing industries were included in the holdings, the forecasted BPP tended to achieve higher excess returns and lower standard deviations on the returns.

All of the forecasted BPP portfolio returns were higher than the naive industry average 0.59 per cent and market-index return 0.1 per cent. The forecasted BPP portfolios achieved a similar level of standard deviation of returns to the naive and market index portfolios when the holdings of the best performing industries increased to five. The Sharpe ratios of the forecasted BPP were higher than the naive and market-index portfolios when the holdings of industry groups exceeded one. However, none of the forecasted BPP portfolios generated a significant alpha.

6.4 Conclusion and discussion

In this chapter several out-of-sample analyses were performed to investigate whether the predictability demonstrated in the previous chapter is exploitable in the out-of-sample. The results suggested that, although the public economic information possessed some predictive power of the industries' excess returns, the predictability was not economically significant in the out-of-sample tests.

The predictability associated with MPP did not exceed the predictive power of a naive forecast. The number of correct forecasts in both of "up" and "down" market was not statistically significant. When the profitability was considered, the results showed that only when trading costs was below 1.9 per cent, the active strategy of MPP could achieve a higher return. The results here imply that, practically, the predictability is less likely to be profitable to the investors.

When the industry-group-rotation strategy was conducted, the results indicated that group rotation could enhance the portfolio return when comparing to holdings of the market-index portfolio or a naive portfolio of industry average. However, when the forecasts from the conditional model were used as the basis of rotation, the enhanced returns were much smaller. The results suggest that the predictability offers little help to the investors in their industry-group-rotation investment as the forecasts would only be able to capture a very small magnitude of enhanced returns.

The insignificant results of the out-of-sample tests imply that the predictability discovered in the dynamic regression model in previous chapter is more likely to be the reflections of time-varying expected returns. Since the predictability is not exploitable and profitable in the out-of-sample analysis, it cannot be taken as the evidence of market inefficiency.

Lo and MacKinlay (1995) found that although the degree and sources of predictability vary among assets and over time, predictability is both statistically and economically significant in both of their in-sample and out-of-sample. A few factors might have contributed to the differences between the present results and theirs.

First, the MPP used in this chapter explains a lesser proportion of the cross-section variation of returns; for example, at the end of March 1995, the MPP only explains around 45 per cent of total industry return variation (see Table 6.2), while in the Lo and MacKinlay (1995) study, the proportion is over 90 per cent. The lesser predictability of MPP itself contributes to the reduction of economic significance.

Second, the predictor variables used in this study might not be the best approximation for the development of the economy. Given the data limitation in Australia, for example, the monthly inflation statistics and Treasury bill rate are not available; the adopted proxy variables might have introduced some errors into the estimation process. This problem can only be solved when more monthly statistics are made available.

Additionally, the Australian stock market is a relatively small but concentrated market. Some of the industry groups are dominated by several big corporations, for example, the Foster group dominates the alcohol and tobacco industry, and AMP dominates the insurance industry. Therefore, the movement of the industry index is more likely to be biased by an individual company's idiosyncratic risk. With the introduction of the GICS index to the Australian Stock Exchange and more companies being listed, it may be possible to find a better representation for industry portfolios.

Table 6.1: The results of in-sample analysis (Jan 1980 – Mar 1995)

Industry	CONST	UEI	UTS	UCB	UTB	DDY	UIP	UUM	UM3	UEX
Alcohol&Tobacco	0.0009	0.0361	-0.2988	-0.2209	-0.1760	0.2002	0.1869	-0.1741	-0.1340	-0.1152
	0.0375	0.1293	-2.2380*	-1.2391	-1.1981	1.4783	0.6494	-0.8723	-0.4721	-0.5089
Banks & Finance	0.0357	-0.0285	-0.3780	-0.0491	-0.2446	0.2410	0.2158	0.0320	-0.1045	0.2687
	2.1092*	-0.1429	-3.9638*	-0.3856	-2.3311*	2.4914*	1.0497	0.2245	-0.5154	1.6618^
Building Materials	-0.0092	-0.0172	-0.4492	-0.0705	-0.2265	0.1766	0.2008	-0.0378	-0.1927	0.2011
	-0.5436	-0.0862	-4.7104*	-0.5536	-2.1586*	1.8257^	0.9768	-0.2651	-0.9505	1.2437
Chemicals	-0.0361	0.1051	-0.2487	-0.1671	-0.0950	0.2028	0.2289	0.1720	0.0784	0.2356
	-1.5799	0.3903	-1.9318^	-0.9720	-0.6706	1.5530	0.8248	0.8937	0.2864	1.0793
Devl. and Contra.	0.0116	-0.0389	-0.3991	-0.0442	-0.3753	0.1748	0.2835	0.0343	-0.0862	0.1338
	0.6853	-0.1950	-4.1850*	-0.3471	-3.5767*	1.8070^	1.3791	0.2406	-0.4252	0.8275
Diversified Ind.	-0.0130	-0.0296	-0.6131	-0.0883	-0.2435	0.1508	0.1390	-0.1672	-0.2177	-0.0302
	-0.7681	-0.1484	-6.4291*	-0.6934	-2.3206*	1.5589	0.6762	-1.1728	-1.0738	-0.1868
Diversified Res.	-0.0379	-0.0819	-0.6389	-0.2652	-0.1919	0.0532	0.0729	-0.2141	-0.2434	0.1297
	-1.3995	-0.2566	-4.1873*	-1.3016	-1.1430	0.3437	0.2216	-0.9386	-0.7503	0.5013
Energy	0.0264	0.0916	-0.2612	-0.0288	-0.2606	0.2046	0.0829	-0.2077	-0.0324	0.1948
	1.0398	0.3061	-1.8260^	-0.1508	-1.6557^	1.4101	0.2688	-0.9712	-0.1065	0.8032
Engineering	-0.0391	-0.1000	-0.5447	-0.1131	-0.2106	0.0099	0.1128	-0.2938	-0.1532	0.1518
	-1.9251^	-0.4178	-4.7598*	-0.7401	-1.6725^	0.0849	0.4573	-1.7173^	-0.6297	0.7824
Food& Household	-0.0174	0.1224	-0.3734	-0.0265	-0.1860	0.2735	0.1292	0.0292	-0.1544	0.0285
	-0.7615	0.4545	-2.9004*	-0.1542	-1.3130	2.0944*	0.4655	0.1517	-0.5641	0.1306
Gold	0.0056	0.4310	-0.2925	-0.0959	-0.4579	0.3884	0.2043	-0.0191	0.0883	0.6845
	0.1253	0.8154	-1.1574	-0.2842	-1.6467^	1.5152	0.3750	-0.0506	0.1644	1.5975
Insurance	0.0164	-0.3471	-0.5122	-0.0664	-0.3109	0.1128	0.0257	-0.5228	-0.1983	0.2924
	0.8074	-1.4501	-4.4758*	-0.4345	-2.4691*	0.9718	0.1042	-3.0558*	-0.8151	1.5070
Invest.&Fin.Servs.	0.0010	-0.1184	-0.3002	-0.1681	-0.1715	0.0303	0.1355	-0.1429	-0.1583	0.1545
	0.0805	-0.8131	-4.3123*	-1.8083^	-2.2389*	0.4291	0.9029	-1.3730	-1.0696	1.3089
Media	0.0542	-0.1803	-0.6951	-0.1249	-0.3230	0.0322	-0.0082	0.0294	-0.3274	-0.0818
	1.6011	-0.4520	-3.6445*	-0.4904	-1.5391	0.1664	-0.0199	0.1031	-0.8074	-0.2529
Other Metals	-0.0178	0.0344	-0.4993	-0.2966	-0.3009	0.1520	0.1345	-0.1697	-0.1329	0.3593
	-0.5843	0.0958	-2.9087*	-1.2940	-1.5931	0.8730	0.3635	-0.6613	-0.3642	1.2345
Paper&Packaging	-0.0087	-0.1480	-0.5273	-0.1221	-0.2638	0.0859	0.0075	-0.1284	-0.3464	-0.0620
	-0.4288	-0.6183	-4.6078*	-0.7990	-2.0950*	0.7400	0.0304	-0.7505	-1.4238	-0.3195
Property Trust	0.0329	-0.0395	-0.1306	-0.0096	-0.2098	0.1146	0.0887	0.0301	-0.0568	0.1218
	2.2215*	-0.2263	-1.5651	-0.0862	-2.2851*	1.3540	0.4931	0.2413	-0.3202	0.8609
Retail	0.0104	0.1013	-0.3717	0.0296	-0.1010	0.1625	0.2039	-0.0140	-0.1870	0.2612
	0.5343	0.4416	-3.3893*	0.2021	-0.8370	1.4608	0.8625	-0.0854	-0.8020	1.4047
Transport	-0.0212	-0.1721	-0.7125	-0.1214	-0.4484	0.1137	0.0888	-0.1676	-0.3382	-0.0591
	-1.0020	-0.6902	-5.9771*	-0.7627	-3.4186*	0.9403	0.3456	-0.9405	-1.3345	-0.2924

Note: The second bold row of each industry presents t-statistics. The significant values are underlined. * represents 95% significance and ^ represents 90% significance.

Table 6.2: Principle components of industrial returns

(March 1995)

	λ_1	λ_2	λ_3	$S\lambda_1$[a]
Alcohol & Tobacco	-0.2335	0.1080	-0.2103	-0.1881
Banks & Finance	-0.1437	0.1646	0.0108	0.7960
Building Mat.	-0.1877	0.1565	0.0659	0.3138
Chemicals	-0.1906	-0.0895	0.2878	0.2820
Devl. Contractor	-0.1511	0.0304	-0.1227	0.7149
Divs. Industrial	-0.1902	0.1156	0.1612	0.2864
Divs. Resources	-0.3135	0.0682	0.3931	-1.0648
Energy	-0.2987	0.1762	-0.1580	-0.9026
Engineering	-0.1381	0.1824	0.3589	0.8574
Food & Household	-0.0371	0.1123	0.0801	1.9642
Gold	-0.408	-0.7439	-0.2347	-2.1005
Insurance	-0.1944	0.0590	0.0757	0.2404
Inv & Fin Servs.	-0.1393	0.0371	0.0182	0.8442
Media	-0.3194	0.3716	-0.5947	-1.1295
Other Metals	-0.3487	-0.2676	0.1938	-1.4506
Paper & Packaging	-0.2110	0.1838	0.0439	0.0585
Property Trusts	-0.1144	-0.0942	-0.0892	1.1171
Retail	-0.1716	0.0746	-0.0497	0.4902
Transport	-0.2281	0.1296	0.2192	-0.1289
% Variation	45.4	17.9	8	-

Notes: a. $S\lambda_1$ represents the weights of MPP which are the standardized first component with sum to unity.

Table 6.3: Out-of-sample predictability of MPP:

1. Significance [a]

	$\widehat{\beta}_0$	$\widehat{\beta}_1$
Coefficients	*0.0582*	*-0.0934*
(t-stat)	*(1.3816)*	*(-0.5286)*

2. Timing [b]

	n1	N1-n1	n2	N2-n2	$\widehat{p}1+\widehat{p}2$	p -Value
Number of Forecasts	*24*	*13*	*14*	*9*	*1.0399*	*0.3410*

3. Profitability [c]

	MPP Passive	MPP Active	Market Index	Switches In-Out MPP	Break-Even cost
Mean Excess Return	*0.0558*	*0.0741*	*0.0010*	*24*	*1.9%*
Stand Dev.	*0.2423*	*0.2516*	*0.0349*		
Sharp Ratio	*0.2303*	*0.2945*	*0.0287*		
Ending Value of $1	*$8.278*	*$13.17*	*$1.747*		

a. Regression of $R_t^* - \widehat{R}_t^n = \beta_0 + \beta_1 \cdot \left[\widehat{R}_t^b - \widehat{R}_t^n \right] + \varepsilon_t$, where R_t^* is the return of MPP. $\widehat{R}_t^n$ is the naive one-step-ahead forecast of MPP and $\widehat{R}_t^b$ is the one-step-ahead forecast of MPP conditioned on the economic variables.

b. Merton market timing ability test. If $\widehat{p}1+\widehat{p}2$ is greater than 1, R_t^* is predictable.

c. The comparison of excess return of a passive and an active investment in MPP as well as the market index excess return.

Table 6.4: Monthly BPP returns:

Apr 1995 – Mar 2000. (Risk-free rate = 0.0189)

Number of Groups	Forecast[a] 1	Forecast[b] 3	Forecast[c] 5	Actual[d] 1	Actual[e] 3	Actual[f] 5	Naive (Group Ave.)	Market Index
Excess Return	0.0075	0.0097	0.0099	0.0963	0.0706	0.0587	0.0059	0.0010
Standard Deviation	0.0664	0.0419	0.0379	0.0615	0.0403	0.0365	0.0372	0.0349
Beta	0.7630	0.7950	0.8518	0.8000	0.9131	0.9426	0.9998	1.0000
Sharpe	0.1130	0.2315	0.2612	1.5659	1.7519	1.6082	0.1586	0.0287
Treynor	0.0010	0.0122	0.0116	0.1204	0.0773	0.0623	0.0059	0.0010
Alpha	-9.8E-05	0.0017	0.0014	0.0883	0.0616	0.0493	-0.0041	-
(t-stat)	(-0.0119)	(0.4107)	(0.4526)	(11.9055)	(18.4855)	(23.0575)	(-2.3563)	

Notes:

a, b, c. The forecasted best performing industry portfolios with 1, 3, or 5 industry groups included.

d, e, f. The actual best performed industry portfolio with 1, 3, or 5 industry groups included.

Chapter 7 Summary and conclusions

7.1 Summary

The predictability of stock returns has always been of great interest to both academics and financial practitioners. A study into the predictability of the stock market is both interesting and challenging as the traditional efficient-market hypothesis implies that stock prices follow a random walk. This thesis provides an empirical study on the predictability of industry-sector returns in the Australian stock market and its implications for market efficiency.

Chapter 2 reviewed the major theoretical and empirical work in the predictability literature. The early testing of predictability was motivated by market-efficiency theory or the random-walk hypothesis. The existence of the mean-reversion property of stock returns, as well as the resulting autocorrelations, indicates the existence of predictable components. As market-efficiency theory suggests that stock returns are not predictable, for many, the evidence on predictability is synonymous with market inefficiency.

The predictable evidence of short-horizon returns is inconclusive as many argue that the results are subject to the market-microstructure effect. The predictability of longer-horizon returns is less controversial, however. There is a wide range of evidence to support predictability in both US and non-US markets.

The early empirical work on predictability adopts either a regression-based method or the variance-ratio method. Many academics argue that the regression-based method and the variance-ratio method suffer from the "small sample" problem as the reliable long-term time series are always limited; therefore, the *t*-statistics drawn from those data are biased (see Kim et al., 1991; Mankiw et al., 1991 and Richardson, 1993).

Additionally, there has been recent criticism that studies using conventional methods are subject to the problem of "ad hoc model certainty" as the parameters of the model are assumed to be fixed throughout the whole sample period (see, for example, Pesaran and Timmermann, 1995, 2000). Since the economic and financial information associated with the stock market is always changing, there is no reason to believe the relationship between newly arrived information and stock returns is constant. The time-varying property of the return-generating process suggests that there is a need to reconsider the predictability problem in a dynamic framework in which the parameters of the model are allowed to vary with the generation of the time series of stock returns.

Some of the latest dynamic frameworks for investigating predictability in stock returns are the state-space model and Bayesian-forecasting techniques. The introduction of those methodologies was presented in Chapter 3. The state-space model was introduced with an emphasis on the estimation algorithm, Kalman filter technique. The Bayesian-forecasting technique was also illustrated with a simple univariate, dynamic, linear system. The benefits of the state-space framework are that the assumption of constant parameters for the whole sample period is not needed. In other words, investors would be able to update their forecasting parameters each time a new observation becomes available. This kind of dynamic setting is more flexible, general and coherent.

Since many existing studies in the equity markets have supported the predictability of stock returns, evidence of predictability can be found either through the autocorrelation of the returns or the explanatory power of predictor variables. Thus, in Chapters 4 and 5, the predictability of stock returns was considered from two different aspects. First, an investigation was performed of the relationship between Australian industrial-portfolio returns and the market return. Second, the relationship between Australian industrial returns and national economic and financial information was discussed. This revealed the predictability of Australian industrial returns using national economic and financial information.

Chapter 4 investigated the problem of choosing a best possible, time-varying beta model for each industrial index using the state-space framework. The results suggest that the single-index model provides a better explanation of industrial returns when the stochastic properties of industrial betas are considered. While it may not be appropriate to use the same time-varying beta model for all the industrial indexes, due to their own stochastic behaviour and characteristics, it has been possible to select a best available model for each industrial index for the purpose of prediction. In general, industry systematic risk is time varying, which justifies the adoption of a dynamic setting for the work of predictability.

Existing studies have already shown that there is a close relationship between Australian industrial returns and some economic and financial information. For example, Faff and Heaney (1999) discussed the relationship between inflation and Australian industrial returns. Chapter 5 systematically investigated the relationship between Australian industrial-stock returns and national economic and financial information. The research shows that the derived term-structure and interest-rate variables, as well as the aggregate dividend-yield variable, are significant in explaining industrial excess returns. The empirical comparisons also show that the methodology based on a multivariate, dynamic model has some advantages over existing methods in terms of taking the correlations among the industrial indexes into account and better explaining the predictability of the excess industrial returns.

A further test of the economic significance of the predictability and profitability was reported in Chapter 6. Though it was found that several economic and financial variables can significantly predict the time series of returns, the predictability power is not economically significant out-of-sample. The predictability cannot thus be exploited by investors in real-life practice. The results of this chapter suggest that the predictability is probably just a reflection of the rational pricing behaviour of the market and should not be viewed as evidence of market inefficiencies.

7.2 Conclusions

Led by the single-index model and the multi-factor model in a state-space framework, this study has undertaken a thorough investigation into the stochastic behaviour of industrial betas and the dynamic relationship between national economic and financial series with industrial stock returns.

This study has presented evidence that the systematic risks of industrial portfolios are stochastic processes. The systematic risks of industry groups were best modelled as mean-reverting processes that had long-term stable or moving means; however, some industry groups were found to have rather random systematic risks. The time-varying market model provides a better description of portfolio returns since it captures the stochastic properties of market risk. The results of this chapter have important implications for portfolio management and securities analysts as industry betas normally serve as the "prior" to individual beta estimation (see Vasicek, 1973, p. 1237). The identification of industry beta stability and the identified best stochastic model will help to determine whether the forecasting method for beta is optimal since the financial industry adopts different estimation methods.

Further, a set of economic and financial variables was found to contain predictive power over industry portfolio returns through a multivariate, Bayesian dynamic-forecasting model. The unanticipated components of the term-structure variable, the interest-rate variable and the aggregate dividend-yield variable were shown to be significant in explaining the industry portfolio's excess returns. The predictability of industry sectors is especially valuable to market participants as the macroeconomic and industry analysis are two major aspects in the process of securities analysis. It is believed that the macroeconomic condition is translated to the securities market through its impacts on corporate profits, investment advice is usually tied to the macroeconomic forecasts. Portfolio managers will recommend special industries when the macroeconomic condition changes. The predictability of industry-sector returns will serve as the basis for future asset allocation and capital construction decisions (see Barberis, 2000).

A maximally predicted portfolio (MPP) based on the predictability discovered here did not show economic significance out-of-sample, however. The insignificant results of the out-of-sample tests indicate that investors are less likely to be able to exploit the time-series predictability to gain excess profit. The results of this study strongly indicate that the variability of excess industrial returns is a reflection of stochastic, systematic risk resulting from the market itself or the economic and financial environment. The predictability of industrial returns is most likely to be driven by the stochastic behaviour of beta or the expected time-changing risk premiums as indicated by some previous studies (for example, Ferson and Harvey 1991; 1998). The market is efficient in that the discovered predictability does not seem to be transferred into a profit in practice.

This study also highlights the importance of a multivariate framework and out-of-sample testing in studies into predictability. A multivariate model incorporates the correlations among the industry sectors, which greatly improves the performance of the model when compared to a univariate model. The superiority of multivariate models suggest that the correlations among the sectors are important. The current research also suggests that an out-of-sample test is necessary for examining the predictability as it only conveys profit if the predictability is economically significant out-of-sample. Any claim for market inefficiency without out-of-sample testing would be hasty.

The results of this study are consistent with previous finding that stock returns are predictable, at least to some degree. As pointed out by Fama and French (1989), the business-cycle pattern of real output has a direct influence on asset yields, and movements in these yields might explain the observed predictability in excess returns. Predictable variation in excess returns is thus a rational response to the general level of expected business conditions.

It should be noted that the evidence for predictability does not necessarily contradict the idea of the market efficiency, as predictability does not guarantee that an investor can earn profits from a trading strategy based on forecasts. The results of this study confirm the notion that predictable patterns exist in the stock market; however, it is unlikely that investors can make a profit from them.

Malkiel (2001, p. 15133) summarises the studies on stock market predictability like so:

> *Pricing irregularities and predictable patterns in stock returns do appear over time and even persist for periods. Undoubtedly, with the passage of time and with the increasing sophistication of our databases and empirical techniques, we will document further apparent departures from efficiency, and further patterns in the development of stock returns. But the end result will not be an abandonment of the belief of many in the profession that the stock market is remarkably efficient in its utilization of information and that whatever patterns do exist are unlikely to provide investors with a method to obtain extraordinary returns.*

Even though this study supports such a claim, it should be noted that this claim is made based on existing testing techniques and existing empirical evidence. Recent developments in the forecasting literature have suggested that the standard constant-parameter model with a simple specification will not continue to be useful as it assumes stationarity (see Timmermann and Granger, 2004).

This study has attempted to handle model uncertainty by the adoption of a dynamic framework with time-varying parameters. Because investors' learning processes affect the path of asset prices, though, the forecasting model is unlikely to remain the same (see Timmermann, 1993). Further consideration should be turned to quickly changing models that can detect and utilise any instances of temporary forecastability that might arise and quickly disappear as learning opportunities arise and close down. As long as predictable patterns of stock returns exist, the question of market efficiency and the effort to discover profitability will continue.

7.3 Future research

This thesis highlights a few interesting issues for future research. First, an interesting question that has not been fully addressed in this study is "How has specific industry structure influenced stock risks and returns?". Brooks and Faff (1995; 1997) have documented that financial deregulation in 1980s affected both the level and stability of beta risk, and the impact varies across industries. Ragunathan, Faff and Brooks (2000) have presented evidence that both domestic and international business cycles impact on the equity betas of industry portfolios. A detailed study on individual industries with a focus on industry cash-flow patterns, leverage and life-cycle dynamics would further enhance understanding of this subject.

Second, the dynamic models that have been adopted in this study can be extended to a more general setting. For example, drawing from previous studies, this research has assumed that the error series of the measurement equation and the transition equation are not correlated with each other. It would be interest to examine the correlated case. The extended version of the Kalman-filter technique is able to handle systems with correlated errors. Furthermore, the existence of outliers is a common fact of stock-return data series due to unexpected events. For example, the stock market crash of October 1987 or the terrorist attack of 11 September 2001. Extra care thus needs to be taken to refine the examination. Lin and Guttman (1993) and Kitagawa (1994) have proposed a Gaussian-sum approach to deal with outliers in the data. Supported by Tanizaki (1993), the Gaussian-sum approach is a feasible method to model the non-normally-distributed return series. Future research could extend the current study by employing more advanced techniques.

Third, with more long-term time series being made available, it may be possible to achieve a better selection of predictor variables. The improved measurement of proxy variables for economic innovations could certainly increase the predictive power of the model.

Additionally, recent developments in behavioural finance suggest an alternative view of stock market predictability by considering investors' psychological behaviour (see Daniel et al., 1998; Shiller, 2000; Hirshleifer, 2001). One strand of this literature suggests that under-reaction and over-reaction to the stock market, based on investors' psychological biases, lead to predictability. An interesting empirical direction would thus be to analyse investors' widespread beliefs to identify ways of predicting returns.

The results of this thesis will serve as a reference to any further studies into the predictability of the Australian stock market and asset-pricing models. Specifically, it offers a framework for further exploration into industry-momentum trading strategies and the industrial-portfolio-allocation model. Further research may also consider the possibility of exploiting predictability for profit by examining industry momentum or contrarian trading strategies. Recent evidence presented by Chordia and Shivakumar (2002) and Moskowitz and Grinblatt (1999) has indicated that time-series patterns in returns can possibly be translated into abnormal profits in the US market.

Appendix A

Mapping of ASX Sectors to GICS Sectors

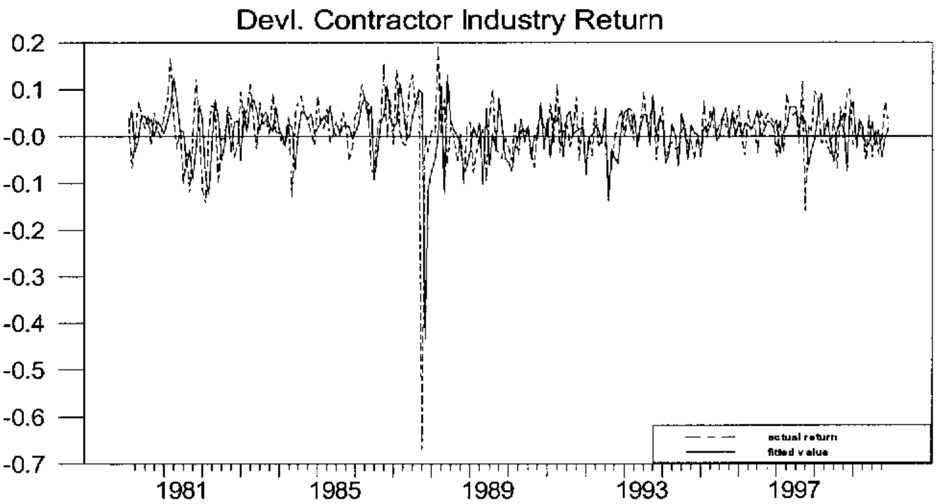
ASX Industry Sectors	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Property Trusts	Financials-x-Property Trusts	Information Technology	Telecommunication Services	Utilities
Gold		100%									
Other Metals		100%									
Diversified Resources	1%	99%									
Energy	99%	1%									
Infrastructure & Utilities	11%		37%					2%			50%
Developers & Contractors			15%					85%			
Building Materials		100%									
Alcohol & Tobacco					100%						
Food & Household					100%						
Chemicals		100%									
Engineering			100%								
Paper & Packaging		100%									
Retail				21%	79%						
Transport			100%								
Media				100%							
Banks								100%			
Insurance								100%			
Telecommunications									1%	99%	
Investment & Fin. Services		2%	38%					60%			
Property							100%				
Health & Biotechnology						100%					
Miscellaneous Industrials		5%	47%	3%					45%		
Diversified Industrials		6%	78%	4%	12%						
Tourism				100%							

At March 31, 2002. Mapping as a % of market capitalisation.

Source: "Understanding GICS", *Standard & Poor's Setting the Standard,* Standard & Poor's Index Services, Sydney.

Appendix B

Figure 5.5: a. Multivariate model fitting Developers and contractors Industry. b. Univariate model fitting Developers and contractors Industry.



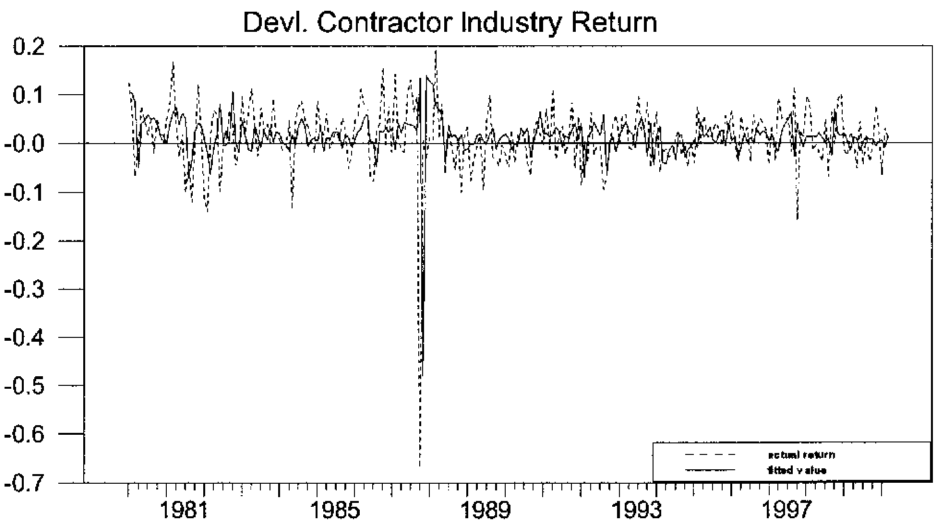
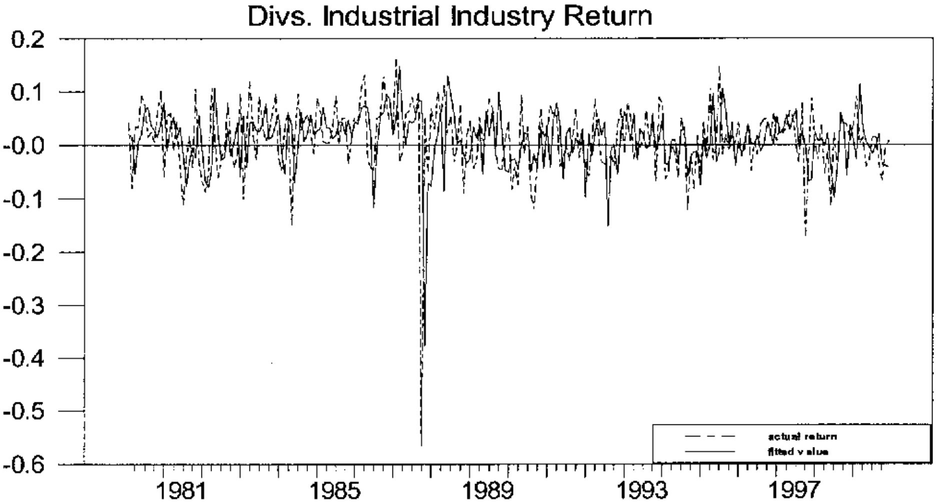


Figure 5.6: a. Multivariate model fitting Diversified Industrial Industry.
b. Univariate model fitting Diversified Industrial Industry.



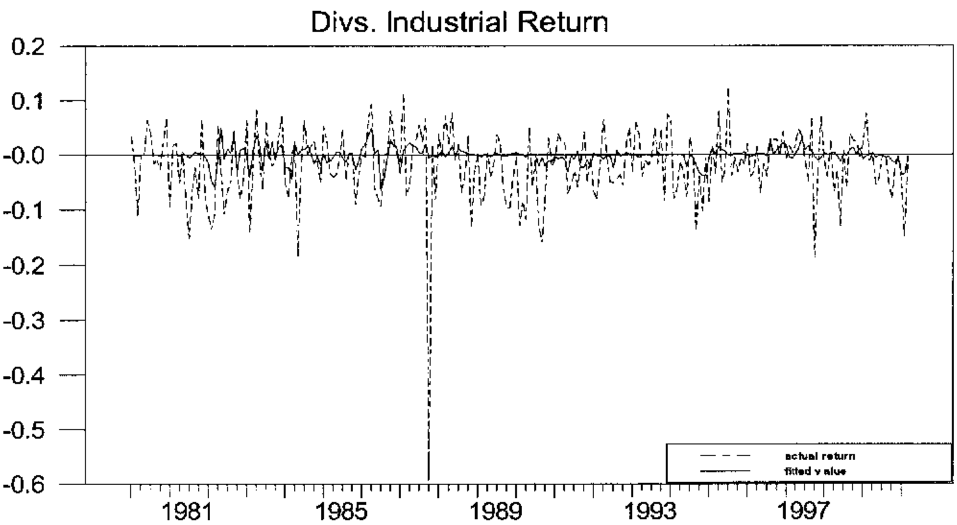
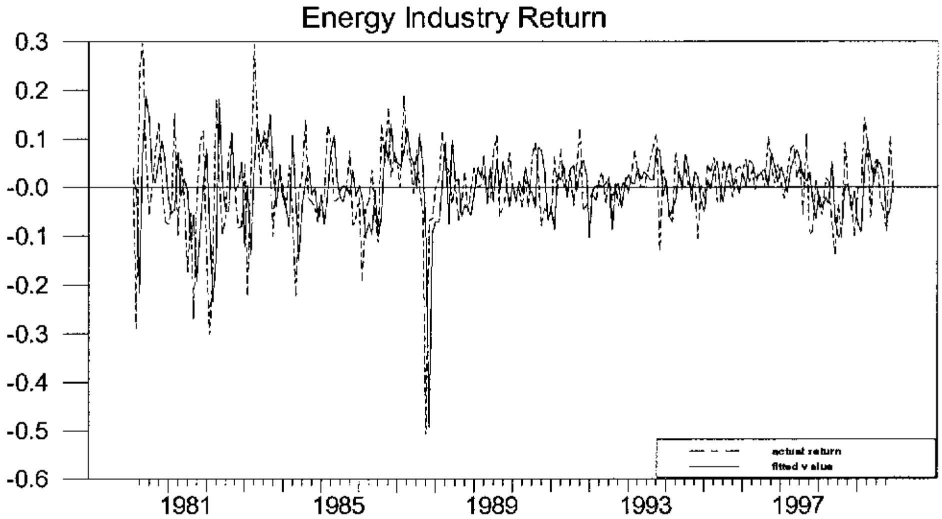


Figure 5.7: a. Multivariate model fitting Energy Industry.
b. Univariate model fitting Energy Industry.



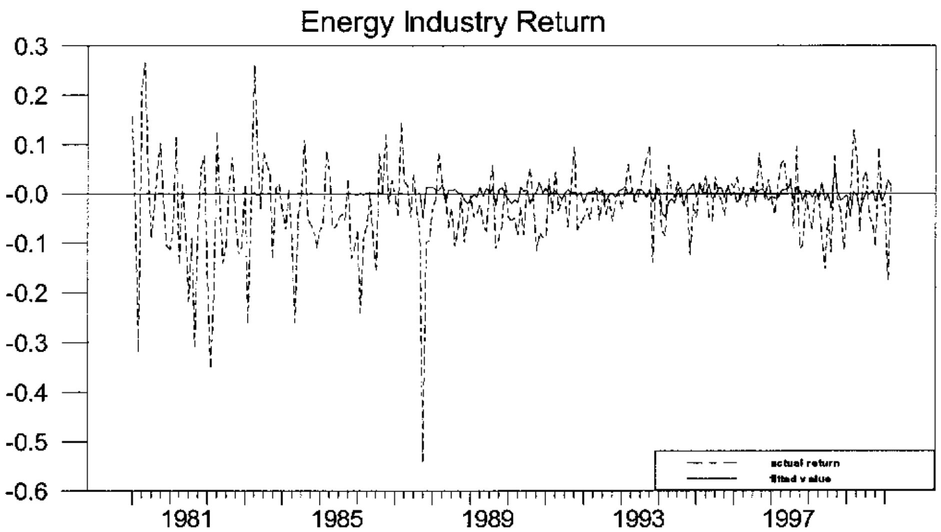
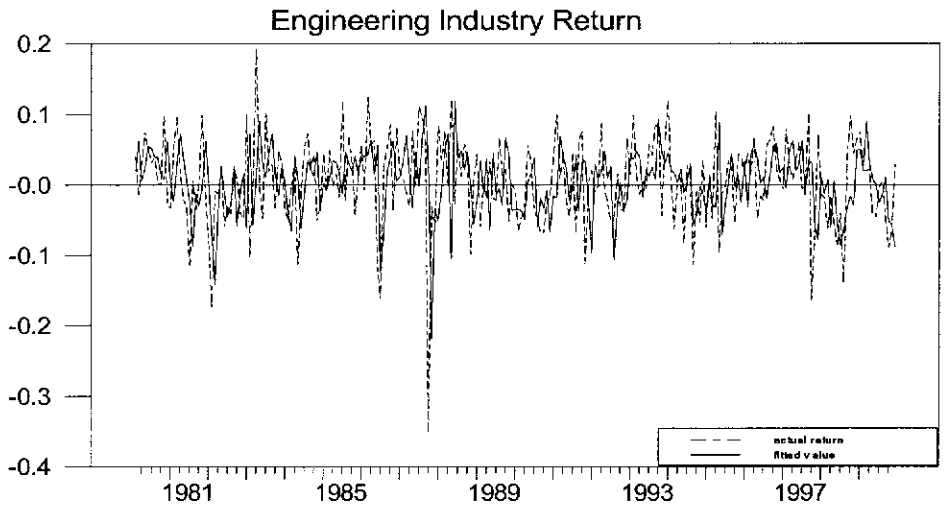


Figure 5.8: a. Multivariate model fitting Engineering Industry.
b. Univariate model fitting Engineering Industry.



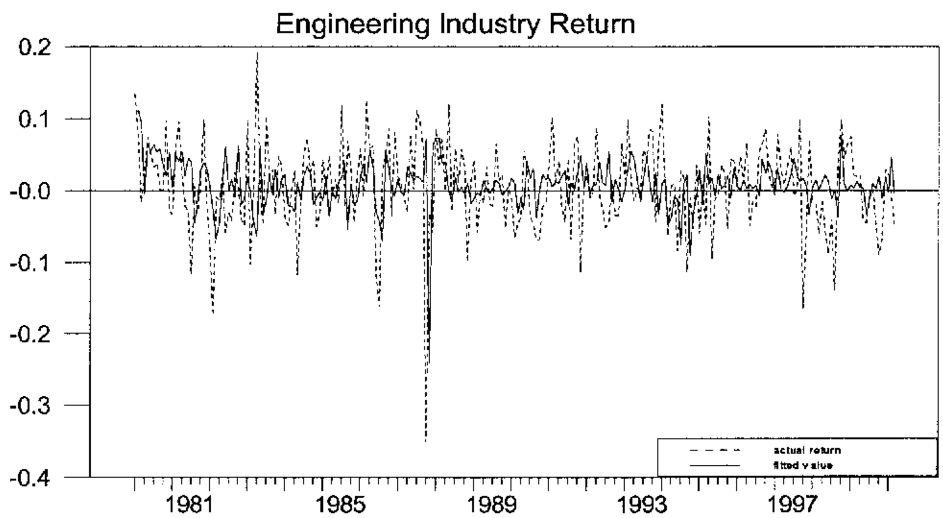
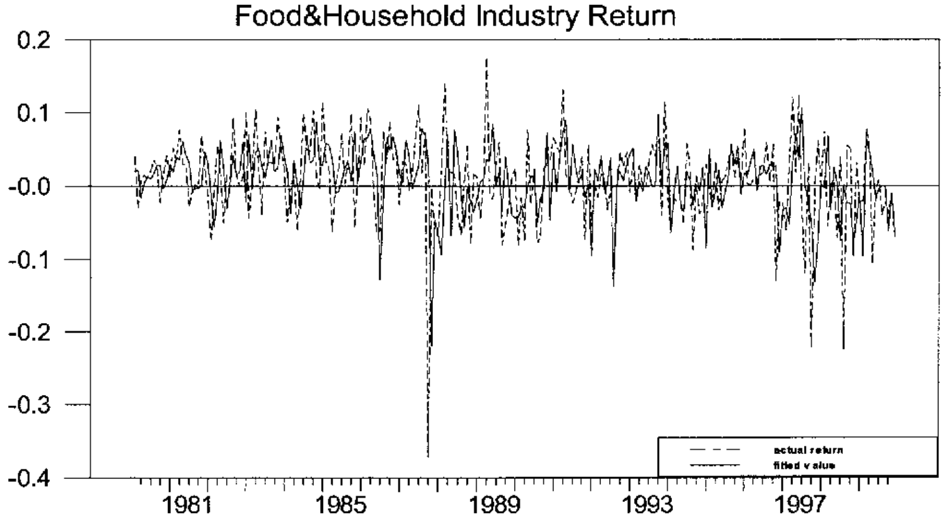


Figure 5.9: a. Multivariate model fitting Food and Household Industry.
b. Univariate model fitting Food and Household Industry.



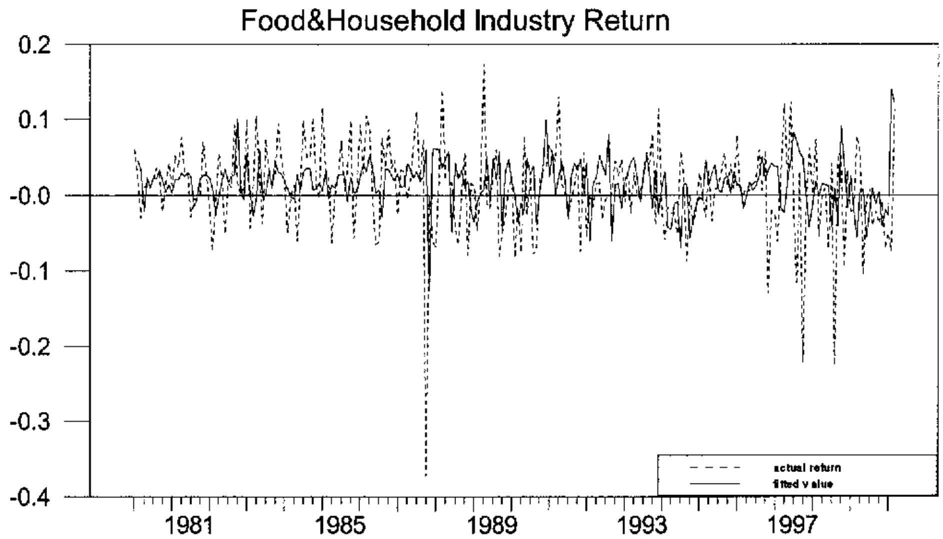


Figure 5.10: a. Multivariate model fitting Gold Industry.
b. Univariate model fitting Gold Industry.

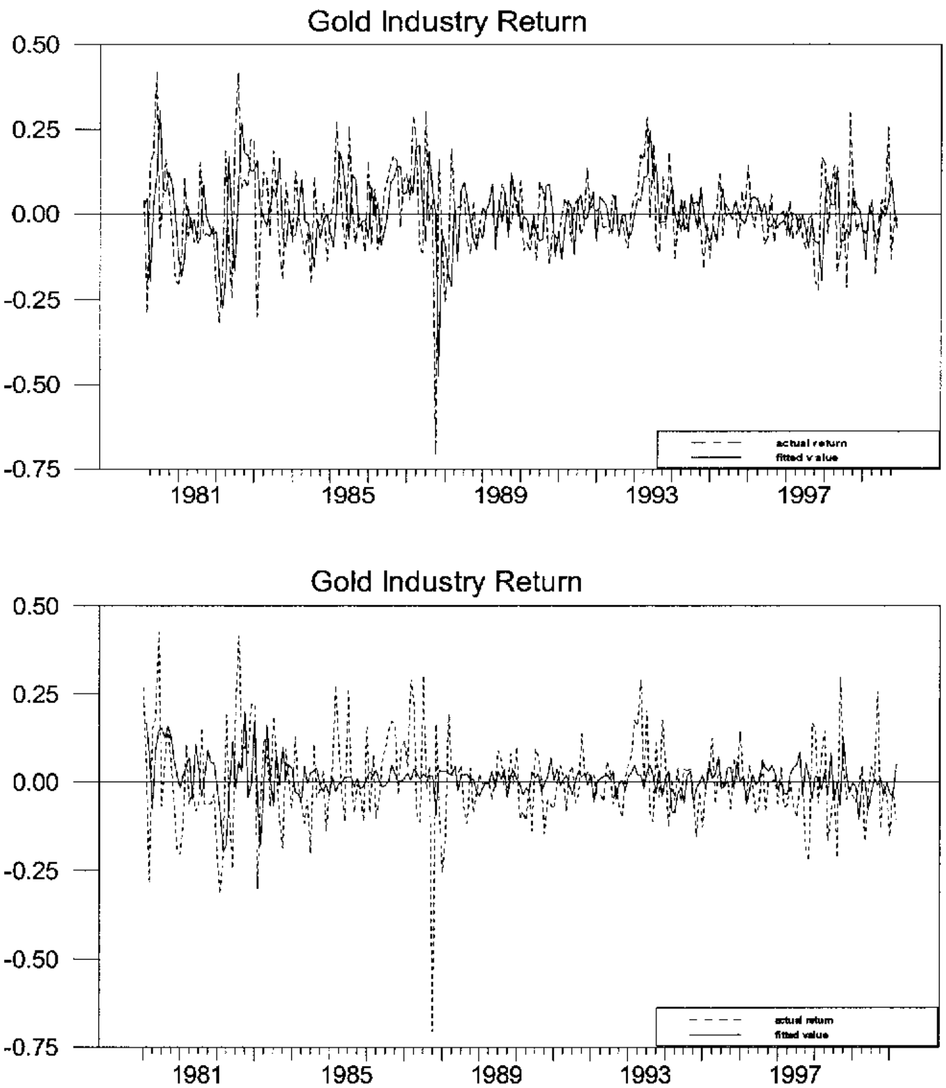
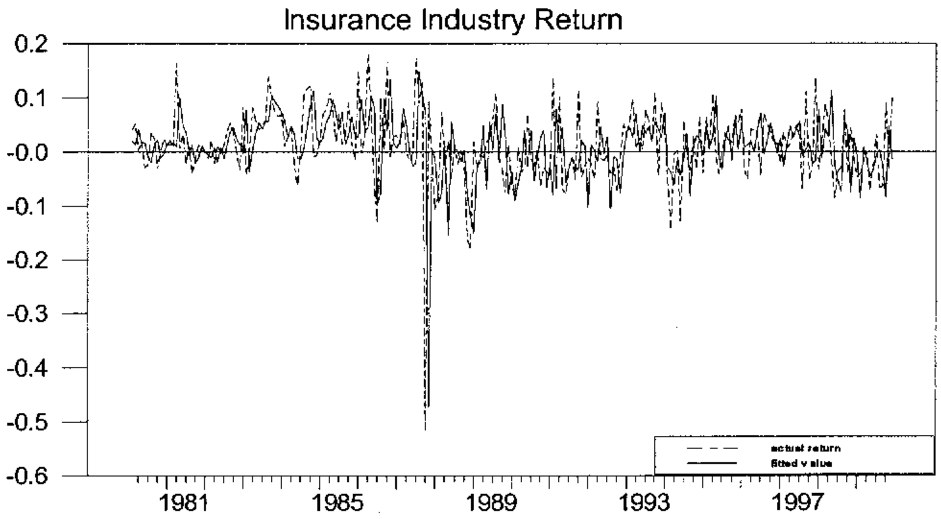


Figure 5.11: a. Multivariate model fitting Insurance Industry.
b. Univariate model fitting Insurance Industry.



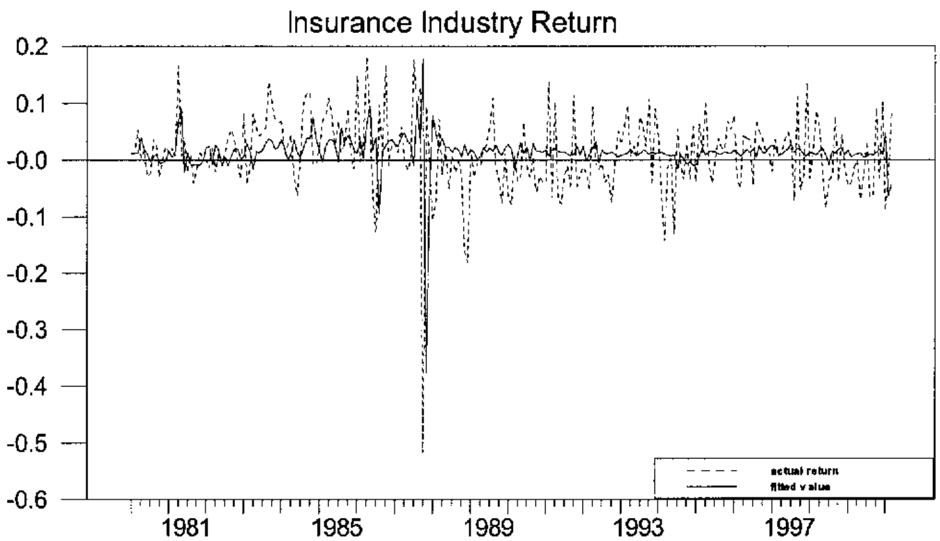
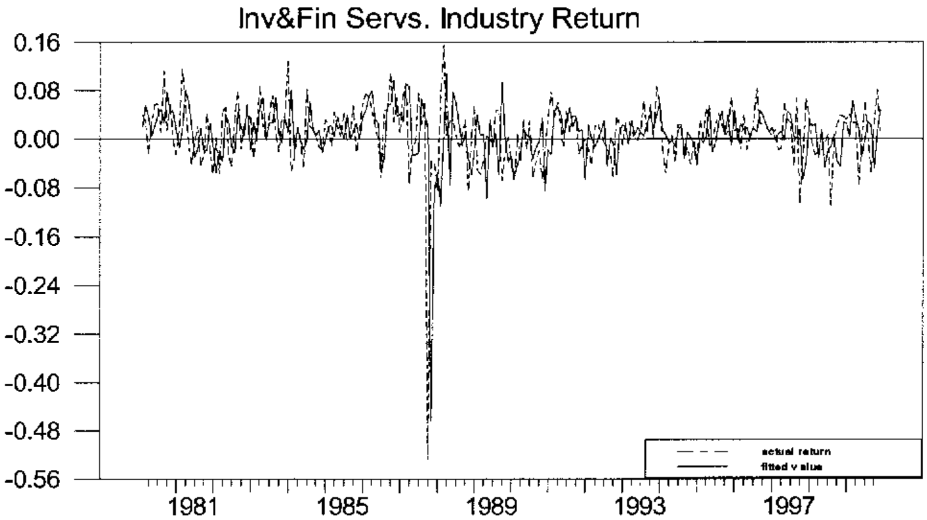


Figure 5.12: a. Multivariate model fitting Inv. & Fin. Services Industry.
b. Univariate model fitting Inv. & Fin. Services Industry.



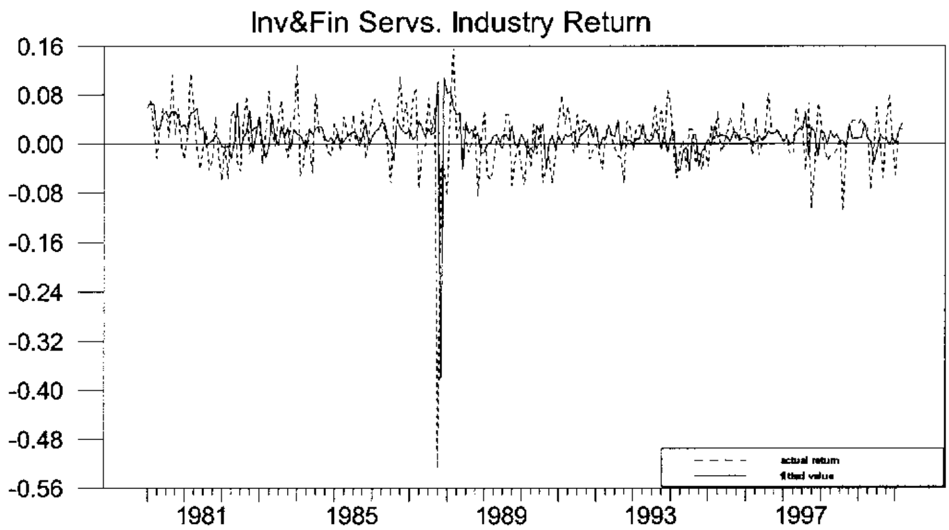
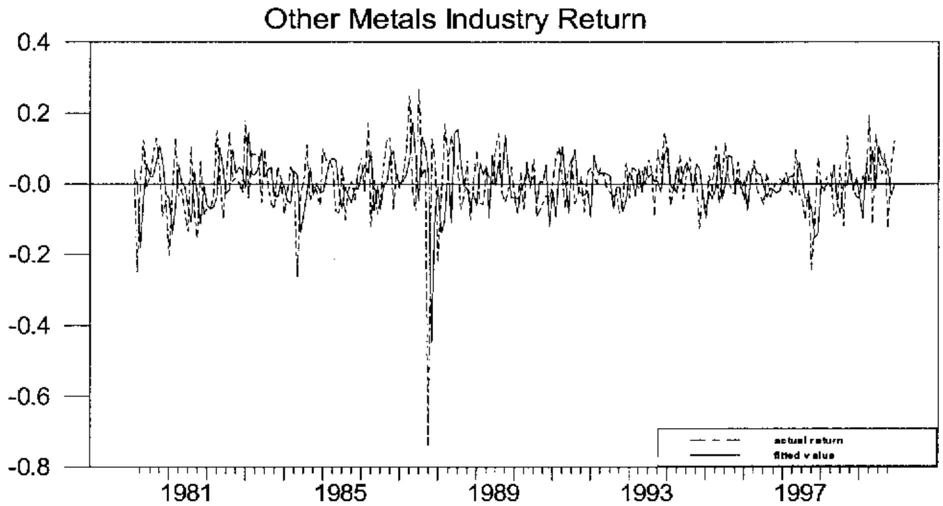


Figure 5.13: a. Multivariate model fitting Other Metals Industry.
b. Univariate model fitting Other Metals Industry.



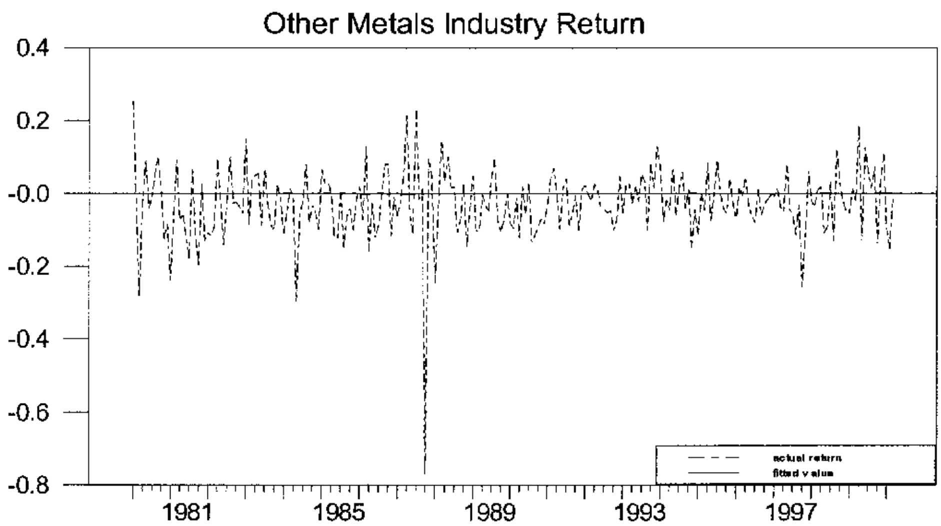
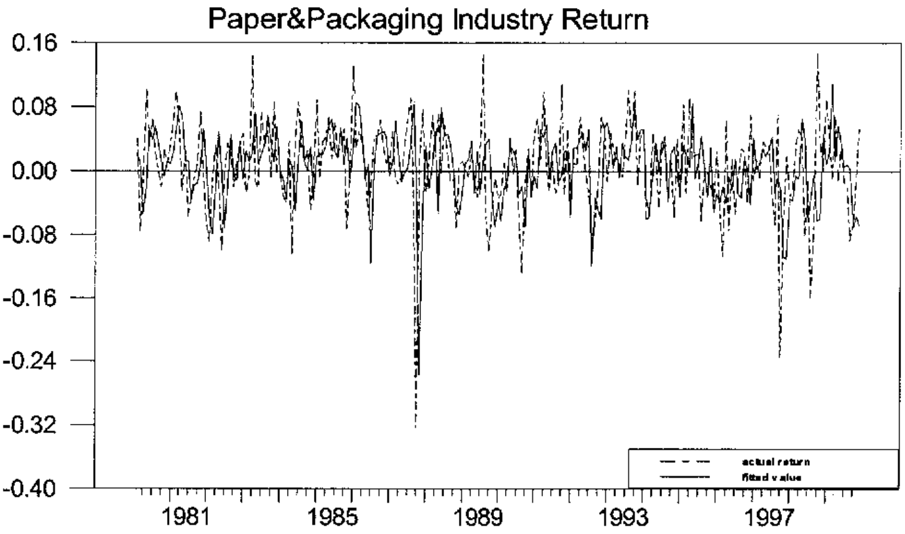


Figure 5.14: a. Multivariate model fitting Paper & Packaging Industry.
b. Univariate model fitting Paper & Packaging Industry.



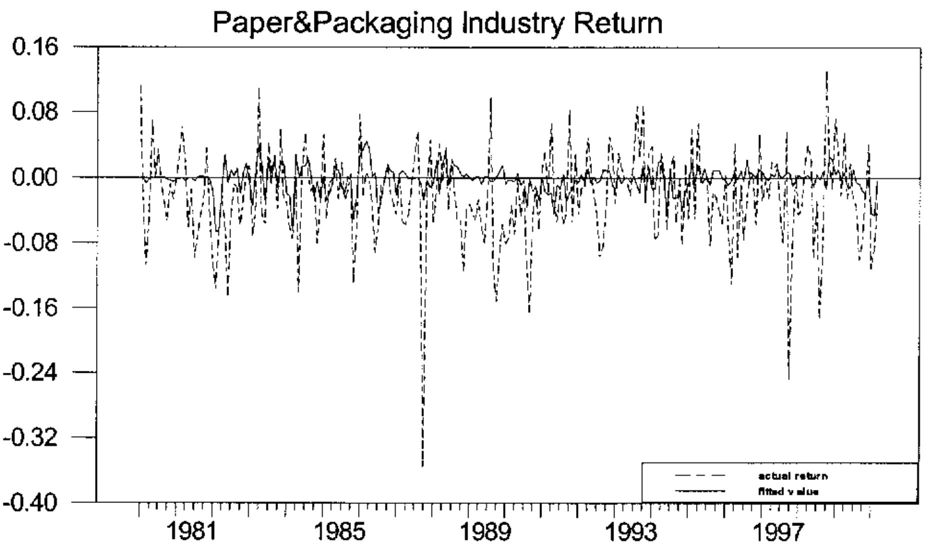
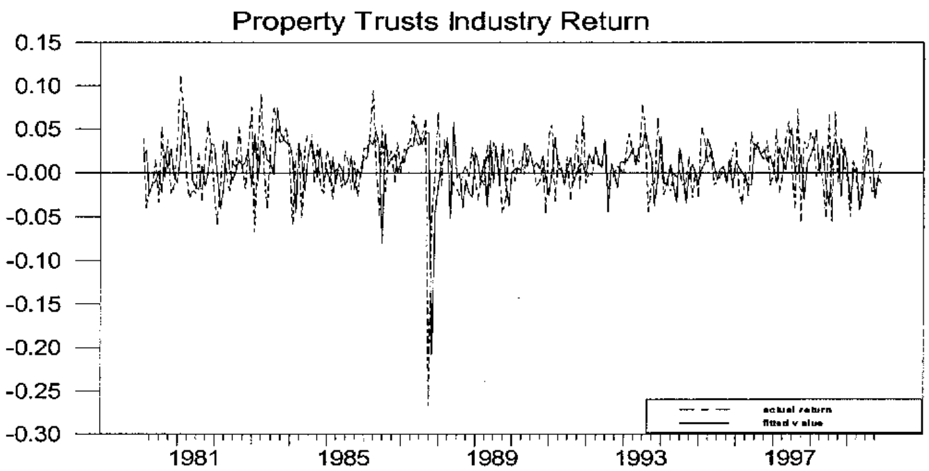


Figure 5.15: a. Multivariate model fitting Property Trusts Industry.
b. Univariate model fitting Property Trusts Industry.



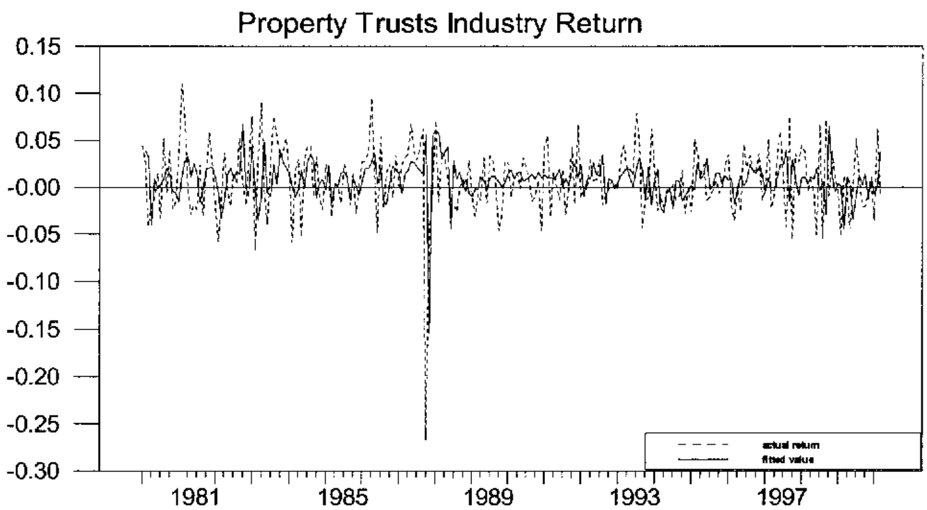


Figure 5.16: a. Multivariate model fitting Retail Industry.
b. Univariate model fitting Retail Industry.

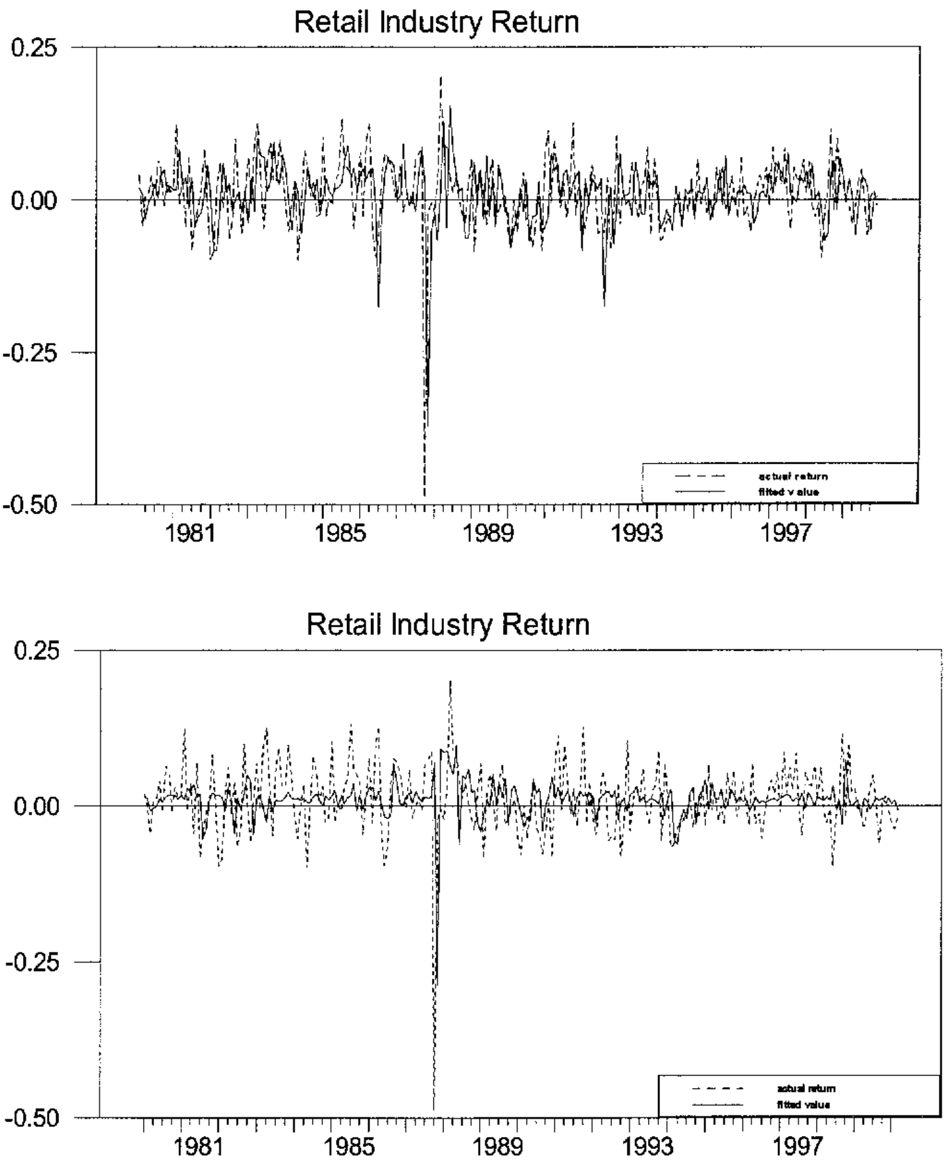
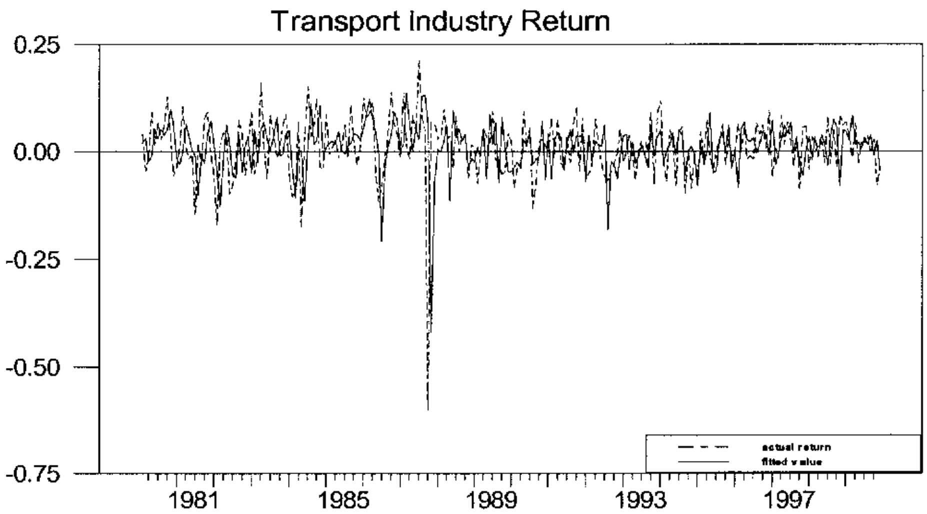


Figure 5.17: a. Multivariate model fitting Transport Industry.
b. Univariate model fitting Transport Industry.



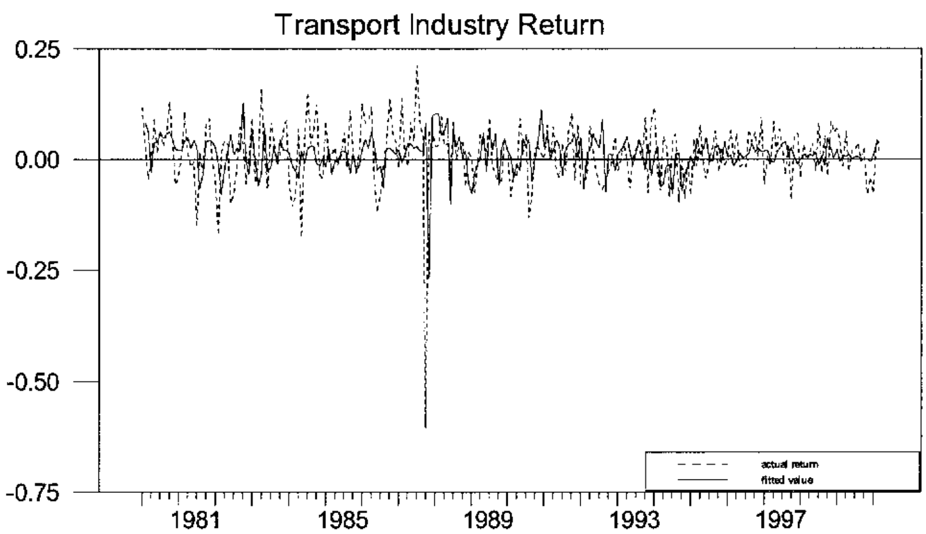


Figure 5.18: a. Multivariate model fitting Diversified Resources Industry.

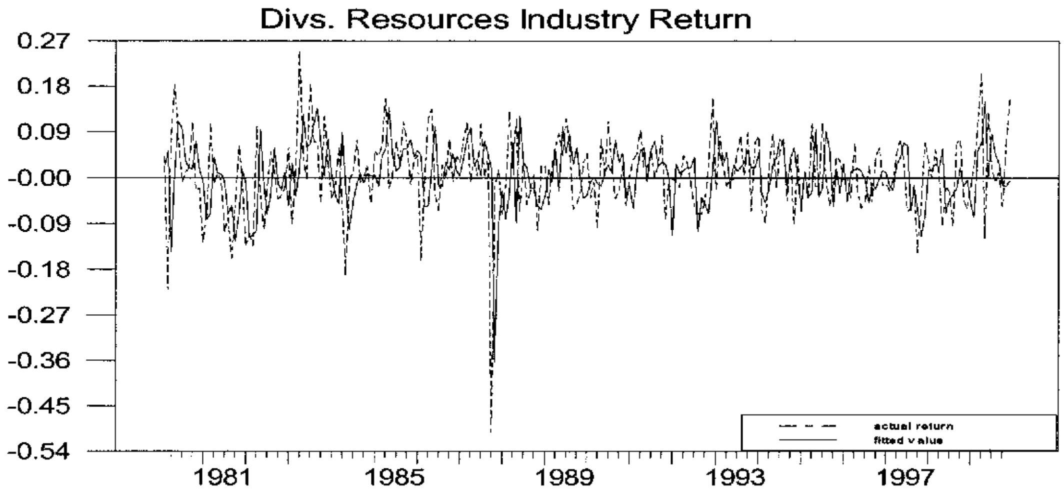
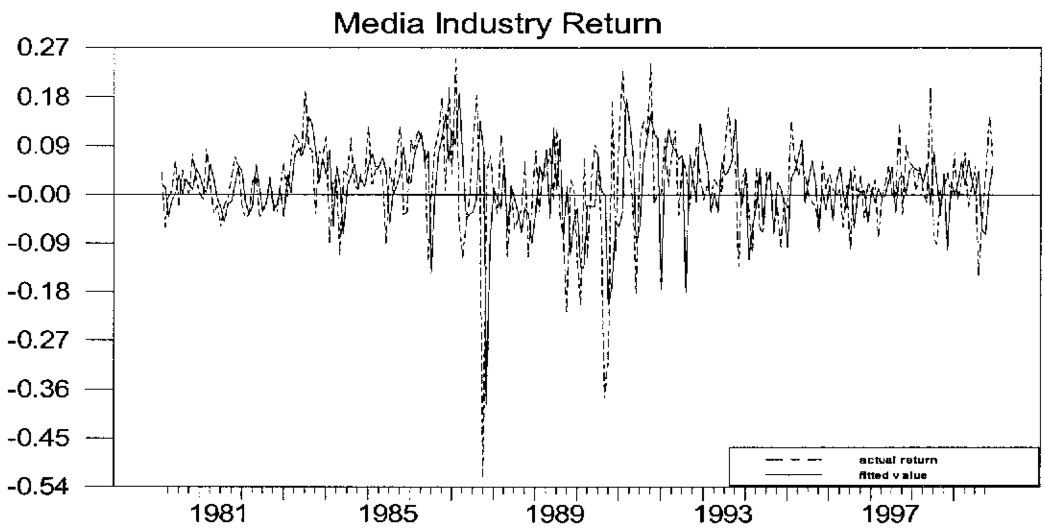


Figure 5.19: a. Multivariate model fitting Media Industry.



References

Abell, J. D. and Krueger, T. M. 1989, "Macroeconomic Influences on Beta", *Journal of Economics and Business*, vol. 41, pp.185-193.

Aggarwal, R., Hiraki, T. and Rao, R. 1988, "Earning/price ratios, size, and seasonal anaomalies in the Japanese Securities market", *working paper, John Carroll University*, Unviersity Heights, Ohio.

Alexander, G. and Benson, G., 1982, "More on Beta as a Random Coefficient", *Journal of Financial and Quantitative Analysis*, vol. 17, no. 1, pp 27-36.

Anderson, B. D. O. and Moore J. B., 1979, *Optimal Filtering.* Englewood Cliffs, Prentice-Hall, INC.

Ang, A. and Bekaert, G. 2003, "Stock Return Predictability: Is It There?" *working paper*, Columbia University and NBER, July, 2003.

Ariff, M. and Johnson, L.W. 1990, "Ex Ante Risk Premia on Macroeconomic Factors in the Pricing of Stocks: An Analysis Using Arbitrage Pricing Theory", in *Securities Markets and Stock Pricing*, Longman, Singapore, pp.194-204.

Asprem, M. 1989, "Stock prices, asset portfolios and macroeconomic variables in ten European countries", *Journal of Banking and Finance*, vol. 13, pp.589-612.

ASX Fact Book, 1999-2000, Australian Stock Exchange, Sydney.

Avramov, D. 2002, "Stock Return Predictability and Model Uncertainty", *Journal of Financial Economics*, vol. 64, pp. 423-458.

Ball, R., Brown, P., and Finn, F. J. 1977, "Share, Capitalisation Changes, Information and the Australian Equity Market", *Australian Journal of Management*, vol. 2 (Oct.), pp.105-125.

Ball, R. and Brown, P., 1980, "Risk and Return from Equity Investments in the Australian Mining Industry: January 1958-February 1979", *Australian Journal of Management*, vol. 5, pp. 45-66.

Balvers, R. J., Cosimano, Thomas F. and McDonald, B. 1990, "Predicting Stock Returns in an Efficient Market", *Journal of Finance*, vol. 45, no. 4 September, pp. 1109-1128.

Balvers, R. J., Wu, Y. and Gilliland, E. 2000, "Mean Reversion across National Stock Markets and Parametric Contrarian Investment Strategies", *Journal of Finance*, vol. 55, no. 2, pp. 745-772.

Banz, R. 1981, "The Relationship between Return and Market Value of Common Stock", *Journal of Financial Economics*, vol. 9, pp.3-18.

Barberis, N. 2000, "Investing for the Long Run when Returns Are Predictable", *Journal of Finance*, vol. 55, no. 1 (February), pp. 225-264.

Basu, S. 1977, "Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratio: A Test of the Efficient Market Hypothesis", *Journal of Finance*, vol. 32, pp.663-682.

Beenstock, M. and Chan, K. 1988, "Economic Forces in the London Stock Market", *Oxford Bulletin of Economics and Statistics*, vol. 50, pp. 27-39.

Beller, K. R., Kling, J. L. and Levinson, M. J. 1998, "Are Industry Stock Returns Predictable?" *Financial Analysts Journal*, vol. 54, no. 5, pp. 42-57.

Bilson, C. M., Brailsford, T. J. and Hooper, V. J. 2001, "Selecting Macroeconomic Variables as Explanatory Factors of Emerging Stock Market Returns", *Pacific-Basin Finance Journal*, vol. 9, pp. 401-426.

Black, A., Buckland, R. and Fraser, P. 2001, "Efficient Portfolio Diversification: Changing UK Stock Market Sector and Sub-sector Volatilities, 1967-2000", Department of Accountancy and Finance, University of Aberdeen.

Black, A. and Fraser, P. 1995, "U.K. Stock Returns: Predictability and Business Conditions", *Manchester School of Economic and Social Studies*, vol. 63, no. Special Supplement, pp. 85-102.

Black, A., Fraser, P. and Groenewold, N. 2003a, "How Big is the Speculative Component in Australian Share Prices?" *Journal of Economics and Business*, vol. 55, pp. 177-195.

Black, A., Fraser, P. and Groenewold, N. 2003b, "US Stock Prices and Macroeconomic Fundamentals", *International Review of Economics and Finance*, vol. 188, pp. 1-23.

Black, A., Fraser, P. and Power, D. 1992, "UK Unit Trust Performance 1980-1989: A Passive Time-Varying Approach", *Journal of Banking and Finance*, vol. 16, pp. 1015-1033.c

Black, F., Jensen, M. C. and Scholes, M. 1972, 'The Capital Asset Pricing Models: Some Empirical Tests", in M. C. Jensen, ed., *Studies in the Theory of Capital Markets*, New York: Praeger.

Blume, M. E. 1971, "On the Assessment of Risk", *Journal of Finance*, vol. 26, pp. 275-288.

Blume, M. E. 1975, "Betas and the Regression Tendencies", *Journal of Finance*, vol. 30, no. 3, pp. 785-795.

Bodie, Z. 1976, "Common Stocks as a Hedge against Inflation", *Journal of Finance*, vol. 31, no. May, pp. 459-470.

Bos, T. and Ferson, T. A. 1992, "Market Model Nonstationarity in the Korean Stock Market", in *Pacific Basin Capital Market Research*, vol. 3, Elsevier Science Publishers, Amsterdam.

Bos, T., Ferson, T. A., Martikainen, T. and Perttunen, J. 1995, "The International Co-movements of Finnish Stocks", *The European Journal of Finance,* vol. 1, pp. 95-111.

Bos, T. and Newbold, P., 1984, "An Empirical Investigation of the Possibility of Stochastic Systematic Risk in the Market model", *Journal of Business*, vol. 57, no. 1, pp.35-42.

Boudoukh, J., Richardson, M. and Whitelaw, R. F. 1994, "Industry Returns and the Fisher Effect", *Journal of Finance*, vol. 49, no. 5 December, pp. 1595-1616.

Boyle, G. W. and Young, L. 1988, "Asset Prices, Commodity Prices, and Money: A General Equilibrium, Rational Expectations Model", *American Economic Review*, vol.78, no. 1, pp.24-45.

Brailsford, T. J. 1992, "A Test for the Winner-Loser Anomaly in the Australian Equity Market: 1958-1987", *Journal of Business Finance and Accounting,* vol. 19, no. 2 (January), pp. 225-241.

Brailsford, T. J. and Faff R. W. 1996, "An Evaluation of Volatility Forecasting Techniques", *Journal of Banking and Finance* vol. 20, pp. 419-438.

Breeden, D. T., Gibbons, M. T. and Litzenberger, R. H. 1989, "Empirical Tests of the Consumption-Oriented CAPM", *Journal of Finance*, vol. 44, no. 2 June, pp. 231-262.

Brenner, M., and Smidt, S. 1977, "A Simple Model of Non-stationary of Systematic Risk", *Journal of Finance,* vol. 32, no. 4, pp. 1081-1092.

Brooks, R. D. and Faff, R. W. 1995, "Financial Market Deregulation and Bank Risk: Testing for Beta Instability", *Australian Economic Papers*, vol. 34, pp. 180-199.

Brooks, R. D. and Faff, R. W. 1997, "Financial Deregulation and Relative Risk of Australian Industry", *Australian Economic Papers*, vol. 36, pp. 308-320.

Brooks, R. D., Faff, R. W. and Ariff, M. 1998, "An Investigation into the Extent of Beta Instability in the Singapore Stock Market", *Pacific-Basin Finance Journal*, vol. 6, pp. 87-101.

Brooks, R. D., Faff, R. W. and Lee, J. H. H. 1992, "The form of Time Variation of Systematic Risk - Some Australian Evidence", *Applied Financial Economics,* vol. 2, pp. 191-198.

Brooks, R. D., Faff, R. W. and Lee, J. H. H. 1994, "Beta Stability and Portfolio Formation", *Pacific Basin Finance Journal,* vol. 2, pp. 463-479.

Brooks, R. D., Faff, R. W. and McKenzie, M. D. 1998, "Time-Varying Beta Risk of Australian Industry Portfolios: A Comparison of Modelling Techniques", *Australian Journal of Management,* vol. 23, no. 1, June, pp. 1-22.

Brooks, R. D., Faff, R. W., Mckenzie, M. D. and Mitchell, H. 2000, "A Multi-country Study of Power ARCH Models and National Stock Market Returns", *Journal of International Money and Finance*, vol. 19, pp. 377-397.

Brooks, R. D., Faff, R. W., and Josev, T. 2001, "An Empirical Investigation of the Cross-Industry Variation in Mean Reversion of Australian Stock Betas", *Pacific Accounting Review*, vol. 13, no. 2, pp.1-16.

Buckland, R. and Fraser, P. 2002, "The Scale and Patterns of Abnormal Returns to Equity Investment in UK Electricity Distribution", *Global Finance Journal*, vol. 13, pp. 39-62.

Calvet, A. and Lefoll, J. 1989, "Risk and Return on Canadian Capital Markets: Seasonality and Size Effect", *Finance*, vol. 10, pp.21-39.

Campagnoli, P., Muliere, P. and Petrone, S., 2001, "Generalized Dynamic Linear Models for Financial Time Series." *Applied Stochastic Models in Business and Industry* vol. 17: pp. 27-39.

Campbell, J. Y. 1987, "Stock Returns and the Term Structure", *Journal of Financial Economics*, vol. 18, no. June, pp. 373-400.

Campbell, J. Y. 1991, "A Variance Decomposition for Stock Returns", *Economics Journal*, vol. 101, pp.157-179.

Campbell, J. Y. and Hamao, Y. 1992 "Predictable Returns in the United States and Japan: A Study of Long-term Capital Market Integration", *Journal of Finance*, vol. 47, no. 1, pp.43-70.

Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y., 2001, "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk", *Journal of Finance*, Vol. 56, pp. 1-44.

Campbell, J. Y. and Yogo, M. 2003, "Efficient Tests of Stock Market Predictability", *NBER Working Paper Series*, National Bureau of Economic Research, October, 2003.

Castagna, A. D. and Matolcsy, Z. P. 1978, "The Relationship between Accounting Variables and Systematic Risk and the Prediction of Systematic Risk", *Australian Journal of Management*, vol. 3, pp. 113-126.

Cavaglia, S., Brightman, C. and Aked, M. 2000, "The Increasing Importance of Industry Factors", *Financial Analyst Journal*, vol. 56, no. 5 (September/October), pp. 41-54.

Chaudhuri, K. and Wu, Y. 2003, "Random Walk Versus Breaking Trend in Stock Prices: Evidence from Emerging Markets", *Journal of Banking and Finance*, vol. 27, pp. 575-592.

Chelley-Steeley, P. 2001, "Mean Reversion in the Short-Horizon Returns of UK Portfolios", *Journal of Business Finance and Accounting*, vol. 28, no. 1 and 2, (January/March), pp. 107-126.

Chen, N.-F., Roll, R. and Ross, S. A. 1986, "Economic Forces and the Stock Market", *Journal of Business*, vol. 59, no. 3, pp. 383-403.

Cheng, A. C. S., 1995, "The UK Stock Market and Economic Factors: A New Approach", *Journal of Business Finance and Accounting*, vol. 22, January, no. 1, pp. 130-142.

Cheng, J. W. 1997, "A Switching Regression Approach to the Stationarity of Systematic and Non-systematic Risks: the Hong Kong Experience", *Applied Financial Economics,* vol. 7, no. 1, pp. 45-58.

Cheung, K. Y. 1993, "Short-term Interest Rates as Predictors of Inflation Revisited: a Signal Extraction Approach", *Applied Financial Economics*, vol. 3, pp. 113-118.

Chordia, T. and Shivakumar, L. 2002, "Momentum, Business Cycle, and Time-varying Expected Returns", *Journal of Finance*, vol. 57, no. 2, pp. 985-1019.

Chordia, T. and Swaminathan, B. 2000, "Trading Volume and Cross-Autocorrelations in Stock Returns", *Journal of Finance*, vol. 55, no. 2, pp. 913-935.

Chou, S. R. and Johnson, K. 1990, "An Empirical Analysis of Stock Market Anomolies: Evidence from the Republic of China in Taiwan", in S.G. Rhee and R.P. Chang (eds.), *Pacific-Basin Capital Markets Research*, vol. I, North Holland, Amsterdam.

Chung, Y. P. and Zhou, Z. G. 1995, "The Predictability of Stock Returns - A Nonparametric Approach", *Econometric Review*, vol. 15, pp. 299-330.

Clare, A. D. and Thomas, S. H. 1994, "Macroeconomic Factors, the APT and the UK Stock Market", *Journal of Business Finance and Accounting*, vol. 46, no. 1, pp. 209-237.

Cochrane, J. H. 1988, "How Big is the Random Walk in GNP?", *Journal of Political Economy*, vol. 96, pp. 893-920.

Cochrane, J. H. 1994, "Permanent and Transitory Components of GNP and Stock Prices", *Quarterly Journal of Economics,* vol. 109, pp.241-265.

Cochrane, J. H. and DeFina, R. H. 1995, "New Evidence on Predictability in World Equity Markets", *Journal of Business Finance and Accounting*, vol. 22, pp. 845-854.

Collins, D. W., Ledolter, J. and Rayburn, J. 1987, "Some Further Evidence on the Stochastic Properties of Systematic Risk", *Journal of Business,* vol. 60, no. 3, pp. 425-448.

Cooper, M. J., Jakson III, W. E. and Patterson, G. A. 2002, "Evidence of Predictability in the Cross-section of Bank Stock Returns", *Journal of Banking and Finance*, Uncorrected Proof.

Conrad, J. and Kaul, G. 1988, "Time-Variation in Expected Returns", *Journal of Business*, vol. 61, pp.409-425.

Conrad, J. and Kaul, G. 1989, "Mean Reversion in Short-Horizon Expected Returns", *Review of Financial Studies*, vol. 2, pp.225-240.

Corhay, A., Hawawini, G. and Michel, P. 1987, "The Pricing of Equity on the London Stock Exchange: Seasonality and Size Premium", in E. Dimson (ed.), *Stock Market Anomalies*, Cambridge University Press, Cambridge.

Cutler, D. M., Poterba, J. M. and Summers, L. H. 1989, "What Moves Stock Prices?" *Journal of Portfolio Management*, vol. 15, pp. 4-12.

Daniel, K., Hirshleifer, D. and Subrahmanyam, A. 1998, "Investor Psychology and Security Market Under- and Overreactions", *Journal of Finance*, vol. 53, no. 6 (December), pp. 1839-1886.

Darling, J. 2000, "Momentum Strategies: Evidence from the Australian Stock Market", *Honours Dissertation*, University of Technology, Sydney.

Dawid, A. P., 1981, "Some Matrix-variate Distribution Theory: Notational Considerations and a Bayesian Application", *Biometrika*, vol. 68, pp. 265-274.

DeJong, D. V. and Collins, D. W. 1985, "Explanations for the Instability of Equity Beta: Risk-Free Rate Changes and Leverage Effects", *Journal of Financial and Quantitative Analysis*, vol. 20, no. 1, pp. 73-94.

Demir, I., Muthuswamy, J. and Walter, T. 2002, "Momentum Returns in Australian Equities: The Influence of Size, Risk, Liquidity and Return Computation", Conference Paper, *The 2002 APFA/PACAP/FMA Finance Conference*, July 14-17, Tokyo.

Diether, K. B., Malloy, C. J. and Scherbina, A. 2002, "Differences of Opinion and the Cross Section of Stock Returns", *Journal of Finance*, vol. 57, no. 5, pp. 2113-2142.

Dimson, E. and Marsh, P. R. 1983, "The Stability of UK Risk Measures and the Problem of Thin Trading", *Journal of Finance*, vol. 38, no. 3, pp.753-783.

Ding, Z. and Granger, C. W. J. 1996, "Modelling Volatility Persistence of Speculative Returns: A New Approach", *Journal of Econometrics*, vol. 73, pp.185-215.

Ding, Z., Granger, C. W. J. and Engle, R. F. 1993, "A Long Memory Property of Stock Market Returns and A New Model", *Journal of Empirical Finance*, vol. 1, pp. 83-105.

Doan, T., Litterman, R. and Sims, C., 1984, "Forecasting and Conditional Projection Using Realistic Prior Distributions", *Econometric Reviews* vol. 3, no.1, pp.1-100.

Durbin, J. and Koopman, S. J. 2001, *Time Series Analysis by State Space Methods*, Oxford University Press, Oxford.

Elgers, P. T., Haltiner, J. R. and Hawthorne, W. H., 1979, "Beta Regression Tendencies: Statistical and Real Causes", *Journal of Finance*, vol. 34, no. 1, pp.261-263.

Engle, R. and Watson M., 1981, "A One Factor Multivariate Time Series of Metropolitan Wage Rates." *Journal of American Statistical Association* vol. December, pp. 774-781.

Episcopos, A. 1996, "Stock Return Volatility and Time-Varying Betas in the Toronto Stock Exchange", *Quarterly Journal of Business and Economics*, vol. 35, no. 4, pp.28-38.

Fabozzi, F. and Francis, J., 1978, "Beta as Random Coefficient", *Journal of Financial and Quantitative Analysis*, vol. 13, no. 1, pp 106-116.

Faff, R. W., 1988, "An Empirical Test of the Arbitrage Pricing Theory on Australian Stock Returns 1974-85", *Accounting and Finance*, vol. 28, no. 2, pp. 23-43.

Faff, R. W. and Brooks, R. D. 1998, "Time-Varying Beta Risk for Australian Industry Portfolios: an Exploratory Analysis", *Journal of Business Finance and Accounting,* vol. 25, no. 5 and 6 June/July, pp. 721-745.

Faff, R. and Chan, H. 1998, "A Multifactor Model of Gold Industry Stock Returns: Evidence from the Australian Equity Market", *Journal of Financial Economics*, vol. 8, no.1 February, pp. 21-28.

Faff, R. and Heaney, R. 1999, "An Examination of the Relationship between Australian Industry Equity Returns and Expected Inflation", *Applied Economics*, vol. 31, pp. 915-933.

Faff, R. W., Lee, J. H. H. and Fry, T. R. L. 1992, "Time Stationarity of Systematic Risk: Some Australian Evidence", *Journal of Business Finance and Accounting,* vol. 19, pp. 253-270.

Fama, E. F. 1970, "Efficient Capital Markets: A Review of Theory and Empirical Work", *Journal of Finance*, vol. 25, pp.383-417.

Fama, E. F. 1976, "Forward Rates as Predictors of Future Spot Rates", *Journal of Financial Economics*, vol. 3, pp. 631-377.

Fama, E. F. 1981, "Stock Returns, Real Activity, Inflation, and Money", *American Economic Review*, vol. 71, no. September, pp. 545-565.

Fama, E. F. 1984, "The Information in the Term Structure", *Journal of Financial Economics*, vol. 13, pp. 509-528.

Fama, E. F. 1986, "Term Premiums and Default Premiums in Money Markets", *Journal of Financial Economics*, vol. 17, pp. 175-196.

Fama, E. F. 1990, "Stock Returns, Expected Returns and Real Activity", Journal of Finance, vol. 45, no. 4, pp. 1089-1108.

Fama, E. F. 1991, "Efficient Capital Markets: II", *Journal of Financial Economics*, vol. 46, no. 5, pp. 1575-1617.

Fama, E. F. 1995, "Random Walks in Stock Market Prices", *Financial Analyst Journal*, January/February, pp. 55-59.

Fama, E. F. 1998, "Market Efficiency, Long-Term Returns, and Behavioral Finance", *Journal of Financial Economics*, vol. 49, pp. 283-306.

Fama, E. F. and Bliss, R. R. 1987, "The Information in Long-Maturity Forward Rates", *American Economic Review*, vol. 77, pp. 680-692.

Fama, E. F. and French, K. R. 1988a, "Permanent and Temporary Components of Stock Prices", *Journal of Political Economy*, vol. 96, pp. 246-273.

Fama, E. F. and French, K. R. 1988b, "Dividend Yields and Expected Stock Returns", *Journal of Financial Economics*, vol. 22, pp. 3-26.

Fama, E. F. and French, K. R. 1989, "Business Conditions and Expected Returns on Stocks and Bonds", *Journal of Financial Economics*, vol. 25, no. 1 November, pp. 23-49.

Fama, E. F. and French, K. R. 1992, "The Cross Section of Expected Stock Returns", *Journal of Finance*, vol. 47, pp.427-466.

Fama, E. F. and French, K. R. 1993, "Common Risk Factors in the Returns on Stocks and Bonds", *Journal of Financial Economics*, vol. 33, pp.3-56.

Fama, E. F. and Gibbons, M. R. 1982, "Inflation, Real Returns and Capital Investment", *Journal of Monetary Economics*, vol. 9, pp.297-323.

Fama, E. F. and MacBeth, J. 1973, "Risk, Return, and Equilibrium: Empirical Tests", *Journal of Political Economy*, vol. 81, no. 3, pp.607-637.

Fama, E. F. and Schwert, G. W. 1977, "Asset Returns and Inflation", *Journal of Financial Economics*, vol. 5, no. November, pp. 115-146.

Ferson, W. E. and Harvey, C. R., 1991a, "Sources of Predictability in Portfolio Returns", *Financial Analysts Journal*, vol. 47, no. 3, pp. 49-56.

Ferson, W. E. and Harvey, C. R., 1991b, "The Variation of Economic Risk Premiums", *Journal of Political Economy*, vol. 99, no. 2, pp. 385-415.

Ferson, W. E. and Harvey, C. R. 1998, "Fundamental Determinants of National Equity Market Returns: A Perspective on Conditional Asset Pricing", *Journal of Banking and Finance*, vol. 21, pp. 1625-1665.

Ferson, W. E. and Harvey C. R. 1999, "Economic, Financial and Fundamental Global Risk in and out of EMU", *Swedish Economic Policy Review,* vol.6, pp.123-184.

Ferson, W. E. and Korajczyk, R. A. 1995, "Do Arbitrage Pricing Models Explain the Predictability of Stock Returns?", *Journal of Business*, vol. 68, no. 3, pp.309-349.

Fischer, D. E. and Jordan, R. J. 1987, *Security Analysis and Portfolio Management*, 4th ed., Prentice-Hall, INC., New Jersey.

Fisher, L. 1971, "On the Estimation of Systematic Risk", *Proceedings of the Wells Fargo Symposium*, July 26-28, 1971.

Fletcher, J. 2001, "An Examination of Predictable Risk and Return in UK Stock Returns", *Journal of Economics and Business*, vol. 53, pp. 527-546.

Foger, H. R., John, K. and Tipton J. 1981, "Three Factors, Interest Rate Differentials and Stock Group", *Journal of Finance*, vol. 36, pp.323-335.

Francis, J. C., 1979, "Statistical Analysis of Risk Surrogates for NYSE Stocks", *Journal of Financial and Quantitative Analysis,*, vol. 14, pp. 981-997.

French, K. R. and Roll, R., 1986, "Stock Return Variances: the Arrival of Information and Reaction of Traders", *Journal of Financial Economics*, vol. 17, pp. 5-26.

French, K. R., Schwert, G. W. and Stambaugh, R. F. 1987, "Expected Stock Returns and Volatility", *Journal of Financial Economics*, vol. 19, no. September, pp. 3-30.

Fung, H. G. and Lie, C. J. 1990, "Stock market and economic activities: a causal analysis", *Pacific-Basin Capital Markets Research* vol. 2, pp.203-214.

Fuller, R. J. and Kling, J. L. 1990, "Is the Stock Market Predictable?" *Journal of Portfolio Management*, vol.16, no. 4, pp. 28-36.

Fuller, R. J. and Kling, J. L. 1994, "Can Regression-Based Models Predict Stock and Bond Returns?" *Journal of Portfolio Management*, vol. 20, no. 3 spring, pp.56-63.

Gallgher, L. A. 1999, "A Multi-country Analysis of the Temporary and Permanent Component of Stock Prices", *Applied Financial Economics*, vol. 9, pp. 129-142.

Gallagher, L. A. and Taylor, M. P. 2000, "Measuring the Temporary Component of Stock Prices: Robust Multivariate Analysis", *Economic Letters*, vol. 67, pp. 193-200.

Gallagher, L. A. and Taylor, M. P. 2002, "Permanent and Temporary Components of Stock Prices: Evidence from Assessing Macroeconomic Shocks", *Southern Economic Journal*, vol. 69, no. 2, pp. 345-362.

Gangemi, M., Brooks, R. and Faff, R., 1999, "Mean Reversion and the Forecasting of Country Betas: a Note", *Global Finance Journal*, vol. 10, no. 2, pp. 231-245.

Gangemi, M., Brooks, R. and Faff, R., 2000, "Modelling Australia's Country Risk: A County Beta Approach", *Journal of Economics and Business*, vol. 52, pp. 259-276.

Gao, J. 2002, "Estimation of Continuous-time Financial Models with Long-range Dependence", working paper, School of Mathematics and Statistics, The University of Western Australia, Perth, Australia.

Gjerde, Øystein and Sættem, F. 1999, "Causal Relations among Stock Returns and Macroeconomic Variables in a Small, Open Economy", *Journal of International Financial Markets*, vol. 9, pp. 61-74.

Granger, C. W. J., 1992, "Forecasting Stock Market Prices: Lessons for Forecasters." *International Journal of Forecasting*, vol. 8, pp.3-13.

Grauer, R. R., Hakansson, N. H. and Shen, F. C. 1990, "Industry Rotation in the U.S. Stock Market: 1934-1986 Returns on Passive, Semi-Passive, and Active Strategies", *Journal of Banking and Finance*, vol. 14, no. 2/3 August, pp. 513-538.

Greb, T. and Reyes, M. G. 2001, "Time-Varying Betas in an Emerging Stock Market: The Case of Brazil", *American Business Review*, January, 2001, pp. 118-124.

Griffiths, W. E., Hill, R. C. and Judge, G. G. 1993, *Learning and Practicing Econometrics*, John Wiley and Sons, New York.

Griffin, J. M. and Lemmon, M. L. 2002, "Book-to-Market Equity, Distress Risk, and Stock Returns", *Journal of Finance*, vol. 57, no. 5, pp. 2317-2337.

Groenewold, N. 1997, "Share Market Efficiency: Testing Using Daily Data for Australia and New Zealand", *Applied Financial Economics* vol. 7, pp. 645-657.

Groenewold, N. and Fraser, P. 1997, "Share Prices and Macroeconomic Factors", *Journal of Business and Accounting,* vol. 24, no. 9 and 10 October and December, pp. 1367-1383.

Groenewold, N. and Fraser, P. 1999, "Time-varying Estimates of CAPM Betas", *Mathematics and Computers in Simulation*, vol. 48, pp.531-539.

Groenewold, N. and Fraser, P. 2002, "Violation of the iid-normal Assumption: Effects on Tests of Asset-pricing Models Using Australian Data", *International Review of Financial Analysis*, vol. 11, pp. 491-510.

Groenewold, N. and Kang, K. C. 1992, "The Semi-Strong Efficiency of the Australian Share Market", *Discussion Paper 1992-01*, Department of Economics, University of Tasmania.

Grundy, B. and Martin, S. 2001, "Understanding the Nature of the Risks and the Source of the Rewords to Momentum Investing", *Review of Financial Studies*, vol. 14, pp. 29-78.

Halliwell, J., Heaney, R. and Sawicki, J. 1999, "Size and Book to Market Effects in Australian Share Markets: A Time Series Analysis", *Accounting Research Journal*, vol. 12, no. 2, pp.122-137.

Hamada, R. S. 1972, "The Effect of the Firm's Capital Structure on the Systematic Risk of Common Stocks", *Journal of Finance*, vol. 27, pp. 435-452.

Hamao, Y. 1988, "An Empirical Examination of the Arbitrage Pricing Theory: Using Japanese Data", *Japan and the World Economy*, vol. 1, pp. 45-61.

Harrison, P. J. and West, M., 1986, *Bayesian Forecasting in Practice*, Bayesian Statistics Study Year Report 13, University of Warwick.

Harrison, P. J. and West, M. 1987, "Practical Bayesian Forecasting", *The Statistician*, vol. 36, pp. 115-125.

Harvey, C. R. 1981, *Time Series Models*, Oxford: Philip Allan and Humanities Press.

Harvey, C. R. 1989, *Forecasting Structural Time Series Models and the Kalman filter*, Cambridge University Press, Cambridge.

Hawawini, G. 1991, "Stock Market Anomalies and the Pricing of Equity on the Tokyo Stock Exchange", in W.T. Zieba, W. Bailey and Y. Hamao (eds.), *Japanese Financial Market Research*, North-Hollandd, Amsterdam.

Hawawini, G., Michel, P. and Corhey, A. 1989, "A Look at the Validity of the Capital Asset Pricing Model in Light of Equity Market Anomalies: The Case of Belgian Common Stocks", in S. Taylor (ed.), *A Reappraisal of the Efficiency of Financial Markets*, NATO ASI Series, Springer-Verlag.

Hawawini, G. and Viallet, C. 1987, "Seasonality, Size Premium and the Relationship between the Risk and Return of French Common Stocks", *working paper, INSEAD and the Wharton School of the University of Pennsylvania.*

Hawawini, G. and Keim, D. B. 1995, "On the Predictability of Common Stock Returns: World-Wide Evidence", *Handbooks in Operations Research and Management Science*, Ed. Jarrow R. et al. vol. 9, chapter 17, pp.498-544.

Henriksson, R. and Merton. R. 1981, "On Market Timing and Investment Performance II: Statistical Procedure for Evaluating Forecasting Skills", *Journal of Business*, vol. 54, pp. 513-533.

Hentschel, L. 1995, "All in the Family: Nesting Symmetric and Asymmetric GARCH Models", *Journal of Financial Economics*, vol. 39, pp. 71-104.

Hewarathna R. and Silvapulle, P. 1999, "An Empirical Investigation of the Relationships among Real, Monetary and Financial Variables: Australian Evidence", *Accounting Research Journal*, vol, 12, no. 1, pp. 6-19.

Hildreth, C. and Houck, J.P. 1968, "Some estimators for a linear model with random coefficients", *Journal of the American Statistical Association*, vol. 63, pp. 584-595.

Hirshleifer, D. 2001, "Investor Psychology and Asset Pricing", *Journal of Finance*, vol. 56, no. 4, pp. 1533-1597.

Hogan, W. P., Sharpe, I. G. and Volker, P. A. 1982, "Capital Market Efficiency and the Relationship between Equity Market Returns, Interest Rates and Monetary Aggregates in Australia", *Journal of Economics and Business*, vol.34, pp.377-385.

Huang, H.-C., 2001, "Tests of CAPM with Nonstationary Beta." *International Journal of Finance and Economics* , vol. 5, pp. 255-268.

Hung, Roger D. and Kracaw, W. A. 1984, "Stock Market Returns and Real Activity: a Note", *Journal of Finance*, vol. 39, pp.267-273.

Jaffe, J. F. and Mandelker, G. 1976, "The 'Fisher Effect' for Risky Assets: An Empirical Investigation", *Journal of Finance*, vol. 31, no. May, pp. 447-458.

Jegadeesh, N., 1990, "Evidence of Predictable Behavior of Security Returns." *Journal of Finance*, vol. 45, no. 3, pp.881-898.

Jegadeesh, N. and Titman, S. 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency", *Journal of Finance*, vol. 48, no. 1, pp. 65-91.

Jegadeesh, N. and Titman, S. 2001, "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations", *Journal of Finance*, vol. 56, no. 2, pp. 699-720.

Jensen, M. C. 1978, "Some Anomalous Evidence Regarding Market Efficiency", *Journal of Financial Economics*, vol. 6, pp.95-101.

Jensen, G. R., Johnson, R. R. and Bauman, W. S. 1997, "Federal Reserve Monetary Policy and Industry Stock Returns", *Journal of Business Finance and Accounting*, vol. 24, no. 5 June, pp. 629-644.

Josev, T., Brooks, R. D. and Faff, R. W. 2001, "Testing a Two-factor APT Model on Australian Industry Equity Portfolios: The Effect of Intervaling", *Applied Financial Economics*, vol. 11, pp. 157-163.

Kale, J. K., Hakansson, N. H. and Platt, G. W. 1991, "Industry vs. Other Factors in Risk Prediction", *Finance Working Paper 201*, Haas School of Business, University of California at Berkeley.

Kalman, R. E. 1960, "A New Approach to Linear Filtering and Prediction Problems", *Journal of Basic Engineering*, vol. 82, pp. 35-45.

Kalman, R. E. 1963, "New Methods in Wiener Filter Theory", in *Proceedings of the First Symposium of Engineering Applications of Random Function Theory and Probability*, J.L. Bogdanoff and F. Kozin (Eds.), Wiley, New York.

Kantor, M. 1971, "Market Sensitivities", *Financial Analyst Journal*, vol. 27, no. 1, pp.64-68.

Kaul, G., 1996, "Predictable Components in Stock Returns." *Handbook of Statistics.* G. S. Maddala and C. R. Rao, North-Holland. vol. 14, pp. 269-296.

Kearns, P. and Pagan, A. R. 1993, "Australian Stock Market Volatility: 1875-1987", *The Economic Record*, vol. 69, no. 205, pp. 163-178.

Keim, D. B.1988, "Stock Market Regularities: A Synthesis of the Evidence and Explanation", in E. Dimson (ed.), *Stock Market Anomalies*, Cambridge University Press, Cambridge, pp.16-39.

Keim, D. B. and Stambaugh, R. F. 1986, "Predicting Returns in the Stock and Bond Markets", *Journal of Financial Economics*, vol. 17, pp. 357-390.

Kennedy, P., 1998, *A Guide to Econometrics.* Massachusetts, The MIT Press Cambridge.

Kim, C.-J. and Nelson, C. R. 1999, *State-Space Models with Regime Switching, Classical and Gibbs-Sampling Approaches with Applications*, The MIT Press, Cambridge.

Kim, D. 1993, "The Extent of Non-stationarity of Beta", *Review of Quantitative Finance and Accounting*, vol. 3, pp. 241-254.

Kim, D. 1997, "A Reeamination of Firm Size, Book-to-Market, and Earnings Price in the Cross-Section of Expected Stock Returns", *Journal of Financial and Quantitative Analysis*, vol. 32, no. 4, pp. 463-489.

Kim, M. J., Nelson, C. R. and Startz, R., 1991, "Mean Reversion in Stock Prices? A Reappraisal of the Empirical Evidence", *Review of Economic Studies*, vol. 58, pp. 515-528.

King, B. F. 1966, "Market and Industry Factors in Stock Price Behavior", *Journal of Business*, vol. 39, no. 1, Part II,, pp. 139-190.

Kirby, C. 1998, "The Restrictions on Predictability Implied by Rational Asset Pricing Models", *Review of Financial Studies*, vol. 11, no. 2, pp. 343-382.

Kitagawa, G. 1994, "The Two-Filter Formula for Smoothing and an Implementation of the Gaussian-sum Smoother", *Annals of the Institute of Statistical Mathematics*, vol. 46, pp. 605-623.

Klein, P. 2001, "The Capital Gain Lock-in Effect and Long-horizon Return Reversal", *Journal of Financial Economics*, vol. 59, no. 1 (January), pp. 33-62.

Knox, D., Zima, P. and Brown, R. 1996, *Mathematics of Finance*, McGraw-Hill Book Company, Sydney.

Kon, S. 1984, "Models of Stock Returns - A Comparison", *Journal of Finance*, vol. 39, no. 1, pp. 147-165.

Koutoulas, G. and Kryzanowski, L. 1996, "Macrofactor conditional volatilities, time-varying risk premia and stock return behavior", *Financial Review*, vol. 31, no. 1, pp.169-195.

Krishnamoorthy, A. 2001, "Industrial Structure and the Exchange-Rate Exposure of Industry Portfolio Returns", *Global Finance Journal*, vol. 12, pp. 285-297.

Krueger, T. M. and Rahbar, M. H. 1995, "Explanation of Industry Returns Using the Variable Beta Model and Lagged Variable Beta Model", *Journal of Financial and Strategic Decisions*, vol. 8, no. 2, pp.35-45.

Kwon, C. S. 1994, "Empirical tests of macroeconomics variables and stock market returns in Korea using cointegration, factor models, and causality analysis", PhD thesis, Virginia Commonwealth University.

Lee, B.-S. 1995, "The Response of Stock Prices to Permanent and Temporary Shocks to Dividends", *Journal of Financial and Quantitative Analysis*, vol. 30, pp. 1-22.

Lee, B.-S. 1998, "Permanent, Temporary, and Non-Fundamental Components of Stock Prices", *Journal of Financial and Quantitative Analysis*, vol. 33, no. 1, pp. 1-31.

Levis, M. 1985, "Are Small Firms Big Performers?" *Investment Analyst Journal*, vol. 76, pp. 21-27.

Lewellen, J. and Shanken, J. 2002, "Learning, Asset-Pricing Tests, and Market Efficiency", *Journal of Finance*, vol. 57, no. 3, pp. 1113-1145.

Lin, D. K. and Guttman, I. 1993, "Handling Spuriosity in the Kalman Filter", *Statistics and Probability Letters*, vol. 16, pp. 259-268.

Litterman, R. B., 1986, "Forecasting with Bayesian Vector Autoregressions - Five Years of Experience." *Journal of Business and Economic Statistics*, vol. 4, no. 1 (January), pp. 25-38.

Lo, A. W. and MacKinlay, A. C. 1988, "Stock Market Prices Do Not Follow Random Walk: Evidence from a Simple Specification Test", *Review of Financial Studies*, vol. 1. pp. 41-66.

Lo, A. W. and MacKinlay, A. C. 1989, "The Size and Power of the Variance Ratio Test in Finite Samples: A Monte Carlo Investigation", *Journal of Econometrics*, vol. 40. pp. 203-238.

Lo, A. W. and MacKinlay, A. C. 1995, "Maximizing Predictability in the Stock and Bond Markets", *NBER Working Paper Series, No. 5027*, National Bureau of Economics Research, Cambridge.

Lo, A. W. and MacKinlay, A. C. 1999, *A Non-Random Walk Down Wall Street*, Princeton University Press, Princeton, New Jersey.

Lo, A. W. 2000, "Finance: A Selective Survey", *Journal of the American Statistical Association*, vol. 95, no. 450, June, pp. 629-635.

Lucas, R. E. J. 1978, "Asset Prices in an Exchange Economy", *Econometrica*, vol.46, pp.1426-1445.

Mankiw, N. G., Romer, D. and Shapiro, M. D. 1991, "Stock Market Forecastability and volatility: A Statistical Appraisal", *Review of Economic Studies*, vol. 58, pp. 455-477.

Malkiel, B. G. 2001, "Stock Market Predictability", *International Encyclopedia of the Social and Behavior Sciences*, pp.15126-15133.

Malliaropulos, D. 1996, "Are Long-Horizon Stock Returns Predictable? A Bootstrap Analysis", *Journal of Business Finance and Accounting*, vol. 23, no.1 (January), pp.93-106.

Malliaropulos, D. and Priestley, R. 1999, "Mean Reversion in Southeast Asian Stock Markets", *Journal of Empirical Finance*, vol.6, pp.355-384.

Meinhold, R. J. and Singpurwalla, N. D. 1983, "Understanding the Kalman filter", *The American Statistician*, vol. May 37, no. 2, pp. 123-127.

Merton, R. 1981, "On Market Timing and Investment Performance I: An Equilibrium Theory of Value for Market Forecasts", *Journal of Business*, vol. 50, pp. 363-406.

Mills, T. C., 1991, "Assessing the Predictability of UK Stock Market Returns Using Statistics Based on Multiperiod Returns", *Applied Financial Economics*, vol. 1, pp. 241-245.

Mills, T. C., 1993, "Is There a Long-Term Memory in UK Stock Returns?", *Applied Financial Economics*, vol. 3, pp. 303-306..

Mills, T. C., 1995, "Estimating the Permanent Component of UK Stock Prices Using Multivariate Evidence on both Prices and Dividends", *Journal of Business Finance and Accounting*, vol. 22, pp.671-680.

Moskowitz, T. and Grinblatt, M. 1999, "Do Industries Explain Momentum?" *Journal of Finance*, vol. 54, no. 4, pp.1249-1290.

Muthuswamy, J. 1988, "Asynchronous Closing Prices and Spurious Autocorrelations in Portfolio Returns", *Working Paper, University of Chicago*, Chicago, IL.

Nelson, C. R. 1976, "Inflation and Rates of Return on Common Stocks", *Journal of Finance*, vol. 31, no. May, pp. 471-483.

Nicholson, S. F. 1960, "Price-Earnings Ratios", *Financial Analyst Journal*, vol. July/August, pp.43-50.

Officer, R. R. 1975, "Seasonality in Australian Capital Markets: Market Efficiency and Empirical Issues", *Journal of Financial Economics* vol. 2, pp. 29-51.

Ohlson, J. and Rosenberg, B., 1982, "Systematic Risk of the CRSP Equal-Weighted Common Stock Index: A History Estimated by Stochastic Parameter Regression", *Journal of Business,* vol. 55, no. 1, pp. 121-145.

O'Neal, E. S. 2000, "Industry Momentum and Sector Mutual Funds", *Financial Analysts Journal*, July/August, pp. 37-49.

Pagan, A. 1996, "The Econometrics of Financial Markets", *Journal of Empirical Finance*, vol. 3. pp. 15-102.

Pankratz, A. 1991, *Forecasting with Dynamic Regression Models*. New York, John Wiley and Sons Inc.

Pesaran, M. H. and Timmermann, A. 1994, "Forecasting Stock Returns: an Examination of Stock Market Trading in the Presence of Transaction Costs." *Journal of Forecasting*, vol. 13, pp. 330-365.

Pesaran, M. H. and Timmermann, A. 1995, "Predictability of Stock Returns: Robustness and Economic Significance", *Journal of Finance*, vol. L, no. 4, pp. 1201-1228.

Pesaran, M. H. and Timmermann, A. 2000, "A Recursive Modeling Approach to Predicting UK Stock Returns." *The Economic Journal*, vol. 110, no. January, pp. 159-191.

Pesaran, M. H. and Timmermann, A. 2002, "Market Timing and Return Prediction under Model Instability", *Journal of Empirical Finance*, vol. 9, pp. 495-510.

Pole, A., West, M. and Harrison, J. 1994, Applied Bayesian Forecasting and Time Series Analysis, Chapman and Hall, New York.

Pope, P. and Warrington, M. 1996, "Time-Varying Properties of the Market Model Coefficients", *Accounting Research Journal,* vol. 9, no. 2, pp. 5-20.

Poterba, J. and Summers, L. 1988, "Mean Reversion in Stock Returns: Evidence and Implications", *Journal of Financial Economics*, vol. 22, no. 1, pp.27-60.

Praetz, P. D., Naptali, M. and Nolan, J. 1975, "A Test of the Efficient Market Theory Using Filter Tests on Stock Prices", *Economic Record* vol. 51, no. March, pp.66-72.

Press, S. James 1972, *Applied Multivariate Analysis*, Holt, Rinehart and Winston, Inc., New York.

Qi, M. and Maddala G. S., 1999, "Economic Factors and the Stock Market: A New Perspective." *Journal of Forecasting*, vol. 18, pp.151-166.

Quintana, J. M., 1987, *Multivariate Bayesian Forecasting Models,* Unpublished Ph.D. thesis, University of Warwick.

Quintana, J. M. and West, M. 1987, "Multivariate Time Series Analysis: New Techniques Applied to International Exchange Rate Data", *The Statistician*, vol. 36, pp. 275-281.

Racine, J. 2001, "On the Nonlinear Predictability of Stock Returns Using Financial and Economic Variable." *Journal of Business and Economic Statistics*, vol. 19, no. 3, pp. 380-382.

Ragunathan, V., Faff, R. W. and Brooks, R. D. 2000, "Australian Industry Beta Risk, the Choice of Market Index and Business Cycles", *Applied Financial Economics*, vol. 10, pp. 49-58.

Ray, B., Chen, S. and Jarrett, J. 1997, "Identifying Permanent and Temporary Components in Daily and Monthly Japanese Stock Prices", *Financial Engineering and the Japanese Markets*, vol. 4, pp. 233-256.

Reichenstein, W. and Rich, S. P. 1993, "The Market Risk Premium and Long-Term Stock Returns." *The Journal of Portfolio Management* vol. 19, no. 4, pp. 63-72.

Reilly, F. K. and Drzycimski, E. F. 1974, "Alternative Industry Performance and Risk", *Journal of Financial and Quantitative Analysis*, vol. 9, no. 3, pp. 423-447.

Reinganum, M. 1981, "A Misspecification of Capital Asset Pricing: Empirical Anomalies Based on Earnings Yields and Market Values", *Journal of Financial Economics*, vol. 9, pp.19-46.

Richardson, M. 1993, "Temporary Components of Stock Prices: A Skeptic's View", *Journal of Business and Economic Statistics*, vol. 11, pp. 199-207.

Roll, R. and Ross S. 1980, "An Empirical Investigation of the Arbitrage Pricing Theory." *Journal of Finance,* vol. 35, pp.1073-1103.

Rosenberg, B. 1973, "Random-coefficient models: the Analysis of a Cross Section of Time Series by Stochastically Convergent Parameter Regression", *Annals of Social and Economics Measurement*, vol. 2, no. 4, pp. 399-428.

Rosenberg, B. 1974, "Extra-Market Components of Covariance in Securities Markets", *Journal of Financial and Quantitative Analysis*, vol. 9, no. 2 March, pp. 263-274.

Rosenberg, B. and Guy, J. 1995, "Prediction of Beta from Investment Fundamentals", *Financial Analysts Journal*, January/February, pp. 101-112.

Rosenberg, B., Reid, K. and Lanstein, R. 1985, "Pervasive Evidence of Market Inefficiency", *Journal of Portfolio Management*, vol.11, no. 3, pp. 9-16.

Rouwenhorst, G. 1998, "International Momentum Strategies", *Journal of Finance*, vol. 53, no. 1. pp. 267-284.

Rouwenhorst, G. 1999, "Local Return Factors and Turnover in Emerging Markets", *Journal of Finance*, vol. 54, no. 4. pp. 1439-1464.

Rubio, G. 1988, "Further International Evidence on Asset Pricing: The Case of the Spanish Capital Market", *Journal of Banking and Finance*, vol. 12, pp.221-242.

Samuelson, P. 1965,"Proof that Properly Anticipated Prices Fluctuate Randomly", *Industrial Management Review*, vol. 6, pp.41-49.

Schaefer, S. M., Brealey, R. A., Hodges, S. D. and Thomas, H. A. 1975, "Alternative Models of Systematic Risk", in E.J. Elton and M.J. Gruber (Eds.) *International Capital Markets: An Inter and Intra Country Analysis*, North Holland, Amsterdam.

Schmitz, J. J. 1996, "Market Risk Premiums and the Macroeconomy: Canadian Evidence of Stock Market Predictability", *Quarterly Journal of Business and Economics* vol. 35, no. 1, pp. 87-113.

Schwert, G. W. and Seguin, P. J. 1990, "Heteroskedasticity in Stock Returns", *The Journal of Finance,* vol. 45, pp. 1129-1155.

Shah, M. and Wadhwani S., 1993, "The Effect of the Term Spread, Dividend Yield and Real Activity on Stock Returns: Evidence from 15 Countries." *LSE Financial Markets Group Discussion Paper* vol. 98.

Sharpe, I. 1983, "New Information and Australian Equity Returns: A Multivariate Analysis", *Australian Journal of Management* vol. 8, pp. 22-34.

Sharpe, I. and Walker R. J. 1975, "Asset Reevaluations and Share Prices", *Journal of Accounting Research* vol. 13 (Fall), pp. 293-310.

Shanken, J. 1990, "Intertemporal Asset Pricing: An Empirical Investigation", *Journal of Econometrics*, vol. 45: pp. 99-120.

Shiller, R. J. 1981, "The Use of Volatility Measures in Assessing Market Efficiency", *Journal of Finance*, vol. 36 (May), pp.291-304.

Shiller, R. J. 1984, "Stock Prices and Social Dynamics", *Brookings Papers on Economic Activity*, vol. 2, pp. 457-498.

Shiller, R. J. 2000, *Irrational Exuberance,* Princeton University Press, Princeton.

Simonds, R. R., LaMotte, L. R. and McWhorter, A. Jr. 1986, "Testing for Non-stationarity of Market Risk: an Exact Test and Power Consideration", *Journal of Financial and Quantitative Analysis,* vol. 21, no. 2, pp. 209-220.

Sorensen, E. H. and Burke, T. 1986, "Portfolio Returns from Active Industry Group Rotation", *Financial Analysts Journal*, vol. 42, no. 5 September/October, pp. 43-50.

Stambaugh, R. F. 1986, "Discussion for Summer (1986)", *Journal of Finance*, vol. 41, pp.601-602.

Stambaugh, R. F. 1999, "Predictive Regressions", *Journal of Financial Economics*, vol. 54, pp. 375-421.

Summers, L. H. 1986, "Does the Stock Market Rationally Reflect Fundamental Values?", *Journal of Finance*, vol. 41, no.3, pp.591-601.

Sunder, S. 1980, "Stationarity of Market Risk: Random Coefficients Test for Individual Stocks", *Journal of Finance*, vol. 35, no. 4, pp. 883-896.

Tanizaki, H. 1993, "Nonlinear Filters Estimation and Applications", *Lecture Notes in Economics and Mathematical Systems 400*, Springer-Verlag, Berlin.

Teresa, P. D. 2000, "How to Profit with Sector Funds", Morningstar Column, Dec. 19th online: news.morningstar.com/doc/document/print/1,3651,4054,00.html.

Timmermann, A. 1993, "How Learning in Financial Markets Generates Excess Volatility and Predictability of Excess Returns." *Quarterly Journal of Economics*, vol.108, pp.1135-1145.

Timmermann, A. and Granger, C. W.J. 2004, "Efficient Market Hypothesis and Forecasting", *International Journal of Forecasting*, vol. 20, pp. 15-27.

Trivedi, A. and Brooks, R. D. 1999, "Autocorrelations, Returns and Australian Stock Indices", *Applied Economics Letters*, vol. 6, pp. 581-584.

Vasicek, O. 1973, "A Note on Using Cross-sectional Information in Bayesian Estimation of Security Betas", *Journal of Finance*, vol. 28, pp. 1233-1239.

Wei, K. C. J. and Wong, K. M. 1992, "Tests of Inflation and Industry Portfolio Stock Returns", *Journal of Economics and Business*, vol. 44, no. 1 Febuary, pp. 77-94.

Wells, C. 1994, "Variable Betas on the Stockholm Exchange 1971-1989", *Applied Economics*, vol. 4, pp. 75-92.

Wells, C. 1996, *The Kalman Filter in Finance*, Kluwer Academic Publishers, Dordrecht.

West, M. and Harrison, J. 1997, *Bayesian Forecasting and Dynamic Models*, 2nd ed., Springer Verkag, New York.

Wong, C. S. and Alles, L. 2001, "The sensitivity of Australian Industry Betas to Macroeconomic Factors", *Working paper*, School of Economics and Finance, Curtin University of Technology.