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Dynamic Asset Allocation, Equity Return Predictability and Market Anomalies

by

Yiwen (Paul) Dou

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Declaration of Authorship

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Abstract

This thesis contains three essays that examine several modern developments in the area of portfolio management, in both global and the Australian market. The thesis considers three important topics in portfolio management, including equity premium forecasts, dynamic asset allocation and stock market anomalies, which are directly related to improved investment outcomes.

The first essay examines the equity premium predictability and its implication to asset allocation. It provides one of the first comprehensive studies on out-of-sample stock returns predictability in Australia. While most of the empirically well-known predictive variables fail to generate out-of-sample predictability, the essay documents a significant out-of-sample prediction in forecasting ahead one-year and, to a lesser extent, one-quarter future excess returns, using a combination forecast of variables. The essay also finds improved asset allocation using the combination forecast of these predictors.

The second essay investigates one specific application of the dynamic asset allocation. Particularly, the study models the nonlinearity of time-series returns using a regime-switching process, and hence examines the asset allocation implication of this dynamic model. The asset allocation is applied across both regions and sectors. The regime-dependent asset allocation potentially adds value to the traditional static mean variance allocation. In addition, optimal allocation across sectors provide greater benefits compared to international diversification, which is characterised by higher returns, lower risks, lower correlations with the world market and a higher Sharpe ratio.

While the first two essays consider the implication of time-series asset pricing on portfolio management, the third essay examines asset pricing in cross-section. In particular, it investigates the pervasiveness of eight well-documented anomalies in global equity markets for the Australian stock market. After partitioning stocks into three size categories (micro, small and big), the study finds that none of the eight anomalies are pervasive across size groups in either sorts or cross-sectional regressions.

The existence of most anomalies is attributable primarily to microcap stocks. By looking at the hedge portfolio returns of anomalies in different regimes, the essay also shows that many anomalies tend to exist in bear markets rather than bull markets. This evidence contradicts the risk-based explanations for the existence of anomalies. The study provides important evidence to portfolio managers seeking to exploit anomalies in different segments of the stock market in Australia.

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Contents

List of Figures

List of Tables

Dedicated to my wife

Chapter 1

Introduction

1.1 Background

Over the last 50 years, academic researchers have made major breakthroughs in advancing modern practice in finance. These include portfolio theory, corporate finance, financial engineering of derivative instruments and many other applications related to financial markets overall. Formal portfolio theory research has seen major advances in the context of optimal portfolio choice, beginning with Harry Markowitz. Parallel with this, we saw new advances in capital market theory in the context of describing risk/return equilibrium propositions, beginning with the Capital Asset Pricing Model (CAPM). Many related academic developments provided rich portfolio management insight, including Arbitrage Pricing Theory (APT), market efficiency hypothesis, market anomalies and behavioural finance.

Against this backdrop, modernising portfolio management has been the ambition of many professional investment management practitioners. In the past three decades, econometric and mathematical models and techniques have been adopted in many forms, including but not limited to predicting market risk and returns, better allocating assets and selecting stocks, pricing financial derivatives and exploiting market anomalies.

The motivation of this thesis is to provide some detailed examination of several modern developments in the area of portfolio management, in both global and the Australian market. The thesis considers a variety of important topics, including equity premium forecasts, dynamic asset allocation and stock market anomalies, which are directly related to improved investment outcomes. Since many new advancements in these topics only pertain to the US market, the thesis provides unique out-of-sample evidence that is potentially of interest to both academics and investment professionals in Australia.

1.2 Chapter outlines

This thesis contains three papers that aim to address three different areas of portfolio management. The first paper considers time-series stock return prediction. It is included in Chapter 2 and part of it has been published as:

Dou, Y., D. S. Gallagher, D. H. Schneider and T. S. Walter, 2012, Out-of-sample stock return predictability in Australia, *Australian Journal of Management*, 37, 461-479.

Chapter 3 contains the second paper that examines dynamic asset allocation across different regions and sectors. It has been accepted for publication as:

Dou, Y., D. S. Gallagher, D. H. Schneider and T. S. Walter, forthcoming, Cross-region and cross-sector asset allocation with regimes, *Accounting and Finance*.

The third paper is included in Chapter 4 and examines the existence and robustness of several anomalies in the Australian stock market. It has been accepted for publication as:

Dou, Y., D. S. Gallagher and D. H. Schneider, forthcoming, Dissecting Anomalies in the Australian Stock Market, *Australian Journal of Management.*

The following exposition introduces each topic in more detail and discuss the contribution to the existing literature.

1.2.1 Return predictability

Return predictability has profound implications for portfolio allocation. If stock returns are indeed predictable, the optimal portfolio allocation would depend on the investment horizon, and the intertemporal hedge demand introduced by Merton [1973] would be central to dynamics of portfolio allocation. Hence, academic researchers have long been interested in attempting to predict stock market returns or the equity premium. Until the mid-1980s, no predictability has been the prevailing view of financial economists. Stock prices are believed to follow the random walk. Any apparent predictability is either a statistical artifact which will quickly vanish out of sample or cannot be exploited after transaction costs. Since the 1980s, a strand of literature has found predictability in a wide array of financial and macroeconomic factors and the predictability of stock returns is by now a well-established phenomenon. The list of factors includes dividend-to-price ratio [Campbell and Shiller, 1988], bond yield [Campbell, 1987], stock volatility [Guo, 2006], GDP growth rate [Chen, Roll, and Ross, 1986], investment-to-capital ratio [Cochrane, 1991], corporate issuing activity [Baker and Wurgler, 2000] and consumption-to-wealth ratio [Lettau and Ludvigson, 2001], to name a few.

Nevertheless, as Welch and Goyal [2008] state, this literature is difficult to absorb and compare in terms of the techniques, variables and time periods adopted in different articles. For example, some studies report the results of estimating in-sample linear time-series regressions of stock returns on one or more predictive variables and document predictability from a statistical perspective (see e.g., Fama and French [1988]). Other papers, on the other hand, found predictability from an asset allocation perspective but not from statistical tests, using a similar set of variables (e.g., Kandel and Stambaugh [1996]). In addition, results from articles that were written years ago may change when more recent data are used. For instance, Pesaran and Timmermann [1995] show that the predictive ability of a number of economic factors varies over time, although it has been economically significant during the volatile market period of the 1970s. In their important paper, Welch and Goyal [2008] show that a long list of predictors from the literature is unable to deliver consistently superior out-of-sample forecasts of the US equity premium relative to a naive forecast based on the historical average.

The lack of consistent out-of-sample evidence in Welch and Goyal [2008] motivates Rapach, Strauss, and Zhou [2010] to seek improved forecasting methods to better predict equity premium. In contrast to Welch and Goyal [2008], Rapach, Strauss, and Zhou [2010] provide evidence that supports out-of-sample return predictability using combination forecasts of 15 financial and economic variables. They argue that the success of the combining method is largely due to two reasons: (1) forecast combination substantially reduces forecast variance of individual forecasts, which often appear too volatile to represent plausible changes in the expected equity premium; and (2) forecast combination includes information from numerous economic variables and thus is superior to historical average, which appears too smooth, thereby ignoring information contained in economic variables that potentially affect the expected equity premium.

The results of Rapach, Strauss, and Zhou [2010] are important and could be extended in several ways. First, their evidence is confined to the US market, hence evidence outside US adds robustness to their proposition. Second, forecasting the aggregate market premium is the primary interest of this study. However, it is unclear whether the models could be applied successfully at forecasting the individual sector/industry level equity premium. Sector return predictability is relevant to investors in market timing and portfolio allocation at the sector level.

Chapter 2 examines whether Australian stock market equity premium could be forecast using the combination forecast methods. The study is not only an out-of-sample examination of Rapach, Strauss, and Zhou [2010], but also provides one of the first comprehensive studies of out-of-sample stock returns predictability in Australia. While most of the empirically well-known predictive variables fail to generate out-of-sample predictability, we document a significant out-of-sample prediction in forecasting ahead one-year and, to a lesser extent, one-quarter future excess returns, using a combination of forecast variables. The economic significance of the predictability is also confirmed through an improved asset allocation. In addition, the combining methods are useful in predicting sector premia. Specifically, a sector rotation strategy relying on the combining methods outperforms the market by 3.27% per annum on a risk-adjusted basis. We thus demonstrate that the combination forecast method proposed by Rapach, Strauss, and Zhou [2010] is an effective method of real-time equity premium forecast in Australia.

1.2.2 Asset allocation with regimes

The mean-variance analysis of Markowitz [1952] has long been recognised as the cornerstone of modern portfolio theory. Its simplicity and intuitive appeal have led to its widespread use in both academia and industry. Markowitz [1952] shows how investors should pick assets if they care only about the mean and variance of portfolio returns over a single period. The single period model typically assumes that asset returns are generated by a stationary process with mean, variances and covariances of returns that are constant over time. However, several studies show that expected returns and covariances of returns are vastly different in different times (see e.g., Ang and Chen [2002] and Longin and Solnik [2001]). This empirical feature of returns highlights the need for a dynamic asset allocation model that accounts for different distributions of asset returns in different times, according to the intertemporal hedging model of Merton [1973].

A growing strand of literature has found regimes in asset returns. That is, asset returns follow a rather more complicated process with multiple regimes, namely different market or economic conditions, each of which is associated with a very different distribution of returns. For example, Ang and Bekaert [2002b,c], Bekaert, Hodrick, and Marshall [2001], Garcia and Perron [1996] and Gray [1996] find strong evidence of regimes in US and international short-term interest rate data. Ang and Bekaert [2002a,b], Ang and Chen [2002], Guidolin and Timmermann [2007], Perez-Quiros and Timmermann [2000] and Whitelaw [2000] report evidence of regimes in stock or bond returns. Many of these studies uses the regime switching model of Hamilton [1989], which assumes the data generating process follows the Markov chain.

Ang and Bekaert [2002a], Ang and Bekaert [2004] and Guidolin and Timmermann

[2007] consider the asset allocation implications of regime switching models, because they capture many of the properties of asset returns that emerge from the empirical studies, such as having regimes with very different means, volatilities or correlations across assets. In particular, Ang and Bekaert [2004] find that the presence of regimes with different correlations and expected returns is exploitable within a cross-country equity allocation framework. This result is important as it indicates that the asset allocation performance could be improved by buying different optimal portfolios in different regimes.

Chapter 3 extends the work of Ang and Bekaert [2004] by considering regime-dependent asset allocation in both cross-country and cross-sector contexts. Examining cross-sector regime-dependent asset allocation adds at least three interesting dimensions to the existing cross-region evidence. First, several studies show that the importance of sector factors in explaining returns has grown to exceed that of country factors, with the increased integration of international capital markets. Hence it is interesting to ask whether sector asset allocation could add benefits to the widely practised international asset allocation. Second, although Ang and Bekaert [2002a] have shown that stock returns across country exhibit asymmetric correlations, there is a lack of empirical evidence on the dynamics of correlation among sector returns. Third, the cross-sector regime-dependent asset allocation is an important out-of-sample test to the extant regime-switching asset allocation literature. In Chapter 3, we find that the regime-dependent asset allocation in general adds value to the traditional static mean-variance allocation. In particular, the optimal allocation across sectors provides greater benefits compared to international diversification, which is characterised by higher returns, lower risks, lower correlations with the world market and a higher Sharpe ratio.

1.2.3 Anomalies

Financial market anomalies are cross-sectional or time-series patterns in security returns that are not predicted by a central paradigm or theory. Discoveries of financial market anomalies typically arise from empirical tests that rely on a joint null hypothesis; that is, security markets are informationally efficient and returns behave according to a prespecified equilibrium model such as the capital asset pricing model (CAPM). If the joint hypothesis is rejected, we cannot attribute the rejection to either branch of the hypothesis. Thus, even though anomalies are often interpreted as evidence of market inefficiency, such a conclusion is inappropriate because the rejection may be due to an incorrect equilibrium model. Although some financial anomalies have dissipated over time, many of the anomalies seem to persist. Among the large and growing number of anomalies, the size anomaly of Banz [1981], the value effect of Rosenberg, Reid, and Lanstein [1985] and the momentum anomaly documented by Jegadeesh and Titman [1993] appear to be most well-known and persisting.

Nevertheless, as Fama and French [2008] discussed, empirical studies of market anomalies have methodological issues. Two approaches are commonly used to identify anomalies: (i) sorts of returns on anomaly variables, and (ii) regressions that use anomaly variables to explain the cross-section of average returns in the spirit of Fama and MacBeth [1973]. Studies use sorts typically construct equal-weight (EW) decile portfolios by sorting stocks on the variable of interest. It is a common approach to focus on the hedge portfolio return obtained from long-short positions in the extreme deciles. A potential problem is that the returns on EW hedge portfolios that use all stocks can be dominated by stocks that are tiny. Fama and French [2008] show that, though microcap stocks represent only 3% of the market cap of the

NYSE-Amex-NASDAQ universe, they account for 60% of the total number of stocks. To alleviate this problem, value-weight (VW) hedge portfolio returns are often shown along with EW returns. But VW hedge returns can be dominated by a few big stocks, resulting again in an unrepresentative picture of the importance of the anomaly. The regression approach also faces similar problems. Regressions estimated on all stocks can be dominated by microcaps because they are so plentiful and because they tend to have more extreme values of the explanatory variables and more extreme returns. Regressions are again unlikely to yield unbiased results due to the influence of tiny stocks.

To address these methodological issues, Fama and French [2008] examine several anomalies using sorts and regressions in three separate size groups (micro, small and big). They find that though net stock issues, accruals and momentum anomalies are still pervasive, the asset growth and profitability anomalies are less robust. Motivated by the findings of Fama and French [2008], Chapter 4 looks at whether anomalies exist or are exploitable in Australia. Dissecting anomalies in the Australian market is interesting in a number of important respects. First, out-of-sample comparisons to the US market provide context to the investment strategies that have been documented in the cross-section by Fama and French [2008] and whether Australian market exhibits robust and/or unique characteristics. The aggregate Australian stock market capitalisation is dominated by a small number of large stocks, coupled with very large number of tiny stocks. Second, evidence of Australian market anomalies is not only limited but also often controversial. These studies tend to focus on EW returns, and hence are largely influenced by the characteristics of micro stocks. Thus, different treatments of these sample stocks may often yield inconsistent results.

Chapter 4 examines the pervasiveness of eight well-documented anomalies identified in global equity markets for the Australian stock market. After partitioning stocks into three size categories, we find that none of the eight anomalies are pervasive across any of the size groups in either sorts or cross-sectional regressions. The existence of size, value, profitability, asset growth and accruals anomalies is primarily attributable to micro-cap stocks. Momentum and asset growth predict the expected returns of big stocks, but momentum does not predict the returns on micro stocks, and asset growth does not matter for small stocks. Contrarian returns are largely explained by stock size and value dimensions. Evidence for the earnings growth anomaly contradicts the growth extrapolation hypothesis. By looking at the hedge portfolio returns of anomalies in different regimes, we also show that many anomalies tend to exist in bear markets rather than bull markets. This evidence contradicts the risk-based explanations for the existence of anomalies.

Chapter 2

Out of Sample Stock Return Predictability in Australia

2.1 Introduction

Stock return predictability has important implications for portfolio allocation, asset pricing and stock market efficiency. A large body of extant literature has examined the predictability of stock returns, using numerous and a growing number of financial, economic, and technical variables as predictors.[1] While many studies report evidence of in-sample return predictability, out-of-sample return predictability remains controversial. As documented by Welch and Goyal [2008], many well-known predictors do not consistently generate superior out-of-sample equity premium prediction relative to a simple forecast based on the historical average. On the other hand, several studies demonstrate that out-of-sample equity premium forecastability can be improved using

[1]Examples include valuation ratios, such as the dividend-price [Fama and French, 1988], earnings-price [Campbell and Shiller, 1988], and book-to-market [Kothari and Shanken, 1997], as well as nominal interest rates [Fama and Schwert, 1977], the inflation rate [Fama and Schwert, 1977], term and default spreads [Campbell, 1987], corporate issuing activity [Baker and Wurgler, 2000], consumption-wealth ratio [Lettau and Ludvigson, 2001], and stock market volatility [Guo, 2006].

various techniques. Particularly, Rapach, Strauss, and Zhou [2010] find that a combination forecast approach is able to deliver consistently superior out-of-sample US equity premium prediction. The implication of Rapach, Strauss, and Zhou [2010] is important as it provides a systematic approach of combining information from various economic data, while reducing the forecast variance in predicting returns.

Most studies on stock return predictability focus almost exclusively on the US stock market, and therefore it is interesting to ask whether the stock return predictability exists outside the US and whether the methodology proposed by Rapach, Strauss, and Zhou [2010] could be applied successfully in other countries. This study focuses on return predictability in the Australian stock market, where empirical evidence is relatively scarce. Faff and Heaney [1999] investigate the relationship between inflation and Australian equity returns but do not find consistent relationships. Using Australian data, Boudry and Gray [2003] document that dividend yield and the term spread have some economically significant influence on the optimal asset allocation. Yao, Gao, and Alles [2005] investigate the relation between Australian industry returns and economic and financial variables. They find that the unexpected changes in dividend yield, term spread and the short rate have some statistically significant predictability for stock returns. Using a series of eight financial and economic predictors, Alcock and Gray [2005] examine the economic significance of return predictability using a variety of model selection criteria. They find that return predictability does not always exist when different selection criteria are used. Using a similar set of variables, Gray [2008] further develops a dynamic portfolio strategy using inferences drawn from a probit model to examine the economic significance of return predictability. He concludes that superior return predictability is not robust to different sample periods.

This study is the first that adopts the methodology proposed by Rapach, Strauss, and Zhou [2010] to comprehensively investigate out-of-sample stock return predictability using a large number of Australia-specific financial and macroeconomic predictors. Examining stock return predictability in Australia is important for at least three reasons. First, investigating Australian stock return predictability is relevant to Australian asset allocators and helps to establish appropriate benchmarks for managed funds in the Australian stock market. Second, analysing Australian equity premium forecastability has important implications for Australian firms and investors in estimating the cost of capital. Third, a detailed examination of return predictability in Australia provides out-of-sample evidence and enhances the understanding of stock return predictability outside the US.

We investigate the market and sector return predictability for one-quarter and one-year ahead horizons in Australia, both in-sample and out-of-sample, using 15 financial and economic variables proposed by previous (primarily US) studies. Our out-of-sample tests focus on whether individual predictors, as well as a forecast combination approach, can out-perform the historical average equity premium with respect to statistical predictability and asset allocation performance. Similar to Rapach, Strauss, and Zhou [2010], our results confirm the superiority of combination forecasts, particularly in the case of one-year ahead and, to a lesser extent, one-quarter ahead Australian stock returns.

The combination of these 15 variables also predicts industry sectors returns. Using these predicted sector returns, we simulate a real-time dynamic sector rotation strategy based on the sector mean-variance optimisation. Using the predicted sector premia, the sector optimal portfolio out-performs the market return by 7.18% per annum (3.27% after adjusting for risk) from 1985 to 2009. The remainder of the paper is organised as follows. Section 2.2 describes the predictive regression and combination forecasts methodology. Section 2.3 provides the data sources and construction. Section 2.4 discusses the empirical results. Section 2.5 concludes the chapter.

2.2 Methodology

In this section, we first describe the predictive regression model and forecast combination framework used by Rapach, Strauss, and Zhou [2010], and then discuss the criteria used to evaluate the out-of-sample forecasts.

2.2.1 Predictive regression model

We follow the standard one period ahead regression model to predict the equity premium:

$$r_{t+1} = \alpha + \beta x_t + \epsilon_{t+1}, \tag{2.1}$$

where r_{t+1} is the difference between stock market index or sector indices raw returns (continuously compounded) and the risk-free interest rate one period (one-quarter) ahead, x_t is a single predictor variable, and ϵ_{t+1} is the regression residual that is assumed to follow a standard normal distribution. The regression is estimated 15 times using each of the 15 individual predictors.

We then divide the total sample of T observations for r_t and x_t into an in-sample period comprising the first p observations and an out-of-sample period comprising the last q observations ($q = T - p$). Thus, Equation 2.1 is initially estimated using the first p observations to obtain the equity premium forecast for period $p+1$. We then re-estimate

Equation 2.1 in every period of the out-of-sample period using an expanding window to generate a series of q out-of-sample equity premium forecasts $\hat{r}_t$, $t = p+1, ..., T$.

The out-of-sample predicted equity premia are then compared with the historical average equity premium, $\bar{r}_{t+1}$, as suggested by Campbell and Thompson [2008]. If a variable x_t contains information useful for predicting the equity premium, then $\hat{r}_{t+1}$ should perform better than $\bar{r}_{t+1}$, which corresponds to a constant expected equity premium. We discuss how to evaluate the performance of $\hat{r}_{t+1}$ relative to $\bar{r}_{t+1}$ in Section 2.2.3.

2.2.2 Forecast combination

In this section, we discuss the methods used to generate combination forecasts. Bates and Granger [1969] is the seminal paper that introduces a combination forecast approach. The combination forecasts can be calculated as:

$$\hat{r}_{c,t+1} = \sum_{i=1}^{N} w_{i,t}\hat{r}_{t+1}, \tag{2.2}$$

where $\hat{r}_{c,t+1}$ is the combination forecast made at time t and is a weighted average of the $N(N = 15)$ individual forecasts generated from Equation 2.1 and $\{w_{i,t}\}_{i=1}^{N}$ are the ex ante combining weights formed at time t. We use different combining methods to compute the weights for individual predictors.

We adopt the combining methods of Rapach, Strauss, and Zhou [2010], which can be classified into two types. The first uses simple averages such as the mean, median and trimmed mean. The mean combination forecast assigns equal weight to each individual forecast, while the median combination forecast is simply the median of 15 individual forecasts. The trimmed mean combination forecast omits those individual forecasts with the smallest and largest values and then assigns equal weights for the remaining individual forecasts.

The second type is called the discount mean square prediction error (DMSPE) combining method, originally proposed by Stock and Watson [2004]. This method assigns higher weights to the predictors that have superior historical forecasting performance (lower mean square prediction error (MSPE)) relative to other predictors. Combining weights can be calculated as:

$$w_{i,t} = \frac{\phi_{i,t}^{-1}}{\sum_{j=1}^{N} \phi_{j,t}^{-1}}, \tag{2.3}$$

where

$$\phi_{i,t} = \sum_{s=p}^{t-1} \theta^{t-1-s}(r_{s+1} - \hat{r}_{i,s+1})^2, \tag{2.4}$$

and $\theta (0 < \theta \leq 1)$ is a discount factor that controls the models view on the relative importance of recent versus past forecast accuracy of the individual predictors. The smaller the θ value, the greater is the weight assigned to the recent forecast accuracy of the individual predictors. When $\theta = 1$ there is no discounting. We consider three values for θ: 1.0, 0.5 and 0.1.

We compare the results of combination forecast methods with a kitchen sink model in the spirit of Welch and Goyal [2008] and Rapach, Strauss, and Zhou [2010]. The kitchen sink model incorporates all 15 economic variables together on the right hand side of a multivariate predictive regression equation, which also generates a series of q out-of-sample forecasts in real time.

2.2.3 Forecast evaluation

To examine the statistical significance of return predictability, we use the out-of-sample R^2 statistic, R^2_{OS}, proposed by Campbell and Thompson [2008]. This compares the predicted equity risk premium $\hat{r}_{t+1}$ generated from the predictive regression model or a combination forecast with the forecasts based on historical average risk premium $\bar{r}_{t+1}$. The R^2_{OS} statistic is calculated close to the spirit of in-sample R^2 statistic:

$$R^2_{OS} = 1 - \frac{\sum_{t=p+1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=p+1}^{T}(r_t - \bar{r}_t)^2}. \tag{2.5}$$

The R^2_{OS} statistic measures the relative value MSPE for the individual predictors or combination forecast compared to the historical average forecast. That is, the $\hat{r}_{t+1}$ forecast statistically outperforms the historical average forecast when $R^2_{OS} > 0$.

To investigate whether the performance of individual predictors or combination forecasts are statistically higher than the historical average forecast, we use the Clark and West [2007] MSPE-adjusted statistic to evaluate the significance of the R^2_{OS} statistics:

$$f_{t+1} = (r_t - \bar{r}_t)^2 - [(r_t - \hat{r}_t)^2 - (\bar{r}_t - \hat{r}_t)^2]. \tag{2.6}$$

We use a one-sided (upper-tail) t-statistic to assess whether the mean of $f_{t+1}(t = p, ..., T-1)$ is significantly above zero.

In addition to the R^2_{OS} measure, we also examine the economic significance, which is the asset allocation inferred from the predicted equity premium, measured by realised utility gains of a mean-variance investor on a real-time basis [Campbell and Thompson, 2008, Marquering and Verbeek, 2004, Rapach, Strauss, and Zhou, 2010].

In the asset allocation strategy with only one risky portfolio, we allow a mean-variance investor with relative risk aversion parameter to switch between the stock market portfolio and cash on a quarterly basis based on predicted equity premia. Similar to Campbell and Thompson [2008] and Rapach, Strauss, and Zhou [2010] we simply assume that the variance to be a 10-year rolling window of quarterly returns. A mean-variance investor who forecasts the equity premium using the predictive model j will decide at the end of period t to invest the following portion of the portfolio to equities in period $t+1$:

$$w_{j,t} = \frac{1}{\lambda} \frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}, \tag{2.7}$$

where $\hat{\sigma}^2_{t+1}$ is the rolling-window estimate of the variance of stock returns. We do not allow short-selling. The investors utility level is given by:

$$\hat{\upsilon}_j = \hat{\mu}_j - \frac{\lambda}{2}\hat{\sigma}^2_j, \tag{2.8}$$

where $\hat{\mu}_j$ and $\hat{\sigma}^2_j$ are the out-of-sample mean and variance of the return on the dynamic portfolio formed utilising predicted equity premia.

We compute the utility for the same investor who uses the historical average equity premium forecast in a similar manner. In addition to Rapach, Strauss, and Zhou [2010], we adopt a static weight strategy (hereafter, static strategy) with 70% equity and 30% cash as a benchmark that mimics the behaviour of some large Australian pension fund investors. We measure the utility gain (or certainty equivalent return) as the extra utility generated from Equation 2.8 relative to these two benchmarks. This difference is multiplied by 400 to express the utility gain in average annualised percentage return. We report results for $\lambda = 3$. Results are qualitatively similar for other λ values.

In the sector allocation program with multiple risky portfolios, we allow a mean-variance investor with relative risk aversion parameter λ to switch amongst ten sectors based on predicted sector equity premia. We again estimate the one period ahead variance-covariance matrix of these ten sectors using a 10-year rolling window of quarterly returns. The risk-free rate is each quarters prevailing 90-day bank bill rate. The sector weights are the mean-variance efficient portfolio weights. Short-selling is not allowed.

In our empirical applications, we also examine the in-sample and out-of-sample stock return predictability using a one-year forecast horizon. Fama and French [1989] document evidence for stock return predictability being significantly stronger for long horizons compared with short horizons. However, Richardson and Smith [1991] argue that regressions with overlapping observations have statistical properties that may inflate statistical significance. Powell, Shi, Smith, and Whaley [2007] and Boudoukh, Richardson, and Whitelaw [2008] propose that significant predictability at longer-term horizons might be spurious, particularly when regressors are persistent. We therefore examine both the statistical significance and the economic significance of return predictability at longer horizons. A four periods (one-year) ahead predictive regression model is a straightforward extension of Equation 2.1:

$$r_{t+1:t+4} = \alpha + \beta x_t + \epsilon_{t+1:t+4}, \tag{2.9}$$

where r_t are continuously compounded returns and $r_{t+1:t+4} = r_{t+1} + ... + r_{t+4}$. The forecasts are again computed recursively. Due to overlapping observations, we use Newey and West [1987] standard error estimates to control for autocorrelation when computing the Clark and West [2007] MSPE-adjusted statistics.

2.3 Data sources and data construction

All data are from January 1970 to September 2010, except sector returns data (from 1974 to 2009), stock variance (starting from 1980), dividend yield, dividend-price ratio and consumer sentiment index (starting from 1974).

The dependent variable is always the equity premium, that is, the total rate of return on the stock market or individual sectors for each quarter minus the prevailing short-term interest rate. We use 15 independent variables that can be classified into three different sets, namely stock characteristics, interest rate statistics and macroeconomic variables. Because the actual announcements of macroeconomic indicators are in the following quarter, we wait for one quarter before using them (except currency movements) in the regression to avoid hindsight bias. See Appendix .1 for the detailed data sources and construction.[2]

Table 2.1 reports the full sample descriptive statistics of all variables. All numbers in the table are reported on a quarterly basis except the log dividend yield, the log dividend-price ratio and the long term bond yield in yearly basis. Most of the 15 predictive variables are highly persistent, with autocorrelation coefficients greater than 0.5. It is interesting to note that the utilities sector generates the highest return (3.95% per quarter) and the consumer staples sector has the lowest volatilities (9.40% per quarter) during the sample period from 1974 to 2009. The technology and telecommunications sectors deliver the lowest returns (1.07% and 2.75% per quarter, respectively) coupled with the highest volatilities (20.33% and 25.37% per quarter, respectively).

[2]We omit some variables that have also demonstrated empirical predictability in US due to data non-availability. These variables include the default premium, earnings-to-price ratio, book-to-market ratio and corporate issuing activity. Although we obtain book value of equity and earnings data from the Aspect-Huntley database starting from 1991, they are omitted because we require these variables to start at least from 1980 to allow performance comparison in different out-of-sample periods.

Table 2.1: Descriptive statistics of all variables for the full sample period

This table reports sample moments and autocorrelation coefficients ρ of all variables for the full sample period. Returns on market and sectors are raw returns. All numbers are reported on a quarterly basis except log dividend yield, dividend-price ratio and long term bond yield in a yearly basis.

	Variables	Data period	Mean	Stdev	Skewness	Kurtosis	ρ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MKT	Market	1974-2009	0.0308	0.0988	-1.8452	10.2903	0.0588
ENE	Energy	1974-2009	0.0315	0.1833	-0.4530	5.4423	0.0515
MAT	Materials	1974-2009	0.0310	0.1200	-1.2799	5.8123	0.0987
IND	Industrials	1974-2009	0.0327	0.1073	-1.3209	7.3048	0.0569
CDI	Consumer discretionary	1974-2009	0.0367	0.1505	-0.881	6.4023	0.1260
CST	Consumer staples	1974-2009	0.0346	0.0940	-1.2741	8.3942	0.0283
HC	Healthcare	1974-2009	0.0354	0.1088	-0.8936	4.9205	0.0601
FIN	Financials	1974-2009	0.0336	0.1143	-1.5322	9.5676	0.0186
IT	Technology	1974-2009	0.0107	0.2033	-0.4238	4.9043	0.2399
TEL	Telecommunications	1974-2009	0.0275	0.2537	0.4423	5.5253	0.1623
UTI	Utilities	1974-2009	0.0395	0.1403	-0.2512	12.466	-0.0553
D/Y_1	Dividend yield	1974-2010	0.0413	0.0088	0.6979	3.3681	0.9486
D/P_1	Dividend-price ratio	1974-2010	0.0398	0.0089	1.0159	4.3650	0.8750
D/Y	Dividend yield (log)	1974-2010	-3.2086	0.2089	0.1697	2.6327	0.9477
D/P	Dividend-price ratio (log)	1974-2010	-3.2460	0.2146	0.2209	3.8967	0.8880
LagR	Lagged excess stock returns	1970-2010	0.0163	0.1042	-1.3366	7.2709	0.0164
SVAR	Sum of daily variance	1980-2010	0.0064	0.0129	8.1603	76.7645	0.0954
SBR	90 days bank accepted bills rate	1970-2010	0.0222	0.0104	0.8023	2.5149	0.9466
LBY	10 years government bond yield	1970-2010	0.0894	0.0321	0.4524	1.8576	0.9871
TMS	Term spread	1970-2010	0.0005	0.0183	-1.4532	8.5174	0.7650
CPI	Inflation rate	1970-2010	0.0142	0.0114	1.0141	4.3253	0.6231
GDP	Nominal GDP growth rate	1970-2010	0.0079	0.0098	0.0840	4.6783	-0.0405
PPI	Δ in manufacturing price index	1970-2010	0.0136	0.0145	-0.2845	4.3261	0.5421
FX	Δ in the Australian dollars TWI	1970-2010	-0.0019	0.0471	-0.6485	4.1056	0.0232
M3	Δ in M3 money supply	1970-2010	0.0274	0.0185	2.5834	21.5497	0.3176
I/K	Fixed non-residential investment / GDP	1970-2010	0.0406	0.0106	1.1181	3.7585	0.9886
C/K	Household consumption / GDP	1970-2010	0.5703	0.0158	-0.0922	2.1219	0.9278
CSI	Consumer sentiment index (log)	1974-2010	4.6120	0.1217	-0.9122	3.7535	0.7662

Table 2.2 reports the Spearmans rank correlation coefficient matrix for the 15 predictors during the full sample period. Significant correlations (greater than 0.5 or less than -0.5) are shown in bold italics. Most variables are not significantly correlated with each other, indicating that these represent a broad range of uncorrelated economic information. The significantly correlated variables are in line with intuition, for example, dividend yield and dividend-price ratio are positively correlated (0.63), inflation rate, short bill rate and long-term bond yield are all positively correlated, and investment-to-capital ratio and consumption-to-wealth ratio are negatively correlated (-0.65).

We consider three different out-of-sample forecast evaluation periods: (i) a full out-of-sample period from January 1985 to September 2010 covering the 1987 market crash,

Table 2.2: Correlation matrix for individual predictors 1970-2010

This table reports correlation coefficients for the individual predictors given in the row and column headings. Significant correlation (greater than 0.5 or less than -0.5) are in bold.

	D/Y	*D/P*	*LagR*	*SVAR*	*SBR*	*LBY*	*TMS*	*CPI*	*GDP*	*PPI*	*FX*	*M3*	*I/K*	*C/K*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	-12	(13)	(14)	(15)
D/Y														
D/P	**0.63**													
LagR	-0.02	-0.35												
SVAR	-0.04	0.04	0.1											
SBR	0.44	0.19	-0.01	0.02										
LBY	0.41	0.19	0.00	0.04	**0.93**									
TMS	-0.29	-0.09	0.03	0.02	**-0.69**	-0.37								
CPI	0.23	0.09	-0.02	0.03	**0.70**	**0.65**	-0.49							
GDP	-0.37	-0.42	0.16	0.02	-0.14	-0.09	0.17	-0.20						
PPI	0.05	-0.07	0.03	-0.02	0.44	0.39	-0.32	**0.58**	-0.11					
FX	-0.03	-0.10	0.02	-0.22	-0.16	-0.14	0.11	-0.14	0.14	-0.07				
M3	0.05	0.02	-0.04	0.06	0.29	0.19	-0.37	0.28	0.12	0.2	0.01			
I/K	0.27	0.14	-0.1	0.25	-0.07	-0.29	-0.41	-0.04	-0.12	-0.05	0.05	0.29		
C/K	-0.25	-0.11	0.12	-0.25	-0.41	-0.24	**0.55**	-0.29	-0.09	-0.17	0.03	-0.48	**-0.65**	
CSI	-0.46	-0.34	0.17	-0.11	-0.43	-0.37	0.35	-0.25	0.34	-0.09	0.27	0.09	-0.06	0.03

(ii) a more recent out-of-sample period covering the last 15 years of the full sample, January 199 to September 2010 and (iii) a recent out-of-sample period covering the last five years of the full sample, January 2005 to September 2010. This later period allows us to analyse how the predictors perform during the recent Global Financial Crisis. Overall, consideration of multiple out-of-sample periods provides us with a sense of the robustness of the inferences.

2.4 Empirical results

In this section, we begin by presenting the in-sample market premium predictive regression results. The out-sample market premium predictability is discussed in Section 2.4.2. We report the empirical results on the sector return predictability and the profitability of the sector rotation strategy in Section 2.4.3.

2.4.1 In-sample market premium predictability results

Table 2.3 reports the in-sample predictive regression results for one-quarter ahead and one-year ahead horizons. [3] While more than half (8 out of 15) of the predictors have negative adjusted R^2 for the one-quarter ahead forecast, dividend yield (D/Y), dividend-to-price ratio (D/P) and consumption-to-GDP ratio (C/K) are significant predictors of equity premium, with adjusted R^2 of 5.73%, 3.14% and 3.82%, respectively.[4] The interest rate, inflation and output related variables generally have relatively low predictability of the equity premium. The one-year horizon forecast reveals D/Y, D/P, long-term bond yield (LBY), currency movements (FX), money supply (M3) and C/K as significant predictors, with adjusted R^2 of 14.43%, 12.72%, 1.28%, 7.69%, 3.33% and 8.54%, respectively. This evidence is generally consistent with previous Australian studies that find dividend yield has some predictability in stock returns [Alcock and Gray, 2005, Boudry and Gray, 2003, Yao, Gao, and Alles, 2005]. However, Yao, Gao, and Alles [2005] do not find the money supply to be a significant predictor, possibly because they use a monthly estimation window. Consistent with Fama and French [1989], the in-sample predictability at longer horizons is more pronounced; however, it does not necessarily translate into equally significant out-of-sample predictability and a superior asset allocation performance due to a potential long-term spurious predictability documented by Richardson and Smith [1991], Powell, Shi, Smith, and Whaley [2007] and Boudoukh, Richardson, and Whitelaw [2008]. We provide the evidence of out-of-sample predictability in the next section.

[3] The t-statistics are calculated using the Newey and West [1987] standard errors.
[4] Results are qualitatively similar between adjusted R^2 and R^2.

Table 2.3: Forecasting Australian MSCI Index Returns 1970-2010

This table reports the in-sample coefficients β, t-statistics and adjusted R^2 of individual predictors regressing on one quarter and one year ahead equity premium, for the full sample period. α denotes the intercept coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	One quarter					One year				
Predictor	α	β	t-stats		R^2 (%)	α	β	t-stats		R^2 (%)
(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)		(9)
D/Y	0.42	0.13	3.25	***	5.73	0.33	0.10	5.19	***	14.43
D/P	0.30	0.08	2.35	**	3.14	0.29	0.08	4.61	**	12.72
LagR	0.02	-0.01	-0.11		-0.62	0.02	-0.01	-0.20		-0.62
SVAR	0.02	0.24	0.36		-0.73	0.02	0.01	0.03		-0.85
SBR	0.02	-0.24	-0.10		-0.62	0.01	1.65	1.35		0.52
LBY	0.00	0.20	0.78		-0.24	0.00	0.23	1.75	*	1.28
TMS	0.02	0.72	1.60		0.97	0.02	0.00	-0.01		-0.64
CPI	0.02	-0.24	-0.33		-0.56	0.02	-0.04	-0.11		-0.63
GDP	0.01	0.80	0.95		-0.06	0.02	-0.69	-1.63		1.04
PPI	0.02	-0.28	-0.50		-0.47	0.02	0.07	0.25		-0.60
FX	0.02	-0.20	-1.12		0.16	0.02	-0.32	-3.74	***	7.69
M3	0.03	-0.54	-1.23		0.32	0.03	-0.57	-2.54	**	3.33
I/K	0.04	-0.63	-0.81		-0.21	0.04	-0.49	-1.21		0.29
C/K	-0.77	1.38	2.73	***	3.82	-0.56	1.02	3.98	***	8.54
CSI	0.34	-0.07	-1.07		0.10	0.23	-0.04	-1.32		0.53

2.4.2 Out-of-sample market premium predictability results

Following Welch and Goyal [2008] and Rapach, Strauss, and Zhou [2010], we begin by presenting time-series plots of the differences between the cumulative square prediction error for the historical average benchmark forecast and the cumulative square prediction error for the forecasts based on the individual and combination predictive regression models for January 1985 to September 2010 in Figure 1 for one quarter ahead and in Figure 2 for one year ahead horizon. Welch and Goyal [2008] emphasise the importance of this type of chart as it visually tracks an individual predictive regression models out-of-sample forecasting performance over time. Whenever the line in each graph increases, the predictive regression model performs better than the historical average, while the opposite holds when the curve decreases. To infer whether a predictive regression model outperforms the historical average in a given out-of-sample period, one can simply compare the height of the curve at the two points corresponding to the beginning and end of that out-of-sample period; thus if the curve is higher (lower) at the end of the out-of-sample period than at the beginning, the predictive regression model has a lower (higher) MSPE than the historical average forecast over the out-of-sample period. A predictive regression model that always outperforms the historical average for any out-of-sample period will thus have a curve with a slope that is always positive.

The solid lines in Panel A of Figure 2.1 and Figure 2.2 indicate that none of the 15 individual economic variables consistently outperforms the historical average in both one-quarter and one-year horizon. Some of the graphs have positively sloped curves during certain periods, but not without extensive periods of downward sloped lines. It is interesting to note that a number of variables such as D/P, stock variance (SVAR) and term spread (TMS) become markedly negatively sloped during the 1987 market crash in the one-quarter ahead forecast.

We then impose restrictions on the predictive regression models following the methods proposed by Campbell and Thompson [2008]. More specifically, we set β_i to zero when recursively estimating Equation 2.1 and Equation 2.9 if the estimated slope does not match the theoretically expected sign; we also set the individual forecast to zero if the predictive regression model generates a negative equity premium forecast. The dotted lines in Figure 2.1 and Figure 2.2 illustrate the effects of these types of restrictions on predictive regression models. Imposing Campbell and Thompson [2008] restrictions indeed improves the out-of-sample performance for most of variables in most of out-of-sample periods, in particular, D/P, TMS, PPI, investment-to-capital ratio (I/K) during the 1987 market crash and most of 1990s. However, the Campbell and Thompson [2008] restrictions on predictive regression models still do not ensure consistent outperformance of individual predictors over the out-of-sample period. Overall, the Australian evidence is consistent with the conclusion drawn by Welch and Goyal [2008] from their US evidence, specifically that it is difficult to identify individual predictors that reliably out-perform the historical average with respect to forecasting the equity premium.

Panel B of Figure 2.1 and Figure 2.2 shows the results for the out-of-sample performance of combination forecasts. The solid line represents the difference between the cumulative square prediction error for the historical average forecasts and that for the combination forecasts. Similarly, the dotted lines demonstrate the results of combination forecasts models with Campbell and Thompson [2008] restrictions. For the one-quarter ahead prediction, the mean, median and trimmed mean combination forecast performances are just able to match the performance of historical average, but stay fairly stable over the sample period. On the other hand, the mean and trimmed mean combination predictions with Campbell and Thompson [2008] restrictions imposed have predominantly positive slopes (only slightly negative for the early 1990s) and clearly out-perform the historical average forecast. Although the DMSPE combination method offers some noticeable degree of out-performance at the end of the sample period when $\theta = 1.0$ and 0.5, it does not consistently out-perform the historical average. The solid lines have negatively slopes in 1987 and around early 1990s. When $\theta = 0.1$, the DMSPE method under-performs the historical average throughout most of 1990s and early 2000s. However, after Campbell and Thompson [2008] restrictions are imposed, the DMSPE method consistently out-performs the historical average in an ample magnitude, especially when $\theta = 1.0$ and 0.5. The benefit of combination forecast approach is particularly evident in the one-year ahead prediction. The curves in panel B of Figure 2 have slopes that are predominantly positive (except the median combination), strongly in the period before 1990, but still consistently positive thereafter. The dotted lines representing the Campbell and Thompson [2008] restrictions overlie with the solid lines in Figure 2.2, indicating that combination forecasts in general satisfy with the restrictions. Overall, the combination forecast approach illustrated in Panel B of Figure 2.1 and Figure 2.2 avoids the frequent and often substantial negative slopes in the individual forecasts in Panel A, indicating that the combination forecasts is a more effective tool to forecast the equity premium in Australia.

We then discuss the forecast performance for the three out-of-sample periods, which are presented in Table 2.4 and Table 2.5 for one-quarter and one-year ahead horizon. These tables report R^2_{OS} statistics and utility gains for each of the predictive regression models relative to the historical average and the static strategy.

Panel A of Table 2.4 reports one quarter-ahead forecast results for the full out-of-sample period from January 1985 to September 2010. Only two, namely, GDP and M3, out of 15 individual predictive variables generate positive R^2_{OS} as shown in columns (2) and (6). None of these positive R^2_{OS} are significant. Variables such as D/Y, D/P and C/K that deliver significantly positive adjusted R^2 in-sample no longer generate positive out-of-sample R^2. The average utility gains reported in columns (3), (4), (7) and (8) lend less support for out-of-sample predictability, as only C/K out-performs both historical average and 70% equity and 30% cash static strategy (3.54% and 2.05% p.a.). For the combination forecasts results in Panel A of Table 2.4, the most interesting result is the relatively high R^2_{OS} generated by each of the combining methods. All of the R^2_{OS} statistics for the combination forecasts are greater than 3% and larger than the largest R^2_{OS} (0.61% for M3) among all of the individual predictors. Nevertheless, only mean combinations with Campbell and Thompson [2008] restrictions ($Mean_{CT}$) generate significantly positive R^2_{OS} (significant at 10% level). With the exception of the

$Mean_{CT}$ method, all other combining methods deliver only positive utility gains relative to the historical average, but fail to out-perform the static strategy. The kitchen sink model generates the worst out-of-sample forecasting result, yielding a -11.48% R^2_{OS} and the lowest utility gains among all combination methods.

Panel B of Table 2.4 reveals an average improvement in one-quarter ahead out-of-sample predictability of individual predictors in the sample period from January 1995 to September 2010. The number of individual predictors with positive R^2_{OS} increases from two in the full sample period to four. Particularly, D/P posits an impressive 11.66% R^2_{OS} and GDP has a significantly positive R^2_{OS} at 5% level. Moreover, many of the negative R^2_{OS} statistics for the individual predictors are smaller in terms of absolute value. The average utility gains generally provide greater support for out-of-sample predictability. Six variables have positive utility gains relative to both historical average and the static strategy. C/K again generates the highest utility gains, out-performs the historical average and the static strategy by 3.11% and 2.66% p.a., respectively. Similar to the improved performance of the individual predictors, the combining methods also generate larger R^2_{OS} statistics from January 1995 to September 2010 compared to the full out-of-sample period, with mean, median and trimmed mean all providing significantly positive R^2_{OS} at 5% level. All combining methods have R^2_{OS} larger than 8% and positive utility gains relative to both historical average and the static strategy, except the DMSPE ($\theta = 0.1$) with R^2_{OS} of 7.45% and under-performing the static strategy. The kitchen sink model again delivers the worst out-of-sample forecasting result, yielding a -30.21% R^2_{OS} and the lowest utility gains. Overall, the markedly improved out-of-sample performances of both individual predictors and combining methods in this sample period indicate that the out-of-sample forecastability is particularly poor during the 1985 to 1995 period, most probably due to the 1987 market crash.

Panel C of Table 2.4 reports one-quarter ahead forecast results for the January 2005 to September 2010 out-of-sample period covering the recent global financial crisis. The columns (2) and (6) of Panel C indicate further improved out-of-sample performance with seven out of 15 variables out-performing the historical average. Most of variables have increased R^2_{OS}, with D/P and C/K having R^2_{OS} larger than 10%. Five variables generate sizable utility gains relative to the historical average and the static strategy in this turbulent period. Again, C/K delivers the highest utility gains with 5.75% and 4.66% per annum out-performance relative to the historical average and the static strategy, respectively. Similar to the previous two sample periods, column (9) of Panel C shows that the combination forecasts again generate higher positive R^2_{OS} than individual predictors, with all of R^2_{OS} greater than 13%. Unlike the results in Panel B, the DMSPE methods produce higher and significant R^2_{OS} during this particular sample period. The superiority of combination forecast methods is further confirmed when all combining methods out-perform both the historical average and static strategy in the asset allocation performance. The kitchen sink model is again the biggest loser in all respects, with -14.96% R^2_{OS} and -3.77% and -4.87% utility gain.

Figure 2.1: One quarter prediction

These graphs plot the time-series difference between cumulative square prediction error (CSPE) for the historical average model and the CSPE for the individual and combination predictive regression models, 1985:1-2010:3. Solid line represents the difference in CSPE without Campbell and Thompson [2008] restriction. Dotted line represents the difference in CSPE with Campbell and Thompson [2008] restriction. When the line in each graph increases, the predictive regression model performs better than the historical average.

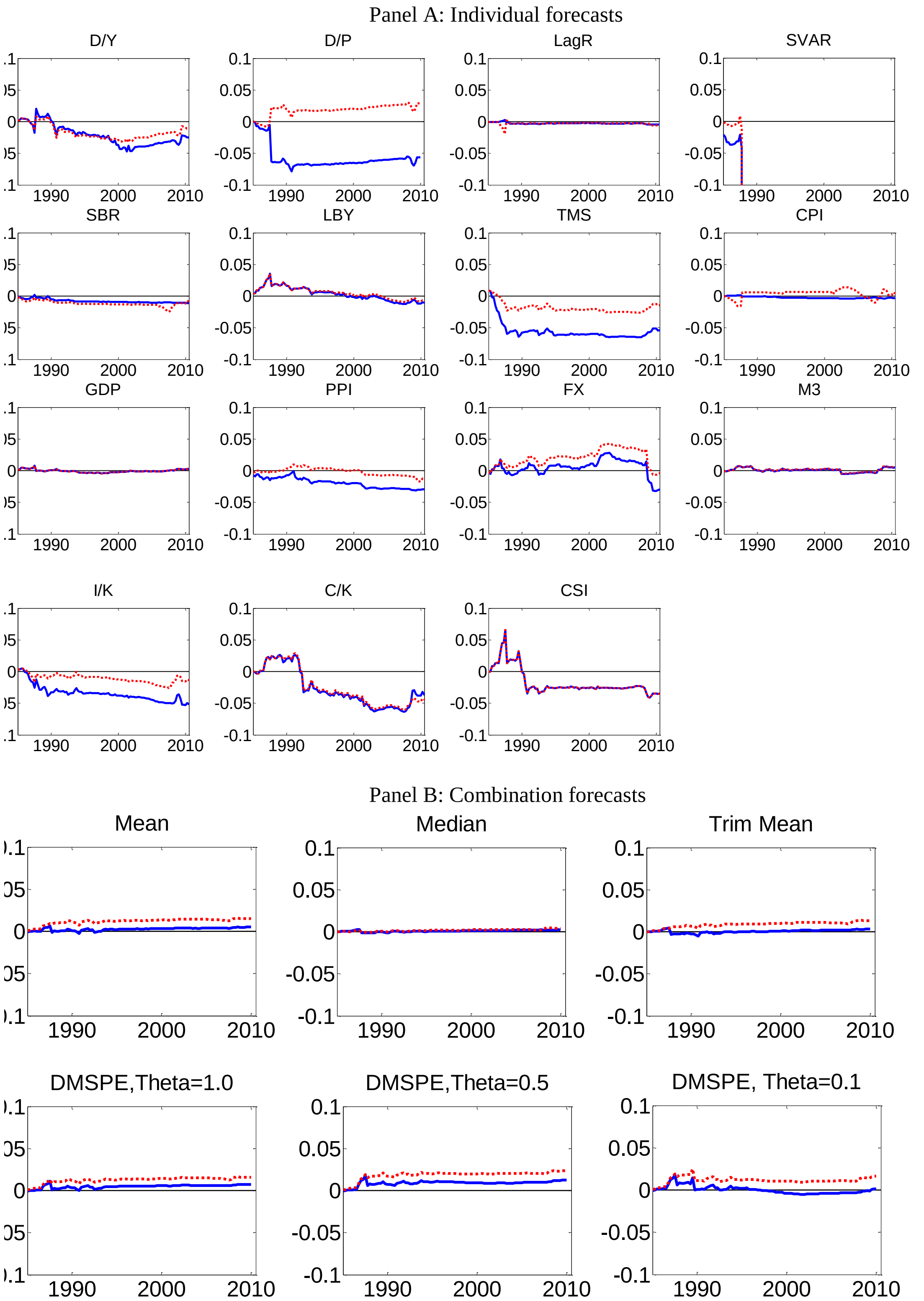


Figure 2.2: One year prediction

These graphs plot the time-series difference between cumulative square prediction error (CSPE) for the historical average model and the CSPE for the individual and combination predictive regression models, 1985:1-2010:3. Solid line represents the difference in CSPE without Campbell and Thompson [2008] restriction. Dotted line represents the difference in CSPE with Campbell and Thompson [2008] restriction. When the line in each graph increases, the predictive regression model performs better than the historical average.

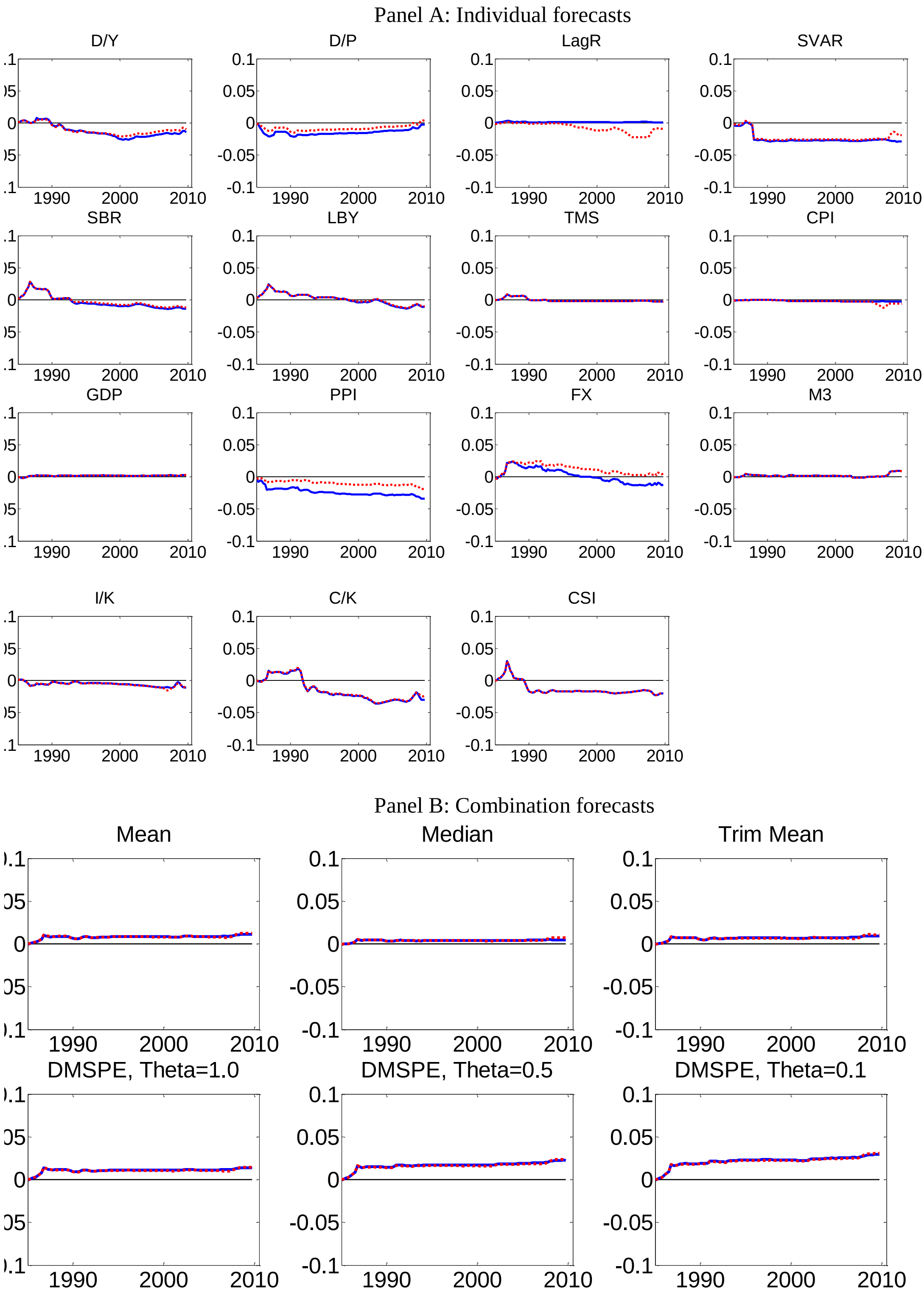


Table 2.4: Equity premium out-of-sample forecasting results for individual forecasts and combining methods - 1 quarter

R^2_{OS} is the Campbell and Thompson [2008] out-of-sample R-square statistic. Utility gain ($\Delta 1$) is the certainty equivalent return (in annualized percentage) that an investor with mean variance preferences and risk aversion coefficient of 3 would obtain using the forecasting model given in Column (1) relative to the historical average benchmark forecasting model; the weight on stocks in the investors portfolio is restricted to lie between 0 and 1 (inclusive). $\Delta 2$ is the portfolio performance of the forecasting model relative to a 70% equity 30% cash buy and hold strategy. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West [2007] out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Individual predictive regression model forecasts								Combination forecasts			
Predictor (1)	R^2_{OS}(%) (2)	$\Delta 1$(%) (3)	$\Delta 2$ (%) (4)	Predictor (5)	R^2_{OS}(%) (6)	$\Delta 1$(%) (7)	$\Delta 2$(%) (8)	Combining method (9)	R^2_{OS}(%) (10)	$\Delta 1$(%) (11)	$\Delta 2$ (%) (12)
Panel A: 1985:1-2010:3 out-of-sample period											
D/Y	-3.01	0.07	-1.42	CPI	-0.37	-0.27	-1.75	Mean	3.61	0.43	-1.06
D/P	-3.76	-0.78	-2.26	GDP	0.33	-0.6	-2.08	Median	3.27	0.37	-1.12
$LagR$	-0.53	-0.30	-1.78	PPI	-3.54	-1.12	-2.60	Trimmed Mean	3.38	0.13	-1.35
$SVAR$	-234.15	-0.92	-2.40	FX	-3.51	0.60	-0.89	DMSPE, θ=1.0	3.89	0.27	-1.21
				$M3$	0.61	1.25	-0.24	DMSPE, θ=0.5	4.49	0.27	-1.21
SBR	-1.35	-0.74	-2.22	I/K	-6.17	0.08	-1.41	DMSPE, θ=0.1	3.12	0.07	-1.41
LBY	-1.29	-2.00	-3.48	C/K	-4.49	3.54	2.05	$Mean_{CT}$	4.80 *	1.52	0.03
TMS	-6.44	-0.63	-2.11	CSI	-4.12	1.10	-0.38	Kitchen Sink	-11.38	-3.02	-4.51
Panel B: 1995:1-2010:3 out-of-sample period											
D/Y	-2.71	-0.92	-1.36	CPI	-0.13	-0.03	-0.47	Mean	8.92 **	0.98	0.54
D/P	11.66	1.53	1.09	GDP	1.99 **	0.16	-0.28	Median	8.64 **	0.92	0.47
$LagR$	-0.42	0.07	-0.37	PPI	-4.10	-1.91	-2.35	Trimmed Mean	9.14 **	0.95	0.51
$SVAR$	-1.88	0.47	0.03	FX	-11.87	-0.17	-0.61	DMSPE, θ=1.0	8.43	0.88	0.44
				$M3$	1.54	1.63	1.19	DMSPE, θ=0.5	8.39	0.69	0.25
SBR	-0.90	-0.14	-0.58	I/K	-5.31	-0.23	-0.67	DMSPE, θ=0.1	7.45	0.13	-0.31
LBY	-5.46	-3.03	-3.48	C/K	-1.70	3.11	2.66	$Mean_{CT}$	8.70	0.92	0.48
TMS	2.45	1.67	1.23	CSI	-2.64	0.66	0.22	Kitchen Sink	-30.21	-1.35	-1.47
Panel C: 2005:1-2010:3 out-of-sample period											
D/Y	6.48	-0.02	-1.11	CPI	0.25	0.04	-1.05	Mean	14.11	2.03	0.93
D/P	15.3	1.99	0.89	GDP	2.02 **	0.24	-0.85	Median	13.70	1.97	0.88
$LagR$	-0.75	-0.07	-1.17	PPI	-0.87	0.25	-0.85	Trimmed Mean	14.20	2.02	0.93
$SVAR$	-4.10	0.13	-0.97	FX	-24.49	-2.19	-3.29	DMSPE, θ=1.0	14.68 **	1.97	0.88
				$M3$	4.77	3.64	2.54	DMSPE, θ=0.5	15.20 **	1.84	0.74
SBR	-0.55	-0.14	-1.23	I/K	-4.03	2.04	0.94	DMSPE, θ=0.1	16.22 *	1.66	0.57
LBY	-2.19	-1.09	-2.18	C/K	10.32	5.75	4.66	$Mean_{CT}$	13.49	2.01	0.91
TMS	5.34	2.83	1.73	CSI	-4.01	0.14	-0.96	Kitchen Sink	-14.96	-3.77	-4.87

Table 2.5: Equity premium out-of-sample forecasting results for individual forecasts and combining methods - 1 year

R^2_{OS} is the Campbell and Thompson [2008] out-of-sample R-square statistic. Utility gain ($\Delta1$) is the certainty equivalent return (in annualized percentage) that an investor with mean variance preferences and risk aversion coefficient of 3 would obtain using the forecasting model given in Column (1) relative to the historical average benchmark forecasting model; the weight on stocks in the investors portfolio is restricted to lie between 0 and 1 (inclusive). $\Delta2$ is the portfolio performance of the forecasting model relative to a 70% equity 30% cash buy and hold strategy. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West [2007] out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Individual predictive regression model forecasts								Combination forecasts			
Predictor (1)	R^2_{OS}(%) (2)	$\Delta1$(%) (3)	$\Delta2$ (%) (4)	Predictor (5)	R^2_{OS}(%) (6)	$\Delta1$(%) (7)	$\Delta2$(%) (8)	Combining method (9)	R^2_{OS}(%) (10)	$\Delta1$(%) (11)	$\Delta2$ (%) (12)
Panel A: 1985:1-2010:3 out-of-sample period											
D/Y	-7.98	0.26	-0.25	*CPI*	-1.58	0.04	-0.48	Mean	6.13 **	1.13	0.62
D/P	-1.61	0.90	0.39	*GDP*	1.37	0.34	-0.17	Median	2.67	0.60	0.09
LagR	0.42	0.12	-0.39	*PPI*	-18.85	-1.26	-1.77	Trimmed Mean	5.12 **	0.96	0.44
SVAR	-15.97	-0.33	-0.84	*FX*	-6.96	0.29	-0.22	DMSPE, θ=1.0	7.63 **	1.19	0.68
				M3	4.53 *	1.97	1.46	DMSPE, θ=0.5	12.39 ***	1.95	1.44
SBR	-7.50	-0.93	-1.44	*I/K*	-6.02	1.28	0.76	DMSPE, θ=0.1	16.13 ***	2.87	2.36
LBY	-5.86	-1.80	-2.31	*C/K*	-16.51	3.39	2.87	$Mean_{CT}$	6.87 **	0.95	0.43
TMS	-1.35	0.85	0.34	*CSI*	-11.16	0.17	-0.34	Kitchen Sink	-18.27	0.80	0.29
Panel B: 1995:1-2010:3 out-of-sample period											
D/Y	-1.49	-0.77	-0.91	*CPI*	-1.21	-0.08	-0.22	Mean	3.06 **	0.08	-0.06
D/P	15.52 ***	0.97	0.83	*GDP*	0.75	-0.05	-0.19	Median	1.05	0.01	-0.13
LagR	-0.24	0.09	-0.05	*PPI*	-11.4	-2.08	-2.22	Trimmed Mean	2.59 **	0.01	-0.12
SVAR	-1.42	0.32	0.19	*FX*	-25.54	-0.07	-0.21	DMSPE, θ=1.0	3.26 ***	0.20	0.07
				M3	7.63 *	2.74	2.60	DMSPE, θ=0.5	6.12 ***	0.23	0.09
SBR	-9.47	-1.37	-1.50	*I/K*	-7.01	1.28	1.14	DMSPE, θ=0.1	6.85 ***	0.35	0.21
LBY	-16.19	-1.84	-1.98	*C/K*	-12.43	3.30	3.16	$Mean_{CT}$	3.50 *	0.00	-0.14
TMS	-0.62	-0.03	-0.17	*CSI*	-3.33	0.61	0.47	Kitchen Sink	-11.8	-1.04	-1.18
Panel C: 2005:1-2010:3 out-of-sample period											
D/Y	7.70 *	0.04	-0.48	*CPI*	-0.44	0.03	-0.50	Mean	3.59 **	0.02	-0.51
D/P	12.91 *	0.81	0.28	*GDP*	1.19	0.04	-0.48	Median	1.02	0.01	-0.51
LagR	-0.70	0.01	-0.51	*PPI*	-9.15	-1.27	-1.79	Trimmed Mean	2.80 **	-0.05	-0.57
SVAR	-2.71	0.17	-0.36	*FX*	-1.34	-2.82	-3.34	DMSPE, θ=1.0	4.08 ***	0.03	-0.49
				M3	12.33 *	7.33	6.80	DMSPE, θ=0.5	5.01 ***	0.04	-0.48
SBR	-3.33	-1.71	-2.23	*I/K*	-1.81	4.42	3.89	DMSPE, θ=0.1	5.85 ***	0.61	0.09
LBY	-3.49	0.34	-0.18	*C/K*	1.88	6.98	6.46	$Mean_{CT}$	2.82	-0.27	-0.79
TMS	-0.94	0.02	-0.51	*CSI*	-2.77	0.01	-0.51	Kitchen Sink	-1.23	-1.52	-2.04

We turn our focus of discussion to the one-year ahead forecast results reported in Table 2.5. Similar to the generally poor performance of individual predictors in the one-quarter ahead forecast, Panel A shows only three out of 15 individual predictors (LagR, GDP and M3) generate positive R^2_{OS} in the full out-of-sample period. M3 produces a significantly positive R^2_{OS} at 10% level. Five variables out-perform both the historical average and the static strategy in the asset allocation performance, with C/K and M3 the best performers. Despite the disappointing results of individual predictors, the performance of combining methods is rather impressive. Not only do all combining methods generate statistically significantly positive R^2_{OS} (except median) (on average 8.13%), but also they all deliver positive gains relative to both benchmarks. Most notably, the DMSPE (θ=0.1) method has a positive R^2_{OS} of 16.13% (significant at 1% level) and out-performs the historical average and the static strategy by 2.87% and 2.36% per annum in the asset allocation performance. Similar to the one-quarter ahead forecast results, the kitchen sink model still has a large and negative R^2_{OS} (-18.27%). However, it produces some small utility gains relative to both benchmarks.

Unlike the one-quarter ahead forecast results, the individual predictors one year ahead out-of-sample predictability does not seem to increase during the sample period from January 1995 to September 2010 as shown in Panel B of Table 2.5. Only three variables have positive R^2_{OS}, with D/P and M3 producing 15.52% and 7.63% R^2_{OS} statistics, significant at 1% and 10% level. C/K and M3 again generate the highest utility gains relative to both benchmarks. All combining methods again deliver significantly positive R^2_{OS} (except median), however, with considerably lower magnitude (on average 3.77%). Only the DMSPE methods out-perform both the historical average and static strategy in the asset allocation performance. The DMSPE (θ=0.1) method still produces the highest R^2_{OS} and utility gains. The kitchen sink model unsurprisingly under-performs. In contrast to the one-quarter ahead forecast results, the one-year ahead forecasts perform extraordinarily well during the 1985 to 1995 period but not particularly impressively during the 1995 to 2010 period.

Those best individual performers in previous sample periods still lead the performance in the last five years sample period. D/Y, D/P, GDP, M3, and C/K all generate positive R^2_{OS} but not at a high significance levels. The utility gains for M3 and C/K are impressive, with 7.33% and 6.98% out-performance relative to the historical average and 6.80% and 6.46% out-performance relative to the static strategy. This is remarkable, given the sample period covers the Global Financial Crisis. These predictors must have successfully detected the market turning points beforehand. Unsurprisingly, all combination methods produce significantly positive R^2_{OS} (except median), with the magnitude of 3.59% on average. However, the asset allocation performance of combining methods deteriorates markedly. Only the DMSPE ($\theta = 0.1$) method out-performs both the benchmarks in the asset allocation performance. The kitchen sink model consistently under-performs all benchmarks.

Overall, we find some statistically significant equity return predictability using combining methods at one-quarter horizon, particularly when Campbell and Thompson [2008] constraints are imposed. The asset allocation performance of the combining methods tends to out-perform other strategies in the second half of the sample period using one quarter ahead forecasts. On the other hand, the one-year ahead equity return predictability using a variety of combining methods is more statistically evident. However, unlike the one-quarter ahead forecasts, the improved asset allocation performance using these combining methods at one-year horizons is mostly concentrated in the first half of the sample period. The C/K ratio is the only predictor that consistently delivers superior asset allocation performance using different out-of-sample periods and different horizon forecasts.

2.4.3 Out-of-sample sector premia predictability results

We apply the same set of 15 variables to predict one-quarter and one-year ahead sector premia. In Table 2.6 and Table 2.7, we examine the statistical significance of individual predictors and the combining methods. For the combining methods, we only provide evidence using the DMSPE ($\theta = 0.1$) combination forecast, as we have demonstrated that it has superior empirical forecastability over the stock market premium relative to other combining methods.

Table 2.6 reports the out of sample R^2_{OS} statistics in predicting one-quarter ahead sector premia for the period from 1985 to 2009. Almost all individual predictors fail to significantly out-perform the forecast based on historical average, except money supply (R^2_{OS}= 7.37%, significant at 1% level) and C/K ratio (R^2_{OS}= 7.38%, significant at 1% level) in predicting the telecommunications sector and C/K ratio (R^2_{OS}= 1.64%, significant at 10% level) in predicting the technology sector. Nevertheless, combining information from these variables using the DMSPE (θ=0.1) method, the 15 variables collectively can predict the consumer discretionary (R^2_{OS}= 2.18%, significant at 5% level), technology (R^2_{OS}= 5.08%, significant at 1% level) and telecommunications sectors (R^2_{OS}= 3.69%, significant at 5% level).

Figure 2.3 plots the time-series differences between the cumulative square prediction error for the historical average benchmark forecast and the cumulative square prediction error for the forecasts based on DMSPE (θ=0.1) method for all ten sectors and sector value weighted market returns for the period from 1985 to 2009. Panel A of Figure 2.3

shows that the combining method can consistently predict the returns for consumer discretionary, technology and telecommunications sectors but fail to predict other sector returns. This results confirm the findings shown in Table 2.6.

Table 2.7 reports the out of sample R^2_{OS} statistics in predicting one-year ahead sector premia, for the period from 1985 to 2009. Similar to the one-quarter forecast horizon result, most of the individual predictors fail to generate significantly positive R^2_{OS}. We find that dividend-to-price ratio is able to predict the utilities sector (R^2_{OS}= 4.26%, significant at 5% level) and current movement can predict the consumer staples (R^2_{OS}= 3.24%, significant at 1% level) and financials sectors (R^2_{OS}= 0.25%, significant at 5% level). However, by combining information from all 15 variables, the DMSPE (θ=0.1) combining methods, both with and without Campbell and Thompson [2008] restrictions, are able to predict returns for all sectors and significantly out-perform the historical average forecasts.

Figure 2.3: Sector return prediction

These graphs plot the time-series difference between cumulative square prediction error (CSPE) of the historical average model and the CSPE of the DMSPE $\theta = 0.1$ combining method, 1985:1-2009:4, for Australian sectors according to the GICS classification standard. Solid line represents the difference in CSPE without Campbell and Thompson [2008] restriction. Dotted line represents the difference in CSPE with Campbell and Thompson [2008] restriction. When the line in each graph increases, the predictive regression model performs better than the historical average.

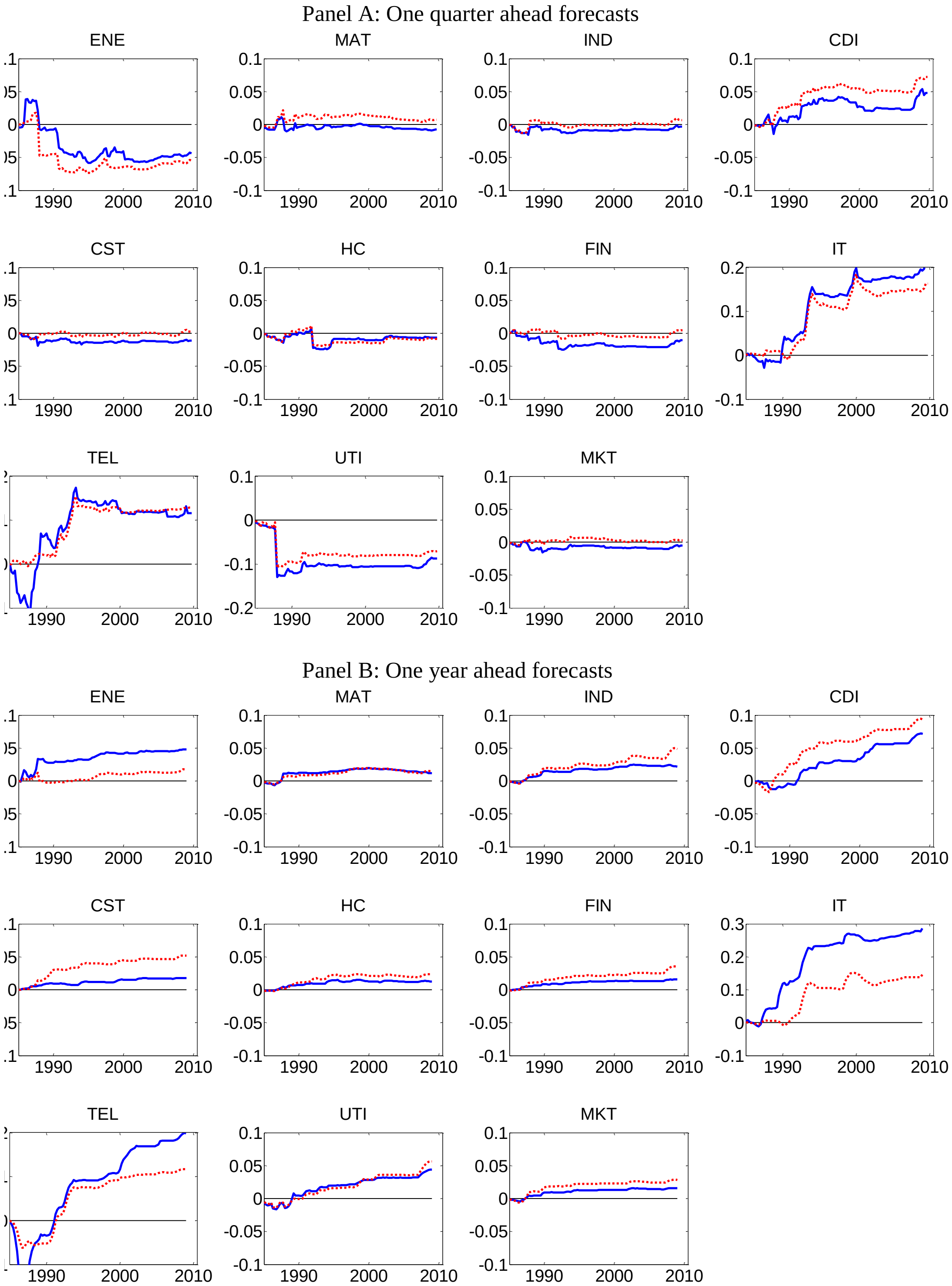


Table 2.6: Sector equity premium out-of-sample R^2_{OS} statistics 1985:1-2009:4 - one quarter horizon

R^2_{OS} is the Campbell and Thompson [2008] Panel A reports the R^2_{OS} for individual predictors and combining methods in predicting one quarter ahead sector equity premium. R^2_{OS} is the Campbell and Thompson [2008] out-of-sample R^2_{OS} statistic. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West [2007] out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Predictor and CM	ENE	MAT	IND	CDI	CST	HC	FIN	IT	TEL	UTI	MKT
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
D/Y	-24.33	-7.10	-1.49	-4.09	-4.39	-4.46	-7.82	-0.17	-9.76	0.50	-7.14
D/P	-7.29	-8.17	-4.68	-2.22	-7.08	-3.83	-4.10	-0.89	-6.19	-5.64	-6.76
LagR	-0.35	-1.10	-0.31	-0.64	-1.03	-3.16	-3.31	-0.50	-1.82	0.82	-0.75
SVAR	-1918.96	-212.90	-122.40	-185.32	-18.04	-58.41	-76.77	-20.72	0.24	-1594.62	-304.90
SBR	-8.91	-6.47	-8.04	-3.34	-2.45	-5.89	-5.93	-2.46	-8.97	-4.52	-8.32
LBY	-2.50	-2.31	-1.79	-0.56	-1.80	-0.59	-1.72	-1.96	-4.86	-2.82	-1.43
TMS	-4.38	-4.17	-4.90	-4.97	-8.44	-7.15	-7.06	-0.39	-2.47	-1.01	-7.13
CPI	-9.53	-0.91	-3.16	-1.51	-2.00	-0.39	-2.81	-0.94	0.13	-2.22	-1.49
GDP	-0.04	-0.40	-0.04	-0.38	-0.76	-0.78	-0.39	-0.36	-4.65	-0.67	-0.22
PPI	-24.43	-4.56	-1.80	-0.62	-3.93	-0.51	-0.70	-4.58	-6.85	-5.78	-3.02
FX	-8.75	-4.04	-1.71	-0.94	-2.19	-1.46	-2.75	-2.10	-9.41	-1.57	-2.52
M3	-0.86	-0.37	-0.57	0.01	-0.50	-0.93	0.61	0.79	7.37***	0.45	-0.06
I/K	-18.33	-6.54	-7.34	-3.26	-6.68	-4.65	-3.99	-8.76	-21.51	-2.80	-8.07
C/K	-11.41	-3.09	-0.94	-4.65	-6.30	-2.37	-1.26	1.64*	7.38***	1.28	-2.37
CSI	-6.17	-5.14	-3.01	-4.10	-4.91	-3.28	-4.33	-1.97	-0.02	-2.00	-5.27
DMSPE, θ=0.1	-2.99	-0.60	-0.28	2.18**	-1.41	-0.71	-1.11	5.08***	3.69**	-5.15	-0.65
$DMSPE_{CT}$, =0.1	-3.07	0.63	0.63	3.29***	0.36	-0.89	0.48	3.98***	4.08**	-4.19	0.36

Table 2.7: Sector equity premium out-of-sample R^2_{OS} statistics 1985:1-2009:4 - one year horizon

R^2_{OS} is the Campbell and Thompson [2008] Panel A reports the R^2_{OS} for individual predictors and combining methods in predicting one year ahead sector equity premium. R^2_{OS} is the Campbell and Thompson [2008] out-of-sample R^2_{OS} statistic. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West [2007] out-of-sample MSPE-adjusted statistic. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Predictor and CM	ENE	MAT	IND	CDI	CST	HC	FIN	IT	TEL	UTI	MKT
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
D/Y	-49.12	-19.00	-0.77	-5.28	-6.73	-6.44	-10.55	-6.05	-34.49	-0.20	-14.11
D/P	-56.29	-38.43	-1.16	-14.35	-10.29	-1.69	-3.85	-2.32	-46.02	4.26**	-13.62
LagR	-2.99	-3.38	-3.62	-6.18	-4.38	-4.00	-2.95	-3.67	-9.57	-5.89	-4.13
SVAR	-614.01	-22.57	-15.32	-15.95	-31.72	-68.19	-45.41	-13.48	-40.21	-118.07	-39.34
SBR	-19.57	-9.71	-12.01	-12.93	-7.66	-6.50	-9.90	-16.11	-47.74	-13.14	-11.90
LBY	-28.09	-11.80	-10.52	-7.85	-5.92	-7.88	-6.97	-21.02	-28.41	-15.21	-9.86
TMS	-4.11	-5.77	-6.85	-10.68	-11.46	-5.37	-4.97	-8.05	-20.25	-2.10	-7.16
CPI	-7.80	-5.78	-3.47	-8.06	-3.94	-0.39	-5.55	-10.62	-13.04	-8.60	-5.29
GDP	-1.39	-1.70	-2.64	-3.66	-2.08	-1.06	-4.15	-4.04	-7.78	-3.48	-2.30
PPI	-51.55	-18.42	-10.47	-9.49	-6.74	-5.40	-9.53	-18.73	-29.67	-14.14	-16.62
FX	-29.77	-4.40	-0.93	-2.11	3.24***	-2.75	0.25**	-5.12	-5.83	-4.03	-1.67
M3	-8.76	-3.84	-4.71	-5.47	-5.64	-4.32	-0.73	-5.26	-4.79	-2.61	-3.26
I/K	-30.20	-18.74	-14.87	-21.08	-20.58	-12.92	-3.08	-18.61	-41.21	-6.32	-13.74
C/K	-19.08	-9.99	-13.80	-19.60	-33.88	-12.85	-13.72	-4.27	-1.48	-2.26	-14.58
CSI	-32.80	-19.34	-12.57	-27.92	-22.46	-13.75	-19.39	-12.85	-9.77	-15.15	-24.73
DMSPE, θ=0.1	13.25***	4.11*	7.53***	10.03***	8.86***	4.98**	7.03***	15.46***	13.39***	9.26***	7.82***
$DMSPE_{CT}$, =0.1	4.76***	5.23**	16.96***	13.06***	26.18***	9.54***	16.01***	7.91***	7.91***	11.91***	14.20***

Panel B of Figure 2.3 shows time-series relative performance of the DMSPE (θ=0.1) combining method using one-year horizon forecast. Not only does the combining method out-perform the historical average forecast benchmark in predicting all sectors at the end of the sample period, but also it appears to generate consistently superior predictability throughout the entire sample periods. This gives further support to the effectiveness of the combination forecast approach.

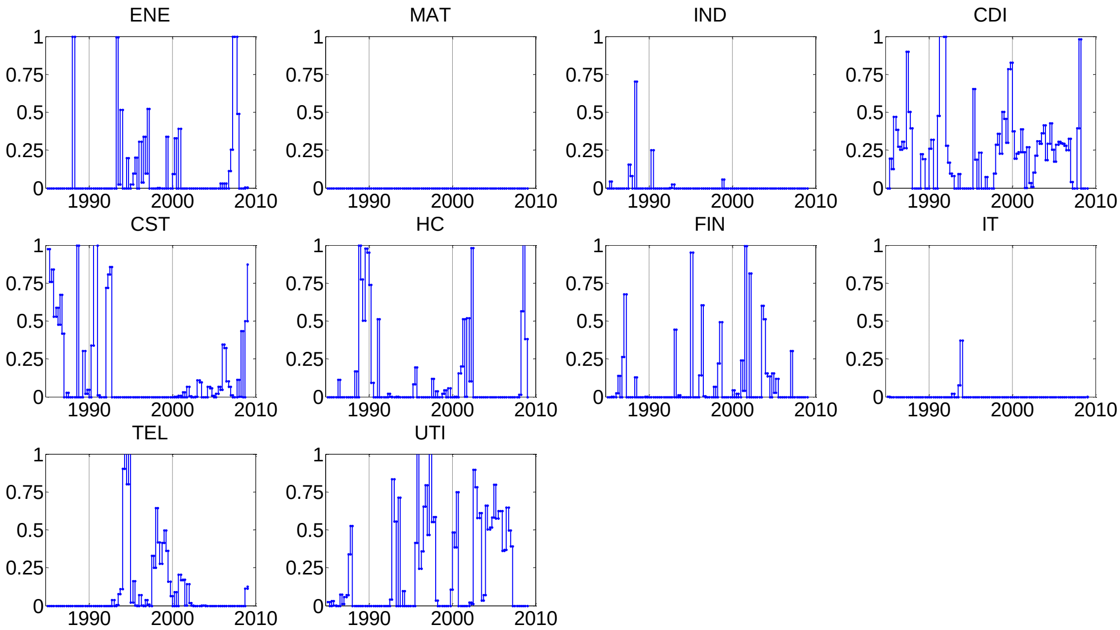
Nevertheless, strong statistical significance does not imply substantial economic gains. We turn our focus on the sector allocation performance using predicted sector returns generated from the combining methods. We report only one-year ahead forecast result as it was shown to have a greater predictability.

Figure 2.4 plots the sector weights for a dynamic sector rotation strategy based on the predicted sector returns using the DMSPE methods (θ= 0.1) for the sample period from 1985 to 2009. Sector weights are determined each quarter using the mean-variance optimisation technique described in Section 2.2.3. As illustrated in Figure 2.4, this strategy tends to overweight consumer discretionary, consumer staples and utilities, which are the three empirically better performing sectors during the sample period. It also invests little in materials, industrials and IT, which have relatively poor performance. This strategy also tilts towards defensive sectors during the economic recessions and takes aggressive positions during economic expansions. For instance, it invests in consumer staples, healthcare and telecommunications during the Global Financial Crisis and assigns a high weight to consumer discretionary during the market boom in 1990s.

Table 2.8 reports the average returns, volatilities and utility gains for the sector rotation strategy relying on the DMSPE methods (θ = 0.1) for the three different

Figure 2.4: Dynamic sector weights based on premia forecasted by the DMSPE $\theta = 0.1$ method

These charts plot the time-series sector weights for the optimal sector portfolio based on the one year ahead sector premia forecasted by the DMSPE $\theta = 0.1$ combing method. We assume the investor has mean variance preferences and a risk aversion coefficient of 3. Short selling is not allowed and the total portfolio weight at each quarter equals to 1. The solid line connects the weights allocated to each sector at each quarter throughout the out-of-sample period 1985 2009.



out-of-sample periods. We compare the utility gains for these sector rotation strategies against the sector value weighted and equally weighted returns. As demonstrated, the sector rotation strategy using the DMSPE ($\theta = 0.1$) method is extremely profitable. Not only do the average returns of this strategy beat the value weighted returns by 7.18% per annum, but also the risk adjusted performances are economically large (3.27%). The out-performance is also economically significant in the other two sample periods. Particularly, this strategy delivers 3.54% higher average returns and 2.95% lower volatilities than the sector value weighted strategies during the last five year sample period containing the recent Global Financial Crisis.

Table 2.8: The profitability of sector rotation strategies based on sectors premium forecasts using combing methods

This table compares the mean and standard deviation of returns for different sector allocation strategies for three different out-of-sample periods. Utility gain (Δ_{VW}) is the certainty equivalent return (in annualized percentage) that an investor with mean variance preferences and risk aversion coefficient of 3 would obtain using the forecasting model given in Column (1) relative to the value weighted sector allocation strategy VW_{MKT}; Δ_{EW} is the sector allocation performance based on the forecasting models relative to a equally weighted sector allocation strategy.

Strategies (1)	Mean (%) (2)	Std (%) (3)	Δ_{VW}(%) (4)	Δ_{EW} (%) (5)
Panel A: 1985:1-2009:4 out-of-sample period				
VW_{MKT}	10.32	17.63	0.00	-0.05
EW_{MKT}	10.83	18.65	-0.05	0.00
DMSPE-CT, θ=0.1	17.51	23.91	3.27	3.32
Panel B: 1995:1-2009:4 out-of-sample period				
VW_{MKT}	8.19	12.82	0.00	0.12
EW_{MKT}	8.28	12.74	0.12	0.00
DMSPE-CT, θ=0.1	15.01	13.46	6.57	6.45
Panel C: 2005:1-2009:4 out-of-sample period				
VW_{MKT}	1.11	18.00	0.00	0.52
EW_{MKT}	0.81	16.41	0.52	0.00
DMSPE-CT, θ=0.1	4.65	15.05	5.00	4.48

2.5 Concluding remarks

This study provides a comprehensive examination of out-of-sample predictability of equity risk premium for both the market and individual sectors in Australia using a variety of individual financial and economic variables and combination forecasts. Similar to Welch and Goyal [2008] and Rapach, Strauss, and Zhou [2010], we demonstrate that it is difficult to identify individual economic variables that can consistently produce reliable out-of-sample forecasts of the equity premium in Australia. Nevertheless, a forecast combination tends to generate significantly positive R^2_{OS} for different out-of-sample periods, particularly for the one-year forecasting horizon. However, the asset allocation out-performance is located mainly in the first half of the sample period. We have demonstrated here that combination forecast approach is potentially an effective method of real time equity premium forecast in Australia.

Investors can also exploit the information provided by these 15 variables in a dynamic sector allocation setting. We demonstrate that, using the predicted returns generated from the combination method, risk-neutral investors can on average earn 7.2% per annum premium over the market returns from 1985 to 2009. On a risk-adjusted basis, an investor (on average) can obtain a 3.3% utility gain compared to the market portfolio.

Our results could be extended in a few directions. For instance, although we select a large number of Australian-specific economic variables, the list of predictors is by no mean exclusive. It would be interesting to also consider other predictors documented by previous US studies such as the book to market ratio and corporate issuing activities. Consensus economic forecast variables may also provide useful information in predicting equity premium. We leave these extensions to future research.

Chapter 3

Cross-Region and Cross-Sector Asset Allocation with Regimes

3.1 Introduction

For international equity fund managers, the asset allocation decision – how much to invest in each major region and sector – is a key determinant of their portfolio performance. Region and sector weights are usually determined on the basis of a model that characterises the joint distribution of equity returns. Most studies assume that equity returns are generated by a stationary process with mean, variances and covariances of returns that are constant over time. However, there is growing empirical evidence that equity returns follow a rather more complicated process with multiple regimes, namely different market or economic conditions, each of which is associated with a very different distribution of returns [Ang and Bekaert, 2002a,b, 2004, Garcia and Perron, 1996, Guidolin and Timmermann, 2007]. This empirical feature of equity returns highlights the need for a dynamic asset allocation model that accounts for different distributions of asset returns in different regimes.

Our paper investigates whether a dynamic asset allocation that accounts for regimes can allocate assets more efficiently across regions and sectors (i.e., generate higher returns for investors) than a static Markowitz [1952]'s mean-variance analysis. Similar to Hamilton [1989]'s regime switching model, we define regimes as unobservable to investors, who can only infer regime probabilities from past return observations. We consider two regimes where the first (second) regime has the characteristics of a bull (bear) market with high (low) returns and low (high) volatilities. These two regimes offer very different investment opportunities so investors asset allocations vary significantly over time as they revise their beliefs about the underlying regime probabilities.

We demonstrate that a regime-dependent asset allocation that holds different mean-variance efficient portfolios in different regimes can potentially outperform the static mean-variance optimal portfolio in both cross-region and cross-sector. Most evidently, sector allocations provide higher diversification benefits and hence perform better than optimal allocation across regions in both in-sample (1995-2002) and out-of-sample (2003-2010).

Our study is most closely related to that of Ang and Bekaert [2004], who document how the presence of regimes can be incorporated into two asset allocation programs – a global asset allocation setting with six equity markets and a market timing setting for US cash, bonds and equity. Ang and Bekaert [2004] find that regime-switching strategies have the potential to outperform the static mean-variance analysis because they are able to capture different distributions of asset returns at different times in the business cycle. However, they indicate that the superior performance of regime-switching strategies may be linked to a specific historical period, in their case 1975 to 2000. Using the same MSCI country dataset in a different period (1995 to 2010), we find that the regime-dependent country portfolio only marginally out-performs the static strategy in the out-of-sample period (2003-2010). On the other hand, the empirical results for our regime switching sector rotation strategy are economically important. In our out-of-sample analysis (2003-2010), the regime-dependent sector allocation delivers an average annual return of 13.13% (Sharpe ratio = 0.93), compared to the annual returns on a static mean-variance sector allocation and the world market portfolio of 7.31% (Sharpe ratio = 0.48) and 7.03% (Sharpe ratio = 0.30), respectively.

We contribute to the asset allocation literature by demonstrating how the presence of regimes is exploitable in a sector allocation program. Previous research that investigates the merits of specific sector rotation strategies is surprisingly scarce, given that the industry-level allocation is a fundamental component of most portfolio constructions. Conventional market wisdom also posits that different sectors perform differently in various stages of the business cycle (or financial conditions). The focus of previous sector rotation studies has been on selecting appropriate indicators that can identify when the portfolio should be shifted to a more defensive or aggressive position [Sassetti and Tani, 2006]. However, techniques used in these studies are often heuristic rather than scientific in nature and lack theoretical justification. Our paper addresses these issues using a regime-switching model that derives the regime-shift indicators statistically from stock return data and volatilities in different regimes, hence allowing investors to strategically invest in the optimal defensive (aggressive) portfolio in bear (bull) markets.

Our paper also contributes to the ongoing debate of whether international diversification is more important and beneficial than allocation across sectors. Earlier researchers find that international diversification matters more than diversification across sectors [Griffin and Karolyi, 1998, Solnik, 1974]. However, more recent studies document that industry factors have grown in importance in recent years [Baca, Garbe, and Weiss, 2000, Cavaglia, Brightman, and Aked, 2000]. Most of these earlier studies use factor approaches and do not directly consider the optimal asset allocation implications. Our optimal asset allocation results indicate that industry diversification yields higher performance in the sample period examined. We document that during the period 1995 to 2010, cross-sector optimal allocation generates higher returns, lower risk, lower correlations with the world market and higher Sharpe ratios than cross-region optimal allocation. In addition, a regime-dependent sector allocation outperforms the regime dependent regional allocation in both in-sample and out-of-sample periods.

The paper is organised as follows. Section 3.2 discusses the previous literature and Section 3.3 describes our data. Section 3.4 documents the regime-switching model and the model estimation. Section 3.5 illustrates the asset allocation methodology and compares the performance of regime-dependent portfolios against the static mean-variance optimal portfolios. Section 3.6 concludes the chapter.

3.2 Literature

3.2.1 Regime switching and asset allocation

Regime switching is first used in Hamilton [1989] to model switches between periods of high and low GNP growth. In a regime-shifting framework, the transition from one regime to another follows a Markov chain. That is, at each point in time, there is a certain probability that the process will stay in the same regime, or transition to another regime in the next period. These transitional probabilities might be constant or they might depend on other variables. Since Hamilton [1989]'s seminal work, a large literature has developed to apply regime-switching models to financial time series variables. Turner, Startz, and Nelson [1989] is the first paper in the finance literature that uses a regime-switching model to find high and low stock returns and variances in different time periods. Ang and Bekaert [2002b,c], Bekaert, Hodrick, and Marshall [2001], Garcia and Perron [1996] and Gray [1996] find strong evidence of regimes in US and international short-term interest rate data. Ang and Bekaert [2002a,b], Ang and Chen [2002], Guidolin and Timmermann [2007], Perez-Quiros and Timmermann [2000] and Whitelaw [2000] all report evidence of regimes in stock or bond returns.

In the asset allocation literature, Ang and Bekaert [2002a], Ang and Bekaert [2004] and Guidolin and Timmermann [2007] consider the asset allocation implications of regime-switching models, because they capture many of the properties of asset returns that emerge from the empirical studies such as having regimes with very different means, volatilities or correlations across assets. Ang and Bekaert [2002a] use a two-state model to evaluate the claim that the home bias observed in holdings of international assets can be explained by return correlations that increase in bear markets. Guidolin and Timmermann [2007] use a four-regime model that has a crash state capturing large negative returns and a bull state capturing large positive returns. They claim that a four-regime model best captures the joint distribution of stock and bond returns. Regime-switching models are also useful in capturing fat tails and skewness in the distribution of asset returns [Guidolin and Timmermann, 2008].

In light of these papers, we consider a two-state Markov switching mean-variance model close in spirit to that of Ang and Bekaert [2004]. They conclude that the presence of regimes with different correlations and expected returns is exploitable within an international equity allocation framework. In addition to examining Ang and Bekaert [2004]'s cross-country asset allocation using a different sample period, our paper contributes the asset allocation literature by also investigating the regime-dependent cross-sector allocation, motivated by the recent literature that discusses the increasing importance of sector diversification.

3.2.2 Cross-region, cross-sector allocation

The risk reduction benefits of international diversification of equity portfolios have been accepted for a long time among academics [Solnik, 1974]. However, knowing what factors drive the co-movement in stock returns internationally has long challenged both academics and professional portfolio managers. A number of studies [Grinold, Rudd, and Stefek, 1989, Heston and Rouwenhorst, 1995] examine the relative importance of country and industry factors in explaining the cross section of expected returns and establish country factors as the major influence on equity returns. Heston and Rouwenhorst [1995] decompose stock return volatility into pure country and industry sources of variation and clearly document the dominance of country-specific effects. Griffin and Karolyi [1998] find that when emerging markets are included in the sample, the proportion of portfolio variance explained by the time-series variation in pure country effects is higher than previously documented, which again indicates investors would be better off in terms of risk reduction if they pursued a geographic diversification strategy rather than an industry-based one.

The relative importance of the country factor has been challenged, however, by Baca, Garbe, and Weiss [2000], Cavaglia, Brightman, and Aked [2000], Cavaglia and Moroz [2002] and Chen, Bennett, and Zheng [2006]. These studies conclude that the importance of sector factors has grown to exceed that of country factors in both developed and emerging markets in recent years. They attribute these empirical findings to an increased level of international capital markets integration, which blurs national borders and hence diminishes the significance of country effects. However, Brooks and Del Negro [2004] argue that the rise in industry effects is simply a temporary phenomenon associated with the information technology bubble, rather than a reflection of greater economic integration across countries. Ferreira and Gama [2005] document that, in the 1990s, correlations among local industries have declined and there is a greater penalty for not being well diversified across industries.

On balance, the studies suggest that industry factors have become as important as, if not more than, country factors. Nevertheless, most of the studies discussed above do not consider the optimal asset allocation implications of the growing importance of sector effects. As the financial markets become increasingly integrated, it makes intuitive sense to ask whether sector asset allocation could add benefits to the widely practised international asset allocation.

A relatively under-exploited area of sector asset allocation is with regard to sector rotation strategies. Most professional investors seem to agree that sector rotation strategies can be extremely profitable with good market timing skills [Stovall, 1996]. However, academic evidence on the profitability of sector rotation strategies is surprisingly scarce. The major obstacle has been to select appropriate and timely indicators that identify the exact jumps or turning points of business cycles or financial conditions. Sorensen and Burke [1986] use relative strength analysis for 43 industries and find that an industry momentum-based rotation strategy produces abnormal profits. Using macroeconomic variables such as the default premium, maturity premium and aggregate dividend yield, Beller, Kling, and Levinson [1998] create an industry trading strategy that earned economically significant profits. Sassetti and

Tani [2006] find that the sector rotation strategy is profitable using a number of technical indicators, including relative strength and moving averages. Conover, Jensen, Johnson, and Mercer [2005, 2008] find that cyclical stocks prosper during expansive monetary policy periods (while a restrictive environment favours defensive stocks) and a sector-rotation strategy based on the monetary policy produces excess returns.

Most of these studies implicitly assume that market timing is driven by exogenous variables. Therefore the success of sector-rotation strategies relies solely on the appropriate choice of exogenous indicators. However, using exogenous indicators suffers from reverse causation or omitted variables problems. Hence such strategies could imperfectly capture the true underlying dynamics of time-varying sector performances. To address these potential problems, we propose a Markov switching process that endogenously derives the turning points or jumps of regime cycles from the statistical features of stock returns, and therefore is not afflicted by reverse causation or omitted variables problems. As discussed in Section 3.2.1, there is mounting evidence that suggests the Markov switching process can capture the time-varying distributions of stock returns.

3.3 Data

In the cross-region asset allocation, we focus on a group of developed equity markets that constitute the MSCI world index for an US based institutional investor. We classify these developed equity markets into six regions: namely North-America, UK, Japan, large European countries, small European countries and the Pacific ex-Japan.[1] Table 3.1

[1] Our region classification is consistent with Ang and Bekaert [2004]. In particular, they split the European countries into large and small markets, primarily because the small European markets may represent a diversified portfolio of economic exposures.

details all countries involved. Following Ang and Bekaert [2004], we obtain all country data from the MSCI. Our sample period is January 1995 through to March 2010.

Table 3.1: Composition of regional returns

The table lists the country composition of the geographic returns. Within each geographic region, we construct monthly returns, value-weighted in US dollars.

North America	UK	Japan	Europe Large	Europe Small	Asia Pacific ex-Japan
Canada			Italy	Austria	Australia
US			France	Belgium	Hong Kong
			Germany	Denmark	Singapore
				Finland	New Zealand
				Ireland	
				Netherlands	
				Norway	
				Spain	
				Sweden	
				Switzerland	

In the cross-sector allocation investigation, we focus on 10 broad sectors classified by the MSCI Global Industry Classification Standard (GICS): Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Healthcare, Financials, Information Technology (IT), Telecommunications and Utilities. All sector data come from the MSCI and the sample period is also January 1995 to March 2010.[2] Stocks contained in these sector portfolios are the same stocks contained in the country portfolios. Both country and sector level data are obtained on a monthly basis.

Table 3.2 and Table 3.3 report some characteristics of the regional and sectoral returns data. We measure all returns in US dollars. These return properties are expected to play a large role in determining mean-variance based asset allocations. For example, it is immediately apparent that the use of historical data may lead to relatively small weights to Japan, because it has witnessed relatively low returns (under-performs the world market by 0.50% per month) in the past 15 years with relatively high volatility (5.61% monthly). Similarly, a simple mean-variance optimisation may lead to some

[2] We do not examine pre-1995 period because different sector classification methods are used by MSCI.

large weights to small European economies, as they have relatively higher returns (outperform the world market by 0.42% per month) with moderate level of volatility (5.31% monthly). It is also interesting to note that the IT sector has the highest mean return during the sample period, although this sector has experienced a major boom and bust.

Table 3.2: Descriptive statistics-regional returns 1995-2010

The table reports summary statistics for the regional returns. Regional returns and standard deviation are expressed as logarithmic price index returns at a monthly frequency in percentages. Regional returns are denominated in U.S. dollars and are from MSCI and are in excess of the U.S. 1-month T-bill return. The row labelled beta is the full-sample beta for each regions excess return with the world market excess return. The sample period for the regional returns is January 1995 to Mar 2010.

Sample Moments	World	North America	UK	Japan	Europe Large	Europe Small	Pacific
Mean	0.18	0.36	0.12	-0.32	0.38	0.60	0.26
Stdev	4.47	4.60	4.46	5.61	5.92	5.31	6.35
Skewness	-0.87	-0.77	-0.53	0.15	-0.63	-0.77	-0.53
Kurtosis	1.90	1.26	2.15	-0.19	1.73	1.72	2.03
Beta		0.98	0.88	0.84	1.18	1.09	1.15

Correlation Matrix	World	North America	UK	Japan	Europe Large	Europe Small	Pacific
North America	0.95						
UK	0.88	0.79					
Japan	0.67	0.52	0.54				
Europe Large	0.89	0.80	0.83	0.48			
Europe Small	0.92	0.82	0.87	0.56	0.94		
Pacific	0.81	0.73	0.74	0.59	0.70	0.74	

Table 3.3: Descriptive statistics-sector returns 1995-2010

The table reports summary statistics for the sector returns. Sector returns and standard deviation are expressed as logarithmic price index returns at a monthly frequency in percentages. Sector returns are denominated in U.S. dollars and are from MSCI and are in excess of the U.S. 1-month T-bill return. The row labelled beta is the full-sample beta for each sector's excess return with the world market excess return. The sample period for the sector returns is Jan 1995 to Mar 2010.

Sample Moments	World	Energy	Materials	Industrials	Consumer Discr	Consumer Staples	Health care	Financials	IT	Telecom	Utilities
Mean	0.18	0.59	0.26	0.14	0.12	0.31	0.41	0.05	0.62	-0.04	0.09
Stdev	4.47	5.08	5.48	4.78	5.02	3.35	3.81	5.71	7.96	5.42	3.42
Skewness	-0.87	-0.18	-0.66	-0.89	-0.39	-0.70	-0.49	-0.62	-0.30	-0.06	-0.95
Kurtosis	1.90	0.86	2.63	2.76	1.51	1.41	0.32	2.77	0.75	2.28	1.25
Beta		0.72	0.99	0.98	0.99	0.46	0.50	1.12	1.43	0.84	0.48

Correlation Matrix	World	Energy	Materials	Industrials	Consumer Discr	Consumer Staples	Health care	Financials	IT	Telecom	Utilities
Energy	0.62										
Materials	0.80	0.70									
Industrials	0.93	0.61	0.85								
Consumer Discr	0.93	0.48	0.75	0.89							
Consumer Staples	0.63	0.41	0.52	0.61	0.53						
Healthcare	0.61	0.35	0.39	0.52	0.47	0.69					
Financials	0.89	0.50	0.71	0.86	0.82	0.68	0.60				
IT	0.84	0.41	0.56	0.72	0.80	0.29	0.38	0.60			
Telecom	0.73	0.32	0.43	0.58	0.66	0.35	0.41	0.53	0.72		
Utilities	0.64	0.57	0.53	0.62	0.51	0.62	0.55	0.61	0.34	0.42	

3.4 Regime-switching model

3.4.1 Description of the model

To maintain the parsimony of the model, we adopt Ang and Bekaert [2004]'s approach, which assumes that there is only one world regime, which drives all other regions/sectors. The equation for the world equity return, in excess of the US T-bill rate is:

$$y_t^w = \mu_{S_t}^w + \sigma_{S_t}^w \epsilon_t^w. \tag{3.1}$$

Here $\mu_{S_t}^w$ denotes the conditional mean (expected returns) and $\sigma_{S_t}^w$ denotes the conditional variance (volatility). We assume the world excess equity returns have two unobserved regimes, regimes 1 and 2. This number of states may be restrictive, but including more regimes poses extreme computational problems. Two states should capture the main effects of higher order moments in equity returns. Therefore $\mu_{S_t}^w$ and $\sigma_{S_t}^w$ can take different values depending on the realisation of the regime variable S_t.

The regimes S_t follow a two-state Markov chain with a transitional matrix:

$$\begin{pmatrix} P & 1-P \\ 1-Q & Q \end{pmatrix},$$

which can be characterised by two transitional probabilities:

$$\begin{aligned} P =& p(S_t = 1|S_{t-1} = 1) \\ Q =& p(S_t = 2|S_{t-1} = 2). \end{aligned} \tag{3.2}$$

If investors know the regime, the expected excess return and volatility for the world market in the next period will be either:

$$e_1^w = P\mu^w_{S_{t+1}=1} + (1-P)\mu^w_{S_{t+1}=2}, \tag{3.3}$$

$$\Sigma_1^w = P(\sigma^w_{S_{t+1}=1})^2 + (1-P)(\sigma^w_{S_{t+1}=2})^2 + P(1-P)[\mu^w_{S_{t+1}=2} - \mu^w_{S_{t+1}=1}]^2, \tag{3.4}$$

when the regime realisation today is $s_t = 1$, or

$$e_2^w = (1-Q)\mu^w_{S_{t+1}=1} + Q\mu^w_{S_{t+1}=2}, \tag{3.5}$$

$$\Sigma_2^w = (1-Q)(\sigma^w_{S_{t+1}=1})^2 + Q(\sigma^w_{S_{t+1}=2})^2 + Q(1-Q)[\mu^w_{S_{t+1}=2} - \mu^w_{S_{t+1}=1}]^2, \tag{3.6}$$

when the regime realisation today is $s_t = 2$.

The first component in Equation 3.4 and Equation 3.6 is a weighted average of the conditional variances in the two regimes; the second component is a jump component that arises because the conditional mean is different across regimes.

We follow Hamilton [1989]'s maximum likelihood estimation algorithms to estimate the parameters in Equation 3.1 to Equation 3.2 and regime probability, which is the probability that tomorrow's regime is a particular regime given current and past information τ_t, that is, the world equity returns data $\breve{y}_T = (y_t^w y_{t-1}^w ... y_1^w y_0^w)$. Because the regimes are unobservable, their effects and incidence must be inferred from the data. Maximising the likelihood function that accounts for all possible regime sequences is the most direct manner to accomplish this task. Let the parameters of the likelihood to be θ, the likelihood function is:

$$f(\breve{y}_T;\theta) = \prod_{t=1}^{T}(\sum_{i=1}^{2} f(y_t|\tau_{t-1}, S_t = i;\theta)p(S_t = i|\tau_{t-1};\theta)). \tag{3.7}$$

A by-product of the model is the ex-ante regime probability $p_t = p(S_t = i|\tau_{t-1};\theta)$. To practically implement the model for asset allocation purposes, we follow Ang and Bekaert [2004] in defining the regimes and assume the regime realisation is observable. When the ex-ante regime probability is larger than 0.5, the regime is classified as 1, otherwise the regime is 2.

The next step is to model the return process for the regional and sector portfolios. The basic framework is CAPM, which is the basis of mean-variance analysis and many asset allocation studies. Hence the regime-switching feature of individual portfolios comes through the switching mean returns of the world portfolio. However, it is also desirable to accommodate regime switching alphas, betas and idiosyncratic volatilities for these portfolios because Ang and Bekaert [2004] find them to fit the data better, thus allowing them to vary in different regimes is an interesting empirical examination.

We impose a two-stage estimation of the model parameters. That is, the regime switching alphas, betas and idiosyncratic volatilities for individual portfolios are estimated separately from the estimation of the world return process parameters and the realisation of the regime probability. Hence the information in individual portfolios does not influence the world return generating process. When the regime probability is realised, the equation for the individual portfolios returns y_t^ν is either:

$$y_t^\nu = \mu_1^\nu + \beta_1^\nu y_t^w + \bar{\sigma}_1^\nu \epsilon_t^\nu, \tag{3.8}$$

when regime probability $p_t > 0.5$, or

$$y_t^\nu = \mu_2^\nu + \beta_2^\nu y_t^w + \bar{\sigma}_2^\nu \epsilon_t^\nu, \tag{3.9}$$

when regime probability $p_t \leq 0.5$.

Where β_1^ν and β_2^ν denote correlations between the individual region/sector excess returns and the world excess returns in regimes 1 and 2, μ_1^ν and μ_1^ν denote alphas in regime 1 and regime 2, and $\bar{\sigma}_1^\nu$ and $\bar{\sigma}_1^\nu$ denote the regime-dependent region/sectors idiosyncratic volatility. These parameters and their standard errors are estimated using ordinary least squares regression when the regime probability is known to the investors. With regime switches, this model captures time-variation in expected returns, volatilities and correlations, driven by the world regime variable and individual regime-varying alphas, betas and volatilities.

It is important to note, however, that the two-stage estimation method assumes that the world portfolio and country/sector portfolios are in the same regime at the same time. The two-stage estimation procedure needs to be adopted because the model is too complex to estimate simultaneously. The regime switching alphas, betas and idiosyncratic volatilities for individual portfolios represent a huge number of parameters. Estimating 16 individual portfolios (six regions and ten sectors) with six parameters each (i.e., two alphas, two betas and two idiosyncratic volatilities) adds another 96 parameters to the existing six parameters for the world return process (two mean returns, two volatilities and transitional matrix P and Q). Estimating this set of parameters jointly is not only infeasible and unstable (low degrees of freedom), but also unrealistically difficult to implement in practice. The two-stage procedure estimates a small set of parameters in each step and hence alleviates these estimation problems.

3.4.2 Model estimation

To reliably estimate the model parameters, we need to use a reasonably long period of time. We split the total 15 years sample period into the first eight years (the in-sample period) and the last seven years (the out-of-sample period).[3] The in-sample period, which runs from January 1995 to December 2002, is used to estimate the parameters of the regime switching model. The out-of-sample period spans January 2003 to March 2010. Table 3.4 contains the estimation results for the region model in Equation 3.1–Equation 3.9, using in-sample data only. The first regime is a bull market, where world excess returns are expected to yield 0.98%, with 2.26% volatility per month. On the other hand, the second regime, a bear market, has a negative mean world excess return (-0.14% per month) and higher volatility (4.92% per month). The negative expected return in the bear market regime may seem extreme and appears to be incompatible with equilibrium arguments by which risky assets should earn a positive risk premium. However, because we have a relatively short sample period (eight years), it is reasonable to expect equity returns to be lower than the risk-free return in the bear market, particularly when the estimation period contains a major market downturn (burst of the tech bubble). The transitional probabilities P and Q are 0.98 and 0.97, respectively, which indicate that, over the sample period, the probability of going into a bull (bear) market next month is 98% (97%), conditional on the current regime being a bull (bear) market. The expected durations of these two regimes are 40 and 29 months, respectively.[4]

Panel A of Figure 3.1 shows the overall expected market risk premium from 2003 to 2010, which is the probability weighted average of the conditional expected returns for

[3]Each sample period would also contain a bull market and a major market down turn, namely the Dot-Com Bubble for the in-sample period and the global financial crisis for the out-of-sample period.

[4]The expected duration of a regime can be calculated as $1/(1-P)$, where P is the transitional probability.

Table 3.4: Regime switching region model in-sample estimates 1995-2002

All parameters are monthly and are expressed in percentages, except for the transitional probabilities P and Q.

A. Transitional probabilities

Measure	P	Q
Estimate	0.98	0.97
Std error	0.07	0.07

B. World market

Measure	μ_1	μ_2	σ_1	σ_2
Estimate	0.98	-0.14	2.26	4.92
Std error	0.35	0.55	0.32	0.62

C. Individual regions - regime 1

Region Betas	N Amer	UK	Japan	Eur lg	Eur sm	Pac
Estimate	0.84	0.69	1.68	0.75	0.67	1.03
Std error	0.12	0.14	0.27	0.16	0.13	0.20

Region Alphas	N Amer	UK	Japan	Eur lg	Eur sm	Pac
Estimate	0.55	0.58	-1.36	0.33	1.05	-0.08
Std error	0.32	0.39	0.73	0.43	0.35	0.53

Idiosyncratic Volatilities	N Amer	UK	Japan	Eur lg	Eur sm	Pac
Estimate	1.76	2.11	3.97	2.38	1.92	2.91
Std error	0.11	0.16	0.56	0.20	0.13	0.30

D. Individual regions - regime 2

Region Betas	N Amer	UK	Japan	Eur lg	Eur sm	Pac
Estimate	0.87	1.01	1.10	0.90	0.90	1.04
Std error	0.05	0.07	0.08	0.07	0.05	0.11

Region Alphas	N Amer	UK	Japan	Eur lg	Eur sm	Pac
Estimate	0.12	0.10	-0.35	0.08	0.18	0.03
Std error	0.29	0.44	0.50	0.42	0.28	0.63

Idiosyncratic Volatilities	N Amer	UK	Japan	Eur lg	Eur sm	Pac
Estimate	2.82	4.46	4.70	4.28	2.86	5.91
Std error	0.28	0.43	0.49	0.41	0.28	0.62

each regime. The expected market risk premium seems reasonable over time (5.29% on average over the sample period) and remains almost always positive, except for a short period of negative expected excess returns during the Global Financial Crisis in late 2008 and early 2009. The negative expected return in the bear market regime is indeed incompatible with equilibrium arguments by which risky assets should earn a positive risk premium. Although we recognise that the model can sometimes predict implausible risk premium, it is important to note that the main goal is to examine whether the regime dependent model improves asset allocation rather than accurately predicts the risk premium.

The estimation procedure also yields the regime probabilities, which infers the prevailing regime in each month. We need to estimate the regime probabilities for both the in-sample (1995 to 2002) and out-of-sample period (2003 to 2010) for performance evaluation purposes. Panel B of Figure 3.1 shows the ex ante (filtered) and ex post (smoothed) regime probabilities. The ex ante probability $p(s_t = 1|I_{t-1})$ is the probability that the regime next month is the bull market regime given past and current information I up to time t, the smoothed probability $p(s_t = 1|I_T)$ is the probability that the regime next month is the bull market regime given all of the information I present in the sample period T, i.e., from January 1995 to March 2010. To avoid hindsight bias, the filtered probability in the out-of-sample period from January 2003 to March 2010 is re-estimated every month. The dotted line represents two economic contraction periods during the sample period identified by the National Bureau of Economic Research (NBER).[5] The financial bear markets identified by the regime-switching algorithms coincide with these economic contraction periods, namely the 2000 Dot-Com Bubble and the Global Financial Crisis.

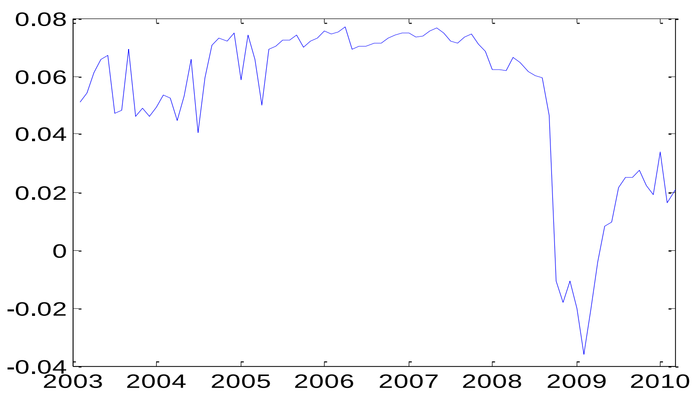
Table 3.4 also reports the parameter estimates for the regional returns process. Regional betas are estimated with a high level of statistical significance in both regimes, and their magnitudes seem economically sensible. Betas for each region increase in the bear regime, apart from Japan, which has a beta of 1.68 during the normal period but lower systematic risk (beta = 1.10) in the bear market. Although Japan is a high beta market, the alphas for Japan are negative in both regimes (-1.36% and -0.35% per month for bull and bear respectively). It appears that the large beta returns are being offset by large negative alphas even in the bull market. This result indicates that, though Japan

[5] NBER business cycle: http://www.nber.org/cycles/cyclesmain.html.

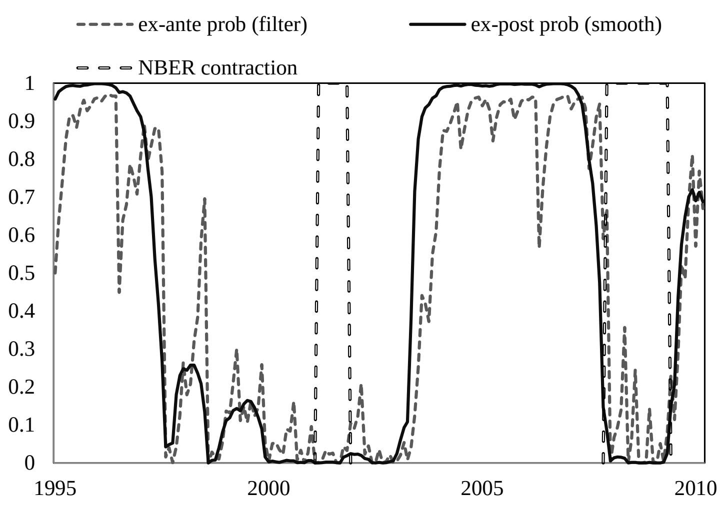
Figure 3.1: Expected Market Risk Premium and Ex ante and Smoothed Regime Probabilities of being in Regime 1

Panel A of the plot shows the expected market risk premium forecasted by the regime switching model. The conditional expected returns for each regime are firstly re-estimated each month from the model using equation (1) to (7). The weighted average market premium is then computed by assuming a 50% probability for each regime realisation. Panel B of the plot shows the ex-ante probabilities $p(s_t = 1|I_{t-1}))$ and the smoothed probabilities $p(s_t = 1|I_T)$ of being in the first regime, where the first regime is the world low variance regime.

A: Expected Market Risk Premium 2003-2010



B: Ex ante and Smoothed Regime Probabilities of being in Regime 1 1995-2010



is regarded as having a high systematic risk, its stock market has delivered much less returns than the amount predicted by beta. This is because while the world market is in a bull regime, the under-performance of the Japanese market is much attributed to its idiosyncratic event, the Japanese stock market collapse in the 1990s.

The alpha parameters are not significantly different from zero for all regions, except the small European economies during the bull market (1.05% per month, $t = 3.00$). Note that alphas for North America and Small European countries are highest (0.12% and 0.18% per month) in bear markets, making equities in these regions more attractive in the bad times. Similar to the world return process, idiosyncratic volatilities for each region are lower in regime one and higher in regime two. Japan and Pacific ex-Japan exhibit the highest idiosyncratic volatilities in both regimes whereas the lowest idiosyncratic volatilities are found in North America, followed by small European economies.

Table 3.5 contains the estimation results for the sector model in Equation 3.1–Equation 3.9. Compared to the bull regime, all sectors are less correlated with the world market in the bear regime except IT (beta=1.89) and Telecommunications (beta=1.15), primarily because the only bear regime in the estimation period is the Dot-Com Bubble, where the influence of IT and Telecommunications sectors on the world return process increased dramatically. It is also reasonable to expect Consumer Staples, Healthcare and Utilities, commonly recognised as defensive sectors, to have low correlations during bad times. Their betas are 0.42, 0.48 and 0.40, respectively. Alphas are lower in the bear regime for most of the sectors. IT has the highest alpha of 0.75% per month in the bear regime, though this is not significantly different to zero. Moreover, IT has the highest volatility among all sectors in both regimes, which the model fits through a high beta and a high idiosyncratic volatility (the highest idiosyncratic volatility of all sectors). As expected, idiosyncratic volatilities are higher in the bear regime for all sectors.

Table 3.5: Regime switching sector model in-sample estimates 1995-2002

All parameters are monthly and are expressed in percentages, except for the transitional probabilities P and Q.

A. Transitional probabilities

Measure	P	Q
Estimate	0.98	0.97
Std error	0.07	0.07

B. World Market

Measure	μ_1	μ_2	σ_1	σ_2
Estimate	0.98	-0.14	2.26	4.92
Std error	0.35	0.55	0.32	0.62

C. Individual sectors - Regime 1

Sector Betas	Energy	Materials	Industrials	Con. Discr	Con. Staples	Healthcare	Financials	IT	Telecom	Utilities
Estimate	0.65	1.19	1.09	1.15	0.67	0.76	1.16	1.35	0.72	0.54
Std error	0.19	0.15	0.08	0.08	0.10	0.15	0.09	0.24	0.12	0.11
Sector Alphas	Energy	Materials	Industrials	Con. Discr	Con. Staples	Healthcare	Financials	IT	Telecom	Utilities
Estimate	0.76	-0.28	-0.10	-0.18	0.40	0.61	-0.15	0.21	-0.10	0.13
Std error	0.46	0.36	0.20	0.21	0.25	0.38	0.22	0.58	0.31	0.27
Idiosyncratic Volatilities	Energy	Materials	Industrials	Con. Discr	Con. Staples	Healthcare	Financials	IT	Telecom	Utilities
Estimate	2.78	2.19	1.20	1.25	1.55	2.30	1.35	3.56	1.86	1.67
Std error	0.41	0.32	0.18	0.18	0.23	0.34	0.20	0.52	0.27	0.25

D. Individual sectors - Regime 2

Sector Betas	Energy	Materials	Industrials	Con. Discr	Con. Staples	Healthcare	Financials	IT	Telecom	Utilities
Estimate	0.62	0.84	0.94	1.08	0.42	0.48	1.07	1.89	1.15	0.40
Std error	0.10	0.09	0.05	0.05	0.08	0.09	0.07	0.13	0.12	0.08
Sector Alphas	Energy	Materials	Industrials	Con. Discr	Con. Staples	Healthcare	Financials	IT	Telecom	Utilities
Estimate	0.23	-0.31	-0.18	-0.01	-0.02	0.32	0.17	0.75	-0.04	-0.19
Std error	0.50	0.44	0.23	0.24	0.42	0.44	0.35	0.63	0.57	0.38
Idiosyncratic Volatilities	Energy	Materials	Industrials	Con. Discr	Con. Staples	Healthcare	Financials	IT	Telecom	Utilities
Estimate	4.23	3.74	1.97	2.05	3.55	3.77	2.94	5.38	4.85	3.25
Std error	0.49	0.43	0.23	0.24	0.41	0.44	0.34	0.63	0.56	0.38

3.5 Asset allocation and performance results

3.5.1 Asset allocation

To derive the expected returns and covariance matrix for the returns on regions/sectors, we let the vector of excess returns of six regions and ten sectors, conditional on todays regime, be denoted by $e_i = e_{s_t=i}$ (with i denoting the current regime), and let variance covariance matrices be denoted by $\Sigma_i = \Sigma_{s_t=i}$.

Since the mean of the world excess return switches between regimes, the expected excess return of region/sector ν is given by $\mu_i^\nu + \beta_i^\nu e_i^w$ for the current regime i, where e_i^w are given in Equation 3.3 and Equation 3.5. Let μ_i and β_i be:

$$\mu_i = \begin{pmatrix} \mu_1 \\ \vdots \\ \vdots \\ \mu_N \end{pmatrix} \qquad \beta_i = \begin{pmatrix} \beta_1 \\ \vdots \\ \vdots \\ \beta_N \end{pmatrix}$$

vectors for the N regions/sectors. Hence the expected return vector is given by:

$$e_i = \mu_i + \beta_i e_i^w. \tag{3.10}$$

Therefore, expected returns differ across individual regions/sectors through their different betas and alphas with respect to the world market.

The variance covariance matrix has three components. First, there is an idiosyncratic part that we capture in a matrix v_i for the current regime i, where v_i is a matrix of zeros with $(\bar{\sigma}_i^v)^2$ along the diagonal. Second, the differences in systematic risk across the different regions/sectors and the correlations are driven by the variance of the world market and the betas as in a typical factor model. Because the world market variance and the betas next period depend on the realization of the regime, we have two possible variance matrices for the unexpected returns next period:

$$\Omega_i = (\beta_i \beta_i')(\sigma_i^w)^2 + v_i. \tag{3.11}$$

Third, the actual covariance matrix today takes into account the regime structure, in that it depends on the realisation of the current regime and it adds a jump component to the conditional variance matrix, which arises because the conditional means change from one regime to the other. As a consequence, the conditional covariance matrices can be written as:

$$\begin{aligned}\Sigma_1 &= P\Omega_1 + (1-P)\Omega_2 + P(1-P)(e_1 - e_2)(e_1 - e_2)' \\ \Sigma_2 &= (1-Q)\Omega_1 + Q\Omega_2 + Q(1-Q)(e_1 - e_2)(e_1 - e_2)',\end{aligned} \tag{3.12}$$

where the subscripts indicate the current regime.

To implement mean-variance optimisation, we also need to make an assumption about the risk-free rate. We assume the risk-free rate to be the 1-month T-bill rate. Hence the risk-free rate and the tangency portfolio for each month will vary over time. One obvious extension discussed in Ang and Bekaert [2004] is to impose constraints on asset allocations. This is because (i) mean-variance portfolios, based on historical data, may be quite unbalanced [Black and Litterman, 1992], and (ii) in practice institutional investors have an intelligence overlay rather than just applying weights based on the straight model outputs. We choose to impose a short sell constraint, and a benchmark constraint that keeps asset allocations close to their market capitalisation weights in the MSCI world index. The short constraint requires weights to be positive, whereas the benchmark constraint does not allow the optimal regional or sector weights to deviate from their MSCI average weights by more than 10%.

3.5.2 Expected returns and Variances

Panel A and B of Table 3.6 show the regime-dependent expected excess returns, covariances and correlations for the regional allocation at January 2003, computed using Equation 3.10–Equation 3.12 and data from 1995 to 2002. Note that the expected excess returns are quite high for North America (16.17%) and Small European (20.20%) regions. The high excess returns may appear to be extreme but they are conditioned on the realization of a bullish regime. An expected 16% to 20% excess return for a bull market is often reasonable. The expected excess returns are lower for all regions in the bear regime, with Japan in particular generating a large negative expected excess return (-5.75% per annum). Again, a negative expected excess return for risky assets is not compatible with the expected relationship between risk and return. However, realisations can sometimes depart from expectations. Further, Japanese stocks performed poorly during the sample period and the bear regime is designed to capture a low return state, it is reasonable to sometimes cross-country expect a negative premium over a short period. In line with the results of Ang and Bekaert [2002a] and Longin and Solnik [2001], our results also indicate that international equity returns are more highly correlated with each other in bear markets than in bull markets. For instance, most of cross-country correlations are less than 0.5 in the bull markets and almost all correlations become greater than 0.5 in the bear markets. The average correlation has increased from 0.43 to 0.57.

Table 3.6: Regime-dependent region model asset allocation at January 2003

We report the regime-dependent means and covariances of excess returns implied by the estimates of the regime-switching region model in Table 3.4. Panel A and B report the regime-dependent excess return means and covariances, where we list correlations in the upper-right triangular matrix. All numbers are listed in percentages, and are annualised. Panel C reports the mean variance efficient (MVE) (tangency) portfolios, computed using an interest rate of 4.55%, which is the average 1-month T-bill rate over the sample. The MSCI Average denotes the average MSCI world index weight of each region across the sample. The short constraint requires weights to be positive, whereas the benchmark constraint does not allow the optimal region weights to deviate from their MSCI average weights by more than 10%.

	N Amer	UK	Japan	Eur lg	Eur sm	Pac
A. Regime-dependent excess returns						
Regime 1	16.17	14.75	2.81	12.44	20.20	10.69
Regime 2	0.26	-0.23	-5.75	-0.31	0.89	-1.10
B. Regime-dependent covariances and correlations						
Regime 1						
N Amer	0.88	**0.46**	**0.51**	**0.45**	**0.49**	**0.47**
UK	0.43	0.97	**0.42**	**0.37**	**0.41**	**0.39**
Japan	0.93	0.79	3.71	**0.41**	**0.44**	**0.43**
Eur lg	0.45	0.39	0.84	1.13	**0.39**	**0.38**
Eur sm	0.41	0.36	0.76	0.38	0.80	**0.41**
Pac	0.60	0.52	1.13	0.55	0.50	1.84
Regime 2						
N Amer	3.10	**0.62**	**0.63**	**0.60**	**0.70**	**0.55**
UK	2.51	5.28	**0.56**	**0.54**	**0.63**	**0.49**
Japan	2.74	3.18	6.11	**0.54**	**0.63**	**0.49**
Eur lg	2.25	2.61	2.85	4.51	**0.60**	**0.47**
Eur sm	2.24	2.61	2.84	2.33	3.29	**0.55**
Pac	2.60	3.02	3.29	2.70	2.69	7.25
C. Tangency portfolio weights						
MSCI Average	0.50	0.09	0.22	0.08	0.07	0.06
C1. No constraints						
Regime 1	0.46	0.28	-0.25	0.04	0.53	-0.06
Regime 2	0.88	0.04	-0.53	-0.06	0.75	-0.08
Static	0.48	0.15	-0.06	0.03	0.50	-0.10
C2. Short constraint						
Regime 1	0.28	0.09	0.00	0.05	0.58	0.00
Regime 2	0.47	0.04	0.00	0.00	0.49	0.00
Static	0.45	0.08	0.00	0.04	0.40	0.03
C3. Benchmark Constraint						
Regime 1	0.41	0.09	0.12	0.18	0.17	0.06
Regime 2	0.60	0.19	0.12	-0.03	0.17	-0.04
Static	0.56	0.08	0.12	0.12	0.17	-0.04

Panel C of Table 3.6 shows the tangency portfolios weights in both regimes and static mean-variance optimisation at an interest rate of 4.55%, the in-sample average. When no constraints are imposed, in the bull regime, the portfolio under-weights North America, Japan, large European countries and Pacific ex-Japan relative to their average MSCI world index weights over the sample period. The high volatility of Japan and Pacific ex-Japan markets is the main problem. Our model also slightly over-estimates the correlation between North America and Europe small returns relative to the data, which may explain the underweight in North America. Both U.K. and small European economies are over-weighted. In the bear regime, investors switch towards the markets with less volatility and higher expected returns, namely, North America and small European countries. Although North America gets assigned a weight of 88%, it does not mean the portfolio is now home biased from an US investor perspective because the investors also invest heavily small European countries (75%).

The ability to invest heavily in the less volatile markets comes from a large short position on Japan, 53%. However, it is probably unrealistic to implement this short position in practice. The optimal portfolio under the static mean-variance analysis sits in between the two regime-dependent portfolios, but under-weights all regions relative to their MSCI world index weights except UK and small European countries. The optimal portfolios weights in both regime switching and static analyses do not change qualitatively under the short constraint and the benchmark constraint. All portfolios still underweight Japan and overweight small European countries. Note that under the benchmark constraint, regime-dependent and static portfolios have exactly the same allocation on Japan and small European countries (12% and 17%, respectively). The benefits of the regime switching allocation therefore only come from investors tilting towards North America and UK and moving away from large European countries and Pacific ex-Japan during the bear markets.

Panel A and B of Table 3.7 show the regime-dependent expected excess returns, covariances and correlations for the sector allocations at January 2003. Energy, Healthcare and IT show the highest expected excess returns in bull regime, whereas cyclical sectors such as Materials, Industrials and Consumer Discretionary are clearly the losers during the bearish regime. Note that the expected excess return for the IT sector in the bear regime is still quite high (6.23%), though this is coupled with an extremely high volatility (37.19%). This is because the bear regime for the world market during the sample estimation period includes part of the Dot-Com Boom in

1999 and 2000, a highly volatile state. Nevertheless, it is perhaps unreasonable to expect such a high bear regime excess return in the long run. Unlike correlations between regions, sector correlations do not increase universally in bad times. For instance, the correlation between Consumer Staples and Telecommunications fall from 0.56 in regime one to 0.21 in regime 2. Out of 45 correlation pairs, 12 pairs have decreased correlations in the bear markets. These pairs mainly come from Consumer Staples, IT, Healthcare, and Telecommunications sectors. The average cross sector correlation has only increased from 0.48 to 0.52. This feature of sector allocation provides good reason as to why diversification across sectors is important not only in good times but also in bad times.

Panel C of Table 3.7 shows the tangency portfolios weights in both regimes and static mean-variance optimisation at an interest rate of 4.55%. With no constraints enforced, the portfolio in bull markets over-weights Energy, Industrials, Consumer Staples, Healthcare and Utilities relative to their average MSCI world index weights over the sample period, but under-weights Materials, Consumer Discretionary, Financials, IT and Telecommunications. The high volatility is still the main problem, although IT yields the highest expect returns. In regime 2, the portfolio borrows money from massively shorting Materials (-40%), Industrials (-117%) and telecommunications (-49%) and invests heavily in a few sectors including Energy (73%), Consumer Staples (58%), Healthcare (84%) and IT (66%). The large short position on Industrials primarily comes from its high correlation with Consumer Discretionary and IT sectors (0.88 and 0.73). This large short position is perhaps neither feasible nor sensible to implement in a practical asset allocation program. This issue can be addressed when constraints are imposed. The static mean-variance optimal portfolio also favours Energy, Consumer Staples, Healthcare and IT and is highly averse to Industrials and

Telecommunications. When short-sell is not allowed, both regime-dependent and static optimal portfolios only invest in Energy, Consumer Staples, Healthcare and IT. The benchmark constraint is so restrictive that the regime-dependent portfolios only deviate from the static optimal portfolio marginally. More aggressive investors can obviously modify the constraint to be less restrictive but we will not demonstrate other restrictions in our simulation.

Table 3.7: Regime-dependent sector model asset allocation at January 2003

We report the regime-dependent means and covariances of excess returns implied by the estimates of the regime-switching sector model in Table 3.4. Panel A and B report the regime-dependent excess return means and covariances, where we list correlations in the upper-right triangular matrix. All numbers are listed in percentages, and are annualised. Panel C reports the mean variance efficient (MVE) (tangency) portfolios, computed using an interest rate of 4.55%, which is the average 1-month T-bill rate over the sample. The MSCI Average denotes the average MSCI world index weight of each sector across the sample. The short constraint requires weights to be positive, whereas the benchmark constraint does not allow the optimal sector weights to deviate from their MSCI average weights by more than 10%.

	Energy	Materials	Industrials	Con. Discr	Con. Staples	Healthcare	Financials	IT	Telecom	Utilities
A. Regime-dependent excess returns										
Regime 1	16.58	10.19	11.07	10.89	12.34	15.88	11.39	17.79	6.96	7.70
Regime 2	1.83	-5.00	-3.51	-1.67	-0.86	3.09	0.53	6.23	-2.13	-2.85
B. Regime-dependent covariances and correlations										
Regime 1										
Energy	1.19	**0.45**	**0.46**	**0.41**	**0.22**	**0.22**	**0.26**	**0.20**	**0.38**	**0.44**
Materials	0.59	1.45	**0.86**	**0.79**	**0.36**	**0.16**	**0.69**	**0.42**	**0.36**	**0.31**
Industrials	0.48	0.98	0.90	**0.88**	**0.48**	**0.33**	**0.77**	**0.54**	**0.52**	**0.44**
Consumer Discr	0.45	0.95	0.84	1.00	**0.60**	**0.39**	**0.75**	**0.54**	**0.52**	**0.44**
Consumer Staples	0.18	0.32	0.35	0.45	0.56	**0.64**	**0.59**	**0.40**	**0.56**	**0.51**
Healthcare	0.24	0.20	0.31	0.39	0.48	0.99	**0.52**	**0.37**	**0.54**	**0.36**
Financials	0.28	0.85	0.75	0.77	0.45	0.53	1.05	**0.41**	**0.52**	**0.57**
IT	0.35	0.83	0.83	0.87	0.49	0.60	0.68	2.64	**0.37**	**0.20**
Telecom	0.35	0.37	0.42	0.45	0.36	0.46	0.45	0.52	0.74	**0.66**
Utilities	0.35	0.27	0.30	0.32	0.27	0.26	0.42	0.23	0.41	0.51
Regime 2										
Energy	3.27	**0.65**	**0.62**	**0.47**	**0.41**	**0.36**	**0.58**	**0.37**	**0.25**	**0.52**
Materials	2.27	3.75	**0.83**	**0.73**	**0.48**	**0.32**	**0.73**	**0.51**	**0.38**	**0.41**
Industrials	1.93	2.80	3.02	**0.88**	**0.51**	**0.47**	**0.84**	**0.73**	**0.57**	**0.54**
Consumer Discr	1.69	2.79	3.01	3.88	**0.39**	**0.38**	**0.78**	**0.82**	**0.70**	**0.41**
Consumer Staples	1.04	1.33	1.27	1.09	2.02	**0.66**	**0.64**	**0.14**	**0.21**	**0.58**
Healthcare	1.00	0.95	1.26	1.17	1.45	2.38	**0.58**	**0.28**	**0.35**	**0.50**
Financials	2.19	2.97	3.06	3.22	1.90	1.86	4.37	**0.59**	**0.55**	**0.57**
IT	2.52	3.68	4.72	6.04	0.72	1.62	4.56	13.83	**0.75**	**0.24**
Telecom	1.16	1.89	2.57	3.59	0.77	1.42	2.96	7.24	6.69	**0.27**
Utilities	1.24	1.06	1.23	1.07	1.09	1.01	1.57	1.17	0.93	1.73

Table 3.7: Regime-dependent sector model asset allocation at January 2003 - continued

	Energy	Materials	Industrials	Con. Discr	Con. Staples	Healthcare	Financials	IT	Telecom	Utilities
C. Tangency portfolio weights										
MSCI Average	0.09	0.06	0.10	0.11	0.09	0.10	0.22	0.12	0.06	0.04
C1. No constraints										
Regime 1	0.24	0.02	0.33	-0.26	0.49	0.27	-0.15	0.05	-0.30	0.30
Regime 2	0.73	-0.40	-1.17	0.16	0.58	0.84	0.21	0.66	-0.49	-0.12
Static	0.49	-0.12	-0.50	0.30	0.41	0.56	-0.19	0.21	-0.18	0.03
C2. Short constraint										
Regime 1	0.29	0.00	0.00	0.00	0.41	0.18	0.00	0.04	0.00	0.09
Regime 2	0.27	0.00	0.00	0.00	0.00	0.67	0.00	0.05	0.00	0.00
Static	0.32	0.00	0.00	0.00	0.14	0.51	0.00	0.04	0.00	0.00
C3. Benchmark Constraint										
Regime 1	0.19	-0.04	0.16	0.01	0.19	0.20	0.12	0.07	-0.04	0.14
Regime 2	0.19	-0.04	0.00	0.01	0.19	0.20	0.15	0.20	-0.04	0.14
Static	0.19	-0.04	0.00	0.14	0.19	0.20	0.12	0.10	-0.04	0.14

3.5.3 Asset allocation simulation

The models that derive the weights for the optimal country and sector portfolios require the estimation of many parameters. The regime switching model generates a set of six parameters and the estimation of country and sector returns generates another 36 and 60 parameters for country and sector allocation, respectively. They together determine the final optimal portfolio weights, but each set of parameters is subject to estimation error. Hence, it is important to consider whether these estimation errors may collectively have a material impact on the stability of the asset allocation recommendations.

To show the sensitivity of the changes in asset allocation weights to the joint changes of the parameters values, we adopt the following steps to perform the simulation:

1. In each simulation, simulated values are randomly drawn from the joint distribution of the parameter estimates. World regime means, country/sector regime-dependent alphas and betas are drawn from the multivariate normal distributions with their mean estimates and covariance matrices estimated from Equation 3.1 to Equation 3.9 (parameters mean estimates and standard errors are reported in Table 3.4 and Table 3.5). We assume the parameters estimated from the first (regime switching) model and those from the second (regression) model are independently distributed.

2. Because the model assumes that the errors are independently distributed, we then independently draw the squares of world/country/sector and regime specific volatility estimates (variances) from the chi-squared distribution (mean estimates are reported in Table 3.4 and Table 3.5), with the degree of freedom being the sample size (from 1995 to 2002) minus one. Note that S^2 (the estimated variance) is an unbiased estimator of σ^2 (population variance) and that $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{n-1}$, hence $\sigma^2 \sim \frac{(n-1)S^2}{\chi^2_{n-1}}$. Therefore the

simulated variance is a function of both the estimated variance and the random draw from the chi-squared distribution.

3. Based on the simulated parameters estimates from step 1 and 2, we then calculate the regime dependent excess returns and covariance matrices for each country/sector, using Equation 3.10 to Equation 3.12, for each simulation.

4. For comparison, we simulate another set of mean excess returns and covariance matrices for the static asset allocation model in each simulation. We (1) calculate the mean excess returns and the estimated covariance matrix for country/sector from the 1995 to 2002 sample period; (2) simulate a set of mean excess returns for country/sector from the multivariate normal distributions with the mean excess return estimates and the estimated covariance matrix calculated in step 1; (3) simulate a covariance matrix by independently drawing covariances and variances from the chi-squared distributions with the estimated mean values of the covariance matrix calculated in step 1 (degree of freedom is the sample size minus 1).

5. Based on the three sets of expected excess returns and covariance matrices for country/sector allocation from step 3 and 4, we derive the weights for the three optimal portfolios using the mean-variance analysis. Portfolio weights are bounded within -1 and 2.

6. The simulated weights from step 5 are then compared against the benchmark case weights (no constraints) reported in Panel C of Table 3.6 and Table 3.7. To evaluate the magnitude of the weight differences, the Mean Absolute Difference (MAD) in weights is calculated for each regime 1, regime 2 and static scenarios. That is, for each of the N country/sector portfolios, the absolute difference between the simulated and the benchmark weight is first calculated, and then we compute the average of these N

absolute differences. To illustrate, the formula we use to calculate mean absolute difference is $MAD = \frac{1}{N}\sum_{j}^{N}|w_{j,s} - w_{j,b}|$, $w_{j,s}$ and $w_{j,b}$ are the simulated weights and benchmark weights for country/sector j, respectively.

7. We repeat step 1 to step 6 1,000 times, hence 1,000 MADs are obtained for each regime 1, regime 2 and static scenarios.

Figure 3.2 reports the distribution of the 1,000 MADs between the simulated weights and the benchmark weights for each asset allocation scenarios. Among the three scenarios, regime 1 has the lowest MADs, indicating that the variation in weights is the lowest for regime 1. The mean and standard deviation of MADs are 2.44% and 0.96% (3.04% and 1.15%) for country (sector) allocation under regime 1. This means, on average, that the simulated weights only deviate from the benchmark weights by 2.44%. This is primarily because of an increase in the precision of the estimates under a more stable regime. On the other hand, the MADs are much larger in regime 2. Under regime 2, the mean and standard deviation of MADs are 13.27% and 6.50% (10.42% and 3.83%) for country (sector) allocation. This increase in the variability of the weights is expected, as regime 2 is designed to capture a more volatile state with larger estimation errors. Nevertheless, assuming a conservative case where the realization of regime 1 and regime 2 is equally likely, the probability weighted mean MADs for the dynamic model is 7.86% (6.73%) for country (sector) allocation. Estimation errors do not seem to have a material impact on the weight variation.

To assess whether the parameter estimation errors for the dynamic model are largely induced from a more complicated model specification or the limited sample size, it would be useful to compare the average variability of the simulated weights for the dynamic model with that for the static model. Panel C of Figure 3.2 reports the distribution of

MADs for the static scenario. The mean and standard deviation of MADs are 7.66% and 4.05% (6.76% and 2.79%) for country (sector) allocation, which are approximately the average of the mean MADs for regime 1 and regime 2. This result indicates that the weight variation for the dynamic model is primarily due to the estimation errors induced from the sample size rather than from model specification. Hence, in the long run where there is an increase in the sample size, the model is likely to produce more stable parameter estimation and weights.

Ultimately investors are interested whether estimation errors are likely to have a material influence on the final asset allocation performance. We provide an alternative approach to assess whether estimation errors may impact asset allocation in the Appendix .2.

3.5.4 Performance of regime switching asset allocation

To evaluate whether regime switching asset allocation adds value to standard mean-variance optimisation, we simulate a time-series of returns generated from a regime switching strategy that switches between holding two regime-dependent optimal portfolios and compare it to the returns generated from holding a static mean-variance efficient portfolio. We estimate the returns of these two strategies both in-sample and out-of-sample, with $1 to start. In-sample simulation assumes the investor knows the parameters estimated from the estimation period (January 1995 to December 2002) and starts trading in January 1995. In the out-of-sample analysis, the regime-dependent and static mean-variance weights are computed using all information available up to the estimation date. Portfolio weights form both regime-switching models and static models are re-estimated every month during the out-of-sample period (January 2003 to March 2010). The performance criterion is the ex-post Sharpe ratio realised by the various strategies.

Panel A of Table 3.8 shows the in-sample average returns, standard deviations and Sharpe ratios realised by the static mean-variance, regime-dependent strategies and the MSCI world index for asset allocation across regions, when various constraints are considered. Compared to the world market portfolio and the static strategy, the regime-dependent strategy has higher return volatilities, compensated by higher average returns under no constraint and short constraint scenarios. The regime switching strategy has the highest ex-post Sharpe ratio when no constraint and short constraint are used, but fails to out-perform when the benchmark constraint is imposed, possibly because the benchmark constraint is so restrictive that the benefit of overweighting small European countries and underweighting Japan is largely removed. The non-constrained regime-dependent strategy does so well (the Sharpe ratio almost doubles that of the static strategy) because over this sample period the US and small European markets generate very large returns and Japan performs very poorly. The reason for the under-performance of the world market portfolio is the presence of a relatively large Japanese equity allocation in the world market. It is perhaps more important to examine the out-of-sample performance because no hindsight bias is introduced into the simulated returns of both strategies.

Panel B of Table 3.8 shows, over the out-of-sample period and with no constraints, the regime-dependent strategys average return is 8.94%, higher than the average return of the static portfolio (7.63%) and the return of the world market portfolio (7.03%). The regime-switching portfolios average Sharpe ratio is 0.36, only slightly higher than the static optimal portfolio Sharpe ratio (0.33), where the world market portfolio produces a Sharpe ratio of 0.30. Note that under the short constraint and the benchmark constraint, the regime-dependent strategy delivers a higher Sharpe ratio in the out-of-sample period, compared to the world market portfolio and the static portfolio, although the out-performance is not economically significant.

Figure 3.3 show how wealth accumulates over time in these strategies with no constraints. Panel A shows the out-performance of the regime-dependent strategy is particularly striking in the first five years of the in-sample period, whereas Panel B shows that the regime switching portfolio does not perform very differently during the out-of-sample period. This is probably because the cross country equity returns become more co-integrated in this period.

The performance of the regime-dependent portfolio and static optimal portfolio for the sector allocation is presented in Table 3.9. For the in-sample analysis, the static optimal portfolio realises slightly lower returns, but does so at substantially lower risk than the regime dependent sector allocations. Hence the regime dependent portfolio leads to a lower in-sample Sharpe ratio than the static optimal portfolio. The under-performance is expected because the regime probabilities might be estimated imprecisely in the earlier trading period due to the limited data availability for estimation. With more data becoming available, the regime switching model is able to estimate the regime probability with higher precision.

Panel B shows the portfolio performance in the out-of-sample period, from January 2003 to March 2010. With no constraints imposed, the regime dependent strategy delivers a sizable 13.13% average annual return (11.74% annualised volatility) in a relatively bearish period, where the static portfolio and the world market portfolio generate an average return of only 7.31% and 7.03% (with 10.65% and 15.87% annualised volatility), respectively. The regime switching portfolios Sharpe ratio is 0.93, almost double the Sharpe ratio of the static strategy (0.48). The regime dependent portfolio consistently out-performs the world market and the static optimal portfolio when the short constraint and the benchmark constraint are imposed. The extremely successful performance of the regime dependent strategy comes from the ability of the model to correctly identify the defensive sectors, such as Energy, Consumer Staples and Healthcare, which hedge against high volatilities and low returns so well in the bear regime.

Figure 3.4 presents results for the wealth accumulated over the in-sample and out-sample period under no constraint scenario. Panel A shows that the regime dependent strategy yields lower returns than the static portfolio during the first three years of the in-sample period, probably due to an imprecise classification of regimes. In Panel B, it is interesting to note that, particularly over the second half of the out-of-sample period, wealth accumulated from the regime dependent strategy is almost unaffected while the world market is deeply in turmoil. Unlike the regional allocation, even the static mean-variance sector allocation produces a defensive portfolio that is more or less decoupled from the world market portfolio in the bear regime.

Figure 3.2: Mean Absolute Differences between Simulated Weights and Benchmark Weights

Figure 2 plots the mean absolute difference between simulated country (left) and sector (right) weights and the benchmark weights for regime 1, regime 2 and static asset allocation. Under each scenario, parameter estimates used to calculate the weights are stimulated 1,000 times from their joint distribution. The simulated weights are compared against the benchmark weights reported in Panel C of Table 3.6 and Table 3.7. For each of the N country/sector portfolios, the absolute difference between the simulated and the benchmark weight is first calculated. The mean absolute difference is the average of these N absolute differences.

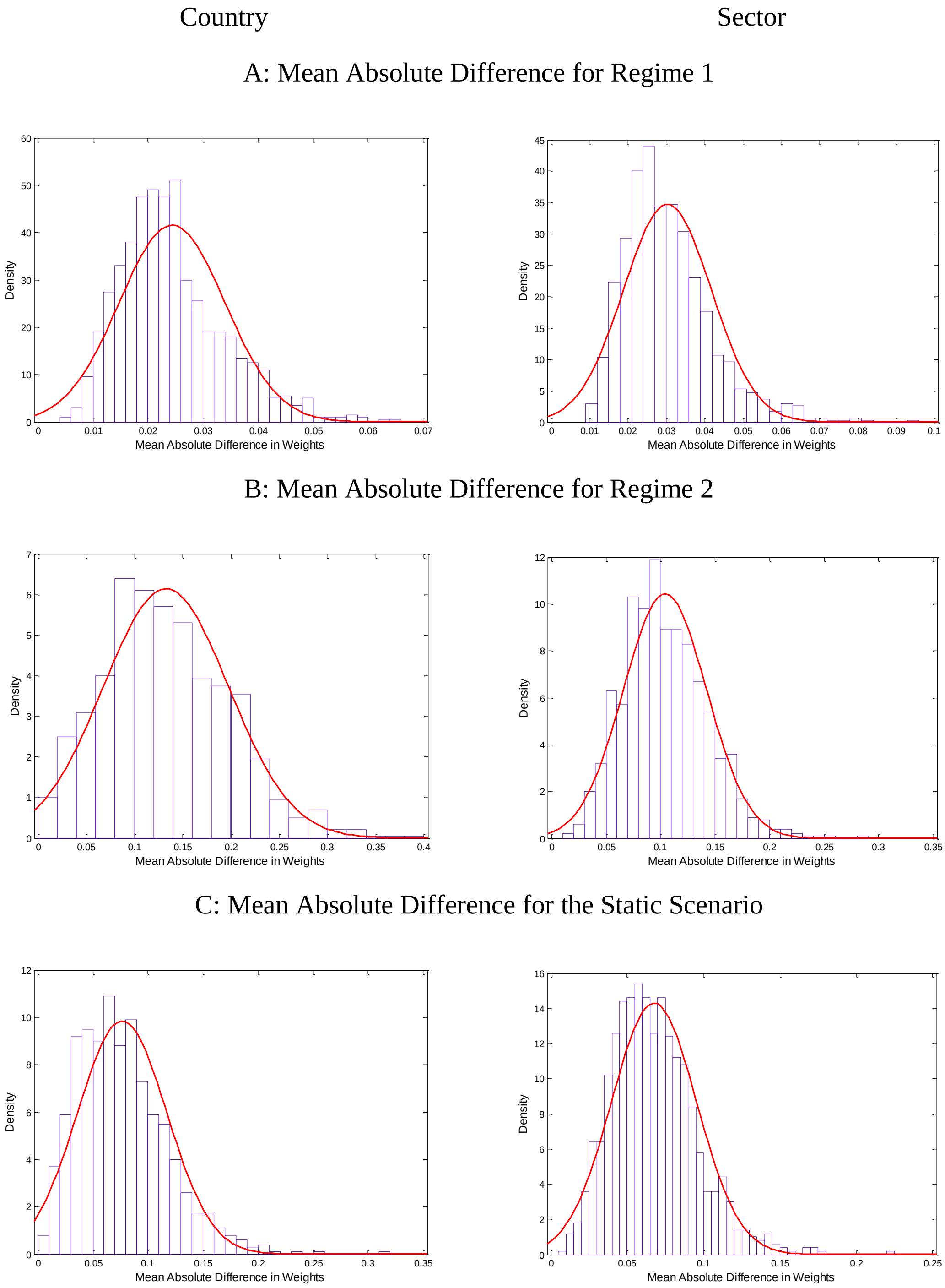


Table 3.8: Performance of regional allocation portfolios

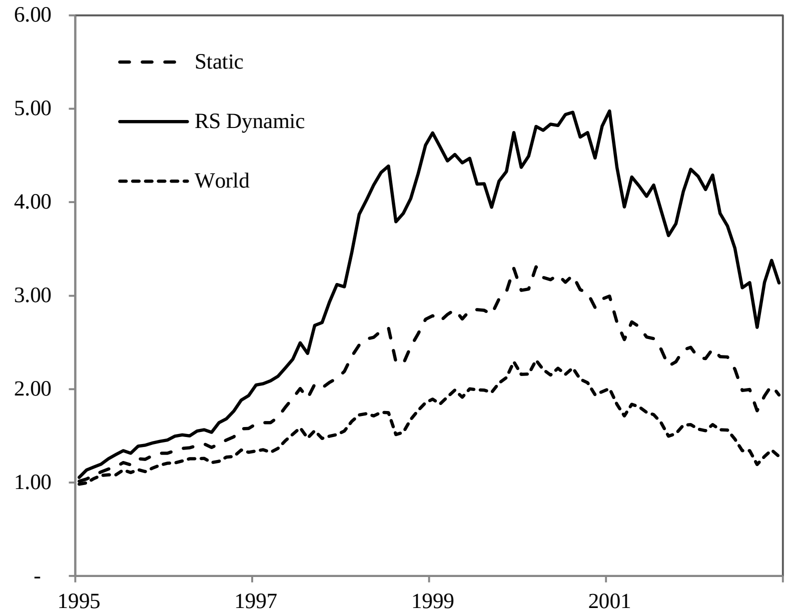
We present the mean, standard deviation and Sharpe ratio of both in-sample and out-of-sample returns following the regime-switching region model and a static non-regime dependent strategy. All returns are annualised and are reported in percentages.

A. In-sample performance 1995 - 2002	**No Constraints**			**Short Constraint**			**Benchmark Constraint**		
	World	Static	RS-Dynamic	World	Static	RS-Dynamic	World	Static	RS-Dynamic
Mean return (%)	4.26	9.53	16.42	4.26	8.58	9.01	4.26	7.08	6.02
Standard deviation (%)	15.20	15.48	20.23	15.20	15.79	15.89	15.20	15.47	15.05
Sharpe ratio	-0.02	0.32	0.59	-0.02	0.26	0.28	-0.02	0.17	0.10
B. Out-of-sample performance 2003 - 2010	**No Constraints**			**Short Constraint**			**Benchmark Constraint**		
	World	Static	RS-Dynamic	World	Static	RS-Dynamic	World	Static	RS-Dynamic
Mean return (%)	7.03	7.63	8.94	7.03	8.71	9.44	7.03	7.22	7.76
Standard deviation (%)	15.87	16.38	18.87	15.87	16.79	16.98	15.87	15.88	15.74
Sharpe ratio	0.30	0.33	0.36	0.30	0.39	0.43	0.30	0.32	0.35

Figure 3.3: In-sample and out-of-sample wealth for the regional allocation model - no Constraints

The top plot shows the in-sample wealth for the value of $1 at January 1995 for the regime-switching regional allocation model with no constraint, contrasted with a static mean-variance strategy, and the returns for the world portfolio. The bottom plot shows the out-of-sample wealth for the value of $1 at Jan 2003 for the regime-switching regional allocation model with no constraint.

A. In-Sample Regional Allocation Model 1995 – 2002



B. Out-of-Sample Regional Allocation Model 2003 – 2010

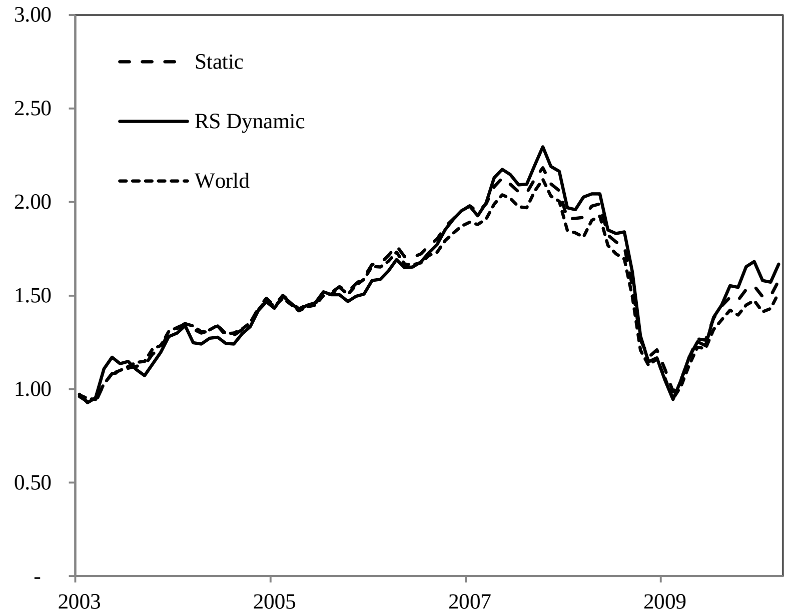


Table 3.9: Performance of sector allocation portfolios

We present the mean, standard deviation and Sharpe ratio of both in-sample and out-of-sample returns following the regime-switching sector model and a static non-regime dependent strategy. All returns are annualised and are reported in percentages.

A. In-sample performance 1995 - 2002

	No Constraints			**Short Constraint**			**Benchmark Constraint**		
	World	Static	RS-Dynamic	World	Static	RS-Dynamic	World	Static	RS-Dynamic
Mean return (%)	4.26	16.31	18.13	4.26	11.42	10.42	4.26	8.82	8.88
Standard deviation (%)	15.20	13.90	19.43	15.20	12.60	12.48	15.20	12.64	13.38
Sharpe ratio	-0.02	0.85	0.70	-0.02	0.55	0.47	-0.02	0.34	0.33

B. Out-of-sample performance 2003 - 2010

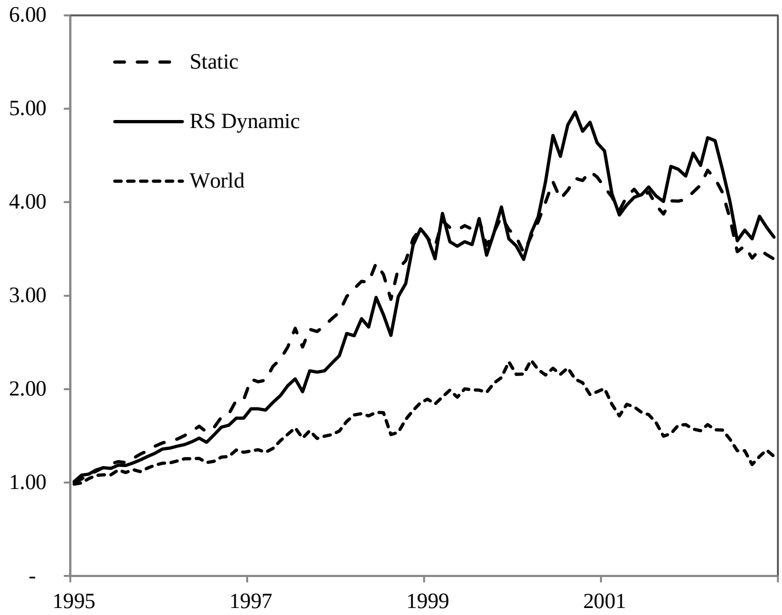
	No Constraints			**Short Constraint**			**Benchmark Constraint**		
	World	Static	RS-Dynamic	World	Static	RS-Dynamic	World	Static	RS-Dynamic
Mean return (%)	7.03	7.31	13.13	7.03	6.61	7.82	7.03	6.15	7.02
Standard deviation (%)	15.87	10.65	11.74	15.87	11.30	11.23	15.87	12.25	12.35
Sharpe ratio	0.30	0.48	0.93	0.30	0.39	0.50	0.30	0.32	0.39

It is worthwhile to compare the performance of static and regime-switching asset allocation across regions and across sectors. Table 3.10 shows the average returns, standard deviations, betas and Sharpe ratios generated by the static and the regime-dependent strategies for region and sector allocations for each year from 1995 to 2009. On average, cross-sector allocation provides higher returns, lower risks, lower betas and higher Sharpe ratios than cross-region allocation. In the cross-region allocation program, the regime-dependent portfolio produces a higher Sharpe ratio (0.59 in-sample and 0.36 out-of-sample), together with a higher beta (1.07 in-sample and 1.11 out-of-sample) than the static strategy. The regime-switching strategy out-performs the static strategy in Sharpe ratio in 10 out of the total 15 years, including the bear market from 2000 to 2002. In the cross-sector allocation, the regime-dependent strategy produces a higher Sharpe ratio (0.93), but a lower beta (0.34) than the static strategy out-of-sample. The regime-switching strategy in sector allocation out-performs the static strategy in 12 out of 15 years. Most remarkably, the regime-switching sector allocation yields an average return of only -0.86% per month and a monthly volatility of 5.65%, compared to the world market average monthly return of -4.21% and volatility of 6.81% in year 2008, the largest stock market decline in a single year since the Great Depression.

Figure 3.4: In-sample and out-of-sample wealth for the sector allocation model - no Constraints

The top plot shows the in-sample wealth for the value of $1 at January 1995 for the regime-switching sector allocation model with no constraint, contrasted with a static mean-variance strategy, and the returns for the world portfolio. The bottom plot shows the out-of-sample wealth for the value of $1 at Jan 2003 for the regime-switching sector allocation model with no constraint.

A. In-sample Sector Allocation Model 1995 – 2002



B. Out-of-Sample Sector Allocation Model 2003 – 2010

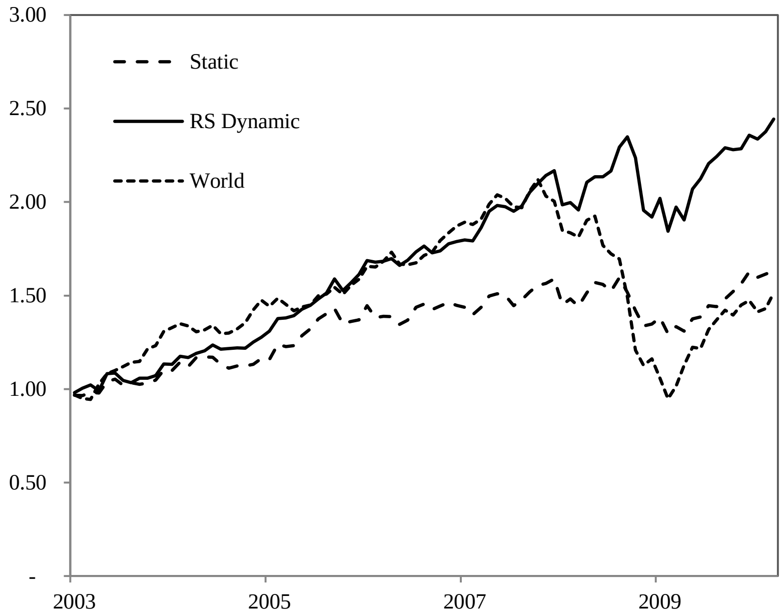


Table 3.10: Comparison of cross-region and cross-sector portfolios performance 1995 - 2009

We compare the mean, standard deviation, beta and alpha generated from static and regime switching regional allocations against their counterparts in the sectoral allocations. All returns and standard deviations are reported monthly and are reported in percentages.

Year	**World**		**Region-Static**				**Region-RS**				**Sector-Static**				**Sector-RS**			
	Mean	Stdev	Mean	Stdev	Beta	SR	Mean	Stdev	Beta	SR	Mean	Stdev	Beta	SR	Mean	Stdev	Beta	SR
A: In-sample period																		
1995	1.46	2.51	2.32	1.98	0.65	3.24	3.13	2.54	0.18	3.63	2.80	1.63	0.39	5.00	2.32	2.01	0.33	3.18
1996	0.95	2.35	1.56	2.07	0.72	1.89	2.49	2.67	0.52	2.67	2.61	3.08	1.21	2.46	2.15	2.44	0.83	2.44
1997	1.18	4.10	2.53	3.71	0.88	1.97	4.15	4.39	0.77	2.95	3.32	5.19	0.93	1.94	2.61	4.47	0.88	1.70
1998	1.87	5.64	2.36	5.73	0.99	1.18	3.52	6.59	0.98	1.64	2.67	5.10	0.64	1.54	4.43	7.76	0.81	1.80
1999	1.83	3.50	1.57	3.30	0.91	1.25	0.35	4.84	1.04	-0.02	0.04	4.15	0.32	-0.28	0.03	7.78	0.34	-0.16
2000	-1.17	4.15	-0.78	4.14	0.96	-1.05	0.22	4.75	0.87	-0.19	1.25	3.71	0.19	0.72	2.28	6.14	0.53	1.01
2001	-1.49	5.24	-1.46	5.19	0.98	-1.17	-0.60	7.09	1.28	-0.44	-0.45	2.72	0.35	-0.96	-0.56	4.71	0.53	-0.64
2002	-1.80	5.56	-1.76	6.20	1.11	-1.06	-2.32	9.16	1.54	-0.93	-1.35	4.03	0.49	-1.27	-1.22	5.75	0.59	-0.81
Average	0.35	4.40	0.79	4.48	0.97	0.32	1.37	5.86	1.07	0.59	1.36	4.07	0.54	0.85	1.50	5.61	0.63	0.70
B: Out-of-sample period																		
2003	2.32	3.54	2.29	4.10	1.14	1.86	2.24	6.20	1.44	1.21	0.84	2.78	0.37	0.94	1.11	3.67	0.17	0.97
2004	1.04	2.36	1.14	2.68	1.11	1.36	1.20	3.49	1.15	1.10	0.49	2.33	0.31	0.58	1.02	1.65	0.39	1.92
2005	0.63	2.36	0.64	2.39	1.00	0.57	0.25	2.52	0.97	0.01	1.42	3.15	0.97	1.28	1.99	2.32	0.69	2.60
2006	1.40	2.14	1.70	2.04	0.94	2.22	2.21	2.06	0.95	3.04	0.50	2.90	0.74	0.12	0.88	1.91	0.56	0.87
2007	0.60	2.68	0.48	2.65	0.97	0.14	0.91	3.49	1.24	0.53	0.80	2.35	0.54	0.62	1.63	1.83	0.44	2.37
2008	-4.21	6.81	-4.12	6.65	0.97	-2.22	-4.74	7.45	1.03	-2.27	-1.26	4.62	0.51	-1.05	-0.86	5.65	0.37	-0.61
2009	2.22	6.72	2.30	6.79	1.01	1.17	3.37	7.71	1.12	1.51	1.62	3.16	0.21	1.77	1.83	4.65	0.27	1.36
Average	0.59	4.58	0.64	4.73	0.99	0.33	0.75	5.45	1.11	0.36	0.61	3.09	0.39	0.48	1.09	3.37	0.34	0.93

3.6 Concluding remarks

Static mean-variance asset allocation fails to exploit the characteristics of high volatility and low equity returns in bad times. Although in high-volatility environments regional returns tend to be more correlated collectively, this is not the case for sector returns. This evidence is consistent with the increased level of global capital market integration and suggests a disappearing benefit of the regional diversification. We show that diversification across sectors adds higher benefits. The regime dependent sector allocation is particularly beneficial as it helps to exploit the defensive nature of some sectors. It would be interesting to develop a theoretical model that predicts whether sector allocations are more beneficial than regional allocations. Nevertheless, this salient empirical feature of regional and sector returns should not be ignored by either practitioners or future researchers.

While it is not our objective to develop the best asset allocation program, we demonstrate how the regime-switching model could match the non-linear feature of returns and improve the performance of asset allocation across regions and sectors. However, the out-performance could be sample specific as a relatively short and perhaps unique sample period is employed. In addition, the performance has not taken into account of market frictions such as transaction costs and taxes. Nevertheless, the regime-switching strategy should be robust to transaction costs because the probability of staying within the same regime is relatively high and portfolio turnover is low (eight regime switches in 15 years).

The performance of the regime-switching strategy could possibly be improved by incorporating the following extensions. First, we only consider a two-regime structure in our study primarily because structures beyond two regimes significantly increase the number of parameters estimated and hence require larger datasets. Future research can look at implications for the performance of cross-region and cross-sector allocations using three- or four- regime structures, which might fit equity returns data better [Guidolin and Timmermann, 2007].

Second, because we use only monthly returns data, it would be interesting to examine regime-switching behaviour on a weekly basis, which might signal more timely information, especially during the start of the bear markets when immediate diversification is needed the most, although using weekly data might create more frequent switches between regimes and generate much higher portfolio turnover and trading costs.

Finally, this study adopts an International CAPM model where beta is the single factor that characterises expected returns. Another viable alternative is to infer the regimes and formulate expected returns from factor models such as macroeconomic variables that can influence stock returns [Fama and Schwert, 1977, Jaffe and Gershon, 1976, Nelson, 1976]. A regime-switching allocation that trades based on macroeconomic and stock characteristic regimes might offer additional benefits.

Chapter 4

Dissecting Anomalies in the Australian Stock Market

4.1 Introduction

Anomalies are empirical patterns in stock returns that violate the efficiency of the market pricing mechanism in the context of the Capital Asset Pricing Model (CAPM). A large amount of US literature is devoted to the discovery of such patterns. For example, Banz [1981] documents the well-known size effect that stocks with low market capitalisation have abnormally high average returns. Rosenberg, Reid, and Lanstein [1985] and Chan, Hamao, and Lakonishok [1991] also find a value effect where stocks with higher book-to-market ratios significantly out-perform the market and stocks with lower book-to-market ratios. A momentum anomaly documented by Jegadeesh and Titman [1993] claims that stocks experienced high (low) past 6 to 12 months returns tend to generate high (low) future 6 to 12 months returns. DeBondt and Thaler [1985] find a longer-term contrarian effect where stocks experienced low (high) long-term (3 to 5 years) returns tend to have high (low) future returns. Stock returns are also shown to be anomalous in pricing accounting information. Haugen and Baker [1996] and Cohen, Gompers, and Vuolteenaho [2002] find that stocks with higher levels of profitability generate higher returns. Lakonishok, Shleifer, and Vishny [1994] document an earnings growth extrapolation effect where stocks with higher (lower) historical earnings growth rates have lower (higher) future returns. Cooper, Gulen, and Schill [2008] find that stocks historical asset growth rates negatively predict future returns. The accruals anomaly initially documented by Sloan [1996] states that stocks with high accruals, the non-cash portion of earnings, have lower average returns.

Nevertheless, Fama and French [2008] partition stocks into different size groups (60% of total number of stocks are micro, 20% of stocks are small and 20% of stocks are big) and find that many of the anomalies are not pervasive across size groups. In some cases, anomalies only exist in micro (extremely small) stocks (i.e., asset growth and profitability). They argue that, because micro stocks are so plentiful and are more likely to be in the extremes, they are influential in cross-sectional asset pricing tests. But because micro stocks are tiny in nature (represent only 3% of the total market capitalisation), anomalous returns associated with them are probably not exploitable because of high illiquidity and trading costs. Therefore, *It is important to know whether anomalous patterns in returns are market-wide or limited to illiquid stocks that represent a small portion of market wealth* [Fama and French, 2008].

Motivated by the findings of Fama and French [2008], this study examines eight well-documented anomalies, namely size, value, momentum, contrarian, profitability, earnings growth, asset growth and accruals, in the Australian stock market, using the methodologies proposed by Fama and French [2008]. Specifically, we investigate whether these anomalies are pervasive across different size groups. In addition, the study is also the first to examine the mainstream anomalies together in the Australian market, and hence assess which anomaly variables provide additional information in determining expected returns in Australian stocks. Furthermore, we examine whether the existence of an anomaly is consistent with risk-based explanations. If an anomaly variable captures information about risk, it is argued by Lakonishok, Shleifer, and Vishny [1994] that the anomaly should under-perform in the state of the world where the marginal utility of wealth is high (i.e., a bear market). We therefore ask whether any of these anomaly variables are risk factors by testing their performance in different market states.

Dissecting anomalies in the Australian market is interesting in a number of important respects. First, out-of-sample comparisons to the US market provide context to the investment strategies that have been documented in the cross-section by Fama and French [2008] and whether Australias market exhibits robust and/or unique characteristics. The aggregate Australian stock market capitalisation is dominated by a small number of large stocks, coupled with very large number of tiny stocks.[1] Past Australian anomaly studies tend to focus on equally weighted (EW) returns of decile or quintile portfolios sorted on anomaly variables.[2] These studies are largely influenced by the characteristics of micro stocks. If historically documented anomalies are primarily associated with micro stocks in Australia, the evidence is not useful to investors due to the costs of exploiting them. Some studies also choose to examine the value-weighted (VW) returns on decile or quintile portfolios [Bettman, Kosev, and

[1]The Australian Stocks Exchange (ASX) has 1,999 stocks with an average of $728 million (USD) market capitalisation, comparing to 2,238 stocks for New York Stock Exchange (NYSE) with an average of $5,985 million (USD) market capitalisation for each stock as at the end of 2010. The top 10 stocks at ASX represent 42% of the total market capitalisation, whereas the top 10 stocks at NYSE only represents 16% of the total market capitalisation. (See the World Federation of Exchanges website for a comparison, http://www.world-exchanges.org/statistics).

[2]See for example Brown, Keim, Kleidon, and Marsh [1983], Halliwell, Heaney, and Sawicki [1999], Demir, Muthuswamy, and Walter [2004], Gaunt [2004], Brailsford and O'Brien [2008], Clinch, Fuller, Govendir, and Wells [2010] and Bettman, Kosev, and Sault [2011]

Sault, 2011, Brailsford and O'Brien, 2008, Gaunt, 2004]. However, if decile or quintile portfolio sorting approaches are used for partitions of micro, small and big stocks, then VW returns can be dominated by a few big stocks. The results again are not representative of the true picture of the anomaly.

Second, evidence of Australian market anomalies is not only limited but also often controversial. Studies in general confirm the existence of the size effect in Australia, but find that the returns across size portfolios are not monotonic, with the smallest two deciles generating particularly high returns [Beedles, Dodd, and Officer, 1988, Brailsford and O'Brien, 2008, Brown, Keim, Kleidon, and Marsh, 1983, Gaunt, 2004, Gaunt, Gray, and McIvor, 2000]. Halliwell, Heaney, and Sawicki [1999] document the existence of a value premium in Australia. However, using VW returns, Gaunt [2004] finds the value premium to be statistically significant only for the largest three quintiles. For evidence on the momentum anomaly, Hurn and Pavlov [2003] find momentum returns to be stronger for larger stocks than smaller stocks. Gaunt and Gray [2003], however, document that smaller stocks exhibit more positive autocorrelation in returns based on 1 month prior returns. Demir, Muthuswamy, and Walter [2004] confirm the existence of momentum profits and also find them to be strongest for smaller stocks. In contrast, recent studies [Brailsford and O'Brien, 2008, OBrien, Brailsford, and Gaunt, 2010] find that the smallest size quintile loser stocks significantly outperform winners. Gray and Johnson [2011] is the first in Australia to adopt the size group partitioning methodology of Fama and French [2008] and find the existence of the asset growth anomaly. However, they find that the VW average hedge return is not statistically significant for big firms. Bettman, Kosev, and Sault [2011] conclude that the asset growth anomaly is attributed to the influence of small stocks. While the evidence of Clinch, Fuller, Govendir, and Wells [2010] confirms the existence of an accruals anomaly in Australia, Anderson, Woodhouse, Ramsay, and Faff [2009] find this anomaly to be more concentrated amongst larger firms. There is a notable gap in the Australian literature examining long-term contrarian, profitability and earnings growth anomalies in Australia.

Using EW and VW hedge returns in sorts and Fama and MacBeth [1973] cross-sectional regressions, we find that none of the eight anomalies are pervasive across the three (big small and micro) stock size groups. Particularly, size, value, contrarian, profitability, earnings growth and accruals anomalies do not predict the cross-sectional returns of big stocks. Momentum and asset growth predict the expected returns of big stocks using regressions; however, EW momentum hedge returns (i.e., long/short portfolio returns) are negative for micro stocks and VW asset growth hedge returns are statistically insignificant for micro and big stocks. Hedge returns on the earnings growth anomaly are negative across the size groups, which contradicts the growth extrapolation hypothesis. High-profitability big stocks tend to under-perform low profitability big stocks, indicating that Australian investors may overly extrapolate past level of earnings, rather than changes in earnings, for big stocks.

By examining the performance of anomalies in different market regimes, we show that many of anomalies (size, value, profitability, asset growth and accruals) tend to generate superior returns in bear markets rather than in bull markets. Our evidence suggests that the existence of anomalies in certain size groups cannot be attributed to risk-based explanations.

The reminder of the paper is organised as follows. Section 4.2 describes the data used for this study. Section 4.3 discusses the empirical results using sorts and cross-sectional regression. Section 4.4 provides the evidence on the performance of anomalies in different regimes. Section 4.5 concludes the chapter.

4.2 Data

Data for the study come from two sources. Monthly stock returns and market capitalisation data are obtained for each firm from the SIRCA Share Price & Price Relative (SPPR) database. The VW market returns are also obtained from the SPPR file, from 1968 to 2010. We obtain data for all stocks listed on the Australian Securities Exchange from January 1974 to December 2010. The accounting data is obtained from Aspect Huntley for the period from 1989 to 2009. This enables us to examine the returns on asset pricing anomalies from January 1992 to December 2010, covering a 19-year period.[3]

Table 4.1 shows the time-series average of the number of stocks and descriptive statistics on market capitalisation of stocks for the SPPR and Aspect Huntley combined file from 1992 to 2010, as well as the two sub-sample periods pre- and post-2000. The table also shows the average market capitalisation composition of different categories of stocks. It is important to note that the average mean market capitalisation is more than 20 times the median market capitalisation and the top 10 stocks represent around 40% of the total market capitalisation, indicating that the distribution of market capitalisation is heavily skewed towards the extremely large stocks. The Australian stock market composition becomes more concentrated in the top 10 stocks in the post-2000 period (42.39%, comparing to 38.04% in the pre-2000 period). The top 100 stocks represent on average 86% of the total market. The penny stocks outside the top 500 stocks (on average 887 number of stocks) comprise less than 2% of the total market. This evidence illustrates that a crude decile or quintile partitioning approach is likely to result a mixture

[3] 1989-1990 period is excluded because cash flow data becomes widely available in 1991. There are 0, 2, and 379 companies that have cash flow data in our sample in 1989, 1990 and 1991 respectively.

of big, small and micro stocks in the same portfolio, and hence a careful size partitioning is required.

Table 4.1: ASX stocks and market capitalisation, 1992-2010

The table shows the time-series average of the number of stocks and descriptive statistics on market capitalisation of stocks for the SPPR and Aspect Huntley combined data from 1992 to 2010, as well as the two sub-sample periods pre- and post-2000. The table also shows the average market capitalisation composition of different categories of stocks.

	Full-sample 1992-2010	Pre-2000	Post-2000
Average number of stocks	1,387	1,122	1,580
Mean market cap	513,669,446	395,742,991	599,434,141
25th percentile	6,731,717	5,416,268	7,688,407
Median market cap	21,462,001	17,228,745	24,540,732
75th percentile	106,227,798	94,070,184	115,069,699
Top 10 stocks weight	40.56%	38.04%	42.39%
11-50 stocks weight	33.75%	37.29%	31.17%
51-100 stocks weight	11.33%	11.43%	11.27%
101-200 stocks weight	7.64%	7.40%	7.82%
201-500 stocks weight	5.07%	4.74%	5.07%
>500 stocks weight	1.65%	1.11%	2.29%

As shown in Table 4.2, the final sample contains on average 1060 firms each year after we eliminate stocks with missing accounting information and negative book-to-market ratio from the merged SPPR and Aspect Huntley file. We then carefully partition the final sample into big, small and micro stocks. Fama and French (2008) use market capitalisation sorted percentile breaks such as 60%, 20% and 20% to divide all US stocks into micro, small and big stocks, respectively. The micro, small and big stocks therefore on average represent 90.48%, 6.45% and 3.07% of total US market cap in their study. Gray and Johnson (2011), instead of using percentile breaks, use the proportion of total market cap composition to classify micro, small and big stocks. That is, big stocks are those that comprise the top 90% of the total market cap. Small stocks are those that comprise the next 7% and micro stocks represent the remaining 3%. Their procedure results in a 70/16/14 split for micro, small and big stocks. Both Fama and French [2008] and Gray [2008] adhere to the partitioning approach that defines big, small and micro stocks as those representing approximately 90%, 7% and 3% of total market capitalisation. We choose to use percentile breaks as it is concise and more similar to industry classification than fixing the market cap composition. For example, because our final sample contains 1,060 stocks, the top 10% stocks would on average resemble the ASX 100 and the top 30% stocks would resemble ASX 300.

The approach in partitioning sample stocks into size groups is similar to that used by Fama and French [2008]. At the end of each December from 1991 to 2009, each stock is allocated to one of the three size groups C micro, small and big stocks. Micro stocks are the bottom 70% stocks, small stocks are between the 70th and 90th percentiles, and big stocks are the top 10% stocks of December-end market cap.[4] The time-series average numbers of stocks are 733, 218 and 108 for micro, small and big stock portfolios, respectively. As a result of the partitioning, micro stocks have $22 million average market cap and represent only 2.50% of the total market cap, whereas small and big stocks represent 8.59% and 88.91% of the total market cap with average market cap of $257 million and $5,376 million, respectively. Although stocks fall outside ASX 300 are generally considered not investable by Australian institutional investors, for better comparison we examine the bottom 70% micro stocks because they are included in most of previous Australian anomaly studies in computing EW returns and performing market-wide regression test [Bettman, Kosev, and Sault, 2011, Brailsford and O'Brien, 2008, Brown, Keim, Kleidon, and Marsh, 1983, Clinch, Fuller, Govendir, and Wells, 2010, Gaunt, 2004].

Table 4.2 also reports the averages and standard deviations of returns for the VW and EW micro, small and big portfolios as well as the market portfolio of all sample stocks. Because the big stocks represent on average more than 90% of market capitalisation,

[4] We perform a variety of alternative partitioning for robustness. This includes the 90%, 7% and 3% market cap fixing approach of Gray and Johnson [2011], 70/20/10 split within the top 500 stocks only or removing the top 10 stocks from the sample. We do not find qualitatively different results using alternative partitioning approaches.

Table 4.2: Value- and equal-weight average monthly returns, and averages and cross-section standard deviations of anomaly variables, 1992-2010

The table shows averages of monthly value-weight (VW) and equal-weight (EW) average stock returns, and monthly cross-section standard deviations of returns for all stocks (Market) and for Micro, Small, and Big stocks. It also shows the average number of stocks, average market capitalisation in millions (market cap) and the percent of the total market cap in each size group each month. It also shows the averages of annual EW average values and annual cross-section standard deviations of the anomaly variables used to sort stocks into portfolios and as independent variables in regressions. We assign stocks to size groups by the market cap at the end of December each year. Micro stocks are the bottom 70% stocks, Small stocks are between the 70th and 90th percentiles, and Big stocks are the top 10% stocks. The anomaly variables, which are used to predict the monthly returns for January of $t+1$ to December of $t+1$ in the tables that follow, are: Size, the natural log of market cap in December of t; BM, the ratio of book equity for the last fiscal year-end t divided by market equity in December of t; Mom (momentum), the 12 month buy-and-hold returns preceding December of t. Con (contrarian), the 60 month buy-and-hold returns preceding December of t. ROA (return on assets), the earnings before interest and taxes (EBIT) in t divided by the average of total assets for t and $t-1$. EG (earnings growth) the trailing 3-year average of changes in EBIT from $t-1$ to t scaled by the average book equity for t and $t-1$. AG (asset growth), natural log of total assets in t divided by total assets in $t-1$. Acc (accruals), the difference between EBIT and cash flow from operations in t, scaled by average total assets in t and $t-1$. Except for Size and BM the variables are multiplied by 100.

Panel A: Average monthly values, 1992-2010								
	Firms	Market	Market	VW returns		EW returns		Dispersion
		Cap ($mil)	Cap (%)	Mean	Std Dev	Mean	Std Dev	of Returns
Market	1060	617.9	100	0.84	3.84	1.28	5.9	18.2
Micro	733	22.3	2.5	0.93	6.29	1.47	6.71	20.08
Small	218	257.8	8.59	1.00	5.02	0.75	5.06	13.71
Big	108	5376.4	88.91	0.83	3.8	0.84	4.17	10.29
Panel B: Average of annual EW average values, 1992-2010								
	Size	BM	Mom	Con	ROA	EG	AG	Acc
Market	17.35	-0.52	23.68	82.90	-7.96	3.53	10.55	-5.11
Micro	16.21	-0.41	17.76	42.10	-14.55	3.66	7.11	-5.96
Small	19.15	-0.75	43.45	180.51	6.31	3.70	20.83	-3.07
Big	21.70	-0.86	25.37	159.41	9.64	2.25	14.03	-3.24
Panel C: Average of Annual Cross-Section Standard Deviations, 1992-2010								
	Size	BM	Mom	Con	ROA	EG	AG	Acc
Market	2.13	1.1	92.05	209.27	31.1	40.17	62.39	21.34
Micro	1.14	1.15	89.37	168.11	33.62	46.52	68.84	24.45
Small	0.61	0.97	101.42	255.75	17.64	18.49	44.44	11.94
Big	1.01	0.77	50.82	210.71	8.62	10.53	31.1	6.04

the VW market portfolio is similar to the VW big portfolio in average returns (0.84% and 0.83% per month, respectively) and volatilities (3.84% and 3.80% per month, respectively). However, the EW market average return and volatility (1.28% and 5.90%) are much higher than those of the VW market portfolio, since 70% of number of stocks in the market portfolio are micro stocks and these have the highest EW average returns and volatilities (1.47% and 6.71%). It is interesting to note that the

VW small stocks portfolio have higher returns and lower volatilities (1.00% and 5.02%) than those of the EW small stocks portfolio (0.75% and 5.06%), indicating that the bigger market cap stocks outperformed the smaller cap stocks in the small size group. The VW big portfolio has similar average returns (0.83%) compared to the EW returns (0.84%). Nevertheless, its volatility is lower than the EW big portfolio by 0.37%.

Table 4.2 also presents the time-series averages and standard deviations of the annual cross-sections of returns and the anomaly variables we use to predict returns. The eight anomaly variables, which are used to predict the monthly returns for January of year $t+1$ to December of year $t+1$ are defined and constructed as:

Size: the natural log of market capitalisation in December of year t;

BM (value): the nature log of the ratio of book equity for the last fiscal year-end t divided by market equity in December of year t;

Mom (momentum): the 12 month buy-and-hold returns preceding December of year t;[5]

Con (contrarian): the 60 month buy-and-hold returns preceding December of year t;

ROA (profitability): the earnings before interest and taxes (EBIT) in year t divided by the average of total assets for year t and year $t-1$;

EG (earnings growth): the trailing 3-year average of changes in EBIT from year $t-1$ to year t scaled by the average book equity for year t and year $t-1$;

AG (asset growth): the natural log of total assets in year t divided by the natural log of total assets in year $t-1$;

[5]Stocks with missing returns in any given month are replaced with zero returns. Stocks delisted during the holding period are included in the portfolio until the next rebalancing date.

Acc (accruals): the difference between EBIT and cash flow from operations in year t, scaled by average total assets in year t and year $t-1$.[6]

Similar to Fama and French [2008], the cross-sectional dispersion is generally largest for micro, and declines from micro to small and then to big stocks for returns and all anomaly variables, except Size, Mom and Con. This result further implies that micro stocks have stronger influence in testing the explanatory power of anomaly variables on stock returns.

It is interesting to note that the average EW returns for Mom and Con are quite large for small and big stocks but not for micro stocks. This can be attributed to the stocks migration effect. To illustrate, stocks experienced extremely large positive (negative) returns in the previous years are more likely to move from micro (big or small) to small or big (micro) size categories. Because of this migration effect, the one year (five years for Con) ahead returns are biased upward for big and small stocks and downward for micro stocks and hence result the larger (smaller) returns for small and big (micro) stocks.

[6]Note that our measure of profitability, asset growth and accruals deviate from those constructed in Fama and French [2008]. Fama and French [2008] use Return on Equity (ROE) whereas we use Return on Assets (ROA) as a measure for profitability. Both ROE and ROA are shown to predict returns in Haugen and Baker [1996]. However, it would be difficult to disentangle the profitability from the financial leverage effect if ROE is used. Nevertheless, results are not substantially different if we use ROE. In addition, Fama and French [2008] use a balance sheet approach (i.e. changes in working capital) in calculating accruals. Hribar and Collins [2002] argue that this approach introduces measurement error into the accruals estimate, primarily due to mergers and acquisitions and discontinued operations, and suggest the cash flow based measure of accruals (difference between operating income and cash flow from operations), which is the approach adopted in our study. Unlike Fama and French [2008], we do not examine net stock issues anomaly in our study primarily due to data non-availability. However, the asset growth variable captures the effect of net stock issues, as discussed in Cooper, Gulen, and Schill [2008]. That is, a stock that has large stock issuance would also result a high asset growth rate. Fama and French [2008] exclude net stock issues from their asset growth variable. Therefore our results on asset growth can be interpreted as a combination of the net stock issues and asset growth effects in Fama and French [2008].

4.3 Empirical results

4.3.1 Sorts

Table 4.3 shows average monthly value-weight and equal-weight returns for quintile portfolios formed using sorts on each anomaly variable for micro, small and big stocks, from January 1992 to December 2010. In December of each year from 1991 to 2009, sample stocks are sorted into quintile portfolios within each size group according to their ranks in each variable in December of year t.[7] The portfolios' equal- and value-weighted returns are then computed for year $t+1$.

To avoid look-ahead bias, we ensure the accounting data are available to the public at the time of portfolio formation. For portfolios formed in December of year t, accounting variables used (book equity, earnings, total assets and cash flows from Aspect Huntley) are those for the fiscal year ending in calendar year $t(tC1)$ if companies' fiscal year end is between January and August (September and December) of year t. The one year changes/averages are calculated as changes/averages from the fiscal year ending in calendar year $tC1(tC2)$ to the fiscal year ending in calendar year $t(tC1)$ if companies' fiscal year end is between January and August (September and December) of year t. This ensures a minimum 3 months or, in most cases, 6 months difference between portfolio formation and report date.[8]

Size, momentum and contrarian which all rely on the SPPR data, are measured in a more timely fashion than accounting-based variables. Size is measured at each December year end. Our methodology in forming momentum and contrarian portfolios

[7] Fama and French [2008] examine portfolios with positive and negative values of some anomaly variables separately. Due to a smaller sample size in Australia, this approach does not ensure a reasonable level of diversification as it would result insignificant number of stocks (less than 5) in some portfolios with negative values, particularly big stocks, in some years. We therefore choose to use a simple quintile portfolio approach.

[8] Minimum lags of 6 months and 12 months are also examined. The results are qualitatively similar.

differs slightly from what is commonly used in the previous literature.[9] That is, at the December end of year t, the momentum variable is the 12-month buy-and-hold returns preceding December. Similar to DeBondt and Thaler [1985], the Contrarian variable is the 60-month buy-and-hold returns preceding December of t. We skip the returns in December to account for illiquidity and market microstructure considerations associated with portfolio implementation. Momentum and contrarian variables are then updated each year.

As discussed in Table 4.2, micro stocks are more influential in EW returns and big stocks matter more in VW returns. The EW returns on quintile portfolios for all stocks reported in Table 4.3 are typically closer to those on micro stocks than those on small and big stocks. This is because micro stocks represent 70% of stocks and hence they have large influence not only on the equal weightings but also on the portfolio sorting of stocks. However, the VW returns on quintile portfolios for all stocks are not necessarily more similar to those on big stocks than those on micro and small stocks. This is because even though big stocks represent on average 90% total market capitalisation, and they absolutely dominate the value weightings, they are however dwarfed on the portfolio sorting of stocks. That is, micro stocks have higher cross-sectional dispersion in anomaly variables, and therefore are more likely to be in the extremes than big stocks. The composition of extreme portfolios for all stocks might be dominated by micro stocks, coupled with few big stocks and thus the VW returns would be distorted by returns on this limited number of big stocks in the portfolio. This is particularly evident on portfolios sorted on ROA, where the average VW returns on the bottom

[9]Previous literature such as Jegadeesh and Titman [1993] typically construct momentum or contrarian portfolios on a monthly basis and hold them for next 1 to 12 months. This methodology is likely to induce overlapping returns observations as the same stock can be included in multiple portfolios. Because all other strategies are updated yearly, to enable comparison across anomalies and avoid overlapping observations, we update momentum and contrarian portfolios on a yearly basis, a style that is implementable by passive investors such as mutual or pension funds. However, similar conclusions hold when monthly updates are used.

ROA portfolio for all stocks (-0.36% per month) is more different to those for big stocks (1.08%) than those for micro and small stocks (0.11% and 0.41%, respectively).

Previous studies on anomalies tend to focus on the absolute returns of long and short stock positions at different extremes of anomaly variables. Table 4.3 also shows the difference in returns between bottom and top quintile portfolios. Whether the spread for a particular anomaly is shown as bottom minus top or top minus bottom depends on what is empirically documented for this anomaly. For example, according to empirical evidence, one would expect the bottom quintile portfolio sorted on size to out-perform the top quintile portfolio, and therefore the spread is calculated as the bottom quintile minus the top quintile. If the spread is positive (negative), then the evidence is consistent (inconsistent) with what empirically suggested. Spreads for Size, Con, EG, AG and Acc are calculated as bottom minus top and denoted with SMB, LLMW, LMH, LMH and LMH, respectively. Spreads for BM, Mom and ROA are calculated as top minus bottom and denoted with HML, SWML and HML, respectively.

Previous studies tend to emphasise the EW hedge returns using all stocks. Table 4.3 supports the existence of five anomalies. That is, when all stocks are used, they generate statistically significant EW hedge returns. Mom, ROA and EG are the exceptions. Particularly, EW hedge returns for EG are significantly negative and the evidence contradicts the extrapolation explanation of Lakonishok, Shleifer, and Vishny [1994]. On the other hand, all anomalies generate statistically significant VW hedge returns using all stocks except Con and EG. If size group partition is not considered, one would conclude that at least four anomalies (Size, BM, AG, Acc) are strong and robust to different weighting methodologies in the Australian stock market.

Which anomalies produce statistically significant average EW and VW hedge returns

Table 4.3: Average returns for portfolios formed using sorts on anomaly variables 1992-2010

In December of each year from 1991 to 2009, sample stocks are sorted into quintile portfolios within each size group according to their ranks in each variable in December of t. The portfolios' equal- and value-weighted returns are then computed for year $t+1$. All returns are reported in percentage form. SMB is the returns on the lowest market cap portfolio minus the returns on the highest market cap portfolio. HML for BM (ROA) is the returns on the highest book-to-market (return on assets) ratio portfolio minus the returns on the lowest book-to-market (return on assets) ratio portfolio. SWML (LLMW) is the returns on the short term winners (long term losers) portfolio minus the returns on the short term losers (long term winners) portfolio. LMH for EG (AG, Acc) is the returns on the lowest earnings growth (asset growth, accrual) portfolio minus the returns on the highest earnings growth (asset growth, accrual) portfolio. The t-statistics are shown in parentheses.

Sorting on Market Capitalisation, Size							SMB	SMB
	Small	2	3	4	Big	SMB	t-statistics	p-value
			Average Equal-Weighted Returns					
Market	3.00	1.18	0.52	0.72	0.80	2.20	5.67	<0.0001
Micro	3.39	1.60	1.06	0.55	0.58	2.80	9.43	<0.0001
Small	0.86	0.72	0.55	0.84	0.72	0.13	0.66	0.5118
Big	0.91	0.98	0.65	0.85	0.76	0.15	0.67	0.5016
			Average Value-Weighted Returns					
Market	1.80	0.76	0.58	1.04	0.84	0.96	1.96	0.0514
Micro	2.10	0.93	0.76	0.64	1.01	1.09	3.02	0.0028
Small	1.05	1.02	0.83	1.04	0.98	0.08	0.34	0.7354
Big	1.10	1.12	0.81	0.86	0.80	0.29	1.25	0.2139
Sorting on Book-to-Market Ratio, BM							HML	HML
	Low	2	3	4	High	HML	t-statistics	p-value
			Average Equal-Weighted Returns					
Market	0.57	0.97	1.28	1.53	2.00	1.44	6.15	<0.0001
Micro	0.62	1.26	1.42	1.86	2.07	1.45	5.33	<0.0001
Small	0.16	0.71	0.86	0.80	1.12	0.96	2.95	0.0035
Big	0.76	0.83	0.91	0.90	0.73	-0.03	-0.10	0.9168
			Average Value-Weighted Returns					
Market	0.61	0.93	0.83	1.05	1.63	1.02	3.42	0.0007
Micro	0.35	0.95	0.80	1.21	1.29	0.94	2.65	0.0086
Small	0.53	1.00	0.95	1.06	1.28	0.74	2.07	0.0398
Big	0.66	0.58	1.08	0.71	1.13	0.48	1.63	0.1053
Sorting on Momentum, Mom							SWML	SWML
	Losers	2	3	4	Winners	SWML	t-statistics	p-value
			Average Equal-Weighted Returns					
Market	1.40	1.16	1.38	1.15	1.20	-0.21	-0.66	0.5114
Micro	1.58	1.44	1.53	1.41	1.24	-0.33	-1.02	0.3091
Small	0.10	0.80	0.95	0.85	0.89	0.79	2.24	0.0258
Big	0.47	0.90	0.72	0.79	1.22	0.74	2.26	0.0249
			Average Value-Weighted Returns					
Market	0.12	0.67	1.01	0.94	1.08	0.96	2.17	0.0308
Micro	0.20	0.50	0.98	1.04	1.17	0.98	2.48	0.0137
Small	0.17	0.92	1.28	0.99	1.18	1.01	2.59	0.0101
Big	0.63	1.02	0.76	0.79	1.12	0.49	1.53	0.1282
Sorting on Contrarian, Con							LLMW	LLMW
	Losers	2	3	4	Winners	LLMW	t-statistics	p-value
			Average Equal-Weighted Returns					
Market	1.70	1.58	1.38	0.99	0.72	0.98	2.55	0.0113
Micro	1.75	1.67	1.69	1.33	0.88	0.88	2.36	0.0191
Small	0.82	0.80	0.99	0.69	0.58	0.24	0.78	0.4390
Big	1.08	0.72	0.98	0.77	0.57	0.51	1.38	0.1700
			Average Value-Weighted Returns					
Market	0.81	1.31	1.15	0.95	0.73	0.08	0.18	0.8600
Micro	0.70	0.98	1.09	0.90	0.69	0.01	0.02	0.9818
Small	1.27	0.86	1.17	0.81	0.95	0.32	0.94	0.3457
Big	1.23	0.88	0.80	0.88	0.62	0.61	1.65	0.0997

Table 4.3: Average returns for portfolios formed using sorts on anomaly variables 1992-2010 - continued

Sorting on Return on Assets, ROA							HML	HML
	Low	2	3	4	High	HML	t-statistics	p-value
Average Equal-Weighted Returns								
Market	1.14	1.46	1.36	1.16	1.09	-0.05	-0.11	0.9091
Micro	1.22	1.39	1.68	1.60	1.25	0.03	0.06	0.9505
Small	-0.06	0.87	0.96	0.85	0.99	1.05	3.60	0.0004
Big	0.95	0.55	0.86	0.89	0.88	-0.07	-0.31	0.7532
Average Value-Weighted Returns								
Market	-0.36	0.48	0.93	0.82	0.84	1.19	2.30	0.0226
Micro	0.11	0.55	0.87	1.27	1.13	1.02	2.21	0.0280
Small	0.41	1.13	1.02	1.06	1.07	0.66	2.12	0.0355
Big	1.08	0.75	0.77	0.76	0.75	-0.33	-1.15	0.2504
Sorting on Earnings Growth, EG							LMH	LMH
	Low	2	3	4	High	LMH	t-statistics	p-value
Average Equal-Weighted Returns								
Market	1.03	1.22	1.35	1.41	1.34	-0.31	-1.87	0.0631
Micro	1.03	1.49	1.50	1.73	1.51	-0.48	-2.51	0.0129
Small	0.26	0.93	0.83	0.93	0.71	-0.45	-2.08	0.0390
Big	0.71	0.83	0.91	0.90	0.74	-0.04	-0.16	0.8714
Average Value-Weighted Returns								
Market	0.31	0.70	0.85	0.92	0.81	-0.49	-1.55	0.1215
Micro	0.06	1.05	1.09	1.17	0.91	-0.85	-2.90	0.0041
Small	0.67	1.07	1.09	1.05	0.77	-0.10	-0.43	0.6661
Big	0.75	0.68	0.79	0.91	0.83	-0.08	-0.30	0.7663
Sorting on Assets Growth, AG							LMH	LMH
	Low	2	3	4	High	LMH	t-statistics	p-value
Average Equal-Weighted Returns								
Market	1.63	1.76	1.40	0.98	0.55	1.08	5.14	<0.0001
Micro	1.73	1.87	1.72	1.21	0.71	1.01	4.46	<0.0001
Small	0.80	1.11	0.76	0.71	0.25	0.55	2.05	0.0411
Big	0.96	1.04	0.85	1.04	0.21	0.74	2.84	0.0049
Average Value-Weighted Returns								
Market	1.13	0.83	0.94	0.80	0.27	0.86	2.52	0.0126
Micro	0.52	1.26	1.22	1.06	0.32	0.19	0.67	0.5047
Small	1.14	1.24	0.88	1.07	0.40	0.74	2.37	0.0185
Big	0.94	1.00	0.64	0.95	0.55	0.39	1.39	0.1644
Sorting on Accruals, Acc							LMH	LMH
	Low	2	3	4	High	LMH	t-statistics	p-value
Average Equal-Weighted Returns								
Market	1.45	1.33	1.31	1.30	0.97	0.49	3.12	0.0021
Micro	1.56	1.60	1.49	1.52	1.10	0.46	2.37	0.0184
Small	0.85	0.69	0.86	0.89	0.37	0.48	2.12	0.0348
Big	0.96	0.92	0.81	0.91	0.56	0.40	1.83	0.0681
Average Value-Weighted Returns								
Market	1.03	0.83	0.95	0.81	0.15	0.88	2.75	0.0064
Micro	0.63	1.06	1.21	0.90	0.57	0.07	0.29	0.7757
Small	1.11	0.88	1.06	1.01	0.63	0.48	1.82	0.0704
Big	0.71	1.08	0.75	0.99	0.64	0.07	0.27	0.7880

across all three size groups? Table 4.3 shows that not a single anomaly passes the test. Although AG and Acc anomalies show statistically significant EW hedge returns for all size groups, all anomalies fail to prove their existence across all three size groups using VW hedge returns. Anomalies tend to be stronger in micro and small stocks than in big stocks. This indicates that the anomalies often documented using all stocks EW returns are largely attributable to empirical irregularities of micro stocks.[10]

Size and BM, the two variables that can explain the cross-sectional US stock returns [Fama and French, 1992], fail to generate positively significant hedge returns, especially for Australian big stocks. Within big stocks, the smallest size quintile out-performs the largest size quintile by 0.15% (0.29%) per month on an EW (VW) basis, but it is statistically insignificant. The EW returns on the highest quintile ranked on BM even slightly under-performs the EW returns on the lowest BM quintile (-0.03%). The evidence also suggests that the majority of the size and value premia (2.20% and 1.44% per month) come from the lowest size quintile (average returns=3.39%) and highest BM quintile (average returns=2.07%) of the micro stocks.

Although constructed differently, the evidence on momentum returns is largely consistent with the findings of Brailsford and O'Brien [2008], who find the momentum returns to be negative for smallest size quintile stocks and positively strongest for mid-cap stocks. In Table 4.3, average momentum returns for micro stocks are negative for EW returns but positively significant for VW returns, indicating that momentum exists primarily in larger Australian stocks. However, momentum returns for big stocks are significant for EW but not significant for VW returns. Contrary to the momentum evidence, contrarian hedge returns are significantly positive for extremely small micro stocks and extremely

[10]The micro stocks anomalies are probably not exploitable due to illiquidity and transaction costs. We do not examine the returns after for transaction costs and taxes because the findings show that the anomalies are not robust across size groups.

large big stocks. This is illustrated by the evidence that the EW hedge returns (0.88%) are much larger than VW hedge returns (0.01%) for micro stocks and that the EW hedge returns (0.51%) are smaller than VW hedge returns (0.61%) for big stocks.

Hedge returns based on ROA show that the profitability anomaly is evident in micro and small stocks. However, the spread is negative for big stocks. Particularly, returns on the lowest ROA quintile stocks generate the highest returns among big stocks on both EW (0.95%) and VW (1.08%) basis. This may indicate that Australian investors overly extrapolate the past level of earnings of big firms. The evidence on earnings growth, as discussed, contradicts the extrapolation explanation of Lakonishok, Shleifer, and Vishny [1994]. This is because Lakonishok, Shleifer, and Vishny [1994] eliminate stocks with negative earnings. We do not delete stocks with negative earnings because they are so common in Australia (almost half of stocks have negative earnings), due primarily to small and unprofitable Australian mining companies.[11] The negative spreads are attributable primarily to the low returns on the lowest EG quintile. This evidence supports an under-reaction to historical earnings growth rather than an excessive extrapolation of EG.

Our evidence on AG is generally consistent with that of Gray and Johnson [2011]. The VW hedge returns are not strong for micro and big stocks however. Similar to the findings of Clinch, Fuller, Govendir, and Wells [2010], the accruals anomaly exists when EW hedge returns are calculated for all stocks. However, VW accruals hedge returns are no longer significant for micro and big stocks.

[11] Lakonishok, Shleifer, and Vishny [1994] state that the strategy incorporating negative earnings stocks may produce different returns and is different from the strategy incorporating positive earnings stocks only. To closely follow the methodology of Lakonishok, Shleifer, and Vishny [1994], we do not find significant difference between returns on high and low earnings growth stocks using stocks with positive earnings only. However we only report the results using the full sample for consistency.

4.3.2 Correlations, volatilities and cross-sectional regressions

In this section, we first examine to what degree, the hedge returns on different anomalies in different size groups are correlated with each other across time. This exercise gives insight on what anomalies are similar and how Australian investors could diversify assets among different anomalies using variance and covariance information. We then use Fama and MacBeth [1973] regressions to show which anomalies offer information in predicting returns and which do not for each size group.

Table 4.4 shows the correlations and volatilities of the VW hedge returns based on the anomalies. Due to the hedging nature, none of the hedge returns are strongly correlated with the market. ROA and AG are the two strategies that mostly negatively correlate with the market. However, the beta neutral strategies generate much higher volatilities than the market (12.55% per annum). The volatilities are on average higher for strategies based on ROA and Con, and lower for strategies based on Size and Acc.

The correlation matrix reviews some interesting stylised empirical facts. Contrarian strategies are strongly correlated with a number of anomalies, most evidently with Size (0.64 for all stocks) and BM (0.35 for all stocks). This is in line with the argument of DeBondt and Thaler [1985], who claim that contrarian profit is a result of long-run overreaction of small stocks. This is also illustrated by the evidence that contrarian profit does not covary much (-0.05) with the size premium for big stocks. Hedge returns on ROA appears to offer some sources of diversification as they are negatively correlated with returns on other strategies (-0.75 with Size, -0.16 with BM, -0.55 with Con and -0.21 with EG for all stocks). It is interesting to note that the hedge returns on ROA are highly negatively correlated with hedge returns on EG (-0.61) for big stocks. Because hedge returns on ROA is high minus low and hedge returns on EG is low minus high, the negative correlation implies that ROA and EG capture similar sources of market anomalies, possibly the investors extrapolation of past earnings. It is also important to note that, in Table 4.4, value and momentum are not only different in nature, but also operate in different directions. The negative correlation between returns on Mom and BM is pervasive across size groups. This empirical feature of value and momentum is both interesting and yet to be explained, and therefore warrants future research.

Similar to Fama and French [2008], we estimate Fama and MacBeth [1973] regressions separately for micro, small and big stocks, because micro stocks are influential in a market-wide regression test. We also measure the difference-of-means to see whether the relations between anomaly variables and stock returns vary across size groups. The regressions are estimated monthly, using all eight anomaly variables at the December of year t as the independent variables and returns for year $t+1$ as the dependent variables. The returns are updated monthly and anomaly variables are updated once a year. Table 4.5 shows average slopes and t-statistics for anomaly variables from monthly cross-section regressions.

Table 4.5 shows that no anomalies demonstrate statistically significant explanatory power on stock returns consistently across all size groups. Size explains only the average returns of micro stocks. The average slope on Size is even positive (0.08, t=1.03) for big stocks, which means bigger stocks slightly out-performs the smaller stocks in the top 10% of market cap stocks. BM and ROA have the strongest explanatory power over returns of both micro (0.37, t=4.42 and 1.87, t=4.54, respectively) and small stocks (0.56, t=4.25 and 4.57, t=4.56, respectively). However, like the sorts, they do not show significance in explaining big stock returns. Only Mom and AG predict average returns of big stocks, with average slopes of 0.66 (t=2.25) and -1.07 (t=-3.39), respectively. However, Mom fails to explain micro stocks average

Table 4.4: Correlations and volatilities of long-short portfolios formed on anomaly variables, 1992-2010

This table reports the monthly correlation coefficients and annualised volatilities for the value-weighted market returns of all stocks and long-short portfolios reported in Table 4.3. Values reported on the diagonals of the correlation matrices are annualised volatilities. me-smb is the returns on the lowest market cap portfolio minus the returns on the highest market cap portfolio. bm-hml (roa-hml) is the returns on the highest book-to-market (return on assets) ratio portfolio minus the returns on the lowest book-to-market (return on assets) ratio portfolio. mom-swml (con-llmw) is the returns on the short term winners (long term losers) portfolio minus the returns on the short term losers (long term winners) portfolio. eg-lmh (ag-lmh, acc-lmh) is the returns on the lowest earnings growth (asset growth, accrual) portfolio minus the returns on the highest earnings growth (asset growth, accrual) portfolio. Correlation coefficients greater than 0.5 or less than -0.5 are shown in bold.

	mkt	me-smb	bm-hml	mom-swml	con-llmw	roa-hml	eg-lmh	ag-lmh	acc-lmh
Market	0.1255								
me-smb	0.1408	0.2567							
bm-hml	-0.0696	0.2032	0.1552						
mom-swml	-0.1383	-0.1847	-0.2894	0.2311					
con-llmw	0.1385	**0.6413**	0.3507	-0.2840	0.2301				
roa-hml	-0.3273	**-0.7472**	-0.1562	0.1845	**-0.5455**	0.2721			
eg-lmh	0.2300	0.0926	0.0040	-0.0434	0.0023	-0.2057	0.1652		
ag-lmh	-0.2216	0.1196	0.1884	-0.0988	0.2667	0.0304	-0.1255	0.1785	
acc-lmh	-0.1769	-0.0256	0.2429	-0.1011	0.0646	0.0266	-0.1110	0.3316	0.1672
Micro	0.1255								
me-smb	0.0653	0.1895							
bm-hml	-0.2025	-0.1080	0.1857						
mom-swml	-0.0523	-0.0539	**-0.6469**	0.2055					
con-llmw	0.0992	0.4894	0.0512	-0.3730	0.1967				
roa-hml	-0.3797	-0.4655	0.3973	0.1036	-0.4722	0.2418			
eg-lmh	0.2043	0.0418	-0.0673	-0.1535	0.1377	-0.4698	0.1529		
ag-lmh	-0.0841	0.2638	0.0317	-0.1464	0.3879	-0.4193	0.2806	0.1509	
acc-lmh	0.1854	0.1216	-0.3111	0.0172	0.1627	-0.3784	0.2711	0.2046	0.1250
Small	0.1255								
me-smb	-0.1092	0.1167							
bm-hml	-0.3301	0.0297	0.1885						
mom-swml	0.0771	0.1537	**-0.5949**	0.2041					
con-llmw	-0.1123	0.1504	**0.5846**	-0.4120	0.1760				
roa-hml	-0.2230	-0.0616	**0.5150**	-0.3560	0.2326	0.1629			
eg-lmh	-0.1013	0.0665	0.1583	-0.0825	0.1020	-0.2829	0.1208		
ag-lmh	-0.3251	-0.0194	0.4732	-0.2983	0.4862	0.2808	0.1658	0.1623	
acc-lmh	-0.0223	-0.1785	0.0169	0.0031	0.0347	0.0115	0.1866	0.2167	0.1391
Big	0.1255								
me-smb	0.0660	0.1236							
bm-hml	0.0419	-0.1313	0.1529						
mom-swml	0.0782	-0.0273	-0.4476	0.1685					
con-llmw	-0.1664	-0.0461	0.4005	-0.4819	0.1926				
roa-hml	-0.0723	0.0861	-0.2790	0.1934	-0.3492	0.1499			
eg-lmh	-0.0838	-0.1354	0.2371	-0.3072	0.4850	**-0.6105**	0.1343		
ag-lmh	-0.2726	-0.1288	0.1818	-0.1685	0.4228	-0.1361	0.3784	0.1471	
acc-lmh	-0.1097	0.1126	-0.2273	-0.0352	0.1448	0.4654	-0.1892	0.1756	0.1396

returns. Unlike sorts, AG, however, does not offer additional information in predicting small stocks, possibly due to the positive correlation with hedge returns on BM shown in Table 4.4. The explanatory power on Con is weak due to its correlation with Size and BM. Similar to sorts, regression results show that EG does not provide information in predicting stock returns. Nevertheless, in the small stock group, a significantly negative coefficient on EG indicates some degree of extrapolation of earnings for small stocks. Acc appears to be a micro cap anomaly only.

On a market-wide basis, four anomaly variables (BM, ROA, AG and Acc) offer useful information in predicting stock returns. Five variables can explain the average returns of micro stocks; however, the eight variables together explain only 4% of variations in stock returns. A large and positively significant alpha (8.69, t=5.56) for micro stocks is still unpredictable, but perhaps also not exploitable due to transaction costs. However, for big stocks, although only two variables show explanatory power, the eight variables on average explain 17% cross-sectional variations of stock returns. Alpha is not only insignificant, but also slight negative, indicating that the big stocks more efficiently price in these variables than micro stocks.

4.4 Anomalies, regimes and risk

In this section, we investigate the performance of anomalies in different times, particularly, in different market regimes. The motivation for this analysis is two-fold. First, from a portfolio management perspective, investors need to understand in what market conditions an anomaly-based strategy is likely to succeed or fail. Second, and more importantly from an asset pricing perspective, it is important to examine whether any of the eight anomaly variables are risk factors. Although our size

Table 4.5: Average slopes and t-statistics from monthly cross-section regressions, 1992-2010

The table shows average slopes and their t-statistics from monthly cross-section regressions to predict stock returns. The variables used to predict returns for January of $t+1$ to December of $t+1$ are: Size, the natural log of market cap in December of t; BM, the ratio of book equity for the last fiscal year-end t divided by market equity in December of t; Mom (momentum), the 12 month buy-and-hold returns preceding December of t. Con (contrarian), the 60 month buy-and-hold returns preceding December of t. ROA (return on assets), the earnings before interest and taxes (EBIT) in t divided by the average of total assets for t and $t-1$. EG (earnings growth) the trailing 3-year average of changes in EBIT from $t-1$ to t scaled by the average book equity for t and $t-1$. AG (asset growth), natural log of total assets in t divided by total assets in $t-1$. Acc (accruals), the difference between EBIT and cash flow from operations in t, scaled by average total assets in t and $t-1$. Each regression includes all the anomaly variables. Int is the average regression intercept and the average regression R^2 is adjusted for degrees of freedom. The t-statistics for the average regression slopes (or for the differences between the average slopes) use the time-series standard deviations of the monthly slopes (or the differences between the monthly slopes) and are shown in parentheses. All regression coefficients are multiplied by 100.

Variables	Int	Size	BM	Mom	Con	ROA	EG	AG	Acc	R^2
Expected signs		(-)	(+)	(+)	(-)	(+)	(-)	(-)	(-)	
Market										
Average	0.54	-0.02	0.48	0.22	0.05	1.73	0.19	-0.50	-1.06	0.04
t-statistic	(0.49)	(-0.49)	(6.34)	(1.61)	(1.56)	(4.18)	(1.04)	(-5.40)	(-3.73)	
Micro										
Average	8.69	-0.54	0.37	0.20	0.06	1.87	0.06	-0.35	-1.02	0.04
t-statistic	(5.56)	(-6.19)	(4.42)	(1.21)	(1.02)	(4.54)	(0.31)	(-3.52)	(-3.16)	
Small										
Average	1.72	-0.09	0.56	0.43	0.05	4.57	-1.79	-0.25	-1.05	0.11
t-statistic	(0.71)	(-0.67)	(4.25)	(2.28)	(1.61)	(4.56)	(-2.04)	(-1.12)	(-1.25)	
Big										
Average	-1.30	0.08	0.25	0.66	-0.01	0.63	1.95	-1.07	-1.76	0.17
t-statistic	(-0.73)	(1.03)	(1.49)	(2.25)	(-0.09)	(0.39)	(0.87)	(-3.39)	(-1.05)	
Big-Micro										
Average	-9.99	0.62	-0.12	0.46	-0.07	-1.24	1.89	-0.73	-0.74	
t-statistic	(-4.47)	(5.41)	(-0.65)	(1.59)	(-0.85)	(-0.80)	(0.85)	(-2.16)	(-0.43)	
Small-Micro										
Average	-6.97	0.46	0.19	0.23	-0.01	2.70	-1.85	0.10	-0.03	
t-statistic	(-2.55)	(3.08)	(1.45)	(1.03)	(-0.12)	(2.87)	(-2.10)	(0.44)	(-0.04)	
Big-Small										
Average	-3.02	0.17	-0.31	0.23	-0.06	-3.94	3.74	-0.83	-0.71	
t-statistic	(-1.01)	(1.12)	(-1.55)	(0.76)	(-0.84)	(-2.48)	(1.61)	(-2.19)	(-0.41)	

grouping analysis in Section 4.3 shows that none of these anomalies are robust across size categories, it is difficult to draw inferences on the future existence of these anomalies based on findings from a specific sample period. If an anomaly variable indeed captures additional information about risk, it is likely to exist in the long term and across different size categories. Lakonishok, Shleifer, and Vishny [1994] state that if the superior returns to an anomaly-based strategy is due to greater risk exposure, the strategy should under-perform in some states of the world, particularly in the bad states, in which the marginal utility wealth is high, therefore making risky assets unattractive to risk-averse investors. While it is difficult to either prove or reject a risk-based explanation, the nonparametric approach of Lakonishok, Shleifer, and Vishny [1994] is a simple and logical methodology for examining whether excess returns are due to risk or mispricing. We therefore examine the success of anomalies in different market regimes.

We follow Lakonishok, Shleifer, and Vishny [1994] by examining the performance of the anomalies in various market states. Table 4.6 reports the performance of the eight anomalies in each of three regimes of the Australian market: a bear regime with the 25 worst stock return months, a bull regime with the 25 best stock return months and a normal regime with the remaining 178 normal stock return months based on the value weighted Australian market portfolio returns from 1992 to 2010.[12] The average difference in EW and VW returns between the highest and lowest quintile portfolios sorted on each anomaly variables along with the t-statistics are calculated for each size category under each regime. A negative return difference or hedge return indicates an underperformance of the anomaly strategy.

The EW hedge returns shown in Panel A of Table 4.6 indicate that, on average, short-term momentum winners and low earnings growth stocks underperform the losers (-0.64% per month, t-stat=-0.63) and high earnings growth stocks (-1.22% per month, t-stat=-2.63) during the worst 25 months period, attributable primarily to micro stocks. In line with the results in the previous section, the low earnings growth stocks do not out-perform the high earnings growth stocks in other periods. The growth extrapolation story of Lakonishok, Shleifer, and Vishny [1994] is found only in big stocks during the bear market, where big stocks with lower earnings growth significantly out-perform the

[12]This classification is similar to Lakonishok, Shleifer, and Vishny [1994]. They define four market states with a 25/122/88/25 months split based on the equally weighted US market returns. We also adopt an alternative regime classification using the Hamilton [1989] regime-switching technique and GDP growth rate instead of the market returns. The results are qualitatively similar.

higher earnings growth counterpart by 2.50% per month. The under-performance of the momentum strategy in bear markets is insignificant. However, the micro losers stocks significantly out-perform the micro winners stocks in the bull market. Therefore, it is difficult to argue that any of these anomaly variables have additional information about risk.

What about the size and value anomalies, the two risk factors along with the market factor that is widely used in Fama-French three factor model? The size and value premia are in fact the strongest during the bearish states, at least for the micro and small stocks. However, the big value stocks underperform the big growth stocks in the most bullish market by -1.25% per month. This evidence is inconsistent with risk-based explanations for size and value effects.

Profitability, asset growth and accruals all appear to be more like bear market strategies rather than bull market strategies. It is particularly interesting to note that, though high profitability stocks significantly out-perform in the bear market (2.64% per month), they significantly under-perform the low profitability stocks in the bull market (-2.98% per month). There is no significant difference in returns between high and low profitability stocks during the normal period. Within the big stocks, the high profitability stocks under-perform the low profitability stocks not only during the bear market (-0.43% per month), but also significantly during the bull market (-1.13% per month). Contrarian profit is more evident in bull market for micro stocks; however, the opposite holds true for big stocks.

VW hedge returns provided in Panel B of Table 4.6 show similar implications. None of the anomalies experience significantly negative returns consistently across size groups in bear market. Again, most anomalies (value, profitability, asset growth, accruals and to

Table 4.6: Anomalies' hedge returns under three regimes, 1992-2010

All months in the sample (228 in total) are divided into 25 worst stock return months (W_{25}), 25 best stock return months (B_{25}) and remaining 178 normal stock return months (N_{178}) based on the value weighted market portfolio returns from 1992 to 2010. Equally weighted (Panel A) and value weighted hedge returns (Panel B) for each anomaly are calculated separately for the three regimes. me-smb is the returns on the lowest market cap portfolio minus the returns on the highest market cap portfolio. bm-hml (roa-hml) is the returns on the highest book-to-market (return on assets) ratio portfolio minus the returns on the lowest book-to-market (return on assets) ratio portfolio. mom-swml (con-llmw) is the returns on the short term winners (long term losers) portfolio minus the returns on the short term losers (long term winners) portfolio. eg-lmh (ag-lmh, acc-lmh) is the returns on the lowest earnings growth (asset growth, accrual) portfolio minus the returns on the highest earnings growth (asset growth, accrual) portfolio. The t-statistics are shown in parentheses.

	me-smb	bm-hml	mom-swml	con-llmw	roa-hml	eg-lmh	ag-lmh	acc-lmh
Panel A. Equally-weighted hedge returns								
Market								
W_{25}	2.75	4.30	-0.64	0.78	2.64	-1.22	1.95	0.41
t-statistic	(3.22)	(5.42)	(-0.63)	(0.65)	(3.05)	(-2.63)	(3.25)	(1.15)
N_{178}	2.02	1.14	0.06	0.77	-0.01	-0.25	1.09	0.51
t-statistic	(4.40)	(4.69)	(0.19)	(1.76)	(-0.03)	(-1.26)	(4.47)	(2.81)
B_{25}	2.95	0.71	-1.72	2.73	-2.98	0.12	0.14	0.40
t-statistic	(2.75)	(0.92)	(-1.56)	(2.47)	(-3.18)	(0.28)	(0.28)	(0.81)
Micro								
W_{25}	3.88	4.72	-0.47	0.27	3.91	-2.16	1.13	0.13
t-statistic	(4.46)	(5.31)	(-0.41)	(0.23)	(4.53)	(-3.82)	(2.15)	(0.26)
N_{178}	2.63	1.13	-0.06	0.69	-0.01	-0.33	1.10	0.50
t-statistic	(7.73)	(3.79)	(-0.17)	(1.65)	(-0.02)	(-1.53)	(4.05)	(2.26)
B_{25}	2.94	0.47	-2.15	2.82	-3.61	0.12	0.26	0.49
t-statistic	(3.48)	(0.73)	(-2.05)	(2.59)	(-3.65)	(0.23)	(0.51)	(0.78)
Small								
W_{25}	1.15	3.36	0.19	1.76	3.09	0.37	3.83	0.75
t-statistic	(1.68)	(2.82)	(0.16)	(1.20)	(3.41)	(0.53)	(3.28)	(1.04)
N_{178}	0.04	0.88	0.95	-0.11	0.91	-0.47	0.38	0.45
t-statistic	(0.18)	(2.53)	(2.47)	(-0.35)	(2.77)	(-1.95)	(1.48)	(1.82)
B_{25}	-0.21	-0.92	0.23	1.24	-0.01	-1.11	-1.56	0.44
t-statistic	(-0.28)	(-1.00)	(0.20)	(1.57)	(-0.01)	(-1.65)	(-1.98)	(0.53)
Big								
W_{25}	-0.12	0.37	-0.88	2.28	-0.43	2.50	3.76	0.45
t-statistic	(-0.14)	(0.36)	(-0.63)	(1.16)	(-0.55)	(2.32)	(3.07)	(0.54)
N_{178}	0.25	0.09	1.01	0.33	0.13	-0.36	0.56	0.51
t-statistic	(0.98)	(0.34)	(2.97)	(0.91)	(0.52)	(-1.54)	(2.22)	(2.16)
B_{25}	-0.23	-1.25	0.49	0.05	-1.13	-0.27	-1.01	-0.41
t-statistic	(-0.37)	(-1.65)	(0.44)	(0.05)	(-1.71)	(-0.42)	(-1.47)	(-0.58)
Panel B. Value-weighted hedge returns								
Market								
W_{25}	-0.46	1.50	1.94	-1.20	5.17	-2.66	2.98	2.36
t-statistic	(-0.41)	(1.53)	(1.25)	(-1.17)	(4.41)	(-2.16)	(1.79)	(1.45)
N_{178}	0.86	0.98	0.99	0.18	1.12	-0.30	0.70	0.90
t-statistic	(1.48)	(2.99)	(2.02)	(0.35)	(1.88)	(-0.88)	(2.02)	(2.79)
B_{25}	3.11	0.81	-0.21	0.63	-2.27	0.32	-0.10	-0.75
t-statistic	(2.51)	(0.80)	(-0.15)	(0.52)	(-1.54)	(0.36)	(-0.12)	(-1.10)
Micro								
W_{25}	1.19	3.29	1.30	-0.87	5.33	-2.81	0.62	-1.04
t-statistic	(1.15)	(2.35)	(0.93)	(-0.64)	(5.42)	(-2.97)	(0.86)	(-1.52)
N_{178}	0.94	0.67	1.00	-0.01	0.96	-0.57	0.30	0.12
t-statistic	(2.28)	(1.71)	(2.24)	(-0.01)	(1.87)	(-1.76)	(0.89)	(0.43)
B_{25}	2.08	0.55	0.47	0.99	-2.86	-0.84	-0.97	0.82
t-statistic	(1.86)	(0.65)	(0.52)	(1.06)	(-1.97)	(-1.01)	(-1.11)	(1.31)
Small								
W_{25}	0.96	3.16	0.38	1.60	2.21	0.69	4.31	0.83
t-statistic	(1.56)	(2.47)	(0.25)	(1.18)	(2.65)	(1.01)	(3.25)	(0.91)
N_{178}	-0.07	0.63	1.18	0.11	0.56	-0.20	0.50	0.42
t-statistic	(-0.28)	(1.61)	(2.78)	(0.30)	(1.64)	(-0.80)	(1.61)	(1.43)
B_{25}	0.23	-0.86	0.43	0.52	-0.22	-0.17	-1.15	0.62
t-statistic	(0.28)	(-0.80)	(0.36)	(0.62)	(-0.20)	(-0.19)	(-1.30)	(0.68)
Big								
W_{25}	-0.18	0.29	-1.08	3.24	0.52	0.99	2.56	1.51
t-statistic	(-0.22)	(0.30)	(-0.88)	(1.72)	(0.38)	(0.70)	(2.07)	(1.25)
N_{178}	0.44	0.42	0.68	0.29	-0.28	-0.30	0.29	0.07
t-statistic	(1.70)	(1.28)	(2.03)	(0.81)	(-0.94)	(-1.25)	(1.03)	(0.26)
B_{25}	-0.25	1.06	0.75	0.26	-1.57	0.46	-1.08	-1.35
t-statistic	(-0.32)	(1.21)	(0.62)	(0.24)	(-1.91)	(0.60)	(-1.31)	(-1.49)

a lesser extent contrarian) have superior returns skewed toward negative market return months rather than positive market return months. The profitability anomaly is the only one that generates significantly negative returns during the bull market.

In summary, not only do the anomaly variables not appear to proxy for systematic risk, but also portfolio strategies based on these anomalies provide some degree of downside risk protection. The evidence provided is therefore not consistent with a risk-based explanation. This also, to some extent, explains why certain anomalies are found in some size groups but not in others.

4.5 Concluding remarks

The study is the first to examine the existence and pervasiveness of eight well documented stock market anomalies together in Australia. While previous anomaly studies in Australia produce some inconsistent and, at times, controversial findings, there are also methodological issues in some of these studies, primarily the use of EW returns computation on decile or quintile portfolios and the market-wide cross-sectional regression test. Because micro stocks in Australia are so numerous and influential in EW returns and market-wide regression tests, we further partition all stocks into micro, small and big stocks and examine the anomalies in each size group separately.

We find that none of these eight anomalies are pervasive across size groups in sorts and cross-sectional regressions. In sorts, the existence of size, value, profitability, asset growth, accruals anomalies is attributable mostly to micro-cap stocks, which are generally considered not investable by Australian institutional investors and therefore are difficult to exploit. While asset growth and accruals generate significantly positive EW hedge returns for all size categories, the VW counterparts are insignificant for micro and big stocks. Momentum returns are significantly positive for big stocks using EW returns,; however, they are negative among micro stocks. Contrarian returns are significantly positive only in EW hedge returns for micro stocks and VW hedge returns for big stocks. The hedge returns on earnings growth are all negative, which contradict the findings of Lakonishok, Shleifer, and Vishny [1994]. In cross-sectional regressions, only momentum and asset growth predict the expected returns of big stocks. However, momentum does not predict returns on micro stocks and asset growth does not matter for small stocks. Contrarian returns are largely explained by size and value.

Our Australian results are quite different from the US results reported in Fama and French [2008], which still find pervasiveness in some of anomalies (e.g., value, momentum and net stock issues). This difference is perhaps due to a different market capitalisation representation or industry composition between these two markets. For example, the Australian market is dominated by the Financials and Resources sectors in both market value and number of stocks. This domination is likely to dictate both EW and VW returns. On the other hand, the US market is much less concentrated and has a more dispersed industry composition.[13] In addition, this study employs a relatively short sample period compares to most of the US studies on market anomalies. Nevertheless, we cannot exclude the possibility that these anomalies are indeed spurious in the Australian stock market.

In an attempt to examine whether any of these market anomalies are risk factors, the current study finds that most of the anomalies (except momentum and earnings growth) tend on average to generate better performance in the bear rather than in the bull market conditions (states). As Lakonishok, Shleifer, and Vishny [1994] argue, high-risk assets must under-perform in those states of the world where the marginal utility of wealth is

[13] See the World Federation of Exchanges website for a comparison, http://www.world-exchanges.org/statistics

high and investors are risk averse, such as the bear market state. Our evidence therefore does not lend support to risk-based explanations of market anomalies.

This study provides implication to academic research on Australian fund managers performance. Given the results concerning anomalies in this study, and other empirical evidence showing fund manager skill in active Australian equities [Chen, Comerton-Forde, Gallagher, and Walter, 2010, Fong, Gallagher, and Lee, 2008], it would appear that fund managers are generating alphas in areas beyond the mainstream anomalies. If this is the case, then active Australian fund managers are providing genuine value-added services. This issue warrants further research.

Chapter 5

Conclusion

This thesis contains three essays which investigate three separate aspects of modern developments in the area of portfolio management. The thesis considers novel techniques in forecasting equity risk premium, methodological improvements in asset allocation and common pitfalls in detecting stock market anomalies. Chapter 1 introduces the motivation of each essay, which contributes to the extant literature in its own ways. Chapter 1 also contains a brief review that highlights existing gaps in the literature which the essays aim to address.

The first essay in this thesis examines the out-of-sample forecastability of equity returns in Australia. In particular, the study adopts the combination forecast method of Rapach, Strauss, and Zhou [2010], who argue that this method is superior because of its ability to include information from numerous variables. Motivated by Rapach, Strauss, and Zhou [2010] and the lack of empirical Australian evidence, this study provides a comprehensive examination of out-of-sample predictability of equity risk premium for both the market and individual sectors in Australia using a variety of individual financial and economic variables and combination forecasts.

Similar to recent US evidence, the results indicate that individual financial and economic variables generally fail to consistently and reliably predict equity premium in Australia. Nevertheless, we document that the combination forecast method is able to consistently generate superior forecasting performance across different sample periods. The results are particularly strong for one-year prediction horizon. In a constrained optimal sector portfolio setting, the study shows that, using the sector premia predicted by the combining method, the sector rotation strategy is able to deliver 7.2% excess performance compared to the market portfolio, from 1985 to 2009. This is 3.3% return on a risk-adjusted basis.

The results have important implications for practitioners and investors alike, since the predictability of asset returns is central to the dynamics of asset allocation. Results of this study show that asset allocators may benefit from actively predicting returns using financial and economic predictors. Certain predictors have useful information in predicting future returns. However, the success will depend on how this information is extracted. The study shows one of the possible ways to achieve more accurate forecasts.

The essay presented in Chapter 2 investigates whether the asset allocation performance could be improved after accounting for the time-varying feature of means, volatilities and correlations of returns. The study accommodates the non-linearity of returns using the regime-switching model that is designed to capture high volatilities and correlations and low returns in bad times. The asset allocation decisions are applied across both regions and sectors, which are one of the most fundamental issues in international equity portfolio management. We also compare the relative importance of sector and country allocation.

Our evidence shows that the regime-switching asset allocation is able to out-perform the static asset allocation. While correlations between regional returns increase collectively during bearish markets (consistent with Ang and Bekaert [2004]), this is not the case for sector returns. The diversification benefits during the bad times are more evident for sectors, which are characterised by higher returns, lower risks, lower correlations with the world market and a higher Sharpe ratio. The regime dependent sector allocation is particularly beneficial as it helps to exploit the defensive nature of some sectors.

Results of the study are useful for portfolio managers concerning dynamic or tactical asset allocation. While it is not our objective to develop the best asset allocation program, we demonstrate a method that constructs multiple portfolios that are optimal in different market conditions. The regime-switching model may not provide the best indicator for predicting or timing the market, but it aims to capture states that are persistent in nature and have similar risk and return profiles across time. The study could be extended in several ways, including multiple regime structures, higher frequency data, and incorporating state variables, each of which represents a direction that may lead to improved asset allocation performance.

The final essay contained in this thesis examines the existence and robustness of eight well-documented stock market anomalies in Australia. Though many of these anomalies have been widely chased by professional equity managers, Fama and French [2008] discuss a common pitfall in empirical anomalies literature and show that some of these anomalies are not robust in different stock size groups. Chapter 4 reviews previous anomalies studies in Australia and finds that these studies produce some inconsistent and, at times, controversial findings. The use of EW returns on decile or quintile portfolios and the market-wide cross-sectional regression test are mostly problematic, particularly when the sample is dominated by tiny stocks.

After the sample stocks are partitioned into big, small and micro categories, we find that none of these eight anomalies are pervasive across size groups in sorts and cross-sectional regressions. Size, value, profitability, asset growth and accruals anomalies are attributable primarily to micro stocks and hence are difficult to exploit by institutional investors. Although momentum returns are significantly positive for big stocks using EW returns, they are totally opposite for micro stocks. Contrarian returns are concentrated mostly in micro stocks. The earnings growth anomaly contradicts the findings of Lakonishok, Shleifer, and Vishny [1994], which finds stocks with low earnings growth out-perform the high-growth counterparts. Our evidence does not lend support to risk-based explanations of anomalies as most of the anomalies tend to exist in the bear rather than the bull market.

The study provides important evidence to portfolio managers seeking to exploit anomalies in different segments of the stock market in Australia. The out-performance of several anomalies during the bear market may offer additional diversification benefits. Furthermore, given other empirical evidence showing fund manager skill in active Australian equities, portfolio managers appear to generate excess returns in areas beyond the anomalies examined in this study. Evidence documented in this study is useful for further research examining the performance of active Australian fund managers.

Appendix

.1 Data sources and construction for Chapter 2

Column (3) shows the data source and methodology used to compute each variable in Column (1). Column (4) shows the previous literatures that examine the empirical predictability of these variables. Note that our construction for the consumption-wealth ratio is different from the method proposed by Lettau and Ludvigson [2001]. We use GDP as a proxy for wealth due to a lack of data accessibility to household asset holdings in Australia.

Variables	**Name**	**Sources and construction**	**Literature**
(1)	(2)	(3)	(4)
Rret	Stock Returns	We use MSCI Australian stock index returns from 1970 to 2010 from MSCI Barra quarter-end values. Stock returns are the continuously compounded returns on the MSCI Australian index, including dividends	N/A
Rf	Risk-free Rate	The risk-free rate from 1970 to 2010 is the 90 days bank accepted bills rate from the Reserve Bank of Australia	N/A
ENE, MAT, IND, CDI, CST, HC, FIN, IT, TEL, UTI	Sector returns	We obtain sector returns from 1974 to 2009 from the Centre for Research in Finance database. Sectors are defined according to the Global Industry Classification Standard (GICS). Sector returns are the continuously compounded returns on the sector index, dividends included.	N/A

Stock characteristics:

D/Y	Dividend yield (log)	Difference between the log of dividends paid on all listed Australian stocks and the log of lagged stock prices, where dividends are measured using a one-year moving sum. Dividends and stock prices are from the Centre for Research in Finance (CRIF) database	
D/P	Dividend-price ratio (log)	Difference between the log of dividends and the log of current stock prices	Campbell [1987], Campbell and Shiller [1988], Fama and French [1988]
LagR	Lagged excess stock returns	One quarter lagged excess stock returns	Rapach, Strauss, and Zhou [2011]
SVAR	Sum of daily variance	Sum of squared daily returns on Australian All Ords price index from DataStream	Guo [2006]
Interest rate related:			
SBR	90 days bank accepted bills rate	90 days bank accepted bills rate from the Reserve Bank of Australia	Campbell [1987]
LBY	10 years government bond yield	10 years government bond yield from the Reserve Bank of Australia	Campbell [1987]
TMS	Term spread	Difference between the 10 years government yield and 90 days bank accepted bill rate	Campbell [1987]
Macroeconomic (all obtained from the Reserve Bank of Australia):			
CPI	Inflation rate	Calculated as the year on year change in the Consumer Price Index	Fama and Schwert [1977]
GDP	Nominal GDP growth rate	Calculated as the year on year change in the nominal GDP	Chen, Roll, and Ross [1986]
PPI	Δ in manufacturing price index	Calculated as the year on year change in the manufacturing price index	Flannery and Protopapadakis [2002]
FX	Δ in the Australian dollars TWI	The year on year change in change in the trade-weighted index of Australian dollars	Roll [1992]
M3	Δ in M3 money supply	The year on year change in M3 money supply, M3 is defined as currency plus bank current and term deposits, certificate of deposits issued by banks and all other non-bank deposits.	Hamburger and Kochin [1972]
I/K	Fixed non-residential investment/GDP	Fixed non-residential investment as a percentage of GDP	Cochrane [1991]

C/K	Household consumption/GDP.	Household consumption as a percentage of GDP	Lettau and Ludvigson [2001]
CSI	Consumer sentiment index (log)	The Westpac-Melbourne Institute consumer sentiment index has a base of 100, at which the optimistic and pessimistic responses to the five questions in the survey are balanced	Fisher and Statman [2003]

.2 An alternative method to assess the impact of estimation errors for Chapter 3

An alternative approach to assess whether the model produces better asset allocation is to examine the simulated performance of the dynamic model relative to the static model. Based on the 1,000 sets of parameters simulated, we also examine the models asset allocation performance. We follow the steps below to construct the simulated portfolio performances:

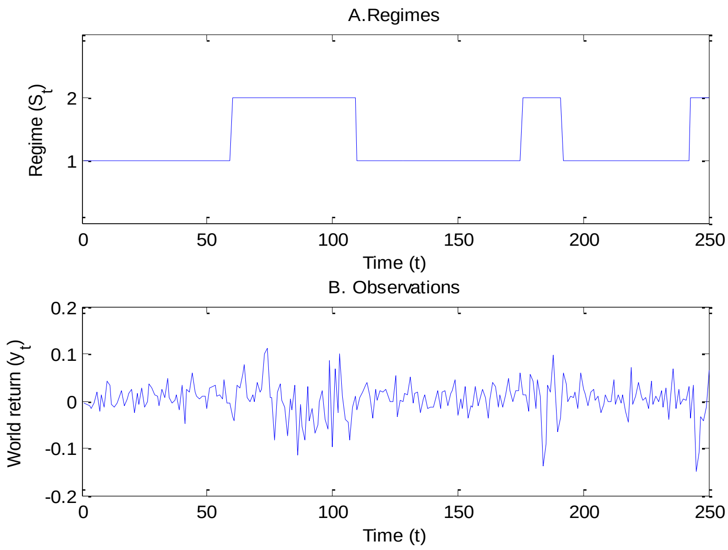
1. For each of the 1,000 sets of parameters, we simulate a new data generating process. Using the Markov chain (Equation 3.1), we simulate 250 time-series observations for the world excess returns. To illustrate, Panel A of Figure 1 shows an example of the regime (S_t) simulated from the transition probability matrix reported in Table 3.4. Once the regime is known, we randomly draw the world excess returns (y_t) (Panel B of Figure 1) from the regime dependent normal distributions with means and standard deviations presented in Table 3.4. As Panel B of Figure 1 shows, regime two is a more volatile state with lower mean returns. Note that for each set of parameters, the new world return process is obtained using simulated parameter values.

2. After the world return process (y_t) is simulated, for each set of parameters, we further apply the parameters values (alphas, betas and volatilities) to Equation 3.8 and Equation 3.9, and hence obtain 250 time-series observations for each country/sector portfolios. That is, we randomly draw observations from regime dependent normal distributions with mean returns determined by simulated alphas, betas and world returns and standard deviations of returns determined by simulated idiosyncratic volatilities.

3. Based on the 250 observations for each country/sector portfolios, we assess the performance of the optimal portfolio weights reported in Table 3.6 and Table 3.7. The optimal portfolio weights are kept fixed. That is, for the dynamic allocation model, portfolio weights change only when the realisation of regime changes. For the static model, the portfolio weights are always the same.

Figure 1: Simulated Markov Switching process

Figure 1 shows an example of the regime (S_t) for 250 simulated time-series observations from Markov Chain and the world excess returns (y_t) drawn from each regime, simulated from the transition probability, regime dependent mean returns and volatilities reported in Table 3.4.



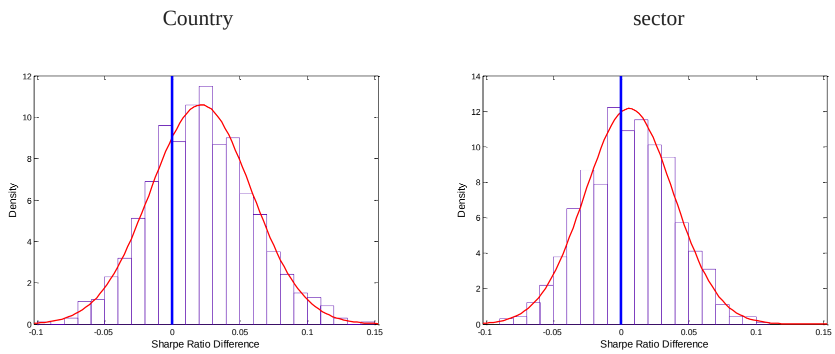
4. The difference between the Sharpe ratios for both dynamic and static models is then calculated.

5. We repeat step 1 to 4 1,000 times and hence obtain 1,000 observations for the Sharpe ratio differences.

Figure 2 reports the distribution of the Sharpe ratio differences between the dynamic and static models from the 1,000 simulations. When the Sharpe ratio difference is greater than zero, the dynamic model outperforms the static model. For both country (left) and sector (right) allocation, we see that the mode for the Sharpe ratio difference is higher than zero. The mean Sharpe ratio difference is 0.021 and 0.006 for country and sector allocation respectively. Out of the 1,000 simulations, the dynamic model beats the static model 703 times for country allocation and 568 times for sector allocation. The results indicate that, given our sample estimates and sampling errors, the dynamic model better characterises the data generating process for the excess returns, and hence is able to outperform the static model in the long run.

Figure 2: Shape Ratio Differences between the Dynamic and Static Allocation

Figure 2 plots the distribution of the Sharpe ratio difference between the dynamic and static models from the 1,000 simulations. When the Sharpe ratio difference is greater than zero, the dynamic model outperforms the static model. The country (sector) allocation is on the left (right).



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