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We provide 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, 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 forecast of variables. We also find improved asset allocation using the combination forecast of these predictors. 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.

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Out of Sample Stock Return Predictability in Australia

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Abstract

We provide one of the first comprehensive studies on the out-of-sample stock returns predictability in Australia. Whilst most of the empirically well-known predictive variables fail to generate out-of-sample predictability compared to forecasts generated from the historical average equity risk premium, we document a statistically significant out-of-sample prediction in forecasting one year, and to a lesser extent, one quarter future excess returns, using a combination forecast of these variables. Money supply, dividend-to-price ratio and consumption-to-GDP ratio contribute the most information in predicting equity premium. We also find an improved asset allocation performance by relying on the predicted returns generated from the combination forecast of these predictors. However, the improvement of the asset allocation performance is not robust to different sample periods examined. The combining methods are also useful in predicting different sector premia. A dynamic sector rotation strategy relying on forecasts generated by the combining methods significantly outperforms the historical market returns.

JEL: C22, C53, G11, G12

Keywords: out-of-sample equity premium predictability, portfolio allocation, sector rotation, predictive regression, combination forecasts.

1. Introduction

Stock return predictability has important implications to several fundamental concepts in financial literature, particularly, portfolio allocation, asset pricing, and stock market efficiency (Cochrane (2008)). A large body of extant literature has been dedicated to examine the predictability of stock returns, using a numerous and growing number of financial, economic, and technical variables as predictors.¹ Whilst many studies report evidence of in-sample return predictability, out-of-sample return predictability remains controversial. As documented by the recent study of Welch and Goyal (2008), many well-known predictors used in the existing finance literature do not consistently generate superior out-of-sample U.S. equity premium prediction relative to a simple forecast based on the historical average.² On the other hand, several studies demonstrate that out-of-sample equity premium forecastability can be improved using various techniques. Campbell and Thompson (2008) find greater out-of-sample forecastability after imposing constraints on the predicted equity premium. Rapach, Strauss and Zhou (2010a) challenge the school of thought of no forecastability and adopt a combination forecast approach, and find that the combining methods are able to deliver consistent superior out-of-sample U.S. equity premium prediction. The implication of Rapach, Strauss and Zhou (2010a) is important and useful as it provides a systematic approach of combining information from various financial and economic data while reducing the forecast variance in predicting returns.

Most studies on stock return predictability focus almost exclusively on the U.S. stock market, therefore it is interesting to ask whether the stock return predictability exists outside U.S. and whether the methodology in predicting equity premium proposed by Rapach, Strauss and Zhou (2010a) could be applied successfully in other countries. This study focuses on the return predictability in the Australian stock market. The empirical evidence is relatively scarce in Australia. Faff and Heaney (1999) investigate the relationship between inflation and Australian equity returns and do not find consistent relationships. Using Australian data, Boudry and Gray (2003) document that dividend yield and term spread have some

¹ Examples include valuation ratios, such as the dividend–price (Dow 1920; Fama and French 1988, 1989), earnings–price (Campbell and Shiller 1988, 1998), and book-to-market (Kothari and Shanken 1997; Pontiff and Schall 1998), as well as nominal interest rates (Fama and Schwert 1977; Campbell 1987; Breen, Glosten, and Jagannathan 1989; Ang and Bekaert 2007), the inflation rate (Nelson 1976; Fama and Schwert 1977; Campbell and Vuolteenaho 2004), term and default spreads (Campbell 1987; Fama and French 1989), corporate issuing activity (Baker and Wurgler 2000; Boudoukh et al. 2007), consumption–wealth ratio (Lettau and Ludvigson 2001), and stock market volatility (Guo 2006).

² Also see Bossaerts and Hillion (1999), Goyal and Welch (2003) and Spiegel (2008).

economically significant influence on investors' 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 short rate have some statistically significant predictability on stock returns. Using a series of eight financial and economic variables, Alcock and Gray (2005) examine the economic significance of return predictability using a variety of model selection criteria and find that return predictability do not always exist when different selection criteria are used. Using the similar set of variables, Gray (2008) develops a dynamic portfolio strategy using inference drawn from a probit model to examine the economic significance of return predictability and conclude that the superior return predictability is not robustness to different sample periods.

This paper, to our knowledge, is the first study that adopts the methodology proposed by Rapach et al. (2010a) and comprehensively investigates the out-of-sample stock return predictability for the Australian market by using a large number of Australian-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 mutual funds specialized in the Australian stock market³. Second, Analyzing Australian equity premium forecastability has important implications for Australian firms and investors in measuring cost of capital. Third, a detailed examination of return predictability in Australia provides out-of-sample evidence and enhances the understanding on stock return predictability outside of US.

We investigate the market and sector returns predictability of one quarter and one year ahead in Australia, both in-sample and out-of-sample, using 15 financial and economic variables proposed by U.S. studies. Our out-of-sample tests focus on whether individual predictors, as well as forecast combination approach, can outperform historical average equity premium with respect to both statistical predictability and asset allocation performance. As demonstrated by Rapach et al. (2010a) in the U.S. stock market, the combination forecast is a plausible way to incorporate information from various indicators and hence generate superior forecast performance than individual predictors. This is found to be the case in forecasting one year ahead, and to a lesser extent, one quarter ahead Australian stock returns as we demonstrate in this study.

³ Particularly, mutual funds investors in Australia have a strong home bias.

Our investigation on Australian stock return predictability also reveals several interesting empirical results. The in-sample tests show that variables such as dividend yield, dividend-price ratio and the consumption to GDP ratio have significant predictability on both one quarter and one year ahead stock market returns. In addition, we find additional variables such as the long-term bond yield, foreign exchange rate and money supply can also significantly predict Australian stock market returns at one year horizons.

The evidence for the out-of-sample Australian stock market predictability is mixed. For the one quarter ahead forecast in the out-of-sample period (January 1985 to September 2010), none of the individual predictors generate significantly positive Campbell and Thompson (2008) out-of-sample R^2 statistics. We find that different combination forecast methods outperform the historical average in different out-of-sample periods. However, the one year ahead combination forecast approach reveals strong predictability in real time. Whilst all individual predictors fail to deliver significantly positive out-of-sample R^2 statistics (except money supply), the predictability of almost all combination forecast methods consistently generate significantly superior performance than the historical average premium forecast. Particularly, the discount mean square prediction error combination method (when $\theta=0.1$) has a out-of-sample R^2 statistics of 16.13% (significant at 1% level), and out-performs the historical average premium forecast and a typical pension fund passive strategy by 2.87% and 2.36% per annum respectively in their asset allocation performance. However, the improvement of the asset allocation performance is concentrated in the first half of the sample period. It is also interesting to note that the combined forecastability increases when greater weights are assigned to individual predictors that have better recent predictability relative to their historical predictability.

The combination of these 15 variables also predicts industry sectors' returns, particularly at one year forecast horizon. Using these predicted sector returns, we simulate a real-time dynamic sector rotation strategy based on the sector mean-variance optimization technique. Using the sector premia generated by the discount mean square prediction error combination method (when $\theta=0.1$), the sector optimal portfolio out-performs the value weighted market returns by 7.18% per annum and 3.27% per annum after adjusting for risk from 1985 to 2009. This out-performance is robust to different out-of-sample period.

The remainder of the paper is organized as follows. Section 2 describes the predictive regression and combination forecasts methodology. Section 3 provides the data source and construction. Section 4 discusses the empirical results. Section 5 concludes.

2. Methodology

In this section, we firstly describe the predictive regression model and forecast combination framework used by Rapach et al. (2010a), and then discuss criteria used to evaluate the out-of-sample forecasts.

2.1 Predictive regression model

We follow the standard one period (one quarter) ahead predictive regression model to predict the equity premium:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1}, \quad (1)$$

where r_{t+1} is the difference between stock market index or sector indices raw returns and the risk-free interest rate one period ahead, $x_{i,t}$ is the predictor variable (because we have 15 individual predictors $i = 1, \dots, N$ and $N = 15$), and ε_{t+1} is the regression residual that follows a standard normal distribution.

We then divide the total sample of T observations for r_t and $x_{i,t}$ into an in-sample period composed of the first p observations and an out-of-sample period composed of the last q observations. The in-sample period is used to estimate the initial equity premium out-of-sample forecast, which can be written as:

$$\hat{r}_{i,p+1} = \hat{\alpha}_{i,p} + \hat{\beta}_{i,p} x_{i,p}, \quad (2)$$

where $\hat{\alpha}_{i,p}$ and $\hat{\beta}_{i,p}$ are estimated in-sample by regressing $\{r_t\}_{t=2}^p$ on a constant and $\{x_{i,t}\}_{t=1}^{p-1}$. Following Welch and Goyal (2008) and Rapach et al. (2010a), the next out-of-sample forecast is generated by recursively expanding the estimation window:

$$\hat{r}_{i,p+2} = \hat{\alpha}_{i,p+1} + \hat{\beta}_{i,p+1} x_{i,p+1}, \quad (3)$$

where we regress $\{r_t\}_{t=2}^{p+1}$ on a constant and $\{x_{i,t}\}_{t=1}^p$ to generate $\hat{\alpha}_{i,p+1}$ and $\hat{\beta}_{i,p+1}$. In each iteration we include one new observation in the regression estimation till the end of the out-

of-sample period. Thus a series of q out-of-sample forecasts of the equity premia can be generated using these estimated coefficients.

The out-of-sample equity premium forecasts generated by the predictors are then compared with the historical average of the equity premium, $\bar{r}_{t+1} = \sum_{j=1}^t r_j$, as suggested by Campbell and Thompson (2008), Welch and Goyal (2008) and Rapach et al. (2010a). If a predictor $x_{i,t}$ contains information useful for predicting the equity premium, then $\hat{r}_{i,t+1}$ should perform better than $\bar{r}_{t+1}$, which corresponds to a constant expected equity premium. We discuss how to evaluate the performance $\hat{r}_{i,t+1}$ relative to $\bar{r}_{t+1}$ in Section 2.3.

2.2 Forecast combination

In this section, we discuss the methodologies used to generate combination forecasts. Bates and Granger (1969) is the seminar paper that documents a superior performance of combinations of individual forecasts than the individual forecasts themselves as they utilize information across uncorrelated individual forecasts. Forecast combination has been used in the finance literature with respect to mutual funds out-of-sample alphas (Mamaysky, Spiegel, and Zhang (2007, 2008)). Rapach et al. (2010a) is the first study that uses this approach to forecast the equity premium in the U.S market.

The combination forecasts can be calculated as:

$$\hat{r}_{c,t+1} = \sum_{i=1}^N \omega_{i,t} \hat{r}_{i,t+1}, \quad (4)$$

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

We adopt Rapach et al. (2010a) combining methods, which can be classified into two types. The first type uses simple averages such as mean, median, and trimmed mean. The mean combination forecast assigns equal weight to each individual predictor $\omega_{i,t} = 1/N$ for $i = 1, \dots, N$, while the median combination forecast is simply the median of $\{\hat{r}_{i,t+1}\}_{i=1}^N$, and 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 $\omega_{i,t} = 1/(N - 2)$.

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

$$\omega_{i,t} = \phi_{i,t}^{-1} / \sum_{j=1}^N \phi_{j,t}^{-1}, \quad (5)$$

where

$$\phi_{i,t} = \sum_{s=p}^{t-1} \theta^{t-1-s} (r_{s+1} - \hat{r}_{i,s+1})^2, \quad (6)$$

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

We compare the results of combination forecast methods with a “kitchen sink” model in the spirit of Welch and Goyal (2008) and Rapach et al. (2010a). The “kitchen sink” model incorporates all 15 economic variables into a multivariate predictive regression model:

$$r_{t+1} = \alpha^{KS} + \beta_1^{KS} x_{1,t} + \dots + \beta_N^{KS} x_{N,t} + \varepsilon_{t+1}, \quad (7)$$

We then also generate a series of q out-of-sample forecasts based on the “kitchen sink” model in real time.

2.3 Forecast evaluation

To examine the statistical significance of return predictability, we use the out-of-sample R^2 statistic, R_{OS}^2 , proposed by Campbell and Thompson (2008). It 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_{OS}^2 statistic is calculated close to the spirit of in-sample R^2 statistic:

$$R_{OS}^2 = 1 - \frac{\sum_{k=q_0+1}^q (r_{p+k} - \hat{r}_{p+k})^2}{\sum_{k=q_0+1}^q (r_{p+k} - \bar{r}_{p+k})^2}. \quad (8)$$

The R_{OS}^2 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 $R_{OS}^2 > 0$.

To investigate whether the performance of individual predictors or combination forecast is statistically significantly better than the historical average forecast, it is equivalent to testing whether R_{OS}^2 is significantly positively deviate from 0. Similar to Rapach et al. (2010a), we use Clark and West (2007) MSPE-adjusted statistic to evaluate the significance of the R_{OS}^2 statistics:

$$f_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - [(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2]. \quad (9)$$

By regressing $\{f_{t+1}\}_{s=p+q_0}^{T-1}$ on a constant, the significance of f_{t+1} can be assessed by examining the p-value for a one-sided (upper-tail) t-statistic corresponding to the constant.

Because statistical significances do not necessarily guarantee economically significant benefits, in addition to the R_{OS}^2 measure, we also examine the economic significance of individual predictors and combination forecast. We investigate the asset allocation performance inferred from the predicted equity premium, measured by realized utility gains for a mean-variance investor on a real-time basis (Marquering and Verbeek (2004), Campbell and Thompson (2008) and Rapach et al. (2010a)).

In the asset allocation strategy with only one risky portfolio, we allow a mean-variance investor with relative risk aversion parameter γ to switch between the stock market portfolio and cash on a quarterly basis based on predicted equity premium calculated from the individual predictive model and combination forecasts. Rather than model the volatility of returns, we simply assume that the variance to be a ten-year rolling window of quarterly returns (Campbell and Thompson (2008) and Rapach et al. (2010a)). A mean-variance investor who forecasts the equity premium using the predictive model and combination forecasts j will decide at the end of period t to invest the following portion of the portfolio to equities in period $t + 1$:

$$w_{j,t} = \left(\frac{1}{\gamma}\right) \left(\frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}^2}\right), \quad (10)$$

where $\hat{\sigma}_{t+1}^2$ is the rolling-window estimate of the variance of stock returns. We do not allow for short selling and therefore the portfolio weight on stocks lies between 0 and 1 (inclusive). the investor's utility level is given by:

$$\hat{u}_j = \hat{\mu}_j - \left(\frac{\gamma}{2}\right) \hat{\sigma}_j^2, \quad (11)$$

where $\hat{\mu}_j$ and $\hat{\sigma}_j^2$ are the out-of-sample mean and variance of the return on the dynamic portfolio formed using predicted equity premium based on the individual predictive regression model and combination forecasts.

We then compute the utility level for the same investor who uses the historical average equity premium forecast in the similar manner. We compare the utility level from the dynamic asset allocation strategy utilizes individual and combination predictors against the strategy relies on the historical average benchmark. In addition to Rapach et al. (2010a) we also adopt a static weight asset allocation strategy with 70% invested in equity and 30% invested in cash as a benchmark that mimics the behavior of some large Australian pension fund investors. We measure the utility gain (or certainty equivalent return) as the extra utility level generated from equation (11) relative to the other two benchmarks. This difference is multiplied by 400 to express the utility gain in average annualized percentage return. We report results for $\gamma = 3$; the results are qualitatively similar for other γ values.

In the sector allocation program with multiple risky portfolios, we allow a mean-variance investor with relative risk aversion parameter γ to switch amongst 10 sectors based on predicted sector equity premia calculated from the combining methods. We again estimate the one period ahead variance-covariance matrix of these 10 sectors using a ten-year rolling window of quarterly returns. The risk-free rate is each quarter's prevailing 90 days bank bill rate. The sector weights are the portfolio weights that compose the tangent portfolio on the efficient frontier at each quarter. We do not allow for short selling and therefore the weight for each sector portfolio lies between 0 and 1 (inclusive). We use equation (11) to measure the utility level generated from this asset allocation program and compare it with both the value weighted and equally weighted sector portfolios. The difference is again multiplied by 400. We report results for $\gamma = 3$; the results are qualitatively similar for other γ values.

In our empirical applications, we also examine the in-sample and out-of-sample stock return predictability using one year forecast horizon. Fama and French (1989) document that the evidence for stock return predictability is significantly stronger for long horizons than for short horizons. However, Richardson and Smith (1991) argue that regressions with overlapping observations have statistical properties that may inflate the statistical significance. Powell, Shi, Smith and Whaley (2007) and Boudoukh, Richardson and Whitelaw (2008) propose that the significant predictability at longer term might be spurious,

particularly when regressors are persistent. We therefore not only examine the statistical significance, but also the economic significance of return predictability at longer horizons.

A four periods (one year) ahead predictive regression model is a straightforward extension of equation (1):

$$r_{t+1:t+4} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1:t+4}, \quad (12)$$

where $r_{t+1:t+4} = r_{t+1} + \dots + r_{t+4}$ and the forecasts are again computed recursively. Due to overlapping observations, we use the Newey and West (1987) standard error estimate to control for autocorrelation when computing the Clark and West (2007) MSPE-adjusted statistics.

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 related and macroeconomic variables. Because the actual announcements of the macroeconomic indicators are released in the following quarter, we wait for one quarter before using them (except FX) in the regression to avoid hindsight bias. See appendix 1 for the detailed data sources and construction⁴.

Table 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.

Table 2 reports the Spearman's 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

⁴ We omit a list of variables that have also demonstrated empirical predictability in US in this study due to data non-availability. These variables include default premium, earnings-to-price ratio, book-to-market ratio and corporate issuing activities. 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.

shown in bold and italic. Most of these variables are not significantly correlated with each other, indicating that these selected variables may represent a broad range of uncorrelated economic information. The significantly correlated variables are in line with the 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, investment and consumption are different components of GDP).

We consider three different out-of-sample forecast evaluation periods. (i) A “full” out-of-sample period covering the 1987 market crash 1985:1~2010:3; (ii) A more recent out-of-sample period covering the last 15 years of the full sample, 1995:1– 2010:3. (iii) We also evaluate a very recent out-of-sample period covering the last five years of the full sample, 2005:1–2010:3, which allows us to analyse how the predictors perform during the recent global financial crisis. Overall, the consideration of multiple out-of-sample periods helps to provide us with a good sense of the robustness of the out-of-sample forecasting results.

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 4.2. We report the empirical results on the sector return predictability and the profitability of the sector rotation strategy in section 4.3.

4.1 In-sample market premium predictability results

Table 3 reports the in-sample predictive regression results for one quarter ahead and one year ahead horizons. While more than half (8 out of 15) of predictors have negative adjusted R^2 for the one quarter ahead forecast, D/Y, D/P and C/K are significant (at 1%, 5% and 1% respectively) predictors of equity premium, with adjusted R^2 of 5.73%, 3.14% and 3.82%. The interest rate, inflation and output related variables in general have relatively low predictability of equity premium. Having controlled for autocorrelation possibly induced by the overlapping observations using Newey and West (1987) standard error estimates, the one year horizon forecast reveals D/Y, D/P, LBY, FX, M3 and C/K as significant (at 1%, 5% 10%, 1%, 5% and 1% respectively) predictors, with adjusted R^2 of 14.43%, 12.72%, 1.28%, 7.69%, 3.33% and 8.54% respectively. This evidence is in general consistent with previous

Australian studies that find dividend yield has some predictability in stock returns (Boudry and Gray (2003), Alcock and Gray (2005) and Yao et al. (2005)). However, Yao et al. (2005) do not find 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 remarkable, however, it does not necessarily translate into an equally significant out-of-sample predictability and a superior asset allocation performance due to the problems raised by Richardson and Smith (1991), Powell et al. (2007) and Boudoukh et al. (2008). We provide the evidence of out-of-sample predictability in the next section.

4.2 Out-of-sample market premium predictability results

Following Welch and Goyal (2008) and Rapach et al. (2010a), 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 1985:1~2010:3 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 model's 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: 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 1 and Figure 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 decreased lines with substantial slopes. It is interesting to note that a number of variables such as D/P, SVAR, TMS become markedly negatively sloped during the 1987 market crash in the one quarter ahead forecast.

We then impose restrictions on predictive regression models following methods proposed by Campbell and Thompson (2008). More specifically, we set β_i to zero when recursively estimating Equation (1) and Equation (12) 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 1 and 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, 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, our Australian evidence is consistent with the conclusion drawn from Welch and Goyal (2008) based on the US evidence: it is difficult to identify individual predictors that reliably outperform the historical average with respect to forecasting the equity premium.

Panel B of figure 1 and 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), particularly, more strongly in the

period before 1990, but still consistently positive thereafter. The dotted lines representing the Campbell and Thompson (2008) restrictions overlay with the solid lines in Figure 4, indicating that combination forecasts in general satisfy with the restrictions. Overall, the combination forecast approach illustrated in panel B of Figure 1 and 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 equity premium in Australia.

We then discuss the detailed results for the three out-of-sample periods, which are presented in Table 4 for one quarter ahead horizon and Table 5 for one year ahead horizon. These two tables reports R_{os}^2 statistics and average utility gains for each of the individual predictive regression models and combining methods relative to the historical average benchmark model and a 70% equity and 30% cash static asset allocation strategy. For R_{os}^2 statistics greater than zero, statistical significance is assessed with the Clark and West (2007) MSPE-adjusted statistic, as discussed in Section 2.3.

Panel A of Table 4 reports one quarter ahead forecast results for the “full” out-of-sample period from 1985:1~2010:3. Only 2, GDP and M3, out of 15 individual predictive variables generate positive R_{os}^2 as shown in column (2) and (6). None of these positive R_{os}^2 are significant. Those 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 column (3), (4), (7) and (8) lend even 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 4, the most impressive result is the relatively high R_{os}^2 generated by each of the combining methods. All of the R_{os}^2 statistics for the combination forecasts are greater than 3% and larger than the largest R_{os}^2 (0.61% for M3) among all of the individual predictors. Nevertheless, only mean combination with Campbell and Thompson (2008) restrictions (Mean, CT) generates significantly positive R_{os}^2 (significant at 10% level). With the exception of the Mean, CT method, all other combining methods only deliver 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_{os}^2 and the lowest utility gains among all combining methods.

Panel B of Table 4 reveals an on average improved one quarter ahead out-of-sample predictability of individual predictors in the sample period from 1995:1~2010:3. The number

of individual predictors with positive R_{os}^2 increases from 2 in the full sample period to 4. Particularly, D/P posits an impressive 11.66% R_{os}^2 and GDP has a significantly positive R_{os}^2 at 5% level. Moreover, many of the negative R_{os}^2 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. 6 variables have positive utility gains relative to both historical average and the static strategy. C/K again generates the highest utility gains, outperforms 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_{os}^2 statistics from 1995:1 to 2010:3 compared to the full out-of-sample period, with mean, median and trimmed mean all provide significantly positive R_{os}^2 at 5% level. All combining methods have R_{os}^2 larger than 8% and positive utility gains relative to both historical average and the static strategy, except the DMSPE ($\theta=0.1$) with R_{os}^2 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_{os}^2 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 1985~1995 period, most probably due to the 1987 market crash.

Panel C of Table 1 reports one quarter ahead forecast results for the 2005:1–2010:3 out-of-sample period covering the recent global financial crisis. The second and sixth columns of Panel C indicate further improved out-of-sample performance with 7 out of 15 variables outperform the historical average. Most of variables have increased R_{os}^2 with D/P and C/K having R_{os}^2 larger than 10%. 5 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% p.a. out-performance relative to the historical average and the static strategy respectively. Similar to the previous two different sample periods, column (9) of Panel C shows that the combination forecasts again generate higher positive R_{os}^2 than individual predictors, with all of R_{os}^2 greater than 13%. Unlike the results in Panel B, the DMSPE methods produce higher and significant R_{os}^2 during this particular sample period. The superiority of combination forecast methods is further confirmed when all combining methods outperform 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_{os}^2 and -3.77% and -4.87% utility gain.

We turn our focus of discussion to the one year ahead forecast results reported in Table 5. Similar to the generally poor performance of individual predictors in the one quarter ahead forecast, Panel A shows only 3 out of 15 individual predictors (LagR, GDP and M3) generate positive R_{os}^2 in the “full” out-of-sample period. M3 produces a significantly positive R_{os}^2 at 10% level. 5 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 all combining methods generate statistically significantly positive R_{os}^2 (except median) (on average 8.13%), but also they all deliver positive gains relative to both benchmarks. Most notably, the DMSPE ($\theta=0.1$) method has a positive R_{os}^2 of 16.13% (significant at 1% level) and out-performs the historical average and the static strategy by 2.87% and 2.36% p.a. in the asset allocation performance. Similar to the one quarter ahead forecast results, the “kitchen sink” model still has a large and negative R_{os}^2 (-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 1995:1 to 2010:3 as shown in Panel B of Table 5. Only 3 variables have positive R_{os}^2 , with D/P and M3 producing 15.52% and 7.63% R_{os}^2 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_{os}^2 (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 ($\theta=0.1$) method still produces the highest R_{os}^2 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 1985~1995 period but not particularly impressive during the 1995~2010 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_{os}^2 but not at a high significance level. 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 stunning given the sample period covers the global financial crisis. These predictors must have successfully detected the market

turning points beforehand. Unsurprisingly, all combining methods produce significantly positive R_{os}^2 (except median), with the magnitude of 3.59% on average. However, The asset allocation performance of combining methods deteriorate 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 forecast. 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 forecast, the improved asset allocation performance using these combining methods at one year horizon is mostly concentrated in the first half of the sample period. Consumption-to-GDP ratio is the only predictor that consistently delivers superior asset allocation performance using different out-of-sample periods and different horizon forecasts.

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 6 and 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 6 reports the out of sample R_{os}^2 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 ($R_{os}^2 = 7.37\%$, significant at 1% level) and consumption-to-GDP ratio ($R_{os}^2 = 7.38\%$, significant at 1% level) in predicting telecommunications sector and consumption-to-GDP ratio ($R_{os}^2 = 1.64\%$, significant at 10% level) in predicting technology sector. Nevertheless, combining information from these variables using the DMSPE ($\theta=0.1$) method, the 15 variables collectively can predict consumer discretionary ($R_{os}^2 = 2.18\%$, significant at 5% level), technology ($R_{os}^2 = 5.08\%$, significant at 1% level) and telecommunications sectors ($R_{os}^2 = 3.69\%$, significant at 5% level).

Figure 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 ($\theta=0.1$) method for all 10 sectors and sector value weighted market returns for the period from 1985 to 2009. Panel A of Figure 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 6.

Table 7 reports the out of sample R_{os}^2 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_{os}^2 . We find that dividend to price ratio is able to predict utilities sector ($R_{os}^2 = 4.26\%$, significant at 5% level) and current movement can predict consumer staples ($R_{os}^2 = 3.24\%$, significant at 1% level) and financials sectors ($R_{os}^2 = 0.25\%$, significant at 5% level). However, by combining information from all 15 variables, the DMSPE ($\theta=0.1$) combining methods, both with and without Campbell and Thompson (2008) restrictions, are able to predict returns for all sectors by significantly outperform the historical average forecasts.

Panel B of Figure 3 shows time-series relative performance of the DMSPE ($\theta=0.1$) combining method using one year horizon forecast. Not only the combining method outperforms the historical average forecast benchmark in predicting all sectors at the end of the sample period, but also it appears to generate consistent 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.

Figure 4 plots the sector weights for a dynamic sector rotation strategy based on the predicted sector returns using the DMSPE methods ($\theta = 0.1$) for the sample period from 1985~2009. Sector weights are determined each quarter using the mean-variance optimization technique described in section 2.3. As illustrated in Figure 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 had relatively poor performances. This strategy also tilts towards defensive sectors during the economic recessions and takes aggressive position during the 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 8 reports the average returns, volatilities, and utility gains (or certainty equivalent returns) for sector rotation strategies relying on various combining methods for three different out-of-sample periods (1) 1985~2009, (2) 1995~2009 and (3) 2005~2009. Both mean and DMSPE methods ($\theta=1.0$, 0.5 or 0.1) are used and Campbell and Thompson (2008) restrictions are applied to all methods. We compare the certainty equivalent returns for these sector rotation strategies against the sector value weighted and equally weighted returns.

As demonstrated in Table 8, the sector rotation strategies relying on the mean combining method and the DMSPE ($\theta=1.0$) method under-perform the sector value weighted and equally weighted returns in both one quarter and one year ahead forecast horizons and in all sample periods. In the one quarter ahead forecast, the sector allocation relying on the DMSPE ($\theta=0.5$ or 0.1) methods only generate marginal out-performance for the full sample period but do not out-perform in the two sub-sample periods. In the one year head forecast horizon, however, the sector rotation strategies using the DMSPE ($\theta=0.5$ or 0.1) methods are extremely profitable. Not only the average returns of these strategies beat the value weighted returns by 7.79% (using the DMSPE ($\theta=0.5$) method) and 7.18% (using the DMSPE ($\theta=0.1$) method) per annum, but also the risk adjusted performances are economically large (4.10% for the DMSPE ($\theta=0.5$) method and 3.27% for the DMSPE ($\theta=0.1$) method). The out-performance of sector rotation strategies relying on sector returns predicted by the DMSPE ($\theta=0.5$ or 0.1) methods are also economically significant in the other two sample periods. Particularly these two strategies (the DMSPE ($\theta=0.5$ and 0.1) methods) deliver higher average returns (1.60% and 3.54% higher) and lower volatilities (3.30% and 2.95% lower) than the sector value weighted strategies during the last 5 years sample period containing the recent Global Financial Crisis.

5. Conclusions

This paper 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 et al. (2010a), 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. Indeed, there is no single variable among the 15 considered that delivers a significantly positive R_{os}^2 over each of the out-of-sample periods examined in Table 4 and 5. However, consumption-to-GDP ratio appears to generate economically sizable utility gains over each of the out-of-sample periods and different forecasting horizons.

Nevertheless, forecast combination tends to generate significantly positive R_{os}^2 for a variety of out-of-sample periods, and particularly for the one year ahead forecasting horizon. However, the asset allocation out-performance is located mainly in the first half of the sample period for one year ahead forecast horizon. We have demonstrated 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 combining methods, risk neutral investors can on average earn 7.2% per annum premium over the value weighted market returns from 1985 to 2009. On a risk-adjusted basis, an investor on average can obtain a 3.3% utility gain than the value weighted market portfolio.

Our results could be extended in some 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 U.S studies such as book to market ratio and corporate issuing activities. We leave these extensions to future research.

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Table 1: Descriptive statistics of all variables for the full sample period

Variables		Data period	Mean	Stdev	Skewness	Kurtosis	ρ
(1)		(2)	(3)	(4)	(5)	(6)	(7)
<i>R</i>	Excess stock returns	1970~2010	0.0166	0.1040	-1.3461	7.3082	0.0116
<i>ENE</i>	Energy sector raw returns	1974~2009	0.0315	0.1833	-0.4530	5.4423	0.0515
<i>MAT</i>	Materials sector raw returns	1974~2009	0.0310	0.1200	-1.2799	5.8123	0.0987
<i>IND</i>	Industrials sector raw returns	1974~2009	0.0327	0.1073	-1.3209	7.3048	0.0569
<i>CDI</i>	Consumer discretionary sector raw returns	1974~2009	0.0367	0.1505	-0.8810	6.4023	0.1260
<i>CST</i>	Consumer staples sector raw returns	1974~2009	0.0346	0.0940	-1.2741	8.3942	0.0283
<i>HC</i>	Healthcare sector raw returns	1974~2009	0.0354	0.1088	-0.8936	4.9205	0.0601
<i>FIN</i>	Financials sector raw returns	1974~2009	0.0336	0.1143	-1.5322	9.5676	0.0186
<i>IT</i>	Technology sector raw returns	1974~2009	0.0107	0.2033	-0.4238	4.9043	0.2399
<i>TEL</i>	Telecommunications sector raw returns	1974~2009	0.0275	0.2537	0.4423	5.5253	0.1623
<i>UTI</i>	Utilities sector raw returns	1974~2009	0.0395	0.1403	-0.2512	12.4660	-0.0553
<i>MKT</i>	Value-weighted market raw returns	1974~2009	0.0308	0.0988	-1.8452	10.2903	0.0588
<i>D/Y</i>	Dividend Yield (log)	1974~2010	- 3.2086	0.2089	0.1697	2.6327	0.9477
<i>D/P</i>	Dividend-price ratio (log)	1974~2010	- 3.2460	0.2146	0.2209	3.8967	0.8880
<i>LagR</i>	Lagged excess stock returns	1970~2010	0.0163	0.1042	-1.3366	7.2709	0.0164
<i>SVAR</i>	Sum of daily variance	1980~2010	0.0064	0.0129	8.1603	76.7645	0.0954
<i>SBR</i>	90 days bank accepted bills rate	1970~2010	0.0074	0.0035	0.8023	2.5149	0.9466
<i>LBY</i>	10 years government bond yield	1970~2010	0.0894	0.0321	0.4524	1.8576	0.9871
<i>TMS</i>	Term spread	1970~2010	0.0005	0.0183	-1.4532	8.5174	0.7650
<i>CPI</i>	Inflation rate	1970~2010	0.0142	0.0114	1.0141	4.3253	0.6231
<i>GDP</i>	Nominal GDP growth rate	1970~2010	0.0079	0.0098	0.0840	4.6783	- 0.0405
<i>PPI</i>	Δ in manufacturing price index	1970~2010	0.0136	0.0145	-0.2845	4.3261	0.5421
<i>FX</i>	Δ in the Australian dollars TWI	1970~2010	- 0.0019	0.0471	-0.6485	4.1056	0.0232
<i>M3</i>	Δ in M3 money supply	1970~2010	0.0274	0.0185	2.5834	21.5497	0.3176
<i>I/K</i>	Fixed non-residential investment / GDP	1970~2010	0.0406	0.0106	1.1181	3.7585	0.9886
<i>C/K</i>	Household consumption / GDP	1970~2010	0.5703	0.0158	-0.0922	2.1219	0.9278
<i>CSI</i>	Consumer sentiment index (log)	1974~2010	4.6120	0.1217	-0.9122	3.7535	0.7662

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

Table 2. Correlation matrix for individual predictors 1970 ~ 2010

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

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 and italic.

Table 3. Forecasting Australian MSCI Index Returns 1970 ~ 2010

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)	
<i>D/Y</i>	0.42	0.13	3.25	***	5.73	0.33	0.10	5.19	***	14.43	
<i>D/P</i>	0.30	0.08	2.35	**	3.14	0.29	0.08	4.61	**	12.72	
<i>LagR</i>	0.02	-0.01	-0.11		-0.62	0.02	-0.01	-0.20		-0.62	
<i>SVAR</i>	0.02	0.24	0.36		-0.73	0.02	0.01	0.03		-0.85	
<i>SBR</i>	0.02	-0.24	-0.10		-0.62	0.01	1.65	1.35		0.52	
<i>LBV</i>	0.00	0.20	0.78		-0.24	0.00	0.23	1.75	*	1.28	
<i>TMS</i>	0.02	0.72	1.60		0.97	0.02	0.00	-0.01		-0.64	
<i>CPI</i>	0.02	-0.24	-0.33		-0.56	0.02	-0.04	-0.11		-0.63	
<i>GDP</i>	0.01	0.80	0.95		-0.06	0.02	-0.69	-1.63		1.04	
<i>PPI</i>	0.02	-0.28	-0.50		-0.47	0.02	0.07	0.25		-0.60	
<i>FX</i>	0.02	-0.20	-1.12		0.16	0.02	-0.32	-3.74	***	7.69	
<i>M3</i>	0.03	-0.54	-1.23		0.32	0.03	-0.57	-2.54	**	3.33	
<i>I/K</i>	0.04	-0.63	-0.81		-0.21	0.04	-0.49	-1.21		0.29	
<i>C/K</i>	-0.77	1.38	2.73	***	3.82	-0.56	1.02	3.98	***	8.54	
<i>CSI</i>	0.34	-0.07	-1.07		0.10	0.23	-0.04	-1.32		0.53	

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.

Table 4: Equity premium out-of-sample forecasting results for individual forecasts and combining methods - 1 quarter

Individual predictive regression model forecasts								Combination forecasts			
Predictor	$R_{os}^2(\%)$	$\Delta 1$ (%)	$\Delta 2$ (%)	Predictor	$R_{os}^2(\%)$	$\Delta 1$ (%)	$\Delta 2$ (%)	Combining method	$R_{os}^2(\%)$	$\Delta 1$ (%)	$\Delta 2$ (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: 1985:1 ~ 2010:3 out-of-sample period											
<i>D/Y</i>	-3.01	0.07	-1.42	<i>CPI</i>	-0.37	-0.27	-1.75	Mean	3.61	0.43	-1.06
<i>D/P</i>	-3.76	-0.78	-2.26	<i>GDP</i>	0.33	-0.60	-2.08	Median	3.27	0.37	-1.12
<i>LagR</i>	-0.53	-0.30	-1.78	<i>PPI</i>	-3.54	-1.12	-2.60	Trimmed Mean	3.38	0.13	-1.35
<i>SVAR</i>	-234.15	-0.92	-2.40	<i>FX</i>	-3.51	0.60	-0.89	DMSPE, $\theta=1.0$	3.89	0.27	-1.21
				<i>M3</i>	0.61	1.25	-0.24	DMSPE, $\theta=0.5$	4.49	0.27	-1.21
<i>SBR</i>	-1.35	-0.74	-2.22	<i>I/K</i>	-6.17	0.08	-1.41	DMSPE, $\theta=0.1$	3.12	0.07	-1.41
<i>LBY</i>	-1.29	-2.00	-3.48	<i>C/K</i>	-4.49	3.54	2.05	Mean, CT	4.80	*	0.03
<i>TMS</i>	-6.44	-0.63	-2.11	<i>CSI</i>	-4.12	1.10	-0.38	Kitchen Sink	-11.38	-3.02	-4.51
Panel B: 1995:1 ~ 2010:3 out-of-sample period											
<i>D/Y</i>	-2.71	-0.92	-1.36	<i>CPI</i>	-0.13	-0.03	-0.47	Mean	8.92	**	0.98
<i>D/P</i>	11.66	1.53	1.09	<i>GDP</i>	1.99	**	0.16	Median	8.64	**	0.92
<i>LagR</i>	-0.42	0.07	-0.37	<i>PPI</i>	-4.10	-1.91	-2.35	Trimmed Mean	9.14	**	0.95
<i>SVAR</i>	-1.88	0.47	0.03	<i>FX</i>	-11.87	-0.17	-0.61	DMSPE, $\theta=1.0$	8.43		0.88
				<i>M3</i>	1.54	1.63	1.19	DMSPE, $\theta=0.5$	8.39		0.69
<i>SBR</i>	-0.90	-0.14	-0.58	<i>I/K</i>	-5.31	-0.23	-0.67	DMSPE, $\theta=0.1$	7.45		0.13
<i>LBY</i>	-5.46	-3.03	-3.48	<i>C/K</i>	-1.70	3.11	2.66	Mean, CT	8.70		0.92
<i>TMS</i>	2.45	1.67	1.23	<i>CSI</i>	-2.64	0.66	0.22	Kitchen Sink	-30.21	-1.35	-1.47
Panel C: 2005:1 ~ 2010:3 out-of-sample period											
<i>D/Y</i>	6.48	-0.02	-1.11	<i>CPI</i>	0.25	0.04	-1.05	Mean	14.11		2.03
<i>D/P</i>	15.30	1.99	0.89	<i>GDP</i>	2.02	**	0.24	Median	13.70		1.97
<i>LagR</i>	-0.75	-0.07	-1.17	<i>PPI</i>	-0.87	0.25	-0.85	Trimmed Mean	14.20		2.02
<i>SVAR</i>	-4.10	0.13	-0.97	<i>FX</i>	-24.49	-2.19	-3.29	DMSPE, $\theta=1.0$	14.68	**	1.97
				<i>M3</i>	4.77	3.64	2.54	DMSPE, $\theta=0.5$	15.20	**	1.84
<i>SBR</i>	-0.55	-0.14	-1.23	<i>I/K</i>	-4.03	2.04	0.94	DMSPE, $\theta=0.1$	16.22	*	1.66
<i>LBY</i>	-2.19	-1.09	-2.18	<i>C/K</i>	10.32	5.75	4.66	Mean, CT	13.49		2.01
<i>TMS</i>	5.34	2.83	1.73	<i>CSI</i>	-4.01	0.14	-0.96	Kitchen Sink	-14.96	-3.77	-4.87

R_{os}^2 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 investor's 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_{os}^2 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.

Table 5: Equity premium out-of-sample forecasting results for individual forecasts and combining methods - 1 year

Individual predictive regression model forecasts								Combination forecasts					
Predictor	$R^2_{os}(\%)$		$\Delta 1(\%)$	$\Delta 2(\%)$	Predictor	$R^2_{os}(\%)$	$\Delta 1(\%)$	$\Delta 2(\%)$	Combining method	$R^2_{os}(\%)$	$\Delta 1(\%)$	$\Delta 2(\%)$	
(1)	(2)		(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Panel A: 1985:1 ~ 2010:3 out-of-sample period													
<i>D/Y</i>	-7.98		0.26	-0.25	<i>CPI</i>	-1.58	0.04	-0.48	Mean	6.13	**	1.13	0.62
<i>D/P</i>	-1.61		0.90	0.39	<i>GDP</i>	1.37	0.34	-0.17	Median	2.67		0.60	0.09
<i>LagR</i>	0.42		0.12	-0.39	<i>PPI</i>	-18.85	-1.26	-1.77	Trimmed Mean	5.12	**	0.96	0.44
<i>SVAR</i>	-15.97		-0.33	-0.84	<i>FX</i>	-6.96	0.29	-0.22	DMSPE, $\theta=1.0$	7.63	**	1.19	0.68
					<i>M3</i>	4.53	*	1.97	DMSPE, $\theta=0.5$	12.39	***	1.95	1.44
<i>SBR</i>	-7.50		-0.93	-1.44	<i>I/K</i>	-6.02	1.28	0.76	DMSPE, $\theta=0.1$	16.13	***	2.87	2.36
<i>LBY</i>	-5.86		-1.80	-2.31	<i>C/K</i>	-16.51	3.39	2.87	Mean, CT	6.87	**	0.95	0.43
<i>TMS</i>	-1.35		0.85	0.34	<i>CSI</i>	-11.16	0.17	-0.34	Kitchen Sink	-18.27		0.80	0.29
Panel B: 1995:1 ~ 2010:3 out-of-sample period													
<i>D/Y</i>	-1.49		-0.77	-0.91	<i>CPI</i>	-1.21	-0.08	-0.22	Mean	3.06	**	0.08	-0.06
<i>D/P</i>	15.52	***	0.97	0.83	<i>GDP</i>	0.75	-0.05	-0.19	Median	1.05		0.01	-0.13
<i>LagR</i>	-0.24		0.09	-0.05	<i>PPI</i>	-11.40	-2.08	-2.22	Trimmed Mean	2.59	**	0.01	-0.12
<i>SVAR</i>	-1.42		0.32	0.19	<i>FX</i>	-25.54	-0.07	-0.21	DMSPE, $\theta=1.0$	3.26	***	0.20	0.07
					<i>M3</i>	7.63	*	2.74	DMSPE, $\theta=0.5$	6.12	***	0.23	0.09
<i>SBR</i>	-9.47		-1.37	-1.50	<i>I/K</i>	-7.01	1.28	1.14	DMSPE, $\theta=0.1$	6.85	***	0.35	0.21
<i>LBY</i>	-16.19		-1.84	-1.98	<i>C/K</i>	-12.43	3.30	3.16	Mean, CT	3.50	*	0.00	-0.14
<i>TMS</i>	-0.62		-0.03	-0.17	<i>CSI</i>	-3.33	0.61	0.47	Kitchen Sink	-11.80		-1.04	-1.18
Panel C: 2005:1 ~ 2010:3 out-of-sample period													
<i>D/Y</i>	7.70	*	0.04	-0.48	<i>CPI</i>	-0.44	0.03	-0.50	Mean	3.59	**	0.02	-0.51
<i>D/P</i>	12.91	*	0.81	0.28	<i>GDP</i>	1.19	0.04	-0.48	Median	1.02		0.01	-0.51
<i>LagR</i>	-0.70		0.01	-0.51	<i>PPI</i>	-9.15	-1.27	-1.79	Trimmed Mean	2.80	**	-0.05	-0.57
<i>SVAR</i>	-2.71		0.17	-0.36	<i>FX</i>	-1.34	-2.82	-3.34	DMSPE, $\theta=1.0$	4.08	***	0.03	-0.49
					<i>M3</i>	12.33	*	7.33	DMSPE, $\theta=0.5$	5.01	***	0.04	-0.48
<i>SBR</i>	-3.33		-1.71	-2.23	<i>I/K</i>	-1.81	4.42	3.89	DMSPE, $\theta=0.1$	5.85	***	0.61	0.09
<i>LBY</i>	-3.49		0.34	-0.18	<i>C/K</i>	1.88	6.98	6.46	Mean, CT	2.82		-0.27	-0.79
<i>TMS</i>	-0.94		0.02	-0.51	<i>CSI</i>	-2.77	0.01	-0.51	Kitchen Sink	-1.23		-1.52	-2.04

R_{os}^2 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 investor's 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_{os}^2 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.

Table 6: Sector equity premium out-of-sample R^2_{os} statistics 1985:1 ~ 2009:4 - 1 quarter horizon

Predictor & 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, $\theta=0.1$	-2.99	-0.60	-0.28	2.18**	-1.41	-0.71	-1.11	5.08***	3.69**	-5.15	-0.65
DMSPE_CT, $\theta=0.1$	-3.07	0.63	0.63	3.29***	0.36	-0.89	0.48	3.98***	4.08**	-4.19	0.36

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.

Table 7: Sector equity premium out-of-sample R_{os}^2 statistics 1985:1 ~ 2009:4 - 1 year horizon

Predictor & 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, $\theta=0.1$	13.25***	4.11*	7.53***	10.03***	8.86***	4.98**	7.03***	15.46***	13.39***	9.26***	7.82***
DMSPE_CT, $\theta=0.1$	4.76***	5.23**	16.96***	13.06***	26.18***	9.54***	16.01***	7.91***	7.91***	11.91***	14.20***

Panel A reports the R_{os}^2 for individual predictors and combining methods in predicting one year ahead sector equity premium. R_{os}^2 is the Campbell and Thompson (2008) out-of-sample R_{os}^2 statistic. Statistical significance for the R_{os}^2 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.

Table 8: The profitability of sector rotation strategies based on sectors premia forecasts using combining methods

Strategies	One quarter ahead forecast				One year ahead forecast			
	Mean (%)	Std (%)	ΔVW (%)	ΔEW (%)	Mean (%)	Std (%)	ΔVW (%)	ΔEW (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: 1985:1 ~ 2009:4 out-of-sample period								
VW_MKT	10.32	17.63	n/a	n/a	10.32	17.63	n/a	n/a
EW_MKT	10.83	18.65	n/a	n/a	10.83	18.65	n/a	n/a
Mean_CT	12.32	21.16	-0.05	0.00	10.83	22.74	-2.58	-2.53
DMSPE_CT, $\theta=1.0$	12.50	21.43	-0.05	0.00	11.88	22.64	-1.47	-1.42
DMSPE_CT, $\theta=0.5$	12.78	21.34	0.29	0.34	18.11	23.61	4.10	4.14
DMSPE_CT, $\theta=0.1$	12.93	20.72	0.84	0.88	17.51	23.91	3.27	3.32
Panel B: 1995:1 ~ 2009:4 out-of-sample period								
VW_MKT	8.19	12.82	n/a	n/a	8.19	12.82	n/a	n/a
EW_MKT	8.28	12.74	n/a	n/a	8.28	12.74	n/a	n/a
Mean_CT	6.82	14.61	-2.11	-2.23	7.08	13.92	-1.55	-1.67
DMSPE_CT, $\theta=1.0$	6.36	15.04	-2.76	-2.88	7.89	14.05	-0.79	-0.91
DMSPE_CT, $\theta=0.5$	6.74	15.61	-2.64	-2.76	11.78	13.66	3.25	3.13
DMSPE_CT, $\theta=0.1$	8.92	15.61	-0.46	-0.58	15.01	13.46	6.57	6.45
Panel C: 2005:1 ~ 2009:4 out-of-sample period								
VW_MKT	1.11	18.00	n/a	n/a	1.11	18.00	n/a	n/a
EW_MKT	0.81	16.41	n/a	n/a	0.81	16.41	n/a	n/a
Mean_CT	-2.34	17.35	-3.11	-3.63	-0.26	15.41	-0.06	-0.58
DMSPE_CT, $\theta=1.0$	-2.30	17.33	-3.05	-3.57	-0.06	15.03	0.31	-0.22
DMSPE_CT, $\theta=0.5$	-2.59	17.37	-3.36	-3.88	2.71	14.70	3.22	2.70
DMSPE_CT, $\theta=0.1$	-0.66	17.25	-1.37	-1.89	4.65	15.05	5.00	4.48

This table compares the mean and standard deviation of returns for different sector allocation strategies for three different out-of-sample periods. Utility gain (ΔVW) 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; ΔEW is the sector allocation performance based on the forecasting models relative to a equally weighted sector allocation strategy.

Figure 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.

Panel A: Individual forecasts

Panel B: Combination forecasts

Figure 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.

Panel A: Individual forecasts

Panel B: Combination forecasts

Figure 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.

Panel A: One quarter ahead forecasts

Panel B: One year ahead forecasts

Figure 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 $\theta=0.1$ combining 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.

Appendix 1: Data sources and construction

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	Campbell (1987), Campbell and Shiller (1988), Campbell and Yogo (2006), Fama and French (1988), Hodrick (1992), Lewellen (2004), Menzly, Santos, and Veronesi (2004)
D/P	Dividend-price ratio (log)	Difference between the log of dividends and the log of current stock prices	
LagR	Lagged excess stock returns	One quarter lagged excess stock returns	Rapach, Strauss and Zhou (2010b)
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) and Hodrick (1992)
LBY	10 years government bond yield	10 years government bond yield from the Reserve Bank of Australia	Campbell (1987) and Fama and French (1989)
TMS	Term spread	Difference between the 10 years government yield and 90 days bank accepted bill rate	Campbell (1987) and Fama and French (1989)
Macroeconomic (all obtained from the Reserve Bank of Australia):			
CPI	Inflation rate	Calculated as the year on year change in the Consumer Price Index	Campbell and Vuolteenaho (2004), Fama (1981), Fama and Schwert (1977) and Lintner (1975)

GDP	Nominal GDP growth rate	Calculated as the year on year change in the nominal GDP	Chen, Roll and Ross (1986) and Fama (1990)
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	Chow et al. (1997) and 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 (2000)

Column (3) shows the data source and methodology used to compute each variable. 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.