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Portfolio Style, Sorting, Diversification & Robustness of Asset-Pricing Models - Evidence from the Australian Market

SABA MALIK, SAZALI ABIDIN, JD VAN HEERDEN,

Abstract

The role of test-portfolios in evaluating asset pricing models is an appealing subject and has stimulated the interest of researchers and fund managers around the globe. We investigated if portfolio style, sorting, or level of diversification affects the performance of prominent asset pricing models. Barillas and Shanken (2016) suggest conducting the test on various subsets of asset returns to better identify a model's effectiveness and robustness while Lewellen, Nagel, and Shanken (2010) suggest expanding the set of test portfolios beyond size-B/M portfolios and using portfolios that do not correlate strongly with SMB and HML. We used a 25-year sample of Australian market data and formed univariate and multi-variate style-based portfolios with a variety of portfolio sorting techniques and levels of diversification. We found that all these factors played a key role into the effectiveness and robustness of asset pricing models in the Australian market during 1993 to 2017. The results imply that candidate models do not seem to be robust across different style or characteristic based portfolios, portfolio sorting techniques, and have relatively lower explanatory power for less diversified or concentrated portfolios. It appears that from a practical point of view, these models may not be of much use for an average Australian retail investor with a poorly diversified or concentrated portfolio. The results also indicate that the quest for a robust equity pricing model is still incomplete.

Authors

Saba Malik[a], *Sazali Abidin*[b], *JD Van Heerden*[c]

a. Department of Financial & Business systems, Lincoln University, Christchurch, New Zealand. (sabasaleem.malik@lincolnuni.ac.nz)

b. Department of Financial & Business systems, Lincoln University, Christchurch, New Zealand.

c. Synlait Milk Ltd, Christchurch, New Zealand.

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I. Background

Modern asset pricing theory started to evolve with Markowitz (1952) and Roy (1952) laying the foundations and introducing the concept of risk minimisation with a few variations. Roy (1952) suggested to widely disperse assets and liabilities to minimise the risk by choosing the portfolio based on mean and variance. Markowitz (1952) suggested forming a portfolio of stocks with maximum discounted return and minimum variance. Sharpe (1963) extended the work of Markowitz (1952 & 1959) and introduced the assumption of interrelationships among securities and introduced a model and a computer program which could efficiently represent the relationships among securities and thus claimed it to be an attractive choice for the initial practical applications of Modern Portfolio Theory (MPT).

Pioneer capital asset pricing models were established during the early 60s'. Treynor (1962), Sharpe (1964) and Lintner (1965) presented the CAPM with slight variations. They added few assumptions to those reported in portfolio theories of Markowitz (1959) and Sharpe (1963), predominantly the assumptions of "complete agreement" and unrestricted lending and borrowing at a risk-free rate for all investors. They reported a linear relationship between expected returns on all assets and their betas, where expected returns of assets are equal to the risk-free interest rate and risk premium of underlying assets. Other prominent studies that introduced their version of the CAPM with slight variations but still considered the market return as the only contributor to asset pricing include, Mossin (1966), Black (1972) and Jensen, Black, and Scholes (1972).

CAPM had been subject to extreme criticism, particularly on the grounds of a single and constant beta. Subsequently, a large number of variations have been proposed to improve the original CAPM. A vast amount of empirical research validates that several other factors in addition to the CAPM beta have a significant and robust (positive or negative) relation with stock return and should be included in an asset pricing model. The most prominent critics of CAPM, Eugene Fama (Nobel laureate in Economics) and Kenneth French presented a multifactor model for asset pricing with two additional betas of "size" and "value" along with a stock's market beta. Though the study of size effect is usually attributed to Fama and French, size effect was first reported by Banz (1981) and then by Arbel, Carvell, and Strebel (1983). Moreover, Value effect was first identified by Graham and Dodd (1934), and in early times supported by Brennan, Chordia, and Subrahmanyam (1998). After (Fama & French, 1992) Fama and French (2015b) introduced a five-factor model by adding profitability factor and an investment factor. Apart from these factors, earnings yield (Basu, 1983), debt/equity ratio (Bhandari, 1988), dividend yield, (Campbell, 1996; Friend & Puckett, 1964), asset growth (Cooper, Gulen, & Schill, 2008) are to name a few.

Harvey, Liu, and Zhu (2016) document more than 300 factors that have historically been tested by researchers for explaining variations in the stock returns. These factors form a universe of asset pricing models. Common risk factors in asset returns represent the sole source of systematic risk; therefore, linear factor models are frequently used to estimate equity return. A model may work better in a market in a given period, and specific market conditions and may fail to perform in a different setting. Fama and French (1993) and Davis, Fama, and French (2000), and Kassimatis (2008) claim that it is factor loadings that explain expected returns, Daniel and Titman (1997) argue that it is characteristics, while Lo (2004) claim that its portfolio formation that affects the effectiveness of asset pricing models in explaining returns. Researchers and investors are always keen to identify the best performing model, but evaluation of asset-pricing models raises some issues, i.e., the aggregational level of returns, portfolio style, sorting and diversification.

II. Introduction

The role of test-assets/portfolio in evaluating asset pricing model is an appealing subject and has stimulated the interest of researchers and fund managers around the globe for a long time now. Gaunt (2004) contend that asset pricing models aim to account or proxy for all sources of risk in explaining returns so models should be robust to portfolios created on the basis of underlying business risk. Lo (2004) investigated the role of portfolios formation in the effectiveness of asset pricing models in explaining returns. Lewellen et al. (2010) show that the Fama French portfolios have a strong factor structure which biases the researcher in favour of factor models. Ernstberger, Haupt, and Vogler (2011) investigated the role of portfolio sorting in asset pricing models.

Asset pricing studies in Australian context have dominantly used conventional double-sorted 25 Size-BM or Size-factor Portfolios as can be seen in Durand, Limkriangkrai, and Smith (2006), Kassimatis (2008), Brailsford, Gaunt, and O'Brien (2012b), Vo (2015), and Durand, Limkriangkrai, and Chai (2016), etc. According to Barillas and Shanken (2016), a common approach to compare asset pricing models involves a competition between asset pricing models in pricing test-asset returns. They suggest conducting the test on various subsets of asset returns to identify a model's effectiveness and robustness better.

To the best of authors' knowledge, there is no study in the Australian context which tests the robustness of asset pricing models to portfolio style, sorting or level of diversification, or which employ such as ours unconventional (non-traditional) universe of test portfolios to study asset pricing models in the Australian market. Therefore, the motivation of our study is to investigate the effectiveness and robustness of asset pricing models in the Australian stock market with an unconventional universe of style portfolios with varied level of portfolio diversification to examine if asset pricing models are robust to portfolio style, sorting or level of diversification or if there is any model which is better suited for any particular style-based portfolio or diversification level.

In this universe of asset-pricing models, few models have always been popular among researchers, investors, and fund managers. CAPM of Sharpe (1964), the 3-factor model of Fama and French (1993), the 4-factor model of Carhart (1997). 5-factor model of Fama and French (2015a) and6-factor model of Fama and French (2018) are a new addition to the universe. This paper investigates if portfolio style, sorting and diversification have any role to play into the effectiveness of these models in explaining variations in market return and up to what extent?

We used a 25-year sample of Australian market data of ASX 300 stocks which represent 93% of market capitalisation. The reason of this sample is twofold; firstly we wanted to cover the stocks that have significance for investors[1] and secondly, we did not want to bias our results

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[1] In addition to examining the applicability of theoretical equity pricing models on a variety of test-portfolios, the results may have practical implication for an average Australian investor who holds a concentrated portfolio. ASIC (2017) reports that more than 60% of Australian investors have either not heard of diversification or don't

with thinly traded- illiquid stocks as Brailsford, Gaunt, and O'Brien (2012a); Brailsford et al. (2012b) indicated that a large proportion of Australian equities are illiquid and that this biases studies of the Australian market. The authors introduced different portfolio formation techniques and used only the top 300 stocks according to market capitalisation to calculate percentile/breakpoints for portfolio formation to analyse asset pricing models in the Australian market. We considered univariate and multi-variate style-based portfolios formed on size, the book to market ratio, investment, profitability and momentum. We also considered multiple sorting levels leading to different levels of diversification to form our universe of test portfolios. In totality, we analysed 25 univariate, diversified portfolios[2], 16 quad-sorted portfolios with a relatively lower level of diversification[3] and 32 quintile-sorted highly concentrated portfolios[4].

This article contributes to the literature in three ways. First, to the authors' best knowledge, this is the first study to assess the impact of portfolio style, sorting and level of diversification on asset pricing models. Second, it considers prominent asset pricing models and third, it is first of its kind study that is being conducted on the Australian stock market. The remainder of this article is organized as follows. Section III offers an introduction of the candidate models, i.e., CAPM and multifactor models and their specifications. In section IV, we report methodology. Section V reports the results and section VI offers the conclusion. Descriptive statistics have been reported in appendices.

III. CAPM and Multi-Factor Models

CAPM - Capital Asset Pricing Model

CAPM can be expressed through a simple linear equation:

$$R_{t-}R_{ft} = \alpha + \beta_1 \left(R_{mt} - R_{ft}\right) + \varepsilon_t \quad (-1)$$

Where, R_t refers to returns of the portfolio at time *t*, R_{ft} refers to the risk-free rate of return at time *t*. ε_t is the error term of the equation.

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understand it. ASX Australian Investor Study 2017) also reveals that 40 % of Australian investors do not have a diversified portfolio and 15% are unsure if they have diversified portfolios. The Australian financial attitudes and behaviour tracker study of 2017 also reported that 68 % of Australian investors don't understand the risk/return trade-off concept.

[2] On average 50-60 stocks in each portfolio
[3] On average 15-16 stocks in each portfolio
[4] On average 7-9 (or less) stocks in each portfolio

Fama and French 3-Factor Model

Fama and French's 3-factor model can be expressed as:

$$R_{t-}R_{ft} = \alpha + \beta_1 \left(R_{mt} - R_{ft}\right) + \beta_2 \left(SMB_t\right) + \beta_3 \left(HML_t\right) + \varepsilon_t \tag{-2}$$

(SMB_t) represents the size risk-factor (small minus big), (HML_t) represents the value risk-factor (high minus low book to market ratio). ε_t is the error term[5] of the equation.

Momentum-Augmented Fama-French-Carhart Model

Chopra, Lakonishok, and Ritter (1992), Jegadeesh and Titman (1993b), Carhart (1997) and Hou, Karolyi, and Kho (2011) introduced momentum in the CAPM along with size and book to market ratio. Carhart (1997)'s momentum-augmented, the four-factor model can be expressed as:

$$R_{t-}R_{ft} = \alpha + \beta_1 \left(R_{mt} - R_{ft}\right) + \beta_2 \left(SMB_t\right) + \beta_3 \left(HML_t\right) + \beta_4 \left(MOM_t\right) + \varepsilon_t \quad \text{-3)}$$

(WML_t) represents the momentum risk-factor (winner minus loser).

Fama and French 5-Factor Model

Fama and French (2015b) introduced a five-factor model by adding profitability factor and an investment factor. The model establishes that stocks of companies with high operating profitability perform better, and stocks of companies with the high total asset growth have below-average returns.

$$\begin{aligned} R_{t-}R_{ft} = \alpha &+ \beta_1 \left(R_{mt} - R_{ft}\right) + \beta_2 \left(SMB_t\right) + \beta_3 \left(HML_t\right) + \beta_4 \left(RMW_t\right) \\ &+ \beta_5 \left(CMA_t\right) + \varepsilon_t \end{aligned} \tag{4}$$

Where, (RMW_t) represents the profitability risk-factor (robust minus weak profitability), and (CMA_t) represents the investment risk-factor (firms with conservative minus aggressive investment strategies).

Momentum Augmented Fama and French Model

When we started working on this article we added a momentum-augmented six-factor model to our test models under consideration, however, while we were working on this paper, Fama and French (2018) introduced the momentum-augmented six-factor model. The model can be expressed as:

$$\begin{aligned} R_{t-}R_{ft} = \alpha &+ \beta_1 \left(R_{mt} - R_{ft}\right) + \beta_2 \left(SMB_t\right) + \beta_3 \left(HML_t\right) + \beta_4 \left(RMW_t\right) \\ &+ \beta_5 \left(CMA_t\right) + +\beta_6 \left(WML_t\right) + \varepsilon_t \end{aligned} \tag{-5}$$

[5] The details of the factors have been discussed in Variable Formation section.

IV. Methodology

Formation of Risk-Factor portfolios

First stage portfolios (can also be referred to as Right hands side portfolios/RHS) are formed for risk-factor construction, i.e. size, value, momentum, quality.

In the first phase, portfolios are formed by sorting stocks on one variable mimicking a specific risk-factor. Median is used as breakpoints for dividing stocks into 2 portfolios while 30^{th} an 70^{th} percentiles are used as breakpoints for dividing stocks into 3 portfolios. For example, to construct the Size-style portfolios, stocks are sorted according to market capitalisation (used as a proxy for size) and formed two portfolios using the median as a breakpoint. The big portfolio contains the top 50%, and Small portfolio contains a bottom 50 % stocks according to market capitalisation.

Bivariate Independent-sorted portfolios are formed to construct risk factors. The first step is to form independent (univariate) single-sorted portfolios on each of the sort variables as explained above, and then bivariate portfolios are formed by the intersection of univariate portfolios. For example, first, all stocks are sorted on size and 2 portfolios Big and Small are formed using the median as a breakpoint and stocks are independently sorted on a book to market ratio and 3 portfolios High Mid and Low value (B/M) are formed using 30^{th} and 70^{th} percentiles as breakpoints. Following Fama and French (2015b), the 2-sort portfolios are the intersections of the groups/portfolios. The common stocks in Big and High-value portfolios make BH (Big-High), Big and Mid value make BM (Big-Mid), Big and Low value make Big-Low Portfolios. The same way, common stocks in Small and High-value portfolios make SH (Small-High), Small and Mid-value make SM (Small-Mid), Small and Low value make Small-Low Portfolios. Thus 6 bivariate portfolios are formed on Size and Value.

Risk Factors

Following Fama and French (2015b), all stocks are sorted on high to low market capitalisation. The median value is used as breakpoints, and two portfolios are formed. Big Portfolio contains the top 50% stocks, while a small portfolio contains bottom 50% stocks. The stocks are double sorted Size and B/M ratio, Momentum, Profitability and Investment as Big (B) and Small (S), B/M ratio High (H), Mid (M), or Low (L), the Operating Profitability, Robust (R), Mid (M), or Weak (W), and the Investment, Conservative (C), Mid (M), or Aggressive. Thus, 4 sets of 2x3 portfolios are formed. Fama and French (2015b) all stocks are sorted on a book to market ratio and are divided into 3 portfolios. The breakpoints for portfolios are 30^{th} percentile and 70^{th} percentile following Fama and French (2015b). Portfolio of top 30 % (high BM stocks) are referred to as high-value stocks, middle 40% Mid-Value, and bottom 30% (low BM) as low-value stocks. Double sorting on size and value is used to construct the HML factor. HML is the difference between value-weighted returns of all portfolios of high B/M stocks and all portfolios of low B/M stocks. The momentum of each stock in this study is the sum of past 6 months' return of stock following Jegadeesh and Titman (1993a). The momentum is calculated as follows:

$$Momentum_{it} = \prod_{i=1}^{6}(r_{im} + 1) - 1$$

Where, r_{im} represents a return of stock i in month m in decimal form.

All stocks are sorted on high to low on the past 6 months return and divided into 3 portfolios using 30^{th} and 70^{th} percentiles as breakpoints. The stocks with high past returns make Winner Portfolio while stocks with low past returns make Looser Portfolio. Following the momentum strategy of buying winners and selling losers, WML is the difference between the value-weighted return on the Winner portfolios and the Loser portfolios. Double sorting on size and momentum is used to construct the WML factor. Profitably calculation in this research is different from that is provided in Fama and French (2015b).

Following Ball, Gerakos, Linnainmaa, and Nikolaev (2016), profitability is calculated as sales minus cost of goods sold minus sales, general, and administrative expenses. This measure captures the performance of the firm's operations and is not affected by non-operating items, such as leverage and taxes whereas the profitability measure of Fama and French (2015b) also deducts interest expense from operating profit and thus is affected by leverage. Then, following Fama and French (2015b) all stocks are sorted on high to low operating profitability. The 30^{th} and 70^{th} percentiles are used as breakpoints, and three portfolios are formed. Robust Profitability-style portfolio contains the top 30% stocks, while Weak Profitability-style portfolio contains bottom 30% stocks. Risk factor RMW is the difference between the value-weighted return of the Robust Profitability portfolios and Weak Profitability portfolios

Investment is measured as the rate of growth of total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1. Following Fama and French (2015b), all stocks are sorted on the percentage change in total assets from t-2 to t-1 and are divided into 3 portfolios. 30^{th} and 70^{th} percentiles are used as data breakpoints. Portfolio of (high) investment stocks or the stocks with greater % change in total assets (top 30%) is named as Aggressive while a portfolio of low investment stocks or the stocks with lower % change in total assets (bottom 30%) is named as conservative. Following the strategy of selling aggressive stocks and retaining conservative stocks, the difference between the value-weighted returns on the portfolio of conservative (low) investment stocks, and the portfolios of aggressive (high) investment stocks are taken and referred as the risk factor.

Formation of Test Portfolios

After risk factor construction using first stage portfolios, the second stage portfolios or test portfolios (can also be referred to as left-hand side/LHS portfolios) are formed to examine the candidate models. Single-sorted five portfolios are formed mimicking the size, value, investment, profitability and momentum factors. For every factor, stocks are ranked from top to bottom on the factors (Size, BM Ratio, Investment, Profitability, and Momentum) and are divided into quintile (five) groups, with each group consisting of 20% stocks. For example, stocks are sorted on size (market capitalisation) and are divided into five groups, with each group containing 20% of stocks. Size 1 portfolios are the portfolios of top 20% stocks, and Size 5 portfolios are the portfolio of bottom 20% stocks. These portfolios are highly diversified as each portfolio contains on average 50-60 stocks. These portfolios are formed to test the difference in the performance and robustness of candidate models between diversified and concentrated (quad-sorted or quintile-sorted) portfolios.

Quad-sorted portfolios are the portfolios which have been formed using the intersection of 4 factors (size, value/BM Ratio, Investment and profitability. All stocks are independently sorted into two groups using the median as a breakpoint, i.e. two groups big/small for size, high/low BMR for a book to market ratio, robust/conservative for investment, and robust/weak for profitability, is formed. Total 8 groups were formed on size, value/BM Ratio, investment and profitability. The overlap of Size-BMR-Investment-Profitability delivers (2x2x2x2) 16 portfolios. Since the sorting is independent, the portfolio flow has been provided to show the combinations that are made to form portfolios, not the process itself. Quad-sorted portfolios offer an in-depth view of the candidate models' performance for concentrated portfolios as the average number of stocks in every portfolio contains on average 16-18 stocks.

As the main objective of the study is to test the performance and robustness of candidate models, and Ernstberger et al. (2011) empirically proved that different sorting strategies influence the success of asset pricing models, including CAPM and multifactor models, so another sorting is added in the analysis to test their claim and see if different sorting affects the performance and robustness of candidate models. Quintile-sorted portfolios are an extension quad-sorted portfolio where stocks are further sorted on momentum. For momentum portfolios, stocks are independently sorted into two groups using the median as a breakpoint, and two groups are formed as winner and loser group. Winner group contains the stocks that generated higher than average excess returns during the past 6 months with the loser group containing the stocks that generated lower than average excess returns during the past 6 months. The overlap of quad-sorted portfolios and momentum delivers (2x2x2x2 x2) 32 portfolios. Quintile-sorted portfolios are highly concentrated as each portfolio contains on average 7-8 stocks or less. Independent sorting also contributes to this concentration as some combinations of stocks are rare if not impossible.

V. Results and discussion

Asset Pricing Models' Comparison Using Single-Sorted Quintile Portfolios

This section reports summary statistics for Single-Sorted quintile portfolios. Portfolio 1 represents the top 20 % while portfolio 5 refers to the bottom 20% of stocks for mimicking risk factor. Size 1 through Size 5 refers to the excess returns of respective quintile portfolios created based on the market capitalisation ranking (big to small). Similarly, BMR 1 to 5 refer to the excess returns of respective quintile portfolios created based on the book to market ratio, INV on the basis of change in total assets (high to low), and OITCE on the basis of operating income to common equity (high to low) and MOM is the excess returns of portfolios created on the basis of past 6 months cumulative returns (high to low). Two commonly used measures to compare the effectiveness of candidate models, Alpha and R^2s have been reported here, while the GRS test statistics and alpha Sharpe ratio have been reported in appendices. Jensen Alpha is viewed as a measure of model mispricing. Jensen (1968) first reported Alpha as an asset's deviation from the expected returns as per CAPM, and it was named after him. Since several risk factors have been added and proposed to improve on the CAPM over the last few decades, but time series Jensen Alpha is still viewed as an asset's deviation from respective Asset Pricing models whereas R^2 is viewed as a measure of power or effectiveness for candidate asset/Asset Pricing models. Jensen Alpha and Adj-R^2 are reported in panel A and B of Table 1, respectively.

Table 1

Panel A Jensen Alpha on Single-Sorted Quintile Portfolios for All Models					
Portfolios	1-Factor	3-factor	4-factor	5-factor	6-factor
Size 1	0.03	-0.01	-0.02	**-0.04***	**-0.04***
Size 2	0.03	0.12	0.13	0.22	**0.21***
Size 3	-0.15	0.07	0.09	0.15	0.16
Size 4	**-0.43****	-0.12	-0.11	0.01	0.00
Size 5	**-0.5***	-0.19	-0.20	0.00	-0.03
BMR 1	0.12	0.15	0.18	**0.25****	**0.26****
BMR 2	-0.18	-0.10	-0.11	-0.03	-0.05
BMR 3	-0.14	0.01	0.01	0.05	0.05
BMR 4	**-0.27***	-0.02	0.00	0.05	0.06
BMR 5	**-0.53****	-0.18	-0.19	-0.02	-0.05
INV 1	-0.04	**0.26***	**0.24***	**0.37****	**0.35****
INV 2	0.09	**0.26****	**0.21****	**0.30****	**0.26****
INV 3	0.02	0.11	0.08	0.10	0.08
INV 4	-0.22	-0.13	-0.14	-0.05	-0.07
INV 5	**-0.84****	**-0.64****	**-0.52****	**-0.44****	**-0.37****
OITCE 1	**0.22***	**0.40****	**0.35****	**0.34****	**0.31****
OITCE 2	0.16	**0.28****	**0.25****	**0.22****	**0.21***
OITCE 3	-0.06	0.05	0.04	0.08	0.08
OITCE 4	**-0.43****	**-0.32****	**-0.31****	**-0.19***	**-0.20***
OITCE 5	**-0.88****	**-0.52****	**-0.41****	-0.11	-0.09
MOM1	0.24	**0.48****	**0.28****	**0.55****	**0.39****
MOM2	0.10	**0.21***	0.09	**0.18***	0.10
MOM3	-0.14	-0.03	-0.04	0.01	0.00
MOM4	-0.23	-0.09	0.00	0.00	0.06
MOM5	**-0.99****	**-0.69****	**-0.44****	-0.40	-0.25

Panel A of table 1 reports Jensen Alpha across all candidate models and single-sorted quintile portfolios.
* represents the coefficients significant at 5% level of significance
** represents the coefficients significant at 1% level of significance
The results were tested for Homoscedasticity using Breusch-Pagan-Godfrey and White test. Some portfolios exhibit the signs of heteroskedasticity with White test results, whereas Breusch-Pagan-Godfrey test statistics exhibited homoscedasticity. However, for such portfolios Newey-West adjusted standard errors were estimated, and corresponding P Values of HAC estimates have been used to represent the significance level.

Table 1 Panel B

Panel B Adj-R² Single-Sorted Quintile Portfolios for All Models					
Portfolios	1 Factor	3-factor	4-factor	5-factor	6-factor
Size 1	0.98	0.99	0.99	0.99	0.99
Size 2	0.81	0.85	0.85	0.86	0.86
Size 3	0.66	0.85	0.86	0.87	0.87
Size 4	0.59	0.90	0.90	0.92	0.92
Size 5	0.50	0.82	0.82	0.86	0.86
BMR 1	0.64	0.87	0.87	0.89	0.89
BMR 2	0.73	0.85	0.85	0.86	0.86
BMR 3	0.80	0.90	0.90	0.90	0.90
BMR 4	0.72	0.88	0.88	0.88	0.88
BMR 5	0.62	0.85	0.85	0.88	0.88
INV 1	0.64	0.86	0.86	0.87	0.87
INV 2	0.77	0.89	0.89	0.89	0.90
INV 3	0.80	0.86	0.87	0.86	0.87
INV 4	0.74	0.84	0.84	0.86	0.86
INV 5	0.61	0.79	0.82	0.84	0.85
OITCE 1	0.79	0.89	0.89	0.90	0.90
OITCE 2	0.82	0.88	0.88	0.89	0.89
OITCE 3	0.76	0.87	0.87	0.88	0.88
OITCE 4	0.72	0.84	0.84	0.86	0.86
OITCE 5	0.49	0.76	0.77	0.90	0.90
MOM1	0.64	0.79	0.86	0.80	0.88
MOM2	0.79	0.86	0.89	0.86	0.89
MOM3	0.79	0.87	0.87	0.88	0.88
MOM4	0.74	0.86	0.88	0.87	0.89
MOM5	0.53	0.75	0.83	0.82	0.87
Panel B of table 1 reports Adj-R² for candidate models across all single-sorted quintile portfolios. Adj-R²s are quite high due to a large number of stocks in each portfolio.					

The results in Panel A of Table 1 show that adding more risk factors to the Fama and French 3-factor model does not necessarily improve the model performance, in fact, for some portfolios, adding more factors to the model generated higher and significant alpha coefficients with each additional factor. CAPM generated significant alphas for 2 portfolios formed on Size and BM Ratio with a relatively lower magnitude of coefficients. The 3-factor and 4-factor model both generated insignificant alphas for all portfolios formed on Size and BM Ratio and Adj-R^2s do not increase from 3-factor model to 4-factor model but take a sharp jump from CAPM to 6-factor models for Size3, Size4 and Size5 portfolios. Looking at individual alphas and Adj-R^2s, it seems that the 3-factor model outperformed all candidate models with insignificant alphas generated across the Size-style portfolios.

An interesting finding is that the 3-factor model fails GRS test[6], while 4, 5 and 6-factor models pass GRS test for overall insignificant alpha across all Size-style portfolios. 5-factor model has the lowest alpha Sharpe ratio out of all models, and we see that Adj-R^2s do not change from the 5-factor model to the 6-factor model. Adding Momentum to 5-factor model does not add any value as WML factor is redundant in Size-style portfolios. For single-sorted Size-style portfolios, HML factor was only significant for Size 5 portfolio across 5 and 6-factor models.

SMB factor is significant for all models across all Size and BM Ratio-style portfolios with positive coefficient with the exception of the negative coefficient for Size 1 portfolio. HML was dominantly significant for single-sorted portfolios formed on BM Ratio, Investment and Profitability but insignificant Mom3, MOM4 and MOM 5 portfolios across all models. We observed an interesting pattern in the HML factor. HML coefficient is positive for all portfolios containing High BM stocks and is negative for the portfolios containing Low BM stocks. This pattern is consistent in quad-sorted and quintile-sorted portfolios. In summary, we found significant HML and size effect across single-sorted portfolios during the full sample period. Our results regarding Value premium support the findings of Vo (2015), Brailsford et al. (2012b), and Brailsford et al. (2012a) but contradicts their finding for size premium. Our finding for size premium is supported by Bettman, Ng, and Sault (2011) and Kassimatis (2008). Similar to Size-style portfolios, 3 and 4-factor models produce all insignificant alphas for BM Ratio-style portfolios. Interestingly all candidate models pass GRS test with overall insignificant alphas which support the claims of Lo (2004) that portfolio formation affects asset pricing tests. Adding more factors subsequently to 3-factor model does not seem to add value to the model, and it can be observed in panel B of Table 1, that Adj-R^2s exhibit trivial increase from 3-factor model to 6-factor model. However, the 6-factor model has the lowest alpha Sharpe ratio that shows the superiority of the 6-factor model overall candidate models for BM Ratio-style portfolios.

CAPM outperformed all multi-factor candidate models for Investment-style portfolios in terms of insignificant alphas with only 1 significant alpha for INV 5 portfolio. It can be observed in the table that none of the candidate models generated insignificant alpha for INV

[6] Results of GTRS test and alpha Sharpe ratio has been reported in appendices.

5 portfolio. All multi-factor models failed to generate insignificant alphas for INV 1 and INV 2 portfolios. It seems that adding additional factor did not contribute to explaining returns, but CAPM, 3-factor and 4-factor model fail GRS test of overall model significance. Adj-R^2s which significantly increased from CAPM to multi-factor models, were nonetheless dominantly similar among multi-factor models, with trivial to no increase at all. CMA factor was dominantly redundant in most of the single-sorted portfolios, including the portfolios formed on Investment. It was only significant for INV 4 portfolio. Across all single-sorted portfolios, it was significant for 2 out of 5 portfolios and 3 out of 5 portfolios for BM Ratio-style portfolios. Our results contradict the finding of Chai, Chiah, and Gharghori (2019) who used quite a similar sample and sample period. The difference could be attributed to the sub-set of test assets, i.e., Portfolios. It indicates that the significance of Investment factor is sensitive to portfolio formation technique.

For Profitability-style (OITCE) portfolios all candidate models generated at least 3 insignificant alphas with a slightly declining magnitude of the coefficient from the CAPM to 6-factor model. All models generated significant alphas for OITCE 1 and OITCE 4. In terms of alpha, CAPM outperformed multi-factor models with the smallest and insignificant alpha coefficient for OITCE 2 and OITCE 3. For OITCE 5 however, the 5-factor model apparently outperformed other models with smallest and insignificant alpha but failed GRS test. 6-factor model is the only model that passes GRS across Profitability-style portfolios. Profitability factor is significant across all single-sorted portfolios with the only exception of INV 3 and MOM 2 portfolios. Though Profitability risk factor is significant, coefficients are dominantly negative. We observed positive profitability effect only in 3 portfolios (across all single-sorted portfolios) which are Size 1, OITCE 1 and OITCE 2 portfolios. Conclusively, it seems that adding Investment factor didn't improve models' performance for a set of portfolios formed on profitability. On the other hand, Profitability factor generated significant negative premium for most of the portfolios. Again, our results regarding negative profitability premium contradict the findings of Chiah, Chai, Zhong, and Li (2016), Fama and French (2017) and Chai et al. (2019) and also their claim regarding the superiority of 5-factor model. From our results, it appears that Profitability premium exists in the Australian market during the sample period, but positive or negative depends on the choice of test-portfolio. For overall model performance, we support the superiority of 5-factor model for portfolios formed on profitability. For Profitability-style portfolios, Adj-R^2 sharply increases from CAPM to 3-factor model; however, for most of the portfolios, 3-factor and 4-factor have the same Adj-R^2 with 5-factor and 6-factor models having the similar Adj-R^2s.

CAPM and 5-factor model apparently performed better than other candidate models for the set of portfolios formed on momentum with only 1 significant alpha coefficient. CAPM generated significant alpha coefficient of -0.99 for MOM 5 portfolio, and 5-factor model produced significant alpha of 0.39 for MOM 1 portfolio which is less extreme than the significant alpha of -0.99 of MOM5 portfolio produced by CAPM. P-Values of GRS test are insignificant across all candidate models for Momentum-style portfolios that show the overall effectiveness of the models in explaining the return of these portfolios. However, the 3-factor model has the lowest alpha Sharpe ratio, which indicates the superiority of the 6-factor model for Momentum-style portfolios during the sample period. HML and CMA factors were dominantly insignificant for MOM portfolios. Size factor exhibits significant positive premium across all Momentum portfolios. Profitability exhibits significant negative premium while Momentum exhibits significant positive premium for MOM1 and MOM2 portfolios and significant negative premium for MOM4 and MOM5 portfolios with no premium for MOM 3 portfolio. Average Momentum premium across all portfolios is 0.001, which seems quite negligible. Our results contradict the findings of Fama and French (2012) who stated Winner minus Loser spread are larger for small stocks, but our results suggest that WML spreads are larger for big stocks and smaller (negative) for small stocks. Our results partially support the finding of Dou, Gallagher, and Schneider (2013) who find significant momentum effect in big stocks (90% of market capitalisation) only. Overall, the 5-factor model outperforms other candidate models for momentum portfolios. Expected, Adj-R^2s of CAPM are relatively lower than those of the 5-factor model.

Asset Pricing Models' Comparison Using Quad-Sorted 16 Portfolios

In this stage of analysis, stocks are divided into 2 groups for each variable, i.e. size, BM Ratio, profitability and Investment and thus 16 portfolios have been formed on 2x2x2x2x2 sorting on these variables. All portfolios consist of a unique set of stocks without replacement. Table 2 reports the alpha coefficient and Adj-R^2 of candidate models for quad-sorted 16 portfolios.

It can be seen in the table that for most of the portfolios of Small stocks, Jensen Alpha is significant for multi-factor models as well as for CAPM in some instances. It is quite interesting that for single-sorted (diversified) Big portfolios (results reported in table 1) 5-factor and 6-factor models generated significant alphas, whereas, for the concentrated portfolios of Big stocks, 5 and 6-factor models generated only 1 significant alpha out of 16 portfolios. It is exactly opposite to the results that have been obtained for single-sorted diversified portfolios where CAPM was the model with a smaller number of significant alphas. 5-factor model does not produce a single significant alpha across all big, concentrated and quad-sorted portfolios.

Table 2

Panel A Jensen-Alpha of Quad-Sorted 16 Portfolios for All Models

Portfolios	1-Factor	3-Factor	4-Factor	5-Factor	6-Factor
BARH	**0.54****	**0.52****	**0.44***	0.41	**0.36***
BARL	0.04	0.06	0.04	-0.09	-0.08
BAWH	**-0.40***	**-0.47****	**-0.39***	-0.35	-0.31
BAWL	-0.37	-0.24	-0.21	0.04	0.02
BCRH	**0.42****	**0.32***	0.32	0.26	0.27
BCRL	0.10	0.09	0.05	0.04	0.02
BCWH	-0.03	-0.15	-0.13	0.03	0.02
BCWL	-0.31	-0.23	-0.20	0.05	0.04
SARH	0.27	**0.44***	0.35	**0.48***	**0.41***
SARL	0.17	**0.49****	**0.40***	**0.40****	**0.34***
SAWH	0.29	**0.47****	**0.43****	**0.62****	**0.57****
SAWL	**-1.01****	**-0.45***	**-0.47***	-0.13	-0.19
SCRH	-0.22	-0.04	-0.06	-0.10	-0.10
SCRL	-0.38	-0.09	0.02	-0.20	-0.10
SCWH	**-0.55****	**-0.38****	**-0.34***	-0.22	-0.21
SCWL	**-1.84****	**-1.3****	**-1.17****	**-0.91****	**-0.87****

Panel A of table 2reports Jensen Alpha across all candidate models for quad-sorted 16 portfolios.

* represents the coefficients significant at 5% level of significance
** represents the coefficients significant at 1% level of significance

The results were tested for autocorrelation using Durbin Watson and for Homoscedasticity using Breusch-Pagan-Godfrey and White test. No autocorrelation was detected while only a few portfolios exhibited the signs of heteroskedasticity with White test results, whereas Breusch-Pagan-Godfrey test statistics exhibited homoscedasticity. However, for such portfolios Newey-West adjusted standard errors were estimated, and corresponding P Values of HAC estimates have been used to represent the significance level.

Table 2 Panel B Adj-R² Quad-Sorted 16 Portfolios for All Models					
Portfolios	1-Factor	3-Factor	4-Factor	5-Factor	6-Factor
BARH	0.56	0.59	0.59	0.60	0.60
BARL	0.79	0.80	0.80	0.83	0.83
BAWH	0.59	0.63	0.64	0.65	0.65
BAWL	0.50	0.52	0.52	0.59	0.59
BCRH	0.60	0.63	0.63	0.64	0.64
BCRL	0.71	0.71	0.71	0.71	0.71
BCWH	0.69	0.73	0.73	0.77	0.77
BCWL	0.46	0.48	0.48	0.54	0.54
SARH	0.44	0.63	0.64	0.64	0.65
SARL	0.54	0.72	0.73	0.72	0.73
SAWH	0.49	0.70	0.70	0.72	0.73
SAWL	0.36	0.68	0.68	0.73	0.74
SCRH	0.39	0.61	0.61	0.62	0.62
SCRL	0.45	0.60	0.62	0.62	0.64
SCWH	0.51	0.76	0.76	0.79	0.78
SCWL	0.32	0.59	0.60	0.66	0.66
Panel B of table 2reports Adj-R^2 for candidate models across all quintile sorted 32 portfolios. Adj-R^2s are comparatively lower than those of single-sorted quintile portfolios. It is surprising to see that for the portfolios of Big stocks, Adj-R^2 hardly increased while moving from single-factor model to 6-factors model, while a significant increase from single-factor model to 3-factor for the portfolios of Small stocks can be observed in the table.					

It can be seen in the table that for most of the portfolios of Small stocks, Jensen Alpha is significant for multi-factor models as well as for CAPM in some instances. It is quite interesting that for single-sorted (diversified) Big portfolios (results reported in table 1) 5-factor and 6-factor models generated significant alphas, whereas, for the concentrated portfolios of Big stocks, 5 and 6-factor models generated only 1 significant alpha out of 16 portfolios. It is exactly opposite to the results that have been obtained for single-sorted diversified portfolios where CAPM was the model with a smaller number of significant alphas. 5-factor model does not produce a single significant alpha across all big, concentrated and quad-sorted portfolios. It indicates that CAPM can be suitable for highly diversified portfolios of big stocks, but the multi-factor model outperforms all candidate models for less diversified portfolios of big stocks. As expected, adj-R^2s are relatively lower than those of single-sorted portfolios, which can be attributed to diversification level or the number of stocks in portfolios. Overall, adj-R^2s do not substantially improve from CAPM to multi-factor models, in fact, there is trivial movement in adj-R^2 of multi-factor models across all portfolios other than Weak-Low portfolios, (portfolios with a combination of Weak profitability and Low BM Ratio stocks).

The alpha coefficient does not exhibit any deterministic overall trend (increase or decrease) when more factors are added to (or taken away from) CAPM. For some portfolios (i.e., BARH, BCRL, SCWH, and SCWL) alpha coefficient declines monotonously as more factors are added to CAPM, while for rest of the portfolios, alpha coefficient does not exhibit any deterministic trend. Moreover, in most of the cases where CAPM exhibits significant alpha, it is also significant after adding more factors to CAPM. The most surprising cases are SARH, SARL and SAWH, where alpha is insignificant for CAPM but becomes significant as more factors are added to the CAPM. The results indicate that adding more factors doesn't necessarily help in improving the overall efficiency of the model, though it leads to a slight increase in model's (Adj-R^2) explanatory power for some test-portfolios.

A significant Size effect is depicted in quad-sorted portfolios which contradicts the findings of Akhtaruzzaman, Docherty, and Shamsuddin (2014) and Vo (2015) and Chiah et al. (2016). The difference in results can also be attributed to the study sample and the sample period. Our results support the presence of significant positive Size effect in the Australian market during the sample period and across the investible universe or big stocks which are also studied by Chai et al. (2019). We also find the evidence of a strong Value (HML) effect during the sample period. HML factor is significant for 14 out of 16 portfolios. An interesting observation is that the coefficient is positive across all portfolios containing High BM stocks and negative for all portfolios containing Low BM stocks. However, average HML coefficient across 16 quad-sorted portfolios is positive. Our findings are in line with the findings of Brailsford et al. (2012a), Brailsford et al. (2012b) and Vo (2015).

Profitability factor is significant for 11 out of 16 test-portfolios but is dominantly negative except BARH (Big-Aggressive-Robust Profitability-High BM Ratio) and BARL (Big-Aggressive-Robust Profitability-Low BM Ratio) portfolios. Investment factor also does not seem to have a strong effect on the Australian market during the sample period. Our findings contradict the findings of Chiah et al. (2016) who document that profitability and asset growth factors are significant in the Australian market. Our findings also contradict Chai et al. (2019), who used the same sample. The contradiction can be attributed to portfolio formation style, and it seems that Investment and Profitability factors are not robust to portfolio style. However, our results are supported by Bettman, Kosev, and Sault (2011) who document that asset growth effect does not exist in the Australian market.

Momentum factor also does not seem to be strong in the Australian market during the sample period. WML factor is significant only for 6 out of 16 portfolios in the 4-factor model but stays significant only for 4 out of 16 portfolios in the 6-factor model. Adding Investment and Profitability factor reduces the power of the momentum factor. Dou et al. (2013) document significant momentum effect in the big stock stocks in the Australian market; however, our results suggest otherwise. Conclusively, we find the value, size and profitability effect in the Australian market during the sample period by using quad-sorted test-portfolios.

Panel B of table 2reports Adj-R^2s of candidate models for quad-sorted 16 portfolios. Adj-R^2s are significantly lower than the Adj-R^2s for single-sorted quintile portfolios which shows that explanatory power of the model is reduced for less diversified portfolios, as these portfolios contain on average 15-18 or fewer stocks. There is a trivial upward change in Adj-R^2 of test-portfolios of Big stocks (i.e., BARH, BARL, BAWH, etc.) during the full sample period, which indicates that multi-factor models are not essentially superior to CAPM for less diversified portfolios during the sample period. Any substantial difference cannot be seen in the performance of 3-factor, 4-factor, 5-factor and 6-factor models in terms of explanatory power or Jensen alpha for 8 portfolios of big stocks. However, for test-portfolios of small stocks, there is a sharp increase in Adj-R^2s of the models from CAPM to -multifactor models.

CAPM has the lowest adj-R^2 for all portfolios containing Small stocks whereas, adj-R^2 of CAPM is not significantly lower than adj-R^2 of multi-factor models for the portfolios containing Big stocks. Adding the size and value factor adds value to the explanatory power of the model for small stocks but after that continuously adding more factors do not add any significant value to the model as there is a slight difference in Adj-R^2 of 3-factor, 4-factor, 5-factor and 6-factor models. However, only 5 and 6-factor model pass GRS test, which indicates the effectiveness of these models in explaining portfolio returns in the Australian market during the sample period. 5-factor model seems to be the best-performing model with the lowest alpha Sharpe ratio across quad-sorted test-portfolios during the full sample period. Our results are in line with the findings of (Chiah et al., 2016), (Fama & French, 2017) and (Chai et al., 2019) who document the superiority of the 5-factor model in the Australian market.

Asset Pricing Models' Comparison Using Quintile-Sorted 32 Portfolios

Sharpe (1964) and Lintner (1965) demonstrate that an asset's return should be positively linearly related to its beta in equilibrium, where beta is a measure of systematic risk or co-movement with the market. In empirical literature of equity pricing, hundreds of models have been proposed which claim to explain the asset return (and capture the variations in asset returns), so it is assumed that these models should be equally effective for a single asset as they are for portfolios containing a large number of stocks.

A different technique of portfolio formation has been used for this stage of analysis to address the issues of less diversified portfolios and the effectiveness of candidate Asset Pricing models. All stocks are sorted in two groups for each of the control variables, i.e. size, BM Ratio, investments, operating profitability, and momentum, and thus 32 portfolios are formed by 2x2x2x2x2 sorting on all control variables. There is no overlapping and each portfolio contains unique stocks, and an average number of stocks in a portfolio in a is 7-9 or lower. In addition to examining the applicability of theoretical Asset Pricing models on less diversified portfolios, the results may have practical implication for an average Australian investor who holds a concentrated portfolio.

Jensen Alpha and Adj-R^2 have been reported in panel A and B of Table 3, respectively. The R^2 is adjusted for the number of explanatory variables and is presented in the table for comparative analysis of candidate models. Panel A of table 3 reports Jensen alphas of all candidate models for quintile sorted 32 portfolios. An interesting observation is that for the portfolios where Jensen alpha of CAPM was significant, adding more factors to CAPM didn't add much value as the alpha remains significant which indicates that the candidate models are not as effective as theory would suggest, or some factors are still missing in these models, or the models are misspecified. Although the coefficient decreases, there is no significant pattern in moving from 4 to 6-factor models, whereas a decreasing pattern can be seen for the significant alpha coefficients when moving from single-factor model to 3-factor model (for example SAWLL, SCWHL portfolios).

Table 3

Panel A Jensen Alpha on Quintile-Sorted 32 Portfolios for All Models					
Portfolios	1 Factor	3-factor	4-factor	5-factor	6-factor
BARHL	0.15	0.16	0.16	0.13	0.14
BARHW	0.44	0.42	0.35	0.28	0.25
BARLL	-0.13	-0.1	-0.04	-0.16	-0.1
BARLW	0.24	0.27	0.22	0.13	0.11
BAWHL	-0.45	-0.40	-0.16	-0.18	-0.04
BAWHW	-0.2	-0.3	-0.3	-0.24	-0.24
BAWLL	-0.51	-0.39	-0.24	-0.19	-0.1
BAWLW	-0.48	-0.28	-0.32	0	-0.07
BCRHL	-0.16	-0.18	-0.04	-0.13	-0.03
BCRHW	0.37	0.26	0.17	0.17	0.13
BCRLL	-0.34	-0.31	-0.19	-0.31	-0.22
BCRLW	0.17	0.15	0.02	0.09	0
BCWHL	-0.34	-0.41	-0.3	-0.19	-0.14
BCWHW	0.05	-0.06	-0.1	0.11	0.06
BCWLL	0.03	0.11	0.36	0.58	0.7
BCWLW	**-0.69***	-0.55	**-0.66***	-0.51	**-0.59***
SARHL	0.06	0.2	0.25	0.38	0.4
SARHW	0.43	**0.63****	**0.51***	**0.59***	**0.51***
SARLL	-0.02	0.27	0.27	0.28	0.27
SARLW	0.22	**0.52****	0.37	0.43	0.33
SAWHL	0.35	0.52	**0.55***	**0.73***	**0.73***
SAWHW	0.34	**0.53***	0.42	**0.61***	0.51
SAWLL	**-1.51****	**-1.01****	**-0.96****	**-0.65***	**-0.67***
SAWLW	-0.54	0.05	-0.04	0.31	0.19
SCRHL	-0.52	-0.29	-0.2	-0.3	-0.23
SCRHW	0.07	0.19	0.07	0.13	0.06
SCRLL	-0.45	-0.11	0.11	-0.23	-0.04
SCRLW	-0.02	0.2	0.18	0.14	0.15
SCWHL	**-0.76****	**-0.58****	**-0.43***	-0.34	-0.26
SCWHW	-0.3	-0.12	-0.19	-0.03	-0.09
SCWLL	**-1.65****	**-1.15****	**-0.97****	**-0.79***	-0.72
SCWLW	**-1.72****	**-1.2***	**-1.11***	-0.63	-0.65

Panel A - table 3 reports Jensen Alpha across all candidate models for quintile sorted 32 portfolios.
* represents the coefficients significant at 5% level of significance
** represents the coefficients significant at 1% level of significance
The results were tested for autocorrelation using Durbin Watson and for Homoscedasticity using Breusch-Pagan-Godfrey and White test. No autocorrelation was detected while only a few portfolios exhibited the signs of heteroskedasticity with White test results, whereas Breusch-Pagan-Godfrey test statistics exhibited homoscedasticity. However, for such portfolios Newey-West adjusted standard errors were estimated, and corresponding P Values of HAC estimates have been used to represent the significance level.

Table 3 Panel B Adj-R² Quintile-Sorted 32 Portfolios for All Models					
Portfolios	1 Factor	3-factor	4-factor	5-factor	6-factor
BARHL	0.27	0.27	0.27	0.27	0.26
BARHW	0.43	0.46	0.47	0.48	0.48
BARLL	0.61	0.62	0.63	0.62	0.63
BARLW	0.69	0.69	0.70	0.73	0.73
BAWHL	0.32	0.37	0.39	0.37	0.40
BAWHW	0.48	0.51	0.50	0.51	0.51
BAWLL	0.36	0.37	0.38	0.39	0.39
BAWLW	0.23	0.26	0.26	0.30	0.30
BCRHL	0.42	0.42	0.45	0.43	0.45
BCRHW	0.41	0.44	0.45	0.47	0.48
BCRLL	0.54	0.54	0.55	0.53	0.55
BCRLW	0.54	0.54	0.58	0.55	0.58
BCWHL	0.54	0.55	0.56	0.59	0.59
BCWHW	0.52	0.54	0.55	0.58	0.58
BCWLL	0.33	0.34	0.37	0.43	0.45
BCWLW	0.30	0.33	0.34	0.34	0.35
SARHL	0.27	0.42	0.41	0.44	0.44
SARHW	0.41	0.54	0.55	0.54	0.55
SARLL	0.40	0.53	0.52	0.52	0.52
SARLW	0.43	0.57	0.60	0.58	0.60
SAWHL	0.36	0.53	0.52	0.55	0.55
SAWHW	0.35	0.48	0.49	0.48	0.50
SAWLL	0.29	0.51	0.51	0.57	0.56
SAWLW	0.26	0.50	0.49	0.51	0.53
SCRHL	0.29	0.49	0.48	0.49	0.50
SCRHW	0.30	0.41	0.42	0.41	0.42
SCRLL	0.35	0.48	0.50	0.48	0.53
SCRLW	0.24	0.35	0.34	0.37	0.37
SCWHL	0.41	0.63	0.64	0.66	0.66
SCWHW	0.38	0.53	0.53	0.56	0.57
SCWLL	0.20	0.40	0.41	0.44	0.45
SCWLW	0.13	0.23	0.22	0.30	0.29

Panel B of table 3 reports Adj-R^2 for candidate models across all quintile sorted 32 portfolios. Adj-R^2s are comparatively lower than those of single-sorted quintile portfolios. It is surprising to see that for some of the portfolios, Adj-R^2 hardly increased while moving from single-factor model to 6-factors model, while a significant increase from single-factor model to 3-factor in only 50% of portfolios.

Panel A of table 3 reports Jensen alphas of all candidate models for quintile sorted 32 portfolios. An interesting observation is that for the portfolios where Jensen alpha of CAPM was significant, adding more factors to CAPM didn't add much value as the alpha remains significant which indicates that the candidate models are not as effective as theory would suggest, or some factors are still missing in these models, or the models are misspecified. Although the coefficient decreases, there is no significant pattern in moving from 4 to 6-factor models, whereas a decreasing pattern can be seen for the significant alpha coefficients when moving from single-factor model to 3-factor model (for example SAWLL, SCWHL portfolios). The number of portfolios with significant alpha is 5 for the single-factor model, 6 for the 3-factor model, 7 for the 4-factor model, 5 for the 5-factor model and 4 for the 6-factor model. The level of significance is high, 1% for a single-factor, 3-factor and 4-factor models' Jensen alphas while the level of significance is lower (0.05) for five and 6-factor models. Partially, based on Jensen alpha analysis, it can be said that overall performance does not necessarily improve by adding more factors to CAPM, dominantly for Big portfolios. However, for small portfolios, 6-factor model generates the lowest number of significant alphas.

Similar to the finding in quad-sorted portfolios, a significant size (SMB) and value (HML) effects are depicted in quintile-sorted portfolios contradicting the findings of Akhtaruzzaman et al. (2014) and others. SMB and HML factors are significant for up to 22 out of 32 portfolios during the full sample period, which seems to be quite strong as these test-portfolios are highly concentrated portfolios. The results indicate the presence of strong Size and Value factors in the Australian market, which also prevail in highly concentrated portfolios.

Profitability factor is also significant for 18 out of 32 test-portfolios but with a negative coefficient which indicates an inverse profitability effect in the Australian market during the sample period. Investment factor seems to positive but dominantly insignificant in quintile-sorted portfolios. Similar to our observations for quad-sorted portfolios, we do not find the evidence to support asset growth effect in the Australian market and support the findings of Bettman, Kosev, et al. (2011) who document that asset growth effect does not exist in the Australian market.

Momentum effect, on the contrary, seems to improve in quintile-sorted portfolios and is significant for at least 50% of the quintile-sorted test-portfolios. We do not find enough evidence to support the presence of momentum effect and observe that the momentum factor is dominantly dependent on the test-portfolio and is not robust in the Australian market during the sample period.

Panel B of table 3 reports Adj-R^2 for candidate models across quintile sorted 32 portfolios. The most important point is that all the portfolios hold unique stocks, so results are not affected by overlapping stocks as was the case in single-sorted quintile portfolios where the overlapping of stocks in Size-style portfolios or Profitability-style portfolios could potentially lead to similar results. We see a sharp increase in Adj-R^2s from CAPM to 3-factor model for some of the portfolios like SCWHW, SCWHL, SAWLL, SARLL and others. The notable point is the common factor in these portfolios, which is small size and weak profitability.

An interesting observation is that using such portfolios gives us an insight into which factor model perform better for any style-based portfolio. It is apparent that for almost all portfolios of small and weak profitability stocks, the model performance sharply increases when changing from the single-factor to the 3-factor model. There is another interesting observation that Adj-R^2s are either approximately equal or trivially different for 3 and 4-factor models and similarly for 5-factor and 6-factor models.

We can see that for big portfolios, Adj-R^2s do not significantly change while we move from single-factor model to 6-factor model as Adj-R^2 for BCRLL is 0.54 with a single-factor model that declines to 0.53 with 5-factor model and increases to 0.55 with 6-factor model. Adj-R^2 for BARLL moves from 0.61 to 0.63 from single factor to the 6-factor model. For BCRHL is increasing from 0.42 to 0.45 while moving from single-factor model to the 6-factor model. The common characteristics of these portfolios are Big and robust profitability. The results give us a new direction that some Asset Pricing models can work better in comparison with other models for a style or characteristic based portfolio.

It is observable that CAPM has the lowest adj-R^2 for some portfolios, however, for some portfolios like BARHL, BARLL, BCRHL, it is quite comparable to adj-R^2 of three, four, five and 6-factor models. Adding the size and value factor adds value to the explanatory power of the

model, however, after that continuously adding more factors do not add any significant value to the model as there is a slight difference in Adj-R^2 of 3-factor, 4-factor, 5-factor and 6-factor models for most of the portfolios. For portfolios of big stocks, Adj-R^2 is quite similar or slightly changes while moving from single-factor model to 6-factor model, while for portfolios of small stocks, a sharp movement can be seen while moving from single factor to 6-factor model. However, Adj-R^2 is quite similar while we move from 3-factor model to the 6-factor model.
All the candidate models produce significant GRS test statistics which indicates that neither of the candidate models is effective in explaining returns for quintile-sorted concentrated portfolios during the sample period. The results imply that candidate models do not seem to be robust to the level of diversification and have relatively lower explanatory power for less diversified or concentrated portfolios. It appears that from a practical point of view, these models may not be of much use for an average Australian retail investor with a poorly diversified or concentrated portfolio. Our results for quintile sorted portfolio disagree with the recent findings of Chai et al. (2019) and supports the findings of Lo (2004), who document that portfolio formation can affect asset pricing tests.

VI. Conclusion

According to Merton (1973) 's no-significant-alpha criterion, the CAPM seems to be the best performing model for single-sorted Investment-style portfolios as the coefficients are small and dominantly insignificant. Significant alphas indicate towards missing factor (/factors) in the model. On the other hand, the 3-factor model outperforms single-sorted Size-style, and BM Ratio-Style portfolio and no significant upgrade is observed in the explanatory power of the multi-factor candidate models by adding more factors to the 3-factor model. However, the 5-factor model outperforms other models for single-sorted Profitability-style and Momentum-style portfolios. Conclusively, there is no consensus for any single model for single-sorted diversified style portfolios. According to insignificant Gibbons, Stephen, and Shanken (1989)'s GRS test statistics criteria; all candidate models pass the GRS test of overall model effectiveness for BM Ratio-style portfolios and Momentum-style portfolios. However, only the 6-factor model passes GRS test for Profitability-style portfolios, 5 and 6-factor model pass for Investment Style portfolios and 4-factor to 6-factor models pass GRS test for Size-style portfolios. As per the lowest Alpha Sharpe ratio, the 3-factor model is the best model for Momentum-style portfolio, 5-factor model for Size and Investment-style portfolios, and

6-factor for BM Ratio and Profitability-style portfolios. For Quad-sorted portfolios, only 5 and 6-factor model pass GRS test, which indicates the effectiveness of these models in explaining portfolio returns in the Australian market during the sample period. 5-factor model seems to be the best-performing model with the lowest alpha Sharpe ratio across quad-sorted test-portfolios during the full sample period. Our results are in line with the findings of (Chiah et al., 2016), (Fama & French, 2017) and (Chai et al., 2019) who document the superiority of the 5-factor model in the Australian market. For quintile-sorted portfolios, all models fail the criteria of overall insignificant alpha. Barillas and Shanken (2016) suggest conducting the test on various subsets of asset returns to better identify a model's effectiveness and robustness while Lewellen et al. (2010) suggest expanding the set of test portfolios beyond size-B/M portfolios and using portfolios that do not correlate strongly with SMB and HML. Our study considered multiple style-based portfolios, with variety of portfolio sorting and different level of portfolio diversification and found that all these factors played a key role into the performance and effectiveness of an asset pricing models in Australian market during 1993 to 2017. Our results support the finding of Lewellen et al. (2010) that choice of test-assets portfolio significantly affects the power of asset pricing model. The results imply that candidate models do not seem to be robust across a different style or characteristic based portfolios and portfolio sorting and have relatively lower explanatory power for less diversified or concentrated portfolios. It appears that from a practical point of view, these models may not be of much use for an average Australian retail investor with a poorly diversified or concentrated portfolio. The results also indicate that the quest for a robust equity pricing model is still incomplete and the results give us a new direction that some equity pricing models can work better in comparison with other models for a style or characteristic based portfolio. We propose to extend the research by analysing different market conditions using a similar setting to investigate the performance of style portfolios and effectiveness of candidate models in varied markets conditions, i.e., recession or depression.

Appendices

Appendix 1

Summary Statistics of Stock Characteristics								
	MCAP	TA	OI	BM R	Chg. TA	OITCE	Momentum	Return
Mean	2160	3930	169	0.64	16.63	13.46	6.02	1.02
Median	477	530	31.93	0.56	6.60	13.81	3.74	0.00
Maximum	58100	172000	5630	2.66	339.45	106.76	312.50	62.47
Minimum	11.63	6.31	-318	0.02	-55.55	-95.36	-86.55	-37.95
Std. Dev.	5590	14200	507	0.43	40.94	23.17	31.43	13.09
Skewness	5.80	7.26	6.15	1.25	3.28	-0.20	1.20	0.72
Kurtosis	43.75	63.07	48.63	5.05	18.33	6.33	8.53	5.61
Obs.	7099	7142	7142	7091	7047	7130	7392	251866

The table presents the summary statistics for the sample. The sample covers the years t from 1993 to 2017 inclusive and includes all the stocks of ASX 300. (As ASX index was only introduced in 2002, before 2002, top 300 stocks based on market capitalisation are included in the sample. MCAP (market capitalisation of the stock, a proxy of size) is reported in AUD millions. TA (total assets) and OI (operating income) are reported in AUD millions. BMR (book-to-market ratio, a proxy of value), Chg. TA (change in total assets, a proxy of investments), OITCE (operating income to common equity, a proxy of profitability), and Momentum, all are reported in percentages. Return is monthly stock return in percentage that has been account for dividends and other distributions. All data series have been reported after trimming at 1% and 99 %.

Appendix 2

Summary Statistics of Risk Factors						
	SMB	HML	CMA	RMW	WML	ERM
Mean	-0.45	0.29	0.32	0.64	0.43	0.69
Median	-0.23	0.39	0.33	0.66	0.33	1.38
Maximum	11.76	9.35	8.01	12.37	11.83	9.00
Minimum	-13.60	-13.00	-7.74	-10.46	-10.11	-11.59
Std. Dev.	3.85	2.63	2.88	2.97	3.22	3.50
Skewness	-0.14	-0.39	-0.06	0.25	0.08	-0.53
Kurtosis	3.20	4.77	2.90	4.36	3.58	3.44
n	300	300	300	300	300	300

The table presents the key statistics for risk factors (SMB, HML, CMA, RMW, WML and ERM).

Appendix 3

A Summary Statistics of Single-Sorted Quintile Portfolios								
Portfolios	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	n
Size 1	0.71	1.30	9.54	-11.49	3.49	-0.51	3.34	300
Size 2	0.76	1.10	13.63	-12.85	4.11	-0.25	3.80	300
Size 3	0.52	0.84	13.55	-12.31	4.22	-0.27	3.30	300
Size 4	0.26	0.39	12.09	-15.83	4.54	-0.28	3.52	300
Size 5	0.19	0.41	14.94	-14.04	4.92	-0.14	3.23	300
BMR 1	0.74	1.19	12.20	-14.99	3.95	-0.43	4.00	300
BMR 2	0.46	0.53	11.55	-11.14	3.74	-0.20	3.62	300
BMR 3	0.59	0.81	13.77	-12.70	4.14	-0.27	3.60	300
BMR 4	0.44	0.97	12.63	-14.95	4.23	-0.40	3.53	300
BMR 5	0.19	0.28	13.88	-12.84	4.58	-0.33	3.25	300
INV 1	0.65	0.90	16.26	-12.18	4.40	-0.19	3.63	300
INV 2	0.77	1.08	10.74	-12.32	3.97	-0.38	3.53	300
INV 3	0.68	0.95	10.91	-12.92	3.72	-0.46	3.76	300
INV 4	0.40	0.60	11.58	-10.86	3.66	-0.30	3.91	300
INV 5	-0.14	-0.05	13.08	-14.59	4.54	-0.22	3.27	300
OITCE 1	0.93	1.22	11.24	-13.79	4.03	-0.50	3.68	300
OITCE 2	0.86	0.91	11.66	-12.32	3.92	-0.18	3.49	300
OITCE 3	0.58	0.74	12.04	-12.13	3.73	-0.30	4.03	300
OITCE 4	0.22	0.52	9.84	-10.75	3.81	-0.30	3.24	300
OITCE 5	-0.17	0.19	14.84	-14.03	5.12	-0.22	3.01	300
MOM1	0.91	1.07	12.55	-13.99	4.29	-0.28	3.33	300
MOM2	0.75	1.05	12.67	-13.22	3.69	-0.51	4.42	300
MOM3	0.53	0.62	16.76	-11.37	3.80	-0.03	4.38	300
MOM4	0.49	0.81	13.53	-12.86	4.19	-0.28	3.62	300
MOM5	-0.22	0.40	12.79	-17.31	5.34	-0.19	3.05	300

The table reports summary statistics of Single-Sorted quintile portfolios' excess return. The sample spans 300 months from Jan 1993 to December 2017. The excess return has been calculated by subtracting the risk-free rate of return from the portfolio return. See chapter 3 Data and Methodology for detailed discussion.

Appendix 4

Summary Statistics of Quad-Sort 16 Portfolios								
Portfolios	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Obs.
BARH [1 2 3 4]	1.22	1.54	13.00	-15.34	4.70	-0.31	3.37	300
BARL	0.75	0.96	10.32	-13.61	4.03	-0.41	3.26	300
BAWH	0.29	0.80	14.68	-19.47	4.49	-0.78	4.93	300
BAWL	0.35	0.77	15.13	-17.58	5.09	-0.45	4.09	300
BCRH	1.10	1.54	25.41	-18.81	4.49	-0.01	6.81	300
BCRL	0.74	0.78	14.32	-11.06	3.86	-0.01	3.98	300
BCWH	0.67	1.11	14.23	-12.47	4.30	-0.27	3.50	300
BCWL	0.49	0.92	21.50	-20.62	5.97	-0.20	4.67	300
SARH	0.99	1.08	19.08	-19.77	5.55	-0.19	4.32	300
SARL	0.90	0.99	15.41	-15.22	5.03	-0.26	3.66	300
SAWH	0.95	1.11	18.26	-13.86	4.90	-0.02	3.79	300
SAWL	-0.22	0.37	20.24	-17.64	6.61	0.04	3.21	300
SCRH	0.44	0.71	20.50	-20.01	5.35	-0.24	4.63	300
SCRL	0.38	0.46	22.90	-17.11	5.70	0.23	4.33	300
SCWH	0.14	0.46	16.62	-17.05	4.88	-0.23	3.49	300
SCWL	-1.09	-0.77	20.25	-17.93	6.88	0.04	2.90	300

The table reports summary statistics for the average excess returns of quad-sorted 16 portfolios.
[1]First letter of portfolio name B or S refers to Size (market capitalisation) Big or Small
[2]Second letter of portfolio name A or C refers to Aggressive of Conservative Investment (change in total assets)
[3]Third letter of portfolio name R or W refers to Profitability Robust or Weak (operating income to common equity)
[4]Fourth letter of portfolio name H or L refers to High or Low book to market ratio

Appendix 5

Summary Statistics of Quintile-Sorted 32 Portfolios								
	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Obs.
BARHL 1 2 3 4 5	0.87	1.19	24.32	-30.41	7.08	-0.62	6.12	300
BARHW	**1.14**	1.44	15.32	-16.31	5.48	-0.27	3.54	300
BARLL	0.59	0.98	13.46	-17.43	4.71	-0.32	3.41	300
BARLW	0.92	1.19	10.62	-13.33	4.14	-0.25	3.26	300
BAWHL	0.27	0.79	22.51	-25.59	6.4	-0.29	5.7	300
BAWHW	0.47	0.84	19.19	-17.72	4.86	-0.28	4.49	300
BAWLL	0.27	0.52	19.86	-21.65	6.49	-0.07	3.51	300
BAWLW	0.15	0.33	43.62	-30.25	6.56	0.41	11	300
BCRHL	0.54	0.81	19.91	-19.95	5.45	-0.33	3.97	300
BCRHW	**1.07**	1.32	41.58	-24.92	5.6	0.94	13.13	300
BCRLL	0.36	0.34	16.49	-16.39	4.8	-0.03	4.11	300
BCRLW	0.75	0.88	10.48	-18.53	4.09	-0.44	4.27	300
BCWHL	0.45	0.47	19.72	-19.66	5.42	-0.11	3.73	300
BCWHW	0.73	0.88	30.2	-18.43	4.79	0.44	7.94	300
BCWLL	0.85	0.43	30.95	-23.99	7.26	0.49	5.29	300
BCWLW	-0.02	0.1	20.14	-20.45	6.18	-0.24	4.17	300
SARHL	0.84	0.93	29.99	-32.65	7.67	-0.28	5.98	300
SARHW	**1.16**	0.96	20.62	-18.01	5.87	-0.09	4.19	300
SARLL	0.73	0.1	26.12	-15.28	6.07	0.53	4.36	300
SARLW	0.89	1.14	16.82	-17.02	5.25	-0.36	3.72	300
SAWHL	**1.11**	0.52	28.35	-20.21	6.63	0.51	5.11	300
SAWHW	**1**	1.06	22.09	-15.9	5.74	0.02	3.59	300
SAWLL	-0.75	-0.78	19.75	-22.71	7.22	0.02	3.11	300
SAWLW	0.26	-0.22	27.99	-18.31	7.82	0.26	3.21	300
SCRHL	0.18	-0.52	24.9	-20.33	6.54	0.18	4.04	300
SCRHW	0.72	0.56	24.21	-31.39	6.01	-0.37	6.48	300
SCRLL	0.38	0.36	30.34	-16.63	7.01	0.49	4.5	300
SCRLW	0.6	0.45	27.68	-21.16	6.37	0.29	5.21	300
SCWHL	0.01	-0.22	17.48	-21.99	6.03	-0.07	3.46	300
SCWHW	0.31	0.27	15.82	-13.93	5.02	-0.08	3.43	300
SCWLL	-0.89	-1.15	39.79	-18.95	8.52	0.71	4.65	300
SCWLW	-1	-0.68	51.99	-37.53	10.19	0.94	7.89	300

The table reports summary statistics for average excess returns of quintile sort 32 portfolios.
1First letter of portfolio name B or S refers to Size (market capitalisation) Big or Small
2Second letter of portfolio name A or C refers to Aggressive of Conservative Investment (change in total assets)
3Third letter of portfolio name R or W refers to Profitability Robust or Weak (operating income to common equity)
4Fourth letter of portfolio name H or L refers to High or Low book to market ratio
5Fifth letter of portfolio name W or L refers to Momentum winner or Loser.

Appendix 6

GRS Test Statistics, P-Value and α Sharpe Ratio – FS					
Period	**Model**	**Test Portfolios**	**FGRS**	**PGRS**	**α Sharpe Ratio**
FS	1-Factor	Size	2.27	0.05	- 0.74
FS	1-Factor	BMR	0.91	0.48	- 0.74
FS	1-Factor	INV	5.03	0.00	- 0.45
FS	1-Factor	OITCE	3.94	0.00	- 0.40
FS	1-Factor	MOM	2.03	0.07	- 0.39
FS	1-Factor	Quad-Sorted	2.71	0.00	- 0.48
FS	1-Factor	Quintile Sorted	2.61	0.00	- 0.48
FS	3-Factor	Size	2.27	0.05	- 0.55
FS	3-Factor	BMR	0.49	0.78	- 0.72
FS	3-Factor	INV	4.01	0.00	- 0.36
FS	3-Factor	OITCE	3.80	0.00	0.05
FS	3-Factor	MOM	1.94	0.09	0.09
FS	3-Factor	Quad-Sorted	2.28	0.00	- 0.32
FS	3-Factor	Quintile Sorted	4.06	0.00	- 0.07
FS	4-Factor	Size	1.65	0.15	- 0.35
FS	4-Factor	BMR	0.28	0.92	- 0.62
FS	4-Factor	INV	3.47	0.00	- 0.40
FS	4-Factor	OITCE	2.71	0.02	0.09
FS	4-Factor	MOM	1.80	0.11	- 0.21
FS	4-Factor	Quad-Sorted	1.95	0.02	- 0.27
FS	4-Factor	Quintile Sorted	3.10	0.00	- 0.07
FS	5-Factor	Size	1.72	0.13	- 0.04
FS	5-Factor	BMR	0.32	0.90	- 0.65
FS	5-Factor	INV	2.22	0.05	- 0.50
FS	5-Factor	OITCE	2.57	0.03	0.09
FS	5-Factor	MOM	2.14	0.06	0.34
FS	5-Factor	Quad-Sorted	1.57	0.08	0.00
FS	5-Factor	Quintile Sorted	3.02	0.00	0.20
FS	6-Factor	Size	1.57	0.17	0.04
FS	6-Factor	BMR	0.15	0.98	- 0.58
FS	6-Factor	INV	2.08	0.07	- 0.53
FS	6-Factor	OITCE	1.98	0.08	0.13
FS	6-Factor	MOM	1.81	0.11	0.09
FS	6-Factor	Quad-Sorted	1.42	0.13	0.03
FS	6-Factor	Quintile Sorted	4.34	0.00	0.20

References

Akhtaruzzaman, M., Docherty, P., & Shamsuddin, A. (2014). Interest rate, size and book-to-market effects in Australian financial firms. *Applied Economics, 46*(25), 3005-3020.

Arbel, A., Carvell, S., & Strebel, P. (1983). Giraffes, institutions and neglected firms. *Financial Analysts Journal*, 57-63.

ASIC, A. S. a. I. C. (2017). *The Australian financial attitudes and behaviour tracker study* Australian Securities and Investments Commission.

. *ASX Australian Investor Study*. (2017): Deloitte Access Economics. Retrieved from https://www.asx.com.au/education/2017-asx-investor-study.htm

Ball, R., Gerakos, J., Linnainmaa, J. T., & Nikolaev, V. (2016). Accruals, cash flows, and operating profitability in the cross section of stock returns. *Journal of Financial Economics, 121*(1), 28-45.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of financial economics, 9*(1), 3-18.

Barillas, F., & Shanken, J. (2016). Which Alpha? *The Review of Financial Studies*. doi:10.1093/rfs/hhw101

Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of financial economics, 12*(1), 129-156.

Bettman, J. L., Kosev, M., & Sault, S. J. (2011). Exploring the asset growth effect in the Australian equity market. *Australian Journal of Management, 36*(2), 200-216.

Bettman, J. L., Ng, W. S. K., & Sault, S. J. (2011). The economic significance of trading based on the size effect in Australia. *Australian Journal of Management, 36*(1), 59-73.

Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. *The journal of finance, 43*(2), 507-528.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *The Journal of Business, 45*(3), 444-455.

Brailsford, T., Gaunt, C., & O'Brien, M. A. (2012a). The investment value of the value premium. *Pacific-Basin Finance Journal, 20*, 416-437.

Brailsford, T., Gaunt, C., & O'Brien, M. A. (2012b). Size and book-to-market factors in Australia. *Australian Journal of Management, 37*(2), 261-281.

Brennan, M. J., Chordia, T., & Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics, 49*(3), 345-373.

Campbell, J. Y. (1996). Understanding risk and return. *Journal of Political economy, 104*(2), 298-345.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance, 52*(1), 57-82.

Chai, D., Chiah, M., & Gharghori, P. (2019). Which model best explains the returns of large Australian stocks? *Pacific-Basin Finance Journal, 55*, 182-191.

Chiah, M., Chai, D., Zhong, A., & Li, S. (2016). A Better Model? An empirical investigation of the Fama–French five-factor model in Australia. *International Review of Finance, 16*(4), 595-638.

Chopra, N., Lakonishok, J., & Ritter, J. R. (1992). Measuring abnormal performance: do stocks overreact? *Journal of financial Economics, 31*(2), 235-268.

Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *The Journal of Finance, 63*(4), 1609-1651.

Daniel, K., & Titman, S. (1997). Evidence on the characteristics of cross sectional variation in stock returns. *The Journal of Finance, 52*(1), 1-33.

Davis, J. L., Fama, E. F., & French, K. R. (2000). Characteristics, covariances, and average returns: 1929 to 1997. *The Journal of Finance, 55*(1), 389-406.

Dou, P. Y., Gallagher, D. R., & Schneider, D. H. (2013). Dissecting anomalies in the Australian stock market. *Australian Journal of Management, 38*(2), 353-373.

Durand, B. R., Limkriangkrai, M., & Chai, D. (2016). The Australian asset-pricing debate. *Accounting and Finance, 56*, 393-421.
Durand, R. B., Limkriangkrai, M., & Smith, G. (2006). In America's thrall: the effects of the US market and US security characteristics on Australian stock returns. *Accounting & Finance, 46*(4), 577-604.
Ernstberger, J., Haupt, H., & Vogler, O. (2011). The role of sorting portfolios in asset-pricing models. *Applied Financial Economics, 21*(18), 1381-1396.
Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance, 47*(2), 427-465.
Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics, 33*(1), 3-56.
Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of financial economics, 105*(3), 457-472.
Fama, E. F., & French, K. R. (2015a). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1-22. doi:10.1016/j.jfineco.2014.10.010
Fama, E. F., & French, K. R. (2015b). A five-factor asset pricing model. *Journal of Financial Economics, 116*, 1-22.
Fama, E. F., & French, K. R. (2017). International tests of a five-factor asset pricing model. *Journal of Financial Economics, 123*(3), 441-463.
Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of Financial Economics, 128*(2), 234-252.
Friend, I., & Puckett, M. (1964). Dividends and stock prices. *The American Economic Review, 54*(5), 656-682.
Gaunt, C. (2004). Size and book to market effects and the Fama French three factor asset pricing model: evidence from the Australian stockmarket. *Accounting & Finance, 44*(1), 27-44.
Gibbons, M. R., Stephen, R., & Shanken, J. (1989). A Test of the Efficiency of a Given Portfolio. *Econometrica, 57*, 1121-1152.
Graham, B., & Dodd, D. L. (1934). *Security analysis: Principles and technique*: McGraw-Hill.
Harvey, C. R., Liu, Y., & Zhu, H. (2016). … and the cross-section of expected returns. *The Review of Financial Studies, 29*(1), 5-68.
Hou, K., Karolyi, G. A., & Kho, B.-C. (2011). What factors drive global stock returns? *Review of Financial Studies, 24*(8), 2527-2574.
Jegadeesh, N., & Titman, S. (1993a). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance, 48*(1), 65-91.
Jegadeesh, N., & Titman, S. (1993b). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance, 48*(1), 65-91.
Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of finance, 23*(2), 389-416.
Jensen, M. C., Black, F., & Scholes, M. S. (1972). The capital asset pricing model: Some empirical tests.
Kassimatis, K. (2008). Size, book to market and momentum effects in the Australian stock market. *Australian Journal of Management, 33*(1), 145-168.
Lewellen, J., Nagel, S., & Shanken, J. (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial economics, 96*(2), 175-194.
Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The review of economics and statistics*, 13-37.
Lo, I. (2004). Portfolio formations can affect asset pricing tests. *Journal of Asset Management, 5*(3), 203-216.
Markowitz, H. (1952). Portfolio selection. *The journal of finance, 7*(1), 77-91.
Markowitz, H. (1959). *Portfolio Selection: Efficient Diversification of Investments*: NewYork:John Wiley & Sons, Inc.
Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica, 41*(5), 867-887.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the econometric society*, 768-783.
Roy, A., &. (1952). *Safety first and the holding of assets, Econo metrica 20 (3): 431–449*.
Sharpe, W. F. (1963). A simplified model for portfolio analysis. *Management science, 9*(2), 277-293.
Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance, 19*(3), 425-442.
Treynor, J. L. (1962). Toward a theory of market value of risky assets. *Unpublished manuscript, 6*.
Vo, D. H. (2015). Which Factors Are Priced? An Application of the Fama French Three-Factor Model in Australia. *Economic Papers, 34*(4), 290-301.