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Size, Book to Market and Momentum Effects in the Australian Stock Market

by
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Abstract:

We examine the significance of the size, book-to-market and momentum risk factors in explaining portfolio returns in the Australian stock market. We compare the CAPM to a four-factor model assuming static risk premia, and find that the additional factors have significant explanatory power. Under the assumption of time-varying factor loadings, though, the significance of the three additional factors becomes marginal, which suggests that size, book-to-market and momentum may proxy for misspecified market risk.

Keywords:

CAPM; SIZE EFFECT; BOOK TO MARKET EFFECT; MOMENTUM; TIME VARYING RISK PREMIA

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1. Introduction

We examine the role of size, book-to-market and momentum factors in explaining stock returns in the Australian stock market, assuming time-varying systematic risk. The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) assumes a linear relationship between an asset's excess return and the excess return of the market portfolio. Although early empirical evidence supported the model, later studies show that the CAPM cannot adequately explain realised returns. Fama and French (1992) present a three-factor model which complements the CAPM and does a better job in explaining realised returns. Fama and French include in their study two additional factors; size and book-to-market (BM). Jegadeesh and Titman (1993) and Carhart (1997) show momentum may also be an additional risk factor. Since the appearance of these models, there has been a plethora of studies examining their power in explaining realised asset returns (see, Fama & French 1993, 1995, 1996; Hong, Lim & Stein 2000; Jegadeesh & Titman 2001; Lakonishok, Shleifer & Vishny 1994; La Porta, Lakonishok, Shleifer & Vishny 1997; Lee & Swaminathan 2000; Lesmond, Schill & Zhou 2004; Rouwenhorst 1998; Wang 2000).

With respect to the Australian stock market, there are few studies examining the role of these factors, mainly due to lack of historical size and BM factor data. The first study to examine the significance of the Fama and French factors in the Australian market is Halliwell, Heaney and Sawicki (1999). Their results do not clearly support or reject the model. While they find evidence of a size effect and some weak evidence of a BM effect, the R^2 of the regressions does not improve much as they move from the CAPM to the three factor model. Also, their weighted average beta is much lower than expected (0,69). This indicates that the Halliwell, Heaney and Sawicki (1999) sample may be problematic. Fama and French (1998) test for a value premium (but not a size premium) using Australian data. They find that of the 12 countries in their sample, Australia exhibits the largest annual BM premium (12.32%). However, their sample is rather limited, as they use an average of 80 firms from the Australian market and these firms are from the MSCI database, which covers large firms. Gaunt (2004) finds a strong size premium and a weak BM premium, but the size and BM factors fail to account for realised returns when applied to portfolios sorted by return on assets. Faff (2001) also tests the Fama and French three-factor model for the period 1991–1999 and finds strong evidence of a negative size premium and a positive BM premium. Similar evidence is also presented by Anderson, Lynch and Mathiou (1990), Beedles, Dodd and Officer (1988), Brown, Keim, Kleidon and Marsh (1983) and Gaunt, Gray and McIvor (2000), among others, who find a significant size premium in Australian equity returns.

With respect to the momentum effect, there is conflicting evidence for the Australian market. For example, Liew and Vassalou (2000), Hurn and Pavlov[1] (2003) and Demir, Muthuswamy and Walter (2004) find that the momentum premium for Australia is statistically significant, while Durand, Limkriangkrai and Smith (2006b) do not find a momentum effect using monthly data. Given the evidence, there are two likely sources of the differences in the reported results: the sample period used and seasonality in returns. Durand, Limkriangkrai and Smith

1. Hurn and Pavlov examine momentum for large stocks only.

(2006b) find that the momentum effect is concentrated in July.[2] Regarding the effect of the sample period used, Durand, Limkriangkrai and Smith (2006b) do not find a momentum effect using daily data for the period 1980 to 2001, but fail to reject this effect for the period 1990 to 2001. Thus, it seems that, if there is a momentum effect present in Australian stock returns, this is confined to the recent past. Although the evidence on momentum is mixed, we include it in our analysis for two reasons. Firstly, because there are numerous studies which document its existence in Australian stock returns. Secondly, because there is increasing evidence of integration between the Australian and the US market (e.g. Durand, Limkriangkrai & Smith 2006a). Integration implies similar risk factors, thus, if momentum is present in US stock returns, it could also be present in Australian stock returns.[3]

Given the empirical evidence of a size, BM and momentum premium in the Australian market, these effects have been characterized as anomalies and are frequently used in asset pricing models. Although the size factor and to a lesser extent the BM factor have been found significant in explaining realized returns (e.g. Gaunt 2004), the Fama-French model has failed to explain Australian stock returns satisfactorily. The failure of the three-factor model to explain stock returns has driven researchers to augment it with factors such as exchange rate and US market factors (Durand, Limkriangkrai & Smith 2006a) and liquidity (Chan & Faff 2005). Some of these factors increase the explanatory power of the model but they all produce mixed results. A possible reason for this failure may be model misspecification. It is well-known that systematic risk as it is captured by beta varies with time.[4] Studies on the Australian market (e.g. Brooks, Faff & Lee 1992; Brooks, Faff and Josev 1997) have shown that systematic risk is not stationary. However, none of the above studies has integrated time-varying systematic risk in the analysis. One exception is Durack, Durand and Maller (2004), who use the Jagannathan and Wang (1996) model to incorporate time variation in beta. Although their model has good explanatory power, the size factor remains significant when added to the regression. Durack, Durand and Maller (2004) conclude that the size factor does not proxy for misspecified market risk. However, their results are dependent on the conditioning variables they use, some of which are drawn from the US market.[5] Faff (1992) also tests for time variation in risk premia using an APT model. Although the model performs better than the CAPM, neither model could explain monthly seasonal mispricing.

There are several reasons why factor loadings may vary over time. Franzoni (2006) finds that small and value stocks' betas tend to decrease over time. The main source of this decrease is a decline in the volatility of these stocks over time. This effect captures long-run variation in betas. In the medium term, variation in betas may be due to the business cycle. The rationale behind this relationship is that

2. The is not true for our sample returns (see section 3, footnote 19).
3. If the Australian and the US markets have become more integrated during the 1990s, this could explain why momentum is rejected for early Australian data but not rejected for more recent data.
4. For example, Ang and Chen (2005), Adrian and Franzoni (2005), Campbell and Vuolteenaho (2004) and Franzoni (2006) use time-varying factor loadings and find that betas of portfolios sorted by size and BM vary considerably.
5. Durack, Durand and Maller (2004) use the yield spread as a conditioning variable and they calculate it from US government bond rates. They argue that, given the documented strong link between the US and the Australian economies, US rates may capture adequately Australian economic conditions.

small and value stocks, in particular, tend to be in relative distress (see, Chan & Chen 1991). Changing economic conditions may affect the severity of their distress, thus changing their riskiness. It is reasonable then to expect that the premiums on their risk factors should depend on the state of the economy. Shanken (1990), for example, models time variation of betas as a function of macroeconomic state variables. Franzoni (2006) finds that the dividend yield and the default spread can track changes in stocks betas. Franzoni (2006) also finds that the term spreads, as well as interest rates, closely follow the business cycle, which is why they can explain betas well.

There is evidence that the Australian business cycle closely follows the business cycle of other major economies (e.g. Debelle & Preston 1995; De Roos & Rusell 1996; Gruen & Shuetrim 1994; Smith & Murphy 1994). De Roos and Rusell (1996) find that the correlation between the Australian and other business cycle is due to Australian exports and the integration of financial markets. The integration between the US and the Australian financial markets documented by Durand, Limkriangkrai and Smith (2006a) seems to have a significant impact on Australian economic activity through its effect on investment. This implies that risk premia and changes in the business cycle may be highly correlated.

There are no studies in the literature examining the role of the size, BM and momentum factors under time-varying systematic risk for Australian equities. Establishing the role of these factors in explaining stock returns is important for two reasons. First, it is now common practice to use the Fama and French model as a benchmark against alternative asset pricing models.[6] Using a model as a benchmark assumes that this model can explain returns better than other models. Thus, it is important to establish if these are indeed systematic factors or if they proxy for market risk not captured by the static CAPM. Second, most of the literature has focused on the US market. If these factors are indeed systematic factors, they should work equally well in markets other than the US. Considering the evidence on the integration between the US and the Australian stock markets, Australia is a good candidate for our tests.[7]

The contribution of the present study is to address a gap in the literature by combining two empirical findings: time variation in Australian market risk, and the significance of the Fama and French factors. Our study is motivated by Fama and French (2006) who find that accounting for unconditional time variation in market risk for the US market improves considerably the power of the CAPM in explaining realized returns[8]. Additionally, we include in the analysis a momentum factor because there is evidence that this factor is significant in the Australian market and the returns achieved by this strategy are not related to size or BM effects (Demir, Muthuswamy & Walter 2004). We begin the analysis by examining the returns of the three arbitrage portfolios on an annual basis. We find that, while the overall returns are statistically significant for the Small-Minus-Big and the High-Minus-Low portfolios, these are driven by few years of sizeable profits. Then

6. Examples of such studies on the Australian market include Durack, Durand and Maller (2004) and Chan and Faff (2005).
7. For evidence on the relationship between the Australian and US markets, see Durand, Limkriangkrai and Smith (2006a), Durand and Scott (2003), Ragunathan, Faff and Brooks (1999).
8. Note that Fama and French (2006) find that although the explanatory power of the CAPM is improved, there is still role for the value premium. We find that this is not the case for Australia.

we replicate tests of previous studies and find that size, BM and, to a lesser extent, momentum are indeed priced in the Australian stock market assuming static factor loadings. If we account for unconditional time variation in market risk, though, their effect becomes diminished. Both the BM and momentum factors become insignificant, while size is still significant but only for few portfolios. The implication is that research on asset pricing for the Australian market should focus on the effect of time variation in systematic risk and incorporate this effect in asset pricing models. Researchers may find that variables besides size, BM and momentum, frequently included in asset pricing models, may be insignificant if time variation in market risk is accounted for.

2. Data and Methodology

We use data available from Datastream, for the period July 1992 to June 2005.[9] Datastream reports stock prices and dividends so, to obtain total returns we spread the annual dividends evenly throughout the year. While this procedure smoothes monthly returns, it does not affect the means of the returns. We use end of month prices, dividends, market capitalization and price to book ratios. The database includes both currently traded and defunct securities. As usual, we exclude from the database all firms from the financial sector as well as preferred shares and warrants. Financial firms have high leverage which does not have the same meaning as non-financial firms where high leverage usually indicates distress. All amounts are in local currency. Before forming the portfolios, we clean the database from errors. To this end, we use four filters as suggested by Ince and Porter (2006): (a) all equities not listed in Australia are deleted; (b) non-common equities are deleted (e.g. ADRs, warrants, etc.); (c) zero returns resulting from the delisting of a stock are deleted;[10] and, (d) extremely high returns (e.g. 300%) which are reversed in the next month are deleted (these returns are very few and are due to incorrect data entries, however, they may have a significant impact on results if not addressed).

We form 25 portfolios based on size and BM. The portfolios are constructed in the same way as in Fama and French (1992). Each year, only stocks with twelve monthly price observations prior to July, June-end market capitalization and December-end of year t-1 positive BM ratio are included in the sample. Following Liew and Vassalou (2000), in case of missing prices during the (post formation) holding period of a stock, we assume that for the period with missing prices the proportion of the funds invested in the stock are invested in the risk-free asset instead. To create the portfolios, we sort all stocks by BM into quintile portfolios. Then, we sort all stocks by size into quintile portfolios. The 25 portfolios are the intersection of each BM quintile portfolio with each of the size quintile portfolios. Table 1 reports descriptive statistics for the 25 portfolios. The average number of

9. There are other databases which keep more detailed data for the Australian market such as the Share Price and Price Relative. However, Datastream is the only database available to us.

10. Datastream often maintains equities in its database and reports a price for them long after they have been delisted. The reported price is always the last closing price before the delisting, resulting in zero returns after that.

Table 1

Descriptive Statistics for the 25 Portfolios Sorted by Size and Book to Market

The sample period is July 1992 to June 2005 and we use monthly data. We construct 25 portfolios according to the Fama and French (1992) methodology. The table reports average values for each portfolio for the sample period. For example, the portfolio of small stocks and low BM contains on average 23 stocks over our sample period, has an average market capitalisation of 26 millions Australian dollars, an average BM ratio of 3% and a 4.49% average excess monthly return. The risk free rate used for the calculation of the excess returns is the monthly return on the 90 day Australian T-bill.

	Low BM	2	3	4	High BM	All
			Panel A: Average no of stocks			
Small	23	16	17	16	33	104
2	19	18	19	20	26	102
3	18	21	20	20	23	102
4	23	21	21	23	15	102
Big	19	27	24	24	8	102
All	102	102	102	102	104	
			Panel B: Average market capitalization ($Am)			
Small	26	27	23	26	22	25
2	80	79	82	76	73	78
3	169	170	168	175	170	170
4	418	463	426	410	386	420
Big	5217	3803	2332	1983	1412	2949
All	1182	908	606	534	412	
			Panel C: Average book to market ratio			
Small	0.03	0.43	0.63	0.88	1.53	0.70
2	0.09	0.43	0.62	0.87	1.36	0.68
3	0.11	0.43	0.63	0.87	1.30	0.67
4	0.14	0.44	0.63	0.87	1.29	0.68
Big	0.18	0.44	0.62	0.85	1.21	0.66
All	0.11	0.43	0.63	0.87	1.34	

Panel D: Excess monthly portfolio returns

	Low BM	2	3	4	High BM
Small	4.49%	2.97%	3.24%	2.18%	2.76%
2	–0.07%	0.23%	0.65%	1.23%	1.76%
3	–0.10%	0.45%	0.62%	1.21%	1.61%
4	0.00%	–0.17%	0.82%	1.20%	1.49%
Big	0.34%	0.73%	0.53%	0.72%	1.15%

stocks per quintile is 102, which is enough to construct well diversified portfolios. The portfolio with the fewest stocks is the high BM / big stock portfolio, with an average number of 8 stocks. Table 1 also reports excess returns[11] for each portfolio.

11. Excess returns are calculated as the difference between the return of a portfolio and the monthly return on the 90 day Australian T-bill.

A comparison of the excess returns in our sample with other studies (e.g. Gaunt 2004) reveals many similarities. The highest returns are those for the small stock quintile, exactly as in the Gaunt (2004) and Haliwell, Heaney and Sawicki (1999) studies. The magnitude of the returns is very similar, too. We conclude that our portfolios are similar to those in other Australian studies, therefore any stocks not included in our database should not cause any problems in the estimation of the size, BM and momentum portfolio returns.

For the construction of the factor returns we use the Liew and Vassalou (2000) procedure. The first step to create the factor portfolios is to sort the sample by BM and create tertile portfolios. Each of the three portfolios is then sorted by size and we create tertile portfolios from each one. This way we have nine portfolios. Finally, we sort each of the nine portfolios by momentum returns and again create tertile portfolios from each one. We end up with 27 portfolios. Nine of these portfolios include only small stocks, nine include medium sized stocks and nine include big stocks.[12] The Small-Minus-Big (SMB) portfolio returns are then constructed as the difference between the weighted average return of the nine Small portfolios and the weighted average return of the nine Big portfolios. Similarly, the High-Minus-Low (HML) portfolio returns are the difference between the weighted average return of the nine High BM portfolios and the nine Low BM portfolios, and the momentum (WML) portfolio returns are the difference between the weighted average return of the nine winner portfolios and the nine loser portfolios. The annual momentum strategy is implemented by measuring the average of past year's return, excluding the most recent month.[13] All portfolios are value weighted. The advantage of the Liew and Vassalou (2000) procedure is that each factor portfolio is a zero investment portfolio which is neutral with respect to the other two factors.[14]

Having constructed the stock portfolios and the factor returns, the next step is to compare the CAPM to the four factor model. Initially, we use ordinary least squares (OLS) regressions assuming that factor loadings remain constant during the entire sample period. For the market portfolio, rather than using the All Ordinaries Accumulation Index which includes only the largest 250 companies of the Australian market, we use a value weighted portfolio of all the stocks in our database. In order to test the CAPM versus the four factor model we run for each portfolio the following regressions:

$$R_{i,t} - RF_t = a + b\,(RM_t - RF_t) + e_t \tag{1}$$

$$R_{i,t} - RF_t = a + b\,(RM_t - RF_t) + s\,SMB_t + h\,HML_t + w\,WML_t + e_t \tag{2}$$

12. Readers wishing for a detailed understanding of the portfolio construction methodology should refer to Liew and Vassalou (2000).
13. Excluding the most recent month eliminates problems associated with microstructure issues (see, Asness 1995).
14. We have also carried out the analysis using the size and BM factor returns as constructed by Fama and French (1992). The results are qualitatively identical. The correlation coefficient between our size and BM factors and those constructed by Fama and French are higher than 90%.

where $R_{i,t}$ is the return of portfolio i for month t, RF is the risk free rate, RM is the return of the market portfolio, and SMB, HML and WML are the size, BM and momentum factor returns respectively. Then, we re-estimate equations (1) and (2) assuming time varying risk premia.

One consideration in our study is to determine the appropriate way to estimate time varying factor loadings. Hildreth and Houck (1968) model betas as random mean reverting variables of the form $\beta_t = \beta + u_t$, where β is the estimated static beta. Another model is proposed by Rosenberg (1973) who models beta as an AR(1) process. Brooks, Faff and Lee (1992) test different models for the Australian stock market and suggest that the Hildreth and Houck (1968) model is the best alternative, so this is the model we employ.[15] Another issue is the estimation period length for the time varying betas. There are no models to help us determine the optimum length of the estimation period for betas. Conventional wisdom suggests the use of five year windows (e.g. Franzoni 2006). However, 5-year windows may be inappropriate if we want to capture variation in factor loadings due to the business cycle. Guidance on this matter is offered from studies on the chronology of the Australian economic cycles. A recent study by Cashin and Ouliaris (2004) identifies the turning points of the Australian business cycle from 1959 to 2000. While the duration of expansion phases is quite long (from 17 to 31 quarters) contraction phases have a life of 2 to 5 quarters. This evidence favours the use of short windows of estimation for our regressions. Fama and French (2006) compare different window lengths for the estimation of portfolio betas and find that one-year windows are the best alternative. If betas are very volatile, a five year window will produce rather stable betas which will not reflect their true variation. On the other hand, short estimation windows could introduce a lot of noise in our beta estimates[16]. Therefore, we consider different estimation window lengths and choose the most appropriate based on the adjusted R^2. A final consideration is the estimation procedure for the betas. Fama and French (2006) use annual dummy variables while others (e.g. Franzoni 2006) use rolling regressions. In the present study we estimate betas from rolling least square (RLS) regressions with one month increments.[17]

3. Empirical Results

Before we begin the analysis we take a closer look at the returns of the three arbitrage portfolios (HML, SMB and WML). If these factors constitute an anomaly, then they should consistently produce significant returns not explained by an asset pricing model. Table 2 reports the annualized returns for each portfolio per year for the sample period. The last two rows of the table report the average annualized return for each portfolio, which in the case of the HML and SMB portfolios is

15. Another reason we employ this model is because it is the least restrictive. The Rosenberg model is a special case of the Hildreth and Houck model. Given the scarcity of research in this area, we are wary of imposing too much structure on the beta generating process without strong empirical evidence to support such a structure.
16. The effect of introducing noise becomes a minor concern if the portfolios we use are well diversified.
17. Our sample covers 14 years so, we would have to use 13 dummy variables to obtain one beta per year. Using rolling regressions with one month increments produces 12 betas per year which can capture time variation more effectively.

statistically significant. Although the overall returns for HML and SMB are statistically significant, the year by year zero-investment returns show a different picture. It seems that the statistical significance of these returns is driven by few years of high returns. For example, for the HML portfolio, returns are statistically significant at the 5% level only in 2001 and 2003. For most years of the sample period returns are statistically insignificant, while for some years returns are negative. With respect to the WML portfolio, it is disturbing that from 2001 to 2004 it produced negative returns.[18] An investor following this strategy would have lost for those four years 27.34% of her capital. Studies which present only annual average returns miss the complete picture and imply that these strategies are a consistent source of abnormal profits. Based on the results presented here, it is evident that an investor following these strategies should be prepared to accept big losses for a considerable amount of time.

Table 2
HML, SMB and WML Annual Returns

The sample period is July 1992 to June 2005 with July of year t-1 being the beginning of each year. So, the year 1993 for example, corresponds to the period July 1992 to June 1993. The table reports the annual returns for the high-minus-low book to market (HML), small-minus-big (SMB) and winners-minus-losers (WML) arbitrage portfolios, constructed using the Liew and Vassalou (2000). The last two rows report the annualized average return over the whole sample period for each portfolio and the associated t-statistics. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

	HML	SMB	WML
1993	7.77%	20.88% *	–2.61%
1994	13.77% *	5.22%	4.52%
1995	3.95%	–16.14% ***	–6.01%
1996	2.52%	23.61% ***	11.24% *
1997	14.26% *	3.89%	2.79%
1998	1.44%	4.09%	14.06%
1999	–7.77%	5.41%	4.82%
2000	3.90%	36.39% **	21.50% ***
2001	40.54% ***	–20.04%	–19.62% **
2002	22.42%	55.85% **	–4.70%
2003	34.75% ***	2.71%	–0.68%
2004	13.21%	40.96%	–4.50%
2005	14.51%	–4.86%	10.43% *
1993–2005	12.60% ***	11.54% **	2.40%
t-statistic	4.10	2.44	0.86

Our results concerning the WML portfolio returns are not necessarily at odds with previous studies. Demir, Muthuswamy and Walter (2004) use a different group of stocks for their analysis and their sample period ends in 2001, which misses the negative momentum returns that we report for later years. We re-estimated

18. The WML returns do not exhibit the seasonality reported by Durand, Limkriangkrai & Smith (2006b). The average July returns (1.2%) are not the highest compared to other months and they are not statistically different from several other months.

momentum returns from 1990 to 2001 and found a statistically significant average annual return of 5.92% which confirms the results reported by Demir, Muthuswamy and Walter (2004) and Liew and Vassalou (2000). Also, Durand, Limkriangkrai and Smith (2006b) find that for the 1990–2001 period, momentum returns are positive and significant. We find that from 2001 onwards momentum returns are mostly negative, which makes them insignificant. We should note that this reversal in momentum returns from 2001 onwards is not confined to Australian stocks. Identical results are presented for US stocks by Henker, Martens and Huynh (2006).

Even if factor returns are not consistent, studies on the Australian market find that the returns of these portfolios can explain realized stock returns which are not adequately explained by the CAPM. We begin the analysis by examining if the CAPM is rejected in favour of a four factor model which, apart from the excess return of the market portfolio also includes the SMB, HML and WML factor portfolio returns. For space considerations we do not report the regressions for the CAPM.[19] Similar regressions have been reported by several researchers and our results confirm the existing evidence. The static CAPM is rejected for the Australian stock market because the intercept for most regressions is statistically significant (see, Gaunt 2004). The four factor model does a much better job at explaining realised returns. The results for this model are reported in table 3.

If the size and BM factors are indeed priced in the Australian stock market, we would expect them to be statistically significant with coefficients rising monotonically from small to big stock portfolios and from low to high BM portfolios. For comparability with previous studies, we do not create portfolios sorted by momentum profits. If however, momentum returns are not dependent on size or BM effects in the Australian market, we should find that the WML factor has some role in explaining realised returns for most portfolios. The results suggest that market betas do not follow any specific pattern with respect to size or BM. However, within each BM quintile, the small stock portfolios have always the highest beta. All market betas are statistically significant. The results with respect to the size and BM factors are consistent with Gaunt's (2004) results. The SMB factor is significant for most portfolios. The exceptions are few portfolios which contain only big stocks. Also, the SMB coefficients of the small stock quintile are all higher than one and within each BM quintile, SMB coefficients rise monotonically. For the HML factor, about half of the factor loadings are statistically significant with some weak evidence of monotonic increase in the coefficients within size quintiles. Finally, the WML factor has some marginal explanatory power, with five statistically significant coefficients at the 5% level and one at the 10% level. This suggests that there may be a momentum factor at work.[20] Overall, our results confirm existing evidence that there is a strong size effect and a weaker BM effect in the Australian stock market. We also find that momentum returns have limited power in explaining realised returns.

19. The results are available from the author upon request.
20. We have also run the regressions in table 3 without the momentum factor (the results are available upon request). The results are not very different to the three-factor model. The intercepts are slightly higher but their p-values do not exhibit much difference and the R2 of the regressions are about the same. This evidence favours Durand, Limkriangkrai & Smith (2006b) who argue against a pervasive momentum effect in Australian stock returns.

Table 3

Australian Static Four Factor Model Regressions

156 monthly observations are used for estimation from July 1992 to June 2005. The sample includes returns for all Australian stocks available on Datastream, except for those in the financial sector. From these stocks we construct 25 portfolios based on size and book to market values, according to Fama and French (1992). The estimated regression for each of the 25 portfolios is: $R_{i,t} – RF_t = a + b\ (RM_t – RF_t) + s\ SMB_t + h\ HML_t + w\ WML_t + e_t$ where R_i is the return for each of the 25 portfolios, RM is the market portfolio, RF is the risk free rate and SMB, HML and WML are the size, BM and momentum factors returns respectively. The factors returns are estimated using the Liew and Vassalou (2000) methodology. The left part of each section of the table reports the regressions coefficients and the right part reports the associated p-values. The bottom section reports the respective adjusted R^2 for each regression.

	Low BM	2	3	4	High BM		Low BM	2	3	4	High BM
intercept						*p value*					
Small	0.04%	–0.08%	0.27%	–0.72%	–0.41%	Small	0.98	0.90	0.64	0.16	0.12
2	–1.14%	–1.23%	–1.18%	–0.69%	–0.28%	2	0.00	0.00	0.00	0.05	0.31
3	–1.07%	–0.96%	–0.61%	–0.62%	–0.27%	3	0.01	0.01	0.06	0.02	0.31
4	–1.15%	–1.33%	–0.68%	–0.08%	0.02%	4	0.01	0.00	0.01	0.81	0.96
Big	–0.89%	–0.44%	–0.63%	–0.51%	–0.16%	Big	0.00	0.04	0.00	0.03	0.71
beta						*p value*					
Small	1.69	1.21	1.26	1.13	1.08	Small	0.01	0.00	0.00	0.00	0.00
2	0.72	0.62	0.81	0.86	0.86	2	0.00	0.00	0.00	0.00	0.00
3	0.91	0.98	0.89	0.87	0.95	3	0.00	0.00	0.00	0.00	0.00
4	1.09	0.95	1.05	0.82	0.86	4	0.00	0.00	0.00	0.00	0.00
Big	1.23	1.08	0.99	0.76	0.75	Big	0.00	0.00	0.00	0.00	0.00

Table 3 Cont.

	Low BM	2	3	4	High BM		Low BM	2	3	4	High BM
s						*p value*					
Small	2.21	1.25	1.26	1.13	1.08	Small	0.01	0.00	0.00	0.00	0.00
2	0.89	0.80	0.75	0.68	0.57	2	0.00	0.00	0.00	0.00	0.00
3	0.53	0.41	0.38	0.47	0.31	3	0.00	0.00	0.00	0.00	0.00
4	0.42	0.28	0.29	0.20	0.24	4	0.00	0.00	0.00	0.00	0.00
Big	–0.08	–0.06	–0.07	–0.08	0.11	Big	0.15	0.11	0.07	0.06	0.18
h						*p value*					
Small	0.61	0.13	0.27	0.47	0.82	Small	0.57	0.63	0.15	0.00	0.00
2	–0.73	–0.25	0.02	0.15	0.37	2	0.00	0.04	0.88	0.21	0.00
3	–0.61	–0.10	–0.17	0.28	0.36	3	0.00	0.44	0.10	0.00	0.00
4	–0.54	–0.26	–0.04	0.03	0.14	4	0.00	0.00	0.63	0.77	0.13
Big	–0.12	–0.08	0.02	0.22	0.18	Big	0.22	0.22	0.77	0.00	0.21
w						*p value*					
Small	1.02	0.55	–0.33	–0.04	–0.12	Small	0.29	0.03	0.06	0.78	0.29
2	–0.07	0.03	0.02	–0.09	0.01	2	0.52	0.78	0.88	0.39	0.90
3	0.02	0.00	–0.28	0.02	0.02	3	0.90	0.98	0.00	0.79	0.86
4	–0.15	–0.17	–0.03	–0.14	–0.07	4	0.22	0.05	0.77	0.15	0.44
Big	–0.01	–0.08	–0.16	–0.10	–0.27	Big	0.94	0.19	0.02	0.22	0.04
Adjusted R^2											
Small	0.23	0.48	0.57	0.56	0.72						
2	0.68	0.57	0.56	0.55	0.55						
3	0.57	0.50	0.56	0.60	0.50						
4	0.59	0.64	0.63	0.42	0.48						
Big	0.72	0.75	0.72	0.48	0.22						

The next step is to run equation (1) again using RLS. We use 1-year, 2-year and 5-year window lengths and choose the window length that produces the highest adjusted R^2s. The results confirm the Fama and French findings that one year regressions maximize adjusted R^2s, so this is the interval we use.[21] The results are reported in table 4.

It is obvious from the results in table 4 that accounting for time variation in factor loadings makes a big difference. The intercepts of the regressions follow the same pattern as in the static regressions. The low BM portfolios have negative intercepts which increase monotonically as we move to high BM portfolios, except for the case of the small portfolio quintile, where all intercepts are positive and quite high compared to the others. This suggests the existence of a strong size effect but only for the smallest stocks. In the other quintiles, the BM effect seems to be at work. What is interesting though, is that none of the intercepts is statistically significant even at the 10% significance level. The largest beta in each BM quintile is the one for the smallest stock portfolio. While this indicates a size effect consistent with previous results, there is no other evidence of a size effect. With respect to the BM effect, there is some tendency for betas to decline from low BM portfolios to high BM portfolios. All betas but one are significant at least at the 10% level.

To examine if the remaining three factors have any role in explaining realised returns in this setting, we re-estimate equation (2) using RLS regressions with one month increments. The results are reported in table 5. The most striking result is that none of the coefficients of the HML and WML factors are significant at the 5% level, while only one HML coefficient is significant at the 10% level. As for the size factor, it is significant only for 3 portfolios at the 5% level and 5 portfolios at the 10% level. Market betas follow the same pattern as in table 4. The only difference is that the inclusion of the additional three factors has made a few market betas statistically insignificant. Finding that the WML factor has no explanatory power under time varying risk comes at no surprise since its explanatory power was weak even when we assumed static factor loadings. What is surprising is that the BM effect has completely disappeared and the size effect has become marginal.[22] Our results confirm Ang and Chen (2005) who find for the US market that once we account for time varying systematic risk the CAPM cannot be rejected.[23]

21. The results using 2 year and 5 year windows are not reported for space considerations. We should note that there is little difference between the estimates obtained using 1 year and 2 year windows. However, using 5 year windows results in lower R^2s and more stable betas.
22. The reader may feel uncomfortable with these results because they were derived from regressions using just twelve monthly observations at a time. Using a rolling estimation window of 24 monthly observations yields qualitatively the same results but slightly lower adjusted R2s.
23. It should be noted though, that Ang and Chen (2005) use a conditional version of the CAPM with rather strict assumptions.

Table 4

Australian CAPM Regressions Using Rolling One-Year Windows

156 monthly observations are used for estimation from July 1992 to June 2005. The sample includes returns for all Australian stocks available on Datastream, except for those in the financial sector. From these stocks we construct 25 portfolios based on size and book to market values, according to Fama and French (1992). The estimated regression for each of the 25 portfolios is: $R_{i,t} – RF_t = a + b\ (RM_t – RF_t) + e_t$ where R_i is the return for each of the 25 portfolios, RM is the market portfolio and RF is the risk free rate. Each regression is estimated on a rolling basis using 12 monthly observations at a time with one month increments. All reported coefficients are average values of the rolling estimated coefficients. p values refer to the average t-ratios from each rolling regression.

	Low BM	2	3	4	High BM		Low BM	2	3	4	High BM
Average intercept						*Average p values*					
Small	3.13%	1.59%	1.87%	0.76%	1.42%	Small	0.48	0.52	0.45	0.71	0.38
2	–1.21%	–0.96%	–0.42%	0.13%	0.69%	2	0.49	0.55	0.76	0.93	0.54
3	–1.30%	–0.78%	–0.66%	0.07%	0.44%	3	0.36	0.51	0.57	0.95	0.68
4	–1.44%	–1.43%	–0.42%	0.19%	0.41%	4	0.31	0.12	0.66	0.84	0.67
Big	–1.30%	–0.62%	–0.63%	–0.32%	0.16%	Big	0.10	0.34	0.32	0.67	0.90
Average beta						*Average p values*					
Small	2.69	1.63	1.74	1.19	1.07	Small	0.12	0.06	0.04	0.09	0.08
2	1.38	1.07	1.09	1.18	0.94	2	0.02	0.05	0.03	0.01	0.02
3	1.49	1.21	1.20	0.92	0.96	3	0.00	0.00	0.00	0.01	0.01
4	1.58	1.21	1.17	0.90	0.91	4	0.00	0.00	0.00	0.01	0.01
Big	1.34	1.15	0.99	0.67	0.90	Big	0.00	0.00	0.00	0.00	0.03
Average adjusted R^2											
Small	0.28	0.32	0.28	0.28	0.31						
2	0.32	0.25	0.36	0.36	0.36						
3	0.48	0.50	0.50	0.43	0.43						
4	0.53	0.58	0.56	0.47	0.44						
Big	0.72	0.74	0.70	0.45	0.34						

Table 5

Australian Four Factor Model Regressions Using Rolling One-Year Windows

156 monthly observations are used for estimation from July 1992 to June 2005. The sample includes returns for all Australian stocks available on Datastream, except for those in the financial sector. From these stocks we construct 25 portfolios based on size and book to market values, according to Fama and French (1992). The estimated regression for each of the 25 portfolios is: $R_{i,t} - RF_t = a + b\,(RM_t - RF_t) + s\,SMB_t + h\,HML_t + w\,WML_t + e_t$. where R_i is the return for each of the 25 portfolios, RM is the market portfolio, RF is the risk free rate and SMB, HML and WML are the size, BM and momentum factors returns respectively. The factors returns are estimated using the Liew and Vassalou (2000) methodology. The left part of each section of the Table reports the regressions coefficients and the right part reports the associated p-values. The bottom section reports the respective adjusted R^2 for each regression. Each rolling regression is estimated using 12 monthly observations at a time with one month increments. All reported coefficients are average values of the rolling estimated coefficients.

	Low BM	2	3	4	High BM		Low BM	2	3	4	High BM
Average intercept						*Average p values*					
Small	–1.19%	1.43%	–0.14%	–1.03%	–0.55%	Small	0.83	0.60	0.96	0.65	0.68
2	–1.12%	–1.42%	–1.42%	–0.87%	–0.11%	2	0.48	0.38	0.35	0.57	0.93
3	–0.84%	–1.03%	–0.81%	–0.82%	–0.22%	3	0.59	0.48	0.54	0.48	0.88
4	–1.68%	–1.38%	–0.66%	0.19%	0.05%	4	0.34	0.27	0.59	0.90	0.97
Big	–0.88%	–0.33%	–0.50%	–0.45%	–0.22%	Big	0.40	0.70	0.57	0.65	0.90
Average beta						*Average p values*					
Small	2.54	0.92	1.63	1.16	1.09	Small	0.30	0.39	0.10	0.19	0.05
2	0.73	0.73	0.86	1.03	0.98	2	0.23	0.22	0.14	0.09	0.03
3	1.16	0.97	0.86	0.96	0.90	3	0.05	0.09	0.09	0.02	0.10
4	1.34	0.96	0.98	0.76	0.81	4	0.04	0.05	0.03	0.21	0.10
Big	1.27	0.93	0.97	0.76	0.93	Big	0.00	0.00	0.00	0.03	0.13

Table 5 Cont.

Average s						*Average p values*				
Small	1.86	0.98	1.21	1.02	0.82	Small	0.10	0.10	0.06	0.04	0.00
2	0.87	0.71	0.63	0.58	0.32	2	0.02	0.09	0.06	0.08	0.26
3	0.41	0.22	0.24	0.39	0.18	3	0.26	0.50	0.43	0.16	0.57
4	0.42	0.28	0.15	–0.02	0.07	4	0.28	0.33	0.61	0.94	0.83
Big	–0.16	–0.22	–0.16	–0.19	–0.12	Big	0.52	0.25	0.47	0.46	0.75
Average h						*Average p values*					
Small	0.68	0.00	0.70	0.55	0.88	Small	0.70	1.00	0.48	0.51	0.06
2	–0.80	–0.19	0.11	0.28	0.36	2	0.17	0.75	0.83	0.61	0.43
3	–0.46	0.03	0.06	0.35	0.45	3	0.41	0.95	0.90	0.41	0.38
4	–0.46	–0.20	0.09	0.00	0.31	4	0.45	0.67	0.84	1.00	0.52
Big	–0.17	–0.07	0.07	0.29	0.44	Big	0.64	0.81	0.82	0.44	0.48
Average w						*Average p values*					
Small	–0.03	0.25	–0.21	–0.02	–0.05	Small	0.98	0.79	0.82	0.98	0.92
2	0.17	0.28	0.01	–0.06	0.06	2	0.76	0.63	0.99	0.91	0.88
3	–0.07	0.36	–0.02	0.18	0.12	3	0.90	0.48	0.96	0.66	0.81
4	–0.06	0.02	0.16	–0.08	0.05	4	0.92	0.96	0.72	0.88	0.92
Big	0.03	–0.12	–0.06	0.00	–0.30	Big	0.93	0.67	0.86	1.00	0.62
Average adjusted R^2											
Small	0.65	0.69	0.68	0.70	0.80						
2	0.75	0.66	0.68	0.73	0.71						
3	0.76	0.73	0.74	0.73	0.67						
4	0.74	0.74	0.74	0.64	0.64						
Big	0.82	0.84	0.80	0.64	0.59						

In order to examine more formally which model best fits the data, we follow Durand, Limkriangkrai and Smith (2006a) and we employ a Kolmogorov-Smirnov test of the null hypothesis that the p-values of the intercepts of the 25 portfolios conform to a uniform distribution.[24] The test statistic for the static four-factor model has a value of 0.54 (p-value of 0.00) which clearly rejects the null hypothesis. The respective test values for the time varying CAPM and four factor model are 0.21 and 0.32 with p-values of 0.30 and 0.025 respectively. Although the Kolmogorov-Smirnov test is not a formal test of model efficiency, it suggests that the p-values of the intercepts of the time-varying CAPM have the distribution we would expect from a complete asset pricing model.[25]

4. Risk Factors and the Business Cycle

Why is the significance of the Fama and French factors as well as the momentum factor so diminished if we introduce time variation in factor loadings? A possible explanation can be found if we consider the empirical findings of Liew and Vassalou (2000) who find that the SMB and HML factors are related to business cycles. In order to examine the cyclicality of factor returns, we estimate the SMB, HML and WML portfolio returns during good states and bad states of the economy, by sorting our sample by GDP growth. A good state is a state when the economy exhibits the highest 20% of GDP growth and a bad state is when the economy exhibits the lowest 20% of GDP growth within our sample period. Panel A of Table 6 reports the average HML, SMB and WML returns during good and bad states. All returns are higher during periods of strong economic growth. The WML premium is in both cases negative, which implies that it is not really related to the state of the economy, a result which confirms the evidence presented by Liew and Vassalou (2000).[26] The HML premium is 0.96% in good states and 0.66% in bad states, and a t-test shows that the difference is not statistically significant. However, there is a big difference between the good and the bad state SMB premium. In bad states it is –0.47% while in good states it is 1.84%. The average SMB premium for the entire sample period is 0.86% per month, indicating a clear relationship between the size effect and the state of the economy, which is verified by a t-test for equality between the good and bad state premium.

24. The efficiency of a model is usually tested with the Gibbons-Ross-Shanken tests of multivariate efficiency. In our study we use rolling regressions which makes the application of this test inappropriate. Durand, Limkriangkrai & Smith (2006a) argue that a complete model of excess returns should result in statistically insignificant intercepts. Considering that we run 25 regressions, one or two intercepts may be significant by chance. Thus, the p values of the intercepts of a complete model should conform to the uniform distribution.

25. We do not argue that the time-varying CAPM is complete. An examination of table 5 indicates that for some portfolios the SMB factor is significant. In other words, a size effect may be present even if we account for time varying systematic risk.

26. Note that the average monthly return of the WML portfolio for the whole sample period is 0,20%. It is negative only during good and bad states of the economy, which is probably a chance finding.

Table 6

Factor Returns and CAPM Betas During Good and Bad Economic States

Panel A reports the average monthly HML, SMB and WML portfolio returns during good and bad states of the economy. A good state is a state when the economy exhibits the highest 20% of GDP growth and a bad state is when the economy exhibits the lowest 20% of GDP growth. The p values refer to t-tests of equality of mean returns between good and bad states. The null hypothesis is equality of mean returns.

Panel B reports average CAPM betas during good and bad states from rolling regressions using 12 monthly observations each and associated p values of statistical significance. To estimate the betas, we identify periods of good and bad economic state, and for each sub-period we estimate the CAPM for each of the 25 portfolios sorted by size and book to market. The bottom section reports the difference between good and bad state betas ($\beta_{good} - \beta_{bad}$) and p values for t-tests of equality between good and bad state betas. The null hypothesis is equality of betas.

Panel A: Factor returns in good and bad economic states

	HML	SMB	WML
Good states	0.96%	1.84%	–0.35%
Bad states	0.66%	–0.47%	–0.77%
P values	0.37	0.04	0.24

Table 6 Cont.

Panel B: Market betas in good and bad economic states

	Low BM	2	3	4	High BM		Low BM	2	3	4	High BM
Good state market betas						*P values*					
Small	2.33	1.69	1.54	1.40	1.07	Small	0.04	0.04	0.07	0.09	0.07
2	1.27	1.12	0.95	1.26	0.75	2	0.05	0.05	0.06	0.01	0.07
3	1.51	1.27	1.14	0.88	0.91	3	0.00	0.00	0.01	0.02	0.01
4	1.48	1.05	1.14	0.77	0.86	4	0.00	0.00	0.00	0.04	0.01
Big	1.34	1.30	0.91	0.65	1.00	Big	0.00	0.00	0.00	0.01	0.04
Bad state market betas						*p values*					
Small	1.20	1.06	0.96	0.78	0.62	Small	0.14	0.08	0.16	0.15	0.06
2	0.92	0.50	0.66	0.69	0.64	2	0.07	0.21	0.05	0.04	0.03
3	1.18	1.00	0.81	0.69	0.75	3	0.00	0.00	0.00	0.02	0.00
4	1.21	0.92	0.89	0.81	0.84	4	0.00	0.00	0.00	0.01	0.00
Big	1.27	1.11	1.00	0.72	0.68	Big	0.00	0.00	0.00	0.00	0.08
Difference in betas						*p values*					
Small	1.12	0.63	0.58	0.63	0.45	Small	0.00	0.01	0.00	0.00	0.01
2	0.35	0.62	0.28	0.57	0.11	2	0.07	0.00	0.01	0.00	0.23
3	0.33	0.27	0.33	0.19	0.16	3	0.02	0.02	0.00	0.01	0.01
4	0.27	0.13	0.26	–0.04	0.02	4	0.01	0.04	0.02	0.27	0.43
Big	0.07	0.20	–0.08	–0.07	0.32	Big	0.21	0.01	0.04	0.14	0.03

While we would expect some difference in the performance of small and value stocks during good and bad times, it is not obvious that their betas should vary with the business cycle.[27] To examine the cyclicality of market risk, we sort our sample by GDP[28] growth and estimate betas using RLS regressions for good and bad states of the economy. Panel B of table 6 reports average CAPM betas from rolling regressions for good states and bad states. From the 25 betas, 22 are higher during good states of the economy. The ones which exhibit the biggest difference within each BM quintile are the betas of the small stock portfolios. The biggest difference in betas is the one for the smallest stocks with low BM, which again confirms that in the Australian market, the size effect is the dominant one with the BM effect following. This is also evident from the difference in betas in the two states, reported at the bottom section of table 6. The difference in betas seems to increase with size, but the same is not true as we move from low BM to high BM portfolios. The p-values reported at the bottom of table 6 show that the difference in betas is statistically insignificant for only 6 portfolios which belong mostly in the quintiles with big stocks. Note that the three betas which are higher in bad states compared to good states also refer to portfolios with big stocks. In other words, the betas of small stock portfolios are higher in good times but this is not the always the case for betas of big stock portfolios. This is strong evidence that market risk varies with the state of the economy and accounting for this variation, results in diminished size, BM and momentum effects.

One more thing we should note is the behaviour of the small stock and high BM factor loadings over time. Franzoni (2006) finds for the US market that while time variation in factor loadings may explain some of the size and BM effect, the two factors still have some role to play because the betas of small and high BM portfolios tend to fall over time. The same result is also reported by Fama and French (2006) for US stock returns. A falling coefficient for the small stock and the high BM portfolio implies that the time varying CAPM was able to capture their superior returns until a few decades ago, but not any more. We find that this is not the case for the Australian market. We estimate rolling betas for the small and high BM portfolios used to construct the SMB and HML factor returns. The average beta for the Small and High BM portfolios during the first half of the sample period is 1.32 and 0.86 respectively, while for the second half of the sample period the respective figures are 1.45 and 0.92. In other words, there is no evidence of decreasing betas.

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27. As Liew and Vassalou (2000) argue, small companies are riskier than large companies which makes them a very risky investment in bad times because they have less chance of survival. However, in good times, they have a good chance of survival and of achieving higher returns compared to large companies. Rational investors will hold small companies during good times, raising their prices, and avoid them during bad times, pushing their returns down. This is the most likely explanation why we see this clear pattern in the SMB premium.

28. GDP data are available quarterly so, for each quarter we have three beta estimates. For example, the highest GDP growth during our sample period was observed for 2005, quarter 2. Thus, the first three observations of rolling beta estimates for the 'good state' sub sample are those for April, May and June 2005.

5. Conclusion

The Fama and French factors, as well as the momentum factor, have attracted the attention of many researchers, who find that the CAPM does not perform adequately in explaining realised returns. A year-by-year analysis of the factors' returns reveals that they produce positive statistically significant returns for very few years. We also find that the returns of SMB, HML and WML arbitrage portfolios are significant in explaining realised returns, assuming static factor loadings. However, our results suggest that time variation in factor loadings is an important consideration when testing asset pricing models. When the CAPM is estimated using static OLS, beta is assumed to be constant throughout the period examined, an assumption which has been refuted by empirical evidence. Under this assumption, our findings confirm previous studies, such as Gaunt (2004). When we introduce time variation in factor loadings, the picture is different. The explanatory power of the returns of the HML and WML portfolios seems to disappear, while the explanatory power of the SMB portfolio returns is diminished. Further tests suggest that the Fama and French factors may account for time variation in market risk which is related to the business cycle.

The results presented here have serious implications for asset pricing in two ways. First, the significant improvement in explanatory power when we move from the static CAPM to the time-varying CAPM suggests that studies on the Australian market should focus on models of time-varying returns. The statistical significance of variables included in static models could be due to misspecified systematic risk. The second implication of our results is that the Fama-French factors, as well as the momentum factor, do not seem to work for the Australian market. The latest studies by Fama and French argue that the value premium is pervasive in almost all major stock markets and cannot be explained by the CAPM. Our findings combined with the results of other researchers suggest that the Australian market is an exception to this rule (and maybe not the only one). This means that if the Fama-French model indeed works for the US market, then the return-generating process may differ from country to country. The causes of these differences are left to future research.

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