

TECHNOLOGY PROSPECT AND THE CROSS-SECTION OF STOCK RETURNS: EVIDENCE FROM THE AUSTRALIAN MARKET

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Abstract

We examine the link between technology prospect and stock returns in the Australian market. Our results suggest that the technology-based asset pricing model outperforms the CAPM and Fama-French three-factor models in explaining the cross-section of the Australian Fama-French 25 size/book-to-market portfolios. The results prove robust to using alternative estimation methods and continue to support the importance of the technology factor for shaping the cross section of the Fama-French portfolios returns****.

Keywords: Technology prospect, ICAPM, asset pricing, Australian stock market

JEL Classification: G12

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****Eduardo Roca provided helpful comments.

1 Introduction

Throughout the 21st century, technology has played an increasingly important role in shaping economic activity in many countries. Previous studies have explored the contribution of technology progress to economic growth both at the global macroeconomic level (Sutton, 1998; Yang, 2006; and Kim, Maskus, and Oh, 2009) and at the firm level (Pakes 1985; Chauvin and Hirschey, 1993; and Eberhart, Maxwell and Siddique, 2004).

Several prior studies support the contention that macroeconomic variables help explain the cross section of stock returns (Campbell, 1996; Jagannathan and Wang, 1996; Vassalou, 2003; Kim, Kim and Min, 2011; and Kang *et al.*, 2011). Technology prospect, being a sensible and distinct macroeconomic risk factor, should be able to help explain the cross-sectional variation of equity returns under Merton's (1973) intertemporal capital asset pricing model (ICAPM) framework.

Merton's ICAPM suggests that all economic variables affecting investment opportunity set might be regarded as systematic risk factors in the pricing kernel. As shown by Cochrane (2005), the ICAPM is a linear factor model of wealth and state variables which forecast changes in the distribution of future returns. The technology literature suggests that technology progress strongly affects macroeconomic growth

which in turn stimulates abnormal returns at the firm level. Therefore, the anticipation of future technology progress acts within Merton's ICAPM as an effective state variable in shaping investment opportunities. Moreover, the production and investment-based models of Cochrane (1996); and Balvers and Huang (2007) indicate that the expectation of technology progress can serve as a state variable in the ICAPM.

Technology prospect is the future news about technology innovation which can play an important role in asset pricing. Yet, only a few studies focus on the expectation of technology progress in the ICAPM context. Most notably, Li (2009) and Hsu and Huang (2010) incorporate the technology prospect as a state variable in the ICAPM and report results in support of a significant role of technology prospect in explaining stock returns in Taiwan and the US, respectively.²¹ In addition, Zhang (2008) finds a Solow residual, representing an additional production systematic risk, to help explain the returns on R&D intensive industries. However, Hsu (2009) presents evidence for G7, China and India showing that technological innovation works better than the Solow residual as a

²¹ Papanikolaou (2008) also finds investment-specific technology change to be a source of systematic risk in the context of a dynamic general equilibrium model. Lin (2012) too supports the role of endogenous technology progress contributing to the cross-sectional variation of stock returns.

proxy for technological progress. In the Australian market, Nguyen, Faff and Gharghori (2009) find that news about future GDP growth is not priced in equity returns.

The present paper explores whether a new macroeconomic factor; namely, the anticipation of technology progress, can help price Australian common shares. Australia is one of the largest Asia-Pacific economies and belongs to the group of developed economies. Its equity market ranks the 8th largest in the world and the 2nd largest in the Asia-Pacific region, with an average daily secondary trading of 5 billion Australia dollars. In the pre-1980s era, Australia's position was mainly a "classical" imitator economy (Gans and Stern, 2003). However, since then, the country has more than doubled its innovation capacity, becoming a second-tier innovator economy with stable technology innovation growth.

This study is perhaps the first to discover that a new macroeconomic variable, namely technology prospect, is priced in the cross section of Australian equity returns. We also find that technology-augmented models outperform both the traditional CAPM and the Fama-French three-factor model. Our results not only provide out-of-sample support for the US evidence in Hsu and Huang (2010), but also imply a fruitful venue for explaining equity returns through macroeconomic asset pricing models.

We use the aggregate number of patents as a proxy for technology level and we construct the factor of technology prospect using Lamont's (2001) tracking portfolio method. We run cross-sectional regressions on the Australian Fama-French 25 size/book-to-market portfolios using Hansen's (1982) Generalized Method of Moments (GMM). And we also check the robustness of our results by Cochrane's (1996) "scaled factor" models in second-stage and GMM. The results we find consistently confirm the usefulness of technology systematic factor in the Australian data.

The remainder of the paper is organised as follows. Section 2 provides a brief background on the theoretical framework and outlines the implied hypotheses. Section 3 discusses the data and the processing of aggregate patent data. Section 4 examines the empirical results and Section 5 concludes.

2 Theoretical Framework and Implied Hypothesis

Like Hsu and Huang (2010), our technology augmented models find their origin in the work of Solow (1957). Solow explains a long-run economic growth through the simple Cobb-Douglas production equation:

$$Y = AL^\alpha K^\beta \quad (1)$$

where Y denotes total production, A denotes the technological variable, L is labor input and K is the capital input. Combining the Solow model with the assumption of aggregate budget constraints (Campbell, 1993) and the permanent income hypothesis (Friedman, 1957), the technology prospect represents a critical factor in determining the investors' optimal consumption choice. If the technology prospect looks brighter in the intra-period utility function, investors would achieve higher production and higher permanent income in the future. Consequently, investors expect less budget constraint inducing them to consume more and maximize their current utilities.

The basic asset pricing model in the stochastic discount framework, according to Cochrane (2005), takes the following Euler equation:

$$E_t[m_{t+1}(1 + R_{i,t+1})] = 1 \quad (2)$$

In the technology prospect-based asset pricing model, the factor of technology prospect serves as a competent state variable affecting the investment opportunity in the ICAPM. The technology factor is then captured by the following stochastic discount factor:

$$m_{t+1} = \frac{\beta w_t V_{ww}(w_t, z_t)}{V_w(w_t, z_t)} \Delta w_{t+1} + \frac{\beta z_t V_{wz}(w_t, z_t)}{V_w(w_t, z_t)} \Delta z_{t+1} \quad (3)$$

where $\Delta w_{t+1} = (w_{t+1} - w_t) / w_t$ is the market wealth growth, $\Delta z_{t+1} = (z_{t+1} - z_t) / z_t$ is the change in the technology prospect. This can be simplified as:

$$m_t = b_0 + b_m MKT_t + b_{tech} R_t^{tech} \quad (4)$$

where $b_{tech} = \frac{\beta z_t V_{wz}(w_t, z_t)}{V_w(w_t, z_t)}$ is the loading of technology risk factor. Moreover, b_{tech} is expected to be negative (see Appendix A for details).

Hsu and Huang (2010) develop the following technology augmented ICAPM model:

$$\text{Model (1)} \begin{cases} m_t = b_0 + b_m MKT_t + b_{tech} R_t^{tech} \\ E(R_i) - R^f = \lambda_m \beta_{m,i} + \lambda_{tech} \beta_{tech,i} \end{cases} \quad (5)$$

where the first equation is stochastic discount factor framework model while the second equation is the expected return-beta representation of the asset pricing model.

They also relate the technology prospect-based ICAPM model to the Fama-French three-factor model as follows:

$$\text{model(2)} \quad \begin{cases} m_t = b_0 + b_m MKT_t + b_{smb} SMB_t + b_{hml} HML_t + b_{tech} R_t^{tech} \\ E(R_i) - R_f = \lambda_m \beta_{m,i} + \lambda_{smb} \beta_{smb,i} + \lambda_{hml} \beta_{hml,i} + \lambda_{tech} \beta_{tech,i} \end{cases} \quad (6)$$

Using these technology-augmented models, we propose the following hypotheses:

H1: The technology factor helps pricing assets, thus the coefficient of the technology factor is negative and significantly different from zero: $b_{tech} < 0$.

H2: The technology factor is priced, thus the value of the technology factor is significantly different from zero: $\lambda_{tech} \neq 0$.

H3: the existence of the technology factor improves the explanation of the cross-sectional variation of stock returns as indicated by the increment of R-square and the significance of JT-difference test.

3 Data and Summary Statistics

3.1 Data

We use the ASX/Standard & Poor's 200 accumulation index for the Australian stock market index. The quarterly data series of ASX/S&P 200 accumulation index is sourced from the bulletin statistics at the Reserve Bank of Australia. The 25 size/BM portfolios are from O'Brien's (2008) who constructs the 25 Size/BM portfolios as follows. All stocks listed on the Australian Stock Exchange (ASX) are sorted into five groups (S, 2, 3, 4, B) from smallest to largest. Independently, all stocks are also sorted into five book-to-market (BM) groups (L, 2, 3, 4, H) from the growth portfolios to value portfolios. Thus, the 25 size/BM portfolios are constructed as the intersections of the five size groups and the five BM groups.

We collect patent data as a proxy for the technology level, i.e., quarterly total number of patents, from IP Australia's Search System for Australia Patents (Auspat) which contains Australian patent records dating back to 1904. The base total number of patents from 1904Q1 to 1983Q4 is 12,566²². We then add quarterly total number of patents to this base every quarter, thus obtaining the time series of "patent stock" as a proxy for the technology level for the period from 1984Q1 to 2006Q4.

3.2 Constructing the Technology Systematic Risk Factor

We follow Hsu and Huang (2010) in constructing the technology systematic factor. We first use the aggregate number of patents to represent the level of

the country's technology development. As in Hsu (2009), the technology shocks are modelled as:

$$Tech_t = \ln(r_{t-1}^{pat}) - \frac{1}{4} \sum_{h=1}^4 \ln(r_{t-h-1}^{pat}) \quad (7)$$

where $Tech_t$ is the patent shocks and r^{pat} is the aggregate number of patents. We assume one quarter lag in r_{t-1}^{pat} to accommodate the delayed time between technological inventions and their influence.

Next, we follow Lamont's (2001) tracking portfolio method to transform the patent shocks into the expectation of the future technology change in terms of monetary forms. We then regress patent shocks data series on base assets' excess returns and lagged control variables using a 5-year rolling-window:

$$Tech_{t,t+1} = a_t + c_t B_{t-1,t} + k_t Z_{t-2,t-1} + e_{t,t+1} \quad (8)$$

where a_t is an intercept, c_t is the vector of portfolio weights (i.e. projection loadings), k is the vector of coefficients for control variables (see Appendix B), $B_{t-1,t}$ is the vector of returns for base assets, $Z_{t-2,t-1}$ is the lagged control variables, and $e_{t,t+1}$ are the residuals. The base assets are 10 industrial portfolios that are most sensitive to technology innovations (see Appendix B). Following these steps, we capture the time series data of the technology risk factor $R_t^{tech} = c B_{t-1,t}$, which represent the expectation of future technology changes.²³ The addition of the specific control variables is suggested by Lamont (2001) and Vassalou (2003) in that they are well positioned to predict asset returns. This is why control variables help filter "noise" and "known information" to allow for measuring the "news" related to future economic activities.

3.3 Summary Statistics

Table 1, Panel A, suggests that the means and standard deviations of all variables are very small indicating minimal fluctuations in the Australia market and

²² The first patent application "Incomotive brake system" was received under the Commonwealth Patents Act of 1904.

²³ Note that the technology factor R_t^{tech} starts from 1988Q4 and ends in 2006Q4 since the first five-year rolling window (1984Q1-1988Q4) is consumed to capture the first point of the technology factor in 1988Q4.

economic indicators. The t-statistics indicate that the technology shock is highly significant.

Panel B shows that the tracking portfolio return of technology R^{tech} is significantly correlated with Hodrick Prescott-growth consumption at the 10% level, implying that the technology factor does have some influence on consumption and marginal utility

and could prove important as a state variable in the ICAPM. Meanwhile, R^{tech} is significantly correlated with the original technology factor $Tech$ at the 10% level since the R^{tech} is correspondingly sourced from $Tech$ in the tracking portfolios approach.

Table 1. Summary Statistics

	R^{tech}	Tech	MKT	SMB	HML	Con.
Panel A: descriptive statistics						
Mean	0.03%	-0.17%	0.43%	0.61%	0.62%	0.75%
Median	0.04%	-0.12%	0.52%	0.30%	0.67%	0.67%
Max (99%)	2.34%	1.23%	3.84%	16.2%	6.07%	2.4%
Min (1%)	-2.11%	-1.92%	-3.85%	-11.75%	-5.45%	-1.1%
Std.dev	0.72%	0.44%	1.84%	0.30%	2.27%	0.65%
Skewness	0.50	-0.92	-0.18	0.55	-0.17	0.11
Kurtosis	5.54	7.50	2.43	4.79	3.21	0.049
t-statistic	0.35	-3.34	2.02	1.19	2.34	9.92
$\rho(1)$	-0.011	0.037	0.037	-0.012	-0.029	-0.043
	[-0.09]	[0.31]	[0.31]	[-0.10]	[-0.24]	[-0.36]
ADF	-8.48	-8.14	-8.04	-8.43	-8.62	-8.65
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: correlation matrix						
R^{tech}	1.0					
Tech	-0.22 (0.053)	1.0				
MKT	0.34 (0.0028)	0.05 (0.67)	1.0			
SMB	0.10 (0.38)	0.036 (0.757)	0.15 (0.20)	1.0		
HML	0.0001 (0.999)	0.089 (0.45)	-0.18 (0.11)	-0.37 (0.001)	1.0	
Con.	0.22 (0.063)	0.023 (0.84)	0.14 (0.25)	-0.10 (0.38)	0.014 (0.91)	1.0

Notes: Panel A reports the descriptive statistic of all variables in Australia sample which are Tech, MKT, SMB, HML, Con. and R^{tech} . All the variables are from the period 1988Q4 to 2006Q4. The numbers in the blanket are Pearson's P-values and the numbers in square brackets are the t-statistic. $\rho(1)$ is the first order correlation of time series in each variable. ADF is the Augmented Dickey-Fully test for a unit root in time series. Panel B reports the pair correlation between each variable. "Con." denotes the consumption growth adjusted by Hodrick and Prescott's (1997) filter which captures the long-term consumption change without temporary noise. "Tech" denotes technology shocks and " R^{tech} " denotes the technology factor.

4 Empirical Results

We use the first-stage Generalized Method of Moment (GMM) methodology of Hansen (1982) to estimate the SDF version of the models, as well as time series/cross-sectional regressions (Cochrane, 2005) to estimate the return-beta representation models. Compared to multiple-stage of GMM, the first-stage GMM estimates are robust to small sample biases and

are more able to capture the underlying characteristics of the assets, as noted by Ludvigson (2013).

Table 2 displays our results for the Fama-French 25 size/book-to-market portfolios. Panel A reports the results for Fama-French 3 (FF3) factor model, as well as the results for the augmented FF3 model in Model (2).

Table 2. FF25 portfolios in one-step GMM and Cochrane's two-step regressions

	Const	MKT	SMB	HML	Tech	R2	JT-test	JT-diff
Panel A								
1. b	0.32	151.65*	-6.84	18.12	-295.75*	65.5%	28.48*	19.5*
t-stat(b)	1.02	4.76	-0.96	1.18	-5.43		(31.41)	(5.02)
λ (%)	3.60*	-3.40*	1.15*	0.06	0.85*			
t-stat(λ)	3.08	-3.03	4.14	0.12	2.32			
2. b	1.01*	41.64*	-13.89*	-19.89*		54.5%	47.98	
t-stat(b)	8.01	3.81	-3.93	-3.06			(32.67)	
λ (%)	1.42	-1.22	1.45*	0.84				
t-stat(λ)	1.43	-1.32	4.92	1.61				
Panel B								
3. b	0.87*	44.21*			-260.25*	25.1%	44.27	13.17*
t-stat(b)	5.70	2.70			-4.27		(33.92)	(5.02)
λ (%)	0.82	-0.08			1.14*			
t-stat(λ)	0.77	-0.08			3.02			
4. b	1.15*	-36.78*				6.1%	57.44	
t-stat(b)	11.37	-3.81					(35.17)	
λ (%)	-0.20	1.46						
t-stat(λ)	-0.18	1.60						

Notes: The figures in the table compare the Fama-French three factor model with technology Model (2) in panel A and compare the CAPM model with the ICAPM technology Model (1) in panel B. Robust t-statistic(b) is subject to GMM asymptotic normal distribution. The JT test examines if the model's goodness of fit and JT-difference test examines if the existence of the technology factor significantly improves the model. R-squares and t-statistic (λ) are subject to cross-sectional Cochrane two-steps OLS regression. The numbers in parentheses are the critical values of the JT-test and the JT-difference test at the 5% level of significance. The starred numbers are significant at the 5% level of significance. The sample period is 1988Q4-2006Q4.

As seen in Panel A for Model (2), the technology factor loading proves statistically significant with a negative value of -295.75; and the technology risk premium of 0.85% per quarter (or 3.40% p.a.) is also statistically significant. These findings support Hypotheses 1 and 2, respectively. Furthermore, the R-square is about 10% higher in FF3 model versus Model (2), and the JT-difference statistic is significant at the 5% level (statistic=19.5). Both of these outcomes support Hypothesis 3.

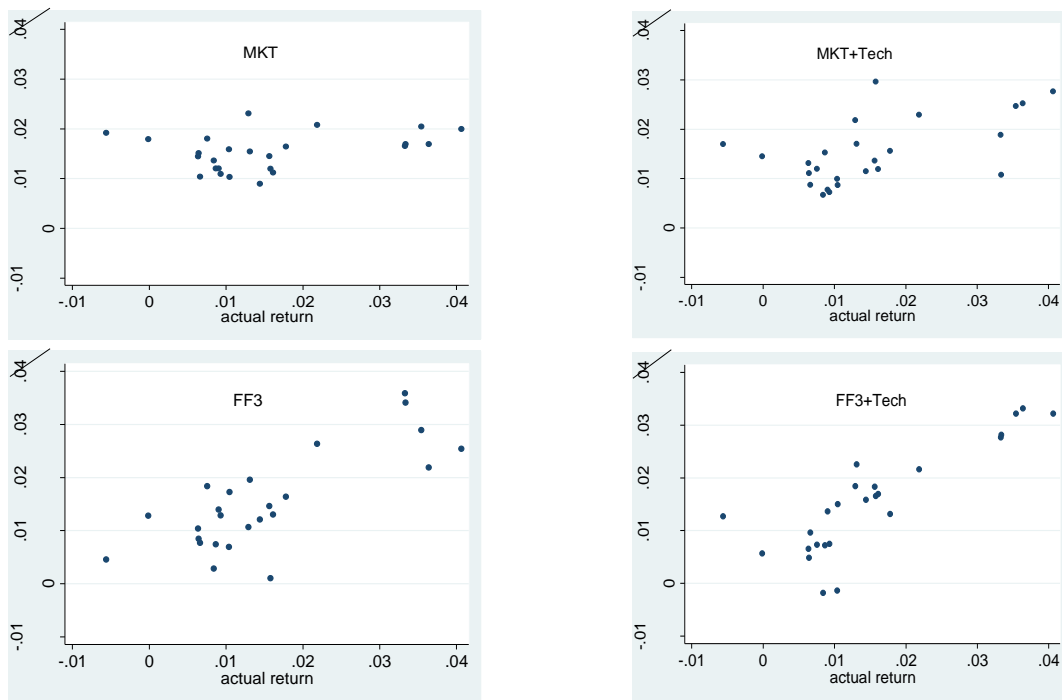
Panel B in Table 2 displays the results from the CAPM model and the technology factor-augmented ICAPM Model (1). Again, we find that the technology factor loading is statistically significant with a negative value of -260.25; and the technology risk premium of 1.14% per quarter (or 4.56% p.a.) is significant. Moreover, the R-square surges by 19% in CAPM model versus Model (1), and the JT difference test is also highly significant (statistic=13.17).

However, the JT-test for the CAPM, for technology ICAPM model and for the Fama-French three-factor model exhibit low goodness of fit. This is often the case, as Vassalou (2003) notes, when testing unconditional models. Our results for Australia on the Fama-French 25 portfolios are broadly consistent with

those reported for the US by Hsu and Huang (2010) and for Taiwan by Li (2009). Observe too that with the introduction of R^{tech} factor (the factor loading of SMB and HML), the risk premium of HML fails to remain statistically significant. In the Solow model, aggregate technology innovations is a key variable for changing GDP, and thus technology prospect should be a part of future news related to GDP growth. Results in Vassalou's (2003) consistently suggest that when news related to future GDP growth is present in the asset-pricing model, HML and SMB lose much of their significance.

Figure 1 depicts predicted versus actual returns. These plots indicate the superiority of the technology models whereby the dots get closer to the diagonal line both in the technology ICAPM model and in the technology model 2 compared to the CAPM model and the Fama-French three factor model. In particular, the five dots in right-hand-side become closer to the diagonal line in the technology ICAPM model compared to the CAPM model; and the center dots cluster more closely in the technology model 2 relative to the Fama-French three-factor model.

Figure 1. Predicted versus Actual Stock Returns



Notes: This plots display the fitness of four types of return-beta representation asset pricing models to the actual expected cross-sectional return in FF25 portfolios. Dots which are located exactly on the diagonal line indicate that the model perfectly predicts the actual return of portfolios. The graph titled “MKT” represents the CAPM model, “MKT+Tech” represents the technology ICAPM model, “FF3” represents Fama-French three factor models, and “FF3+Tech” represents technology model 2.

4.2 Robustness Checks

To ensure that we have not been misled by these results, we use Cochrane’s (1996) “scaled factor” instrumental approach and select two instruments: the inflation rate and the term spread. Model (3) is a

$$\text{Model (3)} \quad m_t = b_0 + b_m MKT_t + b_1 INF + b_2 TS + b_3 MKT_t * INF + b_4 MKT_t * TS \quad (9)$$

$$\text{Model (4)} \quad m_t = b_0 + b_m MKT_t + b_{tech} R_t^{tech} + b_1 INF + b_2 TS + b_3 MKT_t * INF + b_4 MKT_t * TS + b_5 R_t^{tech} * INF + b_6 R_t^{tech} * TS \quad (10)$$

$$\text{Model (5)} \quad m_t = b_0 + b_m MKT_t + b_{smb} SMB_t + b_{hml} HML_t + b_1 INF + b_2 TS + b_3 MKT_t * INF + b_4 MKT_t * TS + b_5 SMB_t * INF + b_6 SMB_t * TS + b_7 HML_t * INF + b_8 HML_t * TS \quad (11)$$

$$\text{Model (6)} \quad m_t = b_0 + b_m MKT_t + b_{smb} SMB_t + b_{hml} HML_t + b_{tech} R_t^{tech} + b_1 INF + b_2 TS + b_3 MKT_t * INF + b_4 MKT_t * TS + b_5 SMB_t * INF + b_6 SMB_t * TS + b_7 HML_t * INF + b_8 HML_t * TS + b_9 R_t^{tech} * TTS + b_{10} R_t^{tech} * IPG \quad (12)$$

where *INF* is the inflation rate, *TS* is the term spread between 10 year Australia government bond and the 90 day Australian accepted bills.

Table 3 provides the results for the 25 Fama-French portfolios using two-step GMM. Panel A displays the comparison between Models (5) and (6)

conditional CAPM model, while Model (4) is a conditional technology factor-augmented ICAPM model. Model (5) is a conditional Fama-French three-factor model and Model (6) is a conditional technology factor augmented Model (2):

and indicates that the technology factor loading remain significantly negative (-513), while the technology premium is significantly positive (1.58%). Panel B compares Models (3) and (4) and suggest that the technology loading and the technology premium are both significant with negative (-443) and positive

(1.30%) values, respectively. R-squared increases significantly in both pair of conditional models. Moreover, the statistical significance of JT tests in these four conditional models dramatically improves.

Hence, it appears that our conditional models overcome some of the problems in the unconditional models.

Table 3. FF25 portfolio in two-step GMM and Cochrane's two-step regressions

Model		Const	MKT	SMB	HML	Tech	Inf	TS	Tech* Inf	Tech*TS	R2	JT-test	
Panel A													
	3	b	2.63	224*	-42.7	-4.05	-513*	-246	21.09	37275	15875	97.9%	3.76*
t-stat(b)			1.42	2.03	-1.02	-0.06	-2.07	-1.20	0.23	1.50	1.61		(18.30)
λ (%)			1.89	-2.00	8.06	-3.34	1.58*	1.51*	-1.17	0.02*	-0.02		
t-stat(λ)			1.75	-1.19	0.93	-1.19	3.85	3.27	-0.37	3.54	-1.67		
	4	b	1.96	83.53	-33.7	-69.16		-207	85			66.1%	18.42*
t-stat(b)			1.61	1.60	-0.98	-1.49		-1.51	1.60				(22.36)
λ (%)			-0.90	2.21	12.94*	-2.58		0.82	-0.14				
t-stat(λ)			-0.65	1.61	2.38	-1.04		1.15	-0.08				
Panel B													
	5	b	2.31*	189*			-443*	-213*	-13.12	29769*	15849*	91.1%	8.98*
t-stat(b)			2.24	2.82			-3.06	-2.11	-0.31	2.21	2.14		(26.29)
λ (%)			2.31*	-2.10*			1.30*	1.28*	-1.13	0.02*	0.01*		
t-stat(λ)			3.04	-2.84			5.21	3.53	-1.30	4.24	-2.34		
	6	b	2.46*	134*				-	-37			58.6%	28.58*
t-stat(b)			3.89	3.06				236*	-3.34	-1.56			(30.14)
λ (%)			0.09	0.45				0.30	0.54				
t-stat(λ)			0.14	0.68				0.68	0.77				

Notes: See notes to Table 2. Panel A displays the comparable test statistics for the conditional Models (5) and (6), while Panel B does the same for the conditional Models (3) and (4). Due to the large size of parameters, the table only reports the main estimates.

In sum, our findings are consistent with Hsu and Huang's (2010) evidence that the captured conditional information improves the model fit. These results and those from the robustness checks strongly suggest that the model adequacy and efficiency require the presence of the technology prospect factor in the stochastic discount domain.

5 Concluding Remarks

Economic growth models ascribe a prominent role for technological progress in determining productivity and accumulating aggregate wealth. Since technology prospects impact investment opportunities, technology prospect can be used as a state variable in Merton's ICAPM. We provide evidence supporting this proposition using data from the Australian stock market.

Consistent with the evidence of Hsu and Huang (2010) for the US, our results for the Australia market lend strong support to the hypotheses we advance in this paper. In particular, we find that the technology factor significantly helps price assets in that its presence markedly improves the explanation of the cross-sectional variation of stock returns, and moreover the technology factor significantly contributes to explaining the time-series of stock returns in different portfolios with varying sensitivity to technology systematic risk.

Our study sheds some light on the usefulness of macroeconomic asset pricing models for explaining the cross section of Australia equity market. Technology prospect, through influencing future investment opportunity, affects asset prices in the ICAPM. Our results provide some clues in the search for better macroeconomic factors to explain asset pricing.

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Appendix A

We take the factor of technology prospect in the ICAPM model:

$$m_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)} = \beta \frac{u'[C(z_t)]}{u'[C(z_{t+1})]} = \beta \frac{V_W(W_{t+1}, z_{t+1})}{V_W(W_t, z_t)} = \frac{\beta w_t V_{ww}(w_t, z_t)}{V_w(w_t, z_t)} \Delta w_{t+1} + \frac{\beta z_t V_{wz}(w_t, z_t)}{V_w(w_t, z_t)} \Delta z_{t+1}$$

where $u(\cdot)$ is a utility function with respect to consumption, W is the total wealth and Z is a technology factor as the state variable, and $V(\cdot)$ is a value function in the Bellman equation. $u'(c_{t+1}) = V_W(W_{t+1}, z_{t+1})$ is the envelope condition.

The utility function for the risk aversion investor has two properties: monotonically increasing $V_w(w_t, z_t) = u_c'(\bullet) > 0$ and concavity, $u_c''(\bullet) < 0$. Since better technology prospect implies more productivity in the future, rational investors would decide to have more consumption currently: $\frac{\partial C(Z_t)}{\partial Z_t} > 0$. Eventually, we

can conclude the negative value of $b_{tech} : V_{wz}(w_t, z_t) = u_c''(\bullet) \frac{\partial C(Z_t)}{\partial Z_t} < 0$ and $b_{tech} = \frac{\beta z_t V_{wz}(w_t, z_t)}{V_w(w_t, z_t)} < 0$.

Appendix B

We follow Li's (2011) approach to obtain ten selected Australian industry portfolios: Energy (G1), Materials (excluding Metals and Mining) (G2), Capital Goods (G4), Automobile & Components (G7), Retailing (G11), Food & Staples Retailing, Household & Personal Products (G12), Pharmaceuticals & Biotechnology & Life Sciences (G15), Banks (G16), Utilities (G24), GICS Pending (G25).

Control variables are from the Australian Bureau of Statistic or DataStream, containing default rates, two sorts of term spread, inflation and industrial production growth. Term spread (1) is the Australian 10-year government bond yield minus 90 days Australian accepted bills. Term spread (2) is the Australian 1-year deposit rate minus Australian 3-month rate. Inflation is the growth rate of quarterly consumer price index in all groups. Default rate is Australian 10 year government bond yield minus Australian 10-year security interest rate yield.