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THE PREDICTABILITY OF AUSTRALIAN LISTED INFRASTRUCTURE RETURNS USING ASSET PRICING MODELS

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ABSTRACT
Can asset pricing models predict the future returns of publicly-listed infrastructure investments in Australia? We find that asset pricing models exhibit poor out-of sample predictive performance when compared to simple, fixed excess return models for the period 1997 through 2012. Similar to the work of Simin (2008) for the U.S., we suggest that using the long-term historical mean return may be a reasonable starting point for superannuation funds seeking to understand the long-term expected returns of publicly-listed infrastructure.
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The Predictability of Australian Listed Infrastructure Returns Using Asset Pricing Models

1. Introduction

It has long been recognised that well designed infrastructure investments deliver long-term benefits to investors and the broader economy alike. the (Demetriades and Mamuneas, 2000; Heintz, 2010; Hulten, 1996; Kamps, 2001, 2004; Munnell, 1992).[1] A number of studies havesuggested that infrastructure investments are low-risk due to: their regular income streams (Newbery, 2002; Rothballer and Kaserer, 2012);the nature of long term contracts in the infrastructure industry (Gregory and Michou, 2009); their position in lowly competitive markets due to high barriers to entry (Regan, Smith and Love, 2011a; Sawant, 2010); and the higher regulatory constraints that infrastructure firms operate in (Beeferman, 2008). The work of Newbery (2002) and Rothballer and Kaserer (2012) suggests that infrastructure investments are low risk due to the steady income stream inherent in these long-life assets.

Against this backdrop,, we examine the predictive (or otherwise) performance of conventional asset pricing models on Australian publicly-listed infrastructure investments returns. There are three motivations for this kind of analysis. First, the works of Lewellen and Nagel (2006), Simin (2008) and Welch and Goyal (2008) in the U.S. setting demonstrate that asset pricing models are poor predictors of U.S. stock returns. This type of work has not been published in the Australian setting and predictability of infrastructure returns have not been considered before. Second, the low-risk perception of infrastructure makes it a perfect candidate to evaluate the predictive performance of Australian asset pricing models. If the risk in infrastructure are lower than conventional equity than there is an increased probability that Australian asset pricing models may be able to forecast infrastructure returns. Third, and perhaps most importantly, respective Australian governments employ the principles of the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965; Mossin, 1966) in their evaluation of public-private partnerships (PPPs) to finance some infrastructure investments. Governments in Australia employ the Infrastructure

[1] However, we also acknowledge that there are a number of studies in Australia and globally that have documented poorly performing infrastructure investments (Cantarelli, Flyvbjerg, Molin and van Wee, 2010; Flyvbjerg, 2009; Regan, Smith and Love, 2011a and 2011b).

Australia (2013) guidelines for the development of discount rates for PPP infrastructure projects. This study will allow us to assess the efficacy of using the CAPM in this public policy setting.

Our results suggest that Australian asset pricing models are poor predictors of future publicly-listed infrastructure returns. Our initial sample from 1997-2007 shows that a fixed excess return of 4-5% per year is a better predictor of infrastructure returns than conventional asset pricing models. We then continue the test from 1997-2012 and find that the best predictor of infrastructure returns is a fixed excess return model of 1% per year. We proceed as follows. Section 2 reviews the literature relating to asset pricing and infrastructure returns. Section 3 explains the methodology employed in this study. Section 4 describes the data used in the study while Section 5 summarises the ex-post and predictive performance of asset pricing models on listed infrastructure returns. Finally, Section 6 provides concluding remarks and the implications that these findings have on investors.

2. Related Literature

Whilst the OECD (2007) and Infrastructure Australia (2013) estimate an infrastructure deficit around the world and in Australia, there is a paucity of research on infrastructure investments. Our understanding of infrastructure is limited by the scarcity of empirical studies in this important type of investment. Early studies by Beeferman (2008) suggest that the analysis of infrastructure is difficult due to the large scale idiosyncratic nature of individual projects. Despite the generally large size of infrastructure transactions, Croce (2011) states that these investments are desirable to pension and superannuation funds because of the long-term nature of these income generating assets which can offset their long-term pension liabilities. This issue becomes ever more important in a modern world where pension funds are exposed to longevity risk.

Others researchers such as Inderst (2009) suggest that institutions are interested in infrastructure investments in order to develop new sources of returns and portfolio diversification. For instance, Finkenzeller, Dechant and Schafers (2010) show that there are sufficient differences in the portfolio characteristics between infrastructure and real estate. Some of the early empirical infrastructure studies provide us with initial insights based on the knowledge available. Newell and Peng (2008) estimate a 0.70 correlation between U.S. stocks and listed infrastructure. Newell, Peng and De Francesco (2011) also report a strong and positive 0.48 correlation between Australian stocks and unlisted infrastructure. Other studies such as Newell and Peng (2007) reveal that various segments of Australian stocks classified as 'infrastructure' may indeed exhibit different return and risk profiles, thereby making it more difficult to determine the systematic return and risk for these types of investments.

In the context of asset pricing, Bird, Liem and Thorp (2012) is one of the first studies to examine the behaviour of infrastructure. Bird *et. al.,* (2012) reveal that infrastructure indices exhibit excess returns with low levels of systematic risks. One explanation for the low systematic risks comes from Rothballer and Kaserer (2012) who suggest that it is caused by the lower competition in infrastructure industries. Others including Newbery (2002) and Finkenzeller *et. al.,* (2010) argue that many infrastructure investments operate in oligopolistic and nearly monopolistic markets and these market structures may explain the low systematic risks identified in infrastructure returns.

Traditional methods of assessing the predictability of asset pricing models by Evans (1993), Ferson and Harvey (1991, 1993), Ferson and Korajczyk (1995) and Ghysels (1998) are based on the comparison of a model's fitted value versus the expected returns based on a long-term mean or a conditional estimate of the mean return. Furthermore, the literature finds it difficult to compare the predictive ability of two or more competing asset pricing models. To resolve these issues, the recent work of Giacomini and White (2006) has developed a two-step procedure to directly evaluate and compare the predictive performance of competing forecasting models in a unified framework. The application of the predictive performance of asset pricing models by Lewellen and Nagel (2006), Simin (2008) and Welch and Goyal (2008) in the U.S. setting demonstrate that U.S. asset pricing models exhibit poor predictive performance. Furthermore, Simin (2008) employs the Giacomini and White (2006) methodology and finds that the variance of asset pricing model forecast errors are so large that they cannot outperform the predictive abilities of a constant benchmark return. In this study, we employ the same methodology to evaluate the predictive performance of asset pricing models on Australian Securities Exchange (ASX) listed infrastructure returns. Given the low-risk nature of infrastructure, we expect the forecastability of asset pricing models to be better suited to infrastructure investments.

In the Australian literature, Durack, Durand and Maller (2004) and Nguyen, Faff and Gharghori (2007) show that information variables provide little or no additional power in explaining the variation of Australian equity returns.[2] In a thorough test of Australian conditional information variables, Whittaker (2013) evaluates conditioning information including inflation, industrial production, dividend yield, short-term interest rate, term premium, the short-term term premium, the January effect and finds that conditional versions of asset pricing models produce higher mean squared errors than unconditional versions for one month step ahead predictions.[3] Consistent with the U.S. literature, it is clear that Australian conditional asset pricing models do not improve the predictive performance of their unconditional counterparts.

3. Data

The analysis in this study is based on 16 years of monthly return data from January 1997 to December 2012. The focus of this study is on the ASX publicly listed infrastructure firms whose individual performances are summarised into four broad based proxies. The first proxy is the MSCI Australia Infrastructure Index which reflects the performance of ASX firms related to infrastructure assets. The MSCI Australia Infrastructure Index is a market capitalisation-weighted index with companies from the telecommunications services, utilities, energy, transportation and social infrastructure sectors. The second proxy for infrastructure used in this study is the S&P/ASX 200 Utilities Index which reflects the performance of companies who operate in the production and/or distribution of electricity, water utilities or gas. The third infrastructure proxy employed in this study is a market value-weighted index of all 37 firms combined from the MSCI Infrastructure Index and the S&P/ASX Utilities Index. We employ this market-valued weighted proxy as a broader summary of the

[2] Durack *et. al.,* (2004) employs the U.S. Government Term premium and Australian average weekly earnings as information variables in Australian conditional asset pricing models. Nguyen *et. al.,* (2007) use the Australian term spread, default spread as their information variables.

[3] Whittaker (2013) finds that Australian inflation and the 90 day bank bill rate are the most important conditioning information variables which report statistical significance at the 10% level over the sample period from 1991 through 2010.

performance of Australian infrastructure firms. The fourth and final proxy is the equal-weighted index of the 37 firms combined.

The analysis of Australian publicly listed firms means that we employ the Australian All Ordinaries Accumulation Index (AAOAI) as the proxy for market beta. We also design and construct the Australian versions of the Fama and French (1993) size (SMB) and value (HML) risk factors. The Australian equivalent of the Fama and Fench (1993) size factor (SMB) was constructed by sorting ASX listed firms according to market capitalisation using the Sirca SPPR database. Sirca data only identifies stocks as 'infrastructure' from the end of 1996 onwards. This is the commencement date of our study. Consistent with Fama and French (1992), the Small and Big portfolios were formed based on the median market capitalisation as the midpoint. The Australian version of the Fama and Fench (1993) value factor (HML) is constructed by sourcing the book values of ASX listed firms from the Morningstar FinAnalytics database. The limited time series of these book values limits the construction of our customised infrastructure indices to a commencement date of January 1997 because the first infrastructure (ie. Hills Motorway) commenced in this year. Consistent with Fama and French (1992), the High and Low HML portfolios were formed based on companies sorted by their book-value-to-market-value with breakpoints at the 30/40/30 intervals. Both SMB and HML risk factor portfolios are calculated as at December each year.

In terms of the risk-free rate, the data sample in our study straddles the period of John Howard federal government where budget surpluses were produced which resulted in Australian Commonwealth Government Treasury Notes no longer being issued from 2003 to 2008. This large five year gap without Treasury Notes means that there are no monthly returns available for these short-term liquid and low-duration risk-free assets known as Treasury Notes. As an alternative, one option is to employ the monthly returns of an Australian Commonwealth government 1 year bond, however, a methodology such as this ignores the interest rate or duration risk exposed to the investor. To offer a pragmatic alternative, this study employs the UBS Australia Bank Bill Index as a proxy for the risk-free rate. The index comprises of seven parcels of 90 day bank accepted bills which mature every 7 days and are reinvested in the index at the current bank bill rate. Furthermore, other studies such as Brailsford, Handley and Maheswaran (2008) also employ bank bills as a proxy for the Australian risk-free rate. It is important to note that records to date show that no Australian bank accepted bill has ever defaulted in the history of the Australian financial system.[4]

Table 1
Summary Statistics and Distributions

This table presents the summary statistics and distributions of the data employed in this study. AOAAI denote the Australian All Ordinaries Accumulation Index. VWAII denotes the Value-Weighted Australian Infrastructure Index constructed from 37 ASX listed firms in the MSCI Infrastructure and S&P Utilities indices. EWAII is the Equal-Weighted Australian Infrastructure Index which is the equal weighted version of the VWAII. MSCI Infra. denotes the MSCI Infrastructure Index. S&P Utilities denotes the S&P Utilities Index. SMB denotes the Fama and French (1993) Small-Minus-Big risk factor portfolio return which captures the Australian size premium. HML denotes the Fama and French (1993) High-Minus-Low risk factor portfolio return which captures the Australian value premium. The heading Start denotes the commencement month and year of the respective time series. Mean denotes the mean monthly rate of return. Std. Deviation denotes the standard deviation of monthly returns. The 5th percentile, median and 95th percentile headings denote the 5th, median and 95th percentile rates of returns of the empirical distribution of returns of the time series. The numbers reported in parentheses are annualised statistics. All time series are stationary based on the Augmented Dickey-Fuller (ADF) test.

	Start	Mean	Std. Deviation	5th percentile	Median	95th percentile
Panel A: Infrastructure Indices						
VWAII	1/1997	0.93%	4.56%	-7.64%	1.11%	7.02%
		(11.19%)	(15.79%)		(13.31%)	
EWAII	1/1997	0.80%	5.32%	-7.86%	0.26%	9.01%
		(9.59%)	(18.44%)		(3.12%)	
MSCI Infra.	1/1999	0.21%	4.37%	-7.10%	0.51%	6.28%
		(2.57%)	(15.14%)		(6.11%)	
S&P Utilities	4/2000	0.82%	4.09%	-6.54%	1.20%	6.21%
		(9.87%)	(14.17%)		(14.34%)	
Panel B: All Ordinaries Accumulation Index						
AAOAI	1/1997	0.67%	3.88%	-6.72%	1.51%	5.78%
		(8.08%)	(13.45%)		(18.08%)	
Panel C: Australian Fama-French Risk Factors						
SMB	1/1997	0.11%	5.15%	-7.83%	-0.07%	8.51%
		(1.32%)	(17.82%)		(-0.90%)	
HML	1/1997	0.38%	3.49%	-5.41%	0.46%	5.58%
		(4.54%)	(12.08%)		(5.48%)	
Panel D: Australian Risk-Free Proxy – UBS Australia Bank Bill Index						
Rf	1/1997	0.44%	0.09%	0.29%	0.43%	0.60%
		(5.28%)	(0.30%)		(5.16%)	

[4] For those readers who feel that the UBS Australia Bank Bill Index is an inadequate proxy for the risk-free rate, other researchers including Brailsford *et. al.,* (2008) also employ Australian bank bills as a proxy for the risk-free rate. In our study, the Australian Commonwealth 1 year Treasury Bond earned a 5.22% annual rate of return which is 6 basis points less than the 5.28% annual return from the bank bill index. In short, the 6 basis point difference between the two risk-free proxies is negligible.

Table 1 presents the summary statistics of the variables of interest. Panel A presents the infrastructure indices while Panel B reports the statistics of the All Ordinaries Accumulation Index (AAOAI). Panel A shows that the value-weighted infrastructure index (VWII) and the equal-weighted infrastructure index (EWII) outperformed the AAOAI over the same sample period. All infrastructure indices exhibit marginally higher levels of volatility in returns. It is unsurprising that the EWII exhibits the highest level of volatility given that smaller capitalisation stocks are more heavily weighted in this index. The median, 5^{th} and 95^{th} percentiles all suggest that the distribution of infrastructure indices are similar to the AAOAI.

Panel C presents the Australian versions of the Fama and French (1993) SMB and HML risk factors while Panel D reports the statistics of the risk-free proxy over the sample period. The interesting features here is the Australian SMB and HML risk factors recorded lower mean returns than the risk-free rate during the sample period, although the median of the HML factor was marginally higher than the risk-free rate. These interesting Australian based SMB and HML statistics are unsurprising given the previous works of Faff (2001) who revealed the negative performance of these Australian risk factors from 1991-1999. Overall, the summary statistics presented in Table 1 reflect the salient empirical features of the time series returns being employed in this study.

4. Methodology

This section of the paper is divided into four distinct parts. The first section details the asset pricing models employed in this study. The second section explains the rationale for employing a constant fixed excess return benchmark as a comparison for the competing asset pricing models. The third section details the state-of-the-art Giacomini and White (2006) methodology to determine the predictive performance of the best asset pricing model.

(i) Asset Pricing Models Tested:

Previous studies in the U.S. setting by Lewellen and Nagel (2006), Simin (2008) and Welch and Goyal (2008) show that conditional models report the worse predictive performance of asset pricing models in comparison to unconditional models. In the Australian setting, Durack *et. al.,* (2004), Nguyen *et. al.,* (2007) and Whittaker (2013) all demonstrate the conditional versions of asset pricing models do not improve the predictive power of their unconditional counterparts. Given these previous findings in the literature, this study examines the predictive power of the following Australian asset pricing models:

- Unconditional CAPM;
- Unconditional Fama and French (1993);
- Unconditional CAPM with intercept suppressed;
- Unconditional Fama and French (1993) with intercept suppressed;

Simin (2008) demonstrates that the suppression of the intercept when estimating the asset pricing model factors, results in an increase in the precision of the regression coefficient estimates. However, the increase in precision of the coefficient estimates is at the cost of increasing forecast bias. This study will follow Simin (2008) and include both types of regressions in the analysis.

The derivation of the forecasted returns follows the methodology of Simin (2008) and Fama and French (1997). Asset pricing parameters are estimated over a 60 month training period and are then multiplied by the average factor returns during the training period.[5] These are then used to predict the returns in the subsequent month.

(ii) Evaluation of Constant Benchmark Models:

We follow Simin (2008) and employ a fixed excess return model from a range of 1% to 10%. There are two rationales for a constant benchmark framework. First, we are interested in whether a fixed excess return model is a better predictor of asset returns than conventional asset pricing models. Simin (2008) finds that a constant U.S. equity risk premium return of 6% per annum is a better predictor of future returns

[5] The 'term training' period is employed to remain consistent with the terminology in Simin (2008).

than any unconditional or conditional asset pricing model. Second, the work of Bishop, Fitzsimmons and Officer (2011) suggest that the market risk premium in Australia is between 6-7% while Brailsford, Handley and Maheswaran (2008) estimate an Australian equity risk premium of 6.8% over bank bills from 1958-2008. In our study, we are interested whether the predictive performance of asset pricing models on infrastructure deliver similar approximations of an excess return of 6% per year (ie. commensurate returns) over the sample period of the available infrastructure data from 1997-2012.

(iii) Evaluation of Predictive Performance

This study follows Simin (2008) as it represents the state-of-the-art methodology for evaluating the predictive performance of asset pricing models to date. Consistent with Simin (2008), unconditional versions of the CAPM and the Fama and French (1993) three-factor model are examined and their performances are compared against a constant (or fixed excess return) benchmark. Following Simin (2008), we employ the fixed benchmark of six per cent per annum however, the performance of various other fixed benchmarks is also included.

Test 1: RMSFE

Following Simin (2008), the Root Mean Square Forecast Error (RMSFE) is employed as a measure of forecast accuracy. RMSFE quantifies the average squared distance between the expected return from the model and the realised return over the specified time horizon. According to Simin (2008), the advantage of the RMSFE is that it can disaggregate a measure of forecast bias to allow for the differentiation in forecasting models. The equation below shows how the forecast bias can be disaggregated from the Mean Square Forecast.

$$\text{MSFE}(\hat{r}_t) = \text{E}\left[\left(r_t\text{-}\hat{r}_t\right)^2\right] = \text{var}(e_t) + [\text{bias}(e_t)]^2 \qquad (1)$$

where $\text{MSFE}(\hat{r}_t)$ is the Mean Square Forecast Error for the model under consideration; r_t is the actual return of the portfolio under examination at time t; $\hat{r}_t$ is the forecast return of the portfolio under examination at time t; $\text{var}(e_t)$ is the variance of the difference between the actual and forecast returns of the portfolio under examination; and, bias(e_t) is the measure of forecast bias. By identifying the sign of the forecast bias, it is possible to identify the tendency of models to over or under predict subsequent returns. The RMSFE is simply the square root of the MSFE.

Test 2: Bias

Following Simin (2008), we derive the Bias from Equation (1). Bias is defined as the tendency of over- or under- prediction around the RMSFE. The nature of the RMSFE as a quadratic function means that under- and over- estimations of a similar magnitude are given an equal weighting in the calculation. By calculating the Bias, this allows us to identify systematic under- or over- estimation of the forecast errors. This Bias is informative for users interested in asymmetric preferences. For example, investment managers may be interested in models that consistently under-estimate long-term rates of return as you would employ those in an investment process rather than models that consistently over-estimate future rate of returns.

Test 3: Giacomini and White (2006) Test

As an alternative test of model performance, the Giacomini and White (2006) conditional predictive ability test is employed. The Giacomini and White (2006) test enables the best performing forecast model to be identified. The Giacomini and White (2006) test is a two-step procedure. The first step of the Giacomini and White (2006) test examines whether there is a statistical difference between two sets of forecast errors. The null hypothesis for this test is given as:

$$H_o\text{: E}\left[\hat{u}^2_{1,t+1} \text{-} \hat{u}^2_{2,t+1} \middle| F_t\right]\text{=}0 \tag{2}$$

where $\hat{u}$ is the forecast error (or the difference between actual and forecast) for model i at time t. The test statistic according to Giacomini and White (2006) for one period ahead forecast is given by nR^2. Where n is the number of forecasts examined and R^2 is the un-centred multiple correlation coefficient from the regression of $\Delta L_{m,t+1}$ on $h_t^{'}$. Giacomini and White (2006) define $\Delta L_{m,t+1}$ as the difference between the forecast error functions, or $\hat{u}^2_{1,t+1}$- $\hat{u}^2_{1,t+1}$ where m observations are employed as the estimation window. The term $h_t^{'}$ is defined by both Giacomini and White (2006) and Simin

(2008) as the vector $(1,\Delta L_{m,t}('$. The null hypothesis is rejected at the α test level when the test statistic is greater than the (1- α) quartile of the χ^2 distribution. For the purposes of this study, the chosen α of significance is ten percent, consistent with Simin (2008).

Once the two forecast series are found to be statistically different to each other, the second step in the Giacomini and White (2006) procedure is to determine which forecast model performs better. Giacomini and White (2006) suggest a decision rule based on the fitted values of the regression of $\Delta L_{m,t+1}$ on h_t'. The number of times the fitted values are positive in comparison to the competing model determines which forecasting model performs better. This decision rule is employed in this study. In this analysis, the predictive performance of the asset pricing models is compared over a number of different time periods, namely, one month, one year and two years. Future versions of this working paper may employ longer time horizons.

5. Results

The results section is divided into two distinct parts. First, we report the historical performance of asset pricing models (*ex post*) to provide the reader with an econometric picture and understanding of the systematic risk factors that explain the variation of Australian listed infrastructure returns. The second part of the results section reports the predictive performance of asset pricing models using the Giacomini and White (2006) and compares their performance with fixed excess return models.

Table 2
Unconditional Asset Pricing Model Regressions (Ex Post)

This table presents the regression results of the CAPM and the Fama-French three-factor model on the various proxies of ASX listed infrastructure indices. The first number is the regression coefficient. The number in brackets is the standard error. The number in curly brackets is the *t*-statistic. The number in parentheses is the *p*-value. Panel A reports the intercept term and the regression coefficient of the single-factor market model. Panel B presents the regression results of the Australian version of the Fama and French (1993) three-factor model. The *p*-values are estimated using Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors. * and ** denote statistical significance at the 5% and 1% levels, respectively.

Index Name	Intercept	Market Beta	SMB	HML	Adj R^2
Panel A: Capital Asset Pricing Model (CAPM)					
VWAII	0.0035	0.6365**			0.2933
	[0.0029]	[0.0673]			
	{1.1986}	{9.4549]			
	(0.2322)	(0.0000)			
EWAII	0.0017	0.8092**			0.3472
	[0.0032]	[0.0703]			
	{0.5392}	{11.5154}			
	(0.5904)	(0.0000)			
MSCI Infrastructure	-0.0031	0.4200**			0.1318
	[0.0029]	[0.0876]			
	{-1.0436]	{4.7922}			
	(0.2982)	(0.0000)			
S&P Utilities	0.0030	0.5076**			0.2314
	[0.0030]	[0.0878]			
	{1.0176}	{5.7838}			
	(0.3105)	(0.0000)			
Panel B: Fama-French Three-Factor Model					
VWAII	0.0032	0.6474**	-0.0185	0.0790	0.2904
	[0.0028]	[0.0703]	[0.0490]	[0.0843]	
	{1.1209}	{9.2030}	{-0.3765}	{0.9366}	
	(0.2638)	(0.0000)	(0.7070)	(0.3502)	
EWAII	0.0012	0.8373**	0.2207**	0.0446	0.3840
	[0.0032]	[0.0644]	[0.0644]	[0.0827]	
	{0.3816}	{12.9972}	{3.4277}	{0.5388}	
	(0.7032)	(0.0000)	(0.0007)	(0.5906)	
MSCI Infrastructure	-0.0034	0.4294**	0.0451	0.0358	0.1242
	[0.0031]	[0.0895]	[0.0629]	[0.0906]	
	{-1.0891}	{4.7967}	{0.7166}	{0.3945}	
	(0.2777)	(0.0000)	(0.4746)	(0.6937)	
	0.0022	0.5445**	0.0575	0.1762*	0.2436
S&P Utilities	[0.0030]	[0.0959]	[0.0474}	[0.0810]	
	{0.7370}	{5.6789}	{1.2114}	{2.1750}	
	(0.4623)	(0.0000)	(0.2277)	(0.0312)	

I. Asset Pricing Models (Ex-Post)

Table 2 presents the conventional asset pricing model regressions on Australian listed infrastructure returns. This provides the reader with a historical picture of the asset pricing model and the systematic risks that explain the variation of infrastructure returns. Panel A shows that all of the infrastructure indices in this study exhibit low systematic risk as expressed by their betas. The value-weighted and equal-weighted infrastructure indices report market betas of 0.65 and 0.84, respectively. It is unsurprising that the equal weighted index exhibits a higher beta due to the higher index weighting across smaller market capitalisation firms which generally tend to exhibit higher betas.

An interesting empirical observation in Table 2 is the joint interaction between the intercept term, the beta, the adjusted R^2, and the direct relevance to asset pricing. The econometric estimation of a systematic risk factor in asset pricing has been documented in the zero-intercept criterion of Merton (1973). According to Merton (1973), the systematic risk factors of an asset pricing model are captured when there is a statistically significant independent variable which coincides with an insignificant intercept term. The insignificant intercept terms in Table 2 means that there are no other systematic risk factors in the asset returns of listed infrastructure. The relatively low adjusted R^2s signify that these infrastructure returns exhibit relatively high levels of idiosyncratic risk.[6] These results differ to Bird *et. al.,* (2012) who estimate statistically significant excess returns in the Australian listed infrastructure returns in their study. The variation in our results and those of Bird *et. al.,* (2012) can be isolated to two main differences. First, their work examined a sample period from 1995-2009 while our study is from 1997-2012. The second difference is that Bird et al (2012) employed an augmented Fama and French (1993) three-factor model with GFR GARCH with *t*-statistic distributed errors while we employ a conventional asset pricing model.

[6] The Merton (1973) zero-intercept criterion has been employed in other asset Griffith (2002) and Fama and French (2004) in the U.S. setting, and by Limkriangkai, Durand and Watson (2008) in the Australian setting.

Table 3
Estimates of RMSFE and Bias

This table presents the RMSFE*100 and the forecast Bais*1000 for one-month, 1 year and two year asset model forecasts. VWII and EWII denote the value-weighted and equal-weighted infrastructure indices, respectively. MSCIAII denotes the MSCI Australia Infrastructure Index. S&PUI denotes the S&P/ASX 200 Utilities Index. The RMSFE with the lowest values for each index are highlighted.

	VWII		EWII		MSCIAII		S&PUI	
	RMSFE	Bias	RMSFE	Bias	RMSFE	Bias	RMSFE	Bias
Panel A: 1 month forecasts								
1%	4.1510	-0.0092	5.6376	-0.0183	3.6767	-0.0148	4.3472	-0.0224
2%	4.1471	-0.0131	5.6353	-0.0205	3.6746	-0.0169	**4.3461**	-0.0235
3%	4.1448	-0.0153	**5.6343**	-0.0216	**3.6744**	-0.0172	4.3466	-0.0231
4%	**4.1443**	-0.0159	5.6345	-0.0214	3.6760	-0.0155	4.3486	-0.0210
5%	4.1454	-0.0148	5.6359	-0.0199	3.6796	-0.0119	4.3523	-0.0173
6%	4.1482	-0.0120	5.6386	-0.0173	3.6850	-0.0065	4.3576	-0.0121
7%	4.1526	-0.0075	5.6425	-0.0134	3.6923	0.0008	4.3644	-0.0052
8%	4.1588	-0.0014	5.6476	-0.0083	3.7015	0.0100	4.3728	0.0032
9%	4.1666	0.0064	5.6539	-0.0019	3.7125	0.0210	4.3828	0.0132
10%	4.1760	0.0158	5.6615	0.0056	3.7253	0.0338	4.3943	0.0247
FF	4.1962	-0.0150	5.7144	-0.0219	3.8284	0.0177	4.4943	-0.0243
FFNI	4.1631	-0.0066	5.6441	-0.0212	3.7273	-0.0153	4.4332	-0.0212
CAPM	4.1996	-0.0146	5.7144	-0.0219	3.8310	0.0159	4.4991	-0.0244
CNI	4.1666	-0.0062	5.6602	-0.0167	3.7329	-0.0157	4.4361	-0.0217
Panel B: 1 year forecasts								
1%	4.2999	2.5709	4.8074	2.3620	**15.9308**	-0.0301	**19.9165**	-0.1223
2%	4.2237	2.4947	4.7369	2.2915	15.9386	-0.0223	19.9171	-0.1217
3%	4.1477	2.4187	4.6668	2.2214	15.9467	-0.0142	19.9180	-0.1208
4%	4.0721	2.3430	4.5971	2.1517	15.9554	-0.0055	19.9193	-0.1195
5%	3.9967	2.2677	4.5279	2.0825	15.9644	0.0035	19.9209	-0.1179
6%	3.9216	2.1926	4.4592	2.0138	15.9739	0.0130	19.9229	-0.1159
7%	3.8469	2.1179	4.3910	1.9456	15.9838	0.0229	19.9252	-0.1136
8%	3.7726	2.0436	4.3233	1.8779	15.9941	0.0332	19.9279	-0.1109
9%	3.6987	1.9697	4.2562	1.8108	16.0049	0.0440	19.9309	-0.1079
10%	**3.6251**	1.8961	**4.1897**	1.7442	16.0160	0.0551	19.9343	-0.1045
FF	7.8585	0.1911	8.1006	-0.0342	21.1628	-0.0449	26.2827	-0.0056
FFNI	6.5257	0.7599	7.4055	0.0289	19.0104	0.2284	26.6290	-0.1329
CAPM	7.8467	0.2543	8.4073	-0.0353	21.1203	-0.0639	26.2761	0.0706
CNI	6.0153	0.8791	6.9275	0.7299	19.0780	0.2530	23.5181	-0.1251
Panel C: 2 year forecasts								
1%	**1.4554**	0.0014	**1.6079**	-0.0076	**22.7795**	-0.1449	**15.1496**	0.1729
2%	1.4666	0.0126	1.6104	-0.0050	22.7827	-0.1417	15.1658	0.1890
3%	1.4824	0.0284	1.6172	0.0018	22.7862	-0.1383	15.1824	0.2057
4%	1.5027	0.0486	1.6282	0.0128	22.7899	-0.1345	15.1995	0.2227
5%	1.5272	0.0732	1.6434	0.0280	22.7940	-0.1304	15.2169	0.2402
6%	1.5558	0.1018	1.6627	0.0472	22.7984	-0.1260	15.2349	0.2581
7%	1.5883	0.1343	1.6858	0.0704	22.8031	-0.1213	15.2532	0.2765
8%	1.6244	0.1704	1.7127	0.0973	22.8081	-0.1164	15.2720	0.2953
9%	1.6639	0.2099	1.7432	0.1278	22.8134	-0.1111	15.2913	0.3145
10%	1.7066	0.2526	1.7770	0.1616	22.8190	-0.1055	15.3109	0.3342
FF	9.9152	2.9807	8.6212	1.4934	29.1224	-0.1530	23.6411	1.1838
FFNI	5.4458	0.2870	7.4857	1.3663	26.3950	0.0931	19.4607	0.4582
CAPM	10.0042	3.2487	8.9718	1.4361	29.0731	-0.1656	23.5416	1.4644
CNI	4.7853	0.2809	5.3002	0.3594	26.6966	0.0861	19.1203	0.5064

II. Predictive Performance of Asset Pricing Models (RMSFE and Bias)

Panel A of Table 3 shows that the fixed excess return models ranging from 2% to 4% exhibit the lowest forecast errors for future one month returns. Another interesting observation is the relatively similar RMSFE values for models that are above and below the lowest RMSFE. This finding suggests that there may be negligible differences between the predictive performance of one asset pricing model versus another. This hypothesis can be verified in the next section of the analysis when the Giacomini and White (2006) test is estimated. Furthermore, Panel A shows that the Bias across all infrastructure indices are generally negative. The negative bias suggests that asset pricing models generally under-estimate future one month returns, on average.

Panel B of Table 3 reports the RMSFE and Biases for 1 year forecasts. The RMSFE values are generally smaller than those reported for 1 month predictions. This finding suggests that the 1 year forecast errors are smaller than the 1 month forecast errors, however, you cannot directly compare RMSFEs across different forecasting time horizons. The exceptions are the MSCI Australia Infrastructure Index and the S&P/ASX 200 Utilities Index which report very large forecast errors. The Bias in Panel B is generally positive for most predictive models. The positive bias means that the asset pricing models in Panel B are over-estimating one year future returns, on average.

Panel C of Table 3 reports three interesting findings. First, the fixed excess return models for VWII and EWII report smaller RMSFEs than their equivalent models used to forecast 1 month and 1 year future returns. This suggests that the forecast errors over a two year time horizon are smaller than those reported in Panels A and B. In comparison, the MSCIAII and S&PUI exhibit the opposite behaviour whereby their RMSFEs based on 1 month forecast are smaller than the 1 year and 2 year forecasts. Second, the CAPM and Fama-French asset pricing models report larger RMSFEs in comparison to the same models when forecasting 1 month and 1 year future returns. This finding suggests that the CAPM and Fama-French models tend to be more effective at forecasting shorter time horizons than two years. Third, the Bias is almost always positive for the two year forecasts (except MSCIAII) which means that asset pricing models are generally over-estimating future two year returns, on average. Superannuation funds and investment managers need to be mindful that these asset pricing models exhibit a tendency to over-estimate expected infrastructure index returns across a longer two year time horizon.

Overall, the RMSFE and Bias estimates provide a summary of the forecast errors calculated in every asset pricing model. The RMSFE and Bias provides an indication of which asset pricing model provides the lowest forecast errors, however, they do not provide a statistical test to evaluate the predictive performance of these models. To address this issue, we now proceed to compare the predictive performance of these asset pricing models by employing the Giacomini and White (2006) test.

Table 4
Relative Forecast Performance of
Asset Pricing Model versus Fixed Excess Returns (pre-GFC)

This table presents the number of times that a fixed excess return and asset pricing model forecast is statistically significantly better than all other alternatives using the Giacomini and White (2006) Conditional Predictive Ability test based on the null hypothesis at the 10% level. The sample period is from January 1997 to December 2007. The independent variables are denoted as follows. VWII denotes the Value-Weighted Infrastructure Index of 37 firms. EWII denotes the Equal Weighted Infrastructure Index of 37 firms. MSCIAII denotes the MSCI Australia Infrastructure Index. S&PUI denotes the S&P/ASX 200 Utilities Index. The asset pricing models being tested are denoted in the column headings. The numbers 1% to 10% are the constant fixed excess returns from 1% to 10% per year. FF denotes the Australian Fama and French (1993) three-factor asset pricing model. FFNI denotes the Australian Fama and French (1993) three-factor asset pricing model with no intercept term. CAPM denotes the Australian single-factor Capital Asset Pricing Model. CAPMNI denotes the Australian single-factor Capital Asset Pricing Model with no intercept term.

	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	FF	FFNI	CAPM	CAPMNI
Panel A: 1 month forecasts														
VWII	0	0	0	0	0	0	0	0	0	0	1	0	0	0
EWII	0	0	0	0	1	1	0	0	0	0	0	0	0	0
MSCIAII	0	0	0	0	0	0	0	0	0	0	1	0	0	0
S&PUI	9	8	7	6	5	4	3	2	1	0	0	0	10	10
TOTAL	9	8	7	6	6	5	3	2	1	0	2	0	**10**	**10**
Panel B: 1 year forecasts														
VWII	2	5	6	7	8	9	10	11	12	13	1	4	0	3
EWII	0	1	2	3	5	7	9	10	11	12	0	0	4	8
MSCIAII	2	5	6	7	8	9	10	11	12	13	0	0	0	1
S&PUI	12	13	8	6	5	4	3	2	1	0	0	0	10	7
TOTAL	16	24	22	23	26	29	32	34	36	**38**	1	4	14	11
Panel C: 2 year forecasts														
VWII	5	7	9	11	10	8	6	4	4	3	0	0	0	10
EWII	4	6	8	10	12	13	11	9	7	5	0	0	0	3
MSCIAII	5	7	9	11	10	8	6	4	4	3	1	13	0	10
S&PUI	12	9	7	6	5	4	3	2	1	0	0	0	8	13
TOTAL	26	29	33	**38**	37	33	26	19	16	11	1	13	8	36

Table 5
Relative Forecast Performance of
Asset Pricing Model versus Fixed Excess Returns (Full Sample)

This table presents the number of times that a fixed excess return and asset pricing model forecast is statistically significantly better than all other alternatives using the Giacomini and White (2006) Conditional Predictive Ability test based on the null hypothesis at the 10% level. The sample period is from January 1997 to December 2012. The independent variables are denoted as follows. VWII denotes the Value-Weighted Infrastructure Index of 37 firms. EWII denotes the Equal Weighted Infrastructure Index of 37 firms. MSCIAII denotes the MSCI Australia Infrastructure Index. S&PUI denotes the S&P/ASX 200 Utilities Index. The asset pricing models being tested are denoted in the column headings. The numbers 1% to 10% are the constant fixed excess returns from 1% to 10% per year. FF denotes the Australian Fama and French (1993) three-factor asset pricing model. FFNI denotes the Australian Fama and French (1993) three-factor asset pricing model with no intercept term. CAPM denotes the Australian single-factor Capital Asset Pricing Model. CAPMNI denotes the Australian single-factor Capital Asset Pricing Model with no intercept term.

	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	FF	FFNI	CAPM	CAPMNI
Panel A: 1 month forecasts														
VWII	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EWII	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MSCIAII	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S&PUI	0	0	0	0	0	0	0	0	0	0	6	6	5	6
TOTAL	0	0	0	0	0	0	0	0	0	0	**6**	**6**	5	**6**
Panel B: 1 year forecasts														
VWII	4	5	6	7	8	9	10	11	12	13	0	2	1	3
EWII	4	5	6	7	8	9	10	11	12	13	2	0	2	0
MSCIAII	4	5	6	7	8	9	10	11	12	13	0	0	1	3
S&PUI	13	10	7	6	5	4	3	2	1	0	8	11	8	12
TOTAL	25	25	25	27	29	31	33	35	37	**39**	10	13	12	20
Panel C: 2 year forecasts														
VWII	4	5	6	7	8	9	10	12	12	13	0	2	1	3
EWII	4	5	6	7	8	9	10	11	12	13	2	0	2	2
MSCIAII	13	12	11	10	9	8	7	6	5	4	0	0	1	2
S&PUI	13	10	7	6	5	4	3	2	1	0	8	11	8	12
TOTAL	**34**	32	30	30	30	30	30	30	30	30	10	13	12	19

III. Predictive Performance using the Giacomini and White (2006) Test

This section of the results evaluates the predictive performance of asset pricing models using the Giacomini and White (2006) test and is divided into two parts. The first part of the analysis examines the predictive performance of asset pricing models on infrastructure returns prior to the GFC from the period 1997 through 2007. The second part of the analysis carries the tests forward and reports the evaluation for the full sample period from 1997-2012. The objective of this analysis is to evaluate the sensitivity of the Giacomini and White (2006) test to changes in market conditions (ie. the GFC in 2008) and to ascertain the differences in the overall results by comparing the two sets of tests.

Table 4 presents the summary of the Giacomini and White (2006) tests on 14 predictive asset pricing models (four asset pricing models and ten constant return benchmarks) on the four infrastructure indices of interest from 1997-2007 which is the sample period prior to the GFC.[7] Panel A reports the predictive performance of asset pricing models based on their 1 month forecasts and reveals that both CAPM and Fama-French asset pricing models outperformed all of the fixed constant return models. The low numbers reported in Panel A suggest that it is difficult for any one single asset pricing model to significantly do better than any other asset pricing models. Panel B of Table 4 reports the predictive performance of asset pricing models in their 1 year forecasts and reports that the 10% fixed excess return model is the best predictor of future returns. In fact, Panel B shows that all constant return models outperformed both CAPM and Fama-French models. Panel C summarises the predictive performance of asset pricing models based on their 2 year forecasts and reveals that the 4% constant return model outperformed all other alternatives. The 5% constant return model was the second best predictor of future returns. The results in Panel C are similar to the findings in Simin (2008) who estimate a 6% constant return model outperforms all other U.S. asset pricing models.

Table 5 reports the Giacomini and White (2006) tests on the 14 predictive asset pricing models across the full sample period from 1997 trough 2012 which includes the GFC.[8] This allows us to compare the results of Tables 4 and 5. Panel A reveals similar results to the sample period prior to the GFC. Both CAPM and Fama-French asset pricing models outperform the constant fixed return models although the low numbers suggest that these models do not outperform the alternatives by very much. Panel B shows that the 10% fixed excess return model continues to be the best predictor of infrastructure returns across the entire 1997-2012 sample period. Again, the 1 year forecasts reveal that all constant return models outperform both CAPM and Fama-French models in predicting 1 year time horizons. Panel C reveals that the best predictor of returns 2 years forward is the 1% fixed excess return model which is

[7] The detailed output of the Giacomini and White (2006) tests from 1997-2007 which compare every asset pricing model with its alternatives are available upon request.

[8] The detailed output of the Giacomini and White (2006) tests from 1997-2012 which compare every asset pricing model with its alternatives are available upon request.

closely followed by the strong performance of the 2% fixed excess return. Again, the CAPM and Fama-French asset pricing models are the worst performers in predicting returns 2 years forward. The finding in Panel C of the 1% excess return model shows that the dynamics of the GFC in 2008 reduced the predictive performance of the 4% model (see Panel C in Table 4) and the 1% excess return model is the best predictor of returns 2 year forward. Another interesting finding in Panel C is the CAPM's predictive performance has deteriorated somewhat since the GFC.

The overall findings from Tables 4 and 5 show that the CAPM with no intercept is the best predictor of future returns when employing conventional asset pricing frameworks. The CAPM with no intercept is best predictor of one month returns, however, the empirical evidence presented in this study suggests that fixed excess return models outperform both CAPM and Fama-French models at both 1 year and 2 year time horizons. This evidence is consistent with the previous work by Simin (2008) in the U.S. setting and Whittaker (2013) in the Australian setting.

6. Concluding Remarks

Our findings suggest that the predictive performance of the CAPM with no intercept is the best out of the conventional asset pricing models examined in this study. However, it is important to note that simple, fixed excess return models outperform the CAPM and Fama-French models. These findings have important implications for practitioners. An interesting finding from the analysis (consistent with Simin, 2008) is that the predictive performance of the constant returns models tends to gravitate towards its long term unconditional historical mean returns. The findings presented in this study (and those of Simin, 2008) suggest that employing the long-term historical mean return is a reasonable starting point for superannuation funds seeking to understand the long-term expected returns of infrastructure. In short, the evidence to date supports employing a simple historical mean return as this seems to outperform conventional asset pricing models.

Our findings provide researchers with a number of avenues for future research. First, our study is limited to the 16 years of empirical data available on Australian infrastructure returns from 1997 through 2012. In comparison, U.S. studies that has evaluated the predictive performance of asset pricing models employ much longer data samples. For instance, Lewellen and Nagel (2006), Simin (2008) and Welch and Goyal (2008) analyse the 1964-2001, 1931-2004, 1926-2005 data sample periods, respectively. A similar type of research on longer term U.S. infrastructure data may be fruitful in understanding infrastructure returns over the long-run.

A second issue is the 60 month rolling window that was employed in this analysis. The standard practice of using a rolling 60 month window to capture the inputs for the asset pricing model must be an issue of contention. Researchers may need to experiment with other time frames to evaluate the crudeness of such a time frame in the finance literature. We leave these challenges for future research endeavours.

References

Beeferman, L., 2008, *Pension Fund Investment in Infrastructure: A Resource Paper*, Occasional Paper Series, No. 3, December, Pensions and Capital Stewardship Project, Labor and Worklife Program, Harvard Law School, Harvard University.

Bianchi, R., Drew, M. and Whittaker, T., 2013, *Cost of equity prediction with asset pricing models*, Working Paper, 23rd June, Griffith University.

Bird, R., Liem, H. and Thorp, S., (forthcoming), 'Infrastructure: Real assets and real returns', *European Financial Management,* doi: 10.1111/j.1468-036X.2012.00650.x

Bishop, S., Fitzsimmons, M. and Officer, B., 2011, Adjusting the market risk premium to reflect the global financial crisis, *JASSA The Finsia Journal of Applied Finance*, Issue 1, 8-14.

Brailsford, T., Handley, J. and Maheswaran, K., 2007, Re-examination of the historical equity risk premium in Australia, *Accounting and Finance* 48, 73-97.

Cantarelli, C., Flyvbjerg, B., Molin, E, and van Wee, B., 2010, Cost overruns in large scale transportation infrastructure projects: Explanations and their theoretical embeddedness, *European Journal of Transport and Infrastructure Research* 10(1), 5-18.

Croce, R.D. 2011, 'Pension funds investment in infrastructure a survey' *Project on strategic transport infrastructure to 2030,* OECD*,* OECD Publishing, Paris.

Demetriades, P. and Mamuneas, T., 2000, Intertemporal output and employment effects of public infrastructure capital: evidence from 12 OECD economies, *Economic Journal* 110(465), 687-712.

Durack, N Durand, R B and Maller, R A 2004, 'A best choice among asset pricing models? The Conditional Capital Asset Pricing Model in Australia', *Accounting & Finance,* Vol. 44, Iss. 2, pp. 139-162.

Faff, R., 2001, An examination of the Fama and French three-factor model using commercially available factors', *Australian Journal of Management* 26(1), 1-17.

Fama, E. and French K., 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33(1), 3–56.

Fama, E. and French, K., 2004, The capital asset pricing model: theory and evidence', *Journal of Economic Perspectives* 18(3), 25-46.

Finkenzeller, K Dechant T & Schafers W 2010, 'Infrastructure : a new dimension of real estate? An asset allocation analysis', *Journal of Property Investment & Finance*, vol. 28, no. 4, pp. 263-274.

Flyvbjerg, B., 2009, Survival of the unfittest: why the worst infrastructure gets built – and what can we do about it, *Oxford Review of Economic Policy* 25(3), 344-367.

Griffin, J., 2002, Are the Fama and French factors global or country specific?, *Review of Financial Studies* 15(3) 783-803.

Heintz, J., 2010, The impact of public capital on the U.S. private economy: New evidence and analysis, *International Review of Applied Economics* 24(5), 619-632.

Hulten, C., 1996, Infrastructure capital and economic growth: How well you use it may be more important then how much you have, *National Bureau of Economic Research (NBER) Working Paper*, No. 5847. Cambridge, MA, NBER.

Inderst, G 2009, 'Pension fund investment in infrastructure', *OECD Working Paper on Insurance and Private Pensions* No. 32.

Infrastructure Australia, 2013, *National Infrastructure Plan*, June, Australian Government, ISBN 978-1-921769-71-9.

Infrastructure Australia, 2013, *National Public Private Partnership Guidelines. Volume 5: discount Rate Methodology Guidance*, August, Australian Government, ISBN 978-1-922205-33-9.

Kamps, C., 2001, New estimates of government net capital stocks for 22 OECD countries 1960-2001, *Public Economics* 5(6), 1-15.

Kamps, C., 2004, The dynamic effects of public capital: VAR evidence for 22 OECD countries, *International Tax and Public Finance* 12(4), 533-558.

Lewellen, J. and Nagel, S., 2006, The conditional CAPM does not explain asset-pricing anomalies, *Journal of Financial Economics* 82(2), 289-314.

Limkriangkrai, M., Durand, R. and Watson, I., 2008, Is liquidity the missing link?, *Accounting and Finance* 48(5), 829–845.

Merton, R., 1973, An intertemporal capital asset pricing model, *Econometrica* 41(5), 867-887.

Munnell, A., 1992, Policy watch: Infrastructure investment and economic growth, *Journal of Economic Perspectives* 6(4), 189-198.

Newbery, D., 2002, *Privatization, Restructuring, and Regulation of Network Utilities*, MIT Press.

Newell, G & Peng, H W 2007, ‘ The significance of infrastructure in Australian investment portfolios’, *Pacific Rim Portfolio Research Journal,* vol 13, pp. 423-450

Newell, G & Peng, H W 2008, ‘The role of U.S. infrastructure in investment portfolios’ *Journal of Real Estate Portfolio Management,* vol. 14, no. 1, pp.21-33

Newell, G, Peng, H W & De Francesco, A 2011, ‘The performance of unlisted infrastructure investments in investment portfolios’, *Journal of Property Research*, vol. 28, no. 1, pp. 59-74

Newey, W. and West, K., 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55(3), 703-708.

Nguyen, A., Faff, R. and Gharghori, P., 2007, An examination of conditional asset pricing models in the Australian equities market, *Applied Financial Economics Letters* 3(5), 307-312.

OECD, 2007, *OECD Principles for Private Sector Participation in Infrastructure*, Organisation for Economic Co-operation and Development, July, OECD Publishing, Paris.

OECD, 2011, *Pension Funds Investment in Infrastructure: A Survey,* Organisation for Economic Co-operation and Development, International Futures Programme: Project on Strategic Transport Infrastructure to 2030, September, OECD Publishing, Paris.

Regan, M., Smith, J. and Love, P., 2011a, Infrastructure Procurement: Learning from private-public partnership experiences ‘down under’, *Environment and Planning C: Government and Policy* 29(2), 363-378.

Regan, M., Smith, J. and Love, P., 2011b, Impact of the Capital Market Collapse on Public-Private Partnership Infrastructure Projects, *Journal of Construction Engineering and Management* 137(1), 6-16.

Rodel, M. and Rothballer, C., 2012, Infrastructure as a hedge against inflation - fact or fantasy?, *Journal of Alternative Investments* 15(1), 110-123.

Rothballer, C. and Kasrerer, C., 2012, The risk profile of infrastructure investments: Challenging conventional wisdom, *Journal of Structured Finance* 18(2), 95-109.

Sawant, R., 2010, The economics of large-scale FDI: The case of project finance, *Journal of International Business Studies* 41(6), 1036-1055.

Simin, T., 2008, The poor predictive performance of asset pricing models, *Journal of Financial and Quantitative Analysis* 43(2), 355-380.

Welch, I. and Goyal, A., 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21(4), 1455-1508.