The Predictability of Australian Listed Infrastructure and Public-Private Partnership Returns Using Asset Pricing Models

Robert J. Bianchi*, Michael E. Drew and Timothy Whittaker

Department of Accounting, Finance and Economics
Griffith Business School
Griffith University
Nathan, Brisbane, Queensland
AUSTRALIA

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Abstract:

Can asset pricing models predict the future returns of publicly-listed infrastructure and public-private partnerships (PPPs) 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 and PPPs.

Keywords: *Asset Pricing, Investment Decisions, Infrastructure.*
JEL Codes: *G11, G12*

* Corresponding author. Email: r.bianchi@griffith.edu.au; Tel: +61-7-3735 7078; Fax: +61-7-3735 3719; Postal address: Griffith Business School, Department of Accounting, Finance and Economics, Nathan campus, Griffith University, 170 Kessels Road, Nathan, Queensland, 4111, Australia. This research was supported by the CSIRO-Monash Superannuation Research Cluster, a collaboration between CSIRO, Monash University, Griffith University, the University of Western Australia, the University of Warwick, and stakeholders of the retirement system in the interest of better outcomes for all. Any remaining errors or ambiguities are our own.

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1. Introduction

It has long been recognised that well designed infrastructure investments deliver long-term benefits to investors and the broader economy alike (Demetriades and Mamuneas, 2000; Heintz, 2010; Hulten, 1996; Kamps, 2001, 2004; Munnell, 1992).[1] A number of studies suggest that infrastructure investments are low-risk due to: their regular income streams (Newbery, 2002; Rothballer and Kaserer, 2012); the nature of long term contracts and high asset-specificity of investments in the infrastructure industry (Dong and Chiara, 2010); 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, this study empirically examines the predictive (or otherwise) performance of conventional asset pricing models on Australian publicly-listed infrastructure and public-private partnership (PPP) investment 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. There is a scarcity of this type of research in the Australian setting and the predictability of infrastructure and PPP returns has never been examined in the literature. Second, the low-risk perception of infrastructure and PPPs makes it a perfect candidate to evaluate the predictive performance of Australian asset pricing models. If infrastructure and PPP risks are lower than conventional equity investments then there is an increased probability that Australian asset pricing models may be able to forecast infrastructure/PPP returns. Third, and perhaps most importantly, respective

[1] However, we also acknowledge that there are a number of recent 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).

Australian governments employ the principles of the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965; Mossin, 1966) in their evaluation of PPPs to finance new infrastructure investments. Governments in Australia employ the Infrastructure Australia (2013b) 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/PPP returns. In fact, a simple fixed excess return model provides similar or better forecasts than conventional asset pricing models in many cases. Our initial tests before the 2008 Global Financial Crisis from 1997-2007 shows that the conventional asset pricing models (including the CAPM and Fama-French three factor model) deliver similar or lower levels of predictive performance than simple fixed excess return 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 10% 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/PPP 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 the performance of these types of investments. Our understanding of infrastructure and PPPs is limited by the scarcity of empirical studies that analyse the behaviour of these types of investments. 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 of 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. Rothballer and Kaserer (2012) argue that the reason for the low systematic risk is due to the lower levels of market competition in infrastructure based industries, due to the high levels of fixed capital investment required. 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 Ferson and Harvey (1991), 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 and PPP returns. Given the low-risk nature of infrastructure, we expect the forecastability of asset pricing models to be better suited to these 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. In our study, we examine the performance of unconditional models on infrastructure/PPP returns.

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 ASX publicly listed infrastructure and PPP firms whose individual performances are summarised into a number of broad based proxies. The first proxy is the MSCI Australia Infrastructure Index which reflects the performance of ASX firms related to infrastructure assets.

[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.

The MSCI Australia Infrastructure Index is a market capitalisation-weighted index of companies from the telecommunications services, utilities, energy, transportation and social infrastructure sectors. The second proxy for infrastructure used in this study is

Table 1
List of ASX Listed Securities

This table presents the Australian Securities Exchange (ASX) publicly listed firms which are the constituents of the various infrastructure, utilities and Public-Private Partnership (PPP) indices employed in this study.

No.	Company Name and ASX ticker	No.	Company Name and ASX ticker
Panel A: Constituents of S&P Utilities and MSCI Infrastructure Indices[4]			
1.	Alinta Limited (AAN)	19.	Gasnet Australia Group (GAS)
2.	AGL Energy Ltd (AGK)	20.	Geodynamics Ltd (GDY)
3.	Aust. Gas Light Company (AGL)	21.	Hastings Div. Utilities Fund (HDF)
4.	Alinta Infrastructure Holdings (AIH)	22.	Hills Motorway Group (HLY)
5.	Aust. Infrastructure Fund (AIX)	23.	Horizon Energy Inv. Group (HRZ)
6.	AJ Lucas Group Limited (AJL)	24.	Infratil Australia Limited (IFA)
7.	Alinta Gas (ALN)	25.	Infigen Energy (IFN)
8.	Aust. Pipeline Ltd (APA)	26.	Infra. Trust of Aust. Group (IFT)
9.	Babcock & Brown Infra. Ltd (BBI)	27.	Macquarie Infrastructure (MIG)
10.	Babcock & Brown Power Ltd (BBP)	28.	Origin Energy Limited (ORG)
11.	Babcock & Brown Wind Partners (BBW)	29.	Pacific Hydro Limited (PHY)
12.	Challenger Infrastructure Fund (CIF)	30.	Prime Infrastructure Group (PIH)
13.	China Construction Holdings Ltd (CIH)	31.	Renewable Energy Corp Ltd (REL)
14.	Duet Group (DUE)	32.	Stadium Australia Group (SAX)
15.	Energy Developments Limited (ENE)	33.	Spark Infrastructure Group (SKI)
16.	Envestra Ltd (ENV)	34.	SP Ausnet Services (SPN)
17.	Environmental Clean Technologies (ESI)	35.	Transurban Group (TLC)
18.	Energy World Corporation Ltd (EWC)	36.	Transfield Services Infra. Fund (TSI)
		37.	United Energy Limited (UEL)
Panel B: ASX Listed Public-Private Partnerships[5]			
1.	ConnectEast Group (CEU)	3.	Rivercity Motorway Group (RCY)
2.	Transurban Group (TLC)	4.	Hills Motorway Group (HLY)

[4] Alinta Limited (AAN) was delisted on 7 September 2007 after being acquired by the Singapore Power/Babcock and Brown consortium. Australian Gas Light Company (AGL) was delisted on 26 October 2006 following the merger of Alinta Limited (AAN) and The Australian Gas Light Company's (AGL) infrastructure businesses. Alinta Infrastructure Holdings (AIH) was delisted on 27 February 2007 when Alinta Limited (AAN) completed the full acquisition of the firm. Alinta Gas (ALN) was renamed to Alinta Limited (AAN) on 14 May 2003. Babcock & Brown Power was renamed Alinta Energy Group (AGK) on 4 January 2010. Babcock & Brown Wind Partners Group (BBW) was renamed to Infigen Energy (IFN) on 4 May 2009. China Construction Holdings Ltd (CIH) was delisted on 27 March 2009. Gasnet Australia Group (GAS) delisted on 17 November 2006 as it was acquired by Australian Pipeline Trust and is now renamed Aust. Pipeline Ltd (APA). Infrastructure Trust of Australia Group (IFT) was renamed Macquarie Infrastructure Group (MIG) from 17 August 1999 and then was renamed again to Intoll Group on 5th February 2010. Prime Infrastructure Group (PIH) was renamed to Babcock & Brown Infrastructure Ltd (BBI) on 5th July 2005 and then renamed itself back to PIH on 7th December 2009. United Energy (UEL) was acquired by Alinta Ltd (AAN) on 28 July 2003.

[5] Horizon Roads completed the 100% acquisition of ConnectEast Group (CEU) on 26 October 2011. Transurban Group (TLC) completed a takeover of Hills Motorway Group (HLY) in April 2005. The Rivercity Motorway Group (RCY) appointed voluntary administrators on 25 February 2011.

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, the S&P/ASX Utilities Index and Sirca database with the industry classification of 'infrastructure'. The fourth and final proxy is a custom portfolio of the four ASX publicly listed PPPs, namely, BrisConnections, ConnectEast, Rivercity Motorways and Transurban.

Table 1 reports the full list of ASX listed companies which are the constituents of the indices employed in this study. Panel A reports the constituents of the S&P Utilities Index and MSIC Infrastructure index and all other firms recorded in the Sirca database with the 'infrastructure' classification. Panel B reports the four ASX listed PPP firms in the sample period.

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, therefore, 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 ASX listed infrastructure (ie. Hills Motorway) company 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.

Table 2
Summary Statistics and Distributions

This table presents the summary statistics and distributions of the data employed in this study. AOAAI denotes 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. PPPI denotes the market-weighted index of the four ASX listed PPP companies. 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: Listed Infrastructure and PPP based 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	0.41%	4.35%	-6.85%	0.64%	7.96%
		(4.88%)	(15.06%)		(7.67%)	
S&P Utilities	4/2000	0.82%	4.09%	-6.54%	1.20%	6.21%
		(9.87%)	(14.17%)		(14.34%)	
PPPI	1/1997	1.24%	6.90%	-10.91%	1.05%	10.83%
		(14.92%)	(23.89%)		(12.58%)	
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%)	

In terms of the risk-free rate, the data sample in our study straddles the period of the John Howard federal government where budget surpluses were delivered resulting 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. 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.[6]

Table 2 presents the summary statistics of the variables of interest. Panel A reports the infrastructure and PPP indices while Panel B presents 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, 5th and 95th percentiles all suggest that the distribution of infrastructure indices are similar to the AAOAI.

[6] A level of critique may be aimed towards the UBS Australia Bank Bill Index is an inadequate proxy for the risk-free rate, however, 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 these two risk-free proxies is negligible.

An interesting observation in Panel A is the higher levels of return and risk characteristics of the PPP index in comparison to the infrastructure counterparts. There are a number of reasons for this finding. First, the PPP index exhibits higher mean returns than its infrastructure counterparts because PPPs generally own assets that do not possess a long-term terminal value as these assets revert back to government hands at the end of their concession period. As a result, PPP equity holders must accumulate the capital value of the PPP asset throughout its concession period, which results in a higher mean return for PPPs than for conventional asset returns where the proceeds of an asset sale can occur at some point in the future. Second, the PPP index exhibits substantially higher levels of risk which is attributable to the fact that all four listed PPPs are toll-road assets which have experienced severe traffic demand risks when shifting from the construction phase to the operations phase (Bureau of Infrastructure, Transport and Regional Economics, 2011; Black, 2014) Whilst PPPs are regarded in the investment industry as a relatively 'low-risk' proposition, the empirical evidence from ASX listed toll road PPPs challenges this perspective.

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 2 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 three 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.[7] 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 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 *et. al.*, (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

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

models. The equation below shows how the forecast bias can be disaggregated from the Mean Square Forecast.

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

where 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; 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 rates of return.

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:

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

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.

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 3
Unconditional Capital Asset Pricing Model (CAPM) Regressions (Ex Post)

This table presents the regression results of the single-factor Capital Asset Pricing Model (CAPM) on the various proxies of ASX listed infrastructure and PPP 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. The *p*-values are estimated using Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. * and ** denote statistical significance at the 5% and 1% levels, respectively.

Index Name	Intercept	Beta (Rm-Rf)	SMB	HML	Adj R^2
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)			
PPPI	0.0063	0.4829**			0.0698
	[0.0046]	[0.1063]			
	{1.3816}	{4.5445}			
	(0.1687)	(0.0000)			

I. Asset Pricing Models (Ex-Post)

Table 3 presents the conventional single-factor CAPM regressions on Australian listed infrastructure and PPP returns from 1997-2012. This provides the reader with an *ex-post* perspective of the CAPM and the systematic risks that explain the variation of infrastructure and PPP returns. The regression results suggest that all infrastructure and PPP indices in this study exhibit low systematic risk as expressed by their market betas. The value-weighted and equal-weighted infrastructure indices report market betas of 0.64 and 0.81, 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.

Table 4

Unconditional Fama-French Three Factor Model Regressions (Ex Post)

This table presents the regression results of the Fama and French (1993) three-factor model on the various proxies of ASX listed infrastructure and PPP 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. The *p*-values are estimated using Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. * and ** denote statistical significance at the 5% and 1% levels, respectively.

Index Name	Intercept	Beta (Rm-Rf)	SMB	HML	Adj R^2
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)	
PPPI	0.0051	0.5264**	-0.0652	0.3104	0.0901
	[0.0046]	[0.1243]	[0.0973]	[0.2151]	
	{1.1165}	{4.2367}	{-0.6699}	{1.4431}	
	(0.2656)	(0.0000)	(0.5038)	(0.1507)	

An interesting empirical observation in Table 3 is the joint interactions 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 originates from the zero-intercept criterion proposed in Merton (1973). The zero-intercept criterion suggests that 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 3 suggest there are no other systematic risk factor that can explain the asset returns of listed infrastructure and PPPs. The relatively low adjusted R^2s signify that these infrastructure returns exhibit relatively high levels of idiosyncratic risk. [8] Furthermore, it is important to note that the extremely low coefficient of determination of 0.0698 for the PPP index is attributable to the portfolio of four listed stocks only, which by construction, carries a high level of idiosyncratic risk in these regression estimates.[9]

Table 4 extends the *ex-post* analysis with the Australian version of the Fama and French (1993) three-factor model. The regression results reveal that the SMB size premium and the HML value premium do not assist in explaining the variation of infrastructure and PPP returns whilst the market beta remains the primary explanatory variable. Again, there are no statistically significant intercept terms (ie. no alpha) in these regression estimates. The regression results in Tables 3 and 4 differ to Bird *et. al.*, (2012) who estimate statistically significant excess returns in 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.

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

[9] Effectively, the underlying asset of BrisConnections was a single investment in Brisbane's AirportlinkM7 toll road. The primary asset of Rivercity Motorways was Brisbane's CLEM7 tunnel. ConnectEast was the owner and operator of Melbourne's EastLink motorway. Transurban is an ASX listed firm that owns and operates numerous toll road assets in Australia and the United States.

Table 5
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. PPPII denotes the value-weighted PPP index. The RMSFE with the lowest values for each index are highlighted.

	VWII		EWII		MSCIAII		S&PUI		PPPII	
	RMSFE	Bias	RMSFE	Bias	RMSFE	Bias	RMSFE	Bias	RMSFE	Bias
Panel A: 1 month forecasts										
1%	4.1510	-0.0092	5.6376	-0.0183	3.6763	-0.0094	4.3472	-0.0224	6.7080	-0.0059
2%	4.1471	-0.0131	5.6353	-0.0205	3.6718	-0.0139	**4.3461**	-0.0235	6.7029	-0.0111
3%	4.1448	-0.0153	**5.6343**	-0.0216	3.6692	-0.0165	4.3466	-0.0231	6.6987	-0.0152
4%	**4.1443**	-0.0159	5.6345	-0.0214	**3.6685**	-0.0173	4.3486	-0.0210	6.6956	-0.0183
5%	4.1454	-0.0148	5.6359	-0.0199	3.6696	-0.0161	4.3523	-0.0173	6.6936	-0.0204
6%	4.1482	-0.0120	5.6386	-0.0173	3.6727	-0.0130	4.3576	-0.0121	**6.6925**	-0.0214
7%	4.1526	-0.0075	5.6425	-0.0134	3.6776	-0.0081	4.3644	-0.0052	**6.6925**	-0.0214
8%	4.1588	-0.0014	5.6476	-0.0083	3.6845	-0.0013	4.3728	0.0032	6.6936	-0.0204
9%	4.1666	0.0064	5.6539	-0.0019	3.6932	0.0074	4.3828	0.0132	6.6957	-0.0183
10%	4.1760	0.0158	5.6615	0.0056	3.7037	0.0180	4.3943	0.0247	6.6988	-0.0152
FF	4.1962	-0.0150	5.7144	-0.0219	3.8245	0.0163	4.4943	-0.0243	6.8055	-0.0186
FFNI	4.1631	-0.0066	5.6441	-0.0212	3.7238	-0.0106	4.4332	-0.0212	6.7334	-0.0054
CAPM	4.1996	-0.0146	5.7144	-0.0219	3.8274	0.0145	4.4991	-0.0244	6.8109	-0.0174
CNI	4.1666	-0.0062	5.6602	-0.0167	3.7303	-0.0111	4.4361	-0.0217	6.7214	-0.0078
Panel B: 1 year forecasts										
1%	4.2999	2.5709	4.8074	2.3620	15.9754	0.0256	**19.9165**	-0.1223	21.8264	0.5706
2%	4.2237	2.4947	4.7369	2.2915	15.9658	0.0160	19.9171	-0.1217	21.8064	0.5507
3%	4.1477	2.4187	4.6668	2.2214	15.9567	0.0069	19.9180	-0.1208	21.7868	0.5310
4%	4.0721	2.3430	4.5971	2.1517	15.9481	-0.0018	19.9193	-0.1195	21.7674	0.5117
5%	3.9967	2.2677	4.5279	2.0825	15.9398	-0.0100	19.9209	-0.1179	21.7484	0.4927
6%	3.9216	2.1926	4.4592	2.0138	15.9320	-0.0178	19.9229	-0.1159	21.7297	0.4739
7%	3.8469	2.1179	4.3910	1.9456	15.9246	-0.0252	19.9252	-0.1136	21.7113	0.4555
8%	3.7726	2.0436	4.3233	1.8779	15.9177	-0.0321	19.9279	-0.1109	21.6931	0.4374
9%	3.6987	1.9697	4.2562	1.8108	15.9111	-0.0387	19.9309	-0.1079	21.6753	0.4196
10%	**3.6251**	1.8961	**4.1897**	1.7442	**15.9051**	-0.0447	19.9343	-0.1045	**21.6578**	0.4021
FF	7.8585	0.1911	8.1006	-0.0342	21.4283	0.2944	26.2827	-0.0056	26.0541	0.2988
FFNI	6.5257	0.7599	7.4055	0.0289	19.2897	0.0322	26.6290	-0.1329	23.8520	0.1555
CAPM	7.8467	0.2543	8.4073	-0.0353	21.3914	0.6760	26.2761	0.0706	26.0791	1.2077
CNI	6.0153	0.8791	6.9275	0.7299	19.3361	0.0201	23.5181	-0.1251	23.2060	0.0976
Panel C: 2 year forecasts										
1%	**1.4554**	0.0014	**1.6079**	-0.0076	23.9523	0.5197	**15.1496**	0.1729	16.5199	0.5600
2%	1.4666	0.0126	1.6104	-0.0050	23.9330	0.5004	15.1658	0.1890	16.4975	0.5376
3%	1.4824	0.0284	1.6172	0.0018	23.9140	0.4814	15.1824	0.2057	16.4754	0.5156
4%	1.5027	0.0486	1.6282	0.0128	23.8952	0.4626	15.1995	0.2227	16.4538	0.4940
5%	1.5272	0.0732	1.6434	0.0280	23.8767	0.4441	15.2169	0.2402	16.4326	0.4727
6%	1.5558	0.1018	1.6627	0.0472	23.8585	0.4259	15.2349	0.2581	16.4117	0.4519
7%	1.5883	0.1343	1.6858	0.0704	23.8406	0.4080	15.2532	0.2765	16.3913	0.4314
8%	1.6244	0.1704	1.7127	0.0973	23.8230	0.3904	15.2720	0.2953	16.3712	0.4114
9%	1.6639	0.2099	1.7432	0.1278	23.8056	0.3730	15.2913	0.3145	16.3516	0.3917
10%	1.7066	0.2526	1.7770	0.1616	**23.7885**	0.3559	15.3109	0.3342	**16.3323**	0.3725
FF	9.9152	2.9807	8.6212	1.4934	30.3811	0.7293	23.6411	1.1838	22.7370	0.9629
FFNI	5.4458	0.2870	7.4857	1.3663	27.2482	0.0322	19.4607	0.4582	19.4021	0.1555
CAPM	10.0042	3.2487	8.9718	1.4361	30.3042	0.6760	23.5416	1.4644	22.4670	1.2077
CNI	4.7853	0.2809	5.3002	0.3594	27.4210	0.0201	19.1203	0.5064	18.4968	0.0976

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

Panel A of Table 5 shows that the fixed excess return models ranging from 2% to 4% exhibit the lowest forecast errors for future one month returns for most indices. 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 5 reports the RMSFE and Biases for 1 year forecasts. The RMSFE values are generally larger than those reported for 1 month predictions, however, you cannot directly compare RMSFEs across different forecasting time horizons. The Bias in Panel B is generally positive for most predictive models. The positive bias suggests that the asset pricing models in Panel B are over-estimating one year future returns, on average.

Panel C of Table 5 reveals two interesting findings. First, the fixed excess return models for VWII and EWII report smaller RMSFEs over the 2 year time horizon 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. The PPPI reports smaller RMSFEs for one month returns and the largest for 1 year time horizons. Second, the Bias is almost always positive for the two year forecasts which suggests that both conventional asset pricing and fixed excess return 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.

Table 6
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. PPPII denotes the value-weighted PPP 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. The best predictive model for every time horizon is highlighted.

	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	3	3	2	0	0	0	0	0	0	0	0	2	0	2
S&PUI	9	8	7	6	5	4	3	2	1	0	0	0	10	10
PPPII	0	0	2	2	2	2	2	2	2	2	0	1	0	2
TOTAL	12	11	11	8	8	7	5	4	3	2	1	3	10	**14**
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	3	4	5	6	7	8	9	10	11	1	13	0	12
S&PUI	12	13	8	6	5	4	3	2	1	0	0	0	10	7
PPPII	2	3	4	5	6	7	8	9	10	11	13	1	0	12
TOTAL	18	25	24	26	30	34	38	41	44	**47**	15	18	14	42
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	2	3	4	5	7	8	9	10	11	12	1	13	0	6
S&PUI	12	9	7	6	5	4	3	2	1	0	0	0	8	13
PPPII	2	3	4	5	6	7	10	11	12	13	7	2	0	9
TOTAL	25	28	32	37	40	40	39	36	35	33	8	15	8	**41**

Table 7
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. PPPII denotes the value-weighted PPP 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. The best predictive model for every time horizon is highlighted.

	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	2	0	0
S&PUI	0	0	0	0	0	0	0	0	0	0	6	6	5	6
PPPII	2	2	2	1	1	0	0	0	0	0	0	0	0	2
TOTAL	2	2	2	1	1	0	0	0	0	0	6	**8**	5	**8**
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	3	1	3
S&PUI	13	10	7	6	5	4	3	2	1	0	8	11	8	12
PPPII	4	5	6	7	8	9	10	11	12	13	0	0	1	3
TOTAL	29	30	31	34	37	40	43	46	49	**52**	10	18	13	23
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	4	5	6	7	8	9	10	11	12	13	0	3	1	2
S&PUI	13	10	7	6	5	4	3	2	1	0	8	11	8	12
PPPII	4	5	6	7	8	9	10	11	12	13	0	0	0	3
TOTAL	29	30	31	34	37	40	43	46	49	**52**	10	16	12	22

Overall, the RMSFE and Bias estimates in Table 5 provide a summary of the forecast errors calculated from every asset pricing model. Whilst the RMSFE and Bias estimates are an indication of which asset pricing model provides the lowest forecast errors, they do not provide a statistical test to evaluate the predictive performance of these models. To address this issue, we proceed to compare the predictive performance of these asset pricing models by employing the Giacomini and White (2006) test.

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

This section of the study evaluates the predictive performance of asset pricing models using the Giacomini and White (2006) test and is divided into two parts. The section 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 2008 GFC) and to ascertain the differences in the overall results by comparing the two sets of tests.

Table 6 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 and the PPP index from 1997-2007 which is the sample period prior to the GFC.[10] 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 excess return models. The very low numbers reported in Panel A signifies that it is difficult for any one single asset pricing model to significantly outperform the predictive performance of other asset pricing models. Panel B presents 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 fixed (ie. constant) excess return models from 2% to 10% per annum

[10] 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.

outperformed both Fama-French models and the conventional CAPM model. Panel C summarises the predictive performance of asset pricing models based on their 2 year forecasts and reveals that the CAPM with no intercept (CAPMNI) marginally outperformed all other alternatives. The 5% fixed excess 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 7 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.[11] This allows us to compare the results of Tables 6 and 7. 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 the magnitude of outperformance against the alternative models is negligible. 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 returns over 1 year time horizons. Panel C reveals that the best predictor of returns 2 years forward is the 10% fixed excess return model which is closely followed by the strong performance of the 9% 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 10% excess return model shows that the dynamics of the GFC in 2008 and the subsequent market improvement afterwards has reduced the predictive performance of the 5% model (see Panel C in Table 6) and the 10% excess return model is now the best predictor of returns 2 year forward. Another interesting finding in Panel C is the predictive performance of the CAPM with no intercept has deteriorated somewhat since the GFC.

The overall findings from Tables 6 and 7 show that the CAPM with no intercept is the best predictor of future returns when employing conventional asset pricing

[11] 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.

frameworks. Whilst the 'CAPM with no intercept' model (CAPMNI) is best predictor of one month returns, 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.

Figure 1

Cumulative Square Prediction Error of Two Best Forecasting Models (1 Month)

Cumulative square prediction error of the best forecasting model minus the cumulative square prediction error of the second best (ie. alternative) forecasting model.

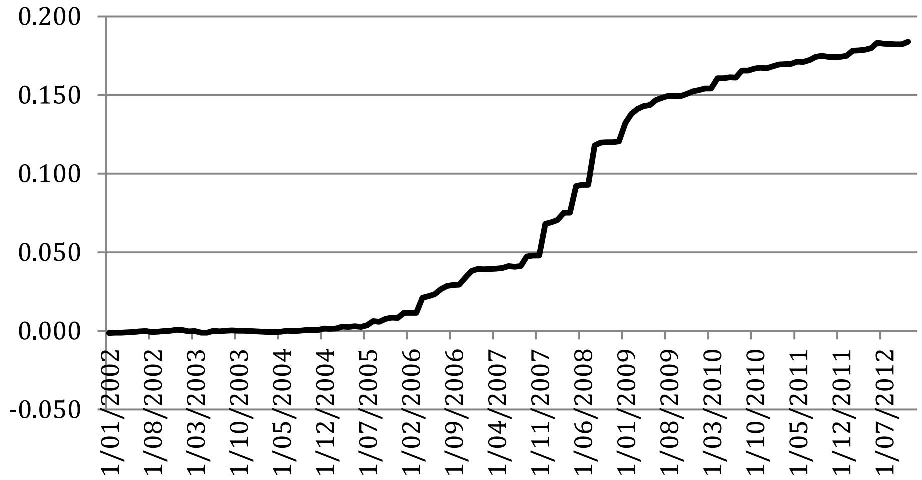


Figure 2

Cumulative Square Prediction Error of Two Best Forecasting Models (1 Year)

Cumulative square prediction error of the best forecasting model minus the cumulative square prediction error of the second best (ie. alternative) forecasting model.

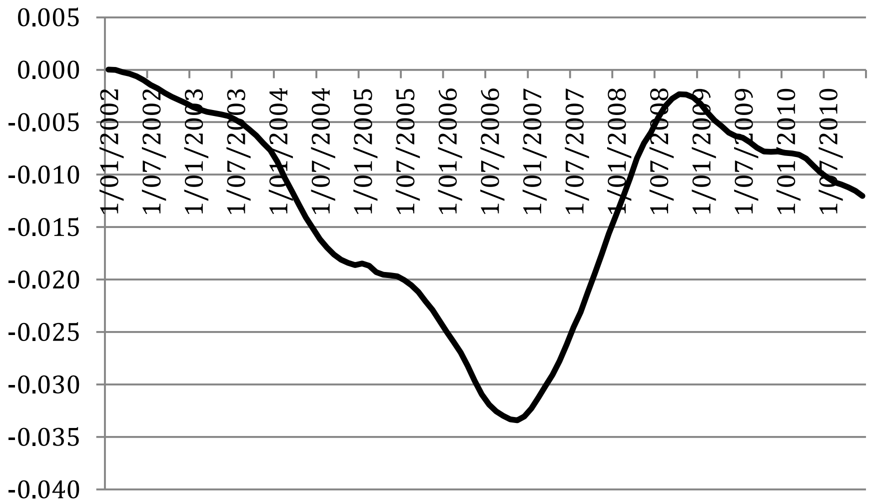
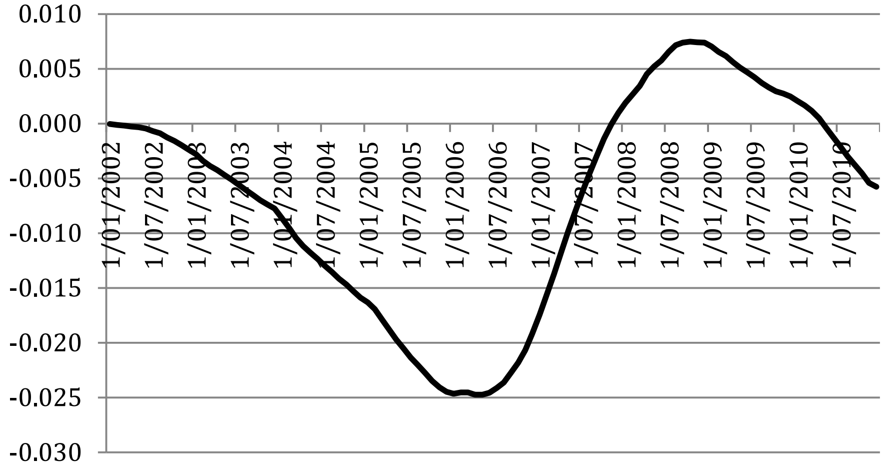


Figure 3

Cumulative Square Prediction Error of Two Best Forecasting Models (2 Years)

Cumulative square prediction error of the best forecasting model minus the cumulative square prediction error of the second best (ie. alternative) forecasting model.



IV. Predictive Performance and the 2008 Global Financial Crisis (GFC)

As a final check of robustness, we follow Rapach, Strauss and Zhou (2010) and we illustrate the cumulative prediction errors of the two best forecasting models. In our case, we combine the prediction errors of all indices and we compare the difference in these errors between the best forecasting model against the second best forecasting model for 1, 12 and 24 month time horizons, respectively. The time series plots in Figures 1 to 3 are important because they illustrate the consistency of the forecasting performance of the two best models for each time horizon.

Figure 1 compares the prediction errors of the two best one month forecasting models, namely, the Australian Fama and French (1993) three-factor asset pricing model with no intercept term (FFNI) versus the single-factor Capital Asset Pricing Model with no intercept term (CAPMNI). Positive values in Figure 1 denote that the FFNI is a better predictor than CAPMNI while negative values illustrates the opposite. Panel A of Table 7 shows that both FFNI and CAPMNI forecasting models report the same level of predictive performance when forecasting 1 month returns, however, on closer inspection, Figure 1 reveals that the FFNI model reports lower cumulative prediction errors than the CAPMNI model. Put simply, an investor is better served in employing the FFNI model when forecasting 1 month returns.

Figures 2 and 3 illustrate the analysis of the two best forecasting models for 1 and 2 year time horizons, respectively, which are the fixed excess return models of 9% versus 10%. Negative values in Figures 2 and 3 indicate that the 10% excess return model exhibits lower prediction errors than the 9% excess return model while positive values indicates the opposite. From the early 2000s to 2006, the 10% fixed excess return model was a better predictor of future returns in comparison to the 9% fixed excess return model. However, as the market stalled preceding the GFC, we observe that the 9% excess return model began to outperform the 10% excess return model. Overall, the differences in the cumulative prediction errors (see the y-axis) are negligible between these two forecasting models for both time horizons.

Overall, the analysis in Figures 1 to 3 shows the importance of visualising the dynamics and the consistency of competing forecasting models and how the consistency changes through time. These illustrations convey the message that even the best predictive model in these studies exhibit changes in consistency over time if investors were to employ them in applied settings over the short, medium and long-term.

6. Concluding Remarks

Our findings suggest that the predictive performance of the CAPM with no intercept is the best performing asset pricing model, however, it is important to note that simple, fixed excess return models generally tend to outperform the CAPM and Fama-French models. These findings in the Australian setting have important implications for practitioners. An interesting finding from the analysis (consistent with Simin, 2008) is that the predictive performance of the constant return models tends to gravitate towards their 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 have 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 avenue for further research is the efficacy of the 60 month rolling window employed in this analysis. It is standard practice in the finance literature to employ a rolling 60 month window to capture the inputs for the asset pricing model, however, this itself must be an issue of contention. Researchers may need to experiment with other time frames to evaluate the efficacy of these methods in the finance literature. We leave these challenges for future research endeavours.

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