Variance of the ZBP Estimator

Report to the ERA on DBP Submission 56

June 2016

Project: 0003_ERA_2016

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Revised following comments by Partington and Satchell (2016)[1]

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Economic Regulatory Authority Western Australia

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[1] Partington, G. and S. Satchell, *Report to the ERA: Comments on Statistical Reports by Pink Lake*, 31st May 2016.

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Executive Summary

The variance of the zero-beta premium (ZBP) estimate provided by DBP in their Submission, entitled '*Proposed Revisions DBNGP Access Arrangement, 2016-2020 Access Arrangement Period Supporting Submission: 56',* is known to be high. However, the impact of uncertainty in the ZBP estimate on the Black CAPM Return on Equity (RoE) calculation has not as yet been measured or fully understood.

Within this report, criteria supporting the Allowed Rate of Return Objective (ARORO) within the Authority's Rate of Return Guidelines are applied to the Authority's and DBP's RoE evaluations. The 'fit for purpose' requirement states in part that the methods employed to calculate the rate of return must be "*able to perform well in estimating the cost of debt and the cost of equity over the regulatory years of the access arrangement period"*.[2] From a statistical perspective this suggests two measures of performance, namely the accuracy and precision of the methods applied in estimating the RoE.

The debate around accuracy centres on what parameters are to be included in the Black Capital Asset Pricing Model (CAPM), argued for by DBP. The accuracy and relevance of the Black CAPM has now been discussed in several different reports, and is not considered here. This report therefore focuses instead on the precision (i.e., variance) of the ZBP and the asset β as the two key inputs into the RoE calculation under the Black CAPM. Hence, the variance of the ZBP may be used to assess the performance of different CAPM models if these models cannot be wholly discriminated against through other measures or means.

Criticisms raised by HoustonKemp (2016)[3], on behalf of DBP, that data processing errors risk invalidating the Authority's estimates needed to be addressed before continuing with estimation of the variance of the various RoE parameters. There was only a slight impact found from a mis-specified denominator in the calculation of returns on the Authority's RoE estimate (0.11%), and a negligible effect on the Authority's RoE estimate arising from the treatment of missing data (in the Authority's case, to be imputed) or the conversion to AUD of foreign dividends. In contrast, the Authority's implementation of DBP's estimator of ZBP was found to be highly influenced by these data issues, which can severely impact on the Black CAPM evaluation of the RoE. This suggests strongly that the ZBP estimate is unduly sensitive to errors in data inputs, and to data processing assumptions.

Application of Monte Carlo simulation to derive the sampling distribution of the ZBP estimate, for a range of Black CAPM models used in the Australian context, demonstrates that the ZBP estimate is associated with high variance (with a standard error of 2.3-4.4%, depending on the parameterisation of the Black CAPM during estimation). This high variance has almost negligible impact on the Black CAPM estimate of the asset β, and has little relative impact on variance of the RoE evaluation (increasing the standard error of the RoE calculation by 0.2% to 0.9% across the different parameterisations of the Black CAPM). However, the impact of the high variance of the ZBP estimate on the 'compensation'[4] for borrowing and/or transaction costs is significant, with a standard error ranging from 1% to 1.6% for different parameterisations of the Black CAPM. This variance measure is

[2] Economic Regulation Authority Western Australia, *Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules*, 16th December 2013, Section 41, p. 10.

[3] HoustonKemp Economists, *The Black CAPM: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2010, A Report for DBP,* February 2016, Appendix H, p. vii.

[4] The level of compensation is defined as the difference between the Black CAPM RoE calculation and that of the SL CAPM. Essentially, this premium above the expected return of the asset or portfolio is intended to compensate for non-free borrowing or other transactional costs in the market.

high when compared to the mean compensation estimates themselves, which range from 0.7% to 2.4% for the variance weighted portfolio (i.e., a coefficient of variation of 70% to 130%, which compares to 45% for the risk-free rate which is projected to be 1.96% per annum).

These results, however, are extremely conservative relative to DBP's position for two reasons. Firstly, these variance measures were significantly higher when serial autocorrelation was included in the modelling (standard error of the ZBP estimate increased from $\sim 3\%$ to $\sim 19\%$; and the RoE standard error increased from $\sim 0.5\%$ to $\sim 6\%$). Secondly, the approach of SFG Consulting (2014) was applied to estimating the ZBP, rather than the DBP approach. DBP's method for estimating ZBP has a much higher variance than the SFG method, due to extreme values in its time-dependent estimates (with a standard error of $\sim 45\%$). This implies that had the present analysis been conducted with DBP's method, the variance estimate would most likely have been much higher.

However, even when the conservative SFG method is employed it is of significant concern that the Black CAPM valuation of the RoE is highly sensitive to modelling assumptions - ZBP estimates are different between the different Black CAPM parameterisations, the choice of which has a significant impact on the RoE (at least in the instance where no serial correlation was considered in the modelling).

Hence, different approaches to estimating the ZBP, based as they are on the specific decisions of the individuals and organisations implementing the model, does not support *"robust, transparent and replicable analyses"*.[5] Moreover, the DBP method for estimating a time-dependent ZBP is less robust to model and data issues than the SFG method studied here.

The opinion, formed during the analysis contained within this report, is that the Black CAPM, due to the ZBP estimate and its high variance, is sufficiently sensitive to any modelling assumptions or data treatment that it should be given zero or minimal weight in any consideration of the RoE evaluation. If the Black CAPM approach to the RoE evaluation is to be reviewed then it should only occur at such a time as when all market participants can agree what form those modelling assumptions should take.

Of the models considered here this leaves only the SL CAPM to be adopted for the RoE evaluation. It is recommended that any adjustments to the Authority's RoE valuation should be made on a basis other than that of the ZBP estimate derived from a Black CAPM, if an adjustment is to be made at all.

The Authority's estimates of β has been revised on 31st May 2016, and are reported in Appendix G. The revised estimates, following re-levering and before any ad hoc adjustment, provide an estimate $\beta = 0.7$ for the purposes of the RoE valuation.

[5] Economic Regulation Authority Western Australia, *Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules*, 16th December 2013, Section 41, p. 10.

Terms of Reference

1. Pink Lake Analytics was engaged by ERA to examine, in depth, the high variability known to be associated with the zero-beta premium (ZBP) estimate, and its impact on the return on equity (RoE) calculation, as part of DBP's 'Submission': *Proposed Revisions DBNGP Access Arrangement, 2016-2020 Access Arrangement Period Supporting Submission: 56*.
2. As such, the following Appendices in support of the Submission have been reviewed:
    - *Evaluating Forecasts: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2020, A Report for DBP*, HoustonKemp Economists, February 2016, Appendix F.
    - *The Black CAPM: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2020*, HoustonKemp Economists, February 2016, Appendix G.
3. In reviewing the Submission reference will be made to the Authority's 'Draft Decision': *Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2020*, and to DBP's original 'Submission 12': *Proposed Revisions DBNGP Access Arrangement, 2016-2020 Regulatory Period, Rate of Return, Supporting Submission: 12.*
4. The scope for this study is set out in Appendix D of *Statistical Advice to the ERA on DBP Submission 56,*[6] and is attached as Appendix A to this report. The report entitled *Statistical Advice to the ERA on DBP Submission 56* provides a broader context to the analysis conducted within this report.
5. This report has been revised following a review of this report by Partington and Satchell (2016).[7]
6. The outcome of this study is to evaluate the reliability (i.e., the precision or variance) of the ZBP estimate provided by DBP for the purposes of satisfying the Allowed Rate of Return Objective (ARORO),[8] in comparison with the Authority's RoE calculation. This falls within the 'fit for purpose' requirement outlined in the Authority's Rate of Return Guidelines, focusing primarily on the component "a*ble to perform well in estimating the cost of debt and the cost of equity over the regulatory years of the access arrangement period".*[9]
7. An extension of the scope enabled the Authority's estimates of β to be re-estimated for the most current period, and are reported in Appendix G.

Declaration

8. This report has been prepared by Rohan Sadler of Pink Lake Analytics Pty Ltd.
9. As the author of this report I have read, understood and complied with the Expert Witness Guidelines entitled *Expert Witnesses in Proceedings in the Federal Court of Australia* (as defined in the Federal Court of Australia's Practice Note CM 7; attached as Appendix B). As the author I have made all the inquiries that I believe are desirable and appropriate and that no matters of significance that I regard as relevant have, to my knowledge, been withheld from this report.
10. A curriculum vitae for the consultant has been provided as Appendix C.

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[6] Pink Lake Analytics, *Statistical Advice to the ERA on DBP Submission 56,* Revised Report, June 2016.
[7] Partington, G. and S. Satchell, *Report to the ERA: Comments on Statistical Reports by Pink Lake*, 31st May 2016.
[8] NGR 87(3) provides a definition of the ARORO: "*The allowed rate of return objective is that the rate of return for a service provider is to be commensurate with the efficient financing costs of a benchmark efficient entity with a similar degree of risk as that which applies to the service provider in respect of the provision of reference services (the allowed rate of return objective).*"
[9] Economic Regulation Authority Western Australia, *Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules*, 16th December 2013, Section 41, p. 10.

Introduction

10. This report focuses on estimating the variance of the zero-beta premium (ZBP) estimate within the Black Capital Asset Pricing Model (CAPM), which is the Return on Equity (RoE) model favoured by DBP. It is the argument of DBP that the ZBP should be included in the RoE calculation as appropriate compensation for any non-free borrowing or other transaction costs associated with standard market activities.
11. The Authority's position is that the ZBP estimate likely possesses high variance, and is highly sensitive to decision parameters, such as the inclusion of a free intercept term in the second-pass of the two-pass estimation of ZBP. Evidence of either high variance, non-stationarity or high sensitivity to decision parameters of the ZBP estimate would require the Authority to give little or zero weight to the Black CAPM estimate of β,[10] and the subsequent Return on Equity (RoE) calculation.
12. This chain of reasoning follows the requirements of the Authority's Rate of Return Guidelines that:[11]

"…the Authority considers it desirable if the proposed rate of return methods are:

- *Driven by economic principles*
  - *Based on a strong theoretical foundation, informed by empirical analysis;*
- *Fit for purpose:*
  - *Able to perform well in estimating the cost of debt and the cost of equity over the regulatory years of the access arrangement period;*
  - *Implemented in accordance with best practice;*
- *Supported by robust, transparent and replicable analysis that is derived from available, credible datasets;*
  - *Based on quantitative modelling that is sufficiently robust as to not be unduly sensitive to small changes in the input data;*
  - *Based on quantitative modelling which avoids arbitrary filtering or adjustment of data, which does not have a sound rationale;*
  - *Capable of reflecting changes in market conditions and able to incorporate new information as it becomes available;"*

13. Both the Black CAPM (which is supported by DBP) and the Sharpe-Lintner (SL) CAPM (which is supported by the Authority) possess a strong theoretical foundation and can be informed by empirical analysis. Details of how these models are estimated (and the Monte Carlo based estimation of the variance of the parameters contained within these models) are outlined in the 'Estimating the ZBP' section below. For these reasons both models can be said to support the *"driven by economic principles"* guideline.
14. In terms of *"Fit for Purpose"* the model must be *"able to perform well in estimating the cost of debt and the cost of equity over the regulatory years of the access arrangement"*. From a statistical perspective this would most likely mean that the selected estimation methods optimise in some way the prediction accuracy of the models or parameter estimates (i.e., minimise prediction error of the model or minimise estimates of parameter uncertainty). Prediction error is often a trade-off between the bias in a statistical estimator and the variance of the estimator (i.e., you can improve one dimension of model 'performance', but at the expense of the other). Hence, bias (also termed accuracy) and variance (also termed precision) are the two key

[10] β is the measure of systematic risk within both the SL and Black CAPM.

[11] Economic Regulation Authority Western Australia, *Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules*, 16th December 2013, Section 41, p. 10.

measures against which statistical performance of a model may be assessed. These measures may be considered either separately or, as a measure of prediction error, in aggregate.

15. Model accuracy comes down to whether abnormal returns[12] are included within the statistical estimation of a CAPM, and whether abnormal returns are included or excluded from the final RoE calculation. DBP preceeds its calculation of the RoE with estimating ZBP, but without explicit consideration of abnormal returns in the estimation of the ZBP.[13]
16. DBP have attempted to argue that their version of the Black CAPM is more accurate than the Authority's SL CAPM. Their position has now been critiqued and rebutted by both Pink Lake Analytics (2016) and Partington and Satchell (2016),[14] from both statistical and economic perspectives. Importantly, the Authority does not admit as DBP have argued that the RoE calculation should predict actual asset returns, simply because a key component of asset returns in abnormal returns are excluded from the final RoE calculation (i.e., the RoE reflects the expected return and not the actual returns, in investment parlance).
17. The Authority's position is that to arrive at 'best practice' estimates of the Black CAPM then abnormal returns should be included in the estimation of the Black CAPM. Inclusion of abnormal returns produces a much lower estimate of the ZBP than what is reported by DBP, as evidenced by the lower ZBP estimates arrived at by SFG (2014).[15]
18. Moreover, estimates of β from the Black CAPM are very similar to that of the SL CAPM if abnormal returns are included in the estimation of β, following estimation of the ZBP. Indeed, the Black CAPM and SL CAPM estimates of β are precisely the same if the risk-free rate[16] is treated as a constant,[17] as is the practice with the Authority's Henry model. Hence, from the Authority's perspective the ZBP estimate is not of use in calculating β. However, the potential of the ZBP estimate is in calculating an appropriate compensation for non-free borrowing or other transactional costs within the final RoE calculation.
19. What will disallow ZBP as an appropriate compensation for non-free borrowing or other transactional costs are the remainder of the ARORO requirements as set out in the Rate of Return Guidelines.[18]
20. The 'fit for purpose' requirement for *"implemented in accordance with best practice"* is loosely defined, but here is taken as consisting of the following two requirements:
    - The RoE model to be implemented follows economic best practice. The general indicators of economic best practice is that the CAPM model in question is employed broadly across

[12] An abnormal return is the return generated by an asset or portfolio that is different from the expected rate of return defined by an asset pricing model. The Authority accounts for any abnormal return through inclusion of a free-intercept parameter in the Henry (2014) model. DBP do not account for abnormal returns in the second-pass of their ZBP estimation, nor in their estimation of β (Pink Lake Analytics, 2016).
Henry, O.T., *Estimating β: An update*, April 2014, [Source: https://www.aer.gov.au/system/files/D14%2052760%20%20Estimating%20Beta_%20An%20update%20Olan%20T%20Henry%20April%202014.pdf].
[13] DBP's estimation of the ZBP is based on the method of NERA Economic Consulting, *Estimates of the Zero-Beta Premium, A report for the Energy Networks Association,* June 2013,
[14] Pink Lake Analytics, *Statistical Advice to the ERA on DBP Submission 56,* Revised Report, June 2016.
Partington, G. and S. Satchell, *Report to the ERA: The Cost of Equity and Asset Pricing Models,* 15st May 2016.
[15] SFG Consulting, *Cost of equity in the Black Capital Asset Pricing Model*, *Report for Jemena Gas Networks, ActewAGL, Networks NSW, Transend, Ergon and SA Power Networks*, 22 May 2014.
[16] The risk-free rate is the rate of return on an investment with zero risk. The Authority adopts the five year Commonwealth Government Security yield as its measure of the risk-free rate when calculating the RoE.
[17] ERA, *Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2020, Appendix 4 Rate of Return,* 22 December 2015, Sections 836-843, pp. 178-179.
[18] Economic Regulation Authority Western Australia, *Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules*, 16th December 2013, Section 41, p. 10.

the investment management industry, and that there are good economic reasons why one model is preferred over another. In this respect Partington and Satchell (2016) argue against the Black CAPM in favour of the SL CAPM.[19]

- Implementation follows best software development practices to minimise errors in the code base and deliver correct results (e.g., unit testing, code versioning, rigorous and regular refactoring, documentation of architecture and design). Other than ensuring as best as possible the reliability of results produced by the relevant code, these practices enhance the maintainability, usability and computational efficiency of the code. A useful perspective to adopt is that the code has its own life cycle that needs to be managed if the code is to be reused and/or trusted.

21. HoustonKemp (2016)[20] correctly identify two data processing errors made by the Authority (i.e., critiqued the Authority's 'best practice' implementation from a code and data processing perspective). As part of best practice, any past errors in data processing are to be quantified in terms of their impacts on past estimates of β and RoE as soon as those errors are detected. Moreover, upon detection of errors, processes are required to be put in place to ensure the sustainable and iterative development of any software code supporting the methods. Criticisms of the Authority's data processing methods submitted by HoustonKemp are addressed in the following 'Data Corrections' section.
22. Examining the impact of the data corrections on estimates of β and the subsequent RoE calculation enables the sensitivity of each model (the Authority's SL CAPM and DBP's Black CAPM) to small changes in input data to be studied. As such quantifying the sensitivity of the CAPM methods to data issues will also be discussed within this report. These sensitivity analyses constitutes an assessment of the requirement to have each method be *"supported by robust, transparent and replicable analysis"*, principally through the need to have the RoE analysis be *"based on quantitative modelling that is sufficiently robust as to not be unduly sensitive to small changes in the input data"*.
23. Both CAPM models can, in principle, be *"based on quantitative modelling that avoids arbitrary adjustment of the data, which does not have a sound rationale*", with methods of data processing most likely to converge over time to a single workflow. This is because the Authority's code base pertaining to decisions is to be made freely available and will therefore be open to critique and improvement to a community of practitioners. Again, this type of convergence in method will likely be the result of the ongoing debate between market actors as to the validity (accuracy) and reliability (precision) of the relevant estimators.
24. For the Authority, this implies the consequent and iterative development of the Authority's code base. Currently, the code base for estimating the RoE is being developed in the open-source R language.[21] The points in Section 14 and in this section are consistent also with 'best practice' from a software perspective. Operationalisation of the code base enables a set of RoE methods that are *"capable of reflecting changes in market conditions and able to incorporate new information as it becomes available"*.
25. However, the objective selection of values for numerous 'decision parameters' involved in the construction of the Black CAPM (and for which a subset apply to the Authority's version of the SL

[19] Partington, G. and S. Satchell, *Report to the ERA: The Cost of Equity and Asset Pricing Models,* 15st May 2016, pp. 30-31.

[20] HoustonKemp Economists, *The Black CAPM: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2010, A Report for DBP,* February 2016, Appendix H, p. vii.

[21] R Core Team, *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2016. [https://www.R-project.org/].

CAPM) have not, as yet, been fully justified by DBP.[22] In particular, different experts on the Black CAPM within the Australian context have in the past put forward different methods for estimating ZBP, with quite divergent results in terms of the ZBP estimate. The choice of these decision parameters currently appears arbitrary. RoE methods "*based on quantitative modelling that avoids arbitrary adjustment of the data"* is a requirement of the Rate of Return Guidelines. It follows that the design of RoE methods should "*avoid arbitrary adjustment of the model implementation*", as the design of the RoE methods may well have more influence on ZBP estimates and subsequent RoE calculation than arbitrary adjustments of the data. This arbitrary selection of decision parameters of a chosen RoE method, while not wholly unavoidable (at which point one would hope for a consensus of method), can still occur even after the other requirements of the Rate of Return Guidelines are met.

26. The remaining requirement of the Rate of Return Guidelines to be addressed is thus the statistical requirement to apply a reliable estimator when evaluating the RoE (i.e., an estimator with low variance, as part of the 'fit for purpose' requirement). Hence, the estimators of interest are those that feed directly into the RoE calculation. For the SL CAPM this is simply the estimate of β, given the risk-free rate and the asset and market returns do not require estimation and so may be considered as fully known. For the Black CAPM both the Black CAPM estimate of β, and the estimate of ZBP, are inputs into the RoE calculation.
27. How uncertainty in the ZBP estimate impacts on the RoE calculation, and its influence on the RoE in comparison with β is unknown. Moreover, theoretically the ZBP estimate equates to compensation for non-free borrowing costs, and this level of compensation may be readily quantified (i.e., as the premium above the sum of the systematic risk and risk-free rate paid to compensate the firm for any borrowing and/or transaction costs). The interaction between uncertainty in the ZBP and β estimates on the RoE calculation is unclear due to the relative complexity involved in deriving a ZBP estimate, and may not be readily deduced through analytical means.
28. A Monte Carlo simulation approach will be applied to both the SL and Black CAPM to examine these issues. Again, the approach is briefly outlined in the section entitled 'Estimating the ZBP', with mathematical detail of the simulations contained within Appendix D. Appendix D has been updated to include serial autocorrelation among the parameters estimated within the first pass of the two pass method used to derive the ZBP, following the recommendation of Partington and Satchell (2016).[23] Other estimators of interest include $\hat{\beta}$, the forward-looking RoE evaluation, and the associated compensation level implied by the Black CAPM relative to the SL CAPM.
29. The results of the Monte Carlo simulation will then be presented within the 'Variance of the ZBP Estimate' section, and conclusions drawn with reference to the Rate of Return Guidelines that inform the Allowed Rate of Return Objective (ARORO).

[22] Pink Lake Analytics, *Statistical Advice to the ERA on DBP Submission 56,* Revised Report, June 2016.
[23] Partington, G. and S. Satchell, *Report to the ERA: Comments on Statistical Reports by Pink Lake*, 31st May 2016, pp. 6-7.

Estimating the ZBP

Model Specification

30. The starting point for the Black CAPM is the SL CAPM, expressed as:

$$\boldsymbol{r_i = r_f + \beta_i^{SL}(r_m - r_f)} \tag{1}$$

where r_i are the asset specific returns;
r_m are the returns on a market index;
r_f is the risk-free rate, treated as a fixed rate, and for the Authority based on the five year Commonwealth Government Security (CGS) yield; and,
β_i^{SL} is the β measure of systematic risk associated with the market index for the SL CAPM.

31. This CAPM expression is the equilibrium result for a risk-efficient market portolio. All diversifiable risk has been diversified away by investing in a weighted selection of assets, and the risk remaining is systematic risk only.
32. The key assumptions of the SL CAPM that enable derivation of Eqn. 1 are that:
    a. The risk-averse investor chooses a portfolio of assets based purely on the mean and variance of the returns on the portfolio to maximise their end-of-period utility of wealth.
    b. The investor can borrow or lend freely at a single risk-free rate.
    c. All investors share a common joint probability distribution for the returns on the available asset, and this probability distribution is normally distributed (or otherwise stable with a characteristic exponent).
33. Much of the criticism of the SL CAPM centres on the validity of the second assumption, namely the ability to lend or borrow at a single risk-free rate. To date, the Authority has acknowledged that borrowing rates may well be higher than lending rates (taken to be the risk-free rate given here by the yield of the five-year CGS).
34. The Black CAPM proposes a mechanism to compensate for the higher borrowing rates, which may arise from the investor being precluded from holding short positions in the risk-free security. This mechanism identifies a zero-beta portfolio that is constructed to have zero systematic risk (i.e., a portfolio that has a beta of zero), and which therefore has the same expected return as the risk-free rate. This zero-beta portfolio would therefore have zero correlation with the market index.
35. The expression for the Black CAPM is given by:

$$\boldsymbol{r_i = r_z + \beta_i^{B}(r_m - r_z)} \tag{2}$$

where r_z is the zero-beta return, with $r_z = ZBP + r_f$; and,
β_i^{B} is the β measure of systematic risk associated with the market index for the Black CAPM.

36. The zero-beta premium (ZBP) is the value of the zero-beta return (ZBR) in excess of the risk-free rate (i.e., $ZBP = r_z - r_f$).
37. The SL CAPM estimate of β is typically derived from a segment of the market whose characteristics correspond closely to the asset being priced. Hence, for gas infrastructure assets only four gas infrastructure companies within the Australian All Ordinaries are considered in the valuation (ASX codes: APA, AST, DUE and SKI; Table 1).
38. Estimation of β for the Black CAPM considers all assets in the market, as the ZBR is a reflection of the whole market, and not a specific segment of the market.

39. The Authority proceeds with the SL CAPM by implementing the Henry model in its estimation of β:[24]

$$\boldsymbol{r_{it}} = \boldsymbol{\alpha_i^H} + \boldsymbol{\beta_i^H}(\boldsymbol{r_{mt}} - \boldsymbol{r_f}) \qquad (3)$$

where t denotes the time specific market (r_{mt}) and asset returns (r_{it});
α_i^H is the Henry intercept term; and,
β_i^H is the β measure of systematic risk given by the Henry model.

40. The Henry intercept term is equivalent to the risk-free rate and the asset-specific abnormal return in excess of the risk-free rate (i.e., $\alpha_i^H = r_f + \alpha_i$). The risk-free rate is a single-value, averaged over the historical assessment period (for the Authority this is five years). If a free-intercept term is included in the CAPM expression the estimate β will be unbiased relative to any model that exclude the free-intercept term. It doesn't matter how this free intercept term is specified (i.e., as a single intercept α_i^H or with the risk-free rate explicitly defined as a model offset term in $r_f + \alpha_i$).

41. It follows that the Authority's RoE expression is defined as:

$$RoE^A = r_f^* + \hat{\beta}_i^H MRP$$

where r_f^* is the forward-looking estimate of the risk-free rate (currently 1.96);
MRP is the forward-looking market risk premium (currently 7.6); and,
$\hat{\beta}_i^H$ is the estimate of β from the Henry model (Equation 3) for asset i, following any re-levering.

Estimation of the asset β for the RoE evaluation is based on the previous five years of data for assets identified as part of the gas infrastructure segment of the market (i.e., similar benchmark efficient entities under the ARORO; Table 1).

Table 1. Assets comprising the gas infrastructure segment of the market

ASX Code	Asset
APA	APA Group
AST	AUSNET Services Limited
DUE	DUET Group
SKI	SPARK Infrastructure Group

42. Estimation of β in the Black CAPM first requires the estimation of the ZBP (or ZBR). Estimation of the ZBP requires a two-pass procedure applied to the long-term market data (i.e., 20 or more years of data). There are alternative ways for specifying this two-pass procedure. In this report, we specify the NERA (2013)[25] procedure (which underpins the DBP analysis), and the SFG (2014)[26] procedure (with the SFG procedure allowing for a more flexible class of second-pass models).

[24] Henry, OT, *Estimating β: An update, Report for the Australian Energy Regulator,* April 2014, p. 6.
[25] NERA Economic Consulting, *Estimates of the Zero-Beta Premium, A report for the Energy Networks Association,* June 2013, Equation A.5, p. 41-42.
[26] SFG Consulting, *Cost of equity in the Black Capital Asset Pricing Model*, *Report for Jemena Gas Networks, ActewAGL, Networks NSW, Transend, Ergon and SA Power Networks*, 22 May 2014.

43. Both NERA and SFG estimate time-varying (or cross-sectional) estimates of β in the first-pass of their approach:

$$r_{i,t-s} = r_{ft} + \alpha_{it}^{FP} + \beta_{it}^{FP}\left(r_{m,t-s} - r_{f,t-s}\right) + \varepsilon_{i,t-s}^{FP} \qquad s = 1,2,\dots,S$$

where β_{it}^{FP} is the cross-sectional β for asset i at time t for the first-pass equation;
S is the size of the rolling window used to calculate the cross-sectional estimates of β_{it}^{FP}, with each observation in the rolling window indexed by s;
α_{it}^{FP} is the cross-sectional abnormal return; and,
$\varepsilon_{i,t-s}^{FP}$ is the asset specific residual term (i.e., the difference between predicted and observed asset returns).

44. NERA define the second-pass equation as equivalent to:[27]

$$r_{it} = r_{ft} + ZBP_t^{SP}\left(1 - \beta_{it}^{FP}\right) + \beta_{it}^{FP}\left(r_{mt} - r_{ft}\right) + \varepsilon_{it}^{SP}$$

where ZBP_t^{SP} is the cross-sectional ZBP estimated at each time step t; and,
ε_{it}^{SP} are the second-pass residuals.

45. The ZBP_t^{SP} are then simply the regression of the r_{it}, offset by the values $r_{ft}+\beta_{it}^{FP}\left(r_{mt} - r_{ft}\right)$, on $\left(1 - \beta_{it}^{FP}\right)$. The Shanken (1992)[28] maximum likelihood estimator allows for bias correction and reciprocal weighting of the ZBP_t^{SP} estimates based on the asset specific variance of the first-pass residuals $\varepsilon_{i,t-s}^{FP}$:

$$\widehat{ZBP}_t^{SP} = \left(\sum_{i=1}^{N_t}\left(\frac{\left(1-\beta_{it}^{FP}\right)^2}{\hat{\sigma}_{it}^2} - \frac{\lambda}{\hat{\sigma}_{mt}^2}\right)\right)^{-1} \sum_{i=1}^{N_t}\left(\frac{\left(1-\beta_{it}^{FP}\right)\left(z_{it} - \beta_{it}^{FP} z_{mt}\right)}{\hat{\sigma}_{it}^2} - \frac{\lambda z_{mt}}{\hat{\sigma}_{mt}^2}\right)$$

where $\widehat{ZBP}_t^{SP}$ is the estimator of ZBP_t^{SP};
$\hat{\sigma}_{it}^2$ is the variance of the residuals $\varepsilon_{i,t-s}^{FP}$;
$\hat{\sigma}_{mt}^2$ is the variance of $z_{m,t-s} = r_{m,t-s} - r_{f,t-s}$ from the first-pass;
z_{it} is the offset asset returns $z_{it} = r_{it} - r_{ft}$;
N_t is the number of assets trading at time t; and,
λ is a bias correction factor given by $\lambda = (S-2)/\big((S-1)(S-4)\big)$.

46. The mean yearly estimate of the ZBP is then:[29]

$$\widehat{ZBP} = \frac{1}{T}\sum_{t=1}^{T}\left(\prod_{v=1+P(t-1)}^{Pt}\left(1 + \widehat{ZBP}_v^{SP}\right) - 1\right)$$

where T is the total number of years spanned by the first-pass estimates of β_{it}^{FP};
P is the number of time steps in each year; and,
v is an index of time.

[27] NERA Economic Consulting, *Estimates of the Zero-Beta Premium, A report for the Energy Networks Association,* June 2013, Equation A.5, p. 41.
[28] Shanken, Jay, “On the estimation of beta pricing models”, *Review of Financial Studies*, 1992, pp. 1-33
[29] NERA Economic Consulting, *Estimates of the Zero-Beta Premium, A report for the Energy Networks Association,* June 2013, Equation A.5, p. 43.

47. The SFG (2014) method for the second-pass differs from that of NERA in two key ways: by first deriving a static, single-valued estimate of ZBP rather than a time-varying estimate of ZBP; and secondly, by allowing a free intercept term to model overall abnormal returns in the market and to relax the constraint on $\beta_{it}^{FP}(r_{mt} - r_{ft})$ as a predictor in the regression equation:[30]

$$r_{it} = r_{ft} + \alpha^{SP} + ZBP^{SP}(1 - \beta_{it}^{FP}) + \eta\beta_{it}^{FP}(r_{mt} - r_{ft}) + \varepsilon_{it}^{SP}$$

where α^{SP} is the second-pass, mean abnormal return for the whole market;
η is the coefficient of the $\beta_{it}^{FP}(r_{mt} - r_{ft})$ predictor term.

48. The mean yearly estimate of the ZBP under the SFG second-pass equation is then:

$$\widehat{ZBP} = \left(1 + \widehat{ZBP}^{SP}\right)^{P} - 1$$

49. The first implication of the SFG method is that the resulting ZBP estimate should not be as heavily influenced by market events during any single time period as the NERA method, as reflected by the β_{it}^{FP} parameter. This is due to the pooling of all time periods into the one regression under the SFG procedure to generate one overall estimate of ZBP. Under the NERA procedure, estimates of β_{it}^{FP} for individual time periods may heavily influence the overall mean yearly ZBP estimate due to time-specific events (such as exceptionally bullish markets for one or more assets). This is despite the individual assets being reweighted for each time period. Consequently, one would expect the variance of the SFG estimate of the ZBP to have lower variance than the NERA estimate.
50. Secondly, the estimate of ZBP^{SP} can be heavily influenced by including both a free-intercept term α^{SP} into the second-pass expression, and through relaxing the constraint that the η coefficient must equal one. A better fitting model results from including these two parameters (i.e., the standard deviation of the ε_{it}^{SP} decreases). Consequently, the estimate of ZBP^{SP} is no longer compensating for the absence of information embodied in α^{SP} and η. As α^{SP} is expected to be greater than zero, and η to be approximately one, the SFG estimate of the ZBP is expected to be lower than that of the NERA estimate.
51. Note that by setting $\alpha^{SP} = 0$ and $\eta = 1$ the equivalent of the NERA second-pass equation for estimating the ZBP is produced. However, this second-pass equation does not produce NERA's time-varying estimate of ZBP, but rather a globally aggregated version of the NERA ZBP estimate.
52. The estimated $\widehat{ZBP}$ is then applied to the five-year history of asset returns of the gas infrastructure segment of the market, to provide the estimate $\hat{\beta}_i^B$ by applying Eqn. 2. These estimates then form the Black CAPM version of the RoE following re-levering of the $\hat{\beta}_i^B$:

$$RoE^B = r_f^* + (1 - \hat{\beta}_i^B)\widehat{ZBP} + \hat{\beta}_i^B MRP$$

53. The ZBP estimate represents a compensation to be paid for the premium of borrowing rates above lending rates under the Black CAPM.[31] This compensation level may be defined simply as the difference between the Authority's RoE (prior to any discretionary adjustment of $\hat{\beta}_i^A$) and that of the Black CAPM derived RoE:

$$Compensation = RoE^B - RoE^A = (1 - \hat{\beta}_i^B)\widehat{ZBP} + (\hat{\beta}_i^B - \hat{\beta}_i^A)MRP$$

[30] SFG Consulting, *Cost of equity in the Black Capital Asset Pricing Model*, *Report for Jemena Gas Networks, ActewAGL, Networks NSW, Transend, Ergon and SA Power Networks*, 22 May 2014, Section 100, p. 27.
[31] Really the Brennan CAPM model, after Partington, G. and S. Satchell, *Report to the ERA: The Cost of Equity and Asset Pricing Models,* 15st May 2016, pp. 12-14.

Estimating the ZBP Variance through Monte Carlo Simulation

54. Monte Carlo simulations were conducted to study the variance of the ZBP estimator and its effects on the estimation of β and the RoE. Specifically, the Monte Carlo simulation procedure employed here is otherwise termed the parametric bootstrap procedure (Efron and Tibshirani, 1994).[32] Monte Carlo simulations work by random sampling from probability distributions ascribed to the data to generate multiple, synthetic versions of the data. The properties of estimators, such as the ZBP, may then be quantified by summarising the statistics generated from these randomly sampled data. A Monte Carlo approach is particularly useful where the sampling distribution of a parameter is largely intractable from a mathematical perspective.
55. The Black CAPM should, in fact, be considered as a three-pass (or three-stage) procedure for the estimation of the asset β. The first two passes are embodied in the estimation of the ZBP described above. The third and final stage is the estimation of the asset β for the gas infrastructure segment of the market using $\widehat{ZBP}$ as a plug-in estimate. In addition, a number of transformations of the estimators are applied, including bias correction, re-levering and aggregating ZBP to a yearly estimate.
56. Each parameter at each pass of the estimation procedure may be described through a probability distribution. Further discussion may be had with regard to what these probability distributions may look like. However, for simplicity, assumption (c) stating that returns are normally distributed will be considered as true. This means that the distributions of any derived parameters will closely approximate normality, in keeping with the Central Limit Theorem[33] and the standard assumptions of the linear regression model.
57. For simplicity, and to ease the computational burden of the simulations, the SFG approach of pooling all β_{it}^{FP} will be applied when estimating ZBP^{SP}. The estimator of ZBP^{SP} in the SFG approach will (as will be argued in a subsequent section), have a lower associated variance than the DBP estimator based on time-dependent ZBP estimates, and is the more desired estimator. Any estimate of the ZBP variance derived from the SFG approach will then a conservative estimate relative to the DBP approach. If the SFG approach still results in high variance of the ZBP estimate, and the ZBP estimate is rejected on that basis, then so too will the DBP approach to valuing the RoE.
58. A distinction therefore has to be made between the estimation approaches of SFG and DBP, as well as the different parameterisations applied by both DBP and SFG. Each of these different parameterisations are termed a 'Scenario'. Hence, the following four model scenarios were considered given the second-pass equation, computed over both weekly and monthly data:
    a. SFG Scenario 1: α^{SP} and η are unconstrained;
    b. SFG Scenario 2: $\alpha^{SP} = 0$ and η is unconstrained; and,
    c. SFG Scenario 3: α^{SP} is unconstrained and $\eta = 1$; and,
    d. DBP Scenario: $\alpha^{SP} = 0$ and $\eta = 1$ (termed SFG Scenario 4).
59. Three layers of simulation were applied to represent the variability in the data at each pass of the estimation for both ZBP and equity β:
    a. Random sampling of time-dependent $\hat{\alpha}_{it}^{FP}$, $\hat{\beta}_{it}^{FP}$, and $\hat{\sigma}_{it}^{2}$ (together as a tuple). This random sampling compensates for the thin-trading and survivorship bias present in the long-term data on asset returns used to estimate the ZBP;

[32] Efron, B. and R. J. Tibshirani. *An introduction to the bootstrap*. CRC press, 1994.

[33] The Central Limit Theorem in its simplest form states that the mean of a sufficiently large number of independently and identically distributed random variables will approximate a normal distribution, regardless of the common underlying distribution of those variables.

b. Simulation of asset returns for the estimation of the ZBP, given the observed history of market returns; and,
c. A simulation of asset returns following simulation of $\hat{\alpha}_i^H$ and $\hat{\beta}_i^H$, as estimated from the last five years of market returns for the four assets within the gas infrastructure segment of the market (i.e., APA, AST, DUE and SKI; Table 1).

These layers of simulation assume that there is no serial autocorrelation through time among the α_{it}^{FP}, β_{it}^{FP} and $\hat{\sigma}_{it}^2$. For this reason this model is termed Model A, given by an assumption of 'independence'.

60. Simulated estimates of the equity β, RoE, ZBP and associated compensation level may then be derived by applying the relevant Black CAPM or Henry regressions to the simulated asset returns. The variance of these quantities (i.e., standard error and 95% confidence band) can then be computed from these simulations. The mathematical detail of these simulations is contained in Appendix D. Note that all simulations of the above quantities are conditional on the observed history of market returns.
61. Following comments from Partington and Satchell (2016)[34] a model incorporating serial autocorrelation among the α_{it}^{FP}, β_{it}^{FP} and $\hat{\sigma}_{it}^2$ estimates in the first pass of the ZBP estimation was developed. This model is described in Appendix D, and results presented in Appendix F.

Data Corrections

62. HoustonKemp (2016) raised a number of concerns with regards to the way in which daily price data was processed by the Authority in its Draft Decision, namely:[35]

"We have examined the ERA's code and found a number of problems with the way in which the regulator assembles its data that are sufficiently serious as to cast doubt on the reliability of the ERA's results.
First, the ERA incorrectly computes the returns to stocks on the days immediately following ex-dividend days. The ERA incorrectly presumes that a purchaser of a share of stock on the ex-dividend day will pay the sum of the price at the close of business and the dividend distributed.
Second, there is no sign in the ERA's code that it takes steps to ensure that dividends and prices are denominated in the same currency. We show that when dividends and prices are denominated in different currencies that returns can be very badly mismeasured.
Third, the ERA selects stocks based on whether they are currently members of the All Ordinaries and so, because membership of the All Ordinaries is determined by market capitalisation, on their current market capitalisations. So the ERA has selected a set of stocks that are known to have performed well on average.
Stocks that over the last five years or 20 years have performed well will be more likely, all else constant, than stocks that have performed badly over the last five years or 20 years to be current members of the All Ordinaries. It is likely, therefore, that the ERA's results suffer from survivorship bias.

[34] Partington, G. and S. Satchell, *Report to the ERA: Comments on Statistical Reports by Pink Lake*, 31st May 2016, pp. 6-7.
[35] Houston Kemp, *The Black CAPM: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016 – 2020: A report for DBP*, February 2016, p.11.

Fourth, rather than setting the return to a stock on a day when it does not trade – or over a week or a month when it does not trade – to missing, the ERA sets the return to zero if a price has previously been recorded.
Treating missing returns as zero returns can lead to estimates of the beta of a stock that are biased towards zero."

63. Each of these issues have been reviewed, with the Authority's code base amended in the case of the first and second points. The third point is rebutted, with the reasoning given below in Sections 76-79 below. The fourth point is also rebutted, but the influence of the treatment of missing data in either ignoring them or assigning zero returns is examined.
64. The Authority's R code controls the automated extraction of price data from the Bloomberg terminal and their conversion into daily, weekly or monthly data. Corrections were made to this code, as reported below, in late April 2016.
65. The Authority's code base is still in development, and does not employ standard software development tools, including requirements and design documentation, unit and integration testing, task tracking, version control or a software maintenance policy. Such tools enable multiple people to develop the code base over time while ensuring longevity of the code and the consistency of its outputs.
66. The benefits of employing software development tools in delivering reliable, error-free outcomes is greatest for code that is repeatedly implemented through time and/or for which an error may have a high value consequence (i.e., benefit = frequency x value). The benefits are minimal where the code involves ad hoc exploration of data or when the endpoint of the analysis is uncertain, say, or where there are only low value consequences to not discovering and excluding software faults.
67. Common practice is to develop code iteratively. Contingency should be made for the iterative development of code that is to be maintained over the long term. The corrections made to the code base to address the issues of HoustonKemp (2016) may be viewed as an iterative improvement to the Authority's code base given the clear need (i.e., requirement) to correct the code base.
68. Although documentation within the Authority's code base is sparse, and the code requires refactoring, faults in the code can be located and corrected for, given there are no real integration or dependency issues between software systems and applications at this time.
69. A simple measure of the impact errors in the code have had on ZBP, β and RoE estimates is to exclude each fault in turn (i.e., a one-at-a-time sensitivity analysis). In this, results from the corrected code are compared to results from code where only one of the faults has been corrected for.
70. Similarly, the aggregate impact of any errors in the code may be quantified by comparing the results from the fully corrected code with results from the original code.

First issue: Denominator in log returns

71. The denominator was mis-specified in the code base.
72. To resolve the first issue the code was corrected in situ to apply the correct denominator when calculating returns on the day following the ex-dividend date. Omitting this correction was found to decrease $\hat{\beta}_i^H$ by 0.015 and decrease the RoE^A by 0.11% (Table 2).

Second issue: Currency denomination of dividends

73. In all, approximately 10% of dividends were paid in foreign currencies. Omission of these dividend conversions to AUD may be hypothesised to very marginally depreciate the returns and inflate $\hat{\beta}_i^H$, given that most of the foreign dividends were paid in USD.

74. A single dividend from 1989 did not have a PGK to AUD currency rate. As such this dividend has been omitted from the Bloomberg data, which in any case is truncated to the most recent 20 years (i.e., to 1996).
75. To resolve the second issue, a new function has been defined which converts dividends paid in foreign currencies into AUD on the ex-dividend date. Omitting this processing step was found to have a negligible effect on $\hat{\beta}_i^H$ and RoE^A.

Third issue: Survivorship Bias

76. HoustonKemp submits that the results of the Authority's ZBP analysis is likely to suffer from survivorship bias. It reasons that this is on account of the Authority using constituents of the All Ordinaries index and that constituents of the All Ordinaries are determined by market capitalisation. Selecting assets based on market capitalisation leads to the selection of assets that have tended to perform well as reflected in the increased market value of these firms relative to the rest of the stock market.[36]
77. The Authority notes that the data underlying DBP's estimates of the ZBP are also derived from the All Ordinaries index, the construction of which is also based on market capitalisation:[37]

> *"we exclude stocks in each year that at the end of the previous year fell outside the top 500 by market capitalisation. We choose the top 500 because the All Ordinaries Index is constructed from the top 500 stocks*."

78. Accordingly, it does not appear that the issue of survivorship bias has been addressed by DBP's treatment of the underlying data, when it comes to estimating the ZBP. In this instance, there is then no basis to consider the Authority's results on this front as any less reliable than DBP's. More importantly, neither HoustonKemp nor DBP have demonstrated that their treatment of survivorship bias does anything to improve the stability of ZBP estimates.
79. Accordingly, the issue of survivorship bias is not dealt with here.

Fourth Issue: Treatment of Missing Data

80. HoustonKemp (2016) submits that by setting returns of an asset on a day when it does not trade to zero rather than omitting the data from the analysis leads to estimates of β that are biased to zero.[38]
81. Assigning non-trading days a zero return has been the standard practice of the Authority, at least since 2009.[39]
82. In this the Authority considers the holding period of the asset. For example, a real-estate asset may be traded only every few years. If property prices were favourable then for many of those days there would be a zero return on the asset, punctuated rarely by a large windfall. This lack of price data is termed thin-trading, and the holding period the decade or so over which prices are monitored and/or analysed. A calculation of the average price increase would consider periods of both zero and non-zero returns together.
83. For a thin-trading asset the asset price may be correlated against the daily changing returns on the overall market. Hence an estimate of β may be derived as an estimate of the slope of the

[36] Houston Kemp, *The Black CAPM: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016 – 2020: A report for DBP*, February 2016, p.11.
[37] NERA Economic Consulting, *Estimates of the Zero-Beta Premium: A report for the Energy Networks Association*, June 2013, p.12.
[38] Houston Kemp, *The Black CAPM: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016 – 2020: A report for DBP*, February 2016, p.11
[39] Henry. O. T., *Estimating Β*, Submitted ACCC, 23 April 2009, p. 19.

relationship between market price and the individual asset return. Estimation of the net returns over a long period of time would result in minimal bias in the estimate of β. In contrast, the estimate of β would potentially have high variance and bias in the short term when only a few trades are completed.

84. If daily trades are to be aggregated into weekly and monthly returns then the impact of thin-trading will be reduced, as months without trades are much fewer, proportionately, than daily trades (i.e., proportionate to the total number of trading months or days in the time series, respectively). This is evidenced by the fact that the proportion of non-trading days for data acquired over the last 5 years decreases significantly for all assets from 23% to 19% for weekly data, and to 17% for monthly data (
85. Table 3). Among the gas stocks thin-trading affects <0.1% of weekly returns. Hence, thin-trading is more of an issue for daily data, which are not analysed by the Authority, and is not an issue for the Authority's estimates of the RoE for gas infrastructure segment of the market.
86. The HoustonKemp argument ignores situations when there is only a small handful of trades in a month or a week. This gives such months equal weight to months during which trading of an asset occurs on all available trading days.
87. An asset not trading for many days equates, in practice, to a zero return, relative to a frequently trading market. For example, Payce Consolidated Ltd. as an All Ordinaries listed stock has traded only 20 days out of the last 5 years (Asset ticker: PAY). Conditionally, on the days that it does trade, it may well be that the trades of this asset are highly correlated with the market index. However, over much of the 5 year holding period the asset is producing minimal returns. The asset prices would therefore have a low correlation with the market index when only the holding period is considered (i.e., over weekly or monthly periods).
88. The question is then for which method, the Black CAPM or SL CAPM, does thin-trading have the most influence.
89. For the SL CAPM, the Authority forms estimates of β over the last 5 years and over the last 20 years. These estimates are formed from the gas utility segment of the market only. If the position of HoustonKemp is accepted then the Authority's 20 year estimate is more subject to a thin-trading bias than the estimate formed over the last 5 years (
90. Table 3).
91. This result supports previous findings of minimal thin-trading bias in the data, for weekly data at least, given the Authority only uses the last 5 years of asset data in forming its RoE valuation.[40] Given that the Authority's analyses are not based on daily data, and the high liquidity of the gas utility sector, then the concerns that HoustonKemp raise in this regard carry little weight.
92. Moreover, the Authority implements the robust LAD (least absolute deviation) and MM (a two-stage maximum likelihood procedure) estimators of β whenever it forms its decision. These estimators may be considered more robust to thin-trading than the OLS regression applied by DBP.[41] However, in practice, little difference has thus far been observed in the estimates of β between the OLS estimator and the robust estimators.
93. Importantly, the Black CAPM method requires the ZBP to be estimated from the price data of all assets in the market, rather than the gas utility segment of the market as in the SL CAPM. This means that the Black CAPM estimate of β is more subject to thin-trading than that of the SL CAPM. This is because of two reasons: firstly, there is a higher observable rate of thin-trading across all assets contained within the All Ordinaries than among the subset of gas infrastructure assets, and, secondly, a longer time-series of market data is required to justify the stability of the ZBP estimate, on which survivorship bias has a stronger influence and novel assets are unlikely to trade over the entire period. For example, weekly data over the last 5 years has a missing rate

[40] Olan T Henry. Estimating B, Submitted ACCC, 23 April 2009, p. 19.

[41] ERA, *Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2020, Appendix 4 Rate of Return,* 22 December 2015*,* Tables 28-30, pp. 193-196.

of 19.0%, and weekly data over the last 20 years over the whole market has a missing rate of 44.2% (Table 3).

94. If non-trading days are omitted from the analysis rather than assigned a zero return, then there becomes a paucity of data for a number of assets, and consequently the variance of the ZBP estimate will likely increase due to a smaller sample size. With zero returns assigned to non-trading days then the variance of the ZBP estimate will be higher under thin trading when there are relatively many non-trading days for strongly appreciating (or depreciating) assets over time. Regardless of how non-grading days are treaded one bias or another is introduced into the ZBP estimate, whereas sampling bias for the SL CAPM model for the gas utilities is minimal in either case. This perspective assumes that non-trading days are assigned a zero return.

Note that missing rates are much higher for the Authority's 20 year record of asset returns than for the 5 year record, representing a number of assets that are relatively novel to the market, and so have missing data at the start of the time series. This contributes to a significant degree to the high observed missing rates for the 20 year record in

95. Table 3, and these data have always been excluded from the Authority's RoE calculations.
96. Review of the Authority's code shows that zero insertion of the returns (i.e., imputation) occurs only after an asset first starts trading in the available time-series record. For the gas utility sector, the influence of zero insertion on SL CAPM model estimates is both the correct means of dealing with the holding period and which has minimal influence on the model estimates due to the low missing data rate.
97. Significantly, the decrease in β resulting from thin-trading when zero returns are inserted influences the ZBP estimate in the second-pass of the Black CAPM estimation procedure (Case Study 1).

Table 2. Impact of code corrections on model estimates for the variance weighted portfolio.

Scenario	$\widehat{ZBP}$ (%)	$\hat{\beta}^B$	RoE^B (%)	$\hat{\beta}^H$	RoE^A (%)	Compensation (%)
Authority's corrected code	2.96	0.537	7.41	0.540	6.06	1.35
Houston Kemp (with no imputation)	19.39	0.524	15.17	0.540	6.06	9.11
With unconverted foreign dividends	19.33	0.524	15.14	0.540	6.06	9.08
With mis-specified denominator	13.95	0.520	12.61	0.525	5.95	6.66
With mis-specified denominator and unconverted dividends (Authority's uncorrected code)	0.48	0.526	6.18	0.525	5.95	0.23

Table 3. Proportion of non-trading days relative to ASX trading days for daily, weekly, and monthly data.

Data Period	Asset	Daily	Weekly	Monthly
Last 5 years	All individual assets	0.228	0.190	0.167
	Gas Utilities[42]	0.004	0.000	0.000
Last 20 years	All individual assets	0.481	0.447	0.423
	Gas Utilities	0.397	0.396	0.396

[42] The gas utilities described here have ASX codes given by APA, AST, DUE and SKI.

CASE STUDY 1: ROBUSTNESS OF ZBP ESTIMATE TO THIN TRADING

The key impact of thin trading is to reduce the estimate of β. This of course has an immediate impact on both the Black CAPM and SL CAPM. The impact on the SL CAPM estimates are however reduced to thin trading on assets within the gas infrastructure of the market. If these assets do not suffer from thin trading then estimates of β are not impacted. However, estimation of the ZBP requires all data in the market to be analysed, and so the prevalence of thin trading may increase. Do then a small handful of thin trading assets contained within the market index have undue influence on the ZBP estimate?

We can study both expressions when we decrease β_{it}^{FP} due to thin trading (as occurs when there is missing returns data). For simplicity, we omit the dependence of the β estimate on time t and asset i. Hence the thin-trading estimate of β^{TT} may be expressed as:

$$\beta^{TT} = \beta^{FP} - \tau$$

where β^{TT} is the estimate of β^{FP} under thin trading, and $0 \leq \tau < \beta^{FP}$ ensures that $0 \leq \beta^{TT} < \beta^{FP}$. Hence, the second-pass expression under thin trading for DBP may be expressed in short form as:

$$r_{DBP} = r_f + ZBP^{TT}(1 - \beta^{FP} + \tau) + (\beta^{FP} - \tau)r_m + \varepsilon$$

Given expected asset returns (i.e., E(ε) = 0) then the ZBP under thin trading is:

$$ZBP^{TT} = \frac{r_{DBP} - r_f - (\beta^{FP} - \tau)r_m}{(1 - \beta^{FP} + \tau)}$$

and the ZBP for the DBP second-pass equation without thin trading is:

$$ZBP = \frac{r - r_f - \beta^{FP} r_m}{(1 - \beta^{FP})}$$

Thus the ZBP is sensitive to thin-trading, as the difference between the two above equations reduces to:

$$ZBP - ZBP^{TT} = \frac{(r - r_{DBP} - \tau r_m)(1 - \beta^{FP}) + \tau r_f \beta}{(1 - \beta^{FP} + \tau)(1 - \beta^{FP})}$$

As $ZBP - ZBP^{TT} \neq 0$ then the estimate of ZBP is influenced by thin trading, over and above the impact on β. A similar expression with further terms resulting from the inclusion of the free intercept term in the second-pass equation may be derived for the SFG method. Note that under thin trading $r - r_{DBP} > 0$ and $\tau r_m \beta > 0$, and so the extent of change in ZBP values is a function both of the severity of the thin trading on mean asset return as well as its influence on estimates of β in the first pass (as measured by τ).

The key conclusion is that the estimate of ZBP depends on the data and on which (unobserved) data are omitted, regardless of whether thin-trading increases or decreases the ZBP estimate. What is clear is that the change in the ZBP resulting from thin-trading is in addition to the change in the estimate of β^{FP}. As such, the Black CAPM method is more sensitive to thin trading than the SL CAPM, and hence to how the data are treated (i.e., omit missing data or consider the holding period and assign zero returns to non-trading days).

98. If non-trading days are omitted from the analysis rather than assigned a zero return, then there becomes a paucity of data for a number of assets, and consequently the variance of the ZBP estimate will likely increase due to a smaller sample size.[43] With zero returns assigned to non-trading days then the variance of the ZBP estimate will be higher under thin trading when there are relatively many non-trading days for strongly appreciating (or depreciating) assets over time. Regardless of how non-trading days are treated one bias or another is introduced into the ZBP estimate, whereas sampling bias for the SL CAPM model for the gas utilities is minimal in either case.
99. In both treatments of non-trading days (i.e., omission or zero insertion), the impact of thin-trading on ZBP estimates can be mitigated in part by an inverse weighting of the variance in returns of each asset.[44]
100. Although HoustonKemp's position, which ignores the holding period, is rejected the impact of the two different treatments of missing values on β estimates under both the SL and Black CAPM is examined.
101. The HoustonKemp position is shown to have negligible effect on $\hat{\beta}_i^H$ and RoE^A. In contrast, thin-trading had a large impact on the estimate of ZBP and consequently RoE^B. Here, the $\widehat{ZBP}$ was estimated using DBP's time-dependent approach, and differs from the scenario with imputation (Authority's corrected positon) by more than 16% (Table 2).
102. A minor error in the code has been corrected for, whereby returns immediately following non-trading days were treated as non-trading days (i.e., assigned zero value). The impact of this error would have been more pronounced in low-volume stock (i.e., for the ZBP estimate, and not for the SL CAPM model estimates on which the Authority's decision has been based).

Data Errors and the ZBP

103. Clearly, the Black CAPM estimates of $\widehat{ZBP}$ and RoE^B were highly influenced by what data corrections were undertaken (Table 2). Here, $\widehat{ZBP}$ estimated under the DBP's time-dependent approach ranged from 0.5%-19%, depending on the data scenario. The estimate $\hat{\beta}^B$ was, in contrast, little influenced by the data scenario.
104. No pattern in the differences in the $\widehat{ZBP}$ estimates may readily be discerned in relation to the different data scenarios. Likely, much of the difference in the $\widehat{ZBP}$ estimates is due to changes in the estimates of α_{it}^{FP} and β_{it}^{FP} resulting from the data corrections, and is consequently unpredictable *a priori*.Notably, the high influence of the different data scenarios on $\widehat{ZBP}$ is consistent with the arguments put forward in Case Study 1. Thin-trading and other data issues have the potential to impact the ZBP estimate over and above any direct impact on the estimate of $\hat{\beta}^B$.
105. In contrast, the Authority's RoE^A is clearly not influenced by the data corrections, because:
    a. The RoE^A is influenced only by the mis-specified denominator, and then only very slightly (i.e., by 0.11%).
    b. The need to convert dividends paid in foreign currencies had negligible effect.
    c. Survivorship bias is seen to apply equally to both DBP's and the Authority's treatment of the data, one way or another.
    d. Missing data (and consequently thin-trading bias) will continue to be imputed by the Authority, consistent with its point of view that the holding period of the asset is paramount in the calculation of asset returns, whether the holding period is daily,

[43] Heinkel, Robert and Alan Kraus, "Measuring Event Impacts in Thinly Traded Stocks", *Journal of Financial and Quantitative Analysis,* 1988, 23, pp. 71-88.
[44] NERA 2013; variance weighting

weekly, monthly or otherwise. Regardless, how missing data are treated has no influence on the Authority's estimates.

106. On this basis, we reject the argument by HoustonKemp that issues with how the Authority assembles its data are *"sufficiently serious so as to cast doubt"* on the reliability of the ERA's results.
107. However, the issue for DBP in turn is that $\widehat{ZBP}$, RoE^B, and indeed the compensation DBP requests for borrowing rates through the Black CAPM are highly sensitive to how the data are treated (Table 2).
108. Subsequently, the only logical conclusion to be made is that DBP's RoE calculation, rather than the Authority's RoE calculation, is unduly sensitive to small changes in the input data. DBP's RoE calculation is therefore not "*sufficiently robust as to not be unduly sensitive to small changes in the input data",* one of the key criteria of the Rate of Return Guidelines.[45]

Variance of the ZBP Estimate

Results

109. The DBP model, by excluding the free intercept term in the second-pass of the estimation procedure, results in a higher estimate of the ZBP (7.27%; Table 8), compared to the SFG model containing no constraints (2.01%; Table 5).
110. In all Black CAPM model scenarios the measure of the ZBP variance was high, with the range of values for the confidence bounds for each ZBP estimate between an annualised 10% and 12%. This is of the same scale as that reported by HoustonKemp (2016) following 25 years of data.[46]
111. The parameter β^B is largely resistant to the magnitude and variance of the ZBP estimate and the form of the Black CAPM model, with estimates consistent with the SL CAPM model. Beta estimates differ by at most 0.01 between the models for the variance-weighted portfolio between the different CAPM models. The standard error of the β estimate is slightly higher for Black CAPM models than for the SL CAPM (by ~0.02 for the variance weighted portfolio; Tables 4-8).
112. The RoE estimates are higher for the ZBP portfolios than for the SL CAPM, adding between 0.6% and 2.4% to the RoE depending on the Black CAPM scenario. The standard error is slightly greater for the Black RoE estimates, with the range of values between the 95% confidence bounds being of the scale of $\sim$3-5% compared to $\sim$3% for the SL CAPM. It appears that most of the variability in the ZBP estimates is a reflection of the high variability of the return data, as observed by the high standard error of the Henry estimate of the abnormal returns α, when β^B is estimated.
113. Critically, the SFG model (SFG Scenario 1 with unconstrained coefficients; Table 5) pays a third less compensation than the DBP model (DBP Scenario with constrained coefficients; Table 8).

[45] Economic Regulation Authority Western Australia, *Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules*, 16th December 2013, Section 41, p. 10.

[46] HoustonKemp Economists, *The Black CAPM: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2010, A Report for DBP,* February 2016, Appendix H, Figure 5, p. 22. An 'eye-balling' of Figure 5 at 1992, 25 years after the inception of the time-series in 1967, displays a confidence band with a spread of around 12%.

Influence of Monthly Aggregation

114. ZBP estimates are lower when estimated from monthly data, but still possess high variance, when compared to the weekly data (Appendix E).
115. The largest influence of monthly aggregation on parameters within the RoE appears to be on the β estimates, reducing them by approximately half for the variance-weighted portfolio. This reduction in β indicates that a significant amount of the correlation between asset and market prices is lost with the aggregation of the data into the longer time unit.
116. This reduction in correlation due to monthly aggregation is 2.5% for the RoE resulting from the SL CAPM model. However, the Black CAPM models have RoE values only marginally reduced, by 0.4% (Table 14) and 1.5% (Table 11) for the DBP Scenario and the SFG Scenario 1, respectively. This outcome for the Black CAPM models is logical given that as β decreases the influence of ZBP in the RoE expression increases. Consequently, the level of compensation paid by the Black CAPM models is higher for monthly aggregated data than weekly data, if monthly data were to be used when estimating β within the Authority's RoE calculation.

Table 4. Henry model of the SL CAPM applied to weekly data.

Portfolio	α (%)	β^H	RoE (%)	Gear	Omega
APA	**27.0**[a] (13.0)[b] (4.20,55.7)[c]	**0.601** (0.071) (0.460,0.736)	**7.69** (0.89) (5.95,9.50)	0.440	1.1
AST	**21.6** (13.0) (-1.0,49.6)	**0.628** (0.072) (0.500,0.764)	**7.94** (0.97) (6.06,9.89)	0.566	1.415
DUE	**23.3** (13.3) (0.01,52.9)	**0.344** (0.074) (0.201,0.483)	**5.26** (1.01) (3.36,7.21)	0.642	1.605
SKI	**23.8** (14.4) (-2.0,52.1)	**0.475** (0.081) (0.316,0.632)	**6.51** (1.01) (4.57,8.58)	0.283	0.705
VW	**23.8** (9.23) (7.1,43.1)	**0.546** (0.048) (0.451,0.643)	**7.12** (0.68) (5.74,8.54)	0.488	1.22
EW	**24.1** (8.96) (6.9,42.8)	**0.516** (0.051) (0.416,0.608)	**6.84** (0.66) (5.48,8.09)	0.483	1.2075

a. The mean estimate for the parameter.
b. The standard error of the estimate
c. The 95% confidence bound for the estimate, generated through Monte Carlo simulation.

Table 5. SFG Scenario 1 applied to weekly data with no constraints.

Portfolio	ZBP (%)	β^B	RoE (%)	Compensation (%)
APA	**2.01** (3.79) (-5.35,9.40)	**0.603** (0.095) (0.419,0.796)	**8.26** (1.14) (5.84,10.4)	**0.57** (1.02) (-1.13,3.05)
AST		**0.630** (0.103) (0.431,0.837)	**8.44** (1.15) (5.5,10.3)	**0.50** (0.96) (-1.16,2.80)
DUE		**0.349** (0.106) (0.155,0.565)	**6.42** (2.32) (1.4,10.5)	**1.16** (2.17) (-2.84,5.60)
SKI		**0.480** (0.107) (0.279,0.700)	**7.33** (1.73) (3.15,10.1)	**0.82** (1.54) (-2.25,4.55)
VW		**0.544** (0.072) (0.399,0.699)	**7.83** (1.30) (5.2,10.1)	**0.71** (1.24) (-1.50,3.30)
EW		**0.514** (0.069) (0.372,0.649)	**7.59** (1.44) (4.71,10.2)	**0.76** (1.35) (-1.65,3.36)

Table 6. SFG Scenario 2 applied to weekly data with constraint $\eta = 1$.

Portfolio	ZBP (%)	β^B	RoE (%)	Compensation (%)
APA	**5.38** (4.35) (-4.03,13.5)	**0.597** (0.094) (0.414,0.790	**9.08** (1.18) (6.7,11.5)	**1.39** (1.37) (-0.56,4.74)
AST		**0.625** (0.102) (0.426,0.831)	**9.14** (1.16) (6.3,11.2)	**1.20** (1.32) (-0.73,4.47)
DUE		**0.344** (0.106) (0.149,0.555)	**8.33** (2.60) (3.1,13.3)	**3.07** (2.68) (-1.91,8.87
SKI		**0.475** (0.107) (0.268,0.693)	**8.67** (1.84) (4.4,12.3)	**2.16** (1.92) (-1.29,6.41)
VW		**0.539** (0.072) (0.392,0.690)	**8.90** (1.47) (6.2,11.6)	**1.78** (1.56) (-0.90,5.10)
EW		**0.508** (0.070) (0.363,0.645)	**8.79** (1.60) (5.7,11.8)	**1.95** (1.65) (-1.03,5.47)

Table 7. SFG Scenario 3 applied to weekly data with constraint $\alpha^{SP} = 0$.

Portfolio	ZBP (%)	β^B	RoE (%)	Compensation (%)
APA	**5.75** (2.37) (1.02,10.78)	**0.596** (0.094) (0.413,0.788)	**9.12** (0.67) (7.8,10.5)	**1.43** (0.97) (0.02,3.67)
AST		**0.624** (0.103) (0.425,0.831)	**9.18** (0.64) (7.8,10.4)	**1.24** (0.95) (-0.28,3.28)
DUE		**0.342** (0.106) (0.148,0.548)	**8.50** (1.43) (5.7,11.3)	**3.25** (1.58) (0.56,7.16)
SKI		**0.474** (0.107) (0.270,0.690)	**8.80** (1.05) (6.41,10.9)	**2.29** (1.24) (0.304,5.24)
VW		**0.537** (0.072) (0.395,0.687)	**8.98** (0.81) (7.44,10.5)	**1.86** (0.97) (0.28,4.01)
EW		**0.507** (0.070) (0.364,0.641)	**8.89** (0.90) (7.07,10.8)	**2.06** (1.00) (0.41,4.26)

Table 8. DBP Scenario applied to weekly data with constraints $\alpha^{SP} = 0$ and $\eta = 1$.

Portfolio	ZBP (%)	β^B	RoE (%)	Compensation (%)
APA	**7.27** (2.84) (1.49,13.0)	**0.593** (0.094) (0.412,0.785)	**9.51** (0.78) (8.0,11.2)	**1.83** (1.20) (0.00,4.78)
AST		**0.622** (0.103) (0.424,0.828)	**9.52** (0.76) (8.0,11.0)	**1.58** (1.19) (-0.33,4.13)
DUE		**0.340** (0.106) (0.147,0.544)	**9.39** (1.72) (6.3,12.8)	**4.14** (2.00) (0.72,8.63)
SKI		**0.472** (0.107) (0.262,0.688)	**9.43** (1.21) (6.60,11.8)	**2.91** (1.53) (0.36,6.37)
VW		**0.535** (0.072) (0.390,0.684)	**9.48** (0.98) (7.7,11.5)	**2.36** (1.21) (0.34,4.82)
EW		**0.505** (0.070) (0.361,0.641)	**9.46** (1.06) (7.3,11.6)	**2.62** (1.23) (0.43,5.27)

Influence of Autocorrelation among the Simulated α_{it}^{FP} and β_{it}^{FP}

117. Following the recommendation of Partington and Satchell (2016) serial autocorrelation among the α_{it}^{FP} and β_{it}^{FP} was modelled.[47] The key influences of serial autocorrelation on the SL CAPM model were (Table 15):
   - little change in the beta estimates and their variances, particularly for the variance and equal weighted portfolios of the gas utility assets.
   - Similar estimates for the RoE of the weighted portfolios, but with slightly lower variance than for the simulations without serial autocorrelation included.
   - Somewhat different estimates of α^H and β^H for the individual assets, which relates to the time-series model generating the simulations being estimated from the full 20 years of Bloomberg data, of which approximately the last 12 years contained non-missing data for the gas utility assets.
118. Overall, the assumption of serial autocorrelation among the α_{it}^{FP} and β_{it}^{FP} provides results that are little different from the assumption of independence among the α_{it}^{FP} and β_{it}^{FP} in terms of estimates of β and the RoE calculation.
119. The impact of serial autocorrelation among the α_{it}^{FP} and β_{it}^{FP} was however significant on the ZBP estimate, inflating both the estimate of ZBP to 11%-14%. The standard error of the ZBP also increased significantly from 2%-4% under the independence assumption, to 19% under an assumption of serial autocorrelation across the different Black CAPM scenarios (Tables 16-19).
120. Significantly, the Black CAPM estimate of β^B was robust, returning similar values regardless of whether serial autocorrelation or independence of the α_{it}^{FP} and β_{it}^{FP} were assumed. However, apart from an increased RoE valuation, and associated estimate of the compensation level, the variance of these calculations increased dramatically (i.e., more than triple the standard error associated with independence assumption with the corresponding models detailed in Tables 4-8).
121. It is hypothesised that the key reason for the increase in the ZBP and RoE variances is a result of as many as 13% of the assets in the market providing models with estimated autoregressive parameters for α_{it}^{FP} and β_{it}^{FP} that were greater than one. Included among this subset was the BHP asset, although this subset included more low capital value stock than those assets with autoregressive parameters less than one. A high autoregressive parameter indicates a non-stationary time series, so when the time-series is simulated then it can diverge from its starting value. Even models with autoregressive parameters below, but close to, one can display long periods of 'drift' in the behaviour away from their mean value. These divergent time-series for the estimated α_{it}^{FP} and β_{it}^{FP} clearly have an effect on the second pass estimation of the ZBP.
122. The time-series model applied in this study to estimate α_{it}^{FP} and β_{it}^{FP} may readily be improved, with much hinging on appropriate model selection. The consistency of the ZBP standard errors across the Black CAPM scenarios (Tables 16-19), and why the ZBP estimate differs little when the parameter η is included in the analysis (returning estimated η values very close to one when it is estimated in SFG scenarios 1 and 3, unlike when independence is assumed), remain largely unexplained (i.e., are outside the current scope to explore).

[47] Partington, G. and S. Satchell, *Report to the ERA: Comments on Statistical Reports by Pink Lake*, 31st May 2016, pp. 6-7.

Stationarity

123. Stationarity is an important property of time-series in the regulatory context as the time-varying quantity being estimated is mean reverting. It may be argued that the regulator should adopt a position that is indifferent to risk. In this sense, as long as the time-series has finite variance (i.e., is stationary) then the mean value of the time series may be applied in a valuation or a decision. That means any large risk associated with high variance of the estimator will balance itself over time.
124. In a brief analysis, the time-series of ZBP estimates resulting from the DBP approach may be applied to study the stationarity of the ZBP estimate. To this end, both the Dickey-Fuller and Priestley-Subba Rao tests were applied to the data.[48] Only the time-varying ZBP estimates was analysed, rather than the mean ZBP derived from of a rolling window of data through time, as has been considered in other studies.[49]
125. The Dickey-Fuller test accepted the hypothesis that the ZBP estimates were stationary (p-value < 0.001), as did the Priestley-Subba Rao tests.
126. However, what was readily apparent from the time-series plot of the data (Figure 1), and confirmed by the Priestly-Subba Rao test (p-value < 0.001), is the extremely high variance of the time-dependent ZBP estimate, and its heteroscedasticity through time.
127. This high variance suggests that a robust estimator of the ZBP should be chosen, to avoid the undue influence of extreme values on the overall mean value. This need is borne out by the fact that the mean of the ZBP time-series generated for this analysis was 7.9%, whereas the median was -1.9%, suggesting significant skewness of the data towards high exceptional values. In the presence of high variance, in this case a standard error of 47.5%, the median would be the preferred estimator of the central tendency of the ZBP time-series.
128. In contrast, the SFG approach of pooling all time- and asset-dependent estimates of β^{FP} within the second-pass of the estimation procedure produces a much more reliable estimate of the ZBP. This is evidenced by the SFG approach generating standard errors for the ZBP estimate of between 2.3-3.4% (Tables 4-8), an order of magnitude lower than for DBP's time-dependent approach.

Findings

129. A Black CAPM approach provides similar β estimates to the SL CAPM, but does not reduce the variance of these estimates. Hence, in terms of estimating β then the Black CAPM approach has nothing to commend it over and above the Authority's approach to estimating β.
130. In summary, applying the ZBP estimate appends only a small amount of variability to the RoE calculation over and above that inherent when estimating β for the SL CAPM model from 'noisy' asset and market returns (i.e., increases the standard deviation of the RoE projection from 1% to 3%). Despite this, the SL CAPM clearly provides a more 'reliable' estimate of the RoE, in terms of minimising the variance of the RoE estimate, than any of the Black CAPM models examined here.

[48] Dickey, D. A. and Fuller, W. A. (1981), Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root, *Econometrica*, **49**, 1057–1072.

Priestley, M. B. and Subba Rao, T. (1969) "A Test for Stationarity of Time Series", *Journal of the Royal Statistical Society*, Series B, **31**, pp. 140–9.

[49] For example, Figure 5 in HoustonKemp Economists, *The Black CAPM: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2010, A Report for DBP,* February 2016, Appendix H, p. 22.

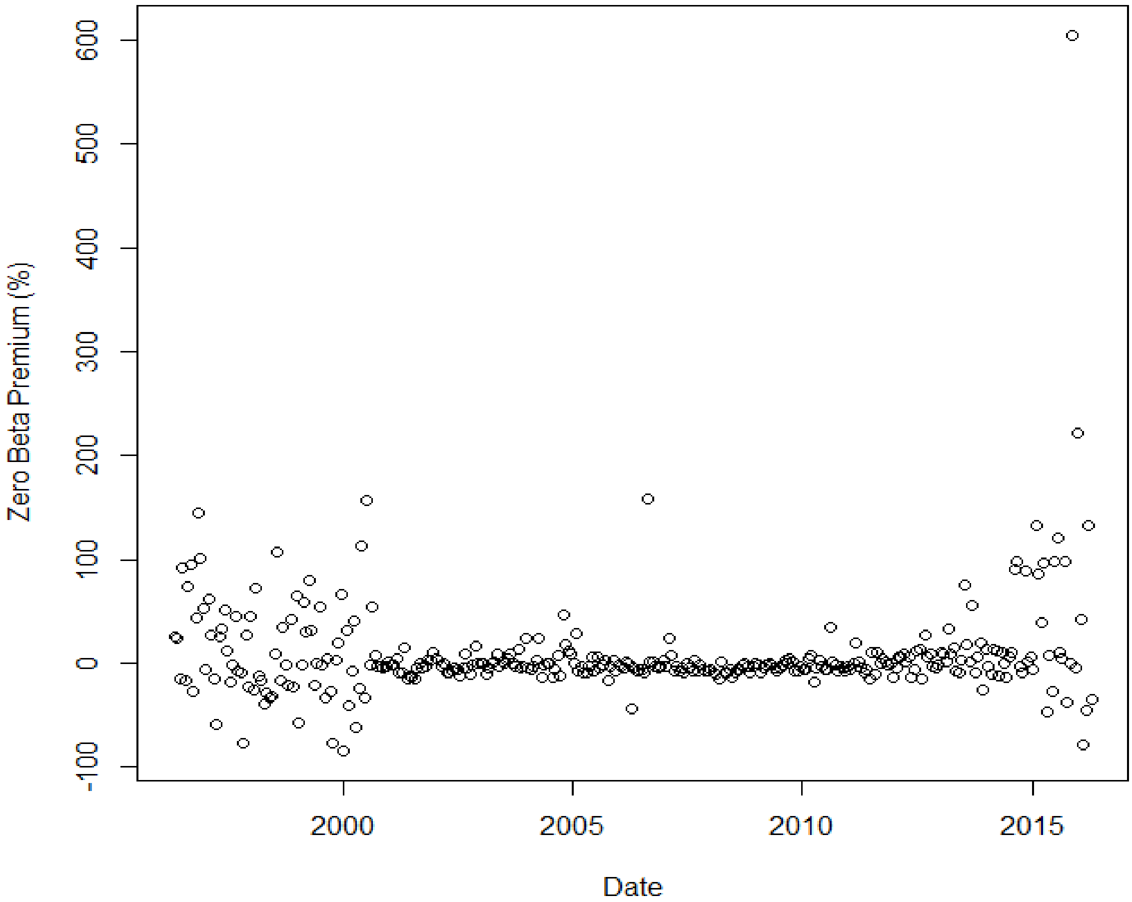

Figure 1. Time-series plot of estimates of the time-dependent ZBP.

131. However, when the variance in ZBP is propagated through to the level of compensation, to be paid in excess of the Authority's RoE calculation, then variance in the compensation level is extremely high relative to the compensation level itself (with a 51% to 175% coefficient-of-variation for the DBP and SFG models, respectively, as may be derived from Tables 3-8).
132. Critically, the ZBP estimate still shows high sensitivity to what decision parameters are chosen during the estimation process, with the ZBP estimate ranging from 2.01% (SFG Scenario 1) to 7.57% (DBP Model) for the weekly data, depending on the parameterisation of the second-pass equation used in estimating the ZBP. These vastly different ZBP estimates result in significantly different compensation levels, with the compensation level requested by the DBP Scenario (2.36%) more than three times that of the SFG Scenario 1 (0.71%).
133. Given that ZBP estimates are highly sensitive to the decision parameters being applied then the only conclusion that can be drawn is that ZBP estimates are highly unreliable for this reason alone. This unreliability of the estimate is over and above the high variance implicit in estimates of the ZBP resulting from any of the Black CAPM models put forward within the Australian context.
134. Given the inability of the ZBP estimate to provide a reliable estimate of an appropriate level of compensation, the only recommendation that can be made is to reject the Black CAPM approach altogether.

135. Another criticism of the ZBP is that the ZBP estimate, and its variance, appear to increase when serial autocorrelation in the α_{it}^{FP} and β_{it}^{FP} is present. This serial autocorrelation in the α_{it}^{FP} and β_{it}^{FP} is highly likely to occur as these estimates result from a rolling window being applied to the data.[50]
136. The time dependent ZBP estimate as formed by DBP may be assumed to be stationary, given the results of the Dickey-Fuller and Priestley-Subba Rao tests rejecting the hypothesis.
137. In all cases, the estimates of ZBP variance reported here are conservative in nature when compared to the DBP approach to estimating the ZBP. This is because the SFG method for estimating the ZBP variance as applied here has lower variance overall. The standard error associated with the DBP estimate of the ZBP was so large (i.e., $\sim 45\%$), as to have the method be wholly discarded in favour of the SFG method for the purposes of conducting the Monte Carlo simulations.
138. Of further concern, with regard to DBP's approach, are the following two findings:
    a. the application of a robust estimator of the central tendency of the time-dependent ZBP can provide a radically different estimate when compared to the average of the time-dependent ZBP (from a median of -1.9% to a mean of 7.9% for the time-dependent ZBP estimate; Figure 1)
    b. the implementation of DBP's approach here resulted in the ZBP estimate being highly sensitive to data assumptions (Table 2).
139. The unconstrained SFG model results in a compensation level of $\sim$ 0.7%. Interestingly, if the SFG model were to be weighted in the second-pass equation, by the reciprocal of the standard deviation of the residuals for each asset from the first-pass equation, then the compensation paid would be $\sim$ 0.2%, and when applied in future this estimate risks becoming negative given the broad confidence band.
140. However, adopting the SFG model over the DBP model would surely invite heated debate. It is highly likely that determining which version of the Black CAPM model is 'best' is analytically intractable, and so may not be resolved through an evidence-based approach. This is because there are many decision parameters to be considered in the estimation of the Black CAPM, and in the data preparation. A number of these decision parameters have been shown to drastically influence the ZBP estimates.
141. Consequently, what constitutes the 'best' implementation of the Black CAPM will remain largely be subject to opinion, given an appropriate test of optimality will be based on the specific opinion of one market participant over another. For example, the question of whether to include abnormal returns in the second-pass equation or not in the estimation of the ZBP, or similarly whether to include abnormal returns alongside the ZBP estimate in the estimation of β from the gas infrastructure segment of the market for the RoE evaluation.
142. In such a situation, it is recommended that the Authority is best served in seeking a more objective (i.e., less sensitive) means of setting the compensation level, if the Authority is to set a compensation level at all for borrowing rates above the risk-free rate.
143. An argument may be made that the Authority should be indifferent to risk, and so long as the time-series of ZBP estimates is stationary (and hence is mean reverting) then the Authority should adopt the ZBP estimate regardless of its high variance. This line of reasoning is obviated by the fact that the ZBP estimate is highly sensitive to the arbitrary choice of decision parameters chosen when applying the estimation. No matter which ZBP estimator is chosen, the chosen ZBP

[50] Partington, G. and S. Satchell, *Report to the ERA: Comments on Statistical Reports by Pink Lake*, 31st May 2016, pp. 6-7.

estimator is likely to be the 'wrong' estimator in the eyes of one-or-more other market participants.

144. Any ZBP estimate that is arrived at by the DBP method is therefore largely non-informative, for the multiple reasons described above, and this additional uncertainty is simply undesirable in the RoE calculation. The Authority's method, through the SL CAPM, provides instead a relatively reliable and low risk RoE calculation.

Conclusions

145. Overall, the SL CAPM is more 'fit for purpose' than the Black CAPM when it comes to satisfying the ARORO when based on a consideration of the variance estimator alone. This finding is the result of:
    - the high variance of the ZBP estimator, particularly as implemented through the DBP approach.
    - the arbitrary nature in deciding which version of the Black CAPM is to be implemented.
    - the high sensitivity of the ZBP estimate to these decisions, and to any issues related to how the data are processed.
146. The SL CAPM results in an RoE calculation with lower associated variance. This is primarily due to the exclusion of the high variance ZBP estimate from the RoE expression under the SL CAPM. Instead estimates of β, as the key input for the RoE calculation under the SL CAPM, are largely robust to data treatment, serial autocorrelation in α and β through time, and to different model assumptions. The SL CAPM is a more parsimonious model[51] to implement than the Black CAPM, with little uncertainty as to how it should be implemented.
147. Hence, the SL CAPM performs better than the Black CAPM in estimating "*the cost of equity over the regulatory years of the access arrangement period*",[52] when the statistical performance of the models is assessed through the variance of the estimates. This conclusion may be drawn independently of any economic arguments for or against the SL CAPM when the comparison is with the Black CAPM.
148. Different methods of estimating the ZBP, based as they are on the specific decisions of the individuals and organisations implementing the model, does not support *"robust, transparent and replicable analyses"*.[53] Moreover, the DBP method for estimating a time-dependent ZBP is less robust to model and data issues than the SFG method, which pools all first-pass estimates of β together in the second-pass equation to estimate the ZBP.
149. The opinion, formed during the analysis contained within this report, is that the Black CAPM should be given zero or little weight in any consideration of the RoE evaluation. This opinion considers that the behaviour of the ZBP estimate, and its high variance, is sufficiently sensitive to any modelling assumptions or data treatment that it should be given minimal weight in any consideration of the RoE evaluation. If the Black CAPM approach to the RoE evaluation is to be reviewed then it should only occur at such a time as when all market participants can agree what form those modelling assumptions should take.
150. Of the models considered in this report this leaves only the SL CAPM to be adopted for the RoE evaluation. It is recommended that any adjustments to the Authority's RoE evaluation should be made on a basis other than that of the ZBP estimate derived from a Black CAPM, if an adjustment is to be made at all.

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[51] AER, "Better Regulation", Explanatory Statement, Rate of Return Guideline, December 2013, Section 2.21(2)(b), p24.

[52] Economic Regulation Authority Western Australia, *Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules*, 16th December 2013, Section 41, p. 10.

[53] Economic Regulation Authority Western Australia, *Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules*, 16th December 2013, Section 41, p. 10.

Glossary

ACRONYM	DEFINITION
ARIMAX	Auto-Regressive Integrated Moving-Average with Covariates Model
ARORO	Allowed Rate of Return Objective
CAPM	Capital Asset Pricing Model
CGS	Commonwealth Government Security
DAA	Data Analysis Australia
DBP	Dampier-Bunbury Pipeline
GARCH	Generalised Auto-Regressive Conditional Heteroskedasticity models
LAD	Least Absolute Deviations Estimator
MM	MM Estimator
MRP	Market Risk Premium
OLS	Ordinary Least Squares
RoE	Return on Equity
SL	Sharpe-Lintner
T-S	Theil-Sen Estimator
ZBP	Zero-beta premium, i.e., the quantity by which the ZBR exceeds the risk-free rate.
ZBR	Zero-beta rate

Mathematical Terms

TERM	DESCRIPTION
A	Denotes both the Authority's method, and the model assumption that the $\hat{\alpha}_{it}^{FP}$,$\hat{\beta}_{it}^{FP}$, $\hat{\sigma}_{it}^{2}$ are not autocorrelated (i.e., an assumption of 'independence'), where applicable.
α_i	The abnormal return over and above the expected return for asset i.
A_{ik}	A vector (over the k) of the asset-specific autoregressive terms for each parameter.
$\hat{\alpha}^{H}$	Estimate of the abnormal return given Henry's method. This abnormal return includes the risk-free rate.
$\hat{\alpha}_{it}^{FP}$	A 'first-pass' estimate of α within the Black CAPM twopass estimation procedure for asset i at time t.
α^{SP}	The intercept term in the second-pass of the SFG approach to estimating the ZBP.
AR	An auto-regression model for a multivariate time series.
B	Denotes a Black CAPM method, or alternatively the model assumption that the $\hat{\alpha}_{it}^{FP}$,$\hat{\beta}_{it}^{FP}$, $\hat{\sigma}_{it}^{2}$ are autocorrelated (i.e., an assumption of 'autocorrelation'), where applicable.
β	A measure of an asset's risk relative to a market index. A low β value indicates a less volatile asset, or a volatile asset whose price movements are not highly correlated with the market. Thus β is a measure of an asset's systematic risk (i.e., the risk that cannot be reduced by diversification to other assets). In principle, the risk represented by β is the only kind of risk for which investors should receive an expected return higher than the risk-free rate of interest.
$\hat{\beta}$	An estimate of β.
$\hat{\beta}^{*}$	The estimate of β following an upwards revision to provide a rate of return equivalent to that of the Black CAPM.
$\hat{\beta}^{A}$	The Authority's estimate of β given by the Henry CAPM and following re-levering.
$\hat{\beta}^{B}$	An estimate of β returned by the Black CAPM.
$\hat{\beta}^{H}$	The Henry estimate of β applied in the Authority's RoE calculation.
$\hat{\beta}_{it}^{FP}$	A 'first-pass' estimate of β within the Black CAPM two-pass estimation procedure for asset i at time t.

$COV(\cdot)$	The variance-covariance matrix of a set of parameters or model terms.
δ_{it}^{FP}	Abnormal return in excess of the risk-free rate in the first pass of the two-pass estimation procedure of the Black CAPM.
δ_{it}^{SP}	Abnormal return in excess of the risk-free rate in the second pass of the two-pass estimation procedure of the Black CAPM.
ε_{it}^{FP}	Residual term for the first-pass equation of the two-pass estimation procedure of the Black CAPM.
ε_{it}^{SP}	Residual term for the second-pass equation of the two-pass estimation procedure of the Black CAPM.
i	An index of each asset
λ	Bias correction factor for the DBP estimate of the ZBP in the second pass equation.
m, M	An index of the Monte Carlo simulation, with total number of simulations M.
MVN	A multivariate normal distribution.
$N(\mu, \sigma^2)$	A (multivariate) normal distribution given by mean μ and variance σ^2.
N_t	The number of assets trading at time t.
η	The co-efficient for the observed risk-adjusted market risk premium in the second pass of the SFG approach.
p	The number of AR (autoregressive) lags.
P	The number of observation periods in a year, given by how the data were aggregated, when calculating an annualised return or rate.
r^A	The Authority's rate of return following gearing and upwards revision of $\hat{\beta}^A$.
r_f	The observed risk-free rate.
r_f^*	The forward looking risk-free rate.
r_{it}	The return of the asset at time t.
r_{mt}	The return given by the market index at time t.
r_z	The zero-beta rate (ZBR).
s, S	Index of set of observations prior to a given time t, in the first pass of the two-pass estimation procedure for the Black CAPM, with total period S.
$SE(\cdot)$	The standard error measure of a parameter.
$\hat{\sigma}_{it}^2$	Sample variance of the residuals ε_{it}^{FP}.
$\hat{\sigma}_{mt}^2$	Sample variance of the market returns from the first pass equation in DBP's approach to estimating the ZBP.
t, T	An index of time, with total number of time periods T.
w_i	A vector-valued intercept term applied in the AR model.
v	An index of time.
$VAR(\cdot)$	Variance measure of a parameter.
z_{it}	Asset returns in excess of the risk-free rate.
z_{mt}	Market returns in excess of the risk-free rate.
$\hat{x}$	An estimate of some quantity x.
$\tilde{x}$	A simulation of some quantity x.
X_{it}	The parameter vector $\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}, \hat{\sigma}_{it}^2$

Appendix A: Terms of reference

A key reason to reject DBP's position is the broad evidence that the ZBP estimate that is relied upon possesses high uncertainty. However, the impact of uncertainty in the ZBP estimate on the Black CAPM RoE calculation has not as yet been measured (both with and without abnormal returns). It is important to understand the effect uncertainty in ZBP estimates has on each of the RoE, β and compensation levels under the Black CAPM, given the significant influence of ZBP estimates on compensation levels (see Case Study 1 for an example). Once these effects of uncertainty in ZBP estimates are quantified then the reliability of the ZBP estimate from one assessment period to another may be assessed.

The key method underlying this approach involves Monte Carlo simulation of data within the Black CAPM two-stage estimation process. Note that

$$r_{it} = r_z + \beta_i^B (r_{mt} - r_z)$$

with the ZBR (r_z) given by ZBP - r_z. In the two-pass estimation process then firstly uncertainty in the ZBP estimate is a function of the uncertainty in β estimates during the first pass of the estimation process. Hence, a model can be constructed of the two-pass methodology using:

$$r_{i,t-s} = r_{ft} + \delta_{it}^{FP} + \beta_{it}^{FP}(r_{m,t-s} - r_{f,t-s}) + \varepsilon_{it}^{FP} \qquad s = 1,2,\dots,S$$ [54]

$$\hat{\beta}_{it}^{FP} \sim N\left(\beta_{it}^{FP}, Var(\beta_{it}^{FP})\right)\ ;\ \hat{\delta}_{it}^{FB} \sim N\left(\delta_{it}^{FP}, Var(\delta_{it}^{FP})\right)$$ [55]

$$r_{i,t-s} = r_{ft} + \delta_{it}^{SP} + ZBP_t^{SP}(1 - \beta_{it}^{FP}) + \lambda(\beta_{it}^{FP} r_{m,t}) + \varepsilon_{it}^{SP}$$ [56]

$$\widehat{ZBP}_t^{SP} \sim N\left(ZBP_t^{SP}, h\left(Var(\beta_{it}^{FP}), Var(\delta_{it}^{SP}), Var(\lambda)\right)\right)$$

where FP and SP refer to first-pass and second-pass estimation steps; $\delta_{it}^{\cdot}$ is the abnormal return over and above the risk-free rate (together they can be modelled as a single intercept term, as occurs in the Henry model); and h is some function of the multivariate co-variance of the parameter estimators in the second pass of the equation. Note that the variance of the estimators of the parameters in each pass of the equation are dependent on the variance of the residuals. Implicitly, realisations of $Var(\beta_{it}^{FP})$ is dependent on the covariance between β_{it}^{FP} and δ_{it}^{FP}. If the residual variance is high, which it most likely will be, then variance of the estimators will also be high. Here the risk-free rate is taken to be known *ex post*.

In practice $\widehat{ZBP}_t^{SP}$ is returned to provide a single mean or annualised estimate of the ZBP. The standard error of ZBP is therefore readily calculable from the $\widehat{ZBP}_t^{SP}$. We would use here the single portfolio method which allows a bias correction of the $\widehat{ZBP}_t^{SP}$ estimates[57]. The variance of the bias-corrected

[54] S is taken to be five years, composed of monthly intervals. NERA Economic Consulting, *Estimates of the Zero-Beta Premium, A report for the Energy Networks Association,* June 2013, Equation A.2, p. 41.

[55] Alternatively, these parameters from the first-pass estimation may be specified together as a multivariate normal distribution.

[56] SFG Consulting, *Cost of equity in the Black Capital Asset Pricing Model*, *Report for Jemena Gas Networks, ActewAGL, Networks NSW, Transend, Ergon and SA Power Networks*, 22 May 2014, Section 100, p. 27.

[57] NERA Economic Consulting, *Estimates of the Zero-Beta Premium, A report for the Energy Networks Association,* June 2013, Equation A.5, p. 42.

ZBP is itself dependent on the variance of the parameters of both the first-pass and second-pass estimations. It is these variance components that are propagated and accumulated through each pass of the estimation procedure into the estimation of β_i^B. In contrast, the SL CAPM depends only on variability embodied in the data, given the standard assumptions of the linear regression model.

What is not considered within this scope is the sensitivity of the ZBP estimate to model form and data processing methods (i.e., a wide range of decision parameters in the formation of the ZBP estimate). Instead, differences in ZBP estimates will be studied in relation to:

- Inclusion of δ_{it}^{FP} and/or δ_{it}^{SP}.
- weekly or monthly data, with S = 28 days or 60 months, respectively.
- calculated over 5 years or 20 years, as specified in the Rate of Return Guidelines.
- λ constrained to a value of one or unconstrained.

These scenarios will be compared with equivalent SL CAPM models to compare uncertainty in RoE estimates with those resulting from applying the ZBP estimate under the Black CAPM.

With autocorrelation in the data known to be low then a Monte Carlo solution may proceed by simulating from the multivariate normal distributions specified above. Moreover, stationarity of the ZBP estimate may also be considered for the five year data by applying rolling windows.

Also included in this scope is the need to deal with the criticism raised by HoustonKemp (2016) of the way in which daily price data was processed by the Authority in its Draft Decision[58]:

> *We have examined the ERA's code and found a number of problems with the way in which the regulator assembles its data that are sufficiently serious as to cast doubt on the reliability of the ERA's results.*
> *First, the ERA incorrectly computes the returns to stocks on the days immediately following ex-dividend days. The ERA incorrectly presumes that a purchaser of a share of stock on the ex-dividend day will pay the sum of the price at the close of business and the dividend distributed.*
> *Second, there is no sign in the ERA's code that it takes steps to ensure that dividends and prices are denominated in the same currency. We show that when dividends and prices are denominated in different currencies that returns can be very badly mismeasured.*
> *Third, the ERA selects stocks based on whether they are currently members of the All Ordinaries and so, because membership of the All Ordinaries is determined by market capitalisation, on their current market capitalisations. So the ERA has selected a set of stocks that are known to have performed well on average.*
> *Stocks that over the last five years or 20 years have performed well will be more likely, all else constant, than stocks that have performed badly over the last five years or 20 years to be current members of the All Ordinaries. It is likely, therefore, that the ERA's results suffer from survivorship bias.*
> *Fourth, rather than setting the return to a stock on a day when it does not trade – or over a week or a month when it does not trade – to missing, the ERA sets the return to zero if a price has previously been recorded.*
> *Treating missing returns as zero returns can lead to estimates of the beta of a stock that are biased towards zero.*

[57] HoustonKemp Economists, *The Black CAPM: Response to the ERA's Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2010, A Report for DBP,* February 2016, Appendix H, p. vii.

These data processing issues will need to be resolved before the proceeding the scope. An initial opinion is that the above changes are readily implemented, and the impact these data processing issues have had on values of $\hat{\beta}$ may be readily quantified. The third criticism with regard to the currency of constituents is perhaps the more important in terms of introducing bias into estimates ofβ. However, upon review it appears that DBP's processing of their data is subject to a similar bias, and no action on this issue should be taken at this point in time.

Deliverables

This scope will therefore be designed to:

1. Resolve the four HoustonKemp (2016) criticisms of the Authority's data processing method, and assess impact of changes to the Final Decision.
2. Develop a Monte Carlo procedure to provide a variance estimate of the ZBP, ZBR and ZBP/MRP estimates, both with and without abnormal returns.
3. Estimate the variance in RoE and β as impacted by the variance of the ZBP estimator under the Black CAPM, and compare this to the SL CAPM.
4. Consequently, evaluate the robustness of the Black CAPM and SL CAPM in terms of meeting the requirements of the allowed rate of return objective.
5. At most, deliver a 20 page report demonstrating both rationale and results, excluding administrative documentation such as Curriculum Vitae and Terms of Reference.

Time and Cost

Scope Activities	**Hours**	**Cost ($120/hr)**
1. Monte Carlo simulation of ZBP Variance Estimates	32	$3,840
2. Sensitivity analysis of RoE and β for Black and SL CAPM	24	$2,880
3. Improving data processing	16	$1,920
4. Deliver Report	96	$11,520
Total	**168**	**$20,160**

The scope and costs are negotiable. Costs exclude GST.

Personnel

Rohan Sadler is an AStat accredited statistician with 8+ years of research and consulting experience for industry and government at state and national levels, primarily in the domains of environmental monitoring, resource economics, data management and remote sensing. A Curriculum Vitae for Rohan is included in Appendix C.

Appendix B: Expert Witnesses in Federal Court Proceedings

FEDERAL COURT OF AUSTRALIA

Practice Note CM 7

EXPERT WITNESSES IN PROCEEDINGS IN THE FEDERAL COURT OF AUSTRALIA

Practice Note CM 7 issued on 1 August 2011 is revoked with effect from midnight on 3 June 2013 and the following Practice Note is substituted.

Commencement

1. This Practice Note commences on 4 June 2013.

Introduction

2. Rule 23.12 of the Federal Court Rules 2011 requires a party to give a copy of the following guidelines to any witness they propose to retain for the purpose of preparing a report or giving evidence in a proceeding as to an opinion held by the witness that is wholly or substantially based on the specialised knowledge of the witness (see **Part 3.3 - Opinion** of the *Evidence Act 1995* (Cth)).

3. The guidelines are not intended to address all aspects of an expert witness's duties, but are intended to facilitate the admission of opinion evidence[59], and to assist experts to understand in general terms what the Court expects of them. Additionally, it is hoped that the guidelines will assist individual expert witnesses to avoid the criticism that is sometimes made (whether rightly or wrongly) that expert witnesses lack objectivity, or have coloured their evidence in favour of the party calling them.

<u>Guidelines</u>

1. General Duty to the Court[60]

1.1 An expert witness has an overriding duty to assist the Court on matters relevant to the expert's area of expertise.

1.2 An expert witness is not an advocate for a party even when giving testimony that is necessarily evaluative rather than inferential.

1.3 An expert witness's paramount duty is to the Court and not to the person retaining the expert.

[59] As to the distinction between expert opinion evidence and expert assistance see *Evans Deakin Pty Ltd v Sebel Furniture Ltd* [2003] FCA 171 per Allsop J at [676].
[60] The "*Ikarian Reefer*" (1993) 20 FSR 563 at 565-566.

2. The Form of the Expert's Report[61]

2.1 An expert's written report must comply with Rule 23.13 and therefore must

(a) be signed by the expert who prepared the report; and

(b) contain an acknowledgement at the beginning of the report that the expert has read, understood and complied with the Practice Note; and

(c) contain particulars of the training, study or experience by which the expert has acquired specialised knowledge; and

(d) identify the questions that the expert was asked to address; and

(e) set out separately each of the factual findings or assumptions on which the expert's opinion is based; and

(f) set out separately from the factual findings or assumptions each of the expert's opinions; and

(g) set out the reasons for each of the expert's opinions; and

(ga) contain an acknowledgment that the expert's opinions are based wholly or substantially on the specialised knowledge mentioned in paragraph (c) above[62]; and

(h) comply with the Practice Note.

2.2 At the end of the report the expert should declare that "[the expert] has *made all the inquiries that* [the expert] *believes are desirable and appropriate and that no matters of significance that* [the expert] *regards as relevant have, to* [the expert's] *knowledge, been withheld from the Court*."

2.3 There should be included in or attached to the report the documents and other materials that the expert has been instructed to consider.

2.4 If, after exchange of reports or at any other stage, an expert witness changes the expert's opinion, having read another expert's report or for any other reason, the change should be communicated as soon as practicable (through the party's lawyers) to each party to whom the expert witness's report has been provided and, when appropriate, to the Court[63].

2.5 If an expert's opinion is not fully researched because the expert considers that insufficient data are available, or for any other reason, this must be stated with an indication that the opinion is no more than a provisional one. Where an expert witness who has prepared a report believes that it may be incomplete or inaccurate without some qualification, that qualification must be stated in the report.

2.6 The expert should make it clear if a particular question or issue falls outside the relevant field of expertise.

2.7 Where an expert's report refers to photographs, plans, calculations, analyses, measurements, survey reports or other extrinsic matter, these must be provided to the opposite party at the same time as the exchange of reports[64].

[61] Rule 23.13.
[62] See also *Dasreef Pty Limited v Nawaf Hawchar* [2011] HCA 21.
[63] The *"Ikarian Reefer"* [1993] 20 FSR 563 at 565
[64] The *"Ikarian Reefer"* [1993] 20 FSR 563 at 565-566. See also Ormrod *"Scientific Evidence in Court"* [1968] Crim LR 240

3. Experts' Conference

3.1 If experts retained by the parties meet at the direction of the Court, it would be improper for an expert to be given, or to accept, instructions not to reach agreement. If, at a meeting directed by the Court, the experts cannot reach agreement about matters of expert opinion, they should specify their reasons for being unable to do so.

J L B ALLSOP

Chief Justice

4 June 2013

Appendix C: Curriculum Vitae of Dr Rohan Sadler

Rohan Sadler

Curriculum Vitae

Profile

Rohan is a professional statistician who is involved in data science, remote sensing, and resource economics with a broad range of clients. With a strong background in the agricultural and environmental domains he has been developing the ecoinformatics capacity of organisations to deliver workflow improvement, data governance, analytics and evidence-based evaluation of management effectiveness.

Education

2006 **PhD**, *The University of Western Australia*, Perth.
Image-based Modelling of Pattern Dynamics in a Semiarid Grassland of the Pilbara, Australia

1993 **B.Sc.Agric.**, *The University of Western Australia*, Perth.

2014- **Diploma of Information Technology**, *TAFE NSW*, Online.

Experience

2016- **Director, Data Scientist**, *Pink Lake Analytics*, Perth.

- Water potential profiles of native seed germination success (Botanic Gardens and Parks Authority, Western Australia).
- Statistical Advice to the ERA on DBP Submission 56 (Economic Regulatory Authority Western Australia, Western Australia).
- Cost-response and power analysis in BACI-type experimental designs (BMT Oceanica, Western Australia).

2015–2016 **Free Lance Data Scientist**, *Bush Futures*, Perth.

- Empirical testing of theoretical capital asset pricing models and portfolio optimisation (Economic Regulatory Authority Western Australia, Western Australia).
- Cleaning, shaping, databasing and analysis of 30+ years of mammal trapping data for the Otways Region (subcontracted through Barbara Wilson on behalf of Department of Environment, Land, Water and Planning, Victoria).
- Heat mapping of availability of mental health services in Perth (Ray Dunne Public Relations, Western Australia).

2012-2015 **Senior Scientist**, *Astron*, Perth.

- Built Astron's remote sensing capacity and team, spanning various platforms and sensors, including product development and delivering client projects both in and outside of Australia.
- Innovated lidar assessments of landform change, and multispectral assessments of vegetation impacts of altered surface water flows and groundwater abstraction for WA's resource industry.
- Initiated data governance and workflow development within Astron.
- Data Team Leader (Emergency Oil Spill Response for various Oil and Gas clients).
- Statistical project support and population modelling for various clients.

2010-2012 **Research Assistant Professor**, *The University of Western Australia*, Perth.
Cooperative Research Centre for Plant Biosecurity

- Research and development evaluation
- Pest Management Area strategy optimisation

2007-2009 **Post-Doc**, *The University of Western Australia*, Perth.
Design of conservation contracts (DAFF, Market Based Instruments)
Fire behaviour in rehabilitated open forest (ARC Linkage with Worsley Alumina).

2005-2010 **Casual Lecturing and Tutoring**, *The University of Western Australia*, Perth.
Statistics, Decision Tools, GIS

Postgraduate Supervision

2014- **Thayse Nery de Figueiredo**, *PhD Thesis*, UWA, in progress.
Optimal land-use change to increase water quality, quantity and biodiversity outcomes

2014- **Maria Solis Aulestia**, *PhD Thesis*, UWA, in progress.
Land use dynamics in the Chure region of Nepal.

2012 **Hoda Abougamous**, *PhD Thesis*, UWA, complete.
An economic analysis of surveillance and quality assurance as strategies to maintain grain market access.

2011 **Bernard Phillimon**, *Masters Thesis*, UWA, complete.
Assessment of bushfire risk through remote sensing.

Professional Affiliations

Accredited Statistician (AStat), Statistical Society of Australia.

Adjunct Senior Lecturer, School of Agricultural and Resource Economics, The University of Western Australia.

Member, The Institute of Analytics Professionals of Australia (IAPA).

Professional Contributions

2014 **Member**, Statistical Society of Australia
Training Committee, National Branch.

2010 **Chairman**, Statistical Society of Australia
Branch Committee, Western Australia.

2008-2009 **Member**, Statistical Society of Australia
Branch Committee, Western Australia.

Awards

2013 **Innovation Award**, Astron Environmental Services.
2012 **Best Paper**, Australian Journal of Agricultural and Resource Economics

Key Projects

Environmental Policy.

- Agent-based modelling of saline water table management, Katanning catchment (DAFF)
- Agricultural Land Retirement as an Environmental Policy (LWA)
- Auctions for Landscape Recovery Under Uncertainty (DAFF)

Pest Management.

- Optimal Investment in Research and Development for Plant Biosecurity (CRC Biosecurity)
- Long Term Weed Management on Barrow Island (Gorgon)
- Leggadina and Mus Population Dynamics on Thevenard Island (Chevron)
- Aerial Survey of Feral Animals, Fortescue Marsh (DPAW)

Data Management.

- Otways Long Term Fauna Trapping Data (Parks Victoria)
- Scientific Monitoring for Oil Spill Response (Apache, ROC, VOGA)
- Data Governance: Strategy, Policy and Standards (Astron)
- Optimal Seed Farm Design (BGPA, Saudi Arabia)

Fauna Monitoring.

- Thevenard Island Mouse (Chevron)
- Northern Quoll (Polaris)
- Macropod Population Viability Analysis (Gorgon)

Remote Sensing.

- Remote Sensing of Pre- and Post- Fuel Loads (Worsley)
- Landform Change Detection (Gorgon)
- Vegetation Impacts of Seismic Surveys (Gorgon)
- Vegetation Mapping (RTTI, India)
- Groundwater Drawdown Impacts on Vegetation (BHPBIO)
- Surface Water Flow Impacts on Vegetation (FMG)

Key Products

ePower Toolbox, *BMT Oceanica, Australian Institute of Marine Science, QUT*. Provides power analysis and cost-response curves for the optimal design of beyond BACI (before-after-control-impact) studies.

Landform Change Analysis, *Astron*.

Provides an error budget for identification of statistically significant areas of landform change from LiDAR and photogrammetric DEM (digital elevation model) change assessment.

Vegetation Impacts of Groundwater and Surface Flow Alteration, *Astron*.

Identifies vegetation areas at greatest impact of groundwater drawdown or surface flow modification, as observed from time series of remote-sensed imagery.

Peer Reviewed Publications

Matthias M Boer, Paul Johnston, and Rohan J Sadler, *Neighbourhood rules make or break spatial scale invariance in a classic model of contagious disturbance*, Ecological Complexity **8** (2011), no. 4, 347–356.

Matthias M Boer, Craig Macfarlane, Jaymie Norris, Rohan J Sadler, Jeremy Wallace, and Pauline F Grierson, *Mapping burned areas and burn severity patterns in SW Australian eucalypt forest using remotely-sensed changes in leaf area index*, Remote Sensing of Environment **112** (2008), no. 12, 4358–4369.

Matthias M Boer, Rohan J Sadler, Ross A Bradstock, A Malcolm Gill, and Pauline F Grierson, *Spatial scale invariance of southern Australian forest fires mirrors the scaling behaviour of fire-driving weather events*, Landscape Ecology **23** (2008), no. 8, 899–913.

Matthias M Boer, Rohan J Sadler, Roy S Wittkuhn, Lachlan McCaw, and Pauline F Grierson, *Long-term impacts of prescribed burning on regional extent and incidence of wildfires—evidence from 50 years of active fire management in SW Australian forests*, Forest Ecology and Management **259** (2009), no. 1, 132–142.

Kerryn A Chia, John M Koch, Rohan J Sadler, and Shane R Turner, *Developmental phenology of Persoonia longifolia (Proteaceae) and the impact of fire on these events*, Australian Journal of Botany **63** (2015), no. 5, 415–425.

_____ , *Establishing Persoonia longifolia (Proteaceae) in restored jarrah forest following bauxite mining in southern Western Australia*, Restoration Ecology (2016) *In press*.

Kerryn A Chia, Rohan J Sadler, Shane R Turner, and Carol C Baskin, *Seasonal con-ditions required for dormancy break of Persoonia longifolia (Protecaeae), a species with a woody indehiscent endocarp*, Annals of Botany (2016). *In press.*

Veronique Florec, Rohan J Sadler, Ben White, and Bernie C Dominiak, *Choosing the battles: The economics of area wide pest management for Queensland fruit fly*, Food Policy **38** (2013), 203–213.

James J Fogarty and Rohan Sadler, *To save or savour: A review of approaches for measuring wine as an investment*, Journal of Wine Economics **9** (2014), no. 03, 225–48.

Aaron D Gove, Rohan Sadler, Mamoru Matsuki, Robert Archibald, Stuart Pearse, and Mark Garkaklis, *Control charts for improved decisions in environmental management: a case study of catchment water supply in south-west Western Australia*, Ecological Management & Restoration **14** (2013), no. 2, 127–134.

Gavan S McGrath, Rohan Sadler, Kevin Fleming, Paul Tregoning, Christoph Hinz, and Erik J Veneklaas, *Tropical cyclones and the ecohydrology of Australia's recent continental-scale drought*, Geophysical Research Letters **39** (2012), no. 3.

Ram Pandit, Maksym Polyakov, and Rohan Sadler, *Valuing public and private urban tree canopy cover*, Australian Journal of Agricultural and Resource Economics **58** (2014), no. 3, 453–470.

Hazel R Parry, Rohan J Sadler, and Darren J Kriticos, *Practical guidelines for modelling post-entry spread in invasion ecology*: *Advancing risk assessment models to address climate change, economics and uncertainty*, NeoBiota **18** (2013), 41–66.

Deanna P Rokich, Jack Harma, Shane R Turner, Rohan J Sadler, and Ben H Tan, *Fluazifop-p-butyl herbicide: Implications for germination, emergence and growth of Australian plant species*, Biological Conservation **142** (2009), no. 4, 850–869.

Rohan J Sadler, Veronique Florec, Ben White, and Bernie C Dominiak, *Calibrating a jump-diffusion model of an endemic invasive: Metamodels, statistics and qfly*, 19th International Congress on Modelling and Simulation, Perth, Australia, 2011, pp. 12–16.

Rohan J Sadler, Martin Hazelton, Matthias M Boer, and Pauline F Grierson, *Deriving state-and-transition models from an image series of grassland pattern dynamics*, Ecological Modelling **221** (2010), no. 3, 433–444.

Rohan J Sadler, Douglas B Purser, and Susan Baker, *Hay quality and intake by dairy cows 2. Predicting feed intake with consumer demand models*, Animal Production Science (2016). *In press.*

Grezegorz Skrzypek, Rohan J Sadler, and Andrzej Wiśniewski, *Reassessment of recommendations for processing mammal phostphate $\delta^{18}O$ data for paleotemperature reconstruction*, Palaeogeography, Palaeoclimatology, Palaeoecology **446** (2016), 162–67.

Grzegorz Skrzypek and Rohan Sadler, *A strategy for selection of reference materials in stable oxygen isotope analyses of solid materials*, Rapid Communications in Mass Spectrometry **25** (2011), no. 11, 1625.

Grzegorz Skrzypek, Rohan Sadler, and Debajyoti Paul, *Error propagation in normalization of stable isotope data: a Monte Carlo analysis*, Rapid Communications in Mass Spectrometry **24** (2010), no. 18, 2697–2705.

Ben White and Rohan Sadler, *Optimal conservation investment for a biodiversity-rich agricultural landscape*, Australian Journal of Agricultural and Resource Economics **56** (2012), no. 1, 1–21.

Appendix D: Monte Carlo Simulations

Simulation of the ZBP

151. Both SFG and NERA share the same first-pass expression. A probability distribution, referred to as Model A, can therefore be defined to generate simulations of the asset and time dependent parameters, α_{it}^{FP} and β_{it}^{FP}:

$$\boldsymbol{\tilde{\alpha}_{it}^{FP}, \tilde{\beta}_{it}^{FP} \sim MVN\left(\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}; COV\left(\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}\right)\right)} \quad (4)$$

where $\tilde{\alpha}_{it}^{FP}, \tilde{\beta}_{it}^{FP}$ are simulations from the assumed distribution of α_{it}^{FP} and β_{it}^{FP};
MVN is a multivariate normal distribution, with mean vector given by the estimates $\hat{\alpha}_{it}^{FP}$ and $\hat{\beta}_{it}^{FP}$ from the first-pass expression of α_{it}^{FP} and β_{it}^{FP}, respectively;
COV refers to the estimated variance-covariance matrix of the estimated parameters.

152. Asset returns may then be simulated for a given market return and risk-free rate:

$$\boldsymbol{r_{it}^{(m)} = \tilde{\alpha}_{it}^{FP(m)} + \tilde{\beta}_{it}^{FP(m)} r_{mt} + \tilde{\varepsilon}_{i,t}^{FP(m)}} \qquad \boldsymbol{m = 1, \dots, M} \quad (5)$$

where m is the m^{th} simulation of M simulations in total;
$r_{it}^{(m)}$ is the m^{th} simulated asset return given a historical market return r_{mt} and the m^{th} set of simulated parameters $\tilde{\alpha}_{it}^{FP(m)}$ and $\tilde{\beta}_{it}^{FP(m)}$; and,
$\tilde{\varepsilon}_{i,t}^{FP(m)}$ is the m^{th} simulated residual term, with the simulations drawn from the normal distribution given by $\tilde{\varepsilon}_{i,t}^{FP} \sim N(0, \hat{\sigma}_{it}^2)$.

153. Hence simulations of the distribution of the ZBP estimate are given by applying the following second-pass regression on the simulated returns:

$$r_{it}^{(m)} = r_{ft} + \alpha^{(m)} + \widetilde{ZBP}^{(m)}\left(1 - \tilde{\beta}_{it}^{FP(m)}\right) + \eta^{(m)} \tilde{\beta}_{it}^{FP(m)} (r_{mt} - r_{ft}) + \varepsilon_{it}^{(m)}$$

where $\alpha^{(m)}$ is the estimated abnormal return from the m^{th} regression of the second-pass model;
$\eta^{(m)}$ is the coefficient of the systematic risk term in the m^{th} regression;
$\widetilde{ZBP}^{(m)}$ is the ZBP estimate from the m^{th} regression.

154. Note that the bias-adjustment proposed by Shanken (1992)[65] cannot be directly applied to the SFG estimate of the ZBP as the other terms in α^{SP} and η are applied in the second-pass regression. Without deriving a bias-adjusted estimator for the SFG equation then little can be said about the influence of the bias-adjustment on the estimate of the ZBP variance.
155. The SFG regression may optionally be weighted by the reciprocal of the $\hat{\sigma}_{it}^2$, in keeping with Litzenberger and Ramaswamy (1979).[66] Furthermore, assets at a given time t with a standard error for $\hat{\beta}_{it}^{FP}$ of greater than 5 were arbitrarily removed from pool of assets to be sampled. This would again result in a more conservative estimate of ZBP than what the data would suggest.

[65] Shanken, J., "On the estimation of beta pricing models*", Review of Financial Studies*, 1992, pp. 1-33
[66] Litzenberger, Robert H. and Krishna Ramaswamy, "The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence, *Journal of Financial Economics*, 1979, pp. 163-195.

156. For computational ease only a single $r_{it}^{(m)}$ has been simulated for each time point t. Alternatively, the data generating mechanism may be more accurately represented by drawing S prior simulations of $r_{i,t-s}$, from which $\tilde{\alpha}_{it}^{FP}$, $\tilde{\beta}_{it}^{FP}$ and $\hat{\sigma}_{it}^{2}$ could be computed at each iteration m. The consequence of omitting the full random draw of the $r_{i,t-s}$ is that the Monte Carlo estimate of the variance of ZBP will be slightly less than if the full draw was implemented. Hence, a conservative estimate of the ZBP variance will result from the simulation of the asset returns $r_{it}^{(m)}$ as implemented here.
157. A key issue surrounding the simulation of the first-pass estimates of $\tilde{\alpha}_{it}^{FP}$ and $\tilde{\beta}_{it}^{FP}$ is the fact that not all assets are sampled at a specific time t, primarily because price data for that time period were not available for a subset of the assets (i.e., there is a thin-trading bias). This issue also arises when the constituents of the market change (i.e., new assets enter the market index and old assets leave). Although different regimes of sampling the constituents at any one time may be suggested when arranging the price data, inevitably this 'constituent' sampling bias, and any sampling bias resulting from thin-trading may be reduced but not eliminated. Together, these sources of sampling bias may be termed asset sampling bias.
158. One way of circumnavigating the issue of asset sampling bias is to draw upon a random set of constituents at each time t. Here we assume that the number of assets sampled at any time is 300, out of a maximum number of assets of around 500 (for the All Ordinaries market index). Over the time series of data this represents an over-estimate of the average of the number of assets being represented in the first-pass equation at any time t, as applied to the Bloomberg data.
159. In all, given 25 years of data, the assets with return data at each time period are randomly drawn with replacement. For each simulation this equates to 391,500 asset draws for the weekly data (1305 weeks x 300 assets), and 90,000 asset draws for the monthly data (300 months x 300 assets).
160. The asset returns for the second-pass of the equation are then randomly simulated given the historical market index and risk-free return at any time t. Hence, for each combination of asset i and time t a single sample of $\tilde{\alpha}_{it}^{FP}$ and $\tilde{\beta}_{it}^{FP}$ is generated, and $\hat{\sigma}_{it}^{2}$ applied to generate a corresponding random residual.
161. In total $M = 500$ simulations are applied for computational feasibility. This number of simulations would be considered sufficient to distinguish whether the magnitude of the variance of ZBP is large or not, and its impact on the RoE in comparison to the SL CAPM. This is in contrast with a common rule-of-thumb where $M = 10{,}000$ simulations are required to derive a suitably precise estimate of the ZBP variance. The number of simulations can be optimised to give a minimum level of precision, but this is requirement falls outside the current scope.
162. The preceding simulation of returns generates M simulations of the estimate $\widehat{ZBP}$, from which a standard error and 95% percentile confidence band for $\widehat{ZBP}$ can be derived, namely:

$$SE\left(\widehat{ZBP}\right) = \left(\frac{1}{M-1}\sum_{m=1}^{M}\left(\widehat{ZBP}^{(m)} - \frac{1}{M}\sum_{m=1}^{M}\widehat{ZBP}^{(m)}\right)^{2}\right)^{\frac{1}{2}}$$

$$95\%\ Confidence\ Band = \left(\widehat{ZBP}_{0.025}, \widehat{ZBP}_{0.975}\right)$$

where $SE\left(\widehat{ZBP}\right)$ is the Monte Carlo generated standard error of $\widehat{ZBP}$, and $\widehat{ZBP}_{p}$ refers to the p^{th} percentile of the value-ordered simulations $\widehat{ZBP}$.

Revised Model for the First-Pass Equation: Partington and Satchell (2016)

163. In their review of this report Partington and Satchell (2016) suggest that incorporating temporal auto-correlation into the simulated $\tilde{\alpha}_{it}^{FP}, \tilde{\beta}_{it}^{FP}$ would better mirror reality.[67] To this end the vectors $\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}$, and $\hat{\sigma}_{it}^{2}$ may be modelled as a multivariate autoregressive (AR) process with p lags,[68] to replace Equation 4 above:

$$\boldsymbol{X}_{it} = \boldsymbol{w_i} + \sum_{k=1}^{p} \boldsymbol{A}_{ik}\boldsymbol{X}_{i,t-k} + \boldsymbol{\varepsilon}_{it}$$

where $\boldsymbol{X}_{it}$ is the parameter vector $\{\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}, \hat{\sigma}_{it}^{2}\}$ which follows a multivariate $AR(p)$ process;
$\boldsymbol{w_i}$ is a vector of asset-specific intercept terms for each parameter;
$\boldsymbol{A}_{ik}$ is a vector of asset-specific autoregressive terms for each parameter; and,
$\boldsymbol{\varepsilon}_{it}$ is a residual process with $\boldsymbol{\varepsilon}_{it} \sim N\big(0, COV(\boldsymbol{X}_{it})\big)$, with $COV(\boldsymbol{X}_{it})$ the variance-covariance matrix of $\boldsymbol{X}_{it}$.

164. This multivariate AR process may be termed Model B (as opposed to the first model without serial autocorrelation of the $\tilde{\alpha}_{it}^{FP}, \tilde{\beta}_{it}^{FP}$). Note that the specification of an appropriate time-series model is largely arbitrary. For example, for ease of implementation then only a multivariate AR processes were considered, rather than allow also for a moving average (MA), or seasonal or other trends to be incorporated into the model. Once a set of models is chosen, then the tuning parameter needs to be selected, in this case the appropriate number of lags p to estimate. Investigation of the $\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}$ shows that the optimal p, as indicated by minimisation of a Bayesian Information Criterion (BIC), varies from asset to asset, and may well exceed $p = 10$. However, a large lag p can result in a large number of parameters, and consequently a high uncertainty associated with the estimated sample variance-covariance matrix of both the residuals and the parameters. This was the case when $p = 5$ (i.e., 57 multivariate AR parameters were to be estimated) and simulations from the model were non-stationary and diverged quickly from the mean. For performance and parsimony then $p = 1$.

165. A filter was applied to the data so that the $\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}$ for an asset i must have greater than 200 observable weekly values over the 20 years of parameter estimates (i.e., $\sim$20% of all possible data). This criterion resulted in 375 assets being applied to generate time-series simulations of the first-pass $\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}$. These assets were sampled with replacement to generate 300 random time-series in total from Model B for each Monte Carlo simulation, i.e.:

$$\widetilde{\boldsymbol{X}}_{it} \sim AR\left(p; \widehat{\boldsymbol{w}}_{\boldsymbol{i}}; \widehat{\boldsymbol{A}}_i; \widehat{COV}(\boldsymbol{X}_{it})\right)$$

where $\widetilde{\boldsymbol{X}}_{it}$ is the simulated time-series of the parameter vector $\{\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}, \hat{\sigma}_{it}^{2}\}$;
$\widehat{\boldsymbol{w}}_{\boldsymbol{i}}$ is a estimated vector of asset-specific intercept terms for each parameter in $\boldsymbol{X}_{it}$;
$\widehat{\boldsymbol{A}}_i$ is the estimated matrix of AR coefficients for each first-pass parameter given $p = 1$ lags; and,

[67] Partington, G. and S. Satchell, *Report to the ERA: Comments on Statistical Reports by Pink Lake*, 31st May 2016, pp. 6-7.
[68] Neumaier, A. and T. Schneider, "Estimation of parameters and eigenmodes of multivariate autoregressive models", *ACM Transactions on Mathematical Software,* 27, pp. 27-57, 2001.

$\widehat{COV}(\boldsymbol{X}_{it})$ is the estimated variance-covariance matrix of the residuals of the process $\boldsymbol{X}_{it}$.

166. The simulated $\widetilde{\boldsymbol{X}}_{it}$ therefore provide the required $\tilde{\alpha}_{it}^{FP(m)}$ and $\tilde{\beta}_{it}^{FP(m)}$ for the second-pass expression. Moreover, the simulation $\tilde{\sigma}_{it}^2$ contained within $\widetilde{\boldsymbol{X}}_{it}$ now replaces $\hat{\sigma}_{it}^2$ in Equation 5.

167. For parsimony of analysis missing data were simply excluded from the time-series $\boldsymbol{X}_{it}$ for Model B. The exclusion of missing data from Model B may result in discontinuities in the time-series of $\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}$, and so perturb the parameters estimates derived from Model B. In contrast, missing data for the $\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}$ is not an issue for Model A given the time-dependent parameters of the first-pass regression are independently sampled. A summary list of pros and cons to compare models A and B is provided in Table 9.

Table 9. Pros and cons of incorporating temporal auto-correlation in modelling $\boldsymbol{\alpha_{it}^{FP}}, \boldsymbol{\beta_{it}^{FP}}$.

Model	Pro	Con
A	Computationally easy to implement as it copes with sparse data well. Maximises re-use of data. Minimal issues with missing data or thin-trading. Parsimonious	Treats the $\tilde{\alpha}_{it}^{FP}, \tilde{\beta}_{it}^{FP}$ as independent, both temporally and between different assets. May lead to an inflated estimate of the ZBP variance as auto-correlation is not explicitly taken into account, although the impact is likely minimal given ZBP estimates are derived from a large set of $\tilde{\alpha}_{it}^{FP}, \tilde{\beta}_{it}^{FP}$ in the second-pass regression equation.
B	Provides a more accurate representation of reality.	Estimation of the multivariate AR requires any missing data to be excluded. This may lead to discontinuities in the time series and a confounding of the estimated model, depending on how the data are treated (i.e., thin-trading will have an influence). Missing data also results in fewer assets being sampled, as fewer assets have time series of sufficient length to support the multivariate AR representation of $\tilde{\alpha}_{it}^{FP}, \tilde{\beta}_{it}^{FP}$ (i.e. lower data re-use, and hence greater sample bias). Difficult to specify an appropriate time-series model (i.e., can all assets be specified by a fixed lag, or require different lags; is an AR process more appropriate than a MA process). Excludes uncertainty in the estimation of the original $\tilde{\alpha}_{it}^{FP}, \tilde{\beta}_{it}^{FP}$, which would ostensibly inflate the variance of the $\widetilde{\boldsymbol{X}}_{it}$. Hence results from these simulations are conservative in nature.

168. Simulation of the asset returns then proceeds as described previously, based on the simulated $\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}$, before estimating both ZBP and β for the RoE calculation. Note that the X_{it} for the gas utility assets is estimated from the full 20 years of data, whereas β is estimated from the last five years of data. Results for Model B are reported in Appendix F.

169. Partington and Satchell (2016)[69] suggest that interest rates should be allowed to vary with time. From a statistical perspective a time-varying interest rate is to be preferred in the estimation of β, over the current Henry method applied by the Authority, which allows only an averaged interest rate to be applied during model estimation. A time-varying risk-free rate should be applied to both the SL and Black CAPM. Time-varying risk-free rates were discussed in the Draft Decision, but results from their preliminary analysis were not published.[70] A time-varying risk-free rate is not applied here, as it does not relate directly to assessing the variance of the ZBP estimator, although the ZBP estimator will likely be sensitive to the which risk-free rate is applied..
170. Partington and Satchell (2016) are also correct in asserting that a time-varying ZBP should also be applied, consistent with the assumption that $\hat{\alpha}_{it}^{FP}, \hat{\beta}_{it}^{FP}$ are time-varying. There was consideration of this point at the start of this analysis. However, DBP's time-varying ZBP estimate was found to perform so poorly compared to the SFG method that allowing for a time-varying ZBP in the simulations becomes a moot point – the variance of the final ZBP estimate simply increases greatly, with the consequent impact on the RoE calculation. Instead, a time-varying version of SFG's ZBP estimator may be considered. However, the benefit of doing so relative to the implementation cost was not judged to be of high value, and so has not been considered at this point in time.
171. Partington and Satchell (2016) suggest a constraint should be applied for the zero-beta return to lie between the borrowing and lending rates. Applying such constraints should be seen as highly desirable. However, these constraints are not applied by DBP in their submitted ZBP value. Moreover, it is not immediately clear as to the best way to apply those constraints (e.g., as box constraints, or as a penalty function). Likely, if constraints were applied, then the upper constraint would frequently be returned as the ZBP estimate, so as to render any estimate of the ZBP simply ineffective –one may as well plug-in the upper constraint into the RoE evaluation as a fixed value. This assumes that the premium for borrowing above the lending rate is known *a priori* for a constraint to be enforced, which it is not.

Simulating β, RoE and Compensation

172. The preceding simulation of $\widehat{ZBP}$ is nominally independent of any estimation of β related to an RoE evaluation of the gas infrastructure segment of the market. This independence is a result mainly of $\widehat{ZBP}$ being estimated from the long-term holding of all stocks (i.e., greater than 20 years of market data), rather than five years of data on a small handful of stocks, most of which have not resided in the market for more than 10 years.
173. Consequently, β can be simulated in much the same way as for $\tilde{\beta}_{it}^{FP}$ to generate randomly asset returns, before proceeding with applying a regression to the simulated returns to derive simulations of β^A and β^B, corresponding to the measures of systematic risk in the Henry and Black CAPM, respectively.
174. The simulation of the last five years of asset returns require that the Henry model, as a model including a free intercept term, be estimated for the last five years of data for each of the gas infrastructure assets listed in the market index. This provides plug-in estimates of the mean and variance of each parameter for the simulation of the parameters:

[69] Partington, G. and S. Satchell, *Report to the ERA: Comments on Statistical Reports by Pink Lake*, 31st May 2016, pp. 7.
[70] ERA, *Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2020, Appendix 4 Rate of Return,* 22 December 2015, Sections 836-843, pp. 178-179.

$$\tilde{\alpha}_i^H, \tilde{\beta}_i^H \sim MVN\left(\hat{\alpha}_i^H, \hat{\beta}_i^H; VCOV\left(\hat{\alpha}_i^H, \hat{\beta}_i^H\right)\right)$$

where $\hat{\alpha}_i^H, \hat{\beta}_i^H$ are estimates of the intercept and slope from the Henry model, and $\tilde{\alpha}_i^H, \tilde{\beta}_i^H$ are corresponding simulations generated from those estimates for each asset i.

175. The simulated asset returns for each simulation m can then be defined as:

$$r_{it}^{(m)} = \tilde{\alpha}_i^{H(m)} + \tilde{\beta}_i^{H(m)}\left(r_{mt} - r_{ft}\right) + \varepsilon_{it}^{(m)}$$

where r_{mt} and r_{ft} are, the historical market returns and risk-free rate, respectively; and,
$\varepsilon_{it}^{(m)}$ are generated from $\varepsilon_{it}^{(m)} \sim N\left(0; \hat{\sigma}_i^2\right)$; and,
$\hat{\sigma}_i^2$ is the estimated variance of the residuals derived from the same regression used to estimate $\hat{\alpha}_i^H$ and $\hat{\beta}_i^H$.

176. For each simulation m then a simulation of the estimate of β^A and β^B can be derived. For the Authority's implementation of the SL CAPM this is simply reapplication of the Henry model to each simulated set of asset returns, namely:

$$r_{it}^{(m)} = \tilde{\alpha}_i^{(m)} + \tilde{\beta}_i^{A(m)}\left(r_{mt} - r_f\right) + \varepsilon_{it}$$

where the estimate of β^A from each of these M simulations therefore corresponds to a single simulation $\tilde{\beta}_i^{A(m)}$.

177. For the Black CAPM simulation of β^B involves applying each simulated $\widetilde{ZBP}^{(m)}$ to each of the simulated sets of returns $r_{it}^{(m)}$:

$$r_{it}^{(m)} = r_f + \widetilde{ZBP}^{(m)} + \tilde{\beta}_i^{B(m)}\left(r_{mt} - r_f - \widetilde{ZBP}^{(m)}\right) + \varepsilon_{it}$$

Similar to the SL CAPM case above, the estimate of β^B from each of these M simulations corresponds to a simulated $\tilde{\beta}_i^{B(m)}$.

178. For simplicity in both of the above equations the risk-free rate r_f is treated as a single, mean value of the historical government bond rate. This then corresponds to the simulated ZBP being treated here as a static, single-valued term in the Black CAPM regression.

179. The simulated sets $\tilde{\beta}_i^{A(m)}$ and $\tilde{\beta}_i^{B(m)}$ are then, following regearing, inputted into their respective RoE equations. For the Authority's assessment this provides:

$$RoE_i^{A(m)} = r_f + \tilde{\beta}_i^{A(m)} MRP$$

where the market-risk premium (MRP) and r_f are forward-looking estimates.

180. For the Black CAPM the RoE expression becomes:

$$RoE_i^{B(m)} = r_f + \widetilde{ZBP}^{(m)} + \tilde{\beta}_i^{B(m)}\left(MRP - \widetilde{ZBP}^{(m)}\right)$$

181. The compensation being paid by the Black CAPM position relative to the SL CAPM position is then:

$$Compensation_i^{(m)} = RoE_i^{B(m)} - RoE_i^{A(m)}$$

182. Akin to Sections 52-53, both the standard error and the 95% confidence bound may be computed for each of the quantities of interest: $\beta^A, \beta^B, RoE^A, RoE^B$ and the level of compensation for the Black CAPM models relative to the SL CAPM. These quantities may be calculated for individual assets or a portfolio of those assets (i.e., value-weighted or equal weighted).

Appendix E: ZBP Estimates for Monthly Data

Table 10. Henry model of the SL CAPM applied to monthly data.

Portfolio	Alpha (%)	Beta	RoE (%)	Gear	Omega
APA	**27.8**[a] (7.55)[b] (13.6,43.4)[c]	**0.384** (0.135) (0.117,0.647)	**5.61** (1.28) (3.07,8.10)	0.440	1.1
AST	**22.3** (7.09) (8.37,36.62)	**0.248** (0.124) (0.014,0.497)	**4.31** (1.18) (2.09,6.68)	0.566	1.415
DUE	**26.1** (7.81) (12.0,41.7)	**0.232** (0.148) (-0.040,0.522)	**4.17** (1.40) (1.58,5.11)	0.642	1.605
SKI	**31.2** (8.81) (13.8,49.9)	**0.043** (0.146) (-0.241,0.427)	**2.37** (1.39) (-0.33,6.02)	0.283	0.705
VW	**26.2** (5.47) (16.2,36.8)	**0.272** (0.090) (0.074,0.427)	**4.55** (0.85) (2.67,6.01)	0.488	1.22
EW	**27.3** (5.62) (16.5,37.7)	**0.223** (0.093) (0.045,0.401)	**4.08** (0.88) (2.39,5.77)	0.483	1.2075

a. The mean estimate for the parameter.

b. The standard error of the estimate

c. The 95% confidence bound for the estimate, generated through Monte Carlo simulation

Table 11. SFG Scenario 1 applied to monthly data with no constraints.

Portfolio	ZBP (%)	Beta	RoE (%)	Compensation (%)
APA	**2.56** (4.17) (-5.84,11.35)	**0.371** (0.143) (0.073,0.644)	**7.17** (2.23) (2.77,11.86)	**1.54** (2.22) (-1.51,6.98)
AST		**0.242** (0.128) (-0.002,0.501)	**6.27** (2.85) (0.82,12.28)	**1.92** (2.72) (-2.39,8.26)
DUE		**0.224** (0.154) (-0.068,0.525)	**6.24** (2.98) (0.035,12.15)	**2.04** (2.94) (-2.61,9.27)
SKI		**0.030** (0.155) (-0.303,0.351)	**5.04** (3.83) (-2.57,12.99)	**2.66** (3.74) (-3.45,11.13)
VW		**0.250** (0.099) (0.056,0.447)	**6.35** (2.66) (1.59,12.14)	**1.89** (2.58) (-2.14,7.51)
EW		**0.213** (0.100) (0.010,0.340)	**6.11** (2.88) (0.64,12.72)	**2.00** (2.77) (-2.71,8.78)

Table 12. SFG Scenario 2 applied to monthly data with constraint $\eta = 1$.

Portfolio	ZBP (%)	Beta	RoE (%)	Compensation (%)
APA	**4.71** (4.84) (-4.80,14.26)	**0.373** (0.142) (0.073,0.644)	**8.31** (2.59) (3.39,13.5)	**2.68** (2.73) (-1.40,9.57)
AST		**0.245** (0.127) (0.001,0.488)	**7.78** (3.33) (1.18,14.5)	**3.43** (3.35) (-2.17,10.7)
DUE		**0.226** (0.153) (-0.065,0.522)	**7.81** (3.50) (0.59,14.4)	**3.61** (3.63) (-2.26,11.7)
SKI		**0.032** (0.154) (-0.296,0.447)	**7.16** (4.42) (-1.29,16.1)	**4.78** (4.50) (-3.13,14.4)
VW		**0.252** (0.097) (0.053,0.447)	**7.84** (3.19) (2.33,14.3)	**3.38** (3.19) (-2.02,10.1)
EW		**0.215** (0.099) (0.018,0.401)	**7.71** (3.40) (1.26,14.6)	**3.60** (3.36) (-2.19,11.0)

Table 13. SFG Scenario 3 applied to monthly data with constraint $\alpha^{SP} = 0$.

Portfolio	ZBP (%)	Beta	RoE (%)	Compensation (%)
APA	**5.05** (3.57) (-2.39,12.22)	**0.373** (0.141) (0.070,0.640)	**8.43** (1.92) (4.96,12.7)	**2.80** (2.15) (-0.07,8.29)
AST		**0.245** (0.127) (0.001,0.490)	**7.95** (2.45) (3.31,13.1)	**3.60** (2.50) (-0.61,9.17)
DUE		**0.225** (0.153) (-0.068,0.341)	**7.96** (2.57) (2.90,13.4)	**3.76** (2.75) (-0.49,10.2)
SKI		**0.031** (0.153) (-0.300,0.448)	**7.37** (3.32) (1.43,14.7)	**4.99** (3.42) (-0.82,12.7)
VW		**0.250** (0.097) (-0.060,0.448)	**8.00** (2.33) (3.81,12.9)	**3.55** (2.35) (-0.37,8.67)
EW		**0.214** (0.098) (-0.014,0.395)	**7.89** (2.51) (2.96,13.6)	**3.78** (2.49) (-0.79,9.73)

Table 14. DBP Scenario applied to monthly data with constraints $\alpha^{SP} = 0$ and $\eta = 1$.

Portfolio	ZBP (%)	Beta	RoE (%)	Compensation (%)
APA	**6.67** (4.23) (-1.80,14.58)	**0.373** (0.141) (0.074,0.644)	**9.28** (2.31) (4.73,13.95)	**3.65** (2.61) (-0.195,10.3)
AST		**0.245** (0.126) (0.003,0.489)	**9.08** (2.95) (3.15,14.5)	**4.72** (3.09) (-0.618,12.23)
DUE		**0.226** (0.152) (-0.068,0.520)	**9.13** (3.10) (3.00,15.0)	**4.94** (3.38) (-0.533,12.32)
SKI		**0.032** (0.152) (-0.294,0.447)	**8.96** (3.91) (1.54,16.64)	**6.58** (4.13) (-1.01,15.57)
VW		**0.252** (0.096) (0.054,0.447)	**9.12** (2.85) (3.97,14.6)	**4.66** (2.92) (-0.466,10.35)
EW		**0.216** (0.098) (0.020,0.396)	**9.07** (3.01) (3.20,15.2)	**4.96** (3.04) (-0.41,11.40)

Appendix F: ZBP Estimates for Autocorrelated α_{it}^{FP} and β_{it}^{FP}

Table 15. Henry model of the SL CAPM applied to weekly data.

Portfolio	Alpha (%)	Beta	RoE (%)	Gear	Omega
APA	**31.4**[a] (12.3)[b] (10.2,57.4)[c]	**0.510** (0.100) (0.272,0.693)	**6.80** (0.95) (4.54,8.54)	0.440	1.1
AST	**24.1** (8.63) (7.8,41.6)	**0.627** (0.116) (0.406,0.855)	**7.91** (1.10) (5.8,10.1)	0.566	1.415
DUE	**26.1** (14.6) (-1.74,55.4)	**0.464** (0.112) (0.243,0.699)	**6.37** (1.07) (4.27,8.60)	0.642	1.605
SKI	**21.1** (11.8) (-0.3,47.1)	**0.389** (0.108) (0.195,0.615)	**5.65** (1.02) (3.81,7.81)	0.283	0.705
VW	**19.2** (5.36) (8.3,29.2)	**0.549** (0.044) (0.439,0.618)	**7.17** (0.41) (6.13,7.83)	0.488	1.22
EW	**18.9** (4.45) (9.1,27.1)	**0.518** (0.032) (0.442,0.564)	**6.88** (0.30) (6.16,7.32)	0.483	1.2075

a. The mean estimate for the parameter.
b. The standard error of the estimate
c. The 95% confidence bound for the estimate, generated through Monte Carlo simulation

Table 16. SFG Scenario 1 applied to weekly data with no constraints.

Portfolio	ZBP (%)	Beta	RoE (%)	Compensation (%)
APA	**11.9** (19.4) (-20.8,51.7)	**0.507** (0.105) (0.271,0.703)	**10.4** (7.2) (1.1,29.0)	**3.55** (7.29) (-5.3,23.5)
AST		**0.626** (0.114) (0.400,0.844)	**9.93** (4.5) (3.9,22.5)	**1.72** (4.75) (-3.30,16.0)
DUE		**0.461** (0.116) (0.242,0.703)	**10.5** (7.9) (0.0,31.1)	4.18 (8.10) (-5.8,25.4)
SKI		**0.394** (0.107) (0.204,0.611)	**10.8** (9.2) (-3.3,33.6)	**4.8** (9.3) (-8.4,29.0)
VW		**0.548** (0.048) (0.446,0.637)	**10.3** (5.6) (2.41,24.3)	**3.13** (5.57) (-4.5,17.2)
EW		**0.517** (0.039) (0.441,0.601)	**10.4** (6.3) (1.93,24.8)	**3.56** (6.27) (-4.8,18.0)

Table 17. SFG Scenario 2 applied to weekly data with constraint $\eta = 1$.

Portfolio	ZBP (%)	Beta	RoE (%)	Compensation (%)
APA	**11.9** (19.4) (-20.8,51.7)	**0.506** (0.105) (0.271,0.703)	**10.4** (7.2) (1.1,29.0)	**3.53** (7.29) (-5.3,23.5)
AST		**0.626** (0.114) (0.400,0.847)	**9.94** (4.5) (3.9,22.5)	**1.72** (4.75) (-3.3,16.0)
DUE		**0.461** (0.116) (0.242,0.703)	**10.5** (7.8) (0.0,31.1)	**4.18** (8.10) (-5.8,25.4)
SKI		**0.394** (0.107) (0.204,0.611)	**10.8** (9.2) (-3.3,33.6)	**4.77** (9.29) (-8.4,29.1)
VW		**0.548** (0.048) (0.446,0.637)	**10.3** (5.6) (2.4,24.3)	**3.13** (5.57) (-4.5,17.2)
EW		**0.517** (0.039) (0.441,0.601)	**10.4** (6.4) (1.9,24.8)	**3.56** (6.27) (-4.8,18.1)

Table 18. SFG Scenario 3 applied to weekly data with constraint $\alpha^{SP} = 0$.

Portfolio	ZBP (%)	Beta	RoE (%)	Compensation (%)
APA	**14.4** (19.4) (-15.7,55.5)	**0.499** (0.104) (0.267,0.691)	**11.0** (7.2) (2.2,30.0)	**4.26** (7.36) (-4.2,24.4)
AST		**0.620** (0.112) (0.395,0.832)	**10.3** (4.6) (4.5,23.6)	**2.29** (4.86) (-2.5,17.2)
DUE		**0.459** (0.114) (0.241,0.699)	**11.3** (7.8) (1.3,32.8)	**4.78** (8.13) (-4.6,27.0)
SKI		**0.392** (0.107) (0.200,0.609)	**11.6** (9.0) (-1.4,33.7)	**5.65** (9.17) (-6.4,29.0)
VW		**0.546** (0.046) (0.446,0.630)	**10.9** (5.5) (3.0,25.3)	**3.75** (5.53) (-4.0,18.2)
EW		**0.516** (0.036) (0.440,0.580)	**11.2** (6.2) (2.7,25.8)	**4.33** (6.24) (-4.0,18.9)

Table 19. DBP Scenario applied to weekly data with constraints $\alpha^{SP} = 0$ and $\eta = 1$.

Portfolio	ZBP (%)	Beta	RoE (%)	Compensation (%)
APA	**14.4** (19.4) (-15.7,55.5)	**0.499** (0.104) (0.267,0.691)	**11.0** (7.2) (2.2,30.0)	**4.25** (7.36) (-4.2,24.4)
AST		**0.620** (0.112) (0.395,0.832)	**10.3** (4.6) (4.5,23.6)	**2.28** (4.86) (-2.5,17.2)
DUE		**0.459** (0.114) (0.241,0.699)	**11.3** (7.8) (1.3,32.8)	**4.76** (8.13) (-4.6,27.0)
SKI		**0.392** (0.107) (0.200,0.609)	**11.6** (9.0) (-1.4,33.7)	**5.64** (9.17) (-6.4,29.0)
VW		**0.546** (0.046) (0.446,0.630)	**10.9** (5.5) (3.0,25.3)	**3.75** (5.53) (-4.0,18.2)
EW		**0.516** (0.036) (0.440,0.580)	**11.2** (6.2) (2.7,25.8)	**4.32** (6.24) (-4.0,18.9)

Appendix G: Update of the Authority's Estimate of β

185. This Appendix reports updated estimates of β for use in the SL CAPM. The methods and assets (Table 20) applied in the estimation of β are the same as those included in the Authority's Draft Decision, and are paraphrased below.[71]

Table 20. List of trading gas infrastructure assets as at June 2016

Name	Bloomberg's Ticker	From	To	Proportional Value Weighting
APA Group	APA	13/06/2000	31/05/2016	0.382
AusNet Services	AST,SPN	14/12/2005	31/05/2016	0.263
DUET Group	DUE	13/08/2004	31/05/2016	0.199
Spark Infrastructure Group	SKI	16/12/2005	31/05/2016	0.156

186. The price data recorded the last daily price for all stocks provided by the Australian Stock Exchange (ASX), acquired through the Bloomberg Terminal (ticker ASA30 for the All Ordinaries index). Dividend data used in the study were gross dividends including cash distributions, but omitting unusual items such as stock distributions and rights offerings. The dividend was then added to the closing price on the Friday after the ex-dividend dates as this is the first day the price would reflect the payout of the dividend in the data.

187. Returns are expressed as continuously compounding values:

$$r_{it} = \ln\left(\frac{p_{it} + d_{it}}{p_{i,t-1}}\right)$$

where r_{it} is the return on asset i at time t; p_{it} is the price; and, d_{it} the dividend. Both the AER and Henry found no evidence that β estimates derived from continuously or discretely compounded data were manifestly different.[72]

188. Henry outlined in his advice to the AER that beta is estimated by applying a regression analysis to the following equation:[73]

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it}$$

[71] ERA, *Draft Decision on Proposed Revisions to the Access Arrangement for the Dampier to Bunbury Natural Gas Pipeline 2016-2020, Appendix 4 Rate of Return,* 22 December 2015.

[72] AER, *Explanatory Statement: Electricity transmission and distribution network service providers*, Review of the Weighted Average Cost of Capital (WACC) Parameters, www.aer.gov.au, p. 200.

[73] O.T. Henry, *Estimating* β, Advice Submitted to the Australian Competition and Consumer Commission, 2009, p. 2.

where

α_i is a time-constant intercept term to account for abnormal returns over and above the risk-free rate;

β_i is the equity beta for asset i;

r_{mt} is the observed market returns; and

$\varepsilon_{it} \sim N\left(0, \sigma^2\right)$ are the residuals assumed to be identically and independently distributed normally, with a time-constant volatility measure σ^2.

189. The above version of the SL CAPM, termed here as the Henry CAPM, may be estimated in a number of different ways. Ordinary least squares (OLS) was supported by the robust estimation methods in LAD (least absolute deviation), MM (robust regression with the MM estimator) and T-S (Thiel-Sen). In general, these robust methods provide regression estimates that are less influenced by outliers and heteroscedasticity in the ε_{it} term. Technical descriptions of these estimators may be found in Appendix 17 of the Rate of Return Guidelines.[74]

190. A further two methods for the estimation of β have been trialled by applying ARIMAX (autoregressive integrated moving average) and GARCH (generalised autoregressive conditional heteroskedastic) models to the data. The ARIMAX model accounts for serial autocorrelation in the returns. The ARIMAX is a special case of the GARCH model where the volatility measure σ^2 is treated as time constant (i.e., homoscedastic). GARCH extends ARIMAX by allowing σ_t^2 to be time-varying as well, to be modelled in the simplest case as an ARMA (autoregressive moving average) process.

191. Hence, ARIMAX and GARCH are simply an alternative to applying robust methods when accounting for heteroscedasticity in the data, and differ by modelling the heteroscedasticity as an explicit, parameterised process. The ARIMAX and GARCH estimates were not used here to form an estimate of β.

192. The potential advantage of ARIMAX and GARCH is to reduce the standard error values of the β estimate, while correcting the small bias in β that may exist by omitting autoregressive terms from the model.

193. All asset β in the following analysis were de-levered using the relevant company's average gearing ratio over the period and re-levered using the 60 per cent assumption. The details of this de-levering/re-levering process can be found in Appendix 20 of the Rate of Return Guidelines.[75]

Results

194. For estimates of individual firms' β, the Authority considers that the sample period of 5 years with weekly intervals is appropriate as it reduces the possibility of long past structural breaks in the data set, whilst encompassing enough data points to estimate β with statistical accuracy.

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[74] ERA, Appendices to the Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules, 16th December 2013, Appendix 17.

[75] ERA, Appendices to the Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules, 16th December 2013, Appendix 20.

195. Here, the epoch where all of the listed gas infrastructure stock are trading begins on 16/12/2005, when SKI enters the market (Table 20), long before the sample period starts on 1/06/2011. In this, portfolios are required to be recreated only when the constituents within the industry change (i.e., when a firm either leaves or enters the industry).

196. The key purpose of a portfolio analysis is to allow a single portfolio to be created and, as such, a single corresponding β value for that portfolio can be estimated as representative of the benchmark sample.

197. Two weighting scenarios were considered in this analysis, which is consistent with the approach of Henry:[76] (i) equally-weighted portfolios (EW); and (ii) value-weighted portfolios (VW). Equally-weighted portfolios simply assign a weight of ¼ to each of the four firms in the benchmark sample. To calculate a value-weighted portfolio the average market capitalisation was calculated for each firm. For each firm in the portfolio, its weight is determined by the ratio between the average of a single firm and the sum of the averages of all firms in each portfolio in terms of market capitalisation. The averages were taken over the sample period for all firms in each portfolio. The weights were then applied to their relevant firms in the portfolio. The construction of equally-weighted and value-weighted portfolios is reported in Appendix 21 of the Rate of Return Guidelines.[77]

198. There is no evidence of thin-trading in this sample, given the assets in the gas infrastructure assets traded on greater than 99.9% of the possible trading days over the last five years (Table 3).

199. Table 21 reports estimates of each asset's β across the different regression methodologies, with a data set from June 2011 to May 2016. Equally-weighted and value-weighted portfolios are also reported.

200. The advice taken from the Authority is that the point estimate of β for purposes of the Authority's RoE evaluation is mean β, averaged across the two weighted portfolios and the OLS, LAD, MM and T-S estimators. This results in a $\beta = 0.699$, rounded to $\beta = 0.7$ (highlighted in Table 21).

201. The results in Table 21 show that, on average, the MM estimator produced a higher equity β, and the T-S estimator a lower equity β, for each firm. Little difference was observed on average between the OLS and LAD estimates.

202. However, LAD estimates were more than 0.1 higher for the equally- and value-weighted portfolios than OLS estimates. For the equally- and value-weighted portfolios both the MM and T-S estimators produced slightly higher estimates of the equity β compared to the OLS estimator (from 0.03 to 0.06 higher). This would be indicative of the DUE asset reporting a much lower β estimate, and with any extreme values in its returns receiving a low weighting and likely being largely ignored by the robust estimators, thereby pushing up the LAD estimate.

203. The ARIMAX and GARCH models, which estimated a small negative auto-regression coefficient, produced estimates that were consistent with the MM and T-S estimators. Small negative auto-regression coefficients identify an oscillating autocorrelation process that dampens with time, indicative of an immediate selling response to positive price fluctuations, and a buying response to negative price fluctuations (i.e., demonstrative of price equilibrium).

[76] O.T. Henry, *Estimating β: An update*, Advice Submitted to the Australian Competition and Consumer Commission. April 2014.

[77] ERA, Appendices to the Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules, 16th December 2013, Appendix 21.

Table 21. Estimates of equity beta for individual firms and the two weighted portfolios in May 2016 for different estimation methods.

	APA	AST	DUE	SKI	Mean Assets	EW	VW	Mean Portfolios	Mean All
Gearing	0.440	0.562	0.627	0.277	**0.476**	0.476	0.484	**0.480**	**0.477**
OLS	0.682	0.671	0.170	0.716	**0.560**	0.638	0.665	**0.652**	**0.591**
LAD	0.662	0.705	0.243	0.724	**0.584**	0.740	0.778	**0.759**	**0.642**
MM	0.665	0.675	0.268	0.776	**0.596**	0.703	0.715	**0.709**	**0.634**
T-S	0.647	0.661	0.263	0.713	**0.571**	0.669	0.681	**0.675**	**0.606**
Mean OLS, LAD, MM, T-S	**0.664**	**0.678**	**0.236**	**0.732**	**0.578**	**0.687**	**0.710**	**0.699**	**0.618**
ARIMAX	0.683	0.636	0.164	0.690	**0.543**	0.620	0.651	**0.636**	**0.574**
GARCH	0.618	0.673	0.254	0.731	**0.569**	0.677	0.681	**0.679**	**0.606**
Mean All Methods above	**0.660**	**0.670**	**0.227**	**0.725**	**0.570**	**0.675**	**0.695**	**0.685**	**0.609**

205. Across the four firms β has increased on average from 0.368 to 0.578 from 2013 to 2016 across all estimators (OLS, LAD, MM, T-S). Hence, elasticity in the response of individual asset returns to market returns has increased within the gas infrastructure sector during a period when mean market returns have decreased, consistent with the findings of CEG.[78]

206. Gearing on average has decreased from 2013 to 2015, from a mean value across the four assets of 0.584 to 0.476, as firms may be seeking to de-lever following lessons learned in the GFC. An across the board decrease in gearing may warrant a revision, if sustained, of the benchmark gearing level of 60% debt and 40% equity applied by Australian economic regulators to calculate equity β. This could occur at the next Guidelines review.

207. Bootstrap simulations of the estimates were performed using the naïve non-parametric approach outlined in Appendix 23 of the Rate of Return Guidelines,[79] where paired observations of asset and market returns are randomly sampled with replacement before applying the CAPM to the sampled dataset.

[78] CEG state that there is a structural clear break in β values, and hence non-stationarity of the time series over recent years. Competition Economists Group, *Estimating beta to be used in the Sharpe-Lintner CAPM,* February 2016, Appendix F, Figures 7-8, p. 41.

[79] ERA, *Appendices to the Explanatory Statement for the Rate of Return Guidelines: Meeting the requirements of the National Gas Rules*, 16th December 2013, Appendix 23.

Table 22. Summary Bootstrap Simulated Statistics of OLS Estimators (B=10,000, n=261)

Model	Estimator	APA	AST	DUE	SKI	Mean Assets	EW	VW	Mean Portfolios	Mean All
OLS	$\hat{\beta}$	0.682	0.671	0.170	0.716	**0.560**	0.638	0.665	**0.652**	**0.591**
	Standard Error $\hat{\beta}$	0.082	0.074	0.072	0.114	**0.085**	0.066	0.064	**0.065**	**0.079**
	Bootstrap $\hat{\beta}$	0.683	0.670	0.171	0.713	**0.559**	0.637	0.665	**0.651**	**0.590**
	Bootstrap S.E. $\hat{\beta}$	0.082	0.075	0.090	0.112	**0.090**	0.073	0.070	**0.072**	**0.084**
	Bootstrap Bias	0.001	-0.001	0.001	-0.003	**-0.001**	-0.001	0.000	**-0.001**	**-0.001**
	Bootstrap LB 2.5%	0.523	0.522	-0.025	0.488	**0.377**	0.491	0.527	**0.509**	**0.421**
	Bootstrap Median	0.683	0.670	0.178	0.715	**0.562**	0.638	0.665	**0.652**	**0.592**
	Bootstrap UB 97.5%	0.845	0.817	0.325	0.925	**0.728**	0.779	0.804	**0.792**	**0.749**

208. All OLS estimates of β were statistically significant at the 5 per cent significance level, as evidenced by the bootstrapped 95 per cent confidence band excluding the value of zero (Table 22). Standard errors for the portfolios estimated through OLS were 0.007 higher on average on May 2016 than in October 2015, scaling with the increase in the estimated value of β over that period. The bootstrapped upper 97.5 per cent confidence bound was 0.728 when averaged across all four assets, and 0.792 for the mean of the portfolios (Table 22). The bootstrapped estimate of the standard error of β (0.072) was slightly higher than that of the standard error estimated from the Henry model (0.065; Table 22).

209. Standard errors were inconsistently estimated for the LAD estimator, and cannot be derived by analytical means for the T-S estimator (Table 23). For the LAD and T-S estimators the bootstrapped standard error is therefore used in drawing inference about β. Standard errors of β were higher for the LAD estimator, and reasonably similar to the T-S and MM estimators, when compared with the OLS estimator.

210. The 97.5 per cent upper bound for the LAD estimator was greater, by up to 0.15 depending on the asset, than for the OLS estimates (Tables 22-23). Upper bound estimates for the MM and T-S were only marginally greater than the OLS asset.

211. A bootstrap procedure was not implemented for ARIMAX or GARCH as these are time-series models, and to simulate the data in this case a bootstrap procedure would be required to maintain the autocorrelation structure of the actual data themselves. Such procedures exist, such as variations of the block and sieve bootstraps, but these were not applied.

212. This confidence interval for the ARIMAX and GARCH models was simply the z-normal confidence band given by 1.96 standard errors either side of the β estimate. Significantly, the z-normal and bootstrapped upper bounds were similar for both OLS and MM to within 0.01 (i.e., where a standard error measure was given), and so it is not incorrect to hypothesise that the ARIMAX and GARCH bootstrapped upper bounds will likewise be similar to their z-normal upper bound. Both the ARIMAX and GARCH standard errors and upper bound estimates were slightly less than that of the OLS estimator (except for the GARCH estimate for the EW portfolio; Table 24).

Table 23. Summary of Bootstrap Simulated Statistics of Robust Estimators (B=10,000, n=261)

Model	Estimator	APA	AST	DUE	SKI	Mean Assets	EW	VW	Mean Portfolios	Mean All
LAD	$\hat{\beta}$	0.662	0.705	0.243	0.724	**0.584**	0.740	0.778	**0.759**	**0.642**
	Standard Error $\hat{\beta}$ [1]	-	-	-	-	-	-	-	-	-
	Bootstrap $\hat{\beta}$	0.654	0.677	0.258	0.789	**0.595**	0.747	0.748	**0.748**	**0.646**
	Bootstrap S.E. $\hat{\beta}$	0.114	0.077	0.066	0.158	**0.104**	0.110	0.084	**0.097**	**0.101**
	Bootstrap Bias	-0.028	0.006	0.088	0.073	**0.035**	0.109	0.082	**0.096**	**0.055**
	Bootstrap LB 2.5%	0.437	0.543	0.156	0.434	**0.392**	0.479	0.529	**0.504**	**0.429**
	Bootstrap Median	0.658	0.678	0.248	0.771	**0.589**	0.765	0.762	**0.764**	**0.647**
	Bootstrap UB 97.5%	0.873	0.847	0.415	1.089	**0.806**	0.896	0.870	**0.883**	**0.832**
MM	$\hat{\beta}$	0.665	0.675	0.268	0.776	**0.596**	0.703	0.715	**0.709**	**0.634**
	Standard Error $\hat{\beta}$	0.079	0.064	0.044	0.111	**0.074**	0.061	0.061	**0.061**	**0.070**
	Bootstrap $\hat{\beta}$	0.664	0.676	0.267	0.774	**0.596**	0.703	0.715	**0.709**	**0.633**
	Bootstrap S.E. $\hat{\beta}$	0.083	0.075	0.054	0.116	**0.082**	0.075	0.073	**0.074**	**0.079**
	Bootstrap Bias	-0.018	0.004	0.097	0.058	**0.036**	0.065	0.049	**0.057**	**0.043**
	Bootstrap LB 2.5%	0.505	0.531	0.161	0.537	**0.434**	0.555	0.571	**0.563**	**0.477**
	Bootstrap Median	0.664	0.676	0.267	0.775	**0.595**	0.703	0.716	**0.710**	**0.633**
	Bootstrap UB 97.5%	0.832	0.822	0.375	0.996	**0.756**	0.846	0.856	**0.851**	**0.788**
T-S	$\hat{\beta}$	0.647	0.661	0.263	0.713	**0.571**	0.669	0.681	**0.675**	**0.606**
	Standard Error $\hat{\beta}$ [1]	-	-	-	-	-	-	-	-	-
	Bootstrap $\hat{\beta}$	0.648	0.661	0.262	0.713	**0.571**	0.666	0.680	**0.673**	**0.605**
	Bootstrap S.E. $\hat{\beta}$	0.085	0.076	0.053	0.125	**0.085**	0.078	0.071	**0.074**	**0.081**
	Bootstrap Bias	-0.034	-0.011	0.092	-0.003	**0.011**	0.028	0.014	**0.021**	**0.014**
	Bootstrap LB 2.5%	0.481	0.508	0.156	0.460	**0.401**	0.510	0.533	**0.522**	**0.441**
	Bootstrap Median	0.647	0.662	0.263	0.713	**0.571**	0.668	0.681	**0.674**	**0.606**
	Bootstrap UB 97.5%	0.818	0.803	0.365	0.960	**0.737**	0.813	0.818	**0.815**	**0.763**

[1]Standard errors of the estimate were either inconsistently returning solvable values (i.e., were not able to converge to a single value) for the LAD estimator, or there was no analytical solution for the T-S estimator. In these two cases the standard error of the estimate should be replaced by the bootstrapped standard error estimate.

Table 24. Summary Statistics of ARIMAX and GARCH Estimators (B=10,000, n=261)

Model	Estimator	APA	AST	DUE	SKI	Mean Assets	EW	VW	Mean Portfolios	Mean
ARIMAX	$\hat{\beta}$	0.683	0.636	0.164	0.690	**0.543**	0.620	0.651	**0.636**	**0.574**
	Standard Error $\hat{\beta}$	0.081	0.073	0.072	0.113	**0.085**	0.066	0.064	**0.065**	**0.078**
	Lower Bound 2.5%	0.524	0.494	0.023	0.467	**0.377**	0.491	0.525	**0.508**	**0.421**
	Upper Bound 97.5%	0.842	0.779	0.305	0.912	**0.710**	0.750	0.776	**0.763**	**0.727**
GARCH	$\hat{\beta}$	0.618	0.673	0.254	0.731	**0.569**	0.677	0.681	**0.679**	**0.606**
	Standard Error $\hat{\beta}$	0.076	0.070	0.036	0.098	**0.070**	0.068	0.062	**0.065**	**0.069**
	Lower Bound 2.5%	0.469	0.536	0.183	0.538	**0.431**	0.544	0.558	**0.551**	**0.471**
	Upper Bound 97.5%	0.768	0.810	0.325	0.923	**0.707**	0.810	0.803	**0.807**	**0.740**