The reliability of empirical beta estimates

Report prepared for ENA, APIA, and Grid Australia

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Executive summary and conclusions

Context

1. This report has been prepared by Professor Stephen Gray, Professor of Finance at the University of Queensland Business School and Managing Director of Strategic Finance Group (SFG Consulting), a corporate finance consultancy specialising in valuation, regulatory and litigation support advice. I have attached a copy of my Curriculum Vitae at Appendix B to this report.

2. I have been engaged by ENA, APIA, and Grid Australia to advise on the statistical reliability of empirical estimates of beta for Australian energy distribution and transmission businesses. Specifically, I have been asked to provide advice, from a statistical perspective, on two issues:

    a. What reliance can be placed on the available Australian utilities data for the purposes of drawing a conclusion on the value of beta (re-levered to 60%) for an Australian regulated electricity utility; and

    b. Does the use of 95% confidence limits address the statistical issues with the Australian data?

R-squared

3. I show that the R-squared statistic in a beta regression has a statistical interpretation in terms of the reliability of the data being used to construct the estimate. Via a simulation analysis, I show that in cases when the R-squared statistic is low the beta estimate is likely to be significantly different (lower) than the true beta. This is particularly apparent when the R-squared statistic is in the order of 10% or lower. However, I conclude against the implementation of a routine R-squared cut-off threshold. Rather, low R-squared statistics in beta regressions are an indicator of statistical reliability problems and should result in more detailed scrutiny of the resulting estimates including the assessment of their economic reasonableness.

4. I also show that recent estimates of beta for the set of Australian energy transmission and distribution firms are characterised by low R-squared statistics which indicate that the relationship between stock and market returns (beta) is swamped many times over by "noise." Consequently, I conclude that these recent estimates have low statistical reliability. After also considering other factors, including the economic reasonableness of those estimates, I conclude that these recent estimates should not be the source of betas used in regulatory decisions.

5. Beta estimates that are based on low R-squared statistics (such as apply to the available Australian data) and which are also considered to be unreliable for other reasons as well, are expected to vary considerably over time. That is, as new data becomes available and is included in the analysis the resulting beta estimates would vary considerably. The fact that beta estimates for the proxy firms have indeed varied dramatically over recent years is expected and is consistent with the conclusion that those estimates are unreliable.

6. This can be contrasted with the results of the ordinary least squares regressions that are used when seeking an estimate of gamma. In that setting, sample sizes are greater, R-squared statistics are higher, confidence intervals are narrower and results are generally more stable over time. For example, Cannavan, Finn and Gray (2004) report R-squared statistics in excess of 65%.[1]

[1] When interpreting estimates of the value of franking credits there are issues around the proper economic interpretation of the resulting estimates, but the point being made here relates only to their statistical precision.

Bias

7. I also use simulation analysis to examine the issue of statistical bias in beta regressions. I show that low beta estimates are more likely to be negatively biased and to be lower than the true beta. The further a beta estimate is below 1, the more likely it is to be negatively biased. This occurs even when all noise or estimation error is perfectly symmetric.

8. I note that this issue of statistical bias is known and has been documented in the literature and that statistical approaches have been developed to help mitigate it. In this regard I recommend the use of the Vasicek bias correction technique.

Confidence intervals

9. I note that the calculation of statistical confidence intervals is not a cure at all for the statistical issues in beta regressions. They are simply one of the statistics that is produced from the analysis of the available empirical data – they provide some indication of the statistical precision of empirical estimates conditional on the data that has been selected for use. Confidence intervals do not correct for bias or for data (such as during the technology bubble period) that is considered to be unrepresentative and unable to produce reliable beta estimates. I also note that statistical confidence intervals do not account for uncertainty about the selection of the set of comparable firms, the re-levering technique to be used, or the appropriate level of gearing.

Economic reasonableness

10. I conclude that, in light of the characteristics of the available Australian data, one should apply considerable caution when interpreting statistical confidence intervals, and that an essential part of interpreting any beta estimate is to determine whether that estimate is economically reasonable.

11. The key part of this analysis is to examine the required return that is implied by the beta estimate. That is, the beta estimate will be used in the CAPM to provide an estimate of the return required by shareholders. If this required return implies a reasonable premium for bearing equity risk, one would have greater confidence in the economic reasonableness of the beta estimate. The reverse would be true if, for example, the implied required return for bearing equity risk were less than the returns available on investment grade debt.

Data quality considerations

12. I note that there are a number of data quality considerations that lead to an expectation that the available Australian data is unlikely to produce beta estimates that are in any way reliable. These considerations include:

   a. The set of "comparable" firms is very small – only two of the comparable firms at the end of 2005 survived to 2008;

   b. The recent data period has been contaminated by:

      i. The technology bubble;

ii. The commodity boom; and

iii. A prolonged period of merger activity, IPOs, and restructuring in the Australian energy distribution sector;

13. None of the "comparable" firms are pure play Australian electricity distribution and transmission firms. All have other assets from gas pipelines and distribution assets to electricity generation and retail. Some own unregulated assets and others have international investments.

Conclusion on statistical reliability

14. I conclude that the available Australian data does not provide persuasive evidence to adopt a value different from 1.

15. I have reached this conclusion because:

a. Recent beta estimates from the available Australian data are characterised by R-squared statistics which indicate that the relationship between stock and market returns (beta) is swamped many times over by "noise." Such R-squared statistics are associated with statistically unreliable (low) beta estimates;

b. I have shown that low beta estimates (less than 1) are more likely to be downwardly biased by estimation error;

c. There are very few firms in the set of "comparables" and many of these have only a short history of data;

d. None of the "comparables" is close to being a pure-play Australian electricity distribution or transmission firm;

e. Empirical beta estimates for Australian firms have varied dramatically over recent years – much more than could plausibly be attributed to changes in true systematic risk;

f. There is a wide range of estimates among the Australian firms, even though they are all supposed to be estimates of the same thing; and

g. Even though standard statistical confidence intervals do not take account of possible bias and uncertainties about the appropriateness of the comparables set, re-levering procedure, or degree of leverage they still contain 1, indicating that the data cannot reject the notion that the appropriate equity beta is 1.

Regulatory returns and efficient costs

16. I have also been asked to provide my opinion on the following question: The most commonly adopted beta value for electricity businesses in past Australian regulatory determinations is 1 but some electricity regulatory decisions have adopted values less than one and your report is to assess statistical reliability of adopting various values with currently available data. In your opinion and considering the statistical reliability of empirical estimates of beta derived from the data that is currently available:

a. Can you confirm that if a decision to adopt a beta value of less than one was made on the basis of the currently available data, would such a decision provide regulated electricity network service providers with a reasonable opportunity to recover *at least* the efficient cost to the operator of the capital employed?

b. If, in your opinion, it is possible that a decision to adopt a beta of less than one may not provide an opportunity for network service providers to recover at least the efficient cost of capital employed by the operator, please describe how significant you consider that risk to be;

c. Is the risk (if any) that the operator may not recover its efficient costs of capital materially lower for decisions with beta values of 1 or above?

17. In my view, there are two key issues to consider when addressing this question:

a. Equity beta, like other WACC parameters, cannot be observed and must be estimated with reference to market data. The resulting *estimate* may be higher or lower than the true (but unobservable) parameter value; and

b. If the beta estimate is *unbiased*, there is a 50/50 chance that the estimate is higher or lower than the true (but unobservable) parameter value. If all other WACC parameters are set at their true values (or are also unbiased estimates) there is, by definition, a 50% chance that the resulting regulatory WACC is sufficient to provide an efficient (or fair) return to investors.

18. That is, even if all other WACC parameters are known values, and even if the equity beta estimate is unbiased, there is a 50% chance that the regulatory return will be insufficient for network service providers to recover at least the efficient cost of capital employed.

19. As noted above, I also demonstrate that the further an equity beta estimate is below 1, the more likely it is to have been negatively affected by estimation error. This occurs even if the estimation error is completely random and symmetric.[2] Moreover, the further the equity beta estimate is below 1, the more likely it is to be negatively biased. Consequently, if an equity beta *estimate* below 1 is used to determine the regulatory return, there is a greater than 50% chance that the regulatory return will be insufficient for network service providers to recover at least the efficient cost of capital employed. The further the estimate is below 1, the more likely it is to be biased by estimation error, and the higher is the probability that the regulatory return is inadequate. To quantify this effect, my simulation analysis indicates that equity beta estimates in the lowest 40% of all equity beta estimates are at least 70% likely to have under-estimated the true beta.

20. The magnitude of the under-estimation depends upon the precision with which the equity beta is estimated and consequently on its statistical reliability – the less precise the estimate, the greater the magnitude of estimation error. To quantify this effect, my simulation analysis shows that when R-squared statistics are in the order of 10% (or less), there is an 80% chance that the estimate will be less than the true value. Correspondingly, there is an 80% chance that the regulatory return will be insufficient for network service providers to recover at least the efficient cost of capital employed.

[2] A symmetric estimation error is one that is equally likely to cause the estimate to be above or below the true value.

21. It follows logically that higher regulatory beta estimates will (other things equal) result in higher regulatory returns and a commensurately higher probability that the regulatory return will be sufficient for network service providers to recover at least the efficient cost of capital employed. As I have noted above, there are two issues with an equity beta estimate less than one: even if that estimate is perfectly unbiased there is a 50% chance that it will be too low to allow the network service providers to recover the efficient cost of equity capital employed; and the further the estimate is below 1 the more likely it is to be negatively biased by statistical estimation error – further increasing the probability that the network service providers would be unable to recover the efficient cost of equity capital employed. The second issue is eliminated if an equity beta estimate of 1 or above is used, and the first issue is also mitigated.

Professor Stephen Gray
15 September 2008

1. Framework for the interpretation of empirical beta estimates

22. My report is made in the context of an issues paper released by the Australian Energy Regulator (AER) on 6 August 2008 entitled "Review of the weighted average cost of capital (WACC) parameters for electricity transmission and distribution." The AER intends to complete a review of WACC parameters for electricity transmission and distribution by 31 March 2009, which will be used in the setting of regulated electricity transmission and distribution prices from 2009 – 2014.

23. I begin by noting that it is generally accepted that WACC parameters cannot be observed or precisely measured – they must be estimated with reference to often noisy and volatile market data. As a result, the estimated value may be above or below the true (but unobservable) value of the parameter. By way of example, in its assessment of Telstra's ULLS and LSS monthly charge undertakings, the ACCC states that:

> Because each WACC parameter cannot be known with certainty, there is a *range* of input parameters which could be termed 'reasonable'. This seems to be an area of common agreement.[3]

And I agree with this assessment.

24. In this regard, it is my view that consideration should be given to the likelihood that a particular parameter estimate is above or below the true (but unobservable) parameter value, and of the reliability and statistical precision of that estimate. This involves a number of formal statistical considerations. It also involves testing each parameter estimate against the standards of economic reasonableness.

25. I note that there is presently a range of views among Australian regulators about the reliance that should be placed on beta estimates that are based on the available Australian data. In its recent gas distribution decision, the Essential Services Commission of Victoria (ESC, 2008) adopted an equity beta of 0.7 based largely on estimates from the available Australian data.

26. By contrast, the most recent energy decision by the Queensland Competition Authority (QCA, 2006) adopts an equity beta of 1.1 and states that:

> [E]mpirical estimates are not currently sufficiently accurate to be heavily relied upon.[4]

This is symptomatic of the substantial degree of uncertainty surrounding the appropriate equity beta value to use, which stems from the lack of statistical precision and robustness of beta estimates for the very small set of available firms.

27. In my view, when estimating all WACC parameters one must consider the statistical robustness of the available market data and empirical estimates. The weight that is applied to a particular estimate should depend upon the precision with which it is estimated, the statistical reliability of that estimate, and whether the estimate is economically reasonable.

[3] ACCC (2005). *Assessment of Telstra's ULLS and LSS monthly charge undertakings: Draft decision,* p.62.
[4] QCA (2006, p. 106).

28. The remainder of this report sets out a number of statistical considerations that one should have regard to when interpreting beta estimates. Specifically, I set out a number of issues that should be considered when determining how much weight should properly be afforded to estimates based on the available Australian data. I also set out a number of considerations that would address the economic reasonableness of estimates that are produced by statistical methods applied to the available data.

2. Statistical Issue 1: R-squared statistics

Interpretation of R-squared statistic

29. The R-squared statistic in regression analysis measures the proportion of variation in the dependent variable which is explained by variation in the independent variable (this might be thought about as a signal-to-noise ratio). The remaining variation must be explained by other factors which have not been incorporated into the regression analysis. In the context of beta estimation, it measures the proportion of variation in stock returns which can be explained by variation in market returns over the sample period (this being the signal). The remaining variation is due to firm-specific effects that are unrelated to market movements (this being the noise). The term "adjusted R-squared" is more commonly used in inferring regression results, as it makes a correction to the R-squared statistic which statisticians have demonstrated has an upwards bias.

30. In *any* regression analysis, a low R-squared means that the signal-to-noise ratio is low and it is more difficult to properly detect the true relationship between the variables. In response to this point made to the ESC in its most recent gas decision, the ESC formed the view that the R-squared statistic merely reflects the substantial proportion of risk associated with security-specific factors.[5] In forming this view, the ESC relies upon a quote from the Australian Graduate School of Management (AGSM) Risk Management Service (RMS) (a commercial provider of empirical beta estimates for Australian firms) which states:

> A high value of R-squared (close to unity) simply implies that much of the risk of this equity is due to market risk: and a low value of R-squared (close to zero) implies that much of the total risk is specific risk. In particular note that R-squared should not in this finance context necessarily be interpreted as a measure of the reliability of the regression equation.

31. In my view, there is a real risk of this quote being mis-interpreted and leading the reader to an incorrect conclusion, not intended by the AGSM-RMS. In particular, the R-squared statistic plays two roles here – a finance role (for this particular case) and a statistics role (that applies in every regression). In a statistics context, the R-squared value can be interpreted as the signal-to-noise ratio. A low signal-to-noise ratio means that it is harder to reliably recover the signal, which in this case means that it is harder to generate reliable estimates of equity beta.

32. Having been made aware of the potential to mis-interpret this quote, the AGSM-RMS has more fully explained its statement as follows, in terms that I believe properly and more thoroughly explains the role of the R-squared statistic in beta regressions:

[5] ESC (2008, p. 468).

> In equity beta regressions, the R-squared statistic has two interpretations – one in the context of finance theory and the other statistical. In finance, a high value of R-squared (close to unity) simply implies that much of the risk of this equity is due to market risk and a low value of R-squared (close to zero) implies that much of the total risk is specific risk. Finance theory recognises that some firms will have low firm-specific risk (and high R-squared in the beta regression) and others will have high firm-specific risk (and low R-squared in the beta regression). The fact that we see several regressions with very low R-squared statistics does not imply that they are wrong or in any way inconsistent with finance theory. R-squared also has a statistical interpretation. It measures the extent to which the model explains variation in the independent variable. A low R-squared indicates that more of the variation in the variables is noise that is unrelated to the effect that is being measured, making it more difficult to obtain statistically reliable estimates.[6]

33. In a statistics context, the R-squared value can be interpreted as the signal-to-noise ratio. A low signal-to-noise ratio means that it is harder to reliably recover the signal, which in this case means that it is harder to generate reliable estimates of equity beta. Consequently, I would caution against significant weight being placed upon beta estimates that have been generated with R-squared statistics which indicate that the relationship between stock and market returns (beta) is swamped many times over by "noise."

Statistical evaluation of R-squared statistics

34. In recent work prepared for submission to the ESC (SFG, 2007, Section 5) we performed a simulation analysis in order to illustrate the association between the R-squared statistic and the equity beta estimates which result from an OLS regression. Our conclusion from that analysis was that beta *estimates* associated with low R-squared statistics which indicate that the relationship between stock and market returns (beta) is swamped many times over by "noise" are highly likely to differ substantially from the *true beta* – low R-squared means statistically unreliable estimates.

35. I have now expanded this simulation exercise by simulating market returns and individual stock returns over 48 months for a company which was assumed to have an equity beta of one. This means that, on average, simulated stock returns will fluctuate in line with market movements, but will deviate from market returns in individual months due to company-specific factors, just like we would expect to observe in market data. I repeated this process one million times in order to generate one million price paths of market movements and individual stock returns.[7]

36. From each price path I generated an equity beta estimate from the OLS regression. Recall that in each price path the *true* equity beta is equal to one, but the equity beta *estimate* from the OLS regression may deviate from one due to estimation error. In some cases, just by chance, there will be unusually high stock returns in months when the market rises, so the OLS regression estimate will be greater than one. In other cases, there will be unusually low stock returns in months when the market rises, so the OLS regression estimate will be less than one. But on average, the OLS estimate will equal one.

37. The assumptions that underlie this analysis are as follows:

[6] Email from David Simmons, Director of RMS, to SFG, 14 August 2008. We understand that AGSM-RMS plans to use this revised quote in material that it distributes in future.

[7] In the earlier analysis we performed 10,000 simulations but have now increased this to one million simulations.

a. For each of the one million simulations, the market has an expected monthly return of 1% and monthly standard deviation of returns which range from 1 – 10% with equal probability, referred to as a uniform distribution. This means that, on average, we expect the market to earn 12.7% per year, and volatility of returns which range from 3.5 – 34.6% per year. In one simulation, the market will be quite stable; in another it will be more volatile.

b. For each month within each simulation, I generate market returns as the sum of the expected value of 1% plus a draw from a normal distribution with mean zero and standard deviation equal to the volatility generated above. For example, suppose the first simulation was a benign market environment, in which monthly volatility was just 1%. There is a 68% chance that a given month's return will range from 0 – 2% and a 95% chance that a given month's return will range from –1 to + 3%. In the extremely volatile market, there is a 68% chance that a given month's return will range from –9 to +11% and a 95% chance that a given month's return will range from –19 to +21%.

c. For each of the one million simulations, the company-specific volatility also has an expected monthly value which is drawn from a uniform distribution ranging from 1 – 10%. This means that, in addition to market risk, stock returns fluctuate according to company-specific factors. In some cases, company-specific volatility will be very high, and in other cases quite low. But the company-specific volatility is assumed to be entirely independent of market volatility.

d. For each month within each simulation, I generate stock returns as the sum of the market return plus a company-specific return drawn from a normal distribution with mean zero and standard deviation equal to the company-specific volatility generated above. Hence, I have assumed that the stock in question has an equity beta of one, so on average it will generate returns equal to the market. But in a given month the stock return could be much higher or lower than the market return.

38. The important issue in the current context is the relationship between the R-squared statistic and the reliability of the estimated equity beta. I grouped the regression results into deciles according to the magnitude of the R-squared statistic and measured the mean and standard deviation of the beta estimates resulting from the regression analysis. I also report the proportion of cases in which the beta estimate would be considered significantly below or above one at the 5% level of significance.

39. The table below illustrates the inverse relationship between the R-squared statistic and the standard deviation of the beta estimate. For cases in the lowest R-squared decile, the standard deviation of beta estimates is 0.50, which declines to just 0.04 as the R-squared statistic increases.

40. The implication of this is that regression analysis in which the R-squared statistic is low (indicating that the relationship between stock and market returns (beta) is swamped many times over by noise) generates highly variable beta estimates which, statistically, should not be relied upon.

41. Furthermore, in the lowest R-squared decile, 80% of beta estimates are below the true beta of one, including 13% of cases in which this difference was statistically significant at the 5% level. In statistical terms, this is referred to as a Type I error – where there is a finding of statistical significance despite the population mean being no different from the null hypothesis. In this instance, the null hypothesis is that the equity beta is equal to one. But even if sampling is done in

an unbiased manner, one out of twenty random samples will generate a mean estimate significantly different from one at the 5% level. In this instance however, at the lowest R-squared decile, 13% of random samples generate beta estimates which are significantly below one and no samples generate beta estimates significantly above one.

Table 1. Simulation results illustrating the relationship between R-squared and beta estimates

Decile	Mean R-squared (%)	Mean beta estimate	Standard deviation of beta estimate	Proportion in which estimates are below one (%)	Proportion in which estimate is reported as significantly below one (%)	Proportion in which estimate is reported as significantly above one (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	4	0.66	0.50	80	13	0
2	15	1.06	0.42	55	5	1
3	25	1.07	0.34	51	5	4
4	36	1.05	0.24	49	4	5
5	46	1.04	0.18	46	4	5
6	56	1.04	0.15	43	3	6
7	65	1.04	0.12	42	3	7
8	75	1.02	0.10	43	4	8
9	86	1.01	0.07	45	4	7
10	95	1.00	0.04	46	4	6
Overall	50	1.00	0.29	50	5	5

42. The key results of this analysis are those that are highlighted in the shaded row of the table above. In all cases the data has been generated with a true beta of 1.00. The samples vary only in the amount of firm-specific noise that is included. I find that when the R-squared statistic in a beta regression is less than 10%, there is a high chance that one would obtain an estimate below 1.00 even when the true beta is exactly 1.00. Consequently, one should be extremely cautious when interpreting estimates from a beta regression in which the R-squared statistic is less than 10%. For this reason, from a statistical perspective one must apply considerable caution before drawing any conclusions from this data set.

43. In this regard, I note that Bowman and Bush (2004) propose a beta estimation procedure that eliminates all individual firm estimates that have R-squared statistics of less than 10%. While I would not necessarily use such a mechanical procedure, this does indicate that the *statistical* interpretation of the R-squared statistic in beta regressions is a live issue in the relevant literature.

R-squared statistics in empirical Australian data

44. Table 2 below reports the R-squared statistics for a sample of nine comparable firms, as reported in recent editions of the AGSM-RMS Beta Service. I note that the estimates based on data through to the end of 2006 are uniformly low, indicating that the relationship between stock and market returns (beta) is swamped many times over by noise. The R-squared statistic for Envestra is zero to two decimal places, which indicates that the data provides no indication as to the relationship between stock returns and market returns and is consequently uninformative about the appropriate equity beta. The R-squared statistics have improved slightly by March 2008 as

new data has become available, but they remain low, indicating that the relationship between stock and market returns (beta) continues to be swamped many times over by noise.[8]

Table 2. R-squared statistics of regression analysis using Australian data

Company	R-squared September 2006	R-squared December 2006	R-squared March 2008
AGL	0.04	--	--
Alinta	0.13	--	--
SP Ausnet	--	--	0.06
Duet Group	0.14	0.14	0.14
Spark Infrastructure	--	--	0.19
APA Group	0.11	0.07	0.21
Envestra Limited	0.00	0.00	0.28
Hastings Diversified	0.15	0.10	0.10

Source: AGSM-RMS Beta service, September 2006, December 2006, March 2008.
Missing data indicates that a beta estimate is not provided due to insufficient data points since listing, or since company restructuring.

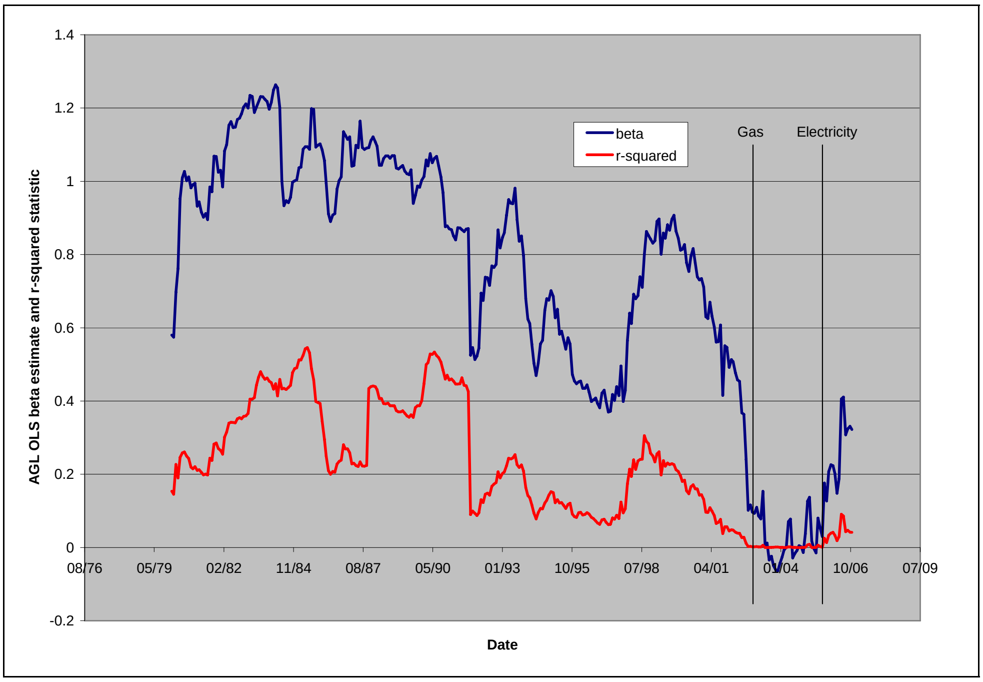
45. In this regard, our report in relation to the ESC gas distribution review displays the following figure for AGL — the only comparable firm for which a long time series of data is available.[9] It shows that there is a close relationship between the (raw) equity beta estimate and the R-squared statistic from the OLS regression. Over recent years, the R-squared statistic has fallen substantially and has been close to zero – indicating that the data being used is almost completely uninformative about the relationship that we are trying to measure. This has coincided with a dramatic fall in the estimated beta.[10]

[8] None of these firms is a perfect comparable for a pure-play Australian electricity transmission or distribution business. But this does illustrate the sort of R-squared statistics that are available for the available set of Australian comparables, such as it is.

[9] None of the other "comparable" firms were listed on the Australian Stock Exchange (ASX) early enough to enable a pre-technology bubble beta to be estimated. That is, none of the other firms has even four years of pre-bubble data available. Other than AGL, we are restricted to the analysis of the post 2001 period. We note that Envestra was listed on the ASX prior to the technology bubble period, but not for sufficient time to enable a pre-bubble beta to be estimated.

[10] We note that in recent times AGL has moved out of energy infrastructure into power generation, energy wholesaling and retailing, and even mobile telephony for a period. It was also involved in merger and acquisition speculation for some time. This may provide some reasons for the drop in the R-squared statistic and the dramatic decline in beta estimates that occurred with it. Whatever the reasons, there is a clear relationship between the loss of statistical explanatory power (R-squared) and the decline in the beta estimate to implausibly low (negative) values.

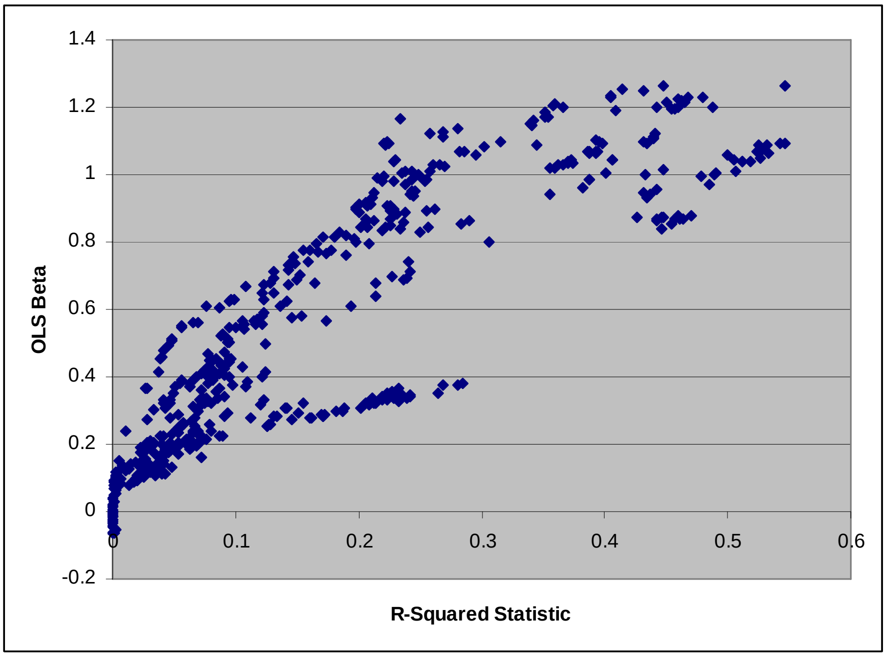
Figure 1: Time series of OLS beta estimates and R-squared statistics for AGL



Source: Stock and market returns from AGSM Centre for Research in Finance, SFG calculations.
All estimates are raw OLS estimates directly from the AGSM Beta Report. They have not been re-levered or adjusted in any other way.

46. This relationship is reinforced by Figure 2 below, which plots the R-squared statistic against the raw OLS beta estimates for AGL in Figure 1 above. There is a clear relationship between the beta estimate from a particular regression and the R-squared statistic from that same regression. In those cases when the R-squared statistic is low, for whatever reason, the beta estimate is also low. For the cases where the R-squared statistic is above 0.3, the OLS beta estimates are centred around 1.

Figure 2: Relationship between R-squared statistics and OLS beta estimates for AGL



Source: Stock and market returns from AGSM Centre for Research in Finance, SFG calculations. All estimates are raw OLS estimates directly from the AGSM Beta Report. They have not been re-levered or adjusted in any other way.

47. There are two explanations for what we see in Figures 1 and 2:

a. The actual systematic risk of AGL fell precipitously, became negative, then started to rise again (implying that shareholders reduced their required return below the risk-free rate for a period, and are now starting to require higher returns); or

b. The actual systematic risk of AGL has not changed precipitously in recent times, but that the *estimates* of beta have been affected by poor quality (statistically noisy) data that results in low R-squared statistics and unreliable estimates.

48. The latter interpretation is the more plausible because it is contrary to any financial model or framework (and to observed practice) for investors to require a return from a risky investment in a stock such as AGL that varies wildly over time and, for some period, is lower than the risk-free return (e.g., as available on government bonds) . The lowest beta estimates for AGL occurred in a period during which the R-squared statistics were low indicating that the data was almost completely uninformative about the relationship to be estimated. The simulation analysis above has established that when R-squared statistics are low, beta estimates are more likely to vary significantly from the true beta.

49. Beta estimates based on regression analysis with low R-squared statistics which indicate that the relationship between stock and market returns (beta) is swamped many times over by noise" are statistically unreliable. This was borne out in the simulation analysis above. I also note that the recent estimates of beta for the set of Australian energy transmission and distribution firms (in the table above) are characterised by such low R-squared statistics. Consequently, I conclude that these recent estimates are not reliable.

50. Moreover, beta estimates that are based on low R-squared statistics (such as apply to the available Australian data) and which are also considered to be unreliable for other reasons as well, are expected to vary considerably over time. That is, as new data becomes available and is included in the analysis the resulting beta estimates would vary considerably. The fact that beta estimates for the proxy firms have indeed varied dramatically over recent years is expected and is consistent with the conclusion that those estimates are unreliable. For example, the AGSM Risk Management Service reports equity beta estimates as follows:

a. For AGL: 0.81 in 2000; -0.07 in 2003; and 0.42 in 2006.

b. For Envestra: 0.65 in 2002; -0.16 in 2006; and 0.64 in 2008.[11]

51. Finally, I note that there is a trade-off involved in seeking to obtain improved R-squared statistics to increase the statistical reliability of the results. One may seek to increase the length of the sample period so that more data is available to provide a more reliable estimate (and a higher R-squared statistic). However, in the present case there is only one comparable firm with a long time series of data – AGL. The other firms in the comparable set have been listed on the Australian Stock Exchange (ASX) for a relatively short time.

52. This reinforces the view that the available Australian data, however it might be analysed, is simply unable to provide precise and statistically reliable estimates of equity beta for this industry.

53. This can be contrasted with the results of the ordinary least squares regressions that are used when seeking an estimate of gamma. In that setting, sample sizes are greater, R-squared statistics are higher, confidence intervals are narrower, and results are generally more stable over time. For example, Cannavan, Finn and Gray (2004) report R-squared statistics in excess of 65%.[12]

Reason for decline in R-squared statistics

54. One reason for the decline in the R-squared statistics of beta regressions using Australian data is the temporary decline in stock market volatility that occurred over the last several years. In our report in relation to the recent Victorian gas distribution review,[13] we noted that every regression requires sufficient variation in the explanatory variable to properly tie down the relationship between the variables. In a beta regression, (monthly) market returns are used to "explain" the returns from a particular stock. If a data period is chosen such that there is little variation in monthly returns, it then is difficult for the regression analysis to properly estimate the relationship and the resulting beta estimates are necessarily less reliable.

55. Our earlier report included the following figure, which illustrates beta estimates for AGL over time. The horizontal axis is stock market return volatility, which is a measure of how informative the regression is likely to be. Low variation in market returns means that the "signal" in the regression is low and the resulting estimate is likely to be less reliable and characterised by a low R-squared statistic. The estimates from 2005 and 2006 are based on the lowest market volatility over the entire period. I have shown above that these estimates also have low R-squared statistics. Consequently, the low beta estimates that result are unreliable.

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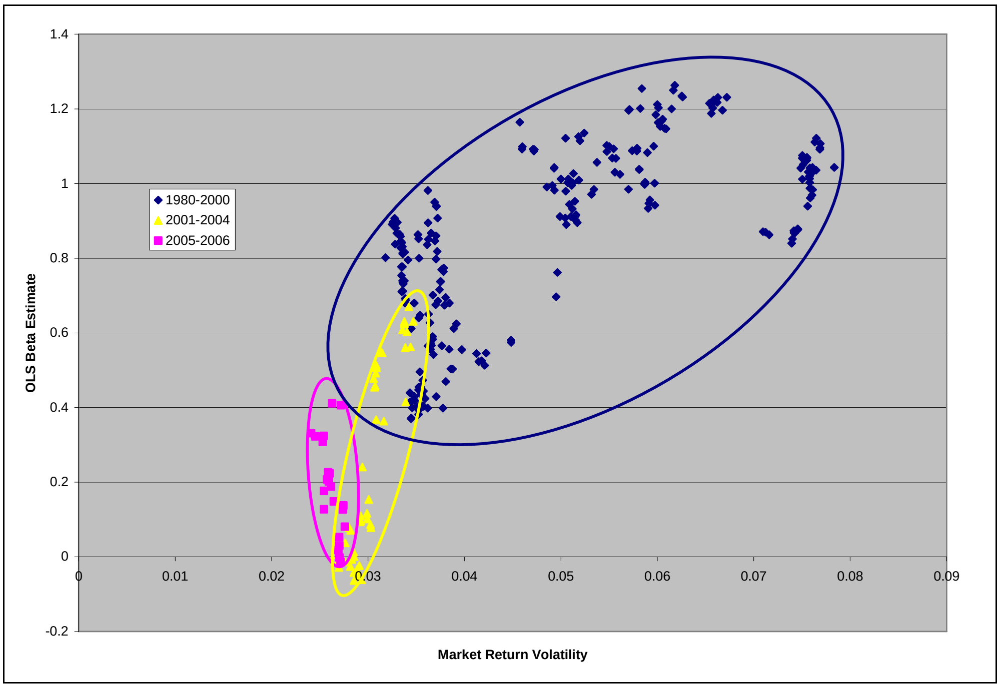
[11] Raw (not re-levered) beta estimates from AGSM.
[12] When interpreting estimates of the value of franking credits there are issues around the proper economic interpretation of the resulting estimates, but the point being made here relates only to their statistical precision.
[13] SFG (2007).

Figure 3: Relationship between OLS beta estimate and market return volatility for AGL

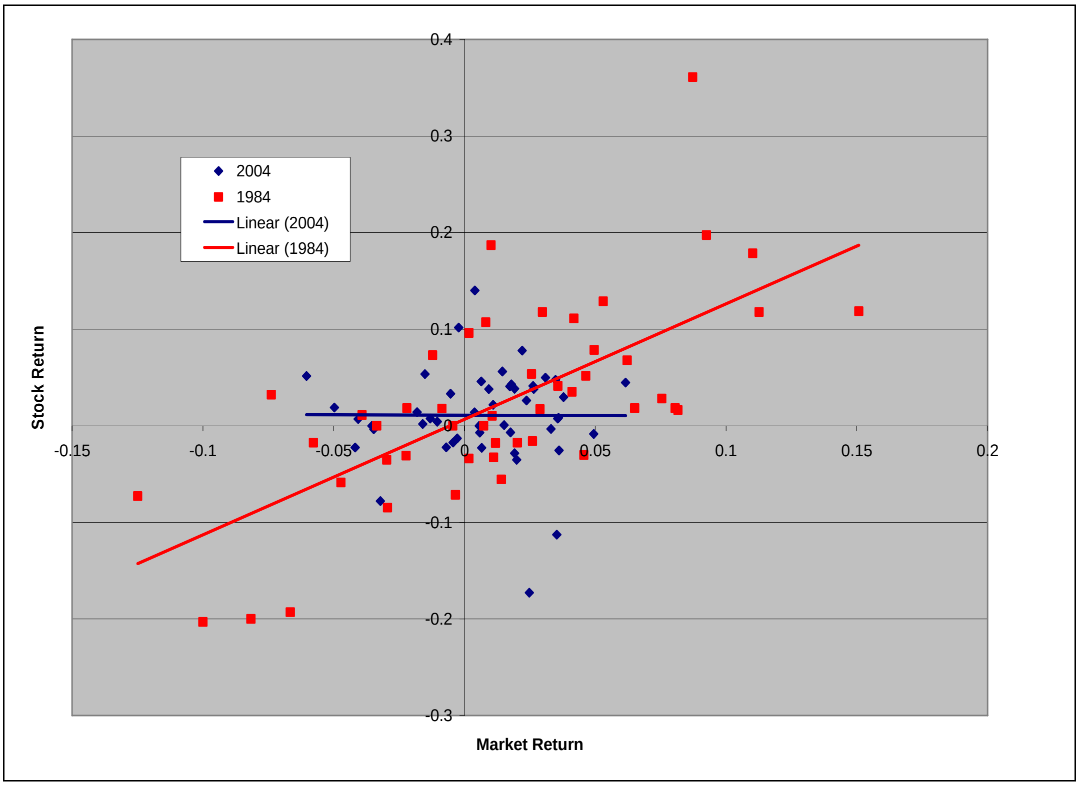


Source: Stock and market returns from AGSM Centre for Research in Finance, SFG calculations.
All estimates are raw OLS estimates directly from the AGSM Beta Report. They have not been re-levered or adjusted in any other way.

56. To see further why this might be the case, our earlier report also plotted the data points that were used in two beta regressions for AGL. The data period ending in August 1984 is characterised by wide variation in market returns, and corresponding variation in AGL stock returns. This enabled the relationship between the two variables to be well estimated (the beta estimate is the slope of the red line in the figure below) with an R-squared statistic of 50%. By contrast, the data period ending in 2004 is based on data that displays almost no variation and has an R-squared statistic of 0% (the blue line in the figure below).

57. The conclusion from this is that when there is little or no variation in market returns, there is little or no opportunity for market returns to explain stock returns, and the resulting beta estimate is unreliable as it is based on data that is uninformative about the relationship that we seek to measure.

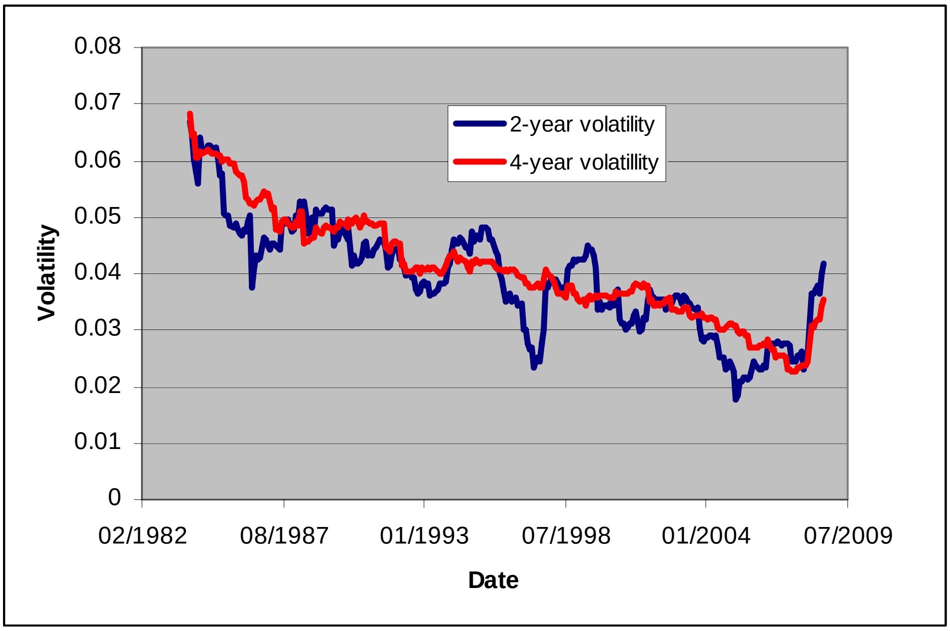
Figure 4: Data points underlying AGL OLS beta estimates for August 1984 and August 2004



Source: Stock and market returns from AGSM Centre for Research in Finance, SFG calculations.

58. This point is made more generally in Figure 5 below, which shows the pattern in Australian stock market volatility over recent times. The basis of this figure is monthly returns on the All Ordinaries Accumulation Index. I have constructed rolling 2-year and 4-year standard deviations. The pattern is clear – the volatility in the independent variable in beta regressions has decreased appreciably in the late 1990s and early 2000s to only a third of its previous level, before increasing again in very recent times.

Figure 5: Historical volatility of Australian stock market returns



Source: Stock and market returns from AGSM Centre for Research in Finance, SFG calculations.

Conclusion

59. The R-squared statistic measures the proportion of variation in stock returns which can be explained by market returns. A low R-squared value can result from a stock bearing a high degree of company-specific risk. But it is also systematically related to the dispersion of beta estimates which will be generated by regression analysis. Even for a set of firms with exactly the same true systematic risk, regressions in which the R-squared statistic is low will generate low and widely dispersed beta estimates, making them inherently unreliable for estimating the cost of capital.

60. The R-squared statistics for beta estimates of Australian energy transmission and distribution firms have been at such a level in recent times that the reliability of the resulting beta estimates must be strongly questioned.

3. Statistical Issue 2: Bias in beta estimates

The statistical source of bias

Overview

61. In this section I discuss the problem of statistical bias in beta estimates. I demonstrate that beta estimates derived from an OLS regression of stock returns against market returns are systematically biased in that low estimates have a high probability of understating the true risk of the stock, and that high estimates are just as likely to overstate the true risk of the stock.

62. Importantly, I show that this statistical bias exists even though "noise" or "random error" in the data is perfectly symmetric – being equally likely to increase or decrease stock prices.

Bias results from symmetric random estimation error

63. The problems of bias and imprecision of beta estimates are distinct, but related issues. Vasicek (1973) recognised that OLS beta estimates are biased in a statistical sense. On average, low beta estimates are likely to understate the true, unobservable systematic risk of the firm, while high beta estimates are, on average, likely to overstate systematic risk. If we observe a beta estimate below one, there is some probability that the firm has below average risk, and some probability that the firm has above average risk, but that we happen to have observed a low number due to random fluctuations in returns data during the sample period.

64. To see this, consider first the following thought experiment. Suppose that every firm is known to have a true beta of 1, but when we run regressions there is estimation error, so the regression estimates can be above 1 or below 1. Those estimates that are below 1 are known to have negative estimation error (as that is the only way the estimate could have been below 1 in this setting) and those that are above one are known to have positive estimation error. That is, by observing the beta estimate, we can infer something about how it has been affected by estimation error.

65. Now suppose that all firms have a beta of either 0.9, 1.0 or 1.1, with one third of stocks in each group. But we don't know which is which, so we have to rely on our beta *estimates*. Also suppose that every time we estimate beta there is a one-third chance that we recover the true value or that our estimate is over- or under-estimated by 0.1. That is, there are a range of true betas, and estimation error for any individual beta estimate is symmetric. Now suppose you estimate a particular firm to have a beta of 0.9. There are two possibilities here (a) the true beta is 0.9 and the estimation error was 0; or (b) the true beta is 1 and the estimation error was -0.1. That is, in this case, we know from observing the beta estimate of 0.9 that it has either zero or negative estimation error – this is a negative bias. But does this negative bias disappear when we introduce the possibility that some stocks might have a true beta of 0.8, so that our estimate of 0.9 has been contaminated by *positive* estimation error? No – imagine betas being normally distributed around 1. There are more firms with a beta close to 1 than with beta far from 1. So there will always be more chance that a beta estimate of 0.9 will be from a true beta of 1 with negative estimation error than from a true beta of 0.8 with positive estimation error. Moreover the further our beta estimate is below 1, the more likely it is to have been affected by negative estimation error.

66. Vasicek (1973) also shows that, the further the observed estimate is from one, the greater the probability that we have observed a high or low estimate purely by chance, rather than the actual risk being below or above the market average.

67. That is, even with perfectly symmetric estimation error, the further a beta *estimate* is below 1, the more likely it is to be a negatively biased estimate. Consequently, beta estimates that are considerably less than 1 should be interpreted with great caution. For example, it would be wrong to simply adopt a beta estimate that is considerably less than 1 without consideration of the extent to which that estimate might have been affected by estimation error. The relevant considerations would include the size of the data set, corroboration of the estimate by comparable firms, the economic reasonableness of the resulting estimate.

Quantifying the statistical bias

68. The phenomenon of statistical bias can be illustrated by the following simulation. Suppose that the true beta distribution for all stocks in the market is normally distributed with a mean of one and a standard deviation of 0.5. This means that 68% of stocks have betas within the range of 0.5 – 1.5 and 95% of stocks have betas within the range of 0.0 – 2.0.[14] The problem with beta estimation is that we cannot directly *observe* the true risk of each stock. We can only *estimate* that risk, with the most common technique being an OLS regression of stock returns against market returns.

69. What could these OLS beta estimates look like? Suppose that the observed beta estimates are also drawn from a normal distribution with a mean estimate equal to their true beta and standard error of 0.8. That is, any estimation error is perfectly symmetric around the true beta. This means that, in an OLS regression, if the stock had a true beta of 0.5, there is a 68% chance that we would observe an OLS beta estimate in the range of –0.3 to +1.3. These are the beta estimates which we actually observe when we run an OLS regression.

70. I generated one million underlying betas and beta estimates according to the assumptions outlined above. So each observation has a *true beta* drawn from a normal distribution with mean one and standard deviation of 0.5 and a beta *estimate* drawn from a normal distribution with mean equal to its true beta estimate and standard deviation equal to 0.8. For example:

   a. Suppose the first observation has a true beta of 0.5 (one standard deviation below the population mean). I generate a beta estimate from a normal distribution with mean 0.5 and standard deviation 0.8. Perhaps this beta estimate turns out to be 0.6. In that case, observation one has a true beta of 0.5 and a beta estimate of 0.6.

   b. Suppose the second observation has a true beta of 1.0 (equal to the population mean). I generate a beta estimate from a normal distribution with mean 1.0 and standard deviation 0.8. Perhaps this beta estimate turns out to be 1.2. In that case, observation two has a true beta of 1.0 and a beta estimate of 1.2.

71. I repeated this process one million times and then grouped observations according to deciles of beta estimates. Observations in the lowest 10% of beta *estimates* are in decile one, observations in the next 10% of beta estimates are in decile two, and so on. Some of these stocks with low beta estimates will be in decile one because they are truly very low risk stocks. But some will be in decile one because they are average or even high risk stocks, but random fluctuations in returns data means that the *estimate* turned out to be very low.

[14] This just comes from the standard statistical properties of a normal distribution – 68% of observations are within one standard deviation of the mean and 95% are within two.

72. The table below shows the mean beta estimate and mean actual betas for each decile. Compare the decile means of the actual and sample betas reported in Columns Two and Three. Recall that, in practice, we can only observe beta estimates (Column Three). Suppose that we observe a set of stocks with mean beta estimates of 0.36, the mean of decile three stocks. The mean of their true betas is 0.82, illustrating that sample beta estimates below one are likely to understate true systematic risk and that sample beta estimates above one are likely to overstate systematic risk.

Table 3. Simulation results illustrating the bias in beta estimates

Decile	Mean actual beta	Mean beta estimate	Prob Estimate > Actual Beta (%)	Mean Vasicek bias corrected beta	Prob Vasicek bias corrected beta > Actual beta (%)
(1)	(2)	(3)	(4)	(5)	(6)
1	0.53	−0.66	1	0.53	50
2	0.72	0.02	5	0.72	50
3	0.82	0.36	14	0.82	50
4	0.90	0.64	27	0.90	50
5	0.97	0.88	42	0.97	50
6	1.03	1.12	58	1.03	50
7	1.10	1.37	73	1.10	50
8	1.18	1.64	86	1.18	50
9	1.28	1.99	95	1.28	50
10	1.46	2.66	99	1.46	50

73. The probability that this bias has influenced the beta estimates is quantified in Column Four. In this column I report the percentage of cases in which the beta estimate exceeded the actual beta. For stocks in the lowest decile of beta estimates there is a 1% chance that the estimate was larger than the actual beta and conversely a 99% chance that the estimate was below the actual beta. (Note that I discuss Columns 5 and 6 in the following sub-section.)

74. The key result is in the shaded row in the table above. Very low beta *estimates* are almost certainly negatively biased – even in a simulation with symmetric estimation error. That is, with perfectly symmetric estimation error, there is a very high chance that low beta *estimates* are substantially below their true values.

75. If this is the case, we would expect to see firms with very low beta *estimates* in one period, having higher beta *estimates* in a subsequent period as new data becomes available and is included in the analysis. This would occur even though the true beta of the firm was constant throughout.

Bias correction techniques

Bias correction methods

76. A number of commercial data providers make adjustments to OLS equity betas to account for the risk that OLS estimates are biased. Adjustments of this type are common amongst data providers who make an adjustment to equity beta estimates to account for observed mean-reversion (Blume, 1971 and 1975). For example, the default beta estimate relied upon by Bloomberg, Merrill Lynch and ValueLine – referred by the AER as the Blume adjustment – is a weighted average of an OLS estimate and a prior estimate of one, according to the following equation:

$$\beta_{Bloomberg} = 0.33 + 0.67 \times \beta_{OLS}.$$

77. Datastream also reports beta estimates which are adjusted from their OLS estimates by removing "exceptionally large stock price changes from the calculation" and with a bias correction which shifts OLS beta estimates closer to the average beta in the market. Datastream states that the historic beta is:

> adjusted using Bayesian techniques to predict the probable behaviour of the stock price on the basis that any extreme behaviour in the past is likely to average out in the future.

78. The Datastream bias correction factor is based upon the work of Cunningham (1973) who derives a beta correction factor consistent with Vasicek (1973) whose work I discuss below. Cunningham summarises the focus of my discussion, which is that we will observe mean-reversion in beta estimates, even if there is no change in the firm's assets towards a more diversified portfolio. He states (p.326) that:

> even if true betas were constant, "regression towards the mean" would be observed in the estimates. In rough terms, a high [beta estimate] is more likely to be an over-estimate than an underestimate, and thus the [beta estimate] for the same stock in the next period is likely to be smaller. If we have a high [beta estimate], the expected value of the true [beta] is smaller. The adjustment to be made to [the beta estimate] depends upon the known error variance of [the beta estimate] and the known true distribution of the [betas]. If [the beta estimate] is very precisely estimated, the revised estimate is close to the [initial estimate]. If [the beta estimate] has a large error variance, little weight is attached to [the beta estimate] and so [the revised estimate] is close to the mean [beta] of the distribution of the true [betas].

79. Whereas the Blume adjustment applies constant weights to the OLS beta estimate and the default value of 1 in all cases, the Vasicek adjustment uses weights that vary according to the statistical precision of the OLS estimate – the more statistically precise the OLS estimate, the more weight it will receive. This has a convenient statistical interpretation – one begins with a "prior expectation" or "default value" and moves away from this only to the extent that they can be convinced to do so by the available data. The more statistically precise the OLS estimate, the more one would be persuaded to move from the prior or default value.

80. That is, the Blume and Vasicek adjustments can both be motivated as a correction for statistical bias. The Blume adjustment is more commonly used in practice as it is trivial to implement. However, it was originally motivated by Blume as a way of accounting for variation in *true* betas over time, and it involves constant weights that are independent of the precision of the empirical estimates. For these reasons, I focus on the Vasicek bias correction in the remainder of this paper.

81. In this regard, I note that AER has formed a view on this issue (AER, 2008, p.62):

> [T]he underlying premise behind the Blume adjustment that a firm may diversify its operations across assets of varying riskiness or may change its gearing to alter its risk profile (if its operations are currently of extreme high or low risk) does not appear consistent with the underlying regulatory regime.

82. I agree that corporate diversification and capital management strategies are not relevant in the present context. However, the reasoning in the above quote does not address the bias in beta estimates which results purely from the statistical properties of beta estimation. The discussion above illustrates that OLS beta *estimates* exhibit mean-reversion as a result of statistical bias, even if the firm makes no change in asset base or leverage whatsoever and the *true* (but unobservable) beta remains constant.

83. The ESC (2008, p.475) also considered that the Blume adjustment was inappropriate where "betas from a number of firms are already being used to improve precision (i.e. reduce estimation error)." This illustrates the important distinction between bias and precision in beta estimates.[15] It is correct that beta estimation over a longer time period and with more comparable firms is likely to increase the *precision* of beta estimates. However, that improvement in precision will be reflected in the weight placed on the OLS estimate in computing the Vasicek bias correction – the more precise the estimate, the more weight it will receive. That is, the precision of the empirical estimate is accounted for in the Vasicek correction, but not in the Blume correction, which applies constant weights regardless of the precision of the OLS estimate.

Vasicek bias correction

84. The equation for the Vasicek bias corrected estimates is as follows:

$$\beta_{Vasicek} = w_{OLS} \times \beta_{OLS} + (1 - w_{OLS}) \times \beta_{prior}$$

$$\beta_{Vasicek} = \frac{\sigma^2_{market}}{\sigma^2_{market} + \sigma^2_{OLS}} \times \beta_{OLS} + \left(1 - \frac{\sigma^2_{market}}{\sigma^2_{market} + \sigma^2_{OLS}}\right) \times 1$$

where:

w_{OLS} = the weight placed on the OLS estimate;
β_{Prior} = a prior beta estimate;
β_{OLS} = the beta estimate from the OLS regression of stock returns on market returns;
σ_{OLS} = the standard error of the beta estimate from the OLS regression; and
σ_{market} = the standard deviation of beta estimates across the sample firms in each period.

85. The Vasicek (1973) bias corrected estimate can be interpreted as an adjustment to the sample beta estimate toward a prior estimate. The size of this adjustment is proportional to the precision of the sample beta estimate relative to uncertainty over the true beta. This is where the concepts of bias and imprecision are related. The more precise the beta estimate – that is, the lower its standard error – the less bias correction is needed. So if beta estimates are generated using the longest available series of returns data, which results in lower standard errors, there more weight is placed on the OLS estimate. There is still some weight placed on the prior estimate, however.

[15] Statistical precision refers to the standard error of the estimate, which determines the width of the confidence interval around the point estimate. A precise estimate is one with a low standard error and a correspondingly narrow confidence interval. Bias refers to whether the point estimate would, in many repeated trials, converge to the true parameter value. To the extent that the estimate is systematically more likely to be below (than above) the true parameter value, the estimate is biased.

86. The Vasicek (1973) bias correction provides an adjustment to account for the statistical bias that is documented in Table 3 above. I have applied the Vasicek bias correction to each of my one million observations and report the mean Vasicek bias corrected beta for each decile. These mean estimates are identical to the means of actual betas and the probability that a Vasicek bias corrected beta exceeds the actual beta is 50% across each decile.

Appropriate reference point for Vasicek beta estimates

Prior distribution based on all betas in market

87. The application of the Vasicek bias correction technique requires a "prior distribution" that plays the role of the prior belief – prior to the estimation of individual stock betas using the available data. The most obvious "prior distribution" is simply the distribution of all betas in the market. This would naturally be the probability distribution that one would use to characterize the possible values for the beta of a randomly-selected stock. I note that this approach is adopted by the London Business School beta service. The Vasicek technique takes this distribution of all betas as a starting point or "prior." It then moves towards the OLS point estimate, depending on the precision of the OLS estimate.

88. Specifically, my view (which is articulated in Gray, Hall, Klease and McCrystal, 2008), is that the appropriate prior distribution is a normal distribution with mean of 1 and standard deviation of 0.5. The mean of 1 represents the mean of all betas. A standard deviation of 0.5 means that there is a small chance of observing a beta less than 0 or above 2,[16] commensurate with the distribution of beta estimates that is observed in practice.

89. Suppose a practitioner was asked to estimate the beta of a company, with no company- or industry-specific information. By construction, the market capitalisation weighted average beta of all companies in the market is one. By making an estimate of one, there is an equal probability that the practitioner has over- or under-estimated systematic risk. Next, the practitioner performs an OLS regression of stock returns against market returns, without any additional company- or industry-specific information, and is able to refine the original estimate. The Vasicek bias correction applies weight to the OLS beta estimate on the basis of its precision, and some weight on the prior estimate of one.

Prior distribution based on regulatory precedent

90. For regulatory purposes at this time, there is an even stronger reason to select a value of 1 as the prior estimate (or reference point) when applying the Vasicek adjustment. The strong Australian regulatory precedent has been to adopt a (re-geared to 60%) equity beta of 1. Consequently, a re-geared equity beta estimate of 1 takes the role of the "default value" or "null hypothesis" in this case. It then seems natural to move from this value, only to the extent that is warranted by the available data. But this is exactly what the Vasicek technique does – it begins with a prior estimate (of 1 in this case) and moves from there in proportion to the statistical precision of empirical estimates using the available data.

[16] That is, the 95% confidence interval is 0 to 2.

Average of beta of comparables cannot be used in this setting

91. The alternative approach that is sometimes suggested in the finance literature is that the reference point (or "prior" estimate) should be set at the average beta estimate of the firms in the comparables set. This approach makes little sense in the present context for two reasons:

   a. We are seeking a reliable estimate of the average equity beta of the set of comparables in the first place. If we already had a reliable estimate of this, to be used in the Vasicek adjustment, the task would already be complete. That is, if we had an estimate of the average beta that was sufficiently reliable to be used in the Vasicek technique, we could simply use that estimate for other purposes;

   b. If we are seeking an estimate of the average beta of a set of comparables, using the Vasicek technique with a "prior" estimate equal to the average beta of the same set would be entirely circular. Adjusting a beta estimate toward itself, clearly serves no purpose at all.

92. For these reasons set out above, it is my view that an equity beta of 1 is an appropriate reference point (or "prior" estimate) to be used when applying the Vasicek bias correction technique.

4. Interpretation of confidence intervals

Use of confidence intervals

93. The construction of a confidence interval is a standard part of statistical inference. In beta regressions, the 95% confidence interval is formed by adding and subtracting two times the standard error to the point estimate. Suppose, for example, that the beta point estimate is 1 and that the standard error is 0.4. The 95% confidence interval would be 0.2 to 1.8 in this case.[17] The proper interpretation of this confidence interval is that there is a 95% chance that the true value of beta lies within the range.

94. The strong Australian regulatory precedent has been to adopt a (re-geared to 60%) equity beta of 1. In a statistical setting, this would involve a formal statistical test of whether the data provides for the rejection of the null hypothesis that the appropriate equity beta is 1. This hypothesis can be statistically rejected if the confidence interval around the beta estimate does not include 1. Consequently, to the extent that the confidence intervals include 1, there is no persuasive evidence to change the estimate of beta from 1.

Further expansion of confidence intervals

95. Confidence intervals reflect the amount of statistical "noise" that is in the data that has been used to estimate beta. However, even this understates the true uncertainty surrounding beta estimates because:

   a. It does not account for uncertainty over whether the firms in question are an appropriate benchmark. Uncertainty about the relevance of the comparable firm set would further widen the confidence interval;

   b. It does not account for uncertainty about whether the simple re-levering procedure is the correct one. At least a dozen alternative approaches have been proposed in the literature[18]; and

   c. It does not account for uncertainty about whether the 60% assumed gearing level, and the correspondence with the assumed credit rating (usually BBB or BBB+) is correct.

96. It is not possible to precisely calculate how much the confidence intervals should be adjusted to take account of these additional uncertainties. I do, however, note that statistical confidence intervals do not address any of these uncertainties – effectively assuming that the items set out in (a) to (c) above are know for sure and are not subject to any uncertainty. Whereas it is not possible to precisely quantify the impact of these uncertainties on the confidence intervals, the directional effect is clear – confidence intervals would need to be widened to take account of these uncertainties.

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[17] Formed by adding and subtracting 0.8 (which is two times the 0.4 standard error) to the mean estimate of 1.

[18] See, for example, the range of methods set out in Cooper and Nyborg (2004).

97. To the extent that there is uncertainty about the matters set out above, the confidence intervals should be widened. Any widening to take account of additional uncertainties would result in all confidence intervals including 1, in which case the data do not allow statistical rejection of the hypothesis that the appropriate equity beta is 1. This provides further support for the conclusion that there is no persuasive evidence to change the estimate of beta from 1.

Confidence intervals should not be relied on inappropriately

98. There is much more to the interpretation of empirical beta estimates than simply testing them against confidence intervals. Confidence intervals reflect statistical noise in the data that is used to produce the beta estimates. Confidence intervals alone do not account for statistical bias or periods of unreliable data and they have nothing to say about the economic reasonableness of resulting beta estimates.

99. By way of example, I have taken the 95% confidence intervals for two sets of estimates produced in recent beta reports from the AGSM Risk Management Service. Table 4 below shows these confidence intervals from December 2005 and March 2008. The first of these pertains to the first set of beta estimates that is based exclusively on data from after the technology bubble period. The second is the most recently available set of estimates form AGSM.

Table 4. 95% confidence intervals for Australian firms

Company	December 2005		March 2008	
	Lower 95% CI	Upper 95% CI	Lower 95% CI	Upper 95% CI
AGL	0.04	0.53	--	--
Alinta	0.13	1.14	--	--
SP Ausnet	--	--	-0.13	0.55
Duet Group	--	--	0.12	0.92
Spark Infrastructure	--	--	0.08	0.92
APA Group	-0.17	0.83	0.32	1.24
Envestra Limited	-0.38	0.22	0.34	0.94
Hastings Diversified	--	--	-0.02	0.90

Source: AGSM-RMS Beta service, December 2005, March 2008.
Missing data indicates that a beta estimate is not provided due to insufficient data points since listing, or since company restructuring.
All estimates are raw OLS estimates directly from the AGSM Beta Report. They have not been re-levered or adjusted in any other way.

100. The figures in Table 4 are raw OLS beta estimates direct from the AGSM data service. They have not been re-levered or adjusted in any other way.

101. I first note that only two of the firms that appear in the March 2008 report also appear in the December 2005 report. This is because AGSM requires a firm to have at least 24 monthly data points available after listing or engaging in a major restructure. The fact that there are only two firms in the entire set of "comparables" that even qualify to have AGSM beta estimates has important implications for the reliance that should be placed on the Australian data.

102. But putting this issue aside, other important conclusions can be drawn from Table 4. Envestra, for example, has 95% confidence intervals that do not even overlap. According to the December

2005 estimates, there is a less than 2.5 % chance that the true systematic risk of Envestra is as *high* as 0.22.[19] But in March 2008 there is only a 2.5% chance that it is as *low* as 0.34!

103. Not only are these supposed to be estimates of the same thing, but the two sets of estimates share almost half the observations in common. AGSM uses 48 monthly observations as the basis for its beta estimates. Consequently, the March 2008 observations are based on data that begins in April 2004. This means that 21 of the 48 observations underlying each set of estimates are in common. Even given that, the 95% confidence intervals for the beta estimate of the same stock do not even overlap.

104. This example helps to illustrate that, in the context of beta regressions based on recent Australian data, one should be very cautious about reading too much into statistical confidence intervals. Reliance on confidence intervals would have led one to conclude that the 2005 and 2008 estimates of beta for Envestra are statistically different – they are not estimates of the same thing.

105. The alternative interpretation is that the beta *estimates* for Envestra, which are known to be affected by estimation error, bias, and so on, have changed substantially over time even though the *true* systematic risk of Australian energy distribution has not.

106. Although the 95% confidence intervals for the APA Group do overlap, they differ appreciably across the two subsamples. In late 2005, a reliance on confidence intervals would have led us to be 97.5% sure[20] that the true beta of APA is less than 0.83. By 2008, the same process would not allow the statistical rejection of a beta estimate as high as 1.2. This provides further strength to the conclusion that statistical confidence intervals should not be given any material weight in the context of beta regressions using recent Australian data.

107. In summary, I note that statistical confidence intervals have nothing to do with bias or estimates being economically unreasonable. A series of examples based on estimates from the AGSM data service shows that undue reliance on confidence intervals can lead to erroneous conclusions.

[19] Note that a 95% confidence interval is such that there is a 2.5% chance of the true value being above the upper bound of the interval and a symmetric 2.5% chance of it being below the lower bound.

[20] A 95% confidence interval allows for 2.5% of the probability mass to lie in each tail of the distribution. That is, there is a 2.5% chance that the true parameter value (that is being estimated) lies above the upper bound or below the lower bound of the confidence interval.

5. Economic reasonableness

Testing beta estimates for economic reasonableness

108. In light of the characteristics of the available Australian data, beta estimates should be based on more than the output of a statistical estimation process. I conclude that one should apply considerable caution when interpreting statistical confidence intervals, and that an essential part of interpreting any beta estimate is to determine whether that estimate is economically reasonable. I have noted above that statistical noise in the data can lead to beta *estimates* that differ substantially from the true beta. I have also shown that confidence intervals do not account for bias in beta estimates. They also do not account for uncertainty in the selection of the comparables set, the re-levering procedure to be used, or the appropriate level of gearing.

109. For all of these reasons, my view is that one should apply considerable caution when interpreting statistical confidence intervals. An essential part of interpreting any beta estimate is to determine whether that estimate is economically reasonable.

110. When testing a beta estimate against the standards of economic reasonableness, one would have regard to the following sorts of considerations:

a. **The size of the set of comparable firms, the length of data available for each, and the consistency of beta estimates for individual firms over time.** A larger set, with long data, and consistent estimates through time would provide greater confidence in the reasonableness of the resulting estimate;

b. **The variation of beta estimates across firms.** Since the betas of all firms (after re-levering) are all estimates of the same thing, they would be expected to be similar. A close grouping of beta estimates across comparable firms would provide greater confidence in the reasonableness of the resulting estimate;

c. **The implied required return.** The beta estimate will be used in the CAPM to provide an estimate of the return required by shareholders. If this required return implies a reasonable premium for bearing equity risk, one would have greater confidence in the economic reasonableness of the beta estimate. The reverse would be true if, for example, the implied required return for bearing equity risk were less than the returns available on investment grade debt.

111. In Appendix A, I apply these considerations to the re-geared equity beta estimate of 0.7 in the recent Victorian gas distribution review.

Qualitative reasons for questioning reliance on particular data periods

112. It has become the common practice in Australian regulatory determinations to remove data from the period known as the "technology bubble." The period that is most often omitted is from July 1998 to December 2001.[21] The reason for doing this is that the first part of this period saw the market advancing on the back of technology, media, and communications stocks. Firms not in those sectors did not perform as well, which reduced their correlation with market returns and had a temporary downward effect on beta estimates. In the second part of this period, the

[21] See, for example, the recent Victorian gas distribution review.

market reversed and non tech firms did not fear as badly – again causing a temporary decrease in correlation with market returns, and consequently beta estimates.

113. This period is now routinely eliminated from consideration, not on the basis of any confidence intervals, but because there is a view that the data period is unlikely to be capable of producing reliable beta estimates.

114. In a similar vein, the Australian stock market has been significantly affected in recent years by the commodity boom. Commodity prices have risen sharply to unprecedented levels over recent years. This has led to substantial increases in the prices of many natural resource firms (and firms in associated industries, such as those providing mining services). Firms whose performance is not linked to commodity prices have not generated such high returns. To the extent that there is a sector-specific boom that drives high positive returns in the market, the beta estimates of those firms that are not in the boom sector will be biased downward. For the same reason that one might omit the technology bubble period from the analysis, one may also seek to omit the commodity boom period – especially when analysing Australian data.

115. Over recent years, the energy distribution sector in Australia has seen considerable merger and acquisition activity. Most notable is the AGL-Alinta asset swap. This led the AGSM Risk Management Service, for example, to immediately cease providing beta estimates for both firms – on the basis that they had become completely new firms for which it was inappropriate to use historical data. In addition to this, GasNet and United Energy are no longer listed on the ASX. Almost all firms in the "comparables" set are recent IPOS or have engaged in merger activity or been the subject of merger speculation. This clearly has an impact on the prices of the securities that is unrelated to the long-run systematic risk of energy distribution. This is a further reason why little weight should be placed on the recent Australian data.

116. The AGSM data service provides a set of beta estimates every quarter for all Australian companies for which there is sufficient data to produce an estimate. The data requirements are not onerous – AGSM only requires 24 monthly data points to produce an estimate. Even so, there is at best a handful of firms in the "comparables" set. Table 4 above shows that only two energy distribution firms appeared in both the December 2005 and March 2008 AGSM reports.

117. Even given the very small set of comparable firms, those that remain are far from being pure play Australian electricity distribution and transmission firms. All have other assets from gas pipelines and distribution assets to electricity generation and retail. Some own unregulated assets and others have international investments. That is, we can have no confidence that the available Australian companies that are listed on the ASX are truly comparable to a pure-play electricity distribution or transmission company.

118. Taking all of these issues into consideration, it is highly unlikely that the recent Australian data would produce any sort of reliable beta estimate. Indeed it seems unreasonable to expect that estimates based on the recent Australian data, which is both scant and contaminated, would produce beta estimates that are in any way reliable.

119. It seems that these data are analysed not because they are expected to produce reliable estimates, but because they are there. That is, the best that can be said about the available Australian data is that it is available and it is Australian.

120. In statistics, this is known as "looking where the light is." The analogy is a person walking through a darkened field at night who drops their keys in the middle. They walk to the edge of the field where there is a street light and begin searching for their keys there – because that's

where the light is. This search will produce some information, but nothing of relevance for the purpose at hand.

6. Conclusions

121. In this report, I have documented a number of reasons why great caution should be applied when interpreting beta estimates that are based on the available Australian data. These include:

a. Recent beta estimates from the available Australian data are characterised by R-squared statistics which indicate that the relationship between stock and market returns (beta) is swamped many times over by noise. Such R-squared statistics are associated with statistically unreliable (low) beta estimates;

b. I have shown that low beta estimates (less than 1) are more likely to be downwardly biased by estimation error;

c. There are very few firms in the set of "comparables" and many of these have only a short history of data;

d. None of the "comparables" is close to being a pure-play Australian electricity distribution or transmission firm;

e. Empirical beta estimates for Australian firms have varied dramatically over recent years – much more than could plausibly be attributed to changes in true systematic risk; and

f. There is a wide range of estimates among the Australian firms, even though they are all supposed to be estimates of the same thing.

122. On the basis of these reasons, I conclude that when one is constructing statistical confidence intervals for use in the context of beta regressions (in an attempt to interpret whatever Australian data is available), those confidence intervals must be:

a. **widened** to take account of uncertainties about the appropriateness of the set of comparables, the re-levering approach that is adopted, or the level of gearing that is assumed;

b. **widened** to take account of any concerns about the representativeness of the data period being analysed – in terms of the effect of a technology bubble or commodity boom, the effects of merger activity and corporate restructuring in the sector being examined, or the effect of low variation in market returns over the period;

c. **shifted upward**[22] to take account of statistical bias in beta estimates that results from symmetric estimation error or "noise." The Vasicek correction can be used in this regard;

d. **afforded little weight** to the extent that the R-squared statistics indicate that the relationship between stock and market returns (beta) is swamped many times over by noise or there is dramatic variation in beta estimates across comparable firms or across time for the same firm; and

e. **afforded little weight** to the extent that the resulting beta estimates fail the standards of economic reasonableness.

[22] Where the raw beta estimates are below 1.

References

Allen Consulting Group, (2007), "Empirical evidence on proxy beta values for regulated gas distribution activities," Report to the Essential Services Commission of Victoria, 27 June.

Australian Energy Regulator, (2008), "Review of the weighted average cost of capital (WACC) parameters for electricity transmission and distribution," 8 August.

Blume, M. E., (1971), "On the assessment of risk," *Journal of Finance,* 25(1), 1–10.

Blume, M. E., (1975), "Betas and their regression tendencies," *Journal of Finance,* 30(3), 785–795.

Bowman, R.J. and S.R. Bush, (2004), "A Test of the Usefulness of Comparable Company Analysis." Department of Accounting and Finance, University of Auckland.

Cannavan, D., Finn, F., & Gray, S., (2004), "The Value of Dividend Imputation Tax Credits in Australia," *Journal of Financial Economics*, 73, 167-197.

Cooper, I.A. and K.G. Nyborg, (2004), "Discount rates and tax," Working paper, London Business School.

Cunningham, S.W., (19730, "The predictability of British Stock Market Prices," *Applied Statistics,* 22(3), 315–331.

Essential Services Commission, (2008), "Gas Access Arrangement Review 2008 – 2012: Final Decision," 7 March.

Essential Services Commission of South Australia, (2006), "Proposed revisions to the access arrangement for the South Australian gas distribution system," 30 June.

Gray, Stephen, Jason Hall, Drew Klease and Alan McCrystal, (2008), "Bias, stability and predictive ability in the measurement of systematic risk," UQ Business School, The University of Queensland. Available at SSRN: http://ssrn.com/abstract=1157667.

Queensland Competition Authority, (2006), "Revised access arrangement for gas distribution networks: Envestra (Final Decision)," May.

Strategic Finance Group: SFG Consulting, (2007), "Equity beta estimates for Victorian gas distribution businesses," Report prepared for Envestra, Multinet and SP Ausnet, 25 October 2007.

Vasicek, O. A., (1973), "A note on using cross-sectional information in Bayesian estimation of security betas," *Journal of Finance,* 28(5), 1233–1239.

Appendix A: Application to the Victorian ESC Gas Distribution Review

123. I note that the most recent gas distribution decision by the Essential Services Commission of Victoria (ESC, 2008) adopts an equity beta of 0.7, which is substantially below the estimates of 1.1 (QCA, 2006) and 0.9 (ESCOSA, 2006) observed recently in other jurisdictions. This estimate relies heavily on the results of a data analysis exercise, the statistical properties of which are discussed in later sections of this report. In this appendix, I begin by testing this estimate of 0.7 against the standards of economic reasonableness that are set out in Section 5 above.

124. In recent work prepared for submission to the ESC (SFG, 2007) we concluded that the adoption of an equity beta estimate of 0.7 ran counter to economic reasonableness for a number of reasons including:

1. There is a very small number of comparable firms, many of which have such a limited trading history that they are not even included in commercial data sources;

2. The beta estimates for the firms in the set of "comparables" are very widely dispersed, yet they are all supposed to be estimates of the same thing. Indeed the vast majority of estimates are not even within the 0.5 to 0.8 range that is proposed to define the bounds of economic reasonableness;

3. Most of the data relied upon for these estimates were drawn from a short period – for one firm the entire analysis was based on just 13 observations;

4. When the estimation technique is applied to other industries for which a longer time series of data is available, the results exhibit extreme variability over time. This is more likely due to random estimation error than the true systematic risk of businesses rising and then falling and then rising again dramatically;

5. An equity beta estimate of 0.7 implies an asset beta of 0.28, using the un-levering process adopted by the ESC and its assumption of 60% gearing.[23] Using a 6% estimate for market risk premium, the premium (over and above the risk-free rate) required by shareholders in an unlevered distribution business would be 1.68% (i.e., 0.28 × 6% = 1.68%). This is an estimate of the premium that shareholders would require in the absence of any leverage – it reflects equity risk in the sense that no particular return is promised or guaranteed, the equity holders simply receive whatever might be available from time to time. Present estimates of the risk premium on investment-grade debt are in the order of 3.48%.[24] This is the return to investors who lend money to a firm with an investment grade credit rating. The payment of the return is specified in a contractual document and will be made on known dates and in known amounts. There is the risk that the company will default on a scheduled payment, but this risk has historically been very low for firms with investment grade ratings. That is, the equity beta estimate of 0.7 implies that shareholders bearing equity risk would require a return that is less than half of what lenders (to an investment grade borrower) would require. In my view this fails the test of economic reasonableness.

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[23] $\beta_a = \beta_e \frac{E}{V} = 0.7 \times 0.4 = 0.28.$

[24] CBA Spectrum 10-year BBB spread to Commonwealth Government Securities, 14 August 2008.

125. In summary, my view is that an empirical estimate should not be adopted without proper consideration of its economic reasonableness. The ESC's response to these points largely centred around their examination of statistical confidence intervals to establish the reliability of the estimates. I note by way of example that no confidence interval could serve as a response to the last point listed above. Even if, statistically, one were convinced that the data supported an estimate of 0.7, it makes no economic sense for an equity risk premium to be less than half of an investment grade debt premium.

Appendix B: Curriculum Vitae of Professor Stephen Gray

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Academic Qualifications

1995 Ph.D. (Finance), Graduate School of Business, Stanford University.
Dissertation Title: Essays in Empirical Finance
Committee Chairman: Ken Singleton

1989 LL.B. (Hons), Bachelor of Laws with Honours, University of Queensland.

1986 B.Com. (Hons), Bachelor of Commerce with Honours, University of Queensland.

Employment History

2000-Present	Professor of Finance, UQ Business School, University of Queensland.
1997-2000	Associate Professor of Finance, Department of Commerce, University of Queensland and Research Associate Professor of Finance, Fuqua School of Business, Duke University.
1994-1997	Assistant Professor of Finance, Fuqua School of Business, Duke University.
1990-1993	Research Assistant, Graduate School of Business, Stanford University.
1988-1990	Assistant Professor of Finance, Department of Commerce, University of Queensland.
1987	Specialist Tutor in Finance, Queensland University of Technology.
1986	Teaching Assistant in Finance, Department of Commerce, University of Queensland.

Academic Awards

2006	Outstanding Professor Award, Global Executive MBA, Fuqua School of Business, Duke University.
2002	Journal of Financial Economics, All-Star Paper Award, for Modeling the Conditional Distribution of Interest Rates as a Regime-Switching Process, JFE, 1996, 42, 27-62.
2002	Australian University Teaching Award – Business (a national award for all university instructors in all disciplines).
2000	University of Queensland Award for Excellence in Teaching (a University-wide award).
1999	Outstanding Professor Award, Global Executive MBA, Fuqua School of Business, Duke University.
1999	KPMG Teaching Prize, Department of Commerce, University of Queensland.
1998	Faculty Teaching Prize (Business, Economics, and Law), University of Queensland.
1991	Jaedicke Fellow in Finance, Doctoral Program, Graduate School of Business, Stanford University.
1989	Touche Ross Teaching Prize, Department of Commerce, University of Queensland.
1986	University Medal in Commerce, University of Queensland.

Large Grants (over $100, 000)

- Australian Research Council Linkage Grant, 2008—2010, Managing Asymmetry Risk ($320,000), with T. Brailsford, J.Alcock, and Tactical Global Management.
- Intelligent Grid Cluster, Distributed Energy – CSIRO Energy Transformed Flagship Collaboration Cluster Grant, 2008-2010 ($552,000)
- Australian Research Council Research Infrastructure Block Grant, 2007—2008, Australian Financial Information Database ($279,754).
- Australian Research Council Discovery Grant, 2006—2008, Capital Management in a Stochastic Earnings Environment ($270,000).

- Australian Research Council Discovery Grant, 2005—2007, Australian Cost of Equity.
- Australian Research Council Discovery Grant, 2002—2004, Quantification Issues in Corporate Valuation, the Cost of Capital, and Optimal Capital Structure.
- Australian Research Council Strategic Partnership Grant, 1997—2000, Electricity Contracts and Securities in a Deregulated Market: Valuation and Risk Management for Market Participants.

Current Research Interests

Benchmark returns and the cost of capital. Corporate Finance. Capital structure. Real and strategic options and corporate valuation. Financial and credit risk management. Empirical finance and asset pricing.

Publications

Gray, S., & Hall, J. (2008) The Relationship Between Franking Credits and the Market Risk Premium: A Reply. Accounting and Finance, 48, 133-142.

Feuerherdt, C., Gray, S., & Hall, J.(2008) The Value of Imputation Tax Credits on Australian Hybrid Securities. International Review of Finance, forthcoming.

Gray, S., Mirkovic, A., & Ragunathan, V. (2006). The Determinants of Credit Ratings: Australian Evidence. Australian Journal of Management, 31(2), 333-354.

Choy, E., Gray, S., & Ragunathan, V. (2006) The Effect of Credit Rating Changes on Australian Stock Returns. Accounting and Finance, 46(5), 755-769.

Gray, S., & Hall, J. (2006) The Relationship Between Franking Credits and the Market Risk Premium. Accounting and Finance,.46(3), 405-428.

Gray, S., & Treepongkaruna, S. (2006). Are there non-linearities in short-term interest rates? Accounting and Finance, 46(1), 149-167.

Gray, P. K., Gray, S., & Roche, T. (2005). A Note on the Efficiency in Football Betting Markets: The Economic Significance of Trading Strategies. Accounting and Finance, 45(2) 269-281.

Duffie, D., Gray, S., & Hoang, P. (2004). Volatility in Energy Prices. In V. Kaminski (Ed.), Managing Energy Price Risk: The New Challenges and Solutions (3rd ed.). London: Risk Books.

Cannavan, D., Finn, F., & Gray, S. (2004). The Value of Dividend Imputation Tax Credits in Australia. Journal of Financial Economics, 73, 167-197.

Gray, S., & Treepongkaruna, S. (2003). Valuing Interest Rate Derivatives Using a Monte-Carlo Approach. Accounting and Finance, 43(2), 231-259.

Gray, S., Smith, T., & Whaley, R. (2003). Stock Splits: Implications for Investor Trading Costs. Journal of Empirical Finance, 10, 271-303.

Gray, S., & Treepongkaruna, S. (2003). On the Robustness of Short-term Interest Rate Models. Accounting and Finance, 43(1), 87-121.

Gray, S., & Treepongkaruna, S. (2002). How to Value Interest Rate Derivatives in a No-Arbitrage Setting. Accounting Research Journal (15), 1.

Gray, P. K., & Gray, S. (2001). A Framework for Valuing Derivative Securities. Financial Markets Institutions & Instruments, 10(5), 253-276.

Gray, P. K., & Gray, S. (2001). Option Pricing: A Synthesis of Alternate Approaches. Accounting Research Journal, 14(1), 75-83.

Dahlquist, M., & Gray, S. (2000). Regime-Switching and Interest Rates in the European Monetary System. Journal of International Economics, 50(2), 399-419.

Bollen, N. P., Gray, S., & Whaley, R. (2000). Regime-Switching in Foreign Exchange Rates: Evidence from Currency Options. Journal of Econometrics, 94, 239-276.

Duffie, D., Gray, S., & Hoang, P. (1999). Volatility in Energy Prices. In R. Jameson (Ed.), Managing Energy Price Risk (2nd ed.). London: Risk Publications.

Gray, S., & Whaley, R. (1999). Reset Put Options: Valuation, Risk Characteristics, and an Example. Australian Journal of Management, 24(1), 1-21.

Bekaert, G., & Gray, S. (1998). Target Zones and Exchange Rates: An Empirical Investigation. Journal of International Economics, 45(1), 1-35.

Gray, S., & Whaley, R. (1997). Valuing S&P 500 Bear Market Warrants with a Periodic Reset. Journal of Derivatives, 5(1), 99-106.

Gray, S., & Gray, P. K. (1997). Testing Market Efficiency: Evidence from the NFL Sports Betting Market. The Journal of Finance, 52(4), 1725-1737.

Gray, S. (1996). Modeling the Conditional Distribution of Interest Rates as a Regime- Switching Process. Journal of Financial Economics, 42, 27-62.

Gray, S. (1996). Regime-Switching in Australian Interest Rates. Accounting and Finance, 36(1), 65-88.

Brailsford, T., Easton, S. E., Gray, P. K., & Gray, S. (1995). The Efficiency of Australian Football Betting Markets. Australian Journal of Management, 20(2), 167-196.

Duffie, D., & Gray, S. (1995). Volatility in Energy Prices. In R. Jameson (Ed.), Managing Energy Price Risk. London: Risk Publications.

Gray, S., & Lynch, A. W. (1990). An Alternative Explanation of the January Anomaly. Accounting Research Journal, 3(1), 19-27.

Gray, S. (1989). Put Call Parity: An Extension of Boundary Conditions. Australian Journal of Management, 14(2), 151-170.

Gray, S. (1988). The Straddle and the Efficiency of the Australian Exchange Traded Options Market. Accounting Research Journal, 1(2), 15-27.

Teaching

Fuqua School of Business, Duke University, Student Evaluations (0-7 scale):

- Financial Management (MBA Core): Average 6.5 over 7 years.
- Advanced Derivatives: Average 6.6 over 4 years.
- Empirical Issues in Asset Pricing: Ph.D. Class

1999, 2006 Outstanding Professor Award, Global Executive MBA, Fuqua School of Business, Duke University.

UQ Business School, University of Queensland, Student Evaluations (0-7 scale):

- Finance (MBA Core): Average 6.6 over 8 years.
- Corporate Finance Honours: Average 6.9 over 8 years.

2002 Australian University Teaching Award – Business (a national award for all university instructors in all disciplines).
2000 University of Queensland Award for Excellence in Teaching.
1999 Department of Commerce KPMG Teaching Prize, University of Queensland.

1998 Faculty Teaching Prize, Faculty of Business Economics and Law, University of Queensland.
1998 Commendation for Excellence in Teaching, University-wide Teaching Awards, University of Queensland.
1989 Touche Ross Teaching Prize, Department of Commerce, University of Queensland.

Board Positions

2002 - Present: Director, Financial Management Association of Australia Ltd.
2003 - Present: Director, Moreton Bay Boys College Ltd. (Chairman since 2007).
2002 - 2007: External Risk Advisor to Board of Enertrade (Queensland Power Trading Corporation Ltd.)

Consulting

Managing Director, Strategic Finance Group: www.sfgconsulting.com.au.

Consulting interests and specialties, with recent examples, include:

- **Corporate finance**
  - ⇒ **Listed multi-business corporation:** Detailed financial modeling of each business unit, analysis of corporate strategy, estimation of effects of alternate strategies, development of capital allocation framework.

- **Capital management and optimal capital structure**
  - ⇒ **State-owned electricity generator:** Built detailed financial model to analyze effects of increased leverage on cost of capital, entity value, credit rating, and stability of dividends. Debt of $500 million issued.

- **Cost of capital**
  - ⇒ **Cost of Capital in the Public Sector:** Provided advice to a government enterprise on how to estimate an appropriate cost of capital and benchmark return for Government-owned enterprises. Appearance as **expert witness** in legal proceedings that followed a regulatory determination.
  - ⇒ **Expert Witness:** Produced a written report and provided court testimony on issues relating to the cost of capital of a cable TV business.
  - ⇒ **Regulatory Cost of Capital:** Extensive work for regulators and regulated entities on all matters relating to estimation of weighted-average cost of capital.

- **Valuation**
  - ⇒ **Expert Witness:** Produced a written report and provided court testimony. The issue was whether, during a takeover offer, the shares of the bidding firm were affected by a liquidity premium due to its incorporation in the major stock market index.
  - ⇒ **Expert Witness:** Produced a written report and provided court testimony in relation to valuation issues involving an integrated mine and refinery.

- **Capital Raising**
  - ⇒ Produced comprehensive valuation models in the context of capital raisings for a range of businesses in a range of industries including manufacturing, film production, and biotechnology.

- **Asset pricing and empirical finance**
  - ⇒ **Expert Witness:** Produced a written report on whether the client’s arbitrage-driven trading strategy caused undue movements in the prices of certain shares.

- **Application of econometric techniques to applied problems in finance**
  - ⇒ **Debt Structure Review:** Provided advice to a large City Council on restructuring their debt portfolio. The issues involved optimisation of a range of performance measures for each business unit in the Council while simultaneously minimizing the volatility of the Council’s equity in each business unit.

⇒ **Superannuation Fund Performance Benchmarking:** Conducted an analysis of the techniques used by a large superannuation fund to benchmark its performance against competing funds.

- **Valuation of derivative securities**
  - ⇒ **Stochastic Volatility Models in Interest Rate Futures Markets:** Estimated and implemented a number of models designed to predict volatility in interest rate futures markets.

- **Application of option-pricing techniques to real project evaluation**
  - ⇒ **Real Option Valuation:** Developed a framework for valuing an option on a large office building. Acted as arbitrator between the various parties involved and reached a consensus valuation.
  - ⇒ **Real Option Valuation:** Used real options framework in the valuation of a bio-tech company in the context of an M&A transaction.

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