The Equity Beta of an Energy Distribution Business

Final report prepared for AGL

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Executive summary

We have been retained by AGL to conduct analyses and to comment on the appropriate equity beta to be used in estimating the weighted-average cost of capital of a typical efficient benchmark Australian energy distribution business. Recent reports in the Australian regulatory setting have proposed beta estimates for energy distribution businesses that are significantly below past estimates. Of course, estimates of individual company equity betas are well-known to be extremely imprecise and unable to provide a high degree of reliability. They are also well-known to be affected by unrepresentative outlier data points. Our focus in this paper is on whether the economic fundamentals of the energy distribution business have recently changed, resulting in a substantial reduction in risk, or whether lower beta estimates are simply the result of statistical aberration.

In this paper, we examine the statistical reliability of standard beta estimates. We demonstrate that beta estimates for individual firms, and for small portfolios of comparable firms, suffer from a high degree of statistical unreliability. We examine a range of methods for estimating betas and conclude that no single method can provide a precise and statistically reliable point estimate. Accordingly, we conclude that:

1. The uncertainty surrounding beta estimates, and the effect this has on estimates of WACC, should be quantified and explicitly addressed (e.g., by specifying ranges rather than point estimates and/or examining the sensitivity of WACC estimates to parameters that are estimated with uncertainty), and
2. Information from a range of data sets and empirical methodologies should be used when estimating equity betas. To the extent that results from different data and different methods corroborate one another, confidence in the equity beta estimate is increased. The weight placed on each piece of evidence should reflect both its relevance and its statistical precision.

Analyses from a range of estimation methods and data sources all support the use of a range centered around 1.0 for Australian energy distribution businesses with 60% gearing[1]. This conclusion is based on the following evidence:

1. It is not possible to conclude that the available data supports a conclusion that the equity beta of an Australian electricity distribution business (re-geared to 60%) is statistically less than one.

[1] This value could also be used as a point estimate where required.

2. The average re-levered equity beta of Australian comparable firms has been 1.0 until very recent times, characterized by unusual market circumstances that have a pronounced effect on the way betas are estimated. By way of illustration, re-geared (to 60%) equity beta for AGL is in the range 0.9 - 1.05 when the effects of influential outliers are removed.
3. The appropriate estimate of the re-geared (to 60%) equity beta from a large industry-level portfolio is a range centered around 1.0.
4. The appropriate estimate of the re-geared (to 60%) equity beta of the much larger set of U.S. comparable firms is a range centered around 1.0.
5. A recent analysis performed by the Allen Consulting Group supports the conclusion that when the effects of the technology bubble are removed "the equity beta of the average Australian DNSP is 1.00 assuming 60% gearing."

In our view, an equity beta below one can only be supported by an incomplete analysis of the scant, unreliable, and contaminated data that is available.

2. Context

In the Australian regulatory environment, the regulated firm's revenue requirement is constructed using a building block approach. One important component of the revenue requirement is the return on capital. This often represents more than 40% of the regulated firm's revenue requirement. The return on capital is computed as the product of the regulatory asset base (RAB) and the weighted-average cost of capital (WACC) which depends on the firm's cost of debt and equity capital. Australian regulators have used the Capital Asset Pricing Model (CAPM) to compute the cost of equity capital. The CAPM provides an estimate of the return that investors would require to compensate them for the risk that is involved in holding shares in the firm. In this context, the appropriate measure of risk is the equity beta. Beta essentially measures the relationship between the returns that are generated by the firm and the returns generated by a broadly diversified market portfolio.

In this paper, we examine the statistical reliability of standard beta estimates. We demonstrate that beta estimates for individual firms, and for small portfolios of comparable firms, suffer from a high degree of statistical unreliability. We examine a range of methods for estimating betas and conclude that no single method can provide a precise and statistically reliable point estimate.

For these reasons, the first part of our paper examines the uncertainty surrounding beta estimates and the effect this has on estimates of WACC. We conclude that, at a minimum, the effect that beta estimation error may have on WACC estimates should be quantified and specifically addressed. The second part of the paper compares beta estimates from a range of data sets and empirical methodologies. We demonstrate that results from different data sets and different methodologies corroborate one another in relation to the estimation of the appropriate equity beta for an Australian energy distribution business.

3. Estimating equity betas

Equity betas cannot be *observed* or *measured*—they must be *estimated*.

The standard method for estimating equity betas is an ordinary least squares (OLS) regression of stock returns on market returns. Most commercial data sources use four or five years of monthly stock returns and monthly returns on a broad stock market index portfolio. The slope coefficient from a standard OLS regression of stock returns on market returns is then used as an estimate of the equity beta.

As with any regression, the estimated coefficient is not a precise calculation, but simply an estimate. The standard statistical (and legitimate) interpretation of the estimated coefficient from any regression is that the true value of this parameter comes from a normal distribution with mean equal to the parameter estimate and standard deviation equal to the standard error of the estimate. That is, the regression approach does not compute the true beta, it merely narrows it down to within some probabilistic range.

The width and range of this distribution depends on how precisely the coefficient can be estimated. It is the standard error of the regression estimate that measures the precision with which it has been estimated. Typically equity beta estimates, computed by regressing stock returns on market returns, have large standard errors. This means that they are imprecisely estimated and cannot be relied upon with any great confidence.

This issue is well-known in the academic and practitioner literature and in commercial and regulatory practice. For example, the Centre for Research in Finance (CRIF) at the Australian Graduate School of Management computes OLS betas as well as Scholes-Williams betas. The Scholes-Williams procedure provides a statistical correction for non-trading. This correction is designed to correct for the fact that a particular stock may trade more or less frequently than the average stock in the index. The AGSM-CRIF Explanatory Notes explain that, "OLS can only be used when the data used satisfies the assumptions which underlie the regression analysis. One assumption, which is of potential importance in the Australian environment, is that the company and index rates of return should be measured contemporaneously; that is, over exactly the same time intervals. Since we are using monthly data, this is equivalent to assuming that all stocks have a trade (establishing the current price) right at the end of each month. While this might be the state of affairs for BHP, it is not so for many of the companies listed by the ASX. In fact, some listed companies exhibit infrequent trading to the point where they do not trade even at regular monthly intervals."

In fact, the problem is more severe than this—many of the stocks that are included in the index also trade infrequently. Therefore, even if we are trying to estimate the beta of a stock that is large and liquid and trades continuously, there is still a mis-match with the trading frequency of the index. The index likely contains stock prices from its smaller constituents. The CRIF Explanatory Notes also recognize this: "This thin trading phenomenon may introduce biases into the OLS estimates. A number of statistical methods exist for estimating beta in the presence of the thin trading phenomena. The CRIF betas are computed using a version of the method first suggested by Scholes and Williams (1977), this technique adjusts for thin trading inherent in both the stock *and* the market index". However, we cannot simply rely on these Scholes-Williams betas for at least three reasons:

1. They tend to be estimated with even less precision than standard OLS betas (i.e., they are designed to correct for non-trading bias, not statistical imprecision);
2. The Scholes-Williams technique is only one of many statistical adjustments to OLS betas that have been proposed (see below); and
3. The Scholes-Williams technique often produces extreme results, at least relative to standard OLS betas, but there is no consistent relationship between the two. For example, in the recent CRIF report (March, 2004), the Scholes-Williams beta is no different from the OLS beta for Envestra, 30% higher for Alinta, and 8 times as large for AGL!

Another reputable data source, Bloomberg, provides a different statistical adjustment. Their Blume-adjusted betas are computed as: $\beta_{e,adjusted} = 0.67 \times \beta_{e,OLS} + 0.33 \times 1$ in order to reduce the variability of the standard OLS beta estimate.

It is well recognized in the academic and practitioner literatures that beta estimates suffer from low statistical reliability. Gahlon and Gentry (1982) review a range of measurement errors that cause statistical estimates of beta to vary from the true value. Alexander and Chervany (1980) point out the instability of standard beta estimates, as do Fabozzi and Francis (1977). Levy (1974) examines the ability of statistical beta estimates to predict future returns. The review by Brailsford, Faff and Oliver (1997) also highlights the imprecision with which betas are estimated. This issue is also of considerable concern in the practitioner literature. Copeland, Koller and Murrin (2000), for example, note that, "beta estimates vary considerably," even over reliable data sources.

Three substantial pieces of work that document other variations in the way that betas are estimated in the Australian context are The Allen Consulting Group's report for the ACCC (2002), the NERA

(2002) response to this report and the research monograph by Brailsford, Faff and Oliver (1997). These sources document more than 20 alternative statistical approaches that have been proposed to estimate equity betas.

Clearly, there is no single consensus approach for estimating equity betas. The very existence of so many alternative approaches is evidence that none are satisfactory, accurate, or robust. There is also a recognition among Australian regulators that equity beta estimates are statistically unreliable. For example, the Essential Services Commission[2] (ESC) has acknowledged their concern for the reliability of beta estimates by noting that, "equity betas cannot be estimated directly". Moreover, "even where equity betas can be estimated directly, it is common practice to combine the beta estimate with information provided by the beta estimate for other firms to reduce the error associated with the beta estimate". The Essential Services Commission of South Australia (ESCOSA) has also recently expressed concerns about the reliability of beta estimates[3] stating that, "it is concerned at the apparent lack of precision with the current market evidence" and stating a view that current statistical beta estimates "may reflect a short-term aberration." ESCOSA also noted in their Preliminary Views Paper (2004, p. 53) that, "beta estimates are also subject to substantial statistical uncertainty" and that, "other regulators have expressed concern about the degree of statistical imprecision with the available beta estimates for the comparable Australian listed entities (p. 54)." Similar concerns have also recently been expressed by the Queensland Competition Authority (QCA)[4] who note that, "Australian regulators have expressed concern about the degree of statistical imprecision associated with available beta estimates for comparable Australian listed entities."

In our view, the conclusion that is to be drawn from the academic and practitioner literature and regulatory and commercial practice is that no single method can provide a precise and statistically reliable point estimate of the appropriate equity beta. Therefore, we recommend that the uncertainty surrounding beta estimates, and the effect this has on estimates of WACC, should be quantified and explicitly addressed. Also, information from a range of data sets and empirical methodologies should be used when estimating equity betas. To the extent that results from different data and different methods corroborate one another, confidence in the equity beta estimate is increased.

[2] ESC. 2001-05 Electricity Distribution Price Determination - Volume 1 (p. 263).
[3] ESCOSA Draft 2005 - 2010 Electricity Distribution Price Determination: Part A - Statement of Reasons, p. 171.
[4] QCA Draft Determination Regulation of Electricity Distribution. December 2004. p. 99.

4. The size of estimation errors in equity beta estimates

4.1. Overview

All Australian regulators and commercial practitioners recognize that equity betas are estimated with potentially large measurement errors. However, not all stakeholders may appreciate just how large these estimation errors can be. In this section, we:

1. Quantify how imprecise beta estimates are;
2. Illustrate how much standard beta estimates vary over time;
3. Show how much beta estimates change if the length of the estimation period changes;
4. Demonstrate the effect of a small number of outlier observations; and
5. Show how much beta estimates can vary with different estimation techniques.

4.2. Statistical imprecision in beta estimates

The CRIF Explanatory Notes document provides details about the estimation procedures that have been used in their calculations and some explanation of how to interpret the results that they report. The standard report format includes point estimates for the equity beta using the standard OLS and Scholes-Williams method. Also reported is a one standard error confidence interval around the point estimate. This is reported to allow standard statistical inference to be applied to the estimates.

It is standard statistical practice to compute a 95% confidence interval around estimated coefficients. The proper interpretation then, is that the true value of the parameter that is being estimated is likely to lie within this range. Alternatively, one can test the hypothesis that the true value of the parameter is x, by examining whether x lies within this confidence interval.

If we examine the most recent report from CRIF (and we argue strongly below that there are many reasons to examine a much broader set of data) we can demonstrate how imprecise these beta estimates are. Table 1, below, contains point estimates and the upper 95% confidence interval (CI) for four listed comparables.

Table 1: Point Estimates and Confidence Intervals for AGL, Alinta, Envestra and APT.

Company	OLS		Scholes-Williams	
	Beta Estimate	Upper 95% CI	Beta Estimate	Upper 95% CI
AGL	-0.02	0.54	-0.16	1.04
Alinta	0.36	0.98	0.47	1.69
Envestra	0.28	0.78	0.29	1.39
APT	0.33	0.77	0.51	1.49

Source: Risk Measurement Service Beta Report, March 2004, CRIF, AGSM.
Note: These are raw beta estimates. They have not been re-geared to 60% gearing, as assumed in Australian regulatory decisions.

The huge width of these confidence intervals illustrates just how imprecise these estimates are. Recall that the Scholes-Williams estimates correct for thin trading in the stocks being examined and in the benchmark index of stocks. For none of the four companies in Table 1 can we reject the hypothesis that the equity beta is equal to one. Of course, for none of them can we reject the hypothesis that the equity beta is zero, either. If the equity beta were set to zero, for example, equity investors are assumed to be satisfied with an expected return that is no higher than the risk-free rate. This is clearly illogical and some degree of pragmatism and common sense must be applied[5]. That is, although no point within the confidence interval can be statistically rejected, some points are clearly inconsistent with common sense (and with the objectives of regulation) and can therefore be rejected. The point here is that the standard statistical confidence intervals are so wide as to provide very limited guidance on the choice of an appropriate beta estimate. Therefore, to choose an appropriate beta estimate, we need to examine other data. This may include an expansion of the period of data being examined, an increase in the number of firms, the elimination of outlier data points and periods, a method of averaging the beta estimates of comparable firms, or examining other sources of data. All of these possibilities are examined in the remainder of this paper.

4.3. Time variation in beta estimates

To further illustrate the unreliability of beta estimates reported at a particular point in time (such as those reported in Table 1) we demonstrate the time variation in comparable betas over the last 10 years (subject to availability of data as not all firms have been listed for the entire period). Figures 1 – 5 contain OLS betas, Scholes-Williams beta estimates and upper 95% confidence intervals reported in the CRIF beta reports over the last ten years for AGL, Alinta, Envestra, United Energy and APT respectively. Again these are raw beta estimates that have not been re-geared.

[5] While it is possible in theory for a stock to have a zero or negative beta, no one would suggest that in practice investors would be happy to earn the risk-free rate of return, or less, from their investment in Australian energy stocks.

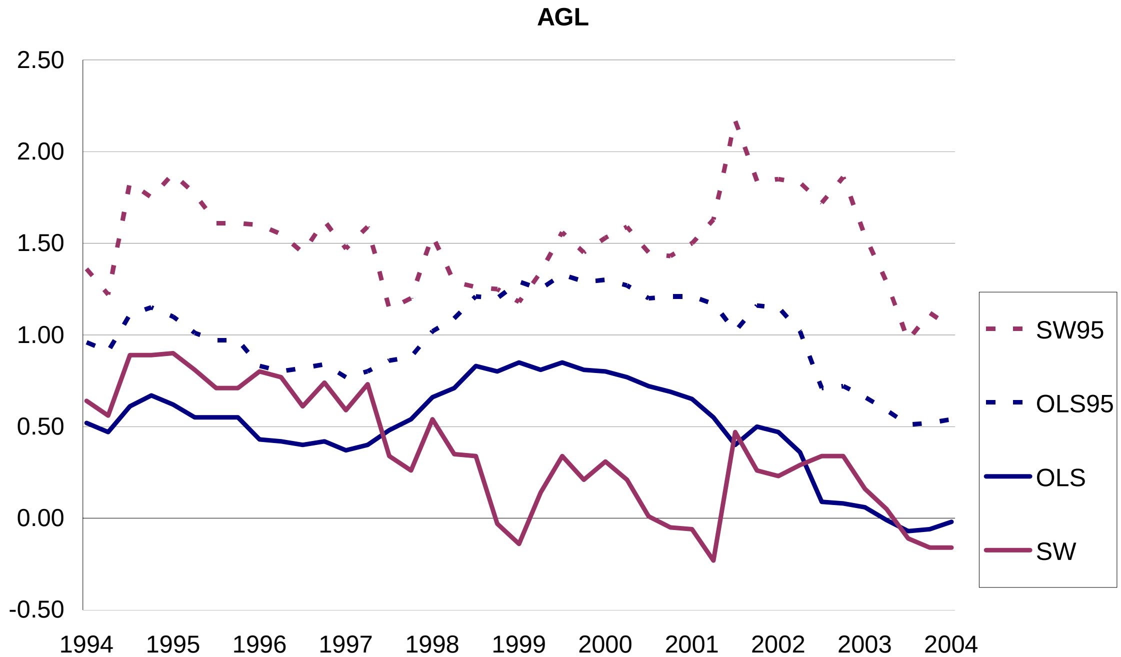


Figure 1: OLS betas, Scholes-Williams beta estimates and upper 95% Confidence Intervals reported in CRIF beta reports for AGL over the last ten years.

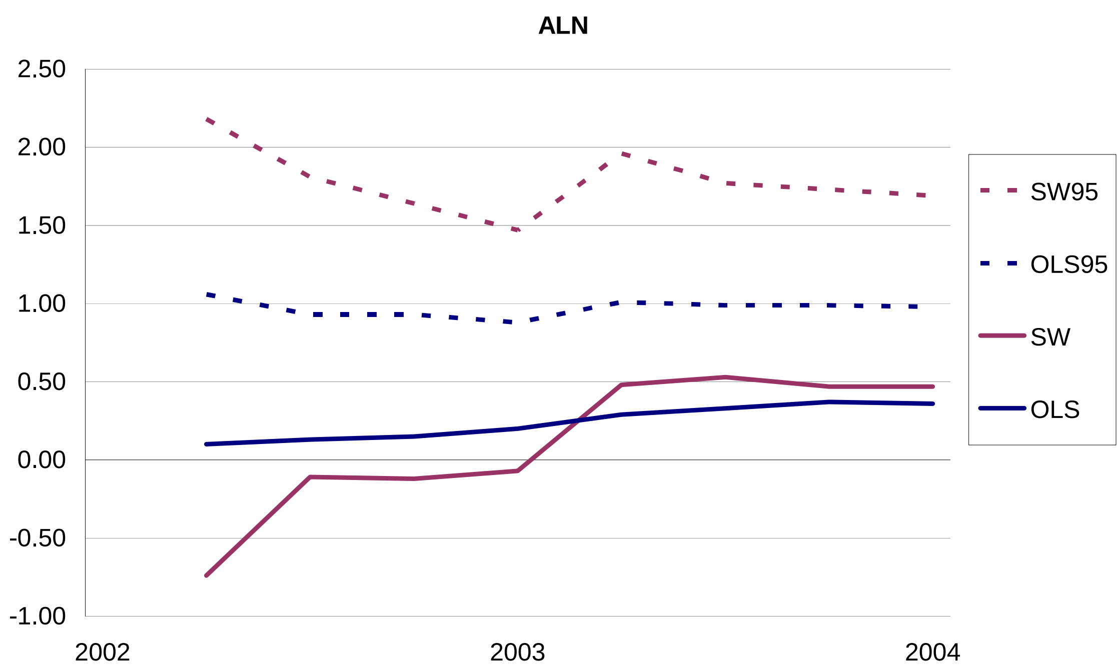


Figure 2: OLS betas, Scholes-Williams beta estimates and upper 95% Confidence Intervals reported in CRIF beta reports for Alinta since listing.

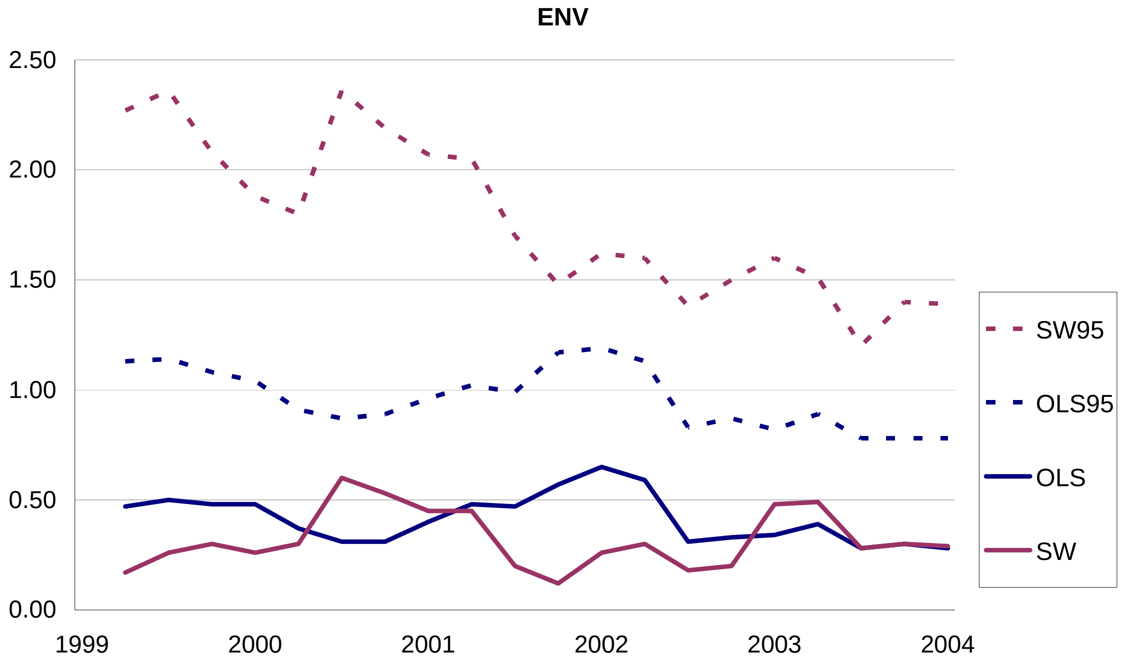


Figure 3: OLS betas, Scholes-Williams beta estimates and upper 95% Confidence Intervals reported in CRIF beta reports for Envestra since listing.

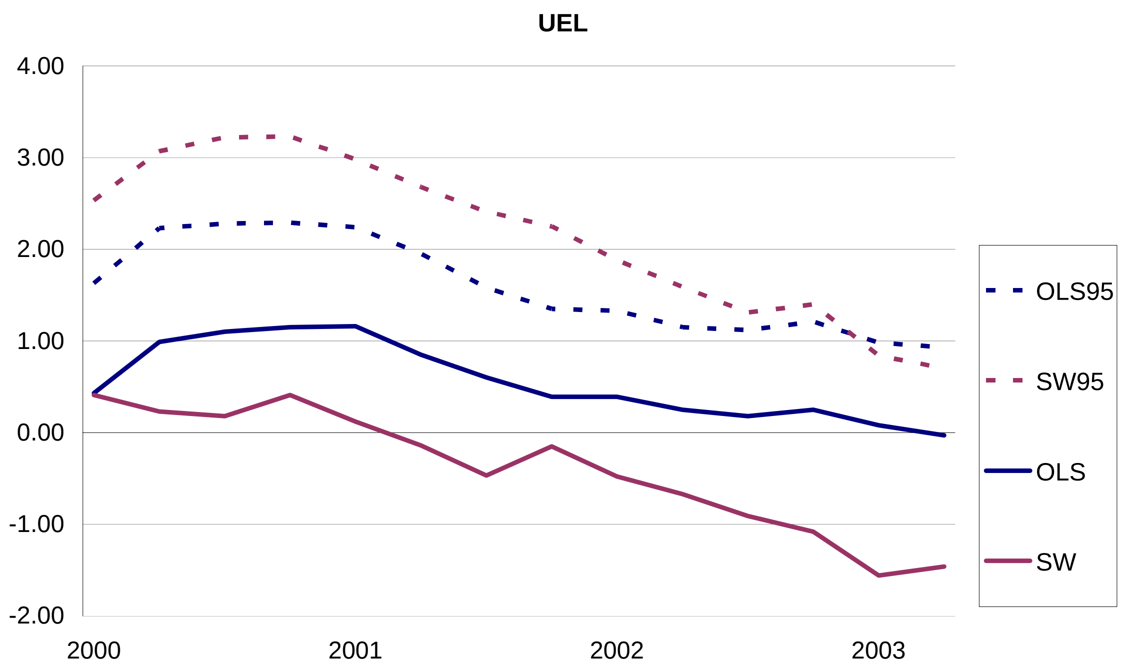


Figure 4: OLS betas, Scholes-Williams beta estimates and upper 95% Confidence Intervals reported in CRIF beta reports for United Energy between listing and de-listing.

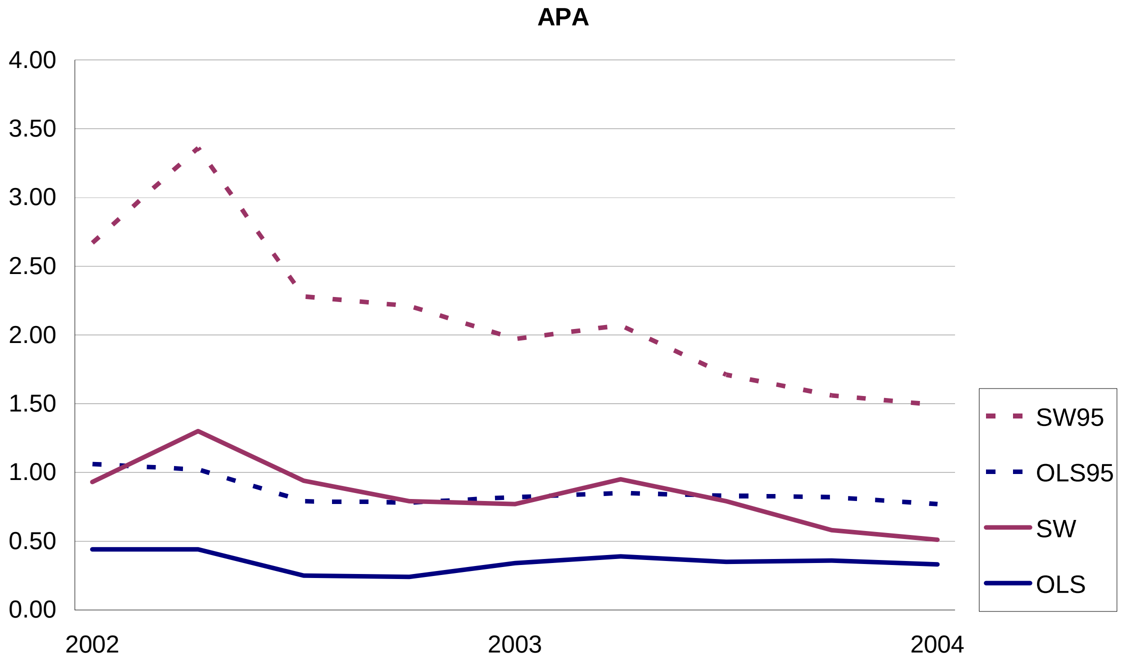


Figure 5: OLS betas, Scholes-Williams beta estimates and upper 95% Confidence Intervals reported in CRIF beta reports for APT since listing.

Clearly, there is significant variation in the time series of beta estimates over the last 10 years (or even shorter periods). Indeed it is not uncommon for beta estimates to change by more than 0.3 from one quarter to the next, even though the samples differ by only three observations. This implies a sudden and dramatic change in the returns required by investors. This further illustrates how fickle and unreliable standard beta estimates are.

A similar picture emerges where we plot the upper 95% confidence bound for comparable firms over the last 10 years. The variability over time is stark.

This time series variation can either be interpreted as:

1. Real fundamental economic changes in the energy distribution businesses and the relationship between these businesses and the broad Australian market; or
2. Evidence of the statistical imprecision and unreliability of the equity beta estimates.

The second interpretation is preferred for two reasons. First, the degree of time series variability in the beta estimates is so large that it cannot possibly be driven by changes in the risk of these businesses—this variability would imply that investors change their required return on these stocks by up to 3% from quarter to quarter. Second, there are several instances where the change from one quarter to the next sees the estimated betas of different firms move in substantially different directions. This is inconsistent with the risk of the energy distribution businesses, generally, having changed—it is more consistent with firm-specific estimation errors.

All of this evidence goes to further reinforce the unreliability of statistical estimates of equity betas.

4.4. Changing the data estimation period

A number of academic papers have examined the appropriate frequency and length of data that should be used to estimate equity betas. A longer data period provides more observations, but it also increases the likelihood that the nature of the business has changed. If, for example, betas were estimated using 20 years of data, it is likely that the business in the early part of the data period varies considerably from the business in the later part. This may occur due to mergers, acquisitions, spin-offs or even expansion of one division at a faster rate than others. All of these things may change the risk profile of the business and therefore the equity beta.

In addition, the number of data points in a standard beta regression approach can be increased by sampling more frequently. For example, if stock and index returns are sampled weekly, rather than monthly, the number or data points increases fourfold.[6] However, this exacerbates any thin trading problem. For example, if a stock does not trade on a particular day, this represents 20% of the weekly return period but less than 5% of the monthly return period.

These tradeoffs tend to be balanced by using four or five years of monthly data to estimate equity betas. However, a number of academic and practitioner publications suggest that longer periods (up to 10 years) of data should be used (e.g., Gonedes 1973; Baesel 1974; Alexander and Chervany 1980; Elgers, Hill et al. 1982; Brailsford et al. 1997). To examine the effect of varying the estimation period, we re-estimate equity betas for a number of comparable firms using 2, 4, and 6 years of monthly returns. AGL is the key comparable firm with sufficient data for this exercise, and is used here as an illustration for that reason. Recall that CRIF reports an OLS equity beta, based on 4 years of monthly returns, of -0.06. This suggests that AGL shares are a hedge asset, moving inversely to the broad market. However, if we use two years of data instead of four, the beta estimate is 0.22, and if six years of data are used the estimate is 0.40. The corresponding results for Scholes-Williams betas are even more variable.

This is not meant to provide guidance on the length of data period that should be used. It simply serves to further illustrate how erratic and unreliable standard beta estimates can be.

[6] In a regulatory setting, the ESC recognizes this in their 2001-05 Electricity Distribution Price Determination (2000, p. 276).

4.5. The effect of outlier observations

Because so few data points are usually used to estimate equity betas (e.g., CRIF betas are based on just 48 return observations) a single outlier can significantly influence the final estimate. In particular, outliers in which the firm's stock moves in a direction opposite to the market can cause a significant reduction in the beta estimate. For example, AGL produced a +5% stock return on the back of positive results announced in September 2001. The fact that this occurred in a month in which the broad market was down 6% (primarily due to terrorist activities in the U.S.) causes the estimated beta to be significantly lower than it would otherwise have been. Also, the AGL stock price fell by 12% in January 2001 amid power rationing and systematic billing problems. These events just happened to occur in a month in which the broad stock market rose.

The questions here are (i) whether these events are one-off chance events or representative of likely future outcomes, and (ii) how much they influence beta estimates. In the remainder of this section, we use a number of statistical techniques to examine and to quantify the effect of outliers on equity beta estimates. Again, these examples are just illustrative, but to the extent that AGL is the largest of the listed Australian energy firms they are potentially important in any statistical estimation of beta. In the remainder of this section, we address various aspects of the influence of outlier data points.

4.5.1. Altering the timing of one or two firm-specific announcements

To examine the sensitivity of beta estimates to a single influential data point, we choose a single observation and ask—how much would the beta estimate change if this observation had occurred in a month in which the market rose instead of falling (or vice versa)? Consider September 2001, for example. If AGL had announced positive results and risen 5% in a month in which the market advanced (instead of declining due to terrorist activity) how much would the beta estimate change?

In Table 2, we show how much the standard OLS beta estimate changes, computed with the most recent four years of monthly data, if one or two outlier observations were changed as described above.

Table 2: Impact of Outliers on OLS Equity Beta Estimates.

Company	OLS Estimate	One Observation Changed OLS Estimate	Two Observations Changed OLS Estimate
AGL	-0.02	0.31	0.55
Alinta	0.36	0.47	0.57
APT	0.28	0.49	0.61
Envestra	0.33	0.43	0.60

The results of this exercise are clear. Had one or two stock observations occurred in a different month, the beta estimate would have been dramatically different. Of course, we are not advocating that betas should be adjusted in this manner and that we should use the estimates in the right-hand column of Table 2. Rather, this exercise is designed to further demonstrate just how tenuous beta estimates can be.

4.5.2. A statistical bootstrap analysis

The impact of outliers can be more formally examined by conducting a standard statistical bootstrap analysis to determine whether data for the most recent 4-year period is "unusual" in the context of the last 10-years of data. Bootstrap analysis is a statistical technique that is used to assess the statistical significance of an event using a re-sampling procedure. It is a non-parametric technique based on the actual data set being analyzed. Thus, no parametric distributional assumptions are required, rather the features of the actual data are incorporated in the statistical test. The bootstrap analysis allows us to determine whether the most recent 4-year period is substantially different from all previous data and to quantify the extent of any such difference. In particular, the most recent 4-year period may contain a disproportionately large number of outliers that cause standard beta estimates to be biased downwards. The bootstrap analysis will determine if this is the case and quantify the effect on beta estimates.

We illustrate the bootstrap procedure using data for AGL as an example. AGL is the largest and most influential firm in the set of comparables for Australian energy distribution firms. AGL also has a long history of available data and a current beta estimate that is below zero. Since this statistical beta *estimate* clearly does not reflect the true economic systematic risk of AGL, this is an ideal candidate to illustrate the bootstrap analysis.

The bootstrap analysis is conducted as follows. First, we collect 10 years of monthly returns for AGL and the broad market index from January 1994 to December 2003. This yields 120 pairs of monthly observations. Next, we randomly select 48 of these 120 observations. We select 48 observations as this is the sample size that is used by CRIF/AGSM to compute beta estimates. We then perform a standard least squares regression of stock returns on market returns using the 48 observations that have been selected. We record the beta estimate from this regression. Then we randomly select another 48 of our 120 observations and repeat this process 10,000 times.

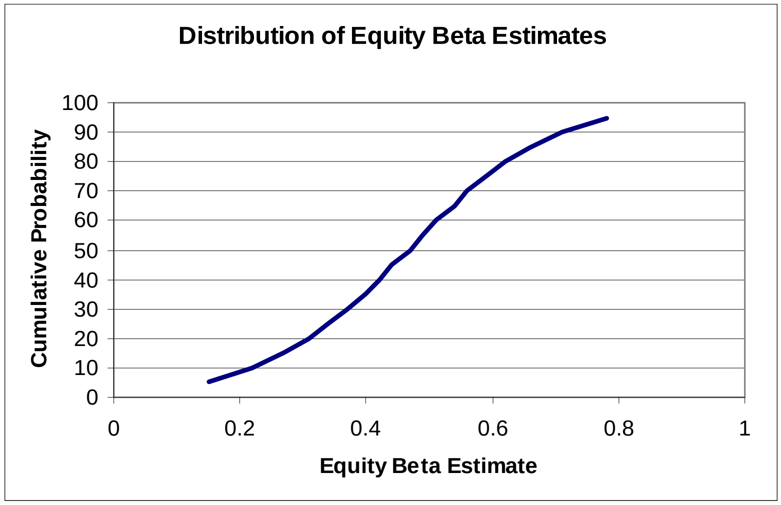
The result of this procedure is 10,000 beta estimates, each computed from a different random sample of 48 monthly observations drawn from the last 10-years of available data. We summarize the results of this exercise in Table 1 and Figure 1 below.

Table 1: Distribution of AGL Equity Beta Estimates from Bootstrap analysis.

Percentile	**Beta Estimate**
5	0.15
10	0.22
15	0.27
20	0.31
25	0.34
30	0.37
35	0.40
40	0.42
45	0.44
50	0.47
55	0.49
60	0.51
65	0.54
70	0.56
75	0.59
80	0.62
85	0.66
90	0.71
95	0.78

Source: Least Squares regression of AGL stock returns on market returns using 48 monthly observations randomly drawn from 1994-2003, repeated 10,000 times.

Figure 1: Cumulative Distribution of AGL Equity Beta Estimates from Bootstrap Analysis.



Source: Least Squares regression of AGL stock returns on market returns using 48 monthly observations randomly drawn from 1994-2003, repeated 10,000 times.

The results of this analysis are stark. The most recent four years of available data (1/2000 to 12/2003) produce a least squares beta estimate of -0.06. This is substantially below the 0.15 beta estimate at the 5th percentile. That is, if 48 monthly observations are randomly selected from the last 10 years, there is a 5% chance that the least squares beta estimate from this sample would be less than 0.15. The probability of selecting a sample that produces a beta estimate as low as -0.06 is less than remote. Yet this is exactly what has occurred over the last 4 years.

That is, in the context of the last 10 years, the most recent 4 year period is unique and extreme in terms of the beta estimate it produces. There are two possible explanations for this dramatic result:

1. The true systematic risk of AGL has been completely eliminated over the last four years and the statistical beta estimate reflects this economic truth, or
2. The true systematic risk of AGL has not materially changed over the last 10 years, and the presently low statistical beta estimate is the result of chance outliers and statistical aberrations (such as a technology bubble) that are known to be able to contaminate least squares estimates in small samples.

There are many reasons to reject the first explanation:

1. A negative beta estimate implies that investors require a return from AGL less than the yield on risk-free government bonds, which is clearly economically implausible.

2. If the most recent four years of monthly data are used, the least squares beta estimate is -0.06. However, if we use the most recent two years of data instead of four, the beta estimate is 0.22, and if the most recent six years of data are used the estimate is 0.40. This is not consistent with a sustained reduction in systematic risk.
3. Replacement of two extreme observations in the last four years of data results in the AGL equity beta estimate increasing to 0.55.

All of these reasons suggest that the true systematic risk of AGL has not materially changed over the last 10 years, and **the presently low statistical beta estimate is the result of outliers and statistical aberrations.** If this is the case, it should be recognized when considering how best to estimate equity betas.

4.5.3. Analysis of why outliers can cause a bias in equity beta estimates

In this section, we explain why a small number of outlier data points can cause a substantial downward bias in equity beta estimates. If firm or industry return shocks are positively correlated with market movements over the estimation period, equity beta estimates will be biased upward. Conversely, if firm or industry return shocks are negatively correlated with market movements over the estimation period (as has been the case for energy distribution firms in recent times), equity beta estimates will be biased downward.

To see why this is the case, first recall that under a standard market model regression, equity betas are estimated as the slope of a regression line:

$$r_{it} = a_i + b_i r_{mt} + \varepsilon_{it}.$$

where:

- r_{it} is the return on stock i in period t;
- r_{mt} is the return on the market portfolio in period t;
- a and b are coefficients to be estimated with b being used as an estimate of the equity beta; and
- ε_{it} is assumed to be normally distributed with constant variances.

Outliers tend to be caused by firm- or industry-specific announcements that shock the stock price, and therefore r_{it}. These can be positive (good news) or negative (bad news). If we represent these shocks as r_{it}, the true model for the way in which returns are generated is:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \eta_{it} + \nu_{it}.$$

That is, we assume that, in truth, stock returns are generated by Model (2) where η_{it} is normally distributed with constant variance (i.e., a well-behaved error term) and ν_{it} equals zero for most observations, but can be large and positive (when the firm announces good news in period *t*) or large and negative (when the firm announces bad news in period *t*). In Model (2), α_i and β_i represent true parameter values.

The issue is then whether the least squares slope estimate b_i in Model (1) is an unbiased estimate of the true parameter β_i. Note that (1) can be thought of as omitting a parameter (ν_{it}) or mis-specifying the error term (assuming ε_{it} is normal, when it is really a mixture of η_{it} and ν_{it}). Either way, the estimation equation (1) differs from the true model (2), and the question is whether b_i estimated from (1) provides a good estimate of the true parameter value β_i.

In statistics, this is known as an errors-in-variables problem. It is well-known that if ν_{it} is correlated with r_{mt}, the regression model (1) is mis-specified and the most basic property of consistency is lost. That is, even in very large samples, the estimate b_i will not converge to the true parameter β_i.

Much of the analysis of this issue addresses asymptotic results—results that apply as sample sizes become very large. For this reason, we perform a simulation analysis to examine the impact of this issue using sample sizes and parameter values that are typically encountered in beta estimation.

We assign parameter values to the true model (2) as summarized in Table 3.

Table 3: Parameter values for true market model: $r_{it} = \alpha_i + \beta_i r_{mt} + \eta_{it} + \nu_{it}$.

Parameter	Value/Distribution
Number of Observations	**48 (monthly)**
α	0
β	1
η_{it}	$N\left(0, \sigma_{\mu}^2\right)$
σ_{μ}	0.005a
r_{mt}	$N\left(\mu_m, \sigma_m^2\right)$
μ_m	0.007a
σ_m	0.03a
ν_{it}	0 for 43 observations $\begin{cases} 0.10 \; w.p. \; 0.5 \\ -0.10 \; w.p. \; 0.5 \end{cases}$ for 5 observations

[a] consistent with observed monthly data 1994 - 2003.

That is, the monthly market return is assumed to be normally distributed with mean 0.7% and standard deviation 3%, consistent with data from 1994 - 2003. We assume that in any sample of 48 observations, 43 are not contaminated by outliers. Five observations in each sample are affected by shocks of $\pm 10\%$, again consistent with data from 1994 - 2003.

We then randomly generate 48 observations consistent with Model (2), estimate b_i as in Model (1), and repeat 10,000 times. Table 4 summarizes the results for three cases, depending on the correlation between the outlier observations and market returns.

Table 4: Relationship between standard beta estimates and in-sample correlation between outliers and market movements.

	Outliers Strongly Positively Correlated with Market ($\rho \geq$ 0.5)	Outliers not Strongly Correlated with Market (- 0.5 < ρ < 0.5)	Outliers Strongly Negatively Correlated with Market ($\rho \leq$ - 0.5)
Distribution of b_i estimates			
5th Percentile	0.71	0.51	0.32
10th Percentile	0.81	0.61	0.42
25th Percentile	0.98	0.77	0.59
50th Percentile	1.15	0.94	0.77
75th Percentile	1.33	1.12	0.95
90th Percentile	1.51	1.27	1.13
95th Percentile	1.62	1.36	1.25

The results of this analysis clearly demonstrate the statistical effect of outliers. Our simulation results are divided into three classes. In all cases, every sample contains 48 observations, five of which are outliers. The outliers are randomly assigned to be positive or negative and may occur in months in which the market rises or falls. Thus, the correlation between the outlier stock returns and market returns (ρ), in a particular sample, may be characterized as:

- Strong Positive Correlation – if positive outliers happen to occur when the market is up and negative outliers happen to occur when the market is down, in that sample;
- Strong Negative Correlation – if positive outliers happen to occur when the market is down and negative outliers happen to occur when the market is up, in that sample; or
- No Strong Correlation – if there is little relationship between outliers and market movements.

We break our analysis into three classes, strong positive correlation ($\rho \geq 0.5$), strong negative correlation ($\rho \leq - 0.5$), and no substantial correlation ($- 0.5 < \rho < 0.5$). In each case, we ignore the presence of outliers and estimate the equity beta using the simple least squares approach as in Model (1).

The results demonstrate that the in-sample correlation between outliers and market movements can have a substantial impact on standard beta estimates, If, in a particular sample, the outliers tend to be negatively correlated with market returns, the median least squares beta estimate is substantially below the true value. The result is reversed if outliers happen to be positively correlated with market returns. That is, there is a clear and significant downward bias in standard beta estimates if the sample on which they are based contains outliers that happen to be negatively correlated with market returns. If, in the particular sample period, bad news happens to be released in months when the market is up, and vice versa, the standard beta estimate is a downwardly biased estimate of the true value. This result is reversed if the correlation happens to be positive.

Our focus here is on the clear directional effects from this exercise, not on the specific numbers in Table 4. This is because a series of 10,000 simulations is considered relatively small when examining the impact of a small number of outliers. Our intention here is simply to explain why outliers can cause a bias in standard OLS beta estimates, and the results in Table 4 are sufficient for this purpose.

Note that our simulation exercise is calibrated to recent market data. Also, in the last four years, AGL has experienced two monthly stock returns of -12% and one of -19%, all in months where the market was up. Indeed, in the 4-year period 2000-2003, AGL experienced six monthly stock returns that were greater than 10% in magnitude. In five of these six months, the market return was in the opposite direction to the AGL return. The correlation between AGL returns and market returns over these six observations is -0.79. Thus, our calibration errs on the side of conservatism. In all of our analyses, shocks were limited to a magnitude of 10%. Increasing the magnitude of shocks increases the bias in the results in Table 4.

4.6. Time variation in re-geared equity betas

In this section, we examine the variation in the equity beta estimates for Australian energy distribution firms over the last several years. We illustrate this variation in terms of the re-geared equity beta from a portfolio of comparables that consists of AGL, APT, Envestra, Alinta, and United Energy. This is because it is that re-geared equity beta that is used to compute the required return on equity in a regulatory determination. Thus, our analysis applies directly to the estimation of the regulatory WACC. We consider whether any variation in the beta estimate is due to permanent changes in economic fundamentals or to statistical aberration.

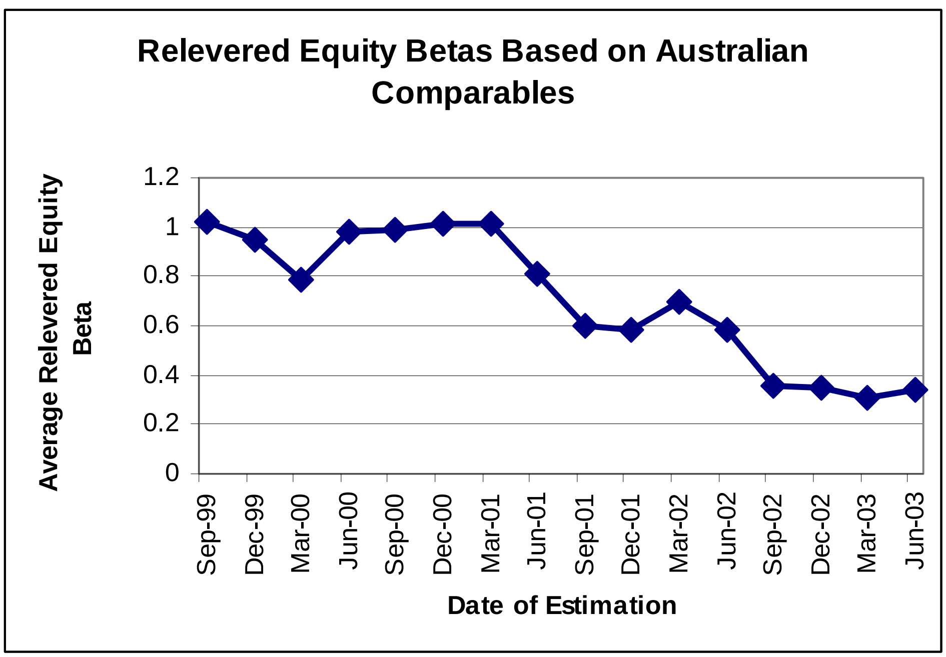
The equity beta is a measure of the systematic risk of owning shares in a company. It reflects (i) the systematic risk of the assets of the business, and (ii) the extent to which this risk has been "levered" or "geared" up by debt financing. The first of these components, the systematic risk of the assets, is often referred to as the asset beta, which is denoted as β_a. This simply recognizes that some types of business are riskier than others. The second component, leverage, recognizes that the amount of debt financing that is employed by the firm also affects the risk of owning shares in the firm. This is because debtholders receive a (usually) fixed return prior to any distribution to shareholders. Thus, the residual (after servicing the debt) is available to the shareholders. The risk of this residual return increases with the amount of prior-ranking debt financing. Therefore, two firms in the same industry may have the same fundamental business risk (asset beta) but different equity betas due to differences in leverage. Shareholders in the more levered firm will face higher risk, even though the two firms operate in the same industry.

Australian regulatory precedent is to use a 60% gearing assumption for energy distribution businesses, so we adopt that assumption in our analysis below. Differences in leverage can be controlled through a procedure known as unlevering and relevering. First, the effects of leverage are removed from the estimated equity betas to produce an estimate of the asset beta. This asset beta is then relevered using the assumed benchmark gearing of 60% to give an estimate of what the equity beta of the comparable firms would have been with 60% debt financing. A number of methods have been proposed for unlevering and relevering. The procedure that has been adopted by many Australian regulators is to relate asset and equity betas as:

$$\beta_a = \beta_e \frac{E}{V} + \beta_d \frac{D}{V}$$

where β_a is the asset beta, β_e is the equity beta, β_d is the debt beta, and E/V and D/V are the proportions of equity and debt financing respectively.[7] The un-levering step is done with the particular comparable firm's capital structure and the relevering step is done with the assumed benchmark gearing. Implementation of this procedure requires an estimate of the debt beta – the risk of owning debt in the firm. Australian regulatory practice is to examine a range of debt betas from zero (consistent with market practice) to an estimate based on the observed debt margin. We focus on the estimates that are based on a debt beta of zero.[8]

This procedure leads to the average relevered equity betas that are produced in the figure below.



[7] Different procedures can be used, but the results will differ only slightly so long as the same procedure is used in both the un-levering and re-levering steps.

[8] Again, the results are relatively insensitive to the choice of debt beta so long as the same value is used in both the un-levering and re-levering steps.

These results indicate that for the first half of the analysis period, the average relevered equity beta was around one. Between mid-2001 and mid-2002 the estimate declined and has been between 0.3 and 0.4 for the last year or so. Of course, we have already established that the estimation error involved in these estimates is so large that it is difficult to establish any sort of statistical significance. This is only exacerbated by the unlevering and relevering process as estimation error in the debt beta is added to the mix. But if these issues are put aside and the results above are taken at face value, the key question is whether the sharp and sudden decline in beta estimates indicates a dramatic change in the risk of energy distribution or whether it is a temporary statistical aberration.

Two pieces of research would support the conclusion that this is a temporary statistical aberration. First, Annema and Goedhart (2003) examine the impact of the telecom-media-technology (TMT) stock market bubble of 1998-2001. They note (p. 1) that, "despite volatility in the market during the 20 years before 1998, industry-specific betas were remarkably stable. But during the bubble, betas for many industries appeared to decline significantly…these apparent decreases actually reflect the influence of telecom, media, and technology share prices on the indexes during the 1998-2001 bubble and distort the real change in the relative risk borne by companies in other industries." They also note (p. 3) that, "recent beta estimates are also more closely in line with pre-1998 values." This is consistent with our analysis above, which indicates that betas estimated using data from only the last two years are substantially higher than those using four years of data.[9]

Annema and Goedhart (2003) suggest that these issues can be best handled by re-estimating betas after excluding the 1998-2001 period. This has the effect of substantially increasing the estimates of utility betas to pre-bubble levels. The conclusion from this is that the recent low estimates of beta for energy distribution companies is more an aberration caused by the dramatic and unusual behavior of companies in other industries and that since such unusual behavior is not predicted to re-occur in a four-yearly cycle it should be removed from beta estimates that are to be used to estimate forward-looking estimates of the cost of equity.[10]

In addition, Blume (1975) shows that beta estimates exhibit mean reversion over time. Blume also develops an estimation methodology to account for mean reversion. A number of reasons have been proposed for this observed phenomenon including the transitory nature of measurement error and a

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[9] In Section 4.4 we report that the OLS beta of AGL is estimated to be -0.06 if the last four years of monthly data are used, but 0.22 if the last two years of monthly data are used and 0.40 if the last six years of monthly data are used. The years 2000-01 contain many extreme market movements (the last part of the stock market bubble and the consequent correction) that give rise to outliers that reduce estimated betas. Note that this point refers to the length of the data period and not the time at which the estimates are made. Here, the point relates to a current beta estimate based on the last two years of data, not an estimate computed two years ago.

[10] See also, Section 6 for the application of this idea to Australian energy firms.

conscious decision by managers to diversify the firm's investments. In a regulatory setting, the conscious decisions of managers to diversify does not justify the use of the Blume adjustment. This is because the regulated firm is unlikely (or unable) to behave in this way over the regulatory cycle. In any event, such diversification should be irrelevant to the regulatory outcome anyway. This adjustment has been examined by the Allen Consulting Group (2002) in a report for the ACCC. In that report (p. 32), ACG notes that "empirically, betas tend to get closer to one over time." They also state that the studies that document this empirical fact, "attribute the regression in equity betas to conscious behavioural decisions of management. For example, by undertaking investment projects with less extreme risk characteristics, or by manipulation of financial structures (e.g., by equity issues, leveraged buy-outs and equity carve-outs)."

Given this reason for the observed mean reversion in beta estimates ACG rightly concludes that, "while allowing for such a management tendency may well be reasonable when projecting forward the estimated equity beta or an actual entity, it has less relevance for the estimation of the cost of capital for the regulated activities of gas transmission entity. In particular, as the objective is to derive the cost of capital associated with a pure-play gas transmission business, any prospective change to the equity beta arising from diversification into other activities would be introducing irrelevant information."

However, the relevant interpretation in the setting is that **beta *estimates* may regress toward one even though true betas are stable**. That is, it is not the true beta that reverts to one due to management decisions. Rather, the true beta is stable, but estimation error is transitory and non-persistent over time. The fact that beta estimates are potentially contaminated by significant measurement error is well accepted. A very low beta estimate is more likely to be contaminated by negative measurement error and a high beta estimate is more likely to be contaminated by positive measurement error. If measurement error is random over time, this would manifest itself as beta *estimates* regressing toward one over time even if true betas are constant. That is, **Blume-type adjustments can be interpreted in the context of measurement error rather than a conscious decision undertaken to move the firm's true beta toward one.**

In summary, **it is likely that the low estimates of relevered equity betas for comparable Australian firms will not persist—they are likely to have been affected by negative measurement and are likely to rise in the future.**

The interpretation of mean reversion as a manifestation of non-persistent measurement error, rather than conscious and deliberate management practices, has also recently been adopted by some

Australian regulators. For example, the QCA (2004), questions only how much higher future equity beta estimates may be, noting that (p. 103) there is a **"market expectation of some upside"** and that, "there is a degree of uncertainty about the level that equity betas might rise to over the next regulatory period[11]." ESCOSA (2000, p. 172) also expresses a concern that **current beta estimates "may materially understate the expected (future) beta."**

4.7. Summary

The analysis in this section demonstrates, in a number of ways, that standard beta estimates are not statistically reliable. This result has important implications for the use of beta estimates in estimating the appropriate WACC. If a primary reliance is placed on a single set of beta estimates from a few comparables, for example, the consequences are:

1. The estimated betas will vary dramatically over time resulting in substantial swings in WACC estimates. In a commercial setting, this would cause the firm's investment strategy to be driven by statistical aberrations in small data sets rather than economic fundamentals. In a regulatory setting it would cause substantial regulatory uncertainty;
2. The estimates could be dramatically different if a different data period, frequency, or statistical method had been adopted; and
3. The estimates could be dramatically different had one or two outlier observations occurred in a different month.

This section has highlighted the dangers of relying too heavily on the scant empirical estimates of equity betas that are available for Australian energy distribution firms. The subsequent sections address how the available data can best be analysed to produce the most reliable result.

[11] The QCA is presumably referring to equity beta *estimates* rather than the equity betas.

5. Obtaining beta estimates from available data.

5.1. Overview

Thus far, we have addressed the statistical unreliability of standard equity beta estimates. We have discussed how outlier data points and market events such as a bubble make present beta estimates unreliable. But beta estimates *are* required for valuation and regulation purposes. So how does one compute a reliable equity beta estimate with the data that is available? Can the statistical problems already documented be overcome?

In this section, we examine a number of ways of mitigating these statistical problems. First, we examine how grouping firms into a portfolio of comparables might be used to reduce the estimation error associated with individual firm betas. Second, we examine evidence from foreign comparables. We also demonstrate how to re-estimate betas after eliminating outliers. We use AGL to illustrate these techniques because other listed comparables have inadequate histories and are small relative to AGL.

5.2. Average betas and portfolio betas

In practice, it is widely recognized that beta estimates for individual firms are too imprecise to be relied on with any confidence. A particular concern in this regard is the influence of firm-specific outlier observations as in 4.5 above. To reduce the impact of such outliers, it is common to compute an average beta for an industry group. Often this is done by separately estimating individual betas for each firm and then taking a simple or weighted average. This procedure ignores the correlation between the beta estimates of each firm which means a reliable standard error of the estimate cannot be obtained. Technically, each beta estimate is a random variable (not a precise number) and they are not independent. Therefore, averaging them without consideration of the correlation structure can produce mis-leading estimates and certainly produces a mis-specified and meaningless standard error. The easiest way to account for these statistical problems is to construct an index of industry returns and then regress those industry returns on market returns. We have performed this exercise by constructing industry index returns in two ways. First, we form a portfolio that consists of all firms in the Energy Distribution and Retailing GICS industry class[12]. We then compute the portfolio return for each month over the last four years and regress this against market returns. This procedure yields a portfolio beta estimate of 1.02 with a standard error of 0.27. There are two problems with this approach. First, some of the firms in this GICS classification are not close

[12] GICS is the Standard and Poors Global Industry Classification Scheme. It is a world standard means of assigning firms to industry portfolios.

comparables for energy distribution businesses. The GICS-based portfolio, for example, include Pacific Hydro and Horizon Energy. Second, there is such variability within the sample and so many extreme returns that the standard error of the portfolio beta estimate is not substantially lower than that of individual beta estimates.

Our second approach is to form a portfolio consisting of closer comparables only. This involves constructing the portfolio returns from the stock returns of AGL, Alinta, APT, Envestra, and United Energy—for the periods over which they were listed. This procedure yields a portfolio beta estimate of 0.24 with standard error of 0.17. However, this portfolio contains a very small number of companies, most of which do not have return data for the full 4-year estimation period. This means that the results are driven, in large part, by AGL. Thus, there are few benefits to be achieved by employing this portfolio grouping technique – we have already addressed the many reasons that the current estimate of AGL's equity beta is statistically unreliable.

The divergence of results between a larger industry portfolio and a very small portfolio of the closest available comparables highlights the tradeoff between comparability and statistical reliability. In this case, the larger portfolio produced an economically reasonable equity beta estimate (point estimate close to 1.0) whereas the small portfolio of closer comparables did not. It is unreasonable to suggest that investors would require returns only 140 basis points above the risk-free rate for equity investments in Alinta, Envestra, and United Energy – this is more like the spread on investment grade debt than on residual equity. Of course, the problem with relying on a very small set of comparables is that outliers and unusual events have a disproportionate influence on the outcome. In a larger portfolio, the effect of an outlier that impacts the beta estimate for a single firm is much less pronounced. That is, noise tends to cancel out in a larger portfolio. Of course, a larger portfolio is likely to contain less comparable firms, but the increase in statistical reliability may more than compensate for this. In this case, the larger portfolio produces economically reasonable results but the small portfolio of closer comparables produces a mechanical beta estimate which implies that the return required on equity is lower than for debt! This illustrates the potential danger of relying on a very small set of comparables.

What we can conclude from this analysis is that the mean equity beta estimate from a large industry-level portfolio is close to 1.0, but that a very small portfolio of closer comparables (relatively more affected by statistical problems relating to beta estimates of individual firms) currently produces a mean equity beta estimate that is too far below 1.0 to be economically plausible.

5.3. Evidence from foreign comparables

As a general rule, one cannot directly use as an estimate of a domestic company's beta, the beta of a comparable company from another market or economy. The different composition of the markets is likely to lead to different estimates of beta and the assumptions required to make them equivalent are usually violated. However, given the lack of domestic comparables for energy distribution firms, it would be improper to pay no attention at all to the foreign comparables. Moreover, it may be possible to draw inferences about an appropriate domestic beta from foreign comparables by making adjustments for the differences between the markets.

The most obvious source of foreign comparables is the United States. The table below contains beta estimates for comparable U.S. firms computed by ValueLine. The table also presents equity beta estimates after re-levering to the benchmark assumption of 60% debt financing. This has been done for two estimates of debt beta, but the results are insensitive to this choice – the re-levered equity betas are very close to 1.0 in both cases.

Table 3: Beta Estimates from Comparable U.S. Firms.

Industry Name	Number of Firms	Mean Equity Beta	Mean Leverage	Equity Beta Relevered with β_d =0	Equity Beta Relevered with β_d =0.15
Electric Utilities (Central)	25	0.82	52.00%	0.98	0.95
Electric Utilities (East)	30	0.76	49.30%	0.96	0.92
Electric Utilities (West)	15	0.82	48.48%	1.06	1.01
Natural Gas Distribution	31	0.65	46.14%	0.88	0.82
Natural Gas	38	0.87	42.36%	1.25	1.19
Mean		0.78		1.03	0.98

Source: ValueLine. Available at http://pages.stern.nyu.edu/~adamodar/pc/datasets/betas.xls.

Of course, these beta estimates cannot be inserted directly into a domestic Australian version of the CAPM for reasons we have already discussed. Beta estimates from U.S. comparables reflect the relationship between U.S. firms and the U.S. market portfolio. The Australian domestic CAPM requires an estimate of the relationship between Australian firms and the Australian market portfolio. Whereas these relationships are likely to be similar, they may not be identical due to differences in the composition of the market portfolios and other institutional and regulatory differences.

To determine whether Australian energy distribution firms are likely to be more closely related to the Australian market portfolio, and therefore warrant a higher beta, than their U.S. counterparts, we conducted a simple correlation analysis. In particular, we have computed the correlation between monthly returns of the Australian Gas Distribution Index[13] and those of the Australian market portfolio.[14] This estimate is 0.24 over the most recent 10-year period. The corresponding correlation for the U.S. Electric Utility Index[15] and the U.S. market portfolio[16] is 0.19. We use the Australian gas distribution index for two reasons. First, no electricity distribution index is available. Second, the gas distribution index in Australia includes AGL, APT, Envestra, Alinta, and GasNet, all of which are usually included in the set of comparables for electricity distribution. That is, given the small number of potential comparables and the structure of the Australian energy market, gas and electricity distribution firms are usually considered to be comparable businesses, at least for the purposes of beta estimation.

The conclusion from this analysis is that the U.S. comparable firms have lower correlation with their local market. This indicates that, if anything, it is likely that the appropriate Australian beta estimate is higher than that of the U.S. comparables. Of course, it would be possible to find other indexes or other time periods over which this result may reverse. But this only goes to confirm our earlier point about the statistical unreliability of these types of estimate.

What we can conclude from this analysis is that the U.S. comparable firms provide information that is useful in helping to estimate the appropriate Australian equity beta and that **the appropriate re-levered (to 60%) equity beta estimate from this data source is centered around 1.0.**

5.4. Statistical analysis to help inform judgment

Various types of statistical analysis can be used to quantify the reliability of evidence on equity betas and to improve this reliability.

1. *Standard errors and confidence intervals.* Every beta estimate should be accompanied by a standard error or confidence interval, as the basis for weighting that evidence.

2. *Bootstrap analysis.* The bootstrap analysis that was performed above indicates the extent to which the data period on which the most recent beta estimate is based differs from other recent data. If we believe that the systematic risk of AGL has not materially changed over the last 10 years, and that outliers have contaminated data from the last four years, the inter-quartile range from our bootstrap analysis could be

[13] Source: Datastream Australia Gas Distribution Total Return Index.
[14] Source: ASX 200 Total Return Index.
[15] Source: S&P 500 Electric Utilities Total Return Index.
[16] Source: S&P 500 Total Return Index.

used as a range for the equity beta. This is simply based on the notion that any data point within the last 10 years is as representative as any other. This would produce a range of around 0.35 to 0.60 for AGL.

Of course, the drawback of this analysis is that the effect of unrepresentative outliers is reduced, but not eliminated. That is, the bootstrap analysis clearly indicates that the last four years of data are highly unusual, contaminated by a number of unrepresentative outliers. While virtually none of the randomly selected bootstrap samples contain as many outliers as we observe in the last four years, they nevertheless contain some outliers. To the extent that this causes a downward bias in the estimated beta (as explained below) all of the bootstrap samples are affected, but the magnitude is less than we observe in the last 4 years of data. This suggests that an approach that identifies and eliminates the effect of outliers might be useful.

3. *Outlier elimination.* There are a number of statistical procedures for identifying outliers in a regression setting. Greene (1993) and Belsley, Kuh and Welsch (1980) describe the standard procedure. This essentially involves leaving out one observation from the data set and re-estimating the regression model using the remaining observations. A residual is then computed for the observation that has been left out, as the difference between the actual value and the fitted value based on the coefficients that were estimated after omitting this observation. That is, this residual measures how well "this observation conforms to the model that is estimated with the other observations."[17] The residual is then standardized by an estimate of its standard error with the resulting standardized residual being (approximately) distributed as a standard normal. Thus any value greater than two in magnitude can be considered to be an outlier that does not conform to the model estimated with the other observations.

We have applied this technique to the estimation of AGL's equity beta as an illustration. Robust results require at least 60 observations after the elimination of outliers, so we begin with six years of monthly return data. The results are reported in Table 2.

[17] Greene (1993, p. 288).

Table 2: Least Squares regression results after removal of outliers.

	Full Sample	Outliers Removed
1996 - 2001		
Number of Observations	72	68
Beta Estimate (t statistic)	0.51 (2.22)	0.56 (2.93)
Adjusted R^2	5.2%	10.1%
1997 - 2002		
Number of Observations	72	67
Beta Estimate (t statistic)	0.47 (2.09)	0.52 (2.99)
Adjusted R^2	5.9%	10.7%
1998 - 2003		
Number of Observations	72	66
Beta Estimate (t statistic)	0.40 (1.67)	0.50 (2.84)
Adjusted R^2	3.8%	9.8%

Table 2 demonstrates that this procedure results in about 5-8% of the observations being removed as outliers. In all cases, removal of the outlier observations results in an increase in the beta estimate (we explain this below). In the earlier period (1996 - 2001) the beta estimate increased by about 10%, whereas the increase in beta estimate was 25% using data from the later period (1998 - 2003). That is, the number of and effect of outliers is more pronounced in recent times. Removal of outliers substantially increases the explanatory power of the model (R2 doubles) and the precision of beta estimates (t - statistics increase by 30 - 70%). Whereas raw beta estimates decline substantially over the period, the outlier resistant betas are quite stable, more in line with economic reason.

We conclude, from this analysis that an appropriate estimate of the equity beta of AGL is in the range of 0.5 to 0.6. This reflects the systematic risk of AGL's portfolio of businesses as well as AGL's present capital structure. The estimate of AGL's equity beta must therefore be re-levered for use in the Australian regulatory setting. In particular, AGL has around 30% leverage whereas 60% leverage is usually assumed for energy distribution businesses by Australian regulators. Using the "vanilla" relevering procedure and an outlier-free beta estimate of 0.5 to 0.6 produces a re-levered equity beta range of 0.9 to 1.05.

That is, an appropriate estimate of AGL's equity beta is around 1.0, after the effects of statistical aberrations have been removed and the gearing adjustment has been applied. This highlights the dangers of taking mechanical beta estimates at face value, given that the most recent CRIF estimate of AGL's equity beta is actually negative!

5.5. Summary of results

In this section, we examine how grouping firms into a portfolio of comparables might be used to reduce the estimation error associated with individual firm betas; we also examine evidence from foreign comparables; and we demonstrate how to re-estimate betas after eliminating outliers. We conclude that:

1. The point estimate equity beta from a large industry-level portfolio is close to 1.0, but that a very small portfolio of closer comparables (relatively more affected by statistical problems relating to beta estimates of individual firms) currently produces an equity beta estimate that is too far below 1.0 to be economically plausible.
2. The U.S. comparable firms provide information that is useful in helping to estimate the appropriate Australian equity beta and that the appropriate re-levered equity beta estimate from this data source is 1.0.
3. An appropriate estimate of AGL's equity beta is around 1.0, after the effects of statistical aberrations have been removed and the gearing adjustment has been applied. This highlights the dangers of taking mechanical beta estimates at face value, given that the most recent CRIF estimate of AGL's equity beta is actually negative!

6. Corroboration from other empirical analysis

As part of its 2005 Electricity Distribution Review, the QCA commissioned the Allen Consulting Group to prepare a report on issues relating to cost of capital estimation (the ACG Report). A large part of that report addresses statistical issues relating to the estimation of equity betas.

The main point that is made in the ACG Report is that data from what they term the "dot-com bubble" may not reflect the true systematic risk of energy distribution businesses over the forthcoming regulatory period. Rather, data from this period reflects more the dramatic movement of funds from the utilities sector to the technology sector in the late 1990s and back again during 2000-2001. The ACG Report recognizes that this effect is quite unique and causes a dramatic downward bias in the beta estimates of utility stocks. Our bootstrap and outlier analyses above quantify just how dramatic this effect can be. The ACG Report concludes (p.44) that:

> *"we consider there to be a sound basis for questioning whether the estimates of betas that include data between the period commencing in about mid 1998 and the end of 2001 would deliver an unbiased estimate of the expected (future) beta for these stocks."*

Accordingly, the ACG Report presents beta estimates based on five years of monthly observations prior to mid-1998 and based on 60 weekly observations post 2001. The effect of the dot-com bubble is starkly illustrated by Table 6.1 in the ACG Report.

Table 6.1

AUSTRALIAN PROXY GROUP: EQUITY BETA RE-LEVERED TO 60%

Re-levered (to 60%) equity beta:	At June 1999 (monthly)	At Oct. 2004 (monthly)	At 11 Nov. 2004 (weekly)
AGL	0.80	-0.30	0.66
Alinta		0.69	1.73
Australian Pipeline Trust		0.67	0.65
Envestra	0.60	0.09	0.58
GasNet Australia		-0.10	0.62
Average	**0.70**	**0.21**	**0.73**

Source: Bloomberg

The ACG Report concludes (p.46) that:

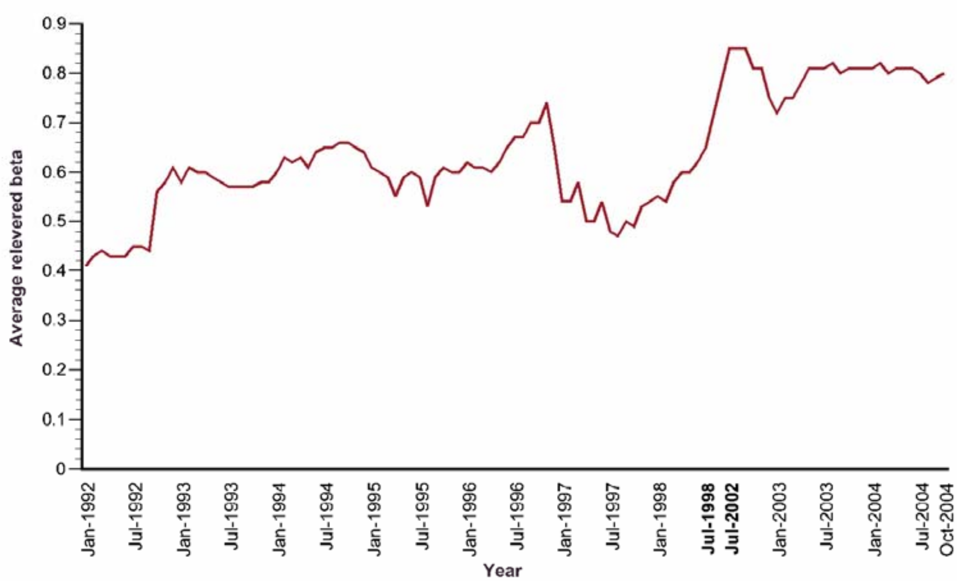
> *"Table 6.1 shows that the average of current (at 11 November, 2004) data indicates an average equity beta of 0.73 based on 60 weekly observations, which is similar to the average level of equity betas observed (for AGL and Envestra only) in June 1999 using 60 monthly observations. Recent 60 week estimates have been in the order of 0.75 to 0.85. Whilst such evidence is not conclusive on the question of where observed 60 month equity betas for Australian energy utilities will settle at over the next 5 years, there is strong evidence that they will be considerably higher than present levels".*

Of course, the real goal for a regulator is *not* to set the regulatory equity beta to match "the 60-month equity betas…over the next 5 years" but to set a regulatory equity beta which results in returns being sufficient to attract a sufficient level of investment. Even if we could perfectly match the 60-month equity beta that will be estimated over the next 5 years, we would only be matching an imprecise and statistically unreliable estimate of the true value.

The ACG report also examines beta estimates for a set of U.S. electricity utilities, after removing data from July 1999 to July 2002 and re-gearing to 60%. The results of this analysis are presented in their Figure 6.4.

Figure 6.4

US ELECTRICITY INDUSTRY: EQUITY BETA EXCLUDING 'BUBBLE' PERIOD (GEARED TO 60%)



Source: Bloomberg, based on 60 monthly observations

Estimates for a range of U.S. gas transmission and distribution firms are presented in their Table 6.3.

Table 6.3

US GAS DISTRIBUTION AND TRANSMISSION: RE-LEVERED EQUITY BETA (TO 60%)

Re-levered equity beta:	At July 1998 (monthly)	At Oct. 2004 (monthly)	At 11 Nov. 2004 (weekly)
Atmos Energy Corp	0.24	-0.17	1.39
Cascade Natural Gas	0.57	0.03	1.72
Delta Natural Gas Co	-0.14	-0.10	0.24
Energy South	0.11	0.24	2.20
The Laclede Group	0.65	0.14	1.43
Northwest Natural Gas	0.96	-0.30	1.56
Southern Union Co	1.04	0.61	0.96
WGL Holdings	2.03	0.25	1.49
Average	**0.68**	**0.09**	**1.37**

Source: Bloomberg,

These results illustrate that beta estimates depend heavily on the period over which data is gathered, the data frequency, and the set of comparable firms that is used.

Taking all of this into account, the ACG Report concludes (p. 51) that "We believe that the equity beta of the average Australian DNSP is 1.00 assuming 60% gearing."
We note that this analysis and conclusion serves to further corroborate the conclusions that we have reached from our own empirical analyses above.

Finally, we note that in two recent determinations on which ACG advised, equity betas below 1.0 were used. The QCA's Draft Determination proposes an equity beta of 0.9 and ESCOSA's Draft Determination proposes an equity beta of 0.8. Given that the ACG believes that the average equity beta is 1.0, and given that these two jurisdictions warrant below-average equity betas (presumably due to factors specific to each jurisdiction), it necessarily follows that the average equity beta for firms operating in other jurisdictions is above 1.0.

7. Summary and conclusions

In this paper, we demonstrate that standard beta estimates are imprecise and statistically unreliable. For this reason, we would advocate that a range be examined when estimating cost of capital. We would advocate that this range be centered around 1.0 for Australian energy distribution businesses with 60% gearing[18]. This conclusion is based on the following evidence:

1. It is not possible to conclude that the available data supports a conclusion that the equity beta of an Australian electricity distribution business (re-geared to 60%) is statistically less than one.

2. The average re-levered equity beta of Australian comparable firms has been 1.0 until very recent times, characterized by unusual market circumstances that have a pronounced effect on the way betas are estimated. By way of illustration, re-geared (to 60%) equity beta for AGL is in the range 0.9 - 1.05 when the effects of influential outliers are removed.

3. The appropriate estimate of the re-geared (to 60%) equity beta from a large industry-level portfolio is a range centered around 1.0.

4. The appropriate estimate of the re-geared (to 60%) equity beta of the much larger set of U.S. comparable firms is a range centered around 1.0.

5. A recent analysis performed by the Allen Consulting Group supports the conclusion that when the effects of the technology bubble are removed "the equity beta of the average Australian DNSP is 1.00 assuming 60% gearing."

In our view, an equity beta below one can only be supported by an incomplete analysis of the scant, unreliable, and contaminated data that is available.

[18] This value could also be used as a point estimate where required.

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