Beta estimation: Considerations for the Economic Regulation Authority

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1. Introduction

1.1 Systematic risk measurement

We have been engaged by the owners of the Dampier to Bunbury Natural Gas Pipeline (DBNGP), DBNGP (WA) Transmission Pty Ltd, to make a submission to the Economic Regulation Authority of Western Australia (ERA). The submission relates to one particular parameter input into the regulated rate of return – the estimate of equity beta. Equity beta is an input into the Sharpe-Linter Capital Asset Pricing Model (CAPM; Sharpe, 1964; and Lintner, 1965) and is a measure of the systematic risk of equity. Systematic risk, also termed economic risk or market risk, is a measure of risk associated with overall economic conditions. It can be contrasted with non-systematic risks, also termed diversifiable risks, which are risks associated with events unrelated to the broader economy.

In this submission we briefly summarise what we believe is the current position of the ERA, both in terms of its preferred estimation techniques and datasets. We then put forward a series of issues for the ERA to consider which are likely to improve the reliability of its beta estimates. For the most part, we refer to recent papers we prepared for the Energy Networks Association (ENA). But we also introduce new information about Australian industry weights which can, in part, affect the difference between beta estimates for energy network businesses listed in Australia and the United States. This provides further support for the inclusion of beta estimates from firms listed in the U.S. as part of the ENA's analysis.

1.2 Current position of the ERA

The most recent determination of the ERA on this issue is in respect to the electricity network of Western Power. In that determination the ERA concluded that an appropriate beta estimate was 0.65 (ERA, 2012, Table 126). This means that the ERA considered equity holders in a regulated electricity network to be exposed to 65% of the risks faced by equity holders of the average listed firm. To place this estimate in context we can consider the figure jointly with two other parameter inputs of the ERA – the market risk premium and the debt risk premium. When the ERA adopted its beta estimate of 0.65, it also adopted an estimate of the market risk premium of 6.00%. This means that its estimate of the cost of equity capital was 3.90% above the risk-free rate of interest, compared to 6.00% for the average firm. In that decision it also adopted an estimate of the debt risk premium of 2.71%, excluding debt raising costs.

The ERA will not necessarily adopt the same equity beta estimate for a gas network as for an electricity network. In its most recent determination with respect to a gas network, that of DBNGP itself, the ERA concluded that an appropriate equity beta estimate was 0.80 (ERA, 2011, Table 43). In that decision, the ERA adopted an estimate of the market risk premium of 6.00%, so its estimate of the cost of equity capital was 4.80% above the risk-free rate of interest. In that decision it also adopted an estimate of the debt risk premium of 3.08%, excluding debt raising costs.

The estimate of 0.65 adopted in the recent electricity decision is the mid-point of a range for the beta estimate of 0.50 to 0.80, which the ERA reported in its draft determination for Western Power in 2009 (ERA, 2009). The range for beta estimates was formed with reference to two sources. First, the ERA considered beta estimates for Australian- and U.S.-listed firms compiled by Allen Consulting Group (ERA, 2009, Tables 80 and 81). Second, the ERA considered estimates compiled for the Australian Energy Regulator (AER) by Professor Olan Henry (ERA, 2009, Tables 82 and 83). The ERA does not specify exactly what determined the upper and lower bound of the range. But in deciding upon a range in 2009 the ERA considered:

- The best estimates of beta values for comparable businesses, placing primary reliance on these estimates. The ERA's estimated range for beta on the basis of Australian-listed firms is 0.45 to 0.70, which we take to be its best estimates for comparable businesses.

- The statistical imprecision of beta estimates, noting that upper bounds of confidence intervals were within the range of 0.85 to 1.05.

- The higher values for USA electricity and gas network businesses, with values up to 1.0.

The ERA's most recent evaluation of this issue is contained in its *Explanatory Statement* accompanying its draft rate of return guidelines (ERA, 2013. The ERA compiled a series of beta estimates for six Australian-listed firms using four regression techniques. Across these four techniques, the average beta estimate for individual firms and for an equal-weighted portfolio, assuming 60% leverage, was 0.50 (Table 19 and Table 21). The ERA did not report estimates for three firms for which data availability ends in 2006 and 2007 (Gasnet, Alinta and AGL; Table 17). One of the remaining firms, Hastings Diversified Utilities Fund (HDUF), only has data available until 23 November 2012, but it is included in the analysis. If HDUF is excluded from analysis, the average beta estimate for the remaining five firms is 0.38.[1]

In the Explanatory Statement the ERA does not reach a conclusion on the appropriate beta estimate for a regulated energy network. But it does conclude that its 2013 analysis satisfies its criteria for choice of method for the equity beta. Throughout the Explanatory Statement the ERA states that only Australian firms are relevant for estimation. It relies exclusively on Australian-listed firms in estimating equity beta, debt risk premium and the value of imputation credits. There are no computations of beta estimates for overseas-listed firms and no comment on beta estimates for these firms reported in other papers.

So we can conclude that the ERA's current position is as follows.

- **Sample = Australian-listed firms only.** Reliable beta estimates can be formed with reference to six Australian-listed energy network businesses, on the basis that there is no computation of beta estimates for firms listed elsewhere and the ERA's consistent statements which constrain the information set to Australian domiciled firms.

- **Information = Stock returns only.** The most relevant information is the results of regression analysis of stock returns on market returns, on the basis that there are no computations which allow for any other information. The ERA has commented upon economic risks which influence beta, but there are no computations which account for these risks. So there is potential for other information to be accounted for in arriving at a beta estimate within an estimated range.

- **Prior expectation cannot be made.** No adjustment towards one is to be made on the basis of bias or imprecision in the regression-based beta estimate, which is clearly stated in the Explanatory Statement.

- **Outlier-resistant regression techniques are preferable to ordinary least squares (OLS) regression.** The ERA presents results from four regression techniques, including OLS and three techniques that can be classed as outlier-resistant because the results exhibit less sensitivity to

[1] We recommend that the ERA check its reported beta estimate for SP Ausnet. The beta estimate for this firm falls substantially over three estimation points used by the ERA, and is well below the beta estimate for SP Ausnet which we compiled. While beta estimates do vary substantially over time this estimate in particular is close to zero, so there could be a transposition or computational error in this estimate.

outliers. While not making explicit statements as to how much weight to place on each technique, the ERA notes a general preference for the outlier-resistant techniques.

- **Beta = 0.50 to 0.80.** An appropriate beta estimate will lie somewhere within the range of 0.50 to 0.80, on the basis that (1) the lower bound of 0.50 is the average beta estimate reported by the ERA from a number of regression techniques and it has provided no indication as to how much consideration will be placed on the statistical imprecision of beta estimates; (2) the upper bound of 0.80 is the current beta estimate for DBNGP and there is no information in the Explanatory Statement to suggest that this estimate will be revised upwards.

1.3 Submission

In this submission, we propose the ERA re-consider its current position on a number of grounds. We point out the specific areas in which our submission differs from the current position of the ERA. Our conclusions with respect to each of the four points listed above are as follows.

- **Sample = Australian- and U.S.-listed firms.** The ERA has acknowledged that the formation of any comparable firm set involves a trade-off between relevance and reliability. We propose that relying on a sample of just six Australian-listed firms is highly unlikely to produce beta estimates that are reliable. We present quantitative evidence that average beta estimates from samples this small are highly variable across samples of firms in the same industry, and over time for the same set of firms. Further, variation across samples can be reduced by around 50% by expanding the comparable firm set to as few as 27 firms (Gray, Hall, Diamond and Brooks, 2013a).

  We refer to beta estimates we compiled for the ENA for U.S.-listed firms selected in an objective, transparent manner by Competition Economists Group (CEG, 2013) and address the ERA's concerns over firm selection and comparability. We introduce data to show that, holding industry composition constant in the two markets, beta estimates from Australia and the U.S. narrow considerably, implying that firms in the two markets have more similarity in terms of risk exposure than previously documented. Our regression-based estimates of beta from these two samples are 0.58 for Australian-listed firms and 0.89 for U.S.-listed firms (SFG, 2013a, Table 4).

- **Information can be expanded beyond stock returns.** Beta estimates do not need to be made purely by regressing stock returns on market returns. The presentation of regression-based estimates of beta as the only way in which systematic risk can be assessed implies that advances in cost of capital estimation over decades are so unreliable that they cannot relied upon whatsoever. One set of information from which beta estimates can be compiled is analyst forecasts. We directly estimated the cost of equity for Australian-listed network businesses using the dividend discount model, and compared this cost of equity estimate to the expected market return. This allows us to measure the relative market risk of energy network businesses. Our estimate of beta based upon analyst forecasts and the dividend discount model is 0.96 (SFG, 2013b, Table 9).

- **Beta estimates are adjusted by a small amount towards a prior expectation of one.** The issue of beta adjustments towards one requires clarity about just what a "prior expectation" means, the reasons for any adjustment towards this value, and the way in which any adjustment is computed. We provide clarity on each of these topics, and re-iterate that there is a sound statistical reason why an adjustment towards one mitigates against bias.

  Given the standard errors of beta estimates from regression, compared to the dispersion of estimates across firms, the adjustment is relatively small, in the order of about 0.04 for Australian-listed firms. But it is most important for beta estimates with low standard errors and which are a long way from one. It is these beta estimates for which there is a high probability that the low or high beta estimate was observed purely by chance. The correction adjusts the estimate so there is an equal chance that it lies above or below the true level of systematic risk. In a large-sample study we document the increased reliability associated with Vasicek-adjusted beta estimates (Gray, Hall, Diamond and Brooks, 2013b).

- **Estimates from least absolute deviation (LAD) regression have a downward bias when used in beta estimation.** When the AER (2009) introduced LAD estimates of beta estimation we noted that, more often than not, the LAD estimates seemed to be lower than OLS estimates. We measured OLS and LAD estimates for a large sample of firms and found that, on average, LAD estimates were lower than OLS estimates by 0.15 (Gray, Hall, Diamond and Brooks, 2013c, Table 1). They were also lower, on average, across all ten industry groups examined (Table 2) and this was a feature of beta estimates in samples from different markets formed for varying research purposes.

  So the issue is, does LAD regression, in the context of beta estimation, produce estimates of beta that have a systematic downward bias? The answer is yes. We formed a market capitalisation-weighted index from all available listed firms and held security weights constant during the period of beta estimation. Under these conditions, the market capitalisation weighted average beta estimate should equal one. This is true for beta estimates generated by OLS regression. But for beta estimates generated by LAD regression, the market capitalisation weighted average beta estimate falls below one (Table 3). The implication is that, in the average case, the LAD beta estimate will be 0.15 below the unbiased OLS estimate.

  The ERA notes that another form of robust regression, MM regression, was used in our dividend drop-off study to estimate the value of imputation credits for the Australian Competition Tribunal (SFG, 2011). We have not performed the same empirical test for bias on the MM regression. But we note that whether the regression technique generates a biased result or not will depend upon the specific characteristics of the type of data being analysed. Our test for bias in LAD estimates is a test of whether the technique leads to downward bias in beta estimates, derived from regressing stock returns on market returns. It is the combination of returns data and the estimation technique which result in the bias. So our recommendation to the ERA is to perform the same empirical test on MM regression, or any other regression technique, in order to document whether or not there is a downward bias in regression-based estimates of beta.

- **Beta = 0.82 to 1.00.** The range we propose for beta is materially different to the range of 0.50 to 0.80 previously adopted by the ERA, and which is consistent with the information provided in the Explanatory Statement. If we were to rely exclusively on regression-based estimates of beta, our estimate would be 0.82, which places twice as much weight on nine Australian-listed firms as 56 U.S.-listed firms. However, we would also place weight on our estimate of 0.96, made directly from analyst forecasts and applying the dividend discount model. Further, we consider that some weight would need to be placed on the very real possibility that systematic risk cannot be distinguished from the market beta of one. So, contingent upon the weights attributed to each piece of evidence, the appropriate beta estimate lies within the range of 0.82 to 1.00.

2. Reliability of a sample of six Australian-listed firms

2.1 Small samples generate unreliable beta estimates

The first issue for consideration is whether a sample of six Australian-listed energy network businesses comprises a sufficiently large sample to draw reasonable conclusions about systematic risk. In its Explanatory Statement the ERA acknowledges there is a trade-off between relevance and reliability in forming a set of comparable firms. It makes this explicit statement with reference to the formation of its comparable firm set in estimating the debt risk premium (pp. 104 and 105). So in relying exclusively on a set of six Australian-listed firms, and placing no weight on estimates from overseas-listed firms, the ERA has concluded that the relevance of these six firms outweighs any concerns over the reliability of the estimates from such a small sample.

The ERA performed regression analysis using four different regression techniques and reported mean beta estimates from these techniques which are all reasonably close to 0.50. It also conducted analysis on individual firms, equal-weighted portfolios and value-weighted portfolios, the results of which also generated beta estimates reasonably close to 0.50. However, this analysis does not address the question of whether the sample size is sufficiently large to draw reliable conclusions.

We addressed this specific issue in a paper entitled *Assessing the reliability of regression-based estimates of risk* (Gray, Hall, Diamond and Brooks, 2013a). We wanted to see just how variable beta estimates are across different samples of firms in the same industry, and over time for the same sample of firms. So we compiled beta estimates for 1,286 Australian-listed firms and formed different-sized samples from these firms on the basis of industry. Sample sizes were nine, 18, 27 and 36 firms, with the minimum value of nine chosen to coincide with the number of Australian-listed energy network businesses historically used by regulators for beta estimation. We repeatedly formed these samples 1,000 times by randomly selecting firms from each industry, and documented the following results.

First, we measured the variation in mean industry beta estimates across different samples from the same industry. This provides an indication of how different beta estimates might be if data was available for a different sample of nine firms from the same industry. A useful metric is the standard error, which is the standard deviation of mean estimates. Across the eight industry groups, and forming beta estimates using 10 years of returns information from 2002 to 2012, the standard error was in the range of 0.15 to 0.22 (Table 2, Panel F). The width of a 90% confidence interval was within the range of 0.49 to 0.75 (Table 3).

These metrics mean that if we could observe a different sample of nine firms from the same industry, the mean beta estimate could be very different. Even for the industry with the most stable beta estimates across samples, in 90% of cases the range for the mean beta estimate spanned 0.49. However, as sample size increases to 18 firms we observe a reduction in the standard errors of about 30%, to a range across the eight industries of 0.11 to 0.15. As we increase sample size further to 27 firms, standard errors are approximately half of the estimates from small firms, within the range of 0.09 to 0.12.

Second, we measured the variation in beta estimates over time for the same samples. For beta estimates computed using consecutive ten-year periods, the difference in average beta estimates across the eight industries ranges from 0.24 to 0.62 (Table 4, Panel B). So in small samples we can easily observe substantial variation in beta estimates over time. This variation across different sample periods is high even for samples in which the variation of estimates across firms is very low. For the 10% of samples on which the dispersion of beta estimates across firms was the lowest, on average there was a variation in average beta estimates from one ten-year period to another within the range of 0.18 to 0.50 (Table 5, Panel A). For larger samples there is less time-series variation in average beta estimates. As sample size increases to 18 firms, the average difference in mean beta estimates falls to a range of 0.21 to 0.61 (Table 4, Panel B). At a sample size of 27 firms the range is 0.21 to 0.58 (Table 4, Panel B).

2.2 Sample size can be increased with inclusion of U.S.-listed firms

Our submission to the ERA is that it is highly unlikely that its analysis of six Australian-listed firms will produce reliable beta estimates and that this unreliability is not addressed by simply applying different regression techniques to the same sample of firms. Further, there is a large sample of energy network businesses listed in the United States which can be analysed.

The ERA's decision not to increase sample size by including overseas-listed firms has been made with reference to the following concerns (pp. 28–29). It notes that there is a question as to how to select and evaluate potentially very large datasets, there is a need to consider whether international firms have the same risks as the benchmark Australian firm, regulatory costs could increase, country risk would need to be considered, and it is difficult to incorporate Australian and international data together.

In analysis for the ENA we compiled beta estimates for 56 U.S.-listed firms and submit to the ERA that analysis of this larger sample of firms provides important and relevant information for estimating systematic risk of an Australian energy network. In giving no consideration of any international evidence, the ERA considers that the concerns listed above are so insurmountable that they outweigh the imprecision associated with a sample of just six Australian-listed firms. As mentioned above, we quantified the imprecision associated with small samples and note that if sample size is as small as the ERA relies upon, beta estimates vary across samples and over time by amounts which will alter the regulated rate of return by a material amount. Furthermore, the rules require consideration of relevant evidence, so we submit that the ERA re-consider its assessment of the issues noted above. We address these issues in turn.

How would the firms be selected? In our report, *Regression-based estimates of risk parameters for the benchmark firm* (SFG, 2013a), the comparable firm set was selected by Competition Economists Group (CEG, 2013). CEG wrote a detailed, transparent assessment of the process by which these firms were considered, which was based primarily upon industry classifications of data providers and the proportion of firm assets that were regulated. We measured liquidity using three metrics that are commonly adopted in the literature and performed analysis based entirely on stock and market returns. So we consider that the issue of which firms should be selected has been addressed in these two papers, at least when it comes to consideration of U.S.-listed firms.

Do international firms face the same risks as the benchmark firm? A related question is, how can we take into account country risk? Another related question is how international and Australian evidence is considered together? The answer to these questions is a matter of degree. The risks facing any firm in the comparable firm set, including Australian-listed firms, will never be *identical* to the risks of the benchmark. But the question is whether the risks of that firm are *sufficiently different* to that faced by the benchmark that the firm should be excluded from consideration. U.S.-listed firms face energy demand risk, regulatory risk and financial risk, as do their Australian counterparts. CEG was able to identify 56 U.S.-listed firms that it considered sufficiently comparable to Australian-listed firms that relevant beta estimates could be compiled. We consider it unlikely that the risks faced by these firms are so different to the benchmark that they should be given zero consideration in reaching a conclusion on beta.

We also consider it unlikely that the country risk of the United States is so different to the country risk of Australia that it should be entirely disregarded. Both countries have highly liquid equities markets, a high degree of investor participation from overseas, regulatory regimes that require disclosure of price-sensitive information and enforcement of contractual and property rights.

The answer could be framed another way. We could ask, what sample size of Australian-listed firms would the ERA consider to be sufficiently small that reliance would have to be placed on firms from offshore in order to make any estimates at all. The ERA considers six firms to be enough to place 100% reliance on these firms. One of these firms is no longer listed, so as time passes the ERA will then rely upon five firms. Will this be sufficient?

Rather than answer the question in terms of whether overseas firms are "in" or "out" of consideration, we submit that weight should be placed on this information according to an assessment of relevance and reliability. In our analysis for the ENA, we submitted that each estimate from an Australian-listed firm be given twice as much weight as each estimate from a U.S.-listed firm. We propose that this represents a reasonable trade-off between relevance and reliability of the two samples.

Will regulatory costs increase? The incremental cost of regulation associated with analysis of international firms is trivial in comparison to the costs to consumers or businesses of a beta estimate that is too high or too low. Furthermore, the cost of analysing the information has already been borne by businesses in preparing their submissions. The cost to the regulator of considering international evidence will be in making an assessment of the evidence before it, in replicating the analysis, or to expand upon the analysis, which could include analysis of different firms, analysis of different data or the use of alternative estimation techniques. Having documented the substantial variation in beta estimates resulting from small samples, is it reasonable to simply re-run regressions on the same sample of small firms each year, when there is a large dataset available for analysis and that analysis has already been compiled in submissions? Put another way, is it reasonable to conclude that regression-based estimates of beta from six firms as so reliable that no cost should be incurred to evaluate the risks of any firms listed outside Australia?

2.3 Sample composition in different parameters

2.3.1 Debt risk premium

We commented above that the ERA referred to the trade-off between relevance and reliability in compiling the comparable firm sample used to estimate the debt risk premium. That sample will be comprised of bonds issued by Australian companies after consideration of term to maturity and credit rating. The ERA also currently requires yields to be observable for at least 10 out of 20 days in the averaging period. Bonds ultimately included in this analysis have varying credit ratings that do not necessarily match the benchmark rating, varying terms to maturity that do not necessarily match the benchmark term to maturity, and varying levels of price transparency, with yield estimates available on 10 to 20 days within the averaging period, and are issued by firms in a variety of industries outside of energy networks.

Ideally, the ERA would observe (1) a large sample of bonds, (2) issued by Australian energy network businesses, (3) with terms to maturity equal to the benchmark term, (4) at the benchmark credit rating and (5) which are heavily traded so yield estimates can be based upon trades rather than quotes. But this ideal sample does not exist, so the ERA relaxes selection criteria to increase sample size to the point where it considers reliable estimates can be made.

2.3.2 Imputation credits

In estimating the value of imputation credits, the ERA proposes to rely upon evidence from dividend drop-off studies (p. 210). The value of imputation credits from these studies is based upon changes in share prices on the ex-dividend date, relative to the amount of the dividend. In almost all dividend drop-off studies, there is no industry decomposition of sample firms. But there is often analysis presented on sub-samples of firms according to dividend yield or market capitalisation. Conclusions are drawn from large samples of firms across industries because there is considerable dispersion in price changes around the ex-dividend date. So a large sample is needed to make reliable conclusions about the average value of imputation credits in that sample. Ideally, the ERA would perform dividend drop-off analysis on a large sample of listed energy network businesses paying franked and unfranked dividends. But instead we must draw conclusions based upon a sample of firms which could have different shareholder clienteles.

2.3.3 Equity beta

The common characteristic of sample firms used to estimate the debt risk premium, the value of imputation credits and equity beta is that the firm is based in Australia. But it seems that any other deviation from the characteristic of the benchmark firm is permissible in order to compile a sufficiently-large sample for analysis. We submit that analysis of firms listed in the United States does not represent such a deviation from the characteristics of the benchmark firm that it should carry zero weight in the analysis. We propose that the ERA re-consider its assessment of relevance and reliability on this issue and place a positive weight on beta estimates from U.S.-listed firms.

3. Industry impacts on beta estimates of Australian-listed firms

3.1 Issue

In our analysis for the ENA we compiled the following beta estimates for Australian and U.S.-listed firms, assuming 60% leverage. Australian-listed firms have a beta estimate of 0.58 and U.S.-listed firms have a beta estimate of 0.89 (SFG, 2013, Table 4). An important issue is to understand why the beta estimates for Australian-listed firms are so much lower than the beta estimates for U.S.-listed firms. More specifically, can we attribute the difference to attributes of the firms analysed, or attributes of the market index proxy that happens to be used to compute the beta *estimates*? The reason this is relevant is that the listed market index is only a proxy for the broader market portfolio, and it is exposure to that broader market portfolio that will be priced by investors if the CAPM holds.

The reason this is a concern is that the industry composition of Australian-listed firms is, at present, highly concentrated in financials and resources. In contrast, listed firms in the U.S. are more evenly spread across industries. So it could well be the case that the beta *estimates* for Australian-listed energy network businesses are low purely because of the currently concentrated industry composition of Australian-listed firms. The systematic risk that is actually priced by investors could be considerably higher than these estimates relative to a currently concentrated proxy.

To address this issue we constructed indices of the Australian listed market assuming both Australian and U.S. industry weights. This compilation of market indices requires two steps. The first step is to disaggregate the two markets into ten industries defined according to the Industry Classification Benchmark (ICB) of FTSE, and determine the market capitalisation weights of those industries on a daily basis. The second step is to apply those industry weights to the historical stock returns of those industries separately for each market. So the re-computed Australian market index is an estimate of Australian market returns as if the U.S. industry weights were adopted.

In Table 1 we present average industry market capitalisation and number of firms in each industry for the period from 2 January 2002 to 6 August 2013. In Australia, the largest listed industries by market capitalisation are Financials (45.3%) and Basic Materials (16.8%), with Oil & Gas contributing an additional 9.4%. So in aggregate, financial firms and resources firms (Basic Materials/Oil & Gas) accounted for 71.5% of market capitalisation. In the United States the largest listed industries by market capitalisation are Financials (19.1%), Technology (15.6%) and Health Care (15.1%). These three industries accounted for 49.7% of market capitalisation. The combination of financials and resources firms accounted for 31.6% of market capitalisation.

There is likely to be a considerable difference between the industry composition of the listed firms in Australia, and the industry composition of the Australian economy in general. Investors are unlikely to price assets entirely on the basis of risk relative to the set of listed firms which happen to be heavily concentrated in financials and resources. The Australian economy, comprising both listed and unlisted firms is likely to be more represented by a broader industry composition as observed in the United States.

To get an idea of the composition of the Australian economy more broadly, we reviewed industry data compiled by the Department of Industry, Innovation, Science, Research and Tertiary Education (the Department). The Department compiles a snapshot of industry value added according to 32 industry sectors, reported in *Key Facts Australian Industry 2011-12*. The original data is sourced from the Australian Bureau of Statistics.

Table 1. Market capitalisation across ten industries in Australia and the United States

Market	Industry	Oil & gas	Basic mat.	Ind-ustrials	Cons. Goods	Health care	Cons. svcs.	Telecom.	Utilities	Fin-ancials	Tech.	Total
Australia	Mkt cap (A$b)	67	152	51	16	31	94	20	15	368	0	815
	Mkt cap (%)	9.4	16.8	5.8	1.8	4.1	12.3	2.7	1.8	45.3	0.0	100.0
	Firms	7	16	13	6	7	19	2	3	30	0	103
United States	Mkt cap (US$b)	1,124	344	1,262	872	1,687	1,488	415	398	2,220	1,805	11,615
	Mkt cap (%)	9.5	2.9	10.7	7.2	15.1	12.8	3.7	3.4	19.1	15.6	100.0
	Firms	39	29	76	53	71	102	16	37	126	73	623
Australia	Ind. val. add. (%)	2.3	14.5	31.0	5.9	7.9	16.2	3.8	3.1	15.5	0.0	100.0

Average values from 1 January 2002 to 6 August 2013. Market capitalisation is compiled from International Classification Board indices of FTSE. The last two of the table contains a breakdown of industry value added from 2011-12 presented by the Department of Industry, Innovation, Science, Research and Tertiary Education, with our mapping of industry sectors to the FTSE industry classifications.

The point of this exercise is not to enter into a debate about the precise industry composition of the Australian economy. Our objective is simply to demonstrate that the Australian economy is not comprised of almost half financial firms, and that the Australian economy is not as dissimilar to the U.S. economy as the listed firm composition would suggest. It is a unique feature of *listed* firms in Australia that the industry composition is skewed towards financial firms.

We mapped the 32 industry value added estimates from the Department onto the ten ICB classifications. We excluded three industry sectors, namely Public administration and safety, Education and training, and Other services, which jointly comprised 12.7% of industry value added, on the basis that these industry sectors are largely government-operated or funded in both Australia and the United States, although the U.S. is likely to have relatively more private education. As mentioned above, our objective is simply to document that the Australian listed firms have a somewhat unusual weight in a small number of industries. We then allocated the remaining 87.3% of industry value added to the remaining sectors. The relationship between the sectors used by the ABS and ICB sectors is presented in Appendix 9.1. These weights appear in the last row of Table 1.

The key point is that the Australian economy is considerably more diverse across industries than is the set of listed firms. Financials are estimated to comprise 15% of the economy, compared to 45% for listed firms, and the resources sector (Basic Materials/Oil & Gas) is estimated to comprise 17% of the economy, compared to 26% for listed firms. In contrast, the economic contribution of Industrials is higher in the broader economy than the proportion of listed firm market capitalisation.

The industry data for the broader Australian economy is not meant to be a comprehensive measure of the market value of all Australian assets. But it demonstrates that if we simply use the *listed* Australian market as a proxy for the market portfolio in the CAPM, the industry weights of the listed sector are considerably different to that in the broader economy. So to use the beta estimates from regressions on this market proxy, without any consideration of industry weights or estimates from overseas-listed firms, is likely to lead to unreliable beta estimates.

We compiled market indices using the Australian and U.S. market capitalisation weights and the industry returns over the period from 2 January 2002 to 6 August 2013, a period of 11.5 years. We then compiled beta estimates for individual firms, and for equal-weighted indices, for Australian- and U.S.-listed firms over the same time period. There are nine Australian-listed firms and 56 U.S.-listed firms. These are the same firms previously analysed in our report *Regression-based estimates of risk parameters for the benchmark firm*.

Our analysis relies upon all available information during this period. Our estimates are based upon four-weekly returns. But we use all daily stock prices in our analysis by repeating the analysis 20 times using different start points to compute four-weekly returns. We present estimates from OLS regression, Vasicek (1973)-adjusted estimates and re-levered Vasicek-adjusted estimates, assuming leverage of 60%.

We adopt the same re-levering process as the ERA.[2] These techniques are also described in detail in our report *Regression-based estimates of risk parameters for the benchmark firm*.

3.2 Australian-listed firms

Our beta estimates for Australian-listed firms are presented in Table 2. The table also presents descriptive information for the firms and confidence intervals for the mean firm beta estimates and the index beta estimates.

For individual firms, and using prevailing ASX industry weights for Australia, the mean beta estimates are 0.49 for the OLS estimate, 0.52 incorporating the Vasicek adjustment and 0.60 if the Vasicek-adjusted beta estimates are re-geared to 60%. The corresponding values for an equal-weighted index are 0.53, 0.58 and 0.61. The estimates for individual firms are very close to those we previously reported based upon the All Ordinaries Index (SFG, 2013, Table 5). So we can conclude that re-constructing the market index based upon industry indices did not materially alter our estimates. According to the estimates for individual firms, a 95% confidence interval for the beta estimate is 0.38 to 0.82. For the equal-weighted index the 95% confidence interval is 0.45 to 0.76.

If, instead, the more diversified prevailing U.S. industry weights are used to compile a market index, the mean beta estimates for individual firms are 0.58 for the OLS estimate, 0.62 Vasicek-adjusted and 0.70 under 60% gearing. For an equal-weighted index the corresponding estimates are 0.64, 0.69 and 0.72. The 95% confidence intervals spanning these estimates are 0.46 to 0.94 for individual firms, and 0.54 to 0.90 for the equal-weighted index.

To summarise, the average beta estimate for Australian-listed firms is 0.60, assuming 60% leverage and placing equal weight on the estimates for individual firms and the equal-weighted index. But under U.S. industry weights the average beta estimate, assuming 60% leverage, increases to 0.71. So the application of industry weights that are less concentrated in financials and resources resulted in beta estimates that are substantially higher than measured relative to the Australian listed market. The beta estimates are closer to those we previously reported for U.S.-listed firms.

The same result occurs if industry weights are set according to the broader Australian economy (as reported in Table 1 above) rather than using the very concentrated stock market index. Again, the stock index is much more heavily concentrated in financial and mining stocks than is the broader economy. If weights from the broader Australian economy are used, the mean beta estimate for the Australian stocks again increases towards the mean beta estimate from the much larger sample of US comparables.

The key point of this analysis is that regression-based beta estimates will vary considerably depending upon the composition of a listed firm index. Australian listed firms are highly concentrated in a small number of industries, and this industry composition has a material impact on beta estimates derived from the relationship with the returns on that index. So to rely exclusively on regression-based beta estimates for Australian-listed firms, computed using the All Ordinaries Index, requires the following rationale:

- Placing 100% reliance on six Australian-listed firms and zero reliance on firms listed overseas is more reliable than placing less than 100% weight on six firms and some positive weight on overseas-

[2] The re-levering equation states that $Equity\ beta = Asset\ beta \times \left(1 + \frac{Debt}{Equity}\right)$. The equity beta for the firm or index is estimated from regression. The asset beta is estimated by incorporating an estimate of the leverage for the firm or the index. The re-levered equity beta is estimated by incorporating an assumed capital structure for the benchmark firm, which in this case is 60% debt to 40% equity. Values for debt and equity are market value estimates, with book value of debt used as a proxy for market value.

listed firms. We submit that a more reasonable assumption is to place positive weight on beta estimates from U.S.-listed firms, with our particular recommendation being to place twice as much weight on each Australian observation as a U.S. observation.

Table 2. Beta estimates for Australian-listed firms

	Descriptive means				Australian industry weights				US industry weights			
Name	Mkt cap	Debt	Leverage	N	OLS beta	Vas beta	Re-geared	RSQ	OLS beta	Vas beta	Re-geared	RSQ
Gasnet	313	624	0.67	59	0.25	0.32	0.27	0.04	0.29	0.36	0.30	0.05
Alinta	1411	865	0.37	68	0.52	0.57	0.90	0.08	0.58	0.63	0.99	0.09
APA	1437	1951	0.56	142	0.57	0.58	0.63	0.20	0.70	0.71	0.78	0.23
DUET	1487	4748	0.76	108	0.59	0.61	0.36	0.16	0.69	0.71	0.42	0.16
HDUF	551	479	0.46	96	0.76	0.80	1.08	0.08	0.93	0.94	1.27	0.08
SP Ausnet	2530	4083	0.62	92	0.29	0.31	0.30	0.08	0.42	0.44	0.43	0.10
Spark	1614	1349	0.45	78	0.39	0.42	0.57	0.10	0.49	0.52	0.72	0.11
Envestra	800	2006	0.72	142	0.66	0.67	0.47	0.17	0.77	0.78	0.55	0.17
AGL	8995	1500	0.14	58	0.34	0.38	0.81	0.09	0.36	0.40	0.85	0.09
Mean	2126	1956	0.53	94	0.49	0.52	0.60	0.11	0.58	0.62	0.70	0.12
Standard error					0.06	0.06	0.09		0.07	0.06	0.10	
Lower bound of 95% confidence interval					0.35	0.39	0.38		0.42	0.46	0.46	
Upper bound of 95% confidence interval					0.62	0.65	0.82		0.74	0.76	0.94	
Index			0.58	142	0.53	0.58	0.61	0.25	0.64	0.69	0.72	0.27
Standard error					0.08	0.08	0.08		0.09	0.09	0.09	
Lower bound of 95% confidence interval					0.38	0.43	0.45		0.46	0.51	0.54	
Upper bound of 95% confidence interval					0.69	0.73	0.76		0.82	0.86	0.90	

If the Vasicek adjustment is not incorporated, we would have the following estimates. Based upon Australian industry weights, a mean estimate across firms of 0.56 within a 95% confidence interval of 0.35 to 0.76, and a mean re-geared estimate for the equal-weighted index of 0.56, within a 95% confidence interval of 0.40 to 0.72. Based upon U.S. industry weights, a mean estimate across firms of 0.78 within a 95% confidence interval of 0.50 to 1.06, and a mean re-geared estimate for the equal-weighted index of 0.79 within a 95% confidence interval of 0.58 to 1.00. The individual re-levered estimates, without the Vasicek adjustment, can be computed according to the following computation, OLS beta ÷ [1 + Leverage/(1 – Leverage)] × [1 + 0.60/0.64].

- Investors will price equities exclusively with respect to risk relative to the Australian market index proxy, which is highly concentrated in just two industries, rather than the broad selection of industries available for investment, comprising both unlisted firms in Australia, listed firms in other markets and unlisted firms in other markets. We submit that a more reasonable assumption is that investors do not price equities exclusively with respect to the concentrated, Australian market index, and that the best way to deal with this is simply to place some positive weight on beta estimates from U.S.-listed firms. The information we presented above is to illustrate one reason why the beta *estimates* for the two sets of firms are different, and that the *actual* systematic risks of the two groups of firms is not as different as appears from the estimates.

To be clear, we do not suggest that altering the industry weights will assist in producing a reliable beta estimate from the small handful of Australian stocks. Rather, what we show is that:

a. When the concentrated Australian stock market index is used as the market proxy, the mean beta estimate from the small sample of Australian stocks is lower than the estimate from the larger sample of US stocks; and

b. When the market proxy is based on weights that better reflect the broad Australian economy, the Australian beta estimates converge towards the US estimate.

This implies that the firms in the two samples have similar systematic risk characteristics in that they demonstrate a similar relationship with less concentrated indexes (that better match the Australian economy).

Table 3. Beta estimates for Australian-listed firms

	Descriptive means				Broad econ. weights			
Name	Mkt cap	Debt	Lev-erage	N	OLS beta	Vas beta	Re-geared	RSQ
Gasnet	313	624	0.67	59	0.25	0.30	0.25	0.04
Alinta	1411	865	0.37	68	0.53	0.58	0.92	0.10
APA	1437	1951	0.56	142	0.61	0.62	0.68	0.21
DUET	1487	4748	0.76	108	0.66	0.68	0.40	0.17
HDUF	551	479	0.46	96	0.96	0.96	1.30	0.10
SP Ausnet	2530	4083	0.62	92	0.35	0.38	0.36	0.09
Spark	1614	1349	0.45	78	0.46	0.49	0.67	0.12
Envestra	800	2006	0.72	142	0.71	0.73	0.51	0.18
AGL	8995	1500	0.14	58	0.25	0.29	0.62	0.06
Mean	2126	1956	0.53	94	0.53	0.56	0.64	0.12
Standard error					0.08	0.07	0.11	
Lower bound of 95% confidence interval					0.35	0.39	0.39	
Upper bound of 95% confidence interval					0.71	0.73	0.88	
Index			0.58	142	0.60	0.64	0.67	
Standard error					0.08	0.08	0.08	
Lower bound of 95% confidence interval					0.44	0.48	0.51	
Upper bound of 95% confidence interval					0.76	0.80	0.83	

4. Information other than stock returns can be informative

4.1 Alternative information and techniques to stock returns and regression

The ERA considers that, in estimating beta, primary reliance should be placed on statistical estimates of beta for comparable firms (p. 163). It also acknowledges that there is a high level of imprecision in beta estimates from empirical studies, but that the best way to handle this imprecision is to use multiple models and techniques so that a range can be considered (p. 167). However, the ERA's definition of empirical beta estimates is restricted to just one estimation technique (regression, albeit in four different forms of regression) and one set of data (historical stock returns). The ERA compiles estimates of the relationship between *realised* stock and index returns in historical data, and uses this as the basis for the relationship between *expected* stock returns and market returns.

Given the imprecision in beta estimates compiled using regressions of stock on market returns, it is worth considering whether beta estimates can be compiled using other information. There is no requirement under the CAPM that beta estimates be compiled in the manner adopted by the ERA. For instance, there is recent evidence that beta can be estimated by considering the relationship between analyst earnings forecast revisions for a stock and the aggregate market (Da and Warachka, 2009). Beta estimates could also be calibrated by examining the relationship between regression-based beta estimates and accounting information, thereby mitigating the imprecision of regression-based estimates (Brimble and Hodgson, 2007). There is also evidence that beta estimates for different firms vary depending upon whether market risk is high or low (measured by dividend yield, default premium, term premium and the risk-free rate), with the implication that firms with greater asymmetric exposure to market risk have a higher cost of equity (Petkova and Zhang, 2005).

This list is not exhaustive, but illustrates that a range of other techniques and information can be used in beta estimation, apart from regressions of stock returns on market returns. The information set could include analyst forecasts, accounting information and information on market conditions, and the estimation techniques adopted vary according to the information being analysed.

The motivation behind these papers is the observation that regression-based estimates of beta have limited reliability. If there was agreement that we could reliably estimate the cost of equity merely by regressing stock returns on market returns, researchers would not have sought to expand the information set and estimation techniques to such an extent.

4.2 Beta estimates derived from analyst expectations

In our analysis for the ENA, we relied upon analyst forecast information to estimate beta for Australian-listed energy networks. In the last two decades there has been extensive research into estimating the cost of equity from analyst forecasts, which is summarised in Fitzgerald, Gray, Hall and Jeyaraj (2013). In our report, *Dividend discount model estimates of the cost of equity,* we estimated the cost of equity as the discount rate which sets the present value of expected dividends equal to the analyst's price target. We analysed all Australian-listed firms from 2002 to 2012 for which data was available. The market capitalisation-weighted average of these individual cost of equity estimates is the expected return on the market. We then measured the market risk premium, and the equity risk premium for listed energy networks, by subtracting the risk-free rate. The ratio of the equity risk premium for the network businesses to the market risk premium was, on average, 0.96 (SFG, 2013b, Table 9).

In Sub-sections 10.2.4.6 and 10.2.4.7 of the Explanatory Statement the ERA makes an assessment of the dividend discount model and the residual income model, as equations used to estimate the cost of equity. There are several clarifying comments that should be made about this assessment.

First, if correctly implemented, the dividend discount model and the residual income model will give precisely the same valuation. Any series of dividend per share and earnings per share forecasts will necessarily imply a series of residual income forecasts, and the present value of the dividend series and residual income series (plus initial book value) will be identical. This clarification was the motivation for the paper by Lundholm and O'Keefe (2001) and we also made this explicit in Sub-section 3.2 of our published paper, and refer in particular to the example summarised in Table 2 (Fitzgerald, Gray, Hall and Jeyaraj, 2013). The ERA acknowledges that the "residual income model in many respects is an identical framework to the DDM approach (p. 125)."

Second, the ERA has expressed a concern over the use of the dividend discount model/residual income model on the basis of its lack of theoretical foundation. We suggest that the ERA re-assess this concern, because the theory underpinning the dividend discount model is simply that the value of an asset can be determined as the present value of expected cash flows. That theory is the entire basis for the regulation of network assets in Australia and the ERA has consistently stated the importance of setting regulated returns such that NPV = 0. It is also the basis upon which the debt risk premium is estimated, as the yield which sets the present value of bond payments equal to the bond price. We simply do not understand why, as a concept, there is a concern with estimating the cost of equity on the same basis.

Third, the ERA has concerns over the quality of data, in terms of the use of analyst forecasts and subjective assessments about growth. In terms of subjective assessment of growth, we have paid considerable attention to implementing techniques that require as little subjective input as possible. We believe the data should be informative about the cost of equity and growth.

In terms of the quality of analyst forecasts, the ERA raised two issues. It has concerns over whether analyst forecasts of dividends will be consistent with the analyst's assessment of the share price. It also has concerns about whether this potential inconsistency can be mitigated by matching analyst forecasts of dividends with analyst price targets. Finally, the ERA raises a concern about the extent to which non-regulated assets impact upon cash flow expectations.

In contrast to these concerns, in Sub-section 10.2.6.3 of its explanatory statement the ERA makes the following statement with regard to reasonableness checks:

> The Authority has significant concerns with regards to the use of brokers' reports, given potential for bias, and the lack of transparency. Nevertheless, the Authority considers that brokers' estimates do provide some relevant information for reasonableness checks, where those reports are transparent, and where a range of different views can be obtained.

In compiling our beta estimate of 0.96 for the ENA (SFG, 2013b) we used *all* available analyst forecasts for Australian-listed firms where sufficient data was available for analysis. We provided a detailed explanation of how we derived the relationship between analyst forecasts and the cost of capital, and summary statistics for the entire sample, for every six month period, for different industries, and provided a six-monthly comparison between our market return estimates and those reported by Bloomberg. So we consider that this analysis meets the ERA's requirements for data quality, transparency and a range of views.

We propose that the ERA review our analysis (SFG, 2013b) and make an assessment of whether it provides a basis for estimating the cost of equity. If the ERA concludes that it is not sufficiently reliable, we ask that it provide guidance as to just what type of analysis would be of sufficient quality, transparency and of a sufficiently-wide range.

4.3 The role of the regulator in expanding the information set

In its Explanatory Statement the ERA has ruled out the use of analyst forecasts and international firm returns in estimating equity beta. We consider that information from analyst forecasts and international firm returns is useful for measuring equity beta and have performed these computations. It is also the case that accounting information and market conditions can be used to estimate equity beta. We have used this information in other contexts.

The ERA has acknowledged that beta estimates derived from regression analysis of historical returns on market returns has limitations. The estimates are imprecise. Where we disagree is the approach to mitigating these limitations. The ERA approach is to repeat the regression analysis using different techniques which place different weight on different observations. That approach does not result in new information – it means that the existing information is re-weighted according to which data points are considered outliers.

We submit that the role of the regulator is a proactive one, in which it considers expanding the information set to take account of the acknowledged limitations of the current data and estimation technique. We question whether the information from analyst forecasts and international returns is truly of such limited relevance and reliability that it should carry zero weight in determining equity beta. The same standard of relevance and reliability does not seem to be applied to regression-based estimates of beta from six firms, given the instability of beta estimates across samples and over time for samples of this size. This information set and estimation technique is given 100% weight in making a quantitative assessment of equity beta.

5. Consideration of the market beta of one

5.1 Vasicek adjustment is a statistical correction

In Sub-section 12.3.1 of the Explanatory Statement the ERA determines that the use of the Blume adjustment to equity beta estimates is not appropriate. It specifically rules out the use of a beta estimate computed as 0.33 + 0.67 × raw beta. This equation places one-third weight on a beta estimate of one, and two-thirds weight on the raw beta estimate from regression analysis. In Section 12 (p. 162) and Sub-section 12.3.2 the ERA states that there is no *a priori* expectation that the beta estimate is equal to one. This is in response to the submission by regulated businesses that, prior to conducting empirical analysis, we do not know whether the effects of low business risk and high financial risk will lead to equity holders facing risks which are above or below the average firm in the market.

This issue requires clarification in a number of respects. The first issue requiring clarification is the use of the terms Blume adjustment, Vasicek adjustment and the weight of 0.33 adopted by Bloomberg.

Over 40 years ago, Blume (1971) documented empirically that if you observe a low beta estimate for a firm in one period, on average you are likely to observe a higher beta estimate for that firm next period. This can be labelled regression towards the mean. In Table 4 of that paper, Blume reports results from a series of regressions of period 1 beta on period 2 beta. Approximately, the regression results suggest that the beta estimate in period 2 = 0.33 + 0.67 × beta estimate in period 1.

These are the coefficients adopted by Bloomberg in reporting what are typically referred to as *Bloomberg beta estimates*. The adjustment adopted by Bloomberg does not take into account the standard error of the beta estimate, which will be influenced by the number of observations available for analysis and the volatility of returns.

Two years later, Vasicek (1973) verified mathematically that the mean-reversion tendency documented by Blume (1971) will be observed even if there is no change whatsoever to the actual systematic risk. He showed that beta estimates will be mean-reverting even if the true beta is constant. The reason this occurs is because when we observe high or low beta estimates, there are two possible reasons for this observation and there is a probability attached to each reason. The first possible reason is that the firm is actually a high or low risk firm, and the beta estimate accurately captures this risk. The second possible reason is that the firm is actually a medium-risk firm, but we observed the high or low beta *estimate* purely by chance.

The important proof of Vasicek was that when the standard error is high, there is an increased chance that the estimate was observed by chance, and less chance that it is really the true beta. Cunningham (1973) also reached this conclusion. So the Vasicek adjustment is different to that used by Bloomberg in that the weight placed on a prior expectation increases when the standard error is high. The equation adjusts the beta estimate so there is an equal chance that the true beta lies above or below the true value. Or, in statistical terms, the adjusted beta will be unbiased. The default beta estimates reported by Datastream are adjusted on the basis of the standard error of the estimate, towards a prior expectation of one.

A further two years later, Blume (1975) tested whether the mean-reversion of beta estimates could be explained entirely by the Vasicek adjustment (which Blume refers to as the order bias) or whether there is still mean-reversion in beta estimates even after this is taken into account. He provides empirical evidence that beta estimates exhibit further mean-reversion, even after the first beta estimate is adjusted (Table 3).

In summary, the Vasicek adjustment is a weighting scheme which accounts only for statistical estimation error. It corrects a bias in regression-based estimates of beta, where bias refers to the tendency for low beta *estimates* to understate the true beta, and high beta *estimates* to overstate the true beta.

5.2 What is the prior expectation?

The ERA does not refer to the Vasicek adjustment but does refer to the Blume adjustment, and the weights adopted by Bloomberg in the implementation of this adjustment. The concern of the ERA is that there is no reason to think that the prior expectation of beta is equal to one. In explaining why there is no adjustment to regression-based beta estimates the ERA states (p. 163):

> Overall, the Authority considers that the lower cash flow risk of regulated businesses results in a lower equity beta compared with the market, even with the higher observed gearing levels.

The ERA's view is that it has no *a priori* expectation of beta. Or in other words, we do not know whether below average cash flow risks or above average financial risks are likely to have the bigger impact on systematic risk. So we perform regression-based estimates of beta to make this assessment.

Our view is that we have *one* dataset available to make an empirical assessment of beta, a series of historical stock and market returns. The beta estimate from this single assessment has some probability of lying above or below the true estimate. As Vasicek (1973) and Cunningham (1973) established, the probability of the estimate being too high or too low, compared to the true beta, increases as the standard error rises. The ERA view is that it has no way to determine in which direction any adjustment should be made, because it does not have a prior expectation.

However, the nature of systematic risk is that there is a prior expectation, and that is the market beta of one. It is a cost of capital parameter in which there is clearly a prior expectation because, by construction, the market capitalisation-weighted average beta is equal to one. To see this result, suppose we had the case in which the regulator was tasked with setting the rate of return for an entirely new industry, call it Industry X. There is no data on listed firms in this industry, no financial statements and no analyst forecasts. We propose that the only feasible course of action would be for the regulator to adopt a beta estimate of one, because it simply has no way to determine whether this is an industry with above- or below-average risk, yet it does know for certain that the typical firm has a beta equal to one.

Now suppose that the regulator learns that the industry has above-average financial leverage. All else being equal, this would imply above-average systematic risk. But the regulator also knows, as pointed out by the ERA, that above-average financial risk is a feature of firms with below-average cash flow risk. Given no other information, we propose that the only feasible course of action would be to continue to assume a beta estimate of one, because the regulator has no data to assess whether above-average financial risk or below-average cash flow risk has the bigger impact.

The regulator is then provided with returns data for a set of listed firms in the same industry, along with market data. The previous day the regulator had no information upon which to depart from an estimate of one. Now the regulator can perform a regression-based estimate of risk. The prior expectation is one, and the adjusted beta estimate would be a weighted average of the prior expectation and the regression-based estimate, given the result that Vasicek (1973) established.

If, in our example, the regulator used some information to quantify the prior expectation prior to performing the regression-based analysis, the prior expectation could be different from one. But the only data used to quantify beta was the regression analysis, so the prior expectation couldn't deviate from one.

In regulating network energy businesses, the ERA is in the same position. It has elected to estimate beta only with regards to regression of stock returns on market returns. So prior to observing the outcome from the regression, it could form no view as to whether financial risk or cash flow risk had a bigger impact on beta. Merely repeating the regression analysis several times with different weights on observations does not attest to the true beta of the firm. This are all measurements of what the association between stock and market returns was during one particular time period.

If, however, the regulator had some information other than regression-based estimates of risk, upon which to form a prior expectation, the prior expectation could be different from one. So we submit to the ERA that it either (a) adopt the Vasicek adjustment with a prior expectation of one; or (b) if it elects to form an alternative prior expectation, quantify this expectation with data analysis.

5.3 Empirical verification that the Vasicek adjustment increases reliability

We performed an empirical analysis of the difference in outcomes from beta estimates that do, and do not, incorporate the Vasicek adjustment. This analysis is contained in our report entitled *The Vasicek adjustment to beta estimates in the Capital Asset Pricing Model* (Gray, Hall, Diamond and Brooks, 2013b). We compiled beta estimates for samples in which at least 36 four-weekly returns were available for analysis (2.75 years) and for which at least 131 four-weekly returns were available for analysis (10 years). Estimates were compiled using all available returns once these thresholds were met. For individual firm estimates, the standard deviation of beta estimates is reduced from 0.53 to 0.43 with the application of the Vasicek adjustment, when at least 10 years of returns are available for analysis (Table 1, Panel A). When at least 36 four-weekly returns are available for analysis, the standard deviation of beta estimates is reduced from 0.77 to 0.46 (Table 1, Panel B).

The empirical question is whether this reduction in dispersion increases the reliability of beta estimates (by mitigating estimation error leading to very high or low OLS estimates) or whether it reduces the reliability of beta estimates (by moving beta estimates further away from the correct estimate of risk). Our contention is that the reliability of beta estimates will be improved, because very high and low beta *estimates* are have a high probability of being observed just by chance. The alternative view, consistent with the ERA's decision not to make an adjustment, is that the unadjusted estimates are more likely to represent the reliable measure of risk.

To answer this question, for each stock we used its beta estimate to form an estimate of expected returns, conditional upon the government bond yield and market return observed over the subsequent four weeks. For example, if the beta estimate from historical returns was 1.20, the government bond yield was 0.5% per four weeks, and the market earned a return of 1.0% in the next four weeks, we would expect the stock to earn a return of 1.1% [$r_f + \beta \times (r_m - r_f) = 0.005 + 1.20 \times 0.010 = 1.1\%$]. We then regressed the actual stock returns against expected returns, for portfolios formed according to industry and high, medium and low beta estimates.

We observed that the Vasicek-adjusted beta estimates performed better than unadjusted estimates. When Vasicek-adjusted estimates are incorporated in expected returns, and estimates are made using at least 10 years of data, we observe the following relationship, Realised returns = 0.31% + 1.01 × Expected returns, with an R-squared of 57.78% (Table 4, Panel A). In contrast, when unadjusted estimates are used the coefficient on expected returns falls to 0.96 and the R-squared falls to 56.59%.

If a beta estimate of one is used for all stocks, the R-squared is 54.54%. So the incremental explanatory power associated with either regression-based estimate is small, even when every beta estimate is compiled using at least 10 years of returns information. This is consistent with our earlier discussion about the variation of beta estimates across different small samples in the same industry, and the variation over time of beta estimates for the same sample. But the evidence shows that if regression-based estimates of beta are going to be used at all, the Vasicek adjustment leads to beta estimates that are more reliable estimates of expected returns. The evidence from this report is also consistent with the evidence we have previously presented in our article *Bias, stability and predictive ability in the measurement of systematic risk* (Gray, Hall, Klease and McCrystal, 2009).

5.4 Other consideration of the market beta of one

There is another reason to give consideration to the market beta of one, which is unrelated to the mechanical, Vasicek adjustment to beta estimates from regression. The reason is that there exists the very real possibility that the implementation of the CAPM, with regression-based estimates of beta on a small sample, generates cost of capital estimates that are entirely unreliable. The ERA has elected to exclude other asset pricing model (Black, 1972; Fama and French, 1993) and other sources of information (in particular, analyst forecasts and overseas-listed firms). So the only quantitative information available to estimate risk is the regression-based estimate of beta using six firms, one of which is no longer listed. In reaching a final beta estimate, we submit that the implementation of the CAPM in this manner is of such low reliability that some weight should be placed upon an alternative view – that the systematic risk could well be equal to the average firm in the market.

The ERA already makes this type of assessment in regulatory decision, but in a manner that is non-transparent. It reports regression-based estimates of beta and then reaches a conclusion on beta which differs from this estimate according to other considerations. This is typically referred to as regulatory judgement. All we propose is that the regulator reach a final conclusion by placing weight on its quantitative assessment of beta, and weight on the market beta of one, with the weights determined according to its regulatory judgement and then written down.

This is exactly the transparency in decision-making that will appeal to investors. If new information comes to hand which increases the reliability of the quantitative assessment of beta, the weight on this estimate can be increased. If new evidence comes to light to suggest the quantitative measurement has limitations, the weight on a beta of one can be increased. This means that the ERA's preference for regulatory stability is achieved, but with clarity as to why estimates change from one decision to the next.

6. Beta estimates from LAD regression have a downward bias

The ERA and the AER have introduced LAD estimates of beta into consideration, in an attempt to mitigate the influence of outliers on OLS estimates. The ERA has introduced another two outlier-resistant estimation techniques, MM the Theil Sen estimates. These techniques are not generally used in estimating beta from the relationship between stock returns and market returns, but are used in other contexts. For instance, the ERA noted that we used MM estimates in our paper *Dividend drop-off estimates of theta,* prepared for the Australian Competition Tribunal (SFG, 2011).

Subsequent to the AER's reliance on LAD regression estimates we investigated whether these estimates are likely to lead to more reliable beta estimates than OLS regression. We performed a large sample analysis on Australian-listed firms using all available returns information from 1976 to 2012 for which at least 36 four-weekly returns are available. There were 2,585 firms in the sample.

We observed the LAD estimates are systematically lower than LAD estimates. For a sample in which at least 10 years of returns information is available for analysis, the average OLS beta estimate was 0.89, compared to 0.76 under LAD estimation (Table 1, Panel A). For a sample in which at least 36 four-weekly returns were available for analysis, the average beta estimates are 0.96 under OLS estimation and 0.81 under LAD estimation (Table 1, Panel B). So, on average, LAD estimates are approximately 0.15 lower than LAD estimates. This is a feature of OLS versus LAD estimates across industries. We compiled mean beta estimates for ten industry groups and observed that, for both samples, LAD estimates are lower than OLS estimates in all ten industries.

This observation is not a unique outcome of our sample of 2,585 Australian-listed firms over 36 years. We observe the same phenomenon in two other empirical papers from different markets relying upon different sample types. Mills, Coutts and Roberts (1996) compiled beta estimates for 65 companies listed in the United Kingdom following the announcement of a management buyout. The mean OLS estimate was 0.82 and the mean LAD estimate was 0.34. Chan and Lakonishok (1992) examined a sample of 661 initial public offerings in the United States. For the first 10 trading days they estimated the systematic risk of this sample by computing OLS estimates and trimmed quantile estimates. Trimmed quantile regression is an alternative technique to LAD estimation which also places less weight on returns further from the mean, and which generates similar coefficient estimates to LAD estimation. In this case, the beta estimate is made not by observing returns in time series for individual stocks, but by observing the returns on the sample of stocks each trading day. Over the 10 trading days examined the average OLS beta estimate was 1.66, the average trimmed quantile estimate was 1.08, and the trimmed quantile estimate is lower than the OLS estimate for every trading day.

Consider the beta estimates from these three papers together. We have samples from three markets (Australia, the United Kingdom and the United States), with different composition (all listed firms, buyout firms, IPOs), and in all three instances the outlier-resistant estimates are materially lower than OLS beta estimates. The justification for LAD estimation is that it leads to lower standard errors in cases in which the variables are not normally distributed. In the particular context of beta estimation, the LAD technique consistently reduces high OLS estimates by far more than it increases low OLS estimates.

Having observed the consistent result that LAD estimates of beta are lower than OLS estimates of beta, we performed a controlled test to ensure this result was not merely an artefact of the three samples described above. We know that the market capitalisation weighted average of beta estimates must be equal to one, provided security weights are constant over the estimation period and all sample firms are used to construct the market. So we formed a market using all firms for which returns information was available over a ten-year period, held weights constant at beginning market value weights, and computed OLS and LAD estimates of beta.

We verified that the market capitalisation-weighted OLS beta estimate was exactly equal to one. We then observed that the market capitalisation-weighted LAD beta estimate was less than one (Table 3). This demonstrates that a bias exists in LAD estimates of beta. For a sample in which 10 years of returns are available for analysis, the market capitalisation weighted average LAD estimate is 0.98.

While this difference may appear small, in application to cost of capital estimation the bias is *much larger,* and will be closer to the figure of 0.15 noted earlier with respect to the descriptive information. We decomposed our sample into the largest 20 stocks by market capitalisation versus the remaining stocks. The average difference between OLS and LAD estimates of beta was 0.03 for the top 20 stocks, but this average difference increases to 0.18 for the remaining stocks in the sample. It is the broad sample of stocks used in comparable firm analysis that forms the basis for conclusions on equity beta. So, on average, across the broad sample of stocks, application of the LAD technique will result in estimates that are understated by about 0.15.

We have not performed the same empirical test for bias on the MM regression. But we note that whether the regression technique generates a biased result or not will depend upon the specific characteristics of the type of data being analysed. Our test for bias in LAD estimates is a test of whether the technique leads to downward bias in beta estimates, derived from regressing stock returns on market returns. It is the combination of returns data and the estimation technique which result in the bias. So our recommendation to the ERA is to perform the same empirical test on MM regression, or any other regression technique, in order to document whether or not there is a downward bias in regression-based estimates of beta.

7. Conclusion

The estimation of systematic risk using regressions of historical stock returns on market returns leads to substantial estimation error. This estimation error is particularly large in small samples. For firms in the same industry, there is large variation across different samples of firms. Holding constant the sample of firms, there is large variation over time in the beta estimates. Furthermore, the ability of regression-based estimates of systematic risk to predict stock returns is only a small degree better than the assumption that all stocks have a beta estimate of one. Merely estimating beta using a set of different regression techniques on the same dataset does not overcome the small sample problem. And with respect to predictive ability, this improves with the application of the Vasicek adjustment.

Given this evidence we submit to the ERA that its beta estimates will be more reliable if it:

- Incorporates evidence from U.S.-listed firms into its analysis, to mitigate against the small sample problem – estimates have already been compiled in an objective and transparent manner in the report *Regression-based estimates of risk parameters for the benchmark firm;*

- Incorporates information other than stock and market returns into its analysis – one set of information which could be used is analyst forecasts, from which we inferred a beta estimate of 0.96, and which is detailed in the report *Dividend discount model estimates of the cost of equity*.

- Adjusts its regression-based estimates slightly towards one on the basis of the Vasicek adjustment, supported by the empirical evidence in the report *The Vasicek adjustment to beta estimates in the Capital Asset Pricing Model.*

- Does not include estimates from LAD regression, on the basis that these estimates have a downward bias, as documented in the report *Comparison of OLS and LAD regression techniques for estimating beta.* Alternative robust regression techniques should also be tested for bias and excluded if a bias is present.

- Places weight in decision-making on a beta estimate of one, on the basis that estimation error is so high that there remains the very real possibility that the systematic risk of a network energy business, geared to 60%, exposes equity holders to the same risk as the average firm in the market.

A beta estimate within the range of 0.82 to 1.00 is consistent with the information presented above and which is contained in those reports. The figure of 0.82 is a weighted average of estimates from Australian- and U.S.-listed firms, which places twice as much weight on each of nine Australian observations compared to each of 56 U.S. observations. The figure of 0.96 estimated from analyst forecasts lies within this range, and the upper bound represents the potential for estimation error to be sufficiently large that it can’t be determined whether there is above- or below-average systematic risk.

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9. Appendices

9.1 Allocation of ABS industry sectors to ICB industry sectors

ABS industry sector	Industry value added ($m)	Industry value added (%)	ICB Industry	ICB Subsector or higher level
Manufacturing				
Food, beverage & tobacco products	22,961	1.8%	3000 Consumer goods	3533 Brewers
				3535 Distillers & vintners
				3537 Soft drinks
				3577 Food products
				3785 Tobacco products
Textile, leather, clothing, footwear	6,775	0.5%	3000 Consumer goods	3763 Clothing & accessories
				3765 Footwear
Wood, pulp & paper products	7,004	0.6%	1000 Basic materials	1733 Forestry
				1737 Paper
Printing & recorded media	3,848	0.3%	5000 Consumer services	5557 Publishing
Petrol., coal, chem., poly., rubber	18,058	1.5%	1000 Basic materials	1350 Chemicals
Non-metallic mineral products	4,615	0.4%	1000 Basic materials	1775 General mining
Primary & fab. metal products	22,331	1.8%	1000 Basic materials	1750 Industrial metals & mining
Tran. equip., mach. & equip. prod.	21,215	1.7%	2000 Industrials	2750 Industrial engineering
Furniture & other manufacturing	na	na	3000 Consumer goods	3720 H'hold goods & home con.
Total manufacturing	106,808	8.6%		
Mining				
Coal	24,597	2.0%	1000 Basic materials	1771 Coal
Oil & gas	24,696	2.0%	0001 Oil & gas	0500 Oil & gas
Other mining	80,514	6.5%	1000 Basic materials	1773 Diamonds & gemstones
				1777 Gold mining
				1779 Platinum & precious met.
Services to mining	10,140	0.8%	2000 Basic materials	2753 Comm. vehicles & trucks
				2757 Industrial machinery
Total mining	139,947	11.3%		
Services				
Elec., gas, water & water svcs	33,358	2.7%	7000 Utilities	7500 Utilities
Construction	107,749	8.7%	2000 Industrials	2530 Construction & materials
Wholesale trade	63,229	5.1%	5000 Consumer services	5333 Drug retailers
				5337 Food retailers & w'salers
				5371 Apparel retailers
				5373 Broadline retailers
				5375 Home improve. retailers
				5379 Specialty retailers
Retail trade	63,573	5.1%	5000 Consumer services	5333 Drug retailers
				5337 Food retailers & w'salers
				5371 Apparel retailers
				5373 Broadline retailers
				5375 Home improve. retailers
				5379 Specialty retailers
Accommodation & food services	33,564	2.7%	5000 Consumer services	5753 Hotels
				5757 Restaurants & bars
Transport, postal & warehousing	70,833	5.7%	2000 Industrials	2771 Delivery services
				2773 Marine transportation
				2775 Railroads
				2777 Transportation services
				2779 Trucking
Information media & telecom.	41,389	3.3%	6000 Telecom.	6535 Fixed line telecom.

ABS industry sector	Industry value added ($m)	Industry value added (%)	ICB Industry	ICB Subsector or higher level
				6575 Mobile communications
Financial & insurance services	137,549	11.1%	8000 Financials	8300 Banks
				8500 Insurance
				8700 Financial services
Rental, hiring & real estate services	30,256	2.4%	8000 Financials	8600 Real estate
Professional, scientific & tech. svcs	92,960	7.5%	2000 Industrials	2790 Support services
Administrative & support services	33,603	2.7%	2000 Industrials	2790 Support services
Public administration and safety	71,421	5.7%	Unclassified	
Education & training	60,714	4.9%	Unclassified	
Health care & social assistance	85,240	6.9%	4000 Health care	4530 Health care equip. & svcs
Arts & recreation services	11,629	0.9%	5000 Consumer services	5755 Recreational services
Other	25,880	2.1%	Unclassified	
Total services	962,947	77.4%		
Agriculture, forestry & fishing				
Agriculture	29,854	2.4%	3000 Consumer goods	3573 Farming & Fishing
Forestry & fishing	4,316	0.3%	3000 Consumer goods	3573 Farming & Fishing
Support services	na	na	3000 Consumer goods	3573 Farming & Fishing
Total agriculture, forestry & fishing	34,170	2.7%		
Total	1,243,872	100.0%		