

Estimating the yield on a benchmark corporate bond in January 2015, June/July 2015 and November/December 2015: Analysis to support the transition to a trailing average rate of return on debt

A SUBMISSION PREPARED FOR UNITED ENERGY TO ACCOMPANY UNITED ENERGY'S REVISED REGULATORY PROPOSAL.

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Introduction

1.1 Overview

1.1.1 Background on transitional issues and third party indicator series

The Australian Energy Regulator (AER) has proposed that the method by which the rate of return on debt is evaluated for a regulated energy utility should transition from an 'on-the-day' approach to a 'trailing average' approach.

In a report prepared for Jemena Gas Networks, the Competition Economists Group, (CEG), argued that there were two distinct steps in estimating the allowed cost of debt for any entity including the benchmark efficient entity that is the focus of the AER's attention^{[1](#page-7-3)}. CEG reported that, as a matter of logic, there was a need to consider the requirements of the National Electricity Rules and/or the National Gas Rules, and then:

- Define a financing strategy for a "benchmark efficient entity with a similar degree of risk as that which applies to the service provider in respect of the provision of reference services"; and
- Estimate the "efficient financing costs" of implementing that strategy.

When considering alternative debt management strategies, CEG examined the hybrid form of the transition to a full trailing average, portfolio return on debt. CEG did not recommend or advocate that a business should adopt the hybrid approach for the transition, as such. However, CEG did suggest that the hybrid method for the transition might be appropriate for a benchmark efficient entity which had, in the past, pursued a hybrid debt management strategy in response to the on-the-day approach to setting the allowed cost of debt. A hybrid debt management strategy would have entailed the active use of interest rate swaps to manage base rate risk. CEG was nonetheless careful to advise that the hybrid technique was one of a number of possible feasible and replicable debt management strategies^{[2](#page-7-4)}. Under a hybrid transition, the cost of debt would be calculated by considering the sum of the following components:

- An historical average value of the spreads over swap, measured over the nine years that precede the current reference period. For the contemporaneous averaging period, the value of the spread to swap is also worked out.
- An average of the swap rates for interest rate swaps that have been taken out in the initial averaging period. The swaps have tenors ranging from one to ten years, and are used to fix base rate exposure on the debt that would have been raised prior to the start of the transition period.
- The transactions costs of engaging in swaps are also included. There may also be an estimate of the new issue premium.

 2 Hird, T. and Young, D. (2015a), paragraphs 47 and 116.

¹Hird, T. and Young, D. (2015a), section 2.1, paragraph 38.

The AER, for its part, has argued that the hybrid debt management strategy was the uniquely efficient debt management strategy in the past. The AER has expressed the view that the hybrid strategy was associated with hedging 100 per cent of the base rate of interest exposure, and that the hybrid also provided the best hedge to the on-the-day allowance. Nevertheless, the AER has still not permitted a direct transition from the hybrid strategy to the trailing average debt management strategy.

More recently, CEG (2015d) has undertaken an empirical analysis of the efficient use of interest rate swaps^{[3](#page-8-1)}. CEG (2015d) made use of datasets from Australia and the USA, and examined the extent of hedging (via the use of interest rate swaps) that would minimise divergences between the regulatory allowance and the cost of debt. CEG (2015d) posited that the percentage use of interest rate swaps that minimised the standard deviation of the divergence between the regulatory allowance and the cost of debt would be the strategy that minimised interest rate risk. CEG (2015d) concluded from its analysis and from a literature review that under the 'on-the-day' regulatory regime, the base rate risk for a benchmark efficient entity would have been attenuated if hedging had been applied to around one third of base interest rate exposure at the beginning of the regulatory period. The remaining two thirds of the debt portfolio would not have been affected by the application of interest rate swaps and would therefore be appropriately modelled by using a trailing average of past debt costs.

There are advantages in using third party data sources to estimate historical values for the spread over swap, or for the debt risk premium. The advantages are simply that the data is readily available, with the AER relying upon the Bloomberg BFV BBB curve, the Bloomberg BVAL BBB curve, and the measures of corporate bond spreads prepared by the Reserve Bank of Australia (RBA)^{[4](#page-8-2)}. However, extrapolation methods must be applied to the results obtained from the third party, published data sources, because, in general, the cost of debt is not published at an actual tenor of ten years. The benchmark efficient entity is presumed to issue debt with a term to maturity of ten years. ESQUANT has analysed different methods of extrapolating the third party indicator series for debt, and has reported separately on the outcomes from the application of these methods (see ESQUANT, 2015a).

For current and prospective averaging periods, third party indicator series can be used to determine a contemporaneous result for the return on debt at a benchmark term to maturity of ten years. ESQUANT (2015c) reported that the extrapolation method described by the SA Power Networks was the best technique overall because it achieved the lowest scores on root mean squared error (RMSE). The SA Power Networks method was compared to Local Linear Smoothing, and to an alternative method described by Lally (2014a).

There is, however, no a priori reason for relying on third party indicator series. In particular, ESQUANT (2015a) did not suggest that there should be a predilection in favour of the use of third party indicator series when primary data on bond yields and prices is simultaneously available, and when robust empirical techniques can be brought to bear in the analysis of that data. For example, Nelson-Siegel yield curves have desirable attributes which include parsimony, in terms of theoretical specification, and flexibility in terms of functional form. ESQUANT has applied Nelson-Siegel yield curve methods in several, separate exercises (see ESQUANT 2013a, 2013b, 2014, 2015a).

1.1.2 Review by Professor Erik Schlögl

Professor Erik Schlögl undertook a review of the CEG report on the hybrid debt management strategy, and the immediate adoption of a transition to a trailing average rate of return on debt (Schlögl, 2015). The comments made by Schlögl can be summarised as follows^{[5](#page-8-3)}:

- As noted by CEG, a belief that the hybrid debt management strategy was uniquely efficient can be regarded as unreasonable.
- • However, under an assumption that the hybrid debt management strategy was uniquely efficient, the regulated cost of debt should be calculated by considering that for ten-year debt issued in the prior regulatory period on an evenly staggered basis, swap arrangements based on

³Hird, T. (2015d). ⁴See AER (2015), section H.2, page 3-539. 5 Schlögl (2015), paragraph 6.

the hybrid strategy would be in place. For the unhedged debt risk premium component of the regulated cost of debt, there should be an immediate transition to the trailing average.

Schlögl also reported that he concurred with the approach, posited by CEG as to how the efficient cost of debt for a benchmark entity should be estimated. Schlögl further stated that he agreed, in broad terms, with the economic and statistical arguments set out in the CEG and ESQUANT reports. Regarding ESQUANT (2015a), Schlögl commented as follows^{[6](#page-9-1)}:

If one restricts oneself to evaluating methods of extrapolation solely as curve-fitting exercises, the analysis presented in the ESQUANT and CEG reports is reasonable and I agree with its conclusions. Alternatively, one could consider applying the method of Nelson and Siegel (1987) for extrapolation, or using a fully consistent, arbitrage-free econometric model for interest rates and credit spreads.

Schlögl therefore lent support to empirical work involving Nelson-Siegel yield curves. The estimation of Nelson-Siegel yield curves and par yield curves forms the focus of the current report. Schlögl referred in passing to a published paper by Christensen et al. (2011). The authors of that paper noted that the Nelson-Siegel model is a flexible curve that provides a remarkably good fit to the cross section of yields in many countries. The NS curve was also reported to be popular among financial market practitioners and central banks.

The empirical exercise undertaken for this report by ESQUANT has benefited from the insights offered by Diebold and Rudebusch (2013), who were co-authors with Christensen.

In principle, there is also no reason as to why Nelson-Siegel yield curves cannot be applied retrospectively, to estimate annual observations on the cost of debt for periods in the past. The only limitation is the availability of data on bond yields and bond prices.

1.2 Summary of Findings

The empirical work that was conducted for this report expands upon the Nelson-Siegel analysis which is described in section 5.5 of CEG (2015a). The findings of this report should therefore be considered in conjunction with the empirical work performed by CEG. The results from the estimation of yield curves and par yield curves should also be considered in the context of the efficient debt management strategies that have been discussed by CEG. The results for the spot cost of debt over a measurement period form an input into one of a number of possible transition approaches.

Under the simple trailing average strategy the business maintains a largely evenly staggered portfolio of 10 year debt. Consequently, the cost of debt for the business in any year is simply the trailing average of the rates or yields on 10 year term to maturity corporate debt that has been issued over the past ten years.

If an optimal hedging ratio is the appropriate method for the transition to a trailing average rate of return on debt, then the results from yield curves can be used to inform the prevailing cost of debt in each year of the transition.

The empirical techniques that have been applied by ESQUANT were discussed in ESQUANT (2013b). Hence, the current report is, in large measure, an update of the earlier developmental work that was undertaken by ESQUANT.

The remainder of the executive summary is divided into sub-headings which correspond to the different sections of the report.

Nelson-Siegel models (sections 2.1, 3.2, 4.2, and 5.2 of this report).

The Nelson-Siegel equation that is used for a significant part of the empirical analysis in this report estimates the yield on a bond with *τ* years to maturity to be:

 6 Schlögl (2015), paragraphs 22 to 24.

$$
y(\tau) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\tau e^{\beta_0}}}{\tau e^{\beta_0}} \right) + \beta_3 \left(\frac{1 - e^{-\tau e^{\beta_0}}}{\tau e^{\beta_0}} - e^{-\tau e^{\beta_0}} \right) +
$$

$$
\beta_4 \text{BBB} - \beta_5 \text{BBB} + \beta_6 A - \beta_7 A
$$

where BBB- is a dummy variable taking the value 1 for BBB- bonds and 0 elsewhere; BBB+ is a dummy variable taking the value 1 for BBB+ bonds and 0 elsewhere, A- is a dummy variable taking the value 1 for A- bonds and 0 elsewhere, A is a dummy variable taking the value 1 for A bonds and 0 elsewhere, and the λ parameter, which should be positive, has been reparameterised as

$$
\lambda=e^{\beta_0}.
$$

Response to Lally (2015b) report, Review of submissions on implementation issues for the cost of debt

ESQUANT (2015) undertook an empirical examination of the possible methods for extrapolating, to an effective tenor of 10 years, the measures of corporate bond spreads that are produced by the RBA.

Lally (2015b) accepted the argument by ESQUANT (2015) that an appropriate method for assessing extrapolation techniques was to examine the root mean squared error (RMSE) associated with each method. Using RMSE, the AER (Lally) extrapolation method was shown to perform relatively poorly, while the SA Power Networks method performed better. Lally then argued, however, that the relative ranking of the AER method would improve in a context in which averaging was applied to monthly figures for the cost of debt. Lally assumed that if the AER's preferred form of the transition to a trailing average, portfolio return on debt were imposed, then the monthly results for the cost of debt would be used as inputs into the calculation of an arithmetic mean. Since the calculation of averages moderates the variability in the results for an estimator over time, then the RMSE of the AER method would progressively diminish over time, and the relative ranking of that technique would improve.

However, Lally (2015b) made a statistical error in his calculations. He treated the monthly results for the cost of debt as a series of independent observations. ESQUANT (2015) had prepared cost of debt figures which were based on the application of an extrapolation technique to the monthly RBA measures of corporate bond spreads. In practice, however, as has been demonstrated by ESQUANT in this report, the monthly results for the extrapolated series are highly serially correlated. In the presence of autocorrelation, the variance of the estimates of the cost of debt does not diminish in proportion to the reciprocal of the square root of the sample size, as had been assumed by Lally. Thus, the averaging of monthly results from the AER extrapolation method will not cause the variance to fall to the same degree, and hence the RMSE will remain above that recorded for other extrapolation methods.

The RBA only produces its results for corporate spread measures on a monthly basis. However, if daily observations for the cost of debt at a 10-year tenor are used from other sources, then the sample autocorrelations are likely to be even higher than those calculated using monthly data. There would then be even less prospect of an improvement in the performance of the AER extrapolation approach as the number of observations available for averaging increased. The reason is that more pronounced serial correlation causes the variance of the estimates to fall by less.

The AER (Lally) extrapolation method, as documented in Lally (2014a) is discussed further in the section on the analysis of third party indicator series (see below).

Data on bond yields and prices (sections 3.1, 4.1, and 5.1 of this report).

The empirical work that was undertaken for this report necessitated the use of data from three averaging periods January 2015, June/July 2015, and November/December 2015. Thus, at a minimum, data was required for the three specific time intervals that were considered. Ultimately, however, data was retrieved for the entire period from 31st December 2014 to 11th December 2015 so as to permit time series investigations to be conducted. Information on bond prices, yields and other variables to do with corporate bonds was sourced using the Bloomberg subscription service.

A broad sample of bonds was considered, with few restrictions imposed on sample selection. The bonds that were analysed were classified as investment grade by Standard and Poor's, and had credit ratings of BBB-, BBB, BBB+, and A- or A (flat). Bonds with a remaining term to maturity of less than three months were not used because these bonds can exert a disproportionate effect on the shape of Nelson-Siegel yield curves. Bonds with negative option adjusted spreads were also not used.

Accordingly, the dataset that was used for the econometric analysis of standard, Nelson-Siegel yield curves was comprised of bonds that possessed the following attributes:

- An investment grade credit rating from Standard and Poors, in the range of A to BBB-. The credit rating that was used was that for the individual bond, for the particular day. However, if a bond credit rating was not available, then an issuer credit rating would be applied.
- The remaining term to maturity was at least three months.
- Option-adjusted spreads were available, and these were positive for at least one day of the relevant averaging period. The core dataset was labelled as Data1, and there are references to this main sample of data throughout the report.

The dataset, Data1, consisted of 844 bonds for the first averaging period, 930 bonds for the second averaging period, and 936 bonds for the third averaging period.

Other sub-samples of data were also employed in different parts of the analysis. Data2 was formed from Data1, but did not contain bonds denominated in foreign currencies. Data3 was also formed as a sub-sample of Data1 but the exclusion in this case was bonds issued by firms operating in the financial sector^{[7](#page-11-0)}. Data4 was a further subset of Data3 which was compiled by dropping the foreign currency denominated bonds from Data3.

When selecting a core sample of bonds for use in the estimation of par yield curves, the criteria that were applied overall were similar. The attributes that were deemed to be relevant can be itemised as follows:

- An investment grade credit rating from Standard and Poor's, in the range of A to BBB-.
- The remaining term to maturity was at least three months.
- Dirty (mid) prices were available for at least one day of the relevant averaging period. The dirty 'mid' price is the full mid-price of the bonds that includes the accrued interest that the seller is entitled to receive.

The framework for the retrieval and processing of bond data was a model that has been developed by the Competition Economists Group (CEG) and which is termed the "RBA replication model". The model compiles and processes bond data for use in empirical analysis. The model also applies the Gaussian kernel calculation method to samples of bonds that have been chosen by the user. The "RBA replication model" was used and updated by ESQUANT with permission from CEG.

For the Nelson-Siegel yield curves, the bonds employed in the analysis were denominated in Australian dollars, British pounds, US dollars and euros. The yields that were used were obtained by adding swap rates (at a commensurate tenor) to option-adjusted spreads. The OAS on foreign currency bonds were transformed into Australian dollar equivalent option-adjusted spreads. The method of transformation has been specified by CEG, and involves the use of conversion factors, basis swaps and basis change swaps.

For the par yield curves, attention was confined to Australian dollar denominated bonds only. Bond prices were used in the analysis, specifically "clean prices" and "dirty prices".

The overall samples of data used were generally large. A limited number of restrictions were imposed, and these are discussed from section 3 onwards.

 7 The industry classification system used was that provided by Bloomberg.

Reporting of the results for different credit ratings

The results from the yield curve estimations that have been presented in this report are commensurate with a credit rating from the broad BBB band. Although separate intercept terms were determined for each of the five credit ratings from A to BBB-, ESQUANT has calculated a weighted average of results across BBB-, BBB, and BBB+ categories. The results that are reported in this manner are the yields at terms to maturity of 7 years and 10 years, respectively.

The weights that were used in the computation of the weighted average depended upon the comparative fractions of BBB- and BBB+ bonds that were in the sample which was used for the particular estimation. The proportions were worked out as ratios of the total number of bonds across the BBB band. Note that there is no separate dummy variable for BBB (flat) bonds, the default value of the intercept term, β_1 , is for BBB (flat).

The numbers of bonds in the A- and A credit rating categories were not relevant to the computation of a weighted average result for debt securities in the BBB band. Although there are separate dummy variables for A- and A rated bonds, the parameter estimates for these intercept terms were not invoked when working out the weighted average yield for bonds in the broad BBB credit rating band.

An explanation of this aspect of the approach has been provided in section 2.1 of this report.

The rationale for reporting the results from yield curves in this manner is so as to ensure proper and fair comparability with the results from the published third party indicators of the cost of debt. ESQUANT is aware of three third party indicator series for Australian corporate BBB rated debt. These third party indicators are the Bloomberg BBB rated BVAL curve, the RBA measure of corporate, nonfinancial spreads for BBB rated bonds, and the Thomson Reuters BBB credit curve for Australian dollar denominated debt. The three third party indicator series publish yields at different tenors for bonds that fall within a broad class of a BBB rating. There is no finer split within the BBB band of BBB-, BBB (flat) and BBB+. In fact, there is documentation available from Thomson Reuters which expressly disavows such a disaggregation 8 .

For the par yield curves, however, the results for the spot rates and for the par yields that are presented in this report are commensurate with a BBB (flat) credit rating.

Results from the standard Nelson-Siegel yield curve estimations

An arithmetic average of the daily observations was used for each of the reference periods.

In order to ascertain the precision of the results, one must calculate standard errors for the parameter estimates, and for the estimates of the debt risk premium. Standard errors from a non-linear regression rely on an assumption that the non-linear mean function can be approximated locally by a linear function of the parameters.

The Nelson-Siegel equation is a non-linear formulation. However, if one of the parameters (β_0) is held constant, then the equation becomes linear in the other parameters, thereby simplifying the analysis. Note, however, that, as was mentioned above, β_0 is the result of a re-parameterisation of the Nelson-Siegel yield curve equation. The re-parameterisation was designed to improve the estimation of the model, rather than to change it.

The reference time interval for the third averaging period was 13th November 2015 to 10th December 2015. As has been noted, the data sub-sample, Data3, was drawn from the broader dataset, Data1, however Data3 excludes the bonds issued by financial institutions. For a benchmark corporate bond with a 10-year term to maturity, the cost of debt obtained by applying the R n1sLM() function to the data sub-sample Data3, was estimated to be 5.670%. This result was in respect of the third averaging period. The arithmetic mean value of the yields on 10-year Commonwealth Government Securities, (CGS), was 2.918% over the same reference period. Hence, the debt risk premium, relative to the yields on 10-year CGS, was worked out to be 2.752%. The standard error corresponding to the DRP estimate of 2.752% was assessed to be 0.070%. The low value of the standard error indicated that the debt risk premium evaluated for a 10-year term to maturity is highly statistically significant.

Again, using the same dataset, Data3, the DRP for a 7-year benchmark corporate bond was calculated to be 2.505%, with a standard error of 0.058%. The increment to the DRP, from 7 years to 10

⁸Thomson Reuters Credit Curve Methods, see references.

years, was calculated to be 8.225 basis points per annum (bppa), with a standard error of 1.337 bppa. Similar results were obtained for the other data sub-samples, Data1, Data2 and Data 4^9 4^9 .

Refinements to the methods applied (sections 3.3, 4.3, and 5.3 of this report):

There were a number of extensions to the methods used in sections 3.2, 4.2 and 5.2.

Robust analysis (sections 3.3.1, 4.3.1, and 5.3.1)

The regression residuals from the preliminary estimations of Nelson-Siegel yield curves were examined. A QQ plot presents the residuals, which are plotted on the y-axis, according to a 'quantile' distribution. Although the regression residuals were generally concentrated along a single trajectory, there was some evidence of the presence of outlying observations in the data. The outliers were apparent across all three of the averaging periods examined, and, in the third averaging period in particular. Accordingly, robust regression methods were employed. Robust regression makes use of MLE-like estimators (Venables and Ripley, 2008) and serves to moderate the impact of outliers. The R command nlrob() in the **robustbase** package was used in conjunction with the Nelson-Siegel model and the four datasets, Data1 to Data4. The results for the debt risk premium across the three averaging periods are shown in Tables 3.11, 4.11, and 5.11. For Data3, in respect of the third averaging period, the DRP at a 10-year tenor was found to be 2.804%, with a standard error of 0.076%. The increment to the DRP, from 7 years to 10 years, was calculated to be 9.216 bppa with a standard error of 1.521 bppa.

Analysis of daily results (sections 3.3.2, 4.3.2, and 5.3.2)

The analysis using robust regressions was carried out on yield data that had been averaged across the relevant reference periods. In other words, an arithmetic average of the daily observations on the yields for each bond had been taken, and the curves were then fitted to the resulting mean values. While the method worked satisfactorily, an alternative avenue for investigation was to examine the daily results within an averaging period so as ascertain whether or not there were wide fluctuations in the results.

Accordingly, Nelson-Siegel yield curves were fitted to the daily data for each of the averaging periods, and estimates were obtained using the R command nlsLM() in the **minpack.lm** package. The yields at a 7-year tenor, and at a 10-year tenor were worked out for each day. The daily results for the debt risk premium at a 7 year tenor, and at a 10-year tenor were also calculated. The estimated standard errors were used to determine 95% confidence intervals. The daily results have been plotted in Figures 3.11, 3.12, 4.10, 4.11, 5.10, and and 5.11.

An examination of the daily results for averaging period two suggests that there was a reasonable degree of stability within the period. The variation from day-to-day in the debt risk premium at 10 years appears to have been within reasonable bounds.

For averaging period three, the daily results also appear to move within relatively narrow confines for the first 14 days of the averaging period. However, there is a wider oscillation over the remaining days from day 15. The pattern of the results also suggests that there is serial correlation, with the outcome for the DRP on any one day bearing a close relation with the DRP outcome for the previous day.

The daily observations of yields, measured over a reference period for a large number of bonds, essentially give rise to a form of non-linear panel data. An appropriate way to analyse the daily results would be to apply a non-linear mixed effects model, with random effects for the long-term parameter for each bond, and auto-correlation from day-to-day for the yields for each bond. ESQUANT ran regressions using a non-linear mixed effects model in an analysis undertaken in 2013 (ESQUANT, 2013c).

⁹The complete sample of bonds, comprised of debt securities issued by firms in both the financial and non-financial sectors, was labeled Data1. The bonds in Data1 that were denominated in Australian dollars made up another dataset, labelled Data2. In addition, the bonds in Data1 and Data2 that were issued by firms other than those in the financial sector, were used in separate data sub-samples that have been labelled Data3 and Data4 respectively.

An advantage of using a mixed model specification is that it then becomes possible to take full account of the fixed effect of the influence of term to maturity on the average yield for bonds of a particular tenor. Hence, the focus is taken away from the yields of individual bonds. In addition, any criticisms about the practice of using an arithmetic average of the daily yield results in Nelson-Siegel equations can be circumvented.

Are common parameters justified? (sections 3.4, 4.4, and 5.4).

The Nelson-Siegel yield curves that have been estimated for this report fit a model for which the intercept terms exhibit variation for the different classes of bonds, but the parameters β_0 , β_2 , and β_3 are common. The assumption that the aforementioned parameters should take on the same values for each of five credit rating groups, for bonds used in the analysis, can be regarded as a form of restriction. The constraint was imposed so as to ensure that the estimated Nelson-Siegel yield curves satisfied certain properties, such as that the curve for a particular category of credit rating would not intersect with the curve for another credit rating category.

A test was devised so as to ascertain whether the restrictions could be justified on empirical grounds. An unrestricted version of the Nelson-Siegel equation was developed so as to allow the slope coefficients to vary across the five credit rating categories from A to BBB-. The unrestricted equation was formulated in such a way that there would still be a relationship between, say, the values of the parameter $β_0$, (now labelled $β_0^*$), across the credit rating categories, but that the relationship would be empirically determined. Additional coefficients were introduced into the unrestricted equation so as to allow for the deviations in the slope coefficients from one credit rating category to the next. When the unrestricted equation was estimated, the further coefficients were unconstrained, however, when the restricted specification was estimated, the further coefficients were set to zero.

A hypothesis test was conducted to investigate the validity of the restrictions. The test was carried out by comparing the residual sum of squares obtained from the restricted equation with the residual sum of squares from the unrestricted specification. The test statistic has an F-distribution under the null hypothesis.

The hypothesis tests were run in each of the averaging periods, and were applied to the four datasets, from Data1 to Data4. As might be expected, the results varied. However, the calculated F statistics were universally large for Data1, and so the null hypothesis that the restrictions were valid could be rejected. For averaging period three, the null hypotheses could not be rejected for Data3 and Data4, and so there was evidence to sustain the more limited parameterisation of the Nelson-Siegel yield curve equation.

Application of Nelson-Siegel yield curves to estimate par yield curves (sections 3.5 and 4.5).

The Nelson-Siegel model is a form of multi-factor, affine term structure model (ATSM), because it is a parametric, parsimonious form of the forward rate function (Christensen et al, 2011). As explained by Nelson and Siegel (1987), the discount rate function is obtained by integrating a forward rate function which is itself the solution to a second-order differential equation with real and unequal roots.

An important contribution of this report has been the development of par yield curves, which are a theoretically correct form of yield curve because the relationship between term to maturity and yield is modelled after adjusting the observations on bond yields for differences in coupon rates. An extended Nelson-Siegel method was applied, following a technique that has been described by Ferstl and Hayden (2010) and Bliss (2007). In the first instance, the method involved constructing a zerocoupon curve or spot rate curve by fitting the discount rate function directly to bond prices. An objective function was used which minimised the weighted squared value of the difference between fitted bond prices and actual (or "dirty") prices. The fitted prices were derived by discounting the stream of cash flows from each bond. The discount rates, in turn, were determined from the estimation of the Nelson-Siegel equation.

When minimising the unweighted price errors (the square of the difference between the fitted price and the actual price), bonds with a longer maturity obtain a higher weighting, due to a higher degree

of price sensitivity, which leads to a less accurate fit at the short end of the spot curve. Therefore, a weighting of the price errors has to be introduced to solve this problem, or to reduce the degree of heteroscedasticity, if this latter condition has affected the regression disturbances.

To quantify the sensitivity of a bond's price to changes in the interest rate, one needs to account for the fact that coupons may be paid during the lifetime of a bond. A standard measure of risk is the Macaulay duration, which is the average maturity of a bond using the present values of its cash flows as weights.

Macaulay duration was used as the weighting scheme under the extended Nelson-Siegel formulation. The contribution of the inverse duration of each bond to the sum of the inverse durations of all bonds was used to determine the weight allocated to each bond.

The spot rate curve or discount rate function was estimated first. Thereafter, a par yield curve was constructed from the term structure of estimated spot rates. The assumption made was that coupon payments would be paid on a semi-annual basis. The relationship between the spot rate curve and the par yield curve is explained by Schaefer (1977). A bond that trades at its 'par' value is a bond for which the coupon rate is equal to its yield.

Applying the results to different scenarios for the transition to a trailing average, portfolio return on debt

The third averaging interval, from 13th November 2015 to 10th December 2015, was nominated by United Energy and is the measurement period that has been used to record the yield on a benchmark 10-year corporate bond. The yield on 10-year debt forms an input into calculations of the rate of return on debt that will apply for the 2016 regulatory year.

ESQUANT has reviewed the output from the regressions for averaging period three. The analysis of variance produced relatively high F-statistics for Data1 and Data2. The implication is that the restricted model, which imposes common values of the slope coefficients for bonds in the five credit rating sub-groups was sub-optimal when the dataset was comprised of both finance and non-finance sector bonds.

For Data3, the null hypothesis of uniform slope coefficients across the sub-groups of credit ratings could not be rejected at the 5 per cent level of significance. Accordingly, the specification for the regression equation was sustained by the data.

The sub-sample of observations that has been labelled as Data3 contains both Australian dollar bonds and bonds denominated in foreign currencies (specifically, US dollars, British pounds, and Euros). However, Data3 omits bonds that have been issued by firms which operate in the finance sector. The industry classification system is that provided by Bloomberg.

Note that an explicit test has not been applied to differentiate between the results for bonds issued by firms which operate in the finance sector, and non-financial sector firms.

The residuals from the regressions that were run using conventional Nelson-Siegel yield curves have been examined. Figure 5.9 presents a quantile plot of the regression residuals and shows that for each of the four data sub-samples, there were outlying bonds that were brought into the estimations. The evidence for the outliers is the dispersion at the tail ends of each of the quantiles.

The presence of outliers suggests that robust regression methods should be used. For Data3, the estimation of the yield curve using a robust regression approach produced a cost of debt estimate of 5.722%, commensurate with a 10-year tenor. The standard error of the estimate was comparatively low at 0.076%. We consider that this result, which is expressed on a semi-annual basis, is the best estimate of the 10-year yield. The value can be used as an input into various transition scenarios for the rate of return on debt.

The estimate itself represents a weighted average of the 10-year yield estimates, obtained from Data3, for BBB-, BBB (flat), and BBB+ bonds. The weights that were applied to the bonds in these subgroups were determined by the shares of the bonds in the sub-groups expressed as a proportion of the total number of bonds in the overall BBB band. The relevant data sample was the list of observations actually used in the regression.

The estimated 10-year yield of 5.722% is not the highest that was recorded for the third averaging period. Table 5.16 shows an estimated 10-year yield of 6.021% which was obtained by running a

robust regression on a further sub-sample of bonds from within Data3. The more limited sub-sample was comprised only of bonds with credit ratings in the broad BBB band. The estimated 10 year yield is defensible and statistically significant, even though the standard error, at 0.148%, is higher than that in the previous example.

The estimated 10-year yield can be factored into one of a number of transition scenarios for the rate of return on debt.

- In the context of an immediate transition to the full trailing average method, the rate of return on debt will be 8.085 per cent for the 2016 regulatory year. The immediate transition makes use of historical data on spreads-to-swap, from 2006 to 2014, and historical 10-year swap rates, recorded over the same period.
- For the hybrid transition, the rate of return on debt will be 5.572 per cent. The hybrid transition also makes use of historical spread-to-swap data from 2006 to 2014. However, swap rates, at tenors from one to ten years, have been recorded during the most recent averaging period only. There are also the transactions costs of using swaps.
- Under the AER's rate of return guideline, the appropriate rate of return on debt for the 2016 regulatory year will be 6.082 per cent.
- Finally, if the approach is to consider the optimal hedging ratio of a benchmark efficient entity, then the appropriate value to use for the rate of return on debt will be 7.247 per cent. The optimal hedging scenario provides intermediate outcomes.

The figures mentioned in the bullet points above have been expressed as annual effective rates. An estimate of the new issue premium, of 27 basis points per annum, has been built into each of the scenarios. Details of the calculations are provided in chapter 6 of this report.

Analysis of third party indicator series including credit curves from Thomson Reuters

ESQUANT has reviewed the underlying data and results for the Thomson Reuters BBBAUD benchmark corporate credit curve for Australia and believes that the curve represents a credible third party indicator series. ESQUANT has also reviewed documents provided by Thomson Reuters (TR) which explain the methodology underpinning the development of the credit curves. ESQUANT believes that TR has applied satisfactory methods, which have been well researched, and that TR has good processes in place for the preparation of a whole suite of credit curves, used internationally. ESQUANT considers that the standard of documentation, in terms of the detail and transparency, surpasses that in the material provided by Bloomberg.

Separately, ESQUANT has reviewed the output from RBA Table F3, which presents aggregate measures of corporate bond spreads and yields, and has sought to reproduce the output using the RBA replication model. In particular, at the time of writing, the published results from RBA Table F3 were not available in relation to December 2015.

The RBA replication model has been applied over the measurement period for United Energy of 13th November 2015 to 10th December 2015. ESQUANT applied curve testing methods to assist in the determination of an appropriate method for extrapolating the spreads-to-swap from an effective tenor of 9.15 years, to an effective tenor of 10 years. The results of the tests, using both weighted and unweighted sums of squares, suggested that the SA Power Networks technique was the most suitable method. The SAPN technique makes use of the gradient of an average curve through the spreads-toswap at various tenors. The resulting spread-to-swap, after extrapolation, at a tenor of 10-years, was found to be 251.06 basis points.

ESQUANT (2015) reported previously that the SAPN method for extrapolating the estimates of the spread to swap produced by the RBA appeared to produce more precise (less variable) estimates than the Lally (2014a) method^{[10](#page-16-0)}. ESQUANT (2015) therefore recommended that consideration be given to use of the SAPN method when preparing estimates of the cost of debt that are based on the corporate bond series published by the RBA.

 10 Diamond, N.T. and Brooks, R. (2015a), page 6.

The Gaussian kernel method, applied by the RBA, has on a number of occasions, over the past 13 months, produced counter-intuitive results. The application of local constant smoothing by the RBA has delivered values for the 10-year spread-to-swap which are below the values for the 7-year spreadto-swap. There are no intrinsic term structure factors which should contribute to such an outcome. For instance, none of the Nelson-Siegel yield curves that have been estimated by ESQUANT show evidence of such a phenomenon. In the recent past, there has similarly been no evidence from other third party indicator series, of inverted yield curves between 7-years and 10-years. The Bloomberg BBB rated BVAL curve does not present a downward slope between the 7-year tenor and the 10-year tenor, when examining spreads-to-swap, and nor for that matter does the BBBAUDBMK credit curve produced by Thomson Reuters. Thus, the downward slope in the spread-to-swap between the 7-year tenor and the 10-year tenor appears to be an artefact of the methodology applied by the RBA.

Lally (2015b) has described the occurrence of the downward slope as being a "highly unusual" fea-ture^{[11](#page-17-0)}. However, he appears to have stepped away from a detailed discussion of the issue. The Lally extrapolation method accentuates the observed anomalies and therefore produces perverse results.

The Bloomberg BVAL BBB rated curve provides a 10-year yield of 5.5440 per cent over the third averaging period for United Energy, while the BBBAUD series from Thomson Reuters shows that the 10-year yield was 5.8528 per cent. An arithmetic average of the two sets of results delivers a 10-year yield of 5.6984 per cent.

The RBA does not prepare daily measures of corporate credit spreads, and its outputs are only available for the penultimate or final business day of the month. Accordingly, the results from the RBA replication model (originally developed by CEG, and then updated by ESQUANT) can be used in place of the published series. The 10-year yield from the RBA replication model, when extrapolated using the SA Power Networks method is 5.5275 per cent.

An arithmetic average of the two third party indicator series, and of the extrapolated yield from the RBA replication model, delivers a 10-year yield of 5.6414 per cent. This value, expressed on a semi-annual basis, can be transformed into an annual equivalent rate, producing a 10-year yield of 5.7210 per cent.

The AER has applied an arithmetic mean of two of out of three third party indicator series in its recent determinations for regulated energy businesses. The AER method has been given impetus by a theoretical analysis undertaken by Lally (2014a) which attempted to show that combining two data series would assist in bringing down the mean squared error (MSE). However, Lally simply assumed that each of the component data series would be unbiased^{[12](#page-17-1)}. Lally (2014a) did not perform empirical analysis.

An average of the published measures provides useful corroborative evidence, at this time, of the results from the application of yield curves and other empirical methods. However, an average of the third party indicator series will not always be optimal. ESQUANT does not provide an unequivocal endorsement of such an approach.

Further details of the third party indicator series are provided in Appendix A.

Conclusions

Nelson-Siegel curves can be used to estimate term structure models which provide an appropriate and accurate method of determining the cost of debt for different tenors.

We have estimated Nelson-Siegel models for four data sets and have also been able to produce standard errors, thereby providing a useful complement to fitting of Yield curves. Standard errors convey information about the precision of the empirical estimates. The results for the debt risk premium at 10-years, and for the increment to the DRP from 7 to 10 years, were shown to have low standard errors and to therefore be precise.

The estimation of par yield curves is a worthy exercise because these curves fully standardise and correct for differences between bonds that are caused by variations in the timing and size of coupon payments. We estimated zero-coupon yield curves or spot rate curves that belong to the family of Nelson-Siegel curves. Subsequently, we used these estimates to generate estimates of par yield curves.

¹²Lally (2014a), section 2.2, pages 21-22.

 11 Lally (2015b), section 2, page 8.

Schaefer (1977) shows how one can uncover the term structure of par yields from the term structure of spot rates.

1.3 Declaration

This report has been prepared by ESQUANT Statistical Consulting. The contact details for ESQUANT Statistical Consulting are:

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The authors of this report have read, understood and complied with the Expert Witness Guidelines as given by the Federal Court of Australia's Practice Note CM 7, entitled "Expert Witnesses in Proceedings in the Federal Court of Australia". We have made all the inquiries that we believe are desirable and appropriate and that no matters of significance that we regard as relevant have, to our knowledge, been withheld from this report.

Chapter 2

Yield curves, par yield curves, and a response to Lally

2.1 Nelson-Siegel Models

The most commonly used yield curve model is that due to Nelson and Siegel (1987). The Nelson-Siegel model is non-linear and must generally be estimated using the method of non-linear least squares. Arsov et al. (2013) report difficulties with fitting the Nelson-Siegel model. Annaert et al. (2013) explain methods which can be used to help overcome these computational problems.

The Nelson-Siegel model (Nelson and Siegel, 1987) relates the yield on a bond, *R*(*m*), to its remaining term to maturity, *m*, as

$$
R(m) = \beta_0 + (\beta_1 + \beta_2) \left(\frac{1 - \exp(-m/\tau)}{m/\tau} \right) - \beta_2 \exp(-m/\tau)
$$

where τ , β_0 , ..., β_2 are parameters to be estimated. The parameter τ is described as the shape parameter, with its value sometimes motivated by prior knowledge about the curvature of the spot rate curve.

Diebold and Li (2006) suggest an alternative parameterization:

$$
y(\tau) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\lambda \tau}}{\lambda \tau} \right) + \beta_3 \left(\frac{1 - e^{-\lambda \tau}}{\lambda \tau} - e^{-\lambda \tau} \right)
$$

where $y(\tau)$ is the expected yield of a bond with maturity τ , β_1 is interpreted as the loading on the "long-term" factor, β_2 is interpreted as the loading on the "short-term" factor, and β_3 is interpreted as the loading on the "medium-term" factor. The parameter λ govern the exponential decay rate; small values of *λ* produce slow decay and can better fit the curve at long maturities, while large values of *λ* produce fast decay and can better fit the curve at short maturities. *λ* also governs where the loading *λ* on *β*₃, that is $\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}-e^{-\lambda\tau}\right)$ reaches its maximum. See Diebold and Li (2006, Paragraph 3, p. 341.).

The equivalence between the two specifications is given below:

Note that *τ* is used as a parameter in the Nelson and Siegel formulation but as the Maturity in the Diebold and Li formulation. Diebold and Li's (2006, p. 341) specification can be written as a function of the three loadings, *F*1, *F*2, and *F*3, the loadings on the 'long-term', 'short-term', and 'medium-term' components with

$$
y(\tau) = \beta_1 F_1 + \beta_2 F_2 + \beta_3 F_3
$$

\n
$$
F_1 = 1
$$

\n
$$
F_2 = \left(\frac{1 - e^{-\lambda \tau}}{\lambda \tau}\right)
$$

\n
$$
F_3 = \left(\frac{1 - e^{-\lambda \tau}}{\lambda \tau} - e^{-\lambda \tau}\right)
$$

Diebold and Li (2006) suggest that, if the maturity is measured in months, that λ be set at 0.0609, since at that value the loading on the medium term factor (denoted by *F*3) is at a maximum when the maturity is 30 months^{[13](#page-20-0)}. Diebold and Li (2006) stated that most of the humps and troughs in the spot rate function are between the second and third years. Fixing *λ* allows the Nelson-Siegel model to be fitted by Ordinary Least Squares. If λ is estimated, then non-linear least squares is required.

In separate exercises, CEG (Hird, 2013c) and ESQUANT (Diamond et al., 2013b) have successfully estimated Nelson-Siegel yield curves for large groups of corporate bonds in credit rating bands from A- to BBB. The data samples were comprised of bonds issued by Australian corporations in Australian dollars and in foreign currencies, as well as Australian dollar bonds placed in the domestic market by foreign corporations. Fixed rate, bullet bonds were considered, as were bonds with optionality features, and floating rate notes. A number of different specifications of the Nelson-Siegel yield curve were trialed.

Following CEG (Hird, 2013c) and ESQUANT (Diamond et al., 2013b), dummy terms are added to take into account the different credit ratings. For example, if bonds in rating classes BBB- to A were to be considered, the model to be fitted is then

$$
y(\tau) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\tau e^{\beta_0}}}{\tau e^{\beta_0}} \right) + \beta_3 \left(\frac{1 - e^{-\tau e^{\beta_0}}}{\tau e^{\beta_0}} - e^{-\tau e^{\beta_0}} \right) + \beta_4 \text{BBB} - \beta_5 \text{BBB} + \beta_6 \text{A} - \beta_7 \text{A}
$$

where BBB- is a dummy variable taking the value 1 for BBB- bonds and 0 elsewhere, BBB+ is a dummy variable taking the value 1 for BBB+ bonds and 0 elsewhere, A- is a dummy variables taking the value 1 for A- bonds and 0 elsewhere, A is a dummy variable taking the value 1 for A bonds and 0 elsewhere, and the λ parameter, which should be positive, has been reparameterised as

$$
\lambda=e^{\beta_0}.
$$

The model assumes that the curves for the different credit ratings are parallel, an assumption that can be validated using a statistical hypothesis test by Diamond et al. (2013, section 4.3). Note that the parameter β_1 represents the average long term yield for a BBB bond. If the sample only includes a limited range of bonds, then the corresponding dummy variables would not be included in the model specification.

In this report we estimate the weighted average yield, at terms to maturity of 7 and 10 years, in respect of bonds which fall within the broad BBB credit rating class. The broad BBB band includes BBB-, BBB, and BBB+ bonds. Let *p*1, *p*2, and *p*³ be the comparative proportions of BBB-, BBB, and BBB+ bonds in the sum total for the BBB band. Then, the estimate of the weighted average yield at a term to maturity of 10 years, will be given by the following formula:

$$
\beta_1 + p_1 \beta_4 + p_3 \beta_5 + \beta_2 \left(\frac{1 - e^{-10e^{\beta_0}}}{10e^{\beta_0}} \right) + \beta_3 \left(\frac{1 - e^{-10e^{\beta_0}}}{10e^{\beta_0}} - e^{-10e^{\beta_0}} \right).
$$

 13 Dr Li has confirmed that the correct number should be 0.0598, rather than the value 0.0609 quoted in the paper and the following literature. For daily data, the maximum was in fact 0.001964-this was rounded to 0.002. Multiplying 0.002 by 365.25/12, the value 0.0609 was obtained. For maturities measured in years the implied value of *λ* is 0.7176 using the correct 0.0598.

The formula uses the parameter estimates from the regression equation. Note that the proportions p_1 , p_2 , and p_3 will change depending upon the sample of bonds that is used for the particular estimation. Indeed, the relative shares of BBB-, BBB, and BBB+ bonds will vary depending upon the averaging period that has been selected, and depending upon the particular dataset that has been selected, Data1, Data2, Data3, or Data4.

A similar formula will apply to the weighted average yield at a term to maturity of 7 years.

2.2 Par yield curves

Lally (2014a) has posited that the regulator should use the yield on a 10-year bond for which the coupon rate is equal to the yield-to-maturity (in other words, a par yield). Lally (2014a) has suggested that a par yield is best suited for application in a building block calculation. However, Lally (2014a) has also asserted that, in most circumstances, the differences between the yields that do not trade at par and par yields are unlikely to be significant. Lally has drawn his conclusions from a stylised analysis, in which present value calculations were applied to a prospective stream of coupon payments from a fixed rate bond. Lally has acknowledged, however, that during times of market uncertainty, such as during the global financial crisis, the differences between the estimates from par yields and from yields to maturity can be material. In the particular example presented, which used data from the RBA indicator series for January 2009, Lally estimated that the yield on a par yield bond would have been 10.85 per cent, whilst yields to maturity on 10-year bonds not trading at par would have varied from 10.78 per cent to 11.09 per cent.

What the Lally analysis shows is that the difference between the yield to maturity on a bond with a remaining term to maturity of 10 years that does not trade at par, and the par yield on a 10-year bond which has just been issued, will depend upon the term structure of spot rates. Lally assumes that the term structure of spot rates is perfectly linear between the one-year spot rate and the 10-year spot rate, however a linear term structure is unlikely to be found in any practical context. Thus, how large is the difference between the par yield on a newly issued 10-year bond, and the yield to maturity on a bond with a residual life of 10 years that does not trade at par, will be an empirical question.

The examples that Lally presents to illustrate his argument are also based entirely on plain vanilla, fixed rate bonds. In practice, however, in an empirical application, a wide array of bonds will be considered concurrently. Thus, in the sample of bonds which was analysed by ESQUANT, there were bonds with varying maturity types (some bonds had put or call options), and bonds with fixed, floating and variable coupons. The proposition by Lally that the gap between yields to maturity (for bonds with a residual life of 10 years) and par yields (for newly issued bonds) is "trivial" should be subjected to empirical testing.

The results for the spot rates and for the par yields that are presented in this report are commensurate with a BBB (flat) credit rating.

2.3 Response to Lally

2.3.1 Extrapolation Methods

To estimate prevailing values of the spread over swap, or the debt risk premium, the AER has relied upon third party data sources. In particular, the AER has used an average of the Bloomberg BVAL BBB curve and the RBA measures of corporate bond spreads for BBB rated debt. However, extrapolation methods must be applied to the results obtained from the RBA series because the Gaussian kernel method applied by the RBA does not produce spreads or yields at an effective tenor of ten years .

ESQUANT^{[14](#page-21-3)} (2015) compared three methods of extrapolation of the RBA series:

1. The AER method^{[15](#page-21-4)}. Under this method the RBA results at target tenors of 7 years and 10 years are used.

¹⁵Diamond, N.T. and Brooks, R. (2015). We referred to the AER method as the Lally method.

¹⁴Lally (2015b) refers to Esquant, but we prefer ESQUANT.

- 2. Local Linear Smoothing. In this method a local linear regression is fitted to a set of bond yields and maturities.
- 3. The South Australian Power Networks (SAPN) method. In this method the RBA results at 3, 5, 7, and 10 years are used. The SAPN method makes use of the gradient of an average curve through the spreads-to-swap at various tenors.

Figure [2.1](#page-22-0) gives a time series plot of the extrapolations in basis points from January 2005 to January 2015 under the AER and SAPN methods, using the data analysed in ESQUANT (2015).

Figure 2.1: Comparison of the AER extrapolation approach (black) and SA Power Networks method (red) over time.

The results are affected by the GFC. Table [2.1](#page-23-0) gives the autocorrelations of the estimated 10-year spreads, after extrapolation has been performed using, alternately, the AER method and the SAPN method, while Figures [2.2](#page-23-1) and [2.3](#page-24-0) give corresponding plots. The autocorrelations are statistically significant^{[16](#page-22-1)} up to about lag 7 and are very similar. Accordingly, in the subsequent analysis we have used the average autocorrelations up to lag 9 and have assumed that subsequent autocorrelations are zero.

ESQUANT (2015) showed that all three of the extrapolation methods are unbiased to first order. However, it is possible to determine the bias to second order and the variance, which depend on the particular method, the squared second derivative of the true yield (or spread) curve, and the underlying variance around the true curve. The bias and variance can be combined to give a formula

¹⁶For white noise, the sample autocorrelations are approximately Normal with zero mean and variance 1/*n* where *n* is the number of observations, and when *n* is assumed to be large (see Brockwell and Davis, 2002, p.20.). Consider the sample value of an autocorrelation. If the true value is zero, then the probability that the sampled value actually falls within the interval of $\pm 1.96/\sqrt{n}$ will be approximately 0.95. The limits $\pm 1.96/\sqrt{n}$ are shown on the acf plot.

ACF of Extrapolation

Figure 2.2: ACF of the estimated spread at a 10-year tenor, after extrapolation of the RBA series using the AER (Lally) extrapolation method.

					$1 \t 7 \t 3 \t 4 \t 5 \t 6 \t 7 \t 8 \t 9$
	AER 1.000 0.905 0.802 0.701 0.600 0.487 0.362 0.245 0.130				
SAPN 1.000 0.902 0.799 0.699 0.597 0.483 0.359 0.239 0.121					
Average 1.000 0.903 0.801 0.700 0.598 0.485 0.360 0.242 0.125					

Table 2.1: Autocorrelation of extrapolation: AER and SAPN extrapolation methods.

for the root mean square error (RMSE). For the AER method, and using Lally's notation,

$$
RMSE(AER) = \sqrt{B_{AER}^2G_{10}^2 + V_{AER}S_e^2}
$$

where *BAER* is a bias multiplier that is unique to the AER's extrapolation method, *VAER* is a variance multiplier that is unique to the AER's extrapolation method, *G*¹⁰ is a measure of the curvature of the Nelson-Siegel curve at a ten-year term to maturity (the second derivative), and *S^e* is the standard deviation of the residuals around the Nelson-Siegel curve. The standard deviation of the residuals around the Nelson-Siegel curve is measured by the standard error of the regressiion.

ESQUANT (2015) analysed 15 months' worth of data from November 2013 to January 2015. The empirical investigations were centred on the last day of each month. For each month, we fitted the Nelson-Siegel yield curve and extracted the second derivative of the curve (at 10 years)^{[17](#page-23-2)} and the standard deviation of the residuals, as well the bias and variance multipliers. Lally averaged these

 17 More correctly, we should have extracted the second derivative of the spread curve, see Appendix B. The differences are very minor. Appendix B also shows that it is better, under each of the methods, to estimate the yield at a 10 year term to maturity and to then subtract the corresponding swap rate, rather than estimate the spread to swap at a ten year term to maturity directly.

ACF of Extrapolation

Figure 2.3: ACF of the estimated spread at a 10-year tenor, after extrapolation of the RBA series using the SAPN extrapolation method.

figures to obtain

$$
RMSE(AER) = \sqrt{(-2.10)^2(-0.011)^2 + (0.244)(0.499)^2} = \sqrt{.023^2 + 0.061} = 0.248
$$

Using the same procedure for the other two methods, Lally obtained

$$
RMSE(LL) = \sqrt{(-2.24)^2(-0.011)^2 + (0.214)(.499)^2} = \sqrt{.025^2 + .053} = 0.232
$$

\n
$$
RMSE(SAPN) = \sqrt{(-4.45)^2(-0.011)^2 + (.152)(.499)^2} = \sqrt{0.049^2 + 0.038} = 0.201.
$$

In ESQUANT (2015), we argued that on the basis of the RMSE, and in spite of the larger bias of the SAPN method relative to the AER method, the SAPN method should be preferred for predictions going forward. Lally (2015b) has set out his opinion that because averages are taken of a series of daily observations, the effect of calculating an average will be to make the AER method the best method well before the end of the ten-year transitional period, or at least as good as Local Linear Smoothing. In the next section we set out why Lally's reasoning is incorrect.

Variance of a Mean

Let *y* be an estimate of the spread to swap at a 10 year tenor with the estimate having been obtained using an extrapolation method.

Hayashi (2000) gives the following formula for the variance of a mean of *n* observations as

$$
n\text{Var}\left(\overline{y}\right) = \gamma_0 + 2\sum_{j=1}^{n} \left(1 - \frac{j}{n}\right)\gamma_j
$$

where *γ^j* is the autocovariance at lag *j*. The autocovariance is related to the autocorrelation function by

$$
\gamma_j=\gamma_0\rho_j
$$

where $\gamma_0 = \text{Var}(y)$ and ρ_j is the autocorrelation at lag *j* and hence

$$
\text{Var}(\overline{y}) = \frac{\text{Var}(y)}{n} \left(1 + 2 \sum_{j=1}^{n} \left(1 - \frac{j}{n} \right) \rho_j \right).
$$

If the data is independent, as Lally has assumed, then $\gamma_i = \rho_i = 0$, $\forall j = 1, 2, 3, \dots$ and the factor

$$
\left(1+2\sum_{j=1}^n\left(1-\frac{j}{n}\right)\rho_j\right)=1,
$$

and therefore

$$
\text{Var}\left(\overline{y}\right) = \frac{\text{Var}(y)}{n}.
$$

On the other hand, when there is dependence, as is the case here, then the factor would usually exceed 1.

Results assuming independence

Table [2.2](#page-25-0) gives the RMSE assuming that the average bias over the period considered is maintained, and that the variance of the mean of the observations is calculated under conditions of independence. This reproduces the results in Lally (2015b), with an additional set of figures for $n = 60$ observations. For small numbers of observations, the SAPN method is superior but as the number of observations increases, both Local Linear smoothing and the AER method are shown to give better results.

	Number of Observations							
	1 10 60 120							
		AER 0.248 0.081 0.039 0.032						
Local Linear Smoothing 0.232 0.077 0.039 0.032								
SAPN 0.201 0.079 0.055 0.052								

Table 2.2: RMSE for various extrapolation methods, assuming independence.

Results assuming dependence

Table [2.3](#page-25-1) gives the RMSE assuming that the average bias over the period considered is maintained, and that the variance of the mean of the observations is calculated in such a way as to take proper account of the autocorrelations. The results in Table [2.3](#page-25-1) are therefore more realistic than those obtained under the approach taken by Lally (2015b). The AER method is the worst of the three methods irrespective of the number of observations. The SAPN method is the superior method up to 60 observations. At the end of the ten-year transitional period, Local Linear smoothing is the best method.

	Number of Observations							
	1 10 60 120							
		AER 0.248 0.215 0.107 0.078						
Local Linear Smoothing 0.232 0.202 0.101 0.074								
SAPN 0.201 0.176 0.096 0.077								

Table 2.3: RMSE for various extrapolation methods, assuming dependence.

Conclusion on extrapolation methods

Lally (2015b) accepted the argument by ESQUANT (2015) that an appropriate method for assessing extrapolation techniques was to examine the root mean squared error (RMSE) associated with each method. Using RMSE, the AER (Lally) extrapolation method was shown to perform relatively poorly, while the SA Power Networks method performed better. Lally then argued, however, that the relative ranking of the AER method would improve in a context in which averaging was applied to monthly figures for the cost of debt. Lally assumed that if the AER's preferred form of the transition to a trailing average, portfolio return on debt were imposed, then the monthly results for the cost of debt would be used as inputs into the calculation of an arithmetic mean. Since the calculation of averages moderates the variability in the results for an estimator over time, then the RMSE of the AER method would progressively diminish over time, and the relative ranking of that technique would improve.

However, Lally (2015b) made a statistical error in his calculations. He treated the monthly results for the cost of debt as a series of independent observations. ESQUANT (2015) had prepared cost of debt figures which were based on the application of an extrapolation technique to the monthly RBA measures of corporate bond spreads. In practice, however, as has been demonstrated by ESQUANT in this report, the monthly results for the extrapolated series are highly serially correlated. In the presence of autocorrelation, the variance of the estimates of the cost of debt does not diminish in proportion to the reciprocal of the square root of the sample size, as had been assumed by Lally. Thus, the averaging of monthly results from the AER extrapolation method will not cause the variance to fall to the same degree, and hence the RMSE will remain above that recorded for other extrapolation methods.

The RBA only produces its results for corporate spread measures on a monthly basis. However, if daily observations for the cost of debt at a 10-year tenor are used from other sources, then the sample autocorrelations are likely to be even higher than those calculated using monthly data. There would then be even less prospect of an improvement in the performance of the AER extrapolation approach as the number of observations available for averaging increased. The reason is that more pronounced serial correlation causes the variance of the estimates to fall by less.

2.3.2 Interpolation Methods

ESQUANT (2014, section 5) reviewed the process used by the AER to obtain daily data for the RBA index. The AER uses linear interpolation of the RBA results, which are assumed to correspond to the end of the month, in order to obtain approximate daily observations. We examined 3,246 daily Bloomberg BBB fair value spreads, which are shown in Figure [2.4.](#page-27-0) We broke the observations down into 162 blocks of 20 observations and evaluated the error of averaging the first and last observation in each block by making comparisons with the average of the block. We defined the relative error as

$$
e = 100 \times \frac{\text{Average of First and Last Observatory} - \text{Average of All Observations}}{\text{Average of All Observations}}.
$$

Lally (2015b) has pointed out that in the first year of the transitional period, up to 12 months of data may be used to determine the cost of debt and hence the standard deviation of the estimation errors should be less than when using just one observation. There will be further reductions in the standard deviation of the estimation errors as the period over which the transition to a trailing average return on debt is occurring, extends towards ten years.

Using the same analysis as in the previous section, we can show that Lally is correct up to a point. Figure [2.4](#page-27-0) presents the sample autocorrelations of the estimation errors. The autocorrelations are generally not statistically significant and are of negligible size for all values of the lags. Hence, unlike in the previous section, the simple formula that is shown below

$$
\text{Var}(\overline{e}) = \frac{\text{Var}(e)}{n}
$$

applies, and as the number of observations increases, then so does the variance of the mean decrease. Although a business could, in principle, choose an averaging period which is up to one year long, Lally's argument that "even for the first year of the transitional period, up to 12 months of data may

Figure 2.4: Daily Bloomberg BBB fair value spreads, 10 year tenor.

Interpolation Errors

Figure 2.5: ACF of interpolation errors for Daily Bloomberg BBB fair value spreads, 10 year tenor.

be used to determine the cost of debt for that year" is of limited practical relevance, because most businesses need to hedge over an averaging period, and 12 months is too long a period for hedging. Thus, in practice, an averaging period would generally only be for 20 to 40 days.

In ESQUANT (2014), the analysis of interpolation methods also considered an ARIMA(0,1,1) model (see, for example, Box, Jenkins and Reinsel, 1994, pages 109 to 114).

ARIMA models were fitted to the daily spread-over-swap data that had been produced using a variety of methods (including the Gaussian kernel estimation method, used by the RBA). The daily ARIMA models showed that past observations for the random disturbance were influential in determining the change in spread from one time period to the next. However, when only monthly data was considered, meaning that one observation per month was sampled, the influence of past random disturbances (which affect the process that gives rise to the change in the spread) was significantly diminished.

The work using ARIMA specifications cast doubt on the AER's (then) proposed practice of interpolating between the end of month values for the RBA measures of corporate bond spreads. However, Lally (2015b) hasn't responded to the ARIMA analysis. Lally (2015b) has confined his arguments to the relative error of interpolation.

At the time at which the ESQUANT (2014) analysis was performed, in May 2014, stakeholders were not aware of how the AER intended to use the RBA measures of corporate bond spreads from Table F3, and the Bloomberg BBB rated BVAL curve.

2.3.3 Other comments on the Lally approach to extrapolation

The analysis that Lally has brought to bear on the methods for measuring the cost of debt is entirely conditioned by his view as to what might be the most appropriate form of the transition to a trailing average, portfolio return on debt. Lally supports the method for the transition that was outlined in the AER's rate of return guideline (AER, 2013). However, the AER's preferred approach to the transition has not been widely accepted.

Lally also appears to have accepted, unquestioningly, the AERs interpretation of clause 6.5.2(l) of the National Electricity Rules (NER), which deals with the updating of the annual revenue requirement (NER, version 77). The clause states that if the return on debt is to be estimated using a methodology of the type referred to in (NER) paragraph (i)(2), then a resulting change to the Distribution Network Service Provider's annual revenue requirement must be effected through the automatic application of a formula that is specified in the distribution determination.

Lally believes that the clause implies that the return on debt should be updated through the automatic use of a formula. However, the clause refers quite clearly to the need to apply a formula when amending the annual revenue requirement. This is not the same as the automatic application of a formula to evaluate the rate of return on debt. The post-tax revenue model (PTRM) provides the mechanism for assessing and implementing changes to the annual revenue requirement (ARR). The ARR can be updated by adjusting the return on capital building block for a particular year. Thus, the PTRM provides the framework for quantifying the changes to total revenues that might result from the use of different inputs for the rate of return on debt. The PTRM will be deployed to determine the associated revisions to weighted average tariffs.

In any event, the Economic Regulation Authority (WA) has, in its final decision for ATCO Gas $(ERA, 2015)^{18}$ $(ERA, 2015)^{18}$ $(ERA, 2015)^{18}$, proposed to use a range of empirical methods for the purpose of preparing annual updates for the rate of return on debt. The ERA (WA) has not simply subscribed to the use of third party indicator series to measure the rate of return on debt.

¹⁸Appendix 8 of the Amended Final Decision, 10th September 2015.

Chapter 3

First Averaging Period

3.1 Data

The first averaging period encompasses the 20 business days from 2nd January 2015 to 30th January 2015^{[19](#page-30-2)}. The first averaging period was selected as a placeholder reference interval to support the analysis that was undertaken for the purpose of the (initial) regulatory proposal that was submitted by United Energy (in April 2015).

The data used in this report was sourced from the RBA replication model, which was updated by ESQUANT^{[20](#page-30-3)}. The RBA replication model was used with the permission of the Competition Economists Group (CEG). The model was updated so as to provide bond price and yield data over an extended period from 31st December 2014 to 11th December 2015.

As a result of earlier empirical work that has been done using the RBA replication model, daily data is now available on an uninterrupted basis from 1st November 2013 to 11th December 2015^{[21](#page-30-4)}. The model includes data on bonds which have been classified into the following credit rating categories by Standard and Poor's: A+, A, A-, BBB+, BBB, and BBB-. The bond search function within Bloomberg has been used, at regular intervals, to retrieve bonds that have credit ratings from Standard and Poor's in the aforementioned categories. In circumstances in which the bond itself is not rated, then the issuer rating has been applied. Bonds have been chosen for which the issuer ratings have fallen into the same credit rating categories. An emphasis has been placed on Standard and Poor's as a credit ratings agency because the Reserve Bank of Australia nominated Standard and Poor's (Arsov et al., 2013). However, the credit ratings from another agency could equally well have been used. Furthermore, Bloomberg Composite Ratings could also have been applied^{[22](#page-30-5)}.

When running searches within Bloomberg, corporate bonds were chosen for which the country of incorporation, or the country of risk was Australia^{[23](#page-30-6)}. Secondary searches were also run without specifying either the country of incorporation or the country of risk. In those circumstances, the filter applied was Australian dollar denominated bonds. The results from the primary and secondary searches were consolidated.

For all bond searches, the issue date was chosen to be after 1st January 1990, while the maturity date was selected to be after 31st October 2013.

A degree of care was also exercised when seeking to identify "duplicate" bonds. The term "du-

 23 The "Country of Incorporation" field specifies the ISO (International Organisation for Standardisation) country code of where a company is incorporated. The "Country of Risk" field returns the ISO country code of the issuer's country of risk. The methodology applied by Bloomberg is comprised of four factors listed in order of importance: Management location, country of primary listing, country or revenue, and reporting currency of the issuer. The management location is defined by the country of domicile unless the location of key players such as the Chief Executive Officer (CEO), Chief Financial Officer (CFO), Chief Operating Officer (COO), and/or General Counsel is proven to be otherwise.

¹⁹United Energy (2015), page 21.

²⁰ESQUANT also amended and updated a separate module on credit ratings.

²¹Refer to Diamond, N.T. and Brooks, R. (2014 and 2015).

²²The Bloomberg Composite (COMP) is a blend of a security's credit ratings from Moody's, S&P, Fitch, and DBRS (the Dominion Bond Ratings Service). The ratings agencies are evenly weighted when calculating the composite. COMP is the average of existing ratings, rounded down to the lower rating in case the composite is between two ratings. Refer to the Rating Scales and Definitions (RATD) resource centre on Bloomberg.

plicate" has a precise connotation in this context and essentially means the same bond that has been issued in two or more markets. Arsov et al. (2013) gave the example of a US dollar-denominated bond line that had both 144A and Regulation S series. Arsov et al. (2013) reported that issuers raising bond funding in US dollars can prepare two types of securities for the same bond line, with the securities intended for different investors. Securities issued under the US Securities and Exchange Commission's Rule 144A are privately placed into the US market and are sold to Qualified Institutional Buyers. In contrast, REG S securities are issued in the Eurobond market for international investors, and are ex-empt from registration under the US Securities Act 1933^{[24](#page-31-0)}. Each security type is typically assigned its own International Securities Identification Number (ISIN).

In order to properly identify and deal with duplicates, ESQUANT made sure to run two variants of each bond search. Under the first variant of the search, no option was chosen, using the Bloomberg search function, to consolidate duplicates. Under the second variant, the facility to screen out duplicates was exercised. A comparison of the results from the two types of searches, which were run sequentially, revealed the particular bonds that had been eliminated. However, Bloomberg would typically eliminate the 144A version of a bond. In contrast, the RBA would prefer that the choice be exercised in such a way as to screen out the REG S version of the bond. This may be because the RBA has recognised that Australian corporations often raise finance through private placements in the 144A market. Hence, ESQUANT was cautious and looked for apparently matched bonds issued by the same company. In those circumstances, the REG S bond would be dropped from the list, while the 144A bond would be retained.

ESQUANT applied further screening to the data before performing estimations of yield curves:

- Bonds for which the average value of option adjusted spreads was found to be negative during the relevant averaging period were not used.
- Bonds with remaining terms to maturity of less than three months were not used. This restriction was applied in order to limit the leverage of bonds with short maturities on the Nelson-Siegel models.
- Bonds with credit ratings from Standard and Poors in the following categories were chosen: A (flat), A-, BBB+, BBB, and BBB-. Thus, although the model includes bonds with credit ratings of A+, these were not used on this occasion.

The RBA replication model applies issuer credit ratings if the rating for an individual bond is not available. Importantly, the model records credit ratings separately for each day of the averaging period.

For those regressions which used average values of bond yields, over the reference period, the relevant credit rating was that on the final day of the averaging period. For regressions which used daily data, such as the estimation of par yield curves, the daily assessments of credit ratings could be applied.

The bonds which satisfied the criteria in the three bullet points listed above have been labelled Data1 in this report. Additionally, the bonds in Data1 that were denominated in Australian Dollars have been labelled as Data2.

The industry of classification was an important variable to consider. Bloomberg provides a classification of the industry of the issuer. The bonds in Data 1 and Data2 that had not been issued by companies operating in the finance sector, were labelled Data3 and Data4, respectively. Thus, Data3 and Data4 were comprised exclusively of "non-financial" sector bonds.

RegS and 144A bonds are generally assigned two separate sets of security identification codes. Typically, RegS bonds get a common code and an International Securities Identification Number (ISIN), and are generally accepted for clearance through the Clearstream, Luxembourg, and Euroclear systems. 144A bonds get a CUSIP number and an ISIN, and are generally accepted for clearance through the DTC system.

²⁴Bloomberg provides the following explanation: Before seasoning, bonds sold under Regulation S (RegS) can only be offered in the U.S. to qualified institutional buyers (QIBs) in reliance on Rule 144A. Rule 144A is an SEC rule issued in 1990 that modified a two-year holding period requirement on privately placed securities by permitting QIBs to trade these positions among themselves.

The numbers of bonds in the four datasets can be summarised as follows: 844, 602, 280, and 146, respectively, for the first averaging period.

3.2 Fitting Yield Curves

The curves were fitted to the data, sourced from the RBA replication model, using the nlsLM() command in the **minpack.lm** package in R (Elzhov et al. 2013). Initially, the empirical work was done in respect of the average yields for bonds over the period from 2nd January 2015 to 30th January 2015. The curves were estimated using yield data rather than data on spreads-to-swap. The estimated parameters are given in Tables 3.1 to 3.4, while the sample bond yields and fitted Nelson-Siegel yield curves are plotted in Figures [3.1](#page-34-0) to [3.8.](#page-41-0) Recall that the intercept term for each yield curve will be determined as a function of the parameters, *β*1, *β*4, *β*5, *β*6, and *β*7, depending upon the credit rating for which the yield curve applies.

The fitted values for yield at a 10-year tenor were converted into spreads-to-swap by subtracting 10-year tenor swap rates from the predicted yields. The swap rates for specific tenors were themselves calculated by applying an interpolation method to the observed data on vanilla interest rate swaps, which was sourced from Bloomberg^{[25](#page-32-3)}. Note that the fitted Nelson-Siegel curves describe "average" behaviour; some bonds give much higher or lower yields than the fitted curve.

		Default					Sandwich	
	Estimate	Std. Error	t value	Pr(> t)		Std. Error	t value	Pr(> t)
beta0	-1.270	0.109	-11.599	0.000		0.172	-7.393	0.000
beta1	7.775	0.271	28.693	0.000		0.599	12.989	0.000
beta2	-3.474	0.337	-10.324	0.000		0.673	-5.162	0.000
beta3	-5.712	0.371	-15.382	0.000		0.558	-10.238	0.000
beta4	0.657	0.085	7.773	0.000		0.119	5.516	0.000
beta5	-0.366	0.059	-6.251	0.000		0.057	-6.438	0.000
beta6	-0.430	0.054	-7.939	0.000		0.052	-8.278	0.000
beta7	-0.620	0.054	-11.505	0.000		0.048	-13.037	0.000

Table 3.1: Regression parameters and standard errors for fitted Nelson-Siegel model, Data1, first averaging period.

		Default					Sandwich	
	Estimate	Std. Error	t value	Pr(> t)		Std. Error	t value	Pr(> t)
beta0	-0.539	0.161	-3.342	0.001		0.220	-2.452	0.015
beta1	5.640	0.217	26.044	0.000		0.316	17.823	0.000
beta2	-0.906	0.404	-2.241	0.025		0.548	-1.653	0.099
beta3	-4.313	0.456	-9.452	0.000		0.431	-10.005	0.000
beta4	0.237	0.117	2.029	0.043		0.119	1.987	0.047
beta ₅	-0.290	0.073	-3.988	0.000		0.060	-4.825	0.000
beta ₆	-0.336	0.067	-4.993	0.000		0.058	-5.831	0.000
beta7	-0.527	0.068	-7.790	0.000		0.051	-10.301	0.000

Table 3.2: Regression parameters and standard errors for fitted Nelson-Siegel model, Data2, first averaging period.

 25 For the periods under consideration, daily values of swap rates were obtained for the Australian dollar swaps curve. The relevant series in Bloomberg includes, as its constituents, variables such as "ADSWAP10 Curncy".

		Default					Sandwich	
	Estimate	Std. Error	t value	Pr(> t)		Std. Error	t value	$>$ t)
beta0	-1.675	0.241	-6.945	0.000		0.241	-6.959	0.000
beta1	9.539	0.787	12.115	0.000		0.838	11.376	0.000
beta2	-5.513	0.906	-6.087	0.000		0.954	-5.779	0.000
beta3	-6.851	0.592	-11.566	0.000		0.668	-10.251	0.000
beta4	0.758	0.099	7.669	0.000		0.131	5.781	0.000
beta ₅	-0.420	0.084	-5.029	0.000		0.078	-5.396	0.000
beta6	-0.586	0.080	-7.312	0.000		0.074	-7.892	0.000
beta7	-0.742	0.089	-8.341	0.000		0.069	-10.786	0.000

Table 3.3: Regression parameters and standard errors for fitted Nelson-Siegel model, Data3, first averaging period.

		Default			Sandwich			
	Estimate	Std. Error	t value	Pr(> t)	Std. Error		t value	> t Pr(
beta0	-0.869	0.203	-4.277	0.000		0.215	-4.045	0.000
beta1	6.711	0.455	14.752	0.000		0.510	13.170	0.000
beta2	-2.215	0.675	-3.281	0.001		0.726	-3.050	0.003
beta3	-5.865	0.849	-6.912	0.000		0.831	-7.056	0.000
beta4	0.447	0.141	3.162	0.002		0.196	2.277	0.024
beta5	-0.430	0.101	-4.254	0.000		0.100	-4.305	0.000
beta6	-0.512	0.091	-5.643	0.000		0.076	-6.704	0.000
beta7	-0.612	0.094	-6.527	0.000		0.077	-7.914	0.000

Table 3.4: Regression parameters and standard errors for fitted Nelson-Siegel model, Data4, first averaging period.

Figure 3.1: Observed average yields against average terms to maturity for Data1, first averaging period.

Figure 3.2: Observed average yields against average terms to maturity by credit rating for Data1, first averaging period.

Figure 3.3: Observed average yields against average terms to maturity for Data2, first averaging period.

Figure 3.4: Observed average yields against average terms to maturity by credit rating for Data2, first averaging period.

Figure 3.5: Observed average yields against average terms to maturity for Data3, first averaging period.

Figure 3.6: Observed average yields against average terms to maturity by credit rating for Data3, first averaging period.

Figure 3.7: Observed average yields against average terms to maturity for Data4, first averaging period.

Figure 3.8: Observed average yields against average terms to maturity by credit rating for Data4, first averaging period.

Fitting the Nelson-Siegel yield curves to the four data sets

The Nelson-Siegel model was fitted to the datasets, Data1, Data2, Data3, and Data4. Estimates of the yield at tenors of 7 years and 10 years were found by inserting the applicable term to maturity into the yield equation for which the regression coefficients had been estimated empirically.

The formulae shown below were then used to work out the debt risk premium (DRP) at 7-year and at 10-year terms to maturity. The calculation for the change in the DRP, ∆DRP, is also shown:

$$
DRP_7 = Yield(7) - 2.396\%
$$

\n
$$
DRP_{10} = Yield(10) - 2.623\%
$$

\n
$$
\triangle DRP = \frac{100(DRP_{10} - DRP_7)}{3}.
$$

The values 2.396% and 2.623% represent the average yields on 7-year and 10-year Commonwealth Government securities, respectively, measured over the 20 business days from 2nd January 2015 to 30th January 2015. These yields were calculated using an interpolation method that was applied to daily data sourced from Table F16, from the RBA website. An arithmetic mean was taken of the daily results for 7-year and 10-year CGS yields over the measurement period. The yields are expressed on a semi-annual basis.

Standard errors were found using the delta method^{[26](#page-42-0)}. Estimates and standard errors^{[27](#page-42-1)} are given in Table [3.5.](#page-42-2) There is some degree of responsiveness of the results to the choice of data.

Table 3.5: Estimated debt risk premiums (DRPs), for bonds in the BBB band, with standard errors, for Data1, Data2, Data3, and Data4, first averaging period. Note that the standard errors for the yields are the same as the standard errors for the corresponding DRPs. Sandwich standard errors are given in brackets.

Similarly, estimates of the spread to swap at a 7-year remaining term to maturity, SS₇, the spread to swap at a 10-year remaining term to maturity, SS₁₀, and the difference, ∆SS, were also found, using the calculation

$$
SS7 = Yield(7) - 2.759%
$$

\n
$$
SS10 = Yield(10) - 2.955%
$$

\n
$$
\Delta SS = \frac{100(SS10 - SS7)}{3}.
$$

The values 2.759% and 2.955% represent the average swap rates at tenors of 7 years and 10 years respectively, measured over January 2015. Table [3.6](#page-43-0) gives the estimates with standard errors.

The results presented in Table [3.5](#page-42-2) and in Table [3.6](#page-43-0) are a weighted average of the results for bonds in the individual rating sub-groups: BBB-, BBB (flat), and BBB+. The weights are determined by the numbers of bonds in each of the sub-groups.

²⁷The sandwich standard errors shown in the table were found using the **sandwich** package (Zeileis, 2004 and 2006) in R.

²⁶In one dimension, Var(*g*(*x*)) ≈ [*g'*(*µ*)]²Var(*x*); in higher dimensions Var(*g*(*x*)) ≈ *d'*Σ*d* where Σ is the variancecovariance matrix of x and \vec{d} is the vector of first derivatives of g evaluated at μ . The delta method was implemented using the delta.method command in the **car** package (Weisburg, 2005) in R.

Table 3.6: Estimated spreads-to-swap for bonds in the BBB band, with standard errors, for Data1, Data2, Data3, and Data4, first averaging period. Note that the standard errors for the yields are the same as the standard errors for the corresponding spreads-to-swap.

The estimates and standard errors in Tables [3.5](#page-42-2) and [3.6](#page-43-0) depend on assumptions that the data are Normally distributed with a common variance. To check the Normality assumption, QQ (Quantile-Quantile) plots are given in Figure [3.9.](#page-44-0) In the QQ plot, the ordered residuals (observed yields minus fitted values) are plotted on the *y*-axis, while expected values from a standard Normal distribution are plotted on the *x*-axis. If the residuals follow a Normal distribution, then the QQ plot should trace out an approximate straight line. Deviations from the line correspond to indications of non-Normality or outliers.

Figure 3.9: QQ plots of residuals from the Nelson-Siegel model fitted to Data1, Data2, Data3, and Data4. Results for the first averaging period.

The normality assumption is suspect because the QQ plots, particularly for Data1 and Data2 (the two datasets that include financial sector bonds), are not straight lines. As Ritz and Streibig (2008, p.83), quoting Carroll and Ruppert (1988, p.128), explain

"In this case, the estimated standard errors from the model assuming normality and variance homogeneity will be inconsistent: They will not approach the true standard errors as the sample size increases."

However, Carroll and Ruppert (1988, pp. 209-213) and Zeileis (2006) show that it is still possible to obtain consistent estimates of the standard errors using the so called sandwich variance-covariance matrix as long as the mean structure is correct, and provided that independence can be assumed. These estimates of the standard errors have been calculated using the **sandwich** package (Zeileis, 2004 and 2006) in R, and have been used in the construction of Tables [3.5](#page-42-2) and [3.6.](#page-43-0)

3.3 Refinements to the analysis

3.3.1 Robust Analysis

As noted by Fox (2008, p. 463), the general nonlinear model is given by the equation:

$$
y_i = f(\beta, x_i^T) + \varepsilon_i
$$

in which

- *yⁱ* is the response-variable value for the *i*th of *n* observations;
- β is a vector of *p* parameters to be estimated from the data;
- x_i^T is a row vector of scores for observation *i* on the *k* explanatory variables (some of which may be qualitative); and
- ε_i is the error for the *i*th observation.

Under the assumption of independent and normally distributed errors, with zero means and common variance, the general nonlinear model has likelihood

$$
L(\beta, \sigma_{\varepsilon}^2) = \frac{1}{2\pi\sigma_{\varepsilon}^2} \exp\left\{-\frac{\sum_{i=1}^n [y_i - f(\beta, x_i^T)]^2}{2\sigma_{\varepsilon}^2}\right\}
$$

= $\frac{1}{2\pi\sigma_{\varepsilon}^2} \exp\left\{-\frac{1}{2\sigma_{\varepsilon}^2}S(\beta)\right\}$

where $S(\beta)$ is the sum of squares function

$$
S(\beta) = \sum_{i=1}^{n} [y_i - f(\beta, x_i^T)]^2]
$$

For the general linear model, we therefore maximise the likelihood by minimising the sum of squared errors $S(\beta)$.

The formulation above indicates that if the errors are Normally distributed then Least Squares corresponds to Maximum Likelihood estimation. It is also true that if the errors are not Normally distributed, then the Least Squares estimates are consistent, that is as the sample size increases, the estimated values of the parameters converge on the true values.

As the QQ plots show, there is some evidence of possible outliers in the bond data that is contained within the RBA replication model. To investigate whether the results depend on only a few observations, the analysis was repeated using a robust non-linear regression method in R, nlrob(), which uses robust M-estimates, and applies iteratively re-weighted least squares to estimate the fitted model.

The name M-estimate derives from 'MLE-like' estimators (Venables and Ripley, 2008, p.122). Consider the case where only a mean μ is to be estimated and it is known that the standard deviation is 1. Assume that the density of the data is f and $\rho = -\log f$. The MLE solves

$$
\min_{\mu} \sum_{i} -\log f(y_i - \mu) = \min_{\mu} \sum_{i} \rho(y_i - \mu)
$$

where the parentheses indicate that *f* and ρ are functions of $y_i - \mu$. Let $\psi = \rho'$, the derivative with respect to μ . Then the MLE can be found by using the equations

$$
\sum_{i} \psi(y_i - \mu) = 0 \text{ or } \sum_{i} w_i(y_i - \mu) = 0
$$

where

$$
w_i = \frac{\psi(y_i - \hat{\mu})}{y_i - \hat{\mu}}.
$$

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The estimate of μ is solved iteratively, with the weights being updated at each iteration. The mean corresponds to $\rho(x) = x^2$. In this case $\psi(x) = 2x$. The idea of a robust M-estimator is to choose a different function for *ψ* where outliers have less of an effect. A popular choice is metric Winsorizing with

$$
\psi(x) = \begin{cases}\n-c & x < -c \\
x & |x| < c \\
c & x > c\n\end{cases}
$$

shown in Figure [3.10.](#page-46-0) Here the effects of outliers are trimmed to $\pm c$. The results depend on the choice of *c*. By choosing $c = 1.345$, it can be shown that the relative efficiency of the robust M-estimator relative to least squares is 95%.[28](#page-46-1)

The standard deviation is never known and so a robust estimator is needed. The choice used in the nlrob() command in the **robustbase** package (Rousseeuw et al., 2015) in R is the MAD (Median Absolute Deviation) estimator, given by the median of the absolute values of the deviations from the mean, divided by 0.6475.

Extensions of the robust M-estimator methodology to multiple linear regression and non-linear estimation follow a similar logic.

Figure 3.10: *ψ* function for Robust regression (solid) and for normal regression (dotted).

The Nelson-Siegel model was fitted to the Data1, Data2, Data3, and Data4 data sets, using nlrob(). The coefficients of the fitted models and associated standard errors are given in Tables [3.7](#page-47-0) to [3.10.](#page-47-1) Estimates of the DRP₇, DRP₁₀, and ∆DRP were found by substituting the parameter estimates into the relevant fitted yield curve models and differencing formulae. Standard errors were found using the delta method and are given, with the estimated yields and DRPs, in Table [3.11.](#page-48-0) The estimates of yields and DRPs, together with the associated standard errors, from the application of nlsLM() have also been presented so as to facilitate comparisons. Corresponding results for the spreads-to-swap are given in Table [3.12.](#page-48-1)

 28 The variance of the least squares estimator would be 95% of the variance of the robust M-estimator if the data were in fact Normally distributed.

	Estimate	Std. Error	t value	Pr(> t)
beta0	-1.342	0.108	-12.465	0.000
beta1	7.955	0.316	25.164	0.000
beta2	-3.707	0.369	-10.053	0.000
beta3	-5.823	0.359	-16.215	0.000
beta4	0.576	0.080	7.220	0.000
beta5	-0.360	0.051	-7.035	0.000
beta6	-0.446	0.047	-9.447	0.000
beta7	-0.578	0.047	-12.369	0.000

Table 3.7: Robust fit for Data1 for the first averaging period.

	Estimate	Std. Error	t value	Pr(> t)
beta0	-0.679	0.136	-4.980	0.000
beta1	5.846	0.224	26.152	0.000
beta2	-1.216	0.350	-3.475	0.001
beta3	-4.464	0.360	-12.402	0.000
beta4	0.216	0.098	2.198	0.028
beta5	-0.282	0.059	-4.765	0.000
beta6	-0.363	0.055	-6.645	0.000
beta7	-0.494	0.055	-9.034	0.000

Table 3.8: Robust fit for Data2 for the first averaging period.

	Estimate	Std. Error	t value	Pr(
beta0	-2.057	0.420	-4.904	0.000
beta1	11.290	2.165	5.216	0.000
beta2	-7.437	2.273	-3.272	0.001
beta3	-7.508	1.179	-6.369	0.000
beta4	0.684	0.106	6.437	0.000
beta5	-0.443	0.086	-5.156	0.000
beta6	-0.599	0.083	-7.225	0.000
beta7	-0.754	0.091	-8.268	0.000

Table 3.9: Robust fit for Data3 for the first averaging period.

	Estimate	Std. Error	t value	t) Pr(
beta0	-0.929	0.219	-4.246	0.000
beta1	6.900	0.538	12.831	0.000
beta2	-2.409	0.759	-3.173	0.002
beta3	-6.117	0.917	-6.670	0.000
beta4	0.428	0.161	2.657	0.009
beta5	-0.476	0.109	-4.358	0.000
beta6	-0.531	0.098	-5.444	0.000
beta7	-0.634	0.101	-6.301	0.000

Table 3.10: Robust fit for Data4 for the first averaging period.

Table 3.11: Comparison of estimated debt risk premiums (DRPs) with standard errors using nlsLM and nlrob for Data1, Data2, Data3, and Data4, first averaging period. Note that the standard errors for the yields are the same as the standard errors for the corresponding DRPs. Results are shown for the first averaging period which was the 20 business days from 2nd January 2015 to 30th January 2015. The applicable credit rating is the broad BBB band.

Table 3.12: Comparison of estimated spreads-to-swap with standard errors using nlsLM and nlrob for Data1, Data2, Data3, and Data4, first averaging period. Note that the standard errors for the yields are the same as the standard errors for the corresponding spreads-to-swap. Results are shown for the first averaging period which was the 20 business days from 2nd January 2015 to 30th January 2015. The applicable credit rating is the broad BBB band.

3.3.2 Analysis of daily results

In previous sections, a monthly average of the daily yields was used. In this section, the data are analysed day by day, in order to assess the stability of the results.

The analysis was carried out on the daily bond yield data, and the results were converted into estimates of the debt risk premium by subtracting, from bond yields, the applicable daily yields on CGS with a corresponding term to maturity. The yields on CGS for a particular term to maturity were calculated by interpolating between the observations for particular Commonwealth Government bonds in relation to which the maturity dates straddled the target maturity date.

For each day, the Nelson-Siegel model was fitted to the data using nlsLM(). Standard errors were calculated using the Delta method. The Daily results for DRP_{10} with 95% confidence intervals calculated as \pm 1.96 standard errors are presented in Figure [3.11.](#page-49-0) Figure [3.11](#page-49-0) shows that the results from day to day are quite autocorrelated but relatively stable. Corresponding figures for DRP₇ and $\Delta(DRP)$ are shown in Figures [3.12](#page-50-0) and [3.13.](#page-50-1)

Figure 3.11: Estimated debt risk premiums at 10 Years for bonds in the BBB band, with 95% confidence intervals by day: Data1, Data2, Data3, and Data4, first averaging period.

Figure 3.12: Estimated debt risk premiums at 7 Years for bonds in the BBB band, with 95% confidence intervals by day: Data1, Data2, Data3, and Data4, first averaging period.

Figure 3.13: Estimated Delta debt risk premiums for bonds in the BBB band, with 95% confidence intervals by day: Data1, Data2, Data3, and Data4, first averaging period.

3.4 Are common parameters justified?

In the models fitted in previous sections, the intercept terms are different for the different classes of bonds, but the parameters β_0 , β_2 , and β_3 are common. The assumption that the aforementioned parameters should take on the same values for each of the four classes of bonds can be regarded as a restriction. In this section, models where the restriction is relaxed are fitted, and tests are applied to ascertain whether there are statistically significant differences between the restricted and unrestricted versions of the model.

The Nelson-Siegel model is

$$
y(\tau) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\tau e^{\beta_0}}}{\tau e^{\beta_0}} \right) + \beta_3 \left(\frac{1 - e^{-\tau e^{\beta_0}}}{\tau e^{\beta_0}} - e^{-\tau e^{\beta_0}} \right) + \beta_4 \text{BBB} - \beta_5 \text{BBB} + \beta_6 A - \beta_7 A
$$

where BBB- is a dummy variable taking the value 1 for BBB- bonds and 0 elsewhere; BBB+ is a dummy variable taking the value 1 for BBB bonds and 0 elsewhere, A- is a dummy variable taking the value 1 for A- bonds and 0 elsewhere, and A is a dummy variable taking the value 1 for A bonds and 0 elsewhere. An extended model which allows all of the parameters to vary by credit rating is given by

$$
y(\tau) = \beta_1^* + \beta_2^* \left(\frac{1 - e^{-\tau e^{\beta_0^*}}}{\tau e^{\beta_0^*}} \right) + \beta_3^* \left(\frac{1 - e^{-\tau e^{\beta_0^*}}}{\tau e^{\beta_0^*}} - e^{-\tau e^{\beta_0^*}} \right)
$$

where

$$
\beta_0^* = \beta_0 + \beta_8 \text{BBB} + \beta_9 \text{BBB} + \beta_{10} \text{A} - \beta_{11} \text{A}
$$

\n
$$
\beta_1^* = \beta_1 + \beta_4 \text{BBB} + \beta_5 \text{BBB} + \beta_6 \text{A} - \beta_7 \text{A}
$$

\n
$$
\beta_2^* = \beta_2 + \beta_{12} \text{BBB} + \beta_{13} \text{BBB} + \beta_{14} \text{A} - \beta_{15} \text{A}
$$

\n
$$
\beta_3^* = \beta_3 + \beta_{16} \text{BBB} + \beta_{17} \text{BBB} + \beta_{18} \text{A} - \beta_{19} \text{A}
$$

where *β*8, *β*9, *β*10, and *β*¹¹ are deviations of the *β*⁰ parameter for BBB-, BBB+, A-, and A bonds, respectively; while $β_{12}$, $β_{13}$, $β_{14}$, and $β_{15}$ are corresponding deviations of the $β_2$ parameter, and $β_{16}$, $β_{17}$, $β_{18}$, and β_{19} are corresponding deviations for the β_3 parameter.

The extended model was fitted to each of the four datasets, using nlsLM(). Equations were estimated using the bond yields that were measured as averages over the relevant reference interval. To test whether the varying curve is justified, a hypothesis test was performed to investigate whether the parameters *β*8, . . . , *β*¹⁹ are significantly different to zero. This was done using Analysis of Variance where the common and extended models were fitted to the data and the change in the residual sum of squares was compared to the residual mean square of the extended model.

In the F-test carried out here, the test statistic is calculated as

$$
F = \frac{\text{(RSS Common} - \text{RSS Varying)}/g}{\text{(RSS Varying)}/(n-k)}
$$

where

 $RSS Common$ = residual sum of squares with common coefficients RSS Varying $=$ residual sum of squares with varying coefficients $g =$ the number of extra parameters

- $n =$ the number of data points
- $k =$ the number of parameters in the model with varying coefficients

The null hypothesis is that the restrictions are valid and that all of the additional parameters are equal to zero, that is

$$
H_0: \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = 0,
$$

while the alternative hypothesis is

*H*¹ : At least one of *β*8, *β*9, *β*10, *β*11, *β*12, *β*13, *β*14, *β*15, *β*16, *β*17, *β*¹⁸ or *β*¹⁹ is non-zero.

Under the null hypothesis, the F statistic has a known distribution and a *p*−value can be calculated, with large values of F and corresponding small values of *p* indicating that the additional parameters may be required. The results of the tests for the four models are given in Table [3.13.](#page-52-0) Only for Data2 and Data4 can the null hypothesis not be rejected at the 5% level. In other words, the evidence suggests that the restricted model is valid or defensible for Data2 and Data4. However, for Data1 and for Data3, the evidence suggests that additional parameters should be added to the Nelson-Siegel yield curve specification. Recall that Data1 and Data3 include bonds denominated in foreign currencies.

Table 3.13: Anova for comparing the model with common β_0 , β_2 , and β_3 parameters with the model where these parameters are not common: Data1, Data2, Data3, and Data4, first averaging period.

3.5 Application of Nelson-Siegel yield curves to estimate par yield curves

Nelson and Siegel (1987) provide a model that, while parsimonious, has the ability to generate the shapes typically associated with yield curves. Their model is widely used by central banks either in its original form or in the modified form that Svensson (1994) provides^{[29](#page-53-0)}. In this section, we estimate zero-coupon yield curves or spot rate curves that belong to the family of Nelson-Siegel curves. Subsequently, we use these estimates to generate estimates of par yield curves. Schaefer (1977) shows how one can uncover the term structure of par yields from the term structure of spot rates.

The approach that we use is to search for a term structure of spot rates that will minimise an objective function that is a weighted sum of the squared differences between the actual prices of a range of bonds and the prices of those bonds that the term structure of spot rates indicates should prevail. The actual bond prices that we use are the so-called 'dirty' prices. The dirty price of a bond, P_i^A , is the price that one must pay to buy the bond. The 'clean' price, P_i^C , is, in contrast, the dirty price less an amount representing 'accrued' interest, *aⁱ* :

$$
P_i^A = P_I^C + a_i
$$

i.e.

Dirty Price = Clean Price + Accrued Interest

The Accrued interest of bond *i* is given by

$$
a_i
$$
 = $\frac{number\ of\ days\ since\ last\ coupon\ payment}{number\ of\ days\ in\ current\ coupon\ period} \times C_i$

where *Cⁱ* is the next coupon payment to be made for bond *i*.

A modification to the Nelson-Siegel method was applied to enforce the restriction that the yield on a zero-coupon bond should reflect the bond's credit rating. The model used was

$$
r(t) = \beta_1 + \beta_2 \left(\frac{1 - e^{-te^{\beta_0}}}{te^{\beta_0}} \right) + \beta_3 \left(\frac{1 - e^{-te^{\beta_0}}}{te^{\beta_0}} - e^{-te^{\beta_0}} \right) + \beta_4BBB - \beta_5BBB + + (\beta_5 + \beta_6)A - + (\beta_5 + \beta_6 + \beta_7)A
$$
\n(3.1)

where $r(t)$ is the yield on a zero-coupon bond that has *t* years to maturity. The parameters $\beta_4 \dots \beta_7$ should be set in such a way as to conform to the constraints in Equation [3.2:](#page-53-1)

$$
\beta_4 \ge 0 \ge \beta_5, \beta_6, \beta_7. \tag{3.2}
$$

This formulation is equivalent to the usual Nelson-Siegel model

$$
r(t) = \beta_1 + \beta_2 \left(\frac{1 - e^{-te^{\beta_0}}}{te^{\beta_0}} \right) + \beta_3 \left(\frac{1 - e^{-te^{\beta_0}}}{te^{\beta_0}} - e^{-te^{\beta_0}} \right) + \beta_4 BBB + \beta_5 BBB + \beta_6 A - \beta_7 A
$$
\n(3.3)

for which the parameters $\beta_4 \dots \beta_7$ should be subject to following constraints:

$$
\beta_4 \ge 0 \ge \beta_5 \ge \beta_6 \ge \beta_7. \tag{3.4}
$$

Equations 3.1 and 3.2 offer an important advantage, however, which is that the constraints are "bound constraints" (see, for example, Nash 2014, Chapter 11). This means that the restrictions on the parameters are independent, and do not involve linear combinations of the parameters. Bound constraints are available in a much wider range of optimisation software.

²⁹See, for example, the discussion in: Bank for International Settlements, Zero-coupon yield curves: Technical documentation, Monetary and Economic Department, October 2005.

The price of a bond that the term structure of spot rates indicates should prevail is simply the cash flows that the bond will deliver discounted using the term structure. The parameters are estimated by minimising the weighted sum of squared pricing errors 30

$$
\sum_{i=1}^N u_i (P_i^A - \hat{P}_i)^2
$$

where

 u_i = weight for bond *i*

- $N =$ Number of bonds in the sample
- P_i^A = the actual "dirty" price of bond *i*
- \hat{P}_i = fitted price of bond *i* given by $\hat{P}_i = \sum_t C_{it} \exp\left[-t \times r(t, \text{rank})\right]$

where *Cit* is a cash flow on bond *i* promised to be paid *t* years from now.

Long-term bonds exhibit greater sensitivity to interest rates than short-term bonds. Therefore, minimising an objective function that is an equally weighted average of the squared differences between the actual prices of a range of bonds and their predicted prices will tend to fit long-term bond prices rather than short-term bond prices. An appropriate adjustment to make, therefore, was to apply a weighting method to the bond observations in the sample, and the scheme which is supported in the literature is a function of the reciprocal of Macaulay duration. The latter is a measure of risk and computes the average maturity of a bond using the present values of its cash flows as weights. The apportioning scheme recorded the inverse duration of each bond as a function of the sum of the inverse durations of all bonds in the particular sub-sample.

Various authors have used slightly different measures of the weights in the objective function, however. For example, Ioannidis (2003) has used

$$
u_i = \frac{(1/d_i)^2}{(\sum_{k=1}^N (1/d_k))^2},
$$

where d_i = Macaulay duration of bond *i*, giving more weight to bonds with shorter durations. He says:

I estimate the Nelson and Siegel . . . I choose to minimise the distance between squared price errors weighted by the inverse of the duration of the issue squared. This weight function best adjusts for the differential importance of small price changes at different maturities on estimates of the yield curve. An error in the price of a three-month treasury bill would not have the same impact as the error in the price of a fifteen year bond. If we assume an equal weight, the pricing of long term issues would be less accurate than the pricing of short term maturity issues due to increasing duration. Similar weighting schemes are adopted by Vasicek and Fong (1982) and Bliss (1997).

On the other hand, Ferstl and Hayden (2010) use the inverse of the duration with

$$
u_i = \frac{(1/d_i)}{\sum_{k=1}^{N} (1/d_i)}.
$$

The advantage of using the inverse of the duration rather than the square of the inverse of the duration is that it prevents only a few bonds being given the majority of the weight. We have used the inverse of the duration.

The parameters were estimated using the optim() command in R, with the L-BFGS optimisation method. When choosing a subset of data for the estimation of zero coupon yields, an important consideration is that overseas bonds cannot readily be applied, because the empirical work makes use of coupon payments. In other parts of the analysis in this report, overseas bonds have been used, with

 30 We found it easier to minimise the natural logarithm of the weighted sum of squared pricing errors.

the spreads-to-swap on foreign currency denominated bonds having been swapped into Australian dollar spreads using transformation functions in the RBA replication model. The transformations in the RBA replication model make use of basis swaps to US dollars from other currencies, Australian dollar basis swaps, conversion factors to US dollars, conversion factors to Australian dollars, and Australian dollar basis change swaps. There does not seem to be a well founded basis for applying these methods directly to a future stream of coupon payments, and so overseas bonds issued by Australian corporations were ruled out of the analysis.

The data sub-sample that was used for this part of the analysis was Data2. The bonds that were suitable for application to the current task possessed the following characteristics: The five credit ratings under consideration were represented (A, A-, BBB+, BBB, and BBB-) and the bonds were denominated in Australian dollars The domicile of the issuer was not restricted to Australia, and the sample was comprised of 602 observations.

An examination of the data revealed that, for some bonds, the dirty price fell markedly on a single day during the averaging period. The price drops generally occurred when the bond became 'ex coupon', which meant on the day on which the beneficial entitlement to a coupon payment was determined. In order to ascertain whether a bond had become ex coupon during the relevant reference period, two variables were examined, notably the 'days accrued' and the 'accrued interest'. The accrued number of days is the number of days' worth of interest payments that have been accrued since the last coupon payment. Similarly, the accrued interest is the amount of interest accumulated but not paid between the most recent payment and the settlement date, per 100 units of face value. If the number of days accrued fell rather than increased, then the bond was adjudged to have become 'ex coupon'. Typically, the number of days accrued would diminish to zero, and this occurrence would coincide with a decline in the dirty price, although the synchronisation of events did not always take place in the exact way that has been described here.

However, if the number of days accrued fell, then ESQUANT would act to bring forward the effective maturity date for the bond by a comparatively small number of days, being the difference between the ex-coupon day and the stated coupon payment date. Thus, a new variable, being the effective maturity date was constructed programmatically.

Application of the data from the Data2 sub-sample

An analysis was undertaken using the Data2 sub-sample, which was made up only of Australian dollar denominated bonds, with issuers in both the finance and non-finance sectors of the economy. The fitted spot rate curves for each day of the averaging period are given in Figure [3.14,](#page-56-0) while the average spot rate curve is given in Figure [3.15.](#page-57-0)

Once the parameters have been estimated, the par yield, which is the coupon rate *C* that causes the bond price to equal its par value, can be calculated. Assuming semi-annual coupon payments for bond maturity *T*, the equation is

$$
100 = \frac{C}{2} \exp [-0.5r_{0.5}] + \frac{C}{2} \exp [-r_1] + \ldots + (100 + \frac{C}{2}) \exp [-Tr_T].
$$

In the CEG report (Hird, 2012), Excel Solver was used to solve for *C* but the following equation can also be used:

$$
C = \frac{200(1 - \exp[-Tr_T])}{\sum_{t=1}^{2T} \exp\left[-\frac{t}{2}r_{\frac{t}{2}}\right]}
$$

The fitted par value curves for each day over the averaging period are given in Figure [3.16,](#page-58-0) while the average par value curve is given in Figure [3.17.](#page-59-0) Table [3.14](#page-60-0) presents the par yields at various terms to maturity.

The average par yield at a 7-year term to maturity was 4.31% leading to a DRP of 1.92%; while the average par yield at a 10-year term to maturity was 4.64% leading to a DRP of 2.02%.

Figure 3.14: Spot rate curves by day: Data 2. Results for the first averaging period.

Figure 3.15: Average spot rate curve: Data 2. Results for the first averaging period.

Figure 3.16: Par Values curve by day: Data 2. Results for the first averaging period.

Figure 3.17: Average par value curve: Data 2. Results for the first averaging period.

Term to Maturity (Years)	Par Value (%)
0.50	3.41
1.00	3.49
1.50	3.57
2.00	3.65
2.50	3.72
3.00	3.79
3.50	3.86
4.00	3.93
4.50	4.00
5.00	4.07
5.50	4.13
6.00	4.19
6.50	4.25
7.00	4.31
7.50	4.37
8.00	4.43
8.50	4.48
9.00	4.54
9.50	4.59
10.00	4.64
10.50	4.69
11.00	4.74
11.50	4.78
12.00	4.83
12.50	4.87
13.00	4.92
13.50	4.96
14.00	5.00
14.50	5.04
15.00	5.08
15.50	5.11
16.00	5.15
16.50	5.18
17.00	5.22
17.50	5.25
18.00	5.28
18.50	5.31
19.00	5.34
19.50	5.37
20.00	5.40

Table 3.14: Par value yields (%) developed from the spot rate curve: Data 2. Results for the first averaging period.

Chapter 4

Second Averaging Period

4.1 Data

The second averaging period encompasses the 20 business days from 10th June 2015 to 7th July 2015. The second averaging period was selected by United Energy as the reference interval for the purpose of measuring the rate of return on debt that would then be incorporated into the AERs preliminary determination^{[31](#page-61-0)}.

A comprehensive discussion of the data that was used in the context of the first, second and third averaging periods is provided in section 3.1. The framework for the retrieval and processing of bond data was a model that has been developed by the Competition Economists Group (CEG) and which is termed the "RBA replication model". The "RBA replication model" was used and updated by ESQUANT with permission from CEG.

As has previously been noted, ESQUANT applied further screening to the data available from the model before performing estimations of yield curves:

- Bonds for which the average value of option adjusted spreads was found to be negative during the relevant averaging period were not used.
- Bonds with remaining terms to maturity of less than three months were not used. This restriction was applied in order to limit the leverage of bonds with short maturities on the Nelson-Siegel models.
- Bonds with credit ratings from Standard and Poor's in the following categories were chosen: A (flat), A-, BBB+, BBB, and BBB-. Thus, although the model includes bonds with credit ratings of A+, these were not used on this occasion.

The bonds which satisfied the criteria in the three bullet points listed above have been labelled Data1 in this report. Additionally, the bonds in Data1 that were denominated in Australian Dollars have been labelled as Data2.

The industry of classification was an important variable to consider. Bloomberg provides a classification of the industry of the issuer. The bonds in Data1 and Data2 that had not been issued by companies operating in the finance sector, were labelled Data3 and Data4, respectively. Thus, Data3 and Data4 were comprised exclusively of "non-financial" sector bonds.

For the second averaging period, the numbers of bonds in the four datasets can be summarised as follows: 930, 659, 309, and 158, respectively.

4.2 Fitting Yield Curves

The curves were fitted to the data, sourced from the RBA replication model, using the nlsLM() command in the **minpack.lm** package in R (Elzhov et al. 2013). The empirical work was done in respect of the average yields for bonds over the period from 10th June 2015 to 7th July 2015. The curves were

 31 Refer to AER (2015b).

estimated using yield data rather than data on spreads-to-swap. The estimated parameters are given in Tables [4.1](#page-62-0) to [4.4,](#page-63-0) while the sample bond yields and fitted Nelson-Siegel yield curves are plotted in Figures [4.1](#page-64-0) to [4.8.](#page-71-0) Recall that the intercept term for each yield curve will be determined as a function of the parameters, *β*1, *β*4, *β*5, *β*6, and *β*7, depending upon the credit rating for which the yield curve applies.

The fitted values for the yield at a 10-year tenor were converted into spreads-to-swap by subtracting 10-year tenor swap rates from the predicted yields. The swap rates for specific tenors were themselves calculated by applying an interpolation method to the observed data on vanilla interest rate swaps, which was sourced from Bloomberg^{[32](#page-62-1)}. Note that the fitted Nelson-Siegel curves describe "average" behaviour; some bonds give much higher or lower yields than the fitted curve.

			Default				Sandwich	
	Estimate	Std. Error	t value	Pr(> t)		Std. Error	t value	Pr(> t)
beta0	-1.163	0.098	-11.881	0.000		0.152	-7.635	0.000
beta1	8.076	0.198	40.748	0.000		0.403	20.045	0.000
beta2	-4.595	0.235	-19.531	0.000		0.457	-10.049	0.000
beta3	-4.573	0.361	-12.656	0.000		0.350	-13.051	0.000
beta4	0.525	0.076	6.872	0.000		0.085	6.160	0.000
beta ₅	-0.237	0.054	-4.403	0.000		0.049	-4.787	0.000
beta ₆	-0.363	0.050	-7.267	0.000		0.049	-7.451	0.000
beta7	-0.534	0.049	-10.886	0.000		0.042	-12.694	0.000

Table 4.1: Regression parameters and standard errors for fitted Nelson-Siegel model, Data1, second averaging period.

			Default				Sandwich	
	Estimate	Std. Error	t value	Pr($\vert t \vert$		Std. Error	t value	Pr(> t)
beta0	-0.832	0.150	-5.532	0.000		0.255	-3.270	0.001
beta1	6.901	0.263	26.231	0.000		0.521	13.255	0.000
beta2	-3.337	0.324	-10.312	0.000		0.616	-5.420	0.000
beta3	-3.885	0.431	-9.007	0.000		0.406	-9.568	0.000
beta4	0.248	0.118	2.096	0.036		0.112	2.216	0.027
beta5	-0.205	0.075	-2.717	0.007		0.067	-3.052	0.002
beta6	-0.334	0.070	-4.781	0.000		0.069	-4.873	0.000
beta7	-0.509	0.070	-7.290	0.000		0.062	-8.266	0.000

Table 4.2: Regression parameters and standard errors for fitted Nelson-Siegel model, Data2, second averaging period.

 32 For the periods under consideration, daily values of swap rates were obtained for the Australian dollar swaps curve. The relevant series in Bloomberg includes, as its constituents, variables such as "ADSWAP10 Curncy".

			Default			Sandwich	
	Estimate	Std. Error	t value	Pr(> t)	Std. Error	t value	$>$ t)
beta0	-1.222	0.114	-10.723	0.000	0.146	-8.356	0.000
beta1	8.709	0.225	38.752	0.000	0.344	25.346	0.000
beta2	-5.297	0.291	-18.184	0.000	0.418	-12.667	0.000
beta3	-5.566	0.537	-10.372	0.000	0.509	-10.940	0.000
beta4	0.586	0.079	7.423	0.000	0.099	5.939	0.000
beta5	-0.323	0.068	-4.780	0.000	0.062	-5.235	0.000
beta6	-0.498	0.064	-7.786	0.000	0.063	-7.851	0.000
beta7	-0.609	0.071	-8.523	0.000	0.062	-9.772	0.000

Table 4.3: Regression parameters and standard errors for fitted Nelson-Siegel model, Data3, second averaging period.

		Default				Sandwich	
	Estimate	Std. Error	t value	Pr(> t)	Std. Error	t value	Pr(> t)
beta0	-0.871	0.135	-6.445	0.000	0.114	-7.631	0.000
beta1	7.876	0.331	23.783	0.000	0.251	31.359	0.000
beta2	-4.228	0.442	-9.561	0.000	0.329	-12.832	0.000
beta3	-6.311	0.724	-8.713	0.000	0.667	-9.458	0.000
beta4	0.439	0.133	3.292	0.001	0.177	2.487	0.014
beta5	-0.346	0.102	-3.399	0.001	0.092	-3.776	0.000
beta6	-0.448	0.088	-5.091	0.000	0.088	-5.086	0.000
beta7	-0.540	0.093	-5.821	0.000	0.079	-6.840	0.000

Table 4.4: Regression parameters and standard errors for fitted Nelson-Siegel model, Data4, second averaging period.

Figure 4.1: Observed average yields against average terms to maturity for Data1, second averaging period.

Figure 4.2: Observed average yields against average terms to maturity by credit rating for Data1, second averaging period.

Figure 4.3: Observed average yields against average terms to maturity for Data2, second averaging period.

Figure 4.4: Observed average yields against average terms to maturity by credit rating for Data2, second averaging period.

Figure 4.5: Observed average yields against average terms to maturity for Data3, second averaging period.

Figure 4.6: Observed average yields against average terms to maturity by credit rating for Data3, second averaging period.

Figure 4.7: Observed average yields against average terms to maturity for Data4, second averaging period.

Figure 4.8: Observed average yields against average terms to maturity by credit rating for Data4, second averaging period.

Fitting the Nelson-Siegel yield curves to the four data sets

The Nelson-Siegel model was fitted to the datasets, Data1, Data2, Data3, and Data4. Estimates of the yield at tenors of 7 years and 10 years were found by inserting the applicable term to maturity into the yield equation for which the regression coefficients had been estimated empirically.

The formulae shown below were then used to work out the debt risk premium (DRP) at 7-year and at 10-year terms to maturity. The calculation for the change in the DRP, ∆DRP, is also shown:

$$
DRP_7 = Yield(7) - 2.649\% DRP_{10} = Yield(10) - 3.018\% ADRP = \frac{100(DRP_{10} - DRP_7)}{3}.
$$

The values 2.649% and 3.018% represent the average yields on 7-year and 10-year Commonwealth Government securities, respectively, measured over the 20 business days from 10th June 2015 to 7th July 2015. These yields were calculated using an interpolation method that was applied to daily data sourced from Table F16, from the RBA website. An arithmetic mean was taken of the daily results for 7-year and 10-year CGS yields over the measurement period. The yields are expressed on a semiannual basis.

Standard errors were found using the delta method 33 . The estimates of the yields, debt risk premiums, and associated standard errors are given in Table [4.5.](#page-72-1) The results are reasonably consistent across the four data sub-samples.

Table 4.5: Estimated debt risk premiums (DRPs), for bonds in the BBB band with standard errors, for Data1, Data2, Data3, and Data4 in respect of the second averaging period. Note that the standard errors for the yields are the same as the standard errors for the corresponding DRPs. Sandwich standard errors are given in brackets,

As well, for the second averaging period, estimates of the spread-to-swap at a 7-year remaining term to maturity, SS_7 , the spread-to-swap at a 10-year remaining term to maturity, SS_{10} , and the difference, ∆SS were also found using the calculations presented below.

$$
SS7 = Yield(7) - 3.056%
$$

\n
$$
SS10 = Yield(10) - 3.371%
$$

\n
$$
\Delta SS = \frac{100(SS10 - SS7)}{3}.
$$

The values 3.056% and 3.371% represent the average swap rates at tenors of 7 years and 10 years, respectively, measured from 10th June 2015 to 7th July 2015. Table [4.6](#page-73-0) gives the estimates with standard errors.

The results presented in Table [4.5](#page-72-1) and in Table [4.6](#page-73-0) are a weighted average of the results for bonds in the individual credit rating sub-groups: BBB-, BBB (flat), and BBB+. The weights are determined by the numbers of bonds in each of the sub-groups.

³³In one dimension, Var(*g*(*x*)) ≈ [*g'*(*µ*)]²Var(*x*); in higher dimensions Var(*g*(*x*)) ≈ *d'*Σ*d* where Σ is the variancecovariance matrix of x and d is the vector of first derivatives of g evaluated at μ . The delta method was implemented with the delta.method command in the car package in R.

Table 4.6: Estimated spreads-to-swap for bonds in the BBB band with standard errors, for Data1, Data2, Data3, and Data4 in respect of the second averaging period. Note that the standard errors for the yields are the same as the standard errors for the corresponding spreads-to-swap.

The estimates and conventional standard errors in Tables [4.5](#page-72-1) and [4.6](#page-73-0) depend on assumptions that the data are Normally distributed with a common variance. To check the Normality assumption, QQ (Quantile-Quantile) plots are given in Figure [4.9.](#page-73-1) In the QQ plot, the ordered residuals (observed yields minus fitted values) are plotted on the *y*-axis, while expected values from a standard Normal distribution are plotted on the *x*-axis. If the residuals follow a Normal distribution, then the QQ plot should trace out an approximate straight line. Deviations from the line correspond to indications of non-Normality or outliers.

Figure 4.9: QQ plots of residuals from the Nelson-Siegel model fitted to Data1, Data2, Data3, and Data4. Results for the second averaging period.

4.3 Refinements to the analysis

4.3.1 Robust Analysis

The Nelson-Siegel model was fitted to the Data1, Data2, Data3, and Data4 datasets, using nlrob(). The estimated parameters are given in Tables [4.7](#page-74-0) to [4.10.](#page-75-0) The parameter estimates which correspond to the dummy variables for different credit ratings are also shown. The parameter estimates for the intercept terms are $β_1 + β_4$, $β_1$, $β_1 + β_5$, $β_1 + β_6$, and $β_1 + β_7$, for BBB-, BBB (flat), BBB+, A-, and A (flat) bonds, respectively. Estimates of the DRP₇, DRP₁₀, and $ΔDRP$ were found by substituting the parameter estimates into the relevant fitted yield curve models. Differencing formulae (used for subtracting the yields on CGS from the yields on corporate bonds) were then applied. Standard errors were found using the delta method and are presented with the estimated yields and DRPs in Table [4.11.](#page-75-1) The estimates of yields and DRPs, together with the associated standard errors, from the application of nlsLM() have also been presented, so as to facilitate comparability. Corresponding results for the spreads-to-swap are given in Table [4.12.](#page-75-2)

	Estimate	Std. Error	t value	Pr(> t)
beta0	-1.248	0.086	-14.453	0.000
beta1	8.342	0.199	41.949	0.000
beta2	-4.932	0.228	-21.632	0.000
beta3	-4.701	0.303	-15.511	0.000
beta4	0.478	0.065	7.335	0.000
beta ₅	-0.208	0.044	-4.693	0.000
beta6	-0.390	0.041	-9.529	0.000
beta7	-0.487	0.040	-12.186	0.000

Table 4.7: Robust fit for Data1, second averaging period.

	Estimate	Std. Error	t value	Pr(> t)
beta0	-1.120	0.130	-8.644	0.000
beta1	7.537	0.294	25.658	0.000
beta2	-4.137	0.329	-12.586	0.000
beta3	-4.028	0.349	-11.542	0.000
beta4	0.297	0.090	3.304	0.001
beta5	-0.140	0.056	-2.486	0.013
beta6	-0.342	0.052	-6.531	0.000
beta7	-0.432	0.052	-8.301	0.000

Table 4.8: Robust fit for Data2, second averaging period.

	Estimate	Std. Error	t value	t) Pr(
beta0	-1.203	0.123	-9.766	0.000
beta1	8.617	0.247	34.871	0.000
beta2	-5.198	0.320	-16.243	0.000
beta3	-5.605	0.571	-9.817	0.000
beta4	0.577	0.088	6.551	0.000
beta ₅	-0.311	0.073	-4.260	0.000
beta6	-0.508	0.069	-7.330	0.000
beta7	-0.609	0.077	-7.881	0.000

Table 4.9: Robust fit for Data3, second averaging period.

Estimate	Std. Error	t value	Pr(> t)
-0.929	0.219	-4.246	0.000
6.900	0.538	12.831	0.000
-2.409	0.759	-3.173	0.002
-6.117	0.917	-6.670	0.000
0.428	0.161	2.657	0.009
-0.476	0.109	-4.357	0.000
-0.531	0.098	-5.443	0.000
-0.634	0.101	-6.301	0.000

Table 4.10: Robust fit for Data4, second averaging period.

Table 4.11: Comparison of estimated debt risk premiums (DRPs), with standard errors, using nlsLM() and nlrob() for Data1, Data2, Data3, and Data4. Note that the standard errors for the yields are the same as the standard errors for the corresponding DRPs. Results are shown for the second averaging period which was the 20 business days from 10th June 2015 to 7th July 2015. The applicable credit rating is the broad BBB band.

Table 4.12: Comparison of estimated spreads to swap with standard errors using nlsLM and nlrob for Data1, Data2, Data3, and Data4. Note that the standard errors for the yields are the same as the standard errors for the corresponding spreads to swap. Results are shown for the second averaging period which was the 20 business days from 10th June 2015 to 7th July 2015. The applicable credit rating is the broad BBB band.

4.3.2 Analysis of daily results

The daily data for the second averaging period was analysed, following the method outlined in section 3.3.2. The analysis was carried out on the daily bond yield data, and the results were converted into estimates of the debt risk premium by subtracting, from bond yields, the applicable daily yields on CGS with a corresponding term to maturity. For each day, the Nelson-Siegel model was fitted to the data using $nlsLM()$. The daily results for DRP_{10} with 95% confidence intervals are presented in Figure [4.10.](#page-76-0) Figure [4.10](#page-76-0) shows that the results from day to day are quite autocorrelated but relatively stable. Corresponding figures for DRP₇ and $\Delta(DRP)$ are shown in Figures [4.11](#page-77-0) and [4.12.](#page-77-1)

mean(deltacgsTwo)

Figure 4.10: Estimated debt risk premiums at 10 Years for bonds in the BBB band, with 95% confidence intervals by day: Data1, Data2, Data3, and Data4, second averaging period.

Figure 4.11: Estimated debt risk premiums at 7 Years for bonds in the BBB band, with 95% confidence intervals by day: Data1, Data2, Data3, and Data4, second averaging period.

Figure 4.12: Estimated Delta debt risk premiums for for bonds in the BBB band, with 95% confidence intervals by day: Data1, Data2, Data3, and Data4, second averaging period.

4.4 Are common parameters justified?

The analysis outlined in section 3.4 was repeated for the second averaging period. The restricted version of the Nelson-Siegel model, with common slope parameters for the different sub-groups of bonds, but varying intercept terms, was compared to an unrestricted (or expanded) version of the model in which all of the parameters could take on different values for the different classes of bonds. An analysis of variance was carried out so as to compare the change in the residual sum of squares from the restricted version of the model to the unrestricted version, with the residual mean square of the unrestricted model. The analysis of variance generates an F-statistic, and the results are shown below in Table [4.13.](#page-78-0) For both Data2 and Data4, the null hypothesis that the slope coefficients are the same across the sub-groups of bonds, stratified by credit rating, could not be rejected by the data. The F-statistics produced by the tests carried out on Data2 and Data4 were low, and the resulting p-values were high. The data sub-samples Data2 and Data4 contain Australian dollar denominated bonds only. Thus, for Australian dollar bonds, there was adequate evidence to sustain a model in which the intercept terms, but not the slope coefficients, varied through the credit rating sub-groups. However, for Data1 and Data3, the null hypotheses were rejected at the 5% levels of significance.

Table 4.13: Anova for comparing the model with common *β*0, *β*2, and *β*³ parameters with the model where these parameters are not common: Data1, Data2, Data3, and Data4, second averaging period.

4.5 Application of Nelson-Siegel yield curves to estimate par yield curves

The parameters were estimated for each day over the second averaging period using the same approach as in section 3.5. The optim() command in R was again used. Figure [4.13](#page-79-0) gives a comparison of the predicted dirty price versus the actual dirty price for each day. An examination of the plots shows that there is a high degree of correspondence between the predicted dirty price and the actual dirty price for each day, although the observations for two outlying bonds are also visible in the charts.

Figure 4.13: Actual vs. predicted dirty price for Data4. Results for the second averaging period.

Figure [4.14](#page-80-0) presents the results for the estimated spot rates by day. The spot rate curves show gradual changes from day to day. The average spot rate curve over the 20 days is given in Figure [4.15.](#page-81-0)

Once the spot rate curves have been estimated, the corresponding par value curves can be derived. These are shown, on a daily basis, in Figure [4.16.](#page-82-0) Again, gradual changes are evident from day to day. The average par value curve is given in Figure [4.17,](#page-83-0) while a tabulation of the par yields for various terms to maturity is given in Table [4.14.](#page-84-0)

The average par yield at a 7-year term to maturity is 4.28% leading to a DRP of 1.63%; while the average par yield at a 10-year term to maturity is 5.34% leading to a DRP of 2.32%. Note that these values have been reported on a semi-annual basis.

Figure 4.14: Spot rate curves by Day: Data 4. Results for the second averaging period.

Figure 4.15: Average spot rate curve: Data4. Results for the second averaging period.

Figure 4.16: Par value curves by day: Data 4. Results for the second averaging period.

Figure 4.17: Average par value curve: Data 4. Results for the second averaging period.

Table 4.14: Par value yields (%) developed from the spot rate curve: Data 4. Results for the second averaging period.

Chapter 5

Third Averaging Period

5.1 Data

The third averaging period encompasses the 20 business days from 13th November 2015 to 10th December 2015. The third averaging period was nominated by United Energy as the reference interval that would be used to measure the rate of return on debt, the value for which would then be incor-porated into the AER's final determination^{[34](#page-85-0)}. ESQUANT understands that the third averaging period will ultimately affect the regulated revenues that are to be earned in the 2016 regulatory year.

A comprehensive discussion of the data that was used in the context of the first, second and third averaging periods is provided in section 3.1. The framework for the retrieval and processing of bond data was a model that has been developed by the Competition Economists Group (CEG) and which is termed the "RBA replication model". The "RBA replication model" was used and updated by ESQUANT with permission from CEG.

As has previously been noted, ESQUANT applied further screening to the data available from the model before performing estimations of yield curves:

- Bonds for which the average value of option adjusted spreads was found to be negative during the relevant averaging period were not used.
- Bonds with remaining terms to maturity of less than three months were not used. This restriction was applied in order to limit the leverage of bonds with short maturities on the Nelson-Siegel models.
- Bonds with credit ratings from Standard and Poor's in the following categories were chosen: A (flat), A-, BBB+, BBB, and BBB-. Thus, although the model includes bonds with credit ratings of A+, these were not used on this occasion.

The bonds which satisfied the criteria in the three bullet points listed above have been labelled Data1 in this report. Additionally, the bonds in Data1 that were denominated in Australian dollars have been labelled as Data2.

The industry of classification was an important variable to consider. Bloomberg provides a classification of the industry of the issuer. The bonds in Data1 and Data2 that had not been issued by companies operating in the finance sector, were labelled Data3 and Data4, respectively. Thus, Data3 and Data4 were comprised exclusively of "non-financial" sector bonds.

The numbers of bonds in the four datasets can be summarised as follows: 936, 657, 310, and 159, respectively, for the third averaging period.

5.2 Fitting Yield Curves

The curves were fitted to the data, sourced from the RBA replication model, using the nlsLM() command in the **minpack.lm** package in R (Elzhov et al. 2013). The empirical work was done in respect

 34 Refer to AER (2015b).

of the average yields for bonds over the period from 13th November 2015 to 10th December 2015. The curves were estimated using yield data rather than data on spreads-to-swap. The estimated parameters are given in Tables [5.1](#page-86-0) to [5.4,](#page-87-0) while the sample bond yields and fitted Nelson-Siegel yield curves are plotted in Figures [5.1](#page-88-0) to [5.8.](#page-95-0) Recall that the intercept term for each yield curve will be determined as a function of the parameters, *β*1, *β*4, *β*5, *β*6, and *β*7, depending upon the credit rating for which the yield curve applies.

The fitted values for yield at a 10-year tenor were converted into spreads-to-swap by subtracting 10-year tenor swap rates from the predicted yields. The swap rates for specific tenors were themselves calculated by applying an interpolation method to the observed data on vanilla interest rate swaps, which was sourced from Bloomberg^{[35](#page-86-1)}. Note that the fitted Nelson-Siegel curves describe average behaviour; some bonds give much higher or lower yields than the fitted curve.

			Default			Sandwich	
	Estimate	Std. Error	t value	Pr(> t)	Std. Error	t value	t Pr(>
beta0	-2.842	315.593	-0.009	0.993	472.263	-0.006	0.995
beta1	11.064	1.000	11.058	0.000	1.516	7.296	0.000
beta ₂	-7.491	1.006	-7.444	0.000	1.512	-4.954	0.000
beta3	0.004	2365.756	0.000	1.000	3540.254	0.000	1.000
beta4	0.968	0.085	11.448	0.000	0.159	6.096	0.000
beta ₅	-0.260	0.061	-4.295	0.000	0.068	-3.851	0.000
beta ₆	-0.474	0.056	-8.482	0.000	0.062	-7.625	0.000
beta7	-0.695	0.055	-12.746	0.000	0.059	-11.852	0.000

Table 5.1: Regression parameters and standard errors for fitted Nelson-Siegel model, Data1, third averaging period.

			Default				Sandwich	
	Estimate	Std. Error	t value	Pr(> t)		Std. Error	t value	Pr(> t)
beta0	-2.455	464.772	-0.005	0.996		529.641	-0.005	0.996
beta1	8.149	1.090	7.473	0.000		1.346	6.056	0.000
beta2	-4.560	1.097	-4.158	0.000		1.339	-3.405	0.001
beta3	-0.003	2117.388	-0.000	1.000		2413.186	-0.000	1.000
beta4	0.313	0.114	2.753	0.006		0.219	1.428	0.154
beta5	-0.240	0.076	-3.152	0.002		0.108	-2.222	0.027
beta6	-0.422	0.070	-6.007	0.000		0.105	-4.005	0.000
beta7	-0.606	0.070	-8.681	0.000		0.104	-5.823	0.000

Table 5.2: Regression parameters and standard errors for fitted Nelson-Siegel model, Data2, third averaging period.

 35 For the periods under consideration, daily values of swap rates were obtained for the Australian dollar swaps curve. The relevant series in Bloomberg includes, as its constituents, variables such as "ADSWAP10 Curncy".

			Default			Sandwich	
	Estimate	Std. Error	t value	Pr(> t)	Std. Error	t value	$>$ $ t)$
beta0	-2.008	0.336	-5.978	0.000	0.417	-4.817	0.000
beta1	10.274	0.577	17.796	0.000	0.789	13.030	0.000
beta2	-6.779	0.611	-11.095	0.000	0.807	-8.399	0.000
beta3	-3.549	1.469	-2.415	0.016	1.628	-2.180	0.030
beta4	1.141	0.125	9.155	0.000	0.193	5.917	0.000
beta ₅	-0.290	0.110	-2.634	0.009	0.104	-2.793	0.006
beta ₆	-0.419	0.103	-4.049	0.000	0.100	-4.206	0.000
beta7	-0.677	0.116	-5.836	0.000	0.097	-6.979	0.000

Table 5.3: Regression parameters and standard errors for fitted Nelson-Siegel model, Data3, third averaging period.

		Default				Sandwich	
	Estimate	Std. Error	t value	Pr(> t)	Std. Error	t value	z Pr()
beta0	-2.026	1.073	-1.888	0.061	0.702	-2.887	0.004
beta1	8.789	1.451	6.055	0.000	0.629	13.982	0.000
beta2	-5.283	1.524	-3.467	0.001	0.614	-8.610	0.000
beta3	-2.421	3.306	-0.732	0.465	2.400	-1.008	0.315
beta4	0.392	0.204	1.921	0.057	0.352	1.115	0.266
beta5	-0.447	0.170	-2.632	0.009	0.161	-2.782	0.006
beta6	-0.333	0.147	-2.272	0.024	0.157	-2.118	0.036
beta7	-0.514	0.152	-3.387	0.001	0.156	-3.284	0.001

Table 5.4: Regression parameters and standard errors for fitted Nelson-Siegel model, Data4, third averaging period.

Figure 5.1: Observed average yields against average terms to maturity for Data1, third averaging period.

Figure 5.2: Observed average yields against average terms to maturity by credit rating for Data1, third averaging period.

Figure 5.3: Observed average yields against average terms to maturity for Data2, third averaging period.

Figure 5.4: Observed average yields against average terms to maturity by credit rating for Data2, third averaging period.

Figure 5.5: Observed average yields against average terms to maturity for Data3, third averaging period.

Figure 5.6: Observed average yields against average terms to maturity by credit rating for Data3, third averaging period.

Figure 5.7: Observed average yields against average terms to maturity for Data4, third averaging period.

Figure 5.8: Observed average yields against average terms to maturity by credit rating for Data4, third averaging period.

Fitting the Nelson-Siegel yield curves to the four data sets

The Nelson-Siegel model was fitted to the datasets, Data1, Data2, Data3, and Data4. Estimates of the yield at tenors of 7 years and 10 years were found by inserting the applicable term to maturity into the yield equation for which the regression coefficients had been estimated empirically.

The formulae shown below were then used to work out the debt risk premium (DRP) at 7-year and at 10-year terms to maturity. The calculation for the change in the DRP, ∆DRP, is also shown:

$$
DRP_7 = Yield(7) - 2.612\%
$$

\n
$$
DRP_{10} = Yield(10) - 2.918\%
$$

\n
$$
\triangle DRP = \frac{100(DRP_{10} - DRP_7)}{3}.
$$

The values 2.612% and 2.918% represent the average yields on 7-year and 10-year Commonwealth Government securities, respectively, measured over the 20 business days from 13th November 2015 to 10th December 2015. These yields were calculated using an interpolation method that was applied to daily data sourced from Table F16, from the RBA website. An arithmetic mean was taken of the daily results for 7-year and 10-year CGS yields over the measurement period. The yields are expressed on a semi-annual basis.

Standard errors were found using the delta method^{[36](#page-96-0)}. The estimates of the yields, debt risk premiums, and associated standard errors are presented below in Table [5.5.](#page-96-1) There is a degree of dispersion of the results across the four data sub-samples.

Table 5.5: Estimated debt risk premiums (DRPs) for bonds in the BBB band with standard errors, for Data1, Data2, Data3, and Data4 in respect of the third averaging period. Note that the standard errors for the yields are the same as the standard errors for the corresponding DRPs. Sandwich standard errors are given in brackets,

For consistency with the methods applied for the first and second averaging periods, the formulations presented below were used, in the current context, to work out the following variables: An estimate of the spread-to-swap at a 7-year remaining term to maturity, SS₇, the spread-to-swap at a 10-year remaining term to maturity, SS_{10} , and the change in the spread-to-swap from 7 to 10 years, ∆SS. The calculations are:

$$
SS7 = Yield(7) - 2.777\%
$$

\n
$$
SS10 = Yield(10) - 3.016\%
$$

\n
$$
\Delta SS = \frac{100(SS10 - SS7)}{3}.
$$

The values 2.777% and 3.016% represent the average swap rates at tenors of 7 years and 10 years, respectively, measured from 13th November 2015 to 10th December 2015. Table [5.6](#page-97-0) presents the estimates of the spreads-to-swap together with the standard errors.

³⁶In one dimension, Var(*g*(*x*)) ≈ [*g'*(*µ*)]²Var(*x*); in higher dimensions Var(*g*(*x*)) ≈ *d'*Σ*d* where Σ is the variancecovariance matrix of x and d is the vector of first derivatives of g evaluated at μ . The delta method was implemented using the delta.method command in the **car** package in R.

The results presented in Table [5.5](#page-96-1) and in Table [5.6](#page-97-0) are, in each case, a weighted average of the results for bonds in the individual credit rating sub-groups: BBB-, BBB (flat), and BBB+. The weights are determined by the numbers of bonds in each of the sub-groups.

The estimates and the conventional standard errors in Tables [5.5](#page-96-1) and [5.6](#page-97-0) depend on assumptions that the data are Normally distributed with a common variance. To check the Normality assumption, QQ (Quantile-Quantile) plots are given in Figure [5.9.](#page-97-1) In the QQ plot, the ordered residuals (observed yields minus fitted values) are plotted on the *y*-axis, while expected values from a standard Normal distribution are plotted on the *x*-axis. If the residuals follow a Normal distribution, then the QQ plot should trace out an approximate straight line. Deviations from the line correspond to indications of non-Normality or outliers.

Figure 5.9: QQ plots of residuals from the Nelson-Siegel model fitted to Data1, Data2, Data3, and Data4. Results for the third averaging period.

5.3 Refinements to the analysis

5.3.1 Robust Analysis

The Nelson-Siegel model was fitted to the Data1, Data2, Data3, and Data4 datasets, using nlrob(). The estimated parameters are given in Tables [5.7](#page-98-0) to [5.10.](#page-99-0) The parameter estimates which correspond to the dummy variables for different credit ratings are also shown. The parameter estimates for the intercept terms are $β_1 + β_4$, $β_1$, $β_1 + β_5$, $β_1 + β_6$, and $β_1 + β_7$, for BBB-, BBB (flat), BBB+, A-, and A (flat) bonds, respectively. Estimates of the DRP₇, DRP₁₀, and $ΔDRP$ were found by substituting the parameter estimates into the relevant fitted yield curve models. Differencing formulae (used for subtracting the yields on CGS from the yields on corporate bonds) were then applied. Standard errors were found using the delta method and are presented with the estimated yields and DRPs in Table [5.11.](#page-99-1) The estimates of yields and DRPs, together with the associated standard errors, from the application of nlsLM() have also been presented, so as to enable comparisons to be made. Corresponding results for the spreads to swap are given in Table [5.12.](#page-99-2)

	Estimate	Std. Error	t value	Pr(> t)
beta0	-1.733	0.233	-7.450	0.000
beta1	8.809	0.523	16.848	0.000
beta2	-5.258	0.544	-9.670	0.000
beta3	-3.235	0.477	-6.777	0.000
beta4	1.023	0.078	13.088	0.000
beta5	-0.248	0.047	-5.341	0.000
beta6	-0.478	0.043	-11.145	0.000
beta7	-0.642	0.042	-15.448	0.000

Table 5.7: Robust fit for Data1, third averaging period.

	Estimate	Std. Error	t value	Pr(> t)
beta0	-1.791	0.435	-4.121	0.000
beta1	7.972	0.926	8.610	0.000
beta2	-4.512	0.946	-4.772	0.000
beta3	-2.558	0.605	-4.231	0.000
beta4	0.236	0.089	2.662	0.008
beta5	-0.127	0.055	-2.289	0.022
beta6	-0.332	0.051	-6.474	0.000
beta7	-0.463	0.051	-9.118	0.000

Table 5.8: Robust fit for Data2, third averaging period.

Table 5.9: Robust fit for Data3, third averaging period.

	Estimate	Std. Error	t value	t) Pr(
beta0	-1.566	0.352	-4.446	0.000
beta1	8.373	0.837	10.003	0.000
beta2	-4.897	0.899	-5.445	0.000
beta3	-4.197	0.699	-6.004	0.000
beta4	0.100	0.113	0.881	0.380
beta5	-0.289	0.083	-3.468	0.001
beta6	-0.287	0.072	-3.967	0.000
beta7	-0.404	0.075	-5.427	0.000

Table 5.10: Robust fit for Data4, third averaging period.

Table 5.11: Comparison of estimated DRPs with standard errors using nlsLM and nlrob for Data1, Data2, Data3, and Data4. Note that the standard errors for the yields are the same as the standard errors for the corresponding DRPs. Results are shown for the third averaging period which was the 20 business days from 13th November 2015 to 10th December 2015. The applicable credit rating is the broad BBB band.

Table 5.12: Comparison of estimated spreads to swap with standard errors using nlsLM and nlrob for Data1, Data2, Data3, and Data4. Note that the standard errors for the yields are the same as the standard errors for the corresponding spreads to swap. Results are shown for the third averaging period which was the 20 business days from 13th November 2015 to 10th December 2015. The applicable credit rating is the broad BBB band.

5.3.2 Analysis of daily results

The daily data for the third averaging period was analysed, following the method outlined in section 3.3.2. The analysis was carried out on the daily bond yield data, and the results were converted into estimates of the debt risk premium by subtracting, from bond yields, the applicable daily yields on CGS with a corresponding term to maturity. For each day, the reparameterised Nelson-Siegel model was fitted to the data using $nlsLM()$. The daily results for DRP_{10} with 95% confidence intervals are presented in Figure [5.10.](#page-100-0) Figure [5.10](#page-100-0) shows that the results from day to day are quite autocorrelated but relatively stable. Corresponding figures for DRP⁷ and ∆(DRP) are shown in Figures [5.11](#page-101-0) and [5.12.](#page-101-1)

Figure 5.10: Estimated debt risk premiums at 10 Years for bonds in the BBB band, with 95% confidence intervals by day: Data1, Data2, Data3, and Data4, third averaging period.

Figure 5.11: Estimated debt risk premiums at 7 Years for bonds in the BBB band, with 95% confidence intervals by day: Data1, Data2, Data3, and Data4, third averaging period.

Figure 5.12: Estimated Delta debt risk premiums for bonds in the BBB band, with 95% confidence intervals by day: Data1, Data2, Data3, and Data4, third averaging period.

5.4 Are common parameters justified?

The analysis outlined in section 3.4 was repeated for the third averaging period. The restricted version of the Nelson-Siegel model, with common slope parameters for the different sub-groups of bonds, but varying intercept terms, was compared to an unrestricted (or expanded) version of the model in which all of the parameters could take on different values for the different classes of bonds. An analysis of variance was carried out so as to compare the change in the residual sum of squares as between the restricted version of the model and the unrestricted version, with the residual mean square of the unrestricted model. The analysis of variance generates an F-statistic, and the results are shown below in Table [5.13.](#page-102-0) For both Data3 and Data4, the null hypothesis that the slope coefficients are the same across the sub-groups of bonds, stratified by credit rating, could not be rejected by the data. The Fstatistics produced by the tests carried out on Data3 and Data4 were low, and the resulting p-values were high.

The data sub-samples Data3 and Data4 are made up of bonds issued by non-finance sector companies only. Thus, for bonds issued by businesses which do not operate in the finance sector, there was adequate evidence to sustain a model in which the intercept terms, but not the slope coefficients, varied through the credit rating sub-groups.

However, for Data1 and Data2, the null hypotheses were rejected at the 5% levels of significance. Thus, the version of the Nelson-Siegel model which applies common slope coefficients across the sub-groups of credit ratings could not be supported as being the optimal model when bonds issued by finance and non-finance sector companies were pooled together. The empirical evidence would support the introduction of additional equation parameters.

The results from the analysis of variance exhibit variation depending upon the time period being examined. Thus, for the first averaging period, the restricted Nelson-Siegel equation could not be rejected for Data2 and Data4, the two sub-samples which are comprised of Australian dollar denominated bonds only. Similar results were recorded during the second averaging period. Therefore, for the first and second averaging periods, the topic of interest was how yields might vary across the credit rating sub-groups, and between Australian dollar bonds and foreign currency denominated bonds issued by Australian corporations.

For the third averaging period, there have been significant developments. In particular, the bonds issued by a number of leading financial institutions were subject to credit rating downgrades in early December 2015. Further information about the affected bonds is provided in Appendix A.

Table 5.13: Anova for comparing the model with common *β*0, *β*2, and *β*³ parameters with the model where these parameters are not common: Data1, Data2, Data3, and Data4, 3rd averaging period.

5.4.1 Analysis of the BBB credit rating band for the third averaging period

The analysis of variance which was undertaken in section 5.4 showed that there was evidence to support a Nelson-Siegel equation, with common slope coefficients but separate intercept terms for different credit rating sub-groups. The empirical evidence was in the form of a low F-statistic, however the evidence was only obtained for the Data3 and Data4 datasets, which are comprised of bonds issued by firms not operating in the finance sector. There were 310 bonds in the Data3 dataset and 159 bonds in the Data4 dataset with observations that were available for analysis over the third averaging period.

A further investigation of the results was undertaken so as to ascertain whether or not robust conclusions could be drawn. The sample of bonds was limited to those in the broad BBB band, in other words bonds in the credit rating sub-groups of BBB-, BBB (flat), and BBB+. The Nelson-Siegel equation that was estimated was structured as follows:

$$
y(\tau) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\tau e^{\beta_0}}}{\tau e^{\beta_0}} \right) + \beta_3 \left(\frac{1 - e^{-\tau e^{\beta_0}}}{\tau e^{\beta_0}} - e^{-\tau e^{\beta_0}} \right) + \beta_4 BBB + \beta_5 BBB +.
$$

In the equation above, BBB- is a dummy variable which takes the value of 1 for BBB- bonds, and 0 elsewhere; BBB+ is a dummy variable which takes the value of 1 for BBB+ bonds, and 0 elsewhere, and the λ parameter, which should be positive, has been reparameterised as:

$$
\lambda=e^{\beta_0}.
$$

To estimate the weighted average yield over the broad BBB rating class, at terms to maturity of 7 and 10 years, let p_1 , p_2 and p_3 be the proportions of BBB-, BBB (flat), and BBB+ bonds. Then, by way of example, the estimate of the weighted average yield at a 10-year term to maturity is given by:

$$
\beta_1 + p_1 \beta_4 + p_3 \beta_5 + \beta_2 \left(\frac{1 - e^{-10e^{\beta_0}}}{10e^{\beta_0}} \right) + \beta_3 \left(\frac{1 - e^{-10e^{\beta_0}}}{10e^{\beta_0}} - e^{-10e^{\beta_0}} \right).
$$

Table [5.14](#page-103-0) shows the results from fitting the model using nlsLM(), while Table [5.15](#page-103-1) presents the results from applying the robust regression estimator, nlrob(). In both cases, all of the parameter estimates are statistically significant.

	Estimate	Std. Error	t value	Pr(> t)
beta0	-1.558	0.481	-3.239	0.001
beta1	9.253	0.834	11.095	0.000
beta2	-5.798	0.973	-5.960	0.000
beta3	-4.095	1.790	-2.288	0.023
beta4	1.152	0.150	7.707	0.000
beta5	-0.286	0.130	-2.191	0.030

Table 5.14: Fit for Data3, third averaging period, using only bonds in the broad BBB credit rating band.

	Estimate	Std. Error	t value	t) Pr(
beta0	-1.374	0.295	-4.656	0.000
beta1	9.020	0.551	16.383	0.000
beta2	-5.500	0.682	-8.065	0.000
beta3	-5.008	1.206	-4.152	0.000
beta4	1.447	0.136	10.638	0.000
beta5	-0.225	0.110	-2.040	0.043

Table 5.15: Robust fit for Data3, third averaging period, using only bonds in the broad BBB credit rating band.

Table [5.16](#page-104-0) gives the estimated cost of debt at terms to maturity of 7 years and 10 years. The debt risk premiums, evaluated over the same period, are also shown, as is the change in the DRP from 7 years to 10 years. The corresponding results for the spread-to-swap are given in Table [5.17.](#page-104-1)

The results reported are consistent with those that were obtained by running regressions on bonds drawn from a wider set of credit rating categories, including bonds rated A and A-. A comparison can be made between the results presented in Table [5.16](#page-104-0) and Table [5.17,](#page-104-1) and those shown in Table [5.11](#page-99-1) and Table [5.12.](#page-99-2) When the pool of bonds is limited to those drawn from the broad BBB rating class, the resulting estimates of the 10-year yield are higher. Thus, using the robust regression estimator, the cost of debt, at a tenor of 10 years, is shown to be 6.021% in Table [5.16,](#page-104-0) as compared to 5.722% in Table [5.11.](#page-99-1) When a standard, non-linear least squares estimator has been used, the cost of debt, at a 10-year tenor, has been found to be 5.782% in Table [5.16,](#page-104-0) as compared to 5.67% in Table [5.11.](#page-99-1)

The standard errors are higher when only bonds in the broad BBB rating class have been brought into the regression, but the estimates of the yield at 10 years are still statistically significant.

The 10-year yield of 6.021% is also of a similar magnitude to the recorded output from the Thomson Reuters (TR) BBBAUD benchmark credit curve. The end of day values for the Australian dollar BBB rated credit curve are available from Thomson Reuters and have been recorded by ESQUANT. Over the period from 13th November 2015 to 10th December 2015, the arithmetic average of the daily results, at a tenor of 10 years, was 5.8528%, as has been noted in Appendix A. This value has been reported on a semi-annual basis.

Thus, the empirical estimates obtained by ESQUANT, using bonds in the BBB credit rating band only, are within a reasonable range of the result from the TR BBB rated corporate credit curve for Australia.

Table 5.16: Comparison of estimated debt risk premiums (DRPs), with standard errors, using nlsLM() and nlrob() for Data3. Note that the standard errors for the yields are the same as the standard errors for the corresponding DRPs. Results are shown for the third averaging period which was the 20 business days from 13th November 2015 to 10th December July 2015. The applicable credit rating is the broad BBB band, and the bonds used were those in the broad BBB credit rating band only.

Table 5.17: Comparison of estimated spreads to swap, with standard errors, using nlsLM() and nlrob() for Data3. Note that the standard errors for the yields are the same as the standard errors for the corresponding spreads to swap. Results are shown for the third averaging period which was the 20 business days from 13th November 2015 to 10th December July 2015. The applicable credit rating is the broad BBB band, and the bonds used were those in the broad BBB credit rating band only.

Chapter 6

Applying the results to different scenarios for the transition to a trailing average, portfolio return on debt

6.1 The cost of debt as observed during the third averaging period, November-December 2015

ESQUANT has considered the various estimates that it has obtained for the yield on a benchmark, 10 year corporate bond. The output from yield curves and par yield curves has been carefully scrutinized, in conjunction with the regression diagnostics. In respect of the third averaging period, from 13th November to 10th December 2015, ESQUANT has formed the view that the most appropriate result to use is the estimate of the cost of debt from a standard Nelson-Siegel yield curve that was fitted to the dataset described as Data3.

The sub-sample of observations that has been labelled as Data3 contains both Australian dollar bonds and bonds denominated in foreign currencies (specifically, US dollars, British pounds, and Euros). However, Data3 omits bonds that have been that have been issued by firms which operate in the finance sector. The industry classification system is that provided by Bloomberg.

The omission of finance sector bonds on this occasion can be justified with reference to the results from F-tests. For both Data1 and Data2, the results from the F-tests showed that the null hypothesis of common parameter estimates across the credit rating bands could be rejected. Thus, for Data1 and Data2, the particular specification of the regression equation could not be supported empirically. The specification assumes that there are common slope parameters across each of the sub-groups of credit ratings from A to BBB-, and that only the intercept terms differ. If the constraint of common slope parameters is relaxed, then different yield curves will be produced for each sub-group of credit ratings. The yield curves will have different shapes across the tenor range and may also cross.

For Data3, the null hypothesis of uniform slope coefficients across the sub-groups of credit ratings could not be rejected at the 5 per cent level of significance. Accordingly, the specification for the regression equation was sustained by the data.

The use of robust regression methods is preferred because the robust techniques serve to limit the influence of outlying observations on the regression parameter estimates. The estimate of the cost of debt is therefore obtained with comparatively low standard errors. For Data3, the estimation of the yield curve using a robust regression approach produced a cost of debt estimate of 5.722 per cent, commensurate with a 10-year tenor. This value can then be used as an input into various transition scenarios for the rate of return on debt.

6.2 Immediate transition to a trailing average, portfolio return on debt

ESQUANT has examined alternative scenarios for the transition to a trailing average, portfolio return on debt. The different forms for the transition have been documented elsewhere by the Competition

Economists Group (CEG), and have been the subject of debate between CEG and advisors acting for the AER. ESQUANT is providing information about the calculated results for the rate of return on debt under different transition scenarios so as to ensure that United Energy has a proper understanding of the broader context. We would also like to be certain that UE has access to the full range of relevant data.

Table [6.1](#page-107-0) below provides details of the components that are used when assessing the rate of return on debt under an immediate transition to a simple trailing average.

The first component in the table is the historical series of 10-year swap rates. The values were sourced from the Bloomberg ADSWAP series. The second component in Table [6.1](#page-107-0) is the historical spread-over-swap data from January 2006 to December 2014. The results were provided by CEG. The historical spreads-over-swap have been calculated using data from the Bloomberg BBB rated fair value curve and from the RBA measure of corporate bond spreads for BBB rated debt. CEG has applied the Lally extrapolation method (based on swap rates only) to the historical data from 2006 to 2014, and has calculated an arithmetic average of the results from the Bloomberg fair value curve and from the RBA series. Note that data from the Bloomberg BBB rated fair value curve for Australia is available from December 2001 to the beginning of April 2014. Historical data from the RBA series of corporate bond spreads is available from January 2005. CEG has previously provided the past spread-over-swap values in a report prepared for United Energy in April 2015^{[37](#page-106-0)}. However, CEG has since amended the historical spread-over-swap values because the RBA itself released amendments to its historical data in October 2015. The changes made by the RBA affected the data going back to January 2005.

A comparison of the historical spreads-over-swap in Table [6.1](#page-107-0) below with the spreads-over-swap reported by CEG (2015c) in April 2015 shows that while there have been revisions from one year to the next, the arithmetic average of the spreads-to-swap over the full period from 2006 to 2014 has altered by only a small amount. Thus, CEG previously assessed that the arithmetic average from 2006 to 2014 was 2.469 per cent, when data from the Bloomberg series and the RBA series was used, and the extrapolation approach applied was consistent with the Lally (swaps) method. The latest version of the historical data, shown in Table [6.1](#page-107-0) below, suggests that the arithmetic mean of the historical values from 2005 to 2014 is 2.455 per cent.

The penultimate numbered row of Table [6.1](#page-107-0) below also provides data for the 2015 calendar year. The results for 2015 are in respect of the United Energy third averaging period from 13th November to 10th December 2015. The cost of debt of 5.722 per cent is the yield that was obtained from the robust regression.

The rate of return on debt under the immediate adoption of the trailing average is simply the trailing average of 10-year spreads-to-swap (2.480 per cent), plus the trailing average of 10-year swap rates (5.177 per cent) measured contemporaneously over each of the 10 years. The sum of the two components results in a return on debt of 7.657 per cent, before transaction costs. This value has been expressed on a semi-annual basis.

To obtain the final result under the immediate transition, there is a requirement to add an estimate of the new issue premium, and to then convert the resulting value into an annual effective rate. CEG derived an estimate of the new issue premium equivalent to 27 basis points, in a report prepared in October 2014^{[38](#page-106-1)}. The 27 basis points was itself calculated as an average of two component values which represented different methods for measuring the way in which the new issue premium ends up being dissipated over time. More recently, CEG has released a report that responds to AER criticisms of the new issue premium^{[39](#page-106-2)}. In view of the analysis that has been undertaken by CEG, and the strength of the case that has been made, ESQUANT considers that 27 basis points is still the best available estimate of the premium on yields that borrowers must, in effect, pay on primary debt issuance.

After allowing for the new issue premium, the value for the return on debt in 2016, under the immediate transition, is equal to 7.927 per cent. This is then converted into an annual equivalent rate giving a value of 8.805 per cent, which is reported in Table [6.3](#page-109-0) below. For the full trailing average rate of return on debt, there is no need to express the return on debt as a combination of a spread-to-swap and a base interest rate, or swap rate. However, since the only difference between the hybrid and

³⁹Hird, T. (2015e).

 37 Hird (2015b), Table 12, section 7, page 76. See also Hird (2015a), Table 21, page 92.

³⁸Hird, T. (2014), section 7.3, page 54.

trailing average measures is in respect of the base interest rate, the decomposition thus described is nonetheless useful.

Table 6.1: Components of the historical data used under an immediate transition to a trailing average rate of return on debt.

Source: Data for previous periods is based on calculations by CEG. The historical spread-over-swap data is an update of the information in Table 21, *Critique of the AER's JGN draft decision on the cost of debt*, CEG, April 2015. The historical 10-year swap rate has been calculated using Bloomberg end-of-day 10-year swap rates; the series is ADSWAP10 Curncy. The estimate of the cost of debt for the November-December 2015 averaging period is based on yield curve estimations by ESQUANT. The full period average of 7.657% (semi-annual) is used as the rate of return on debt under the immediate transition. To this value is added an estimate of the new issue premium. The semi-annual value is then transformed into an annual effective rate.

6.3 Hybrid method for the transition to a trailing average

Table [6.2](#page-108-0) below presents the swap rates at different tenors that were recorded during the November-December 2015 averaging period. The values shown are averages computed over the 20 business days.

Under a transition from the hybrid to a simple trailing average debt management strategy, the rate of return on debt for the regulatory year 2016 is equal to the sum of the components listed below:

- The trailing average of 10-year spreads-to-swap, measured relative to swap rates over the period from 2006 to 2015; plus
- The average of 1 to 10 year swap rates over the averaging period for United Energy.
- The costs of swap transactions that are required to give effect to the transition.

Under the hybrid strategy, the use of a swap portfolio overlay allows base interest rates to be reset during the final averaging period before the commencement of the regulatory control period. A regulated business can hedge the base rate by entering into "pay fixed, receive floating" swap transactions. The tenor of the swaps will align with the remaining terms to maturity of the bonds in the underlying bond portfolio. Thus, the business can, in effect, "lock in" swap rates. However, the business will not necessarily undertake hedging for the full value of the debt portfolio.

Since the tenor of debt at issuance is assumed to be ten years, then historical spreads-over-swap (or debt risk premiums) will continue to be paid on bonds that were issued up to 10 years ago (and for which there is still a certain time period remaining to maturity). The historical spread-to-swap for each bond is matched with a swap rate, the tenor of which is equal to the bond's remaining term to

Table 6.2: End-of-day swap rates recorded during the third averaging period

Source: Bloomberg ADSWAP series. The results shown are arithmetic averages over the period from 13th November to 10th December, inclusive. The swap rates of different tenors that have been recorded during the November-December averaging period are used as an input into calculations of the rate of return on debt under the hybrid form of the transition. This table is an updated version of Table 4.2, *Rate of Return on Debt: Proposal for the 2016 to 2020 Regulatory Period*, Attachment to UE Regulatory Proposal.

maturity. Thus, for a bond issued 9 years' ago, the spread-to-swap will reflect the spread-to-swap on a 10-year bond which was issued at the time, and the particular value of the spread will be matched with a one-year swap rate.

Therefore, the hybrid method establishes a synthetic form of trailing average. The historical spreadsto-swap are brought into alignment with prevailing swap rates with the same remaining term to maturity. After the first year, the calculation of the return on debt can be updated in a similar manner to the calculation of the return on debt under the full trailing average.

By way of example, in 2016, the oldest tranche of debt, assumed to have been issued in 2006, will mature, and payments of the spread-to-swap for that debt instrument will cease. Similarly, the one-year hedge that has been taken out during the final averaging period in 2015 will mature. These elements of the synthetic trailing average will be replaced by new debt issues occurring during 2016.

Table [6.1](#page-107-0) shows that the trailing average spread-to-swap was 2.480 per cent, when measured from 2006 to 2015 inclusive. Table [6.2](#page-108-0) shows that the average of one to ten year swap rates recorded during the final averaging period for 2015 was 2.631 per cent. Accordingly, the rate of return on debt associated with a transition from the hybrid to the full trailing average is equal to 5.112 per cent during the regulatory year 2016. To this value must be added swap transactions costs and the new issue premium. For swap transactions costs, ESQUANT has chosen to apply a value of 11.5 basis points per annum which has been drawn from advice provided to the Economic Regulation Authority (Western Australia) by Chairmont Consulting^{[40](#page-108-1)}. For the new issue premium, the best currently available estimate is 27 basis points, as previously noted. Accordingly, the overall return on debt is 5.497 per cent (on a semi-annual basis), or 5.572 per cent when transformed into an annual equivalent rate.

6.4 Optimal hedging ratios

CEG (2015d) examined the issue of determining the optimal response of a regulated entity to the efficient cost of debt calculated under the previous regulatory methodology. The optimal response would consist of minimizing the expected (risk adjusted) costs of financing.

The AER has argued that the "hybrid" debt management strategy was the most efficient for minimizing risk under the previous regulatory methodology. This strategy decomposes the risk of mis-

⁴⁰Chairmont (2015a), section 4.3.4, page 6.

match into two parts, one due to the variation in the level of interest rates, as represented by ten-year swap rates, and the other due to variation of the DRP, as represented by the spread between ten-year yields on BBB rated debt and ten-year swap rates. The risk due to the variation of ten-year swap rates is then eliminated by using interest rate swaps, while the risk due to the variation in the DRP remains unhedged. Thus, the strategy favoured by the AER is a simplistic one: If one cannot hedge the risk of mismatch between the actual and regulated cost of debt for the DRP component, but one can hedge the base interest rate exposure in full, then one should do the latter. As noted by CEG (2015d), the AER's approach is optimal only if the DRP and the base interest rate are uncorrelated 41 41 41 .

A more sophisticated approach would necessitate determining the optimal hedge using available instruments, which both the AER and CEG (2015d) assume to be interest rate swaps only. There is strong empirical support for a negative correlation between the debt risk premium and base interest rates. CEG (2015d) provided empirical evidence of the negative correlation, and also reviewed the existing finance literature. In the presence of a negative correlation between the DRP and the base interest rate, the optimal hedge using interest rate swaps will necessarily cover less than 100% of the base interest rate exposure. A business will want to make use of the "natural hedge" between the DRP and the base interest rate component so as to deal with the mismatch that arises between the actual and the regulated cost of debt. This qualitative result holds regardless of the level of the negative correlation. Quantitatively, the stronger the negative correlation, then the smaller will be the proportion of the base interest rate exposure which should be optimally hedged using interest rate swaps.

Thus, there are no practical reasons as to why a business could not hedge only a fraction of its base interest rate exposure in order to take advantage of the natural hedge between base interest rates and the DRP.

CEG (2015d) undertook empirical analysis using a similar dataset for Australia as had been compiled by Chairmont. CEG (2015d) regressed the spread-to-swap on the swap rate, using monthly data, and obtained a parameter estimate on the swap rate of -0.33^{[42](#page-109-1)}. Other empirical estimates that were de-rived using Australian data were found to be in the vicinity of this value ^{[43](#page-109-2)}. CEG (2015d) has therefore suggested that 33 per cent might be an appropriate optimal hedging ratio to use in calculations.

Table 6.3: Results for the rate of return on debt under alternative transition scenarios (annual effective rates).

Source: Calculations by ESQUANT; historical data from CEG. The values shown are annual effective rates. Under each of the scenarios for the transition, the return on debt includes an annual allowance for the new issue premium of 27 basis points (0.27%), before annualisation. Refer to: *Critique of AER Analysis of New Issue Premium*, prepared by Tom Hird, Competition Economists Group, December 2015. Under the hybrid form of the transition, there is also an annual allowance for swap transaction costs of 11.5 basis points (0.115%), before annualisation. The results under the optimal hedging ratio are predicated on a hedging proportion of one third (33.3%), consistent with the advice from CEG, and the empirical work undertaken by CEG.

⁴¹Hird, T., (2015d), section 3.3, page 12.

⁴²Hird, T., (2015d), section C.2.3, page 93.

⁴³Hird, T., (2015d), section 5.4, Table 8, page 67.

The final column of Table [6.3](#page-109-3) above presents the results for the return on debt under a scenario in which a business is deemed to apply an optimal hedging ratio of one third. The business thus applies interest rate hedges to only a proportion of its overall debt portfolio. Therefore, the hybrid form of the transition to a full trailing average will be relevant only in respect of the portion of the debt portfolio that has been hedged using interest rate swaps.

The rate of return on debt for a benchmark efficient entity that follows the practice of optimal hedging will be calculated as an intermediate outcome between the rate of return on debt under the immediate transition to a full trailing average, and the rate of return under the hybrid form of the transition to a portfolio average. The results under optimal hedging are determined by using a weight of one third for the hybrid transition, and two thirds for the immediate or instantaneous transition.

For 2016, the rate of return on debt under optimal hedging should be set at 7.247 per cent, which is a value expressed as an annual effective rate.

Table [6.3](#page-109-3) presents a summary of the results under the four transition scenarios: Immediate, Hybrid, Guideline and Optimal Hedge. In addition to showing the values for the 2016 regulatory year, the table also presents forecasts for the remaining years of the 2016 to 2020 regulatory period, and for other future years.

The forecasts take into account the shedding of past values of variables, as the particular component of the return on debt becomes more than ten years' old. Thus, for instance, the forecast, under the immediate transition, for the return on debt in 2017 does not use any historical data from 2006, because the calculation of the average will have essentially been rolled forward. Similarly, under the hybrid approach, the return on debt in 2017 will be measured using historical spread-over-swap data from 2007 to 2016. The calculated swap rate itself will be a combination of an average of the 2 to 10 year tenor swap rates that were recorded during the final averaging period in 2015, and a 10-year tenor swap rate that is measured during the reference period in 2016.

For ease of exposition, the forecasts do, however, assume that the spot cost of debt that is measured during an averaging period in 2016, will be the same as the spot cost of debt that was recorded during the final averaging period for 2015. The assumption that has been made here is pragmatic and is aimed at allowing a regulated business to use the predictions for the final four years of the regulatory period as inputs into the post-tax revenue model (PTRM). However, the predictions are indicative, and the PTRM will be subject to annual updating of the rate of return on debt.

Table [6.4](#page-110-0) below provides actual transitional values that can be incorporated into the calculations of the return on debt for years' two to five of the forthcoming regulatory period. The transitional values in the hybrid column provide an update of the numbers written down in the initial regulatory proposal for United Energy (April 2015)^{[44](#page-110-1)}. Those numbers were previously provided by CEG.

Under the immediate transition, the transitional values shown in the second column of the table would be used in a similar manner.

Table 6.4: Return on debt for United Energy (2016), and transitional values to be used in the annual update formulas for subsequent years.

Source: Calculations by ESQUANT; historical data from CEG. The values shown have been presented as annual effective rates. The transitional values that are shown provide an update for those in section 7, *Rate of Return on Debt: Proposal for the 2016 to 2020 Regulatory Period*, Attachment to UE Regulatory Proposal. The transitional values were previously provided by CEG.

⁴⁴United Energy, (2015), section 4.2, page 19.

6.5 Summary of the results against a background of the transition scenarios

- In the context of an immediate transition to the full trailing average method, the rate of return on debt will be 8.085 per cent for the 2016 regulatory year.
- For the hybrid transition, the rate of return on debt will be 5.572 per cent.
- Under the AER's rate of return guideline, the appropriate rate of return on debt for the 2016 regulatory year will be 6.082 per cent.
- Finally, if the approach is to consider the optimal hedging ratio of a benchmark efficient entity, then the appropriate value to use for the rate of return on debt will be 7.247 per cent.

The figures mentioned in the bullet points above have been expressed as annual effective rates. For each of the four scenarios, the values to be used in the post-tax revenue model for the regulatory years from 2016 to 2020 are shown in the relevant columns of Table [6.3](#page-109-3) above. The results for 2017, 2018, 2019 and 2020 are, in a sense, placeholder values which will be subject to annual updating.

In contrast to Table [6.3,](#page-109-3) Table [6.4](#page-110-0) provides the transitional values (T2017, T2018, T2019, and T2020) that can be used formulaically in the annual updating calculations as each regulatory year from 2017 to 2020 comes to pass.

Chapter 7

Conclusions

7.1 Conclusions

Nelson-Siegel curves can be used to estimate term structure models which provide an appropriate and accurate method of determining the cost of debt for different tenors.

We have estimated Nelson-Siegel models for four Data sets and have also been able to produce standard errors, thereby providing a useful complement to fitting of yield curves. Standard errors convey information about the precision of the empirical estimates. The results for the debt risk premium at 10 years, and for the increment to the DRP from 7 to 10 years, were shown to have low standard errors and to therefore be precise.

The estimation of par yield curves is a worthy exercise because these curves fully standardise and correct for differences between bonds that are caused by variations in the timing and size of coupon payments. We estimated zero-coupon yield curves or spot rate curves that belong to the family of Nelson-Siegel curves. Subsequently, we used these estimates to generate estimates of par yield curves. Schaefer (1977) shows how one can uncover the term structure of par yields from the term structure of spot rates.

ESQUANT has undertaken extensive empirical work in the course of preparing this report. Based on its knowledge and experience from undertaking the current assignment, and similar assignments, ESQUANT considers that the AER's existing approach to the return on debt is not capable of producing an estimate of the rate of return on debt that will contribute to the achievement of the allowed rate of return objective (ARORO). The allowed rate of return objective is set out in clause 6.5.2 (h) of the National Electricity Rules (NER, version 77). Similarly, ESQUANT believes that the results from the application of the AERs current method would be unlikely to meet the requirements of clause 6.5.2 of the National Electricity Rules.

ESQUANT believes that an estimate of the return on debt that would be obtained by using the approach adopted by the AER would not produce a result that is consistent with the achievement of the National Electricity Objective (NEO), and the Revenue and Pricing Principles (RPP).

Chapter 8

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Appendix A

Analysis of third party indicator series including credit curves from Thomson Reuters

ESQUANT₁ Statistical Consulting

ANALYSIS OF THIRD PARTY INDICATOR SERIES, INCLUDING CREDIT CURVES FROM THOMSON REUTERS

A review of the evidence with reference to the measurement period for United Energy

1 Table of Contents

1

2 Assessment of published credit curves prepared by Thomson Reuters

2.1 Background

Thomson Reuters (TR), a leading information services provider, produces measures of corporate credit spreads for BBB rated bonds that are denominated in Australian dollars. A key indicator that is prepared is the corporate cash credit curve for Australia. The values for the summary corporate credit curve are available on a daily basis at tenors within a range from 3 months up to ten years. ESQUANT believes that the TR corporate credit curve provides useful corroborative evidence about the yield for a ten-year benchmark corporate bond that is commensurate with prevailing conditions in financial markets. A further discussion about the TR credit curve is provided in the subsequent sections of this chapter.

2.2 An overview of the credit curves produced by Thomson Reuters

Thomson Reuters (TR) has provided documentation to ESQUANT which explains the construction and application of TR credit curves. The information supplied includes an overview document, a more detailed report on credit curve methods, and a separate technical appendix which is the "Adfin" term structure calculation guide for Thomson Reuters Eikon¹. The material that has been provided to ESQUANT is confidential to TR subscribers.

There are currently around 480 Thomson Reuters ratings and sector curves covering 20 currencies. For each curve, TR provides a par yield and a zero coupon yield, a benchmark spread, a spread to swap, an asset swap spread, and a Z-spread. In addition, a credit event probability score that is derived from the credit curves for the individual bonds, is also available.

Time series data can be sourced for the credit curves, with the length of history dependent upon when coverage was initiated for the particular curve.

2.3 Curve construction method

The construction of a bond credit curve takes place over several distinct steps which can be summarized as follows:

- Building a bond universe.
- Allocating the bonds to constituent groups
- Calculating the term structure
- Deriving a pure discount curve, a par yield curve, and other analytics; and
- Generating output for individual records.

According to TR, each set of curves starts with a universe of bonds that is developed using an appropriate search query. Only bonds that are actively priced are employed in the construction process. From the universe of bonds, a term structure is derived by using a curve model. By making use of the resulting term structure, TR can then calculate the spot curve or zero coupon curve, and thereafter the par yield curve. Other analytics such as the benchmark spread, and spread to swap are then calculated off the par yield curve.

 ¹ The explanatory materials are listed in the references section.

2.3.1 Building a suitable bond universe

TR reports that all ratings and sector curves are based on a set of criteria that is standard across all curves. In addition to the standard criteria, there are some non-standard criteria that can be changed or modified according to the needs of specific markets.

The terms and conditions for each bond are retrieved from EJV, which is the main fixed income database of records for Thomson Reuters. The **standard criteria** that are applied can be set out as follows:

- **Bond Type**. TR uses only plain vanilla, fixed rate or zero coupon bullet bonds for the construction of the curves. Bonds with any form of embedded optionality are excluded, as are index-linked bonds.
- **Seniority**. Only senior unsecured issues are used,
- **Debt Type.** TR reports that it does not mix the various debt types. The main ratings curves comprise notes, bonds, debentures, and loan stocks, but exclude commercial paper (CP), certificates of deposits (CD) and covered bonds.
- **Sectors**. Sovereigns, including states, provincials and municipals are excluded from the TR bond universe retrieval process. Agencies are included in the retrieval process but are separated into a different curve universe at the construction and output stage. In other words, TR constructs agency curves separately from corporate curves.
- **Guarantees**. TR excludes bonds that are guaranteed by the sovereign government. Only bonds that carry a non-sovereign parent guarantee are included as these are usually parent guarantees of a financial subsidiary or special purpose company set up for the purpose of raising funds.
- **Private Placements**. Private placements are excluded.

The **non-standard criteria** that are evaluated by Thomson Reuters can be explained with reference to the considerations that are described below:

Amount Outstanding. TR reports that it has set a minimum amount outstanding for each bond that is greater than or equal to EUR150 million, or an equivalent amount. However, the minimum amount outstanding can be changed depending on the currency and the market for which curves are being built.

Rating Agencies. The credit ratings and the agencies that are used vary according to the currency and the market of application. In circumstances in which domestic or local ratings are available, these will tend to be used in preference to the ratings from the international agencies. For instance, TR uses ratings from the Japanese agencies for the Japanese domestic curves. Similarly, the credit ratings from domestic agencies are used for China and Malaysia. International agencies would only be used in such cases if the ratings that they provide are considered equivalent to the domestic or local scale ratings.

Market of issue. TR does not generally include any specific market of issue when it derives the bond universe. However, when the requirement arises, TR can and does provide domestic versus offshore curves for some currencies. A split between domestic and offshore issuance is necessary for currencies that are also issuance currencies in the Eurobond market. Thus, there are currently two sets of curves for the US Dollar and for the Japanese Yen. The domestic curves are based purely on bonds for which the market of issue has been flagged as the domestic market in the United States or in Japan. The international USD and JPY curves are comprised mainly of Eurobonds.

Pricing source. The pricing sources that are used include the Thomson Reuters Fixed Income Trading (TRFIT) composite, which is comprised of data that has been derived using executable prices from price makers. The TR curve development models also use evaluated prices from Thomson Reuters Pricing (TRPS), and the Thomson Reuters 'SuperRIC' which can be described as the super composite that represents the best available tolerance-checked price for a particular bond.

The choice of which source is used depends upon the market of application. For instance, the Euro, pound sterling, and US dollar markets are more liquid and actively traded on the TR trading platform, and so the curve development team will tend to select TRFIT prices, in the first instance, for curves in those currencies. The curve development models then use 'SuperRIC' pricing as the second choice to cover those bonds that are less actively quoted on trading platforms. TRPS pricing is used in those markets for which there isn't sufficient liquidity to cover all rated issues.

2.3.2 Constituent grouping and output curves

TR has stated that the bond universe is broken down into different sector and ratings groups before the term structure and curve calculations can take place. A curve will be constructed for each group provided that there are a sufficient number of qualifying bonds. Currently, the pre-requisite is for there to be a minimum of five qualifying bonds in order for a curve to be generated.

Industry curves are produced for sectors of the economy that can be classified as follows:

- Communications (COM)
- Consumer Goods and Services (CON)
- Financial Services (FIN)
- Industrials (IND)
- Utilities (UTI)
- Transportation (TRA)
- Agencies (AGE)

TR applies a mapping table to re-classify and aggregate various business sectors into the broader industry sectors noted above. The sector grouping to which the ultimate parent entity belongs is generally used for the mapping exercise.

TR does not currently produce sector curves with greater granularity because the number of eligible bonds diminishes significantly if the focus of attention is confined to sub-sector levels. When examining disaggregated industry classifications, there is a strong likelihood that the number of qualifying bonds will fall below the minimum threshold of five bonds.

In the case of Japan, TR produces another set of sector curves that follows the local industry sector classification scheme. The production of these curves was initiated in response to requests from customers for curves that align with the market sectors to which listed issuers belong on the Tokyo Stock Exchange.

For credit ratings, TR has adopted symbols and terminology which match those used by Standard and Poor's. Credit rating curves are produced for the main credit ratings bands, notably AAA, AA, A, BBB, and others. TR does not produce curves for finer sub-categories of ratings within the main credit ratings bands. Thus,

curves are not available for more disaggregated groupings of ratings such as AA+, AA-, and BBB+. TR has explained its reasoning for the non-availability as follows:

- For many markets and industry sectors, the total number of bonds available within each notched credit rating is insufficient to allow curve construction; and
- Since a number of corporate bonds carry split credit ratings, then there may be difficulties inherent in the process of assigning bonds to more unique credit rating sub-categories.

More generally, when dividing up the bond universe, TR places more weight on the latest available credit ratings information. To resolve an issue that might arise when a bond has split ratings, TR takes the minimum available rating for that bond.

2.3.3 Term structure calculations and curve construction

TR uses a basis spline model to derive the term structure of a particular credit curve. The term structure provides the foundation from which a spot rate curve, or zero coupon curve, can be produced. Thereafter, a par yield curve can be generated, and other analytical outputs can be produced.

TR has explained that the basis model provides a good estimation of forward rates at all points on the curve, whilst also providing a degree of smoothness. TR has also expressed the view that the spline-based model tends to generate more accurate pricing of the constituent bonds because the curve provides an exceptionally good representation of the market's current term structure.

2.3.3.1 Basis spline model

In the separate technical annex, TR has provided further detail about the specific implementation of term structure calculations². A number of basis splines are combined linearly so as to produce a forward function which will generate term structure coefficients. The basis functions are cubic polynomials defined on overlapping sets of four consecutive nodes. At each node, the polynomials that meet are restricted so that their first and second derivatives are continuous. There are two variants of the model: The regression spline and the smoothing spline.

- The regression spline method aims to minimise residual errors between the theoretical prices and market prices; and
- The smoothing spline method aims to minimise the sum of the residual errors and a "roughness penalty" that describes the smoothness of the curve. The roughness penalty, $\lambda(t)$, limits the oscillation of the polynomials between nodes, but also decreases the goodness of fit.

There are several variants of the smoothing spline using different roughness penalties, which may vary with maturity. The Waggoner method has been found to be more appropriate for US markets, while Anderson's method is more appropriate for UK markets.

Under the Waggoner method, the roughness penalty is a step function with three levels, constant over the maturity intervals 0 to 1 year, 1 to 10 years, and greater than 10 years. These divisions correspond to the markets for bills, notes and bonds. Under the Anderson (Bank of England) method, the roughness penalty is a continuous function. It does not focus on a special part of the curve because the UK market is not split into different instruments.

 ² Thomson Reuters Eikon Adfin Term Structure Calculation Guide, Document Number 601637.4, 1st March 2011.

2.3.3.2 Choice of nodes

The nodes are chosen from the maturities of the input bonds and are evenly distributed between them. The number of nodes is a significant choice for the term structure. The default choice is given by $\binom{n}{3}$ + 2), where n is the number of distinct maturities. The number of nodes can be set by the user.

The number of nodes is capped at 20, because too many splines have the effect of decreasing the smoothness of the curve. The method of choosing nodes has been taken from the paper by Waggoner (1997) 3. The nodes are positioned in such a way that the instrument maturities are evenly spaced between nodes.

2.3.3.3 Output of the basis spline model

The output of the model is a series of parameters that provide an estimation of the forward rate given at maturity. The form of the output is a two-column array. The first column contains the dates of the nodes, and two measures of the model: The fitness and smoothness. The second column contains the linear coefficients of the forward function in the B-spline base.

2.3.4 Implementation of term structure calculations and curve fitting

The basis spline model is implemented in 'Adfin', a Thomson Reuters program, so as to generate the term structures. A group of bonds is set out in an array, and the term structure coefficients are calculated by the spline model. The term structure coefficients are then applied by a separate program to produce a discount curve, which has corresponding spot rates or zero coupon rates. The discount curve has a start date, and an array of dates. Subsequently, a par yield curve is estimated so as to produce a series of par rates for a corresponding set of par curve maturities.

Other analytical outputs can also be produced:

- **Benchmark spreads**. The benchmark spread is calculated as the difference between the par yield curve and the corresponding government benchmark curve. Thus, the 5-year benchmark spread will be calculated as the difference between the 5-year par rate and the 5-yearr government benchmark midyield. If there is no corresponding benchmark, the spread is calculated using the interpolated government benchmark yield.
- **Swap spread**. The swap spread is calculated as the difference between the par yield curve and the corresponding interest rate swap curve. Where the corresponding swap tenors are not available, the interpolated swap rate is used.
- **Asset swap spread.** The asset swap spread is calculated as the spread over Libor (or equivalent short rate) paid on the floating leg in a hypothetical asset swap with the par rate as the fixed coupon on the fixed-rate asset. A particular function is used in the TR 'Adfin' program.
- **Z-spread**. The Z-spread or zero-volatility spread is calculated as the number of basis points to be added to the discount curve in order for the present value of the bond to be equal to the market price. The par rate is taken to be the coupon of the bond with a par price in the Z-spread calculations⁴.

 ³ 'Spline Methods for Extracting Interest Rate Curves from Coupon Bond Prices' by Daniel Waggoner (Federal Reserve Bank of Atlanta, Working Paper Series, 1997, pp. 97-10).

Bloomberg identifies the Z-spread as the implied spread of an underlying bond off a yield curve, in basis points. If the underlying bond has no embedded options, then this spread is usually referred to as the Option-Adjusted-Spread

2.3.5 Checks for outliers

TR reports that a check for outlier bonds is conducted by the credit curve application prior to the generation of the term structure. This is not a price check aimed at investigating whether the latest prices are at the appropriate market levels. Such market level checks are conducted by the system that generates the composite prices.

The bond universe tolerance check is aimed at allowing a term structure to be generated. The objective is not about forcing the curve to take on a certain shape. TR relies on the model underpinning the curve to deliver the smoothest curve with the best feasible fit to the data. The principal variable that is used for checks on outlier bonds is the Z-spread.

2.3.6 Comparison with information provided by Bloomberg about the BVAL series

ESQUANT has examined two documents prepared by Bloomberg about the BVAL sector curves and issuer curves. The two documents (Bloomberg 2013, and 2015) were sourced from the Bloomberg subscription service, with one document having been downloaded in 2013, and the other document having been retrieved more recently. There is slightly more information contained within the older publication. In any event, ESQUANT has found that Bloomberg provides far less detail about its BVAL curves than Thomson Reuters has provided about the TR credit curves. There is significantly better information available from TR about bond selection processes, constituent groupings, term structure calculations and curve fitting. The information from TR has also been buttressed with references to the academic and professional literature.

2.4 Application of the investment grade credit curves published by Thomson Reuters

ESQUANT Statistical Consulting has compiled information about the corporate cash credit curve for Australia that is prepared and published by Thomson Reuters (TR). The TR BBB Rating AUD Credit Curve is produced without regard for any regulatory process in Australia and should thus qualify as a third party indicator series for measuring the rate of return on debt.

ESQUANT has collected data for the BBB rated AUD credit curve in respect of the third averaging period for United Energy, which runs from 13th November to 10th December 2015. The data that has been gathered by ESQUANT includes detailed compositional information which shows the make-up of the curve in terms of its constituent bonds. There are also summary statistics which show the key attributes of the curve.

There are live snapshots of the curve, which are captured in images, stored as adobe acrobat files, and end of day results for the curve, and for the curve components. The stored, live images for the curve and for its components are available from ESQUANT, with selected examples appended to this report. The end of day values have been downloaded into a spread sheet workbook using the Thomson Reuters Eikon interface for Excel.

As previously noted, there appears to be more information available about the TR credit curves than there is about the Bloomberg BVAL issuer and sector curves.

Table 2.1 presents the results of an examination of the bonds that were used separately by Bloomberg and by TR for the construction of their respective composite yield curves or credit curves. A consolidated list

⁽OAS). It refers to a spread off the stripped, zero-coupon curve using semi-annual compounding. If the underlying bond has embedded options, then they are ignored when computing this spread so that the Z-Spread does not match the usual OAS.

of bonds has been prepared for 13th November 2015, which was the first day of the averaging period for United Energy.

The evidence indicates that Bloomberg used 22 corporate bonds in the construction of its BVAL BBB rated curve. TR made use of 24 constituent bonds when estimating the shape and position of the TR BBBAUDBMK credit curve. There were only 7 individual bonds that were used by both of the providers.

Source: Bloomberg BVAL BBB-rated curve, Thomson Reuters BBBAUD benchmark curve. ISIN = International Securities Identification Number. Analysis by ESQUANT. There were 7 bonds in common as between the Bloomberg BVAL BBB-rated corporate curve for Australia, and the Reuters BBBAUD benchmark credit curve. The total number of bonds used by Bloomberg to construct its BVAL BBBrated curve was 22. The total number of bonds used by Reuters to construct its BBBAUD corporate cash credit curve was 24.

Table 2.2 provides some information about the constituent bonds that were used by TR to formulate and construct the BBBAUDBMK credit curve as at 30th November 2015. The list of bonds was derived from a live snapshot of the curve taken on the day. The end of day bid yields and ask yields for the individual bonds, as reported by TR, have been shown in the table. For the purposes of comparison, the yields for the same bonds, as calculated by the CEG RBA replication model, are also shown in the table. An important point to note, however, is that the RBA replication model applies an option-adjusted spread (OAS) method in the main part of the model. The OAS method produces spreads which are then converted to yields by applying swap rates with commensurate terms to maturity. The RBA replication model is also currently configured to source data from Bloomberg.

In contrast, the yields that have been sourced from TR for the purposes of the table below are yields to maturity. The bid yields and ask yields have been formulated from the clean prices, and are used by TR in the curve construction process.

A small number of the bonds used by Thomson Reuters do not have credit ratings from Standard and Poor's. However, these bonds have been rated by Moody's, and the ratings awarded mean that the bonds can be placed firmly within a band which is equivalent to the Standard and Poor's BBB band. The bonds in question can be itemized as follows:

- AU3CB0220861, a bond issued by Emirates NBD PJSC, a financial institution. On 13th November 2015, the Moody's credit rating for the bond was Baa1 which is equivalent to an S&P credit rating of BBB+. The company also had a long-term credit rating of Baa1. Senior unsecured debt was rated Baa1. The credit rating for the Emirates bond did not alter over the averaging period for United Energy.
- AU3CB0212967, a bond issued by Connect East Finance Pty Ltd. On 13th November 2015, the Moody's credit rating for the bond was Baa2 which is equivalent to an S&P credit rating of BBB (flat). The company also had a long-term credit rating of Baa2. The credit rating for the Connect East bond did not alter over the averaging period for United Energy.
- AU3CB0226264, a bond issued by Australian Gas Networks Vic 3 Pty Ltd. On 13th November 2015, the Moody's credit rating for the bond was Baa1 which is equivalent to an S&P credit rating of BBB+. The long-term credit rating for the issuer was also Baa1. The credit rating for the bond issued by Australian Gas Networks did not alter over the averaging period for United Energy.
- AU3CB0227411, a further bond issued by Emirates NBD PJSC, a financial institution. On $13th$ November 2015, the Moody's credit rating for the bond was Baa1 which is equivalent to an S&P credit rating of BBB+. As has been noted, the company also had a long-term credit rating of Baa1. Senior

unsecured debt was rated Baa1. The credit rating for this Emirates bond did not alter over the averaging period for United Energy.

ISIN for bond	Full company name	Issue date	Maturity date	Coupon rate	Yield from RBA replication model	Bid yield (end of day) from Reuters	Ask yield (end of day) from Reuters	Average (of bid and ask yields)
					30/11/2015	30/11/2015	30/11/2015	30/11/2015
AU3CB0172039	Woolworths Ltd	22/03/2011	22/03/2016	6.75	3.31	3.03	2.98	3.01
AU3CB0160687	Mirvac Group Finance Ltd	29/09/2010	16/09/2016	8	3.50	3.34	3.25	3.30
XS0857206782	Daiwa Securities Group Inc.	4/12/2012	5/12/2016	3.8	3.64	3.84	3.79	3.82
AU3CB0192599	United Energy Distribution Pty Ltd	11/04/2012	11/04/2017	6.25	3.68	3.58	3.53	3.55
AU3CB0196699	Holcim Finance Australia Pty Ltd	18/07/2012	18/07/2017	6	3.68	3.51	3.46	3.49
AU3CB0196848	Crown Group Finance Ltd	18/07/2012	18/07/2017	5.75	3.71	3.60	3.55	3.58
AU3CB0208775	Bank of America Corp	23/05/2013	23/08/2018	4.5	3.59	3.48	3.44	3.46
AU3CB0215457	Adani Abbot Point Terminal Pty Ltd	1/11/2013	1/11/2018	5.75	5.80	5.72	5.67	5.69
AU3CB0208494	Lend Lease Finance Ltd	13/05/2013	13/11/2018	5.5	4.45	4.33	4.24	4.28
AU0000AQMHA7	Anglo American Capital PLC	27/11/2013	27/11/2018	5.75	7.62	7.34	7.29	7.31
AU3CB0191815	Woolworths Ltd	21/03/2012	21/03/2019	6	3.97	3.86	3.81	3.83
AU3CB0220861	Emirates NBD PJSC	8/05/2014	8/05/2019	5.75	N/A	4.38	4.33	4.35
AU3CB0225324	Crown Group Finance Ltd	18/11/2014	18/11/2019	4.5	4.37	4.37	4.32	4.35
AU3CB0223675	Bank of America Corp	5/09/2014	5/03/2020	4.25	3.78	3.78	3.72	3.75
AU3CB0228286	Holcim Finance Australia Pty Ltd	19/03/2015	19/03/2020	3.75	3.86	3.84	3.79	3.82
AU3CB0208122	Qantas Airways Ltd	26/04/2013	27/04/2020	6.5	4.88	5.19	5.14	5.17
AU3CB0208502	Lend Lease Finance Ltd	13/05/2013	13/05/2020	6	4.70	4.77	4.63	4.70

Table 2.2: The constituent bonds of the Reuters BBBAUDBMK credit curve, and the yields on those bonds, as at 30th November 2015

Source: CEG RBA replication model, updated by ESQUANT. Thomson Reuters BBBAUD benchmark curve. Analysis by ESQUANT.

Table 2.3 presents a consolidated list of the bonds that were used by the three third party data service providers on 30th November 2015. The corporate bonds shown were those used for the construction of the three respective third party indicator series.

Source: Bloomberg, Reserve Bank of Australia Table F3, Thomson Reuters. Analysis by ESQUANT.

As is apparent from Table 2.3, the largest number of bonds was used by the RBA in its formulation of the corporate bond spreads for BBB rated bonds. The spreads and yields are reported in Table F3. The RBA makes use of bonds issued by Australian corporations that are denominated in Australian dollars or in foreign currency. The currencies considered are US dollars, Euros, and British pounds. In contrast, the Bloomberg BBB rated BVAL curve, and the TR BBBAUD corporate credit curve are both developed from bonds denominated in the domestic currency only.

From 13th November to 30th November 2015, there was an increase in the number of bonds used by TR from 24 to 29.

There are wide divergences between the three third party data providers in terms of the bond samples that have been used. This evidence would appear to support the use, by ESQUANT, of a broad sample of bonds when empirical work is being undertaken. Since the external data or indicator providers have not settled upon a "consensus" list of bonds, then there are advantages in drawing upon a database of bonds which is as broad and as representative as a data sample needs to be.

Table 2.4 confirms that there is comparatively little overlap in terms of the bonds that have been chosen by the three third party, cost of debt indicator providers. In fact, there are only 7 bonds that are common to all three of the third party indicator providers (this value is not shown in Table 2.4 but can be inferred by examining the results from the previous table).

In the narrow subset of bonds that were used by all three of the third party indicator providers, on $30th$ November 2015, there were two bonds for which the issuer is Qantas Airways Ltd. The bonds from Qantas were re-rated to BBB- on 16th November 2015. The previous credit rating of BB+ had been in place for nearly two years. The long-term, foreign issuer credit rating was also upgraded to BBB- from BB+ on $16th$ November.

	Bloomberg BVAL BBB	Reuters BBBAUDBMK	RBA Table F3 BBB
Bloomberg BVAL BBB	23	10	12
Reuters BBBAUDBMK	10	29	16
RBA Table F3 BBB	12	16	89

Table 2.4: Bonds in common between the three sources, as at 30th November 2015.

Source: Bloomberg, Reserve Bank of Australia Table F3, Thomson Reuters. Analysis by ESQUANT. Note: There were 7 bonds that were common to all three of the third party indicator series.

On 3rd December 2015, the number of bonds that were incorporated into the Reuters BBB AUD credit curve increased from 29 to 32 as a result of the inclusion of three bonds that had been issued by Volkswagen Financial Services Australia Pty Ltd. These bonds were subjected to a credit ratings downgrade from Standard and Poor's on $1st$ December 2015. The new rating for the bonds was BBB+. The bonds had also been subjected to an earlier credit ratings downgrade on 12th October 2015. At that time, the rating was changed from A to A-.

On 4th December 2015, the number of bonds that were used in the computations for the Reuters BBB AUD benchmark credit curve rose further from 32 to 40 as a result of the inclusion of a significant number of bonds which suddenly met the criteria for inclusion. These bonds had also been subject to unprecedented credit ratings downgrades that had taken place on 2nd December. The bonds in question had been issued by financial institutions, notably Citigroup (one bond), Goldman Sachs (four bonds), and Morgan Stanley (three bonds). Thereafter, on 7th December 2015, TR added a further bond from Goldman Sachs, and three additional bonds from Morgan Stanley.

Notwithstanding the incorporation of a significant number of new bonds, the results for the 10-year rate from the TR BBBAUD credit curve have been relatively stable over the November-December averaging period for United Energy.

The Bloomberg BVAL curve did not appear to be affected by the developments in financial markets. The composition of the curve hardly altered at the start of December 2015. In fact, over the period from 30th November to 4th December 2015, the two bonds issued by Oantas, which Bloomberg had incorporated into the sample for the curve on $18th$ November, were sequentially dropped from the curve.

In 2014, a report from the Regulatory Economic Unit of the ACCC noted that the Bloomberg BBB rated BVAL curve includes both financial sector and non-financial sector bonds⁵. However, in November and December 2015, Bloomberg appears to have incorporated only a limited number of bonds from financial institutions.

The BVAL curve is published out to a 30-year tenor, but the number of bonds used is somewhat less than the number of bonds that are incorporated into the Reuters BBBAUD benchmark credit curve.

Table 2.5 presents selected data series for the constituent bonds of the TR BBBAUD credit curve, as at 4th December 2015. The end-of-day bid and ask yields are reported from Thomson Reuters. These yields are compared with the yields (based on OAS) from the RBA replication model.

 ⁵ Moore, Y. (2014), table showing a comparison of the RBA and BVAL bond samples, page 8.

Table 2.5: The constituent bonds of the Reuters BBBAUDBMK credit curve, and the yields on those bonds, as at 4th December 2015

NB: The yields from the RBA replication model are derived from the application of an option-adjusted spread methodology; Bloomberg data has been used, with the calculations performed by ESQUANT.

Table 2.6 below has an effective date of 4th December 2015. A consolidated list of bonds has been prepared, showing the bonds that are used in the Bloomberg BVAL BBB rated curve, vis-a-vis the bonds that were employed in the construction of the TR BBBAUD credit curve.

Regarding the composition of the Bloomberg BVAL BBB rated curve, the bonds issued by Qantas Airways were "in" on some days, and were "out" on others.

Table 2.6: A comparison of the constituent bonds as between the Bloomberg BVAL BBB rated curve and the Thomson Reuters BBBAUD benchmark curve – effective date, 4th December 2015.

Consolidated list of bonds for 04/12/2015	Full company name	Issue date	Maturity date	Bloomberg BVAL BBB	Reuters BBBAUDBMK
AU0000AQMHA7	Anglo American Capital PLC	27/11/2013	27/11/2018		Yes
AU3CB0155133	APT Pipelines Ltd	22/07/2010	22/07/2020		Yes
AU3CB0160687	Mirvac Group Finance Ltd	29/09/2010	16/09/2016	Yes	Yes
AU3CB0172039	Woolworths Ltd	22/03/2011	22/03/2016		Yes
AU3CB0176014	Goodman Australia Industrial Fund Bond Issuer Pty Ltd	19/05/2011	19/05/2016	Yes	
AU3CB0190122	SGSP Australia Assets Pty Ltd	21/02/2012	21/02/2017	Yes	
AU3CB0191815	Woolworths Ltd	21/03/2012	21/03/2019	Yes	Yes
AU3CB0192599	United Energy Distribution Pty Ltd	11/04/2012	11/04/2017	Yes	Yes
AU3CB0193274	Victoria Power Networks Finance Pty Ltd	27/04/2012	27/04/2017	Yes	
AU3CB0195964	Volkswagen Financial Services Australia Pty Ltd	27/06/2012	27/06/2017		Yes
AU3CB0196699	Holcim Finance Australia Pty Ltd	18/07/2012	18/07/2017		Yes
AU3CB0196848	Crown Group Finance Ltd	18/07/2012	18/07/2017	Yes	Yes
AU3CB0201515	Investa Office Fund	7/11/2012	7/11/2017	Yes	
AU3CB0202414	Goldman Sachs Group Inc/The	29/11/2012	29/11/2017		Yes
AU3CB0202422	Mirvac Group Finance Ltd	5/12/2012	18/12/2017	Yes	
AU3CB0204808	Citigroup Inc	5/02/2013	5/02/2018		Yes
AU3CB0206803	Goodman Australia Industrial Fund Bond Issuer Pty Ltd	22/03/2013	20/03/2018	Yes	

Source: Bloomberg BVAL BBB-rated curve, Thomson Reuters BBBAUD benchmark curve. Analysis by ESQUANT. There were 8 bonds in common as between the Bloomberg BVAL BBB-rated corporate curve for Australia, and the Reuters BBBAUD benchmark credit curve.

Further information about the TR BBBAUD credit curve is shown in Table 2.7 and in Table 2.8. This information is in respect of the business day of the $7th$ December 2015.

Table 2.7: The constituent bonds of the Reuters BBBAUDBMK credit curve, and the yields on those bonds, as at 7th December 2015

NB: The yields from the RBA replication model are derived from the application of an option-adjusted spread methodology; Bloomberg data has been used, with the calculations performed by ESQUANT.

Source: Bloomberg BVAL BBB-rated curve, Thomson Reuters BBBAUD benchmark curve. Analysis by ESQUANT. There were 10 bonds in common as between the Bloomberg BVAL BBB-rated corporate curve for Australia, and the Reuters BBBAUD benchmark credit curve.

There was no change in the composition of the TR BBBAUD credit curve on either 8th December or 9th December, 2015. However, a bond from Mirvac Group Finance Ltd, with a relatively short remaining term to maturity of less than one year, was dropped from the sample used for curve construction on 10th December 2015.

3 Extrapolation of corporate credit spreads from the RBA replication model

3.1 Application of the Gaussian kernel technique to the November-December averaging period for United Energy

As has been noted elsewhere in this report, ESQUANT has made use of the spread sheet based, RBA replication model that has been developed by the Competition Economists Group (CEG). ESQUANT has updated the RBA replication model for all bonds that fall within the Standard and Poor's ratings categories of A+ to BBB-. The model is used to produce option-adjusted spreads (OAS) for all bonds for which data is available through the Bloomberg subscription service. The OAS for bonds denominated in foreign currencies (US dollars, Euros, and pounds sterling) are transformed into Australian dollar equivalent spreads via a series of calculations. The model also records price data for bonds, and retrieves yield-tomaturity data separately from the calculations of OAS.

The model itself contains a large number of corporate bonds (about 2,600) but only a limited number of those bonds are actually employed in the Gaussian kernel calculations to produce a smoothed curve based on the method published by the Reserve Bank of Australia (Arsov et al., 2013). The RBA applies the Gaussian kernel technique, also known as local constant smoothing, with an additional weighting applied to each bond that is based on the issue amount. ESQUANT has implemented the same method in its approach to the task of producing estimates of the spreads on corporate debt using local constant smoothing.

The sub-sample of bonds that was chosen from the main database for the purpose of the RBA "matching" exercise possessed the following attributes:

The bonds were issued by businesses that are domiciled in Australia.

- The currency of denomination was Australian dollars, United States dollars, or Euros.
- The bonds were not issued by businesses in the financial or government sectors.
- The minimum remaining term to maturity of any of the bonds was one year.
- The face value of the bond, or size of the issue, was A\$100 million or more. For foreign currency bonds, the relevant threshold was also A\$100 million, with the issue amount having been converted into Australian dollars using the exchange rate on the date of issue.
- The bonds were rated BBB-, BBB (flat), or BBB+ by Standard and Poor's. If the bond did not have its own credit rating, then the relevant credit rating would be that of the issuer. The long-term credit rating for the issuing entity would need to fall within the same range of BBB- to BBB+.

In addition, the value of sigma, the smoothing parameter used by the RBA in its Gaussian kernel calculations, was set to be 1.5.

Table 3.1 shows that, as at 30th October 2015, there is a close correspondence between the results from the RBA replication model, as updated by ESQUANT, and the published results for corporate bond spreads and yields, from the RBA. There is a close alignment between the reported bond yields, at tenors of 3, 5, 7, and 10 years. There are some differences between the recorded spreads, in particular at a tenor of 3 years, however the reason for this is not known. The published result for the spread-to-swap at a tenor of 3 years from RBA Table F3 does appear to be somewhat implausibly high.

There is also some uncertainty as to the actual swap rates that are used by the RBA. ESQUANT has made use of the swap rates from the ADSWAP series that is published by Bloomberg.

Source: CEG RBA replication model, updated by ESQUANT. Table F3, Aggregate Measures of Australian Corporate Bond Spreads and Yields: Non-Financial Corporate (NFC) Bonds. Yields are presented on a semi-annual basis.

As of September 2015, the RBA has been publishing a list of the bonds for which it has been compiling data for use in its Table F3 computations. ESQUANT has made use of all of the bonds that the RBA has incorporated into its own assessment. However, a comparison of the RBA list for 30th October 2015 with the ESQUANT list for the same date has revealed that ESQUANT has included a further seven bonds. These bonds appear to meet the various qualifying criteria, and there is some uncertainty as to why the RBA has either omitted these bonds or else has chosen to exclude them. The seven additional bonds do not appear to be duplicates of each other or of any other bond already chosen by the RBA. Moreover, one of the seven bonds, which was excluded from the RBA's list for $30th$ October 2015, was subsequently incorporated into the RBA's list for 30th November 2015. The bond in question is a US dollar denominated, 144a bond issued by the Transurban Finance Company.

Table 3.2: Additional bonds in the ESQUANT sample which matched the RBA selection criteria, 30th October 2015.

Bloomberg ID $(9-digit)$	Company name	Issue Date	Maturity Date	Credit Rating (30/10/2015)	Currency of issue
ED6159096 Corp	Sydney Airport Finance Co Pty Ltd	20/09/2004	20/11/2020	BBB	AUD
EH7255530 Corp	Transurban Finance Co Pty Ltd	14/11/2006	14/11/2018	$BBB+$	USD
EI0099933 Corp	Barrick PD Australia Finance Pty Ltd	16/10/2009	15/10/2039	BBB-	USD
EI1592258 Corp	Transurban Finance Co Pty Ltd	31/08/2005	31/08/2017	$BBB+$	USD
EI1592290 Corp	Transurban Finance Co Pty Ltd	31/08/2005	10/08/2020	$BBB+$	USD
EJ4317107 Corp	Cimic Finance USA Pty Ltd (previously Leighton Finance)	13/11/2012	13/11/2022	BBB-	USD
QJ4132016 Corp	Transurban Finance Co Pty Ltd	2/11/2015	2/02/2026	$BBB+$	USD

Source: CEG RBA replication model, updated by ESQUANT. Note that the credit ratings which are shown are those recorded for 30th October 2015.

The US dollar denominated bond from the Transurban Finance Company with Bloomberg identifier QJ4132016 is shown above in Table 3.2. The bond was announced to the market as a private placement on 27/10/2015, and there is data available from 28/10/2015. Although the issue date is given as 02/11/2015, this is actually the interest accrual date and first settlement date.

In any event, the inclusion, by ESQUANT, of a further seven bonds, by comparison with the sample used by the RBA, did not have a material impact on the calculated results for 30th October 2015.

Regarding the results for 30th November 2015, there is less similarity between the figures obtained by ESQUANT from the RBA replication model, and the spreads and yields published by the RBA. However we note that the spread obtained by ESQUANT at a target tenor of 10-years (248.18 basis points) is below the 10-year spread obtained and published by the RBA (253.81 basis points). In addition, the 10-year yield derived by ESQUANT (5.46 per cent) is below that reported by the RBA (5.53 per cent). Thus the predictions made by the RBA replication model can be regarded as being relatively conservative, at least as at the end of November 2015.

30/11/2015	RBA replication model (ESQUANT)						
Credit rating band	BBB	BBB	BBB	BBB	BBB		
Numbers of bonds by tenor category	1 to 4 years	$4 \text{ to } 6$ years	$6 \text{ to } 8$ years	8 to 12 years	More than 12		
					years		
Bond numbers	31	35	13	11	5		
Spread over swap (basis points)	223.53	242.71	257.67	248.18			
Effective tenor	3.77	5.01	6.56	9.14			
Effective credit rating	2.06	2.01	2.04	2.49			
Implied yield (%)	4.60	4.97	5.32	5.46			
Target maturity -->	3	$\overline{\mathbf{5}}$	$\overline{7}$	10			
30/11/2015	RBA Table F3						
Credit rating band	BBB	BBB	BBB	BBB	BBB		
Numbers of bonds by tenor	1 to 4	$4 \text{ to } 6$	$6 \text{ to } 8$	8 to 12	More		
category	years	years	years	years	than 12		
Bond numbers	29	33	12	11	years 4		
Spread over swap (basis points)	240.71	246.01	260.07	253.81			
Effective tenor	3.76	5.00	6.59	9.16			
Implied yield (%)	4.62	5.01	5.36	5.53			
Target maturity -->	3	$\overline{5}$	$\overline{7}$	10			

Table 3.3: A comparison of results between the CEG RBA replication model and the published RBA Table F3 results, 30th November 2015.

Source: CEG RBA replication model, updated by ESQUANT. Table F3, Aggregate Measures of Australian Corporate Bond Spreads and Yields: Non-Financial Corporate (NFC) Bonds. Yields are presented on a semi-annual basis.

The RBA replication model has been applied over the measurement period for United Energy of 13th November 2015 to 10th December 2015. The results are reproduced below. The model calculations have been performed on the arithmetic average values of the relevant data series. Assessments of credit ratings have been made as at the end of the reference period, although the model does record credit ratings of bonds and of issuers on a day-to-day basis.

13/11/2015 to 10/12/2015	RBA replication model (ESQUANT)						
Credit rating band	BBB	BBB	BBB	BBB	BBB		
Numbers of bonds by tenor category	1 to 4 years	4 to 6 years	6 to 8 years	8 to 12 years	More than 12 years		
Bond numbers	36	35	13	11	5		
Spread over swap (basis points)	223.55	241.99	257.89	247.53			
Effective tenor	3.71	4.98	6.55	9.15			
Effective credit rating	2.11	2.02	2.04	2.49			
Implied yield $(\%)$	4.61	4.98	5.36	5.49			
Target maturity -->	3	5	7	10			

Table 3.4: Results from the CEG RBA replication model over the averaging period.

Source: CEG RBA replication model, updated by ESQUANT. Yields are presented on a semi-annual basis.

Figure 3.1 below provides an exposition of the bonds which fall in to the sample that was used by ESQUANT for the purpose of replicating the approach that is taken by the RBA. As may be apparent from Table 3.4 above, there were 100 bonds which satisfied the RBA's selection criteria over the United Energy averaging period $(13th$ November to $10th$ December). The graph below shows the average spread-to-swap for each of those bonds over the reference period. The variable presented on the x-axis is the currency in which the bond was issued. In the RBA sample, bonds can also be classified according to other variables, such as the unique credit rating within the BBB band. A chart showing the distribution by credit rating is also provided in this chapter of the report.

Figure 3.1: RBA replication model: Bonds which satisfy the selection criteria applied by the RBA

Source: CEG RBA replication model, updated by ESQUANT. The sample period for the analysis is the third averaging period for United Energy, 13th November to 10th December 2015. The bonds shown in the chart are those which satisfy the selection criteria set by the RBA.

3.2 A comparison of the results from the AER and SAPN extrapolation methods

The AER's consultant, Martin Lally, has recognized the need to extrapolate measures of corporate bond spreads produced via the application of a Gaussian kernel smoothing technique. In November 2014, Lally $(2014a)$ reported that⁶:

Both the RBA and BVAL indexes require extension out to ten years, the latter because the longest tenor is only seven years, and the former because the effective tenor for the DRP component of the ten-year term is generally less than ten years (and has averaged 8.7 years since its inception). I therefore examine techniques for extending the index values out to ten years subject to these techniques involving the automatic application of a formula.

Lally (2014a) stated further that:

The RBA index values for ten-year bonds are biased at the very least because the weightings given to bonds used for this purpose do not have a weighted-average tenor equal to ten years and

 6 Lally (2014a), section 7, page 38.

this point is even acknowledged by the RBA (Arsov et al., 2013, page 10). In fact, across the entire period for which the RBA series is presented (from January 2005), the average tenor of the bonds used to form the index value for ten years is 8.7 years and has been as low as 6.11 years (in August 2005).

Lally's recognition of a requirement for extrapolation arose partly in response to a report by ESQUANT which found that local constant smoothing delivers a result for the cost of debt which is biased at the boundary regions (meaning at 3 years, and at 10 years, in this context). ESQUANT (2014) noted that when the Gaussian kernel estimate is applied at the right hand side boundary, at a target tenor of ten years, most of the observations used to construct the weighted average have a remaining term to maturity of less than ten years, and, correspondingly, the slope of the true relation induces boundary bias into the estimate of the spread-to-swap⁷.

To overcome the bias, an adjustment must be made to the RBA estimates of the cost of debt for nonfinancial corporate, BBB rated bonds. One possibility would be for the RBA to apply local linear smoothing to its bond data (rather than the Gaussian kernel, or local constant smoother), because local linear smoothing removes the bias to first order⁸. Another possibility, suggested by Lally (2014a), would be to use linear extrapolation based on the aggregate credit spreads reported by the RBA (in Table F3) at target tenors of 7 years and 10 years⁹. The Lally (2014) method also makes use of the effective tenors corresponding to the target tenors of 7 years and 10 years. A further possibility would be to use an extrapolation method suggested by the SA Power Networks, which draws upon the RBA aggregate credit spreads for 3, 5, 7, and 10 years 10 .

ESQUANT (2015) evaluated the results from local linear smoothing, and also compared the outputs from the two alternative extrapolation methods, the Lally (2014) approach and the SA Power Networks extrapolation technique. ESQUANT (2015) used statistical theory and empirical methods to quantify the bias and variance that would result from the use of either of the three methods. The results for bias and variance were then combined with other multipliers to produce a root mean square error (RMSE) under each approach.

ESQUANT (2015) reported that the SAPN method for extrapolating the estimates of the spread to swap produced by the RBA appeared to produce more precise (less variable) estimates than the Lally (2014) method¹¹. ESQUANT (2015) therefore recommended that consideration be given to use of the SAPN method when preparing estimates of the cost of debt that are based on the corporate bond series published by the RBA.

The SA Power Networks method was found to deliver a lower RMSE than the Lally (2014) method in every month that was examined, because curves extrapolated under the SAPN technique were relatively straight, while the variability was low when compared against the bias¹². The SAPN method was therefore reported to be superior in totality.

ESQUANT (2015) noted further that when using the published RBA series on spreads over swap for current and prospective averaging periods, the SAPN extrapolation method would, in all likelihood, be an

⁷ Diamond, N.T. and Brooks, R. (2014), section 3.1.2, page 15.

⁸ Diamond, N.T. and Brooks, R. (2014), section 3.2.

 9 Lally (2014a), section 7.

¹⁰ SA Power Networks (2014), chapter 26, page 340.
¹¹ Diamond, N.T. and Brooks, R. (2015a), page 6.

¹² ESQUANT (2015) examined end of month data from November 2013 through to January 2015.

appropriate technique to apply because the results from the application of the method had been shown to have low variance. ESQUANT (2015) made clear that it was referring to comparatively short averaging periods, comprised of time intervals which varied from 10 to 40 trading days.

In a recent report prepared for the AER, Lally (2015b) has conceded that the RMSE is an appropriate criterion to use when assessing the relative merits of the AER and SAPN extrapolation methods for the purpose of extending the RBA corporate bond index out to ten years¹³.

ESQUANT has now considered the Lally (2014) and SAPN extrapolation techniques in the context of the November to December 2015 averaging period for United Energy. Specifically, ESQUANT has evaluated the two alternative extension methods by applying them to the results from the RBA replication model that were reported in Table 3.4.

There are actually two variants of the Lally (2014) extrapolation technique, with both having been described in the Lally (2014a) report on implementation issues. The first variant makes use of both CGS yields and swap rates, and the results from the application of this approach to the outputs from the RBA replication model are demonstrated below in Table 3.5. Reference should be made to the part of the Table which describes the "Lally correction using CGS yields and swap rates". Lally (2014a) has previously indicated that he favors the use of a method which draws upon CGS yields. The second variant of the Lally extrapolation technique makes use of swap rates only, and is more straightforward to apply. Reference should be made to the bottom rows of the Table which describe the "Lally correction using swap rates only". The second variant of the Lally extrapolation approach has been adopted by the AER.

Local constant smoothing, as applied in the CEG RBA replication model, has produced anomalous results over the averaging period for United Energy (13th November to 10th December, 2015). The results are anomalous because the 10-year spread to swap (calculated to be 247.53 basis points) lies below the 7-year spread-to-swap (which was worked out to be 257.89 basis points). These outputs do not, however, signify any errors in the application of the CEG RBA replication model. An inference about the absence of errors can be drawn because the published results from RBA Table F3 have also shown lower spreads-to-swap at a 10-year tenor than at a 7-year tenor in recent months.

From December 2014 to February 2015, the 10-year spread-to-swap in the published RBA series was markedly below the 7-year spread-to-swap. Thereafter, in each month from July 2015 to October 2015, the 10-year spread was marginally below the 7-year spread, with the gap then widening in November 2015.

From $13th$ November to $10th$ December 2015, the 10-year spread-to-swap is 247.53 basis points, as noted. However, the effect of the two versions of the Lally extrapolation approach is to further depress this spread. The Lally extrapolation method that makes use of both CGS yields and swap rates causes the spread to drop to 241.27 basis points. The Lally extrapolation method that makes use of swap rates only causes the spread to drop to 244.12 basis points.

The two Lally approaches therefore result in a continued downward slope of the curve from the RBA replication model between the effective tenors of 6.55 years and 10 years.

In contrast to the Lally methods, the SAPN method makes use of the gradient of an average curve through the spreads-to-swap at various tenors.

 13 Lally (2015b), section 4, page 27.

- Specifically, the spreads-to-swap obtained from the RBA replication model at the target tenors of 3, 5, 7, and 10 years are regressed on the corresponding effective tenors, giving a fitted equation with a slope coefficient.
- The 10-year spread-to-swap is then estimated by taking the spread-to-swap for the longest available maturity, and then extrapolating that spread from its current tenor to 10 years by assuming a straight line with the slope having been calculated in the prior step.

ESQUANT (2015) showed that the SAPN extrapolation technique delivers a weighted average outcome¹⁴.

On this occasion, the application of the SAPN method produces a 10-year spread-to-swap of 251.06 basis points. This result is shown below in Table 4.1.

Table 3.5: Application of Lally extrapolation methods to results from the CEG RBA replication model, as applied from 13th November to 10th December 2015.

 ¹⁴ Diamond, N.T. and Brooks, R. (2015a), section 8, page 20.

Source: ESQUANT analysis. Results from CEG RBA replication model, updated by ESQUANT. Yields are presented on a semi-annual basis.

3.3 The application of goodness-of-fit tests to evaluate the extrapolation approaches

ESQUANT has used goodness-of-fit measures to assess the properties of the curve from the RBA replication model when it has been extrapolated using the three approaches discussed in the previous section. The goodness-of-fit method determines the best fit curve as the curve with a particular extrapolation method that delivers the lowest sum of squared errors when using observed bond data.

For each of the three extrapolated versions of the curve from the RBA replication model, weighted and unweighted sums of squared errors were computed.

- An un-weighted sum of squared errors (SSE) is simply the sum of the squared differences between the observed spreads-to-swap for bonds in the relevant sample, and the fitted spread-to-swap for a commensurate, remaining term to maturity that has been read off the particular RBA replication curve that is being tested. The fitted spread-to-swap for a comparable tenor can be regarded as the "predicted value".
- A weighted SSE is calculated by applying a weight to each squared error term, where the weight is estimated as a Gaussian kernel with a mean of 10 years and a standard deviation of 1.5 years. Note that the standard deviation, sigma, is regarded as the smoothing parameter in the Gaussian kernel.

Additional, multiplicative weights were also applied to correspond with the sizes of the issue amounts (or face values of the bonds).

In this report, ESQUANT has applied the testing methodology by allowing linear extrapolation both backwards for maturities less than the shortest maturity yield estimate, and forwards for maturities greater than the longest maturity yield estimate, assuming a straight line between the two nearest defined yield observations. ESQUANT does not consider that its results will be greatly affected by sensitivities to this assumption because:

- Almost all bonds with maturities of close to 10 years have maturities of less than 10 years. The choice of extrapolation for spread to swap beyond 10 years is unlikely to be critical to the results of most tests; and
- The weight given under the Gaussian kernel method to bonds with maturities of 3 years or less is, in essence, negligible. Excluding these bonds would not be expected to make an important difference to the results of the tests.

The bond sample that was used for the empirical assessment was, in the first instance, a narrow sample. The bonds used were limited to those that satisfied the RBA's stringent selection criteria. These were the same bonds that had been used to produce Gaussian kernel estimates at tenors of 3, 5, 7 and 10 years.

Figure 3.2 shows the curve from the RBA replication model with the extrapolated results, at an effective tenor of 10-years, shown under two scenarios. The scenarios are distinguished by the Lally extrapolation method, based on CGS yields and swap rates, and the SAPN extrapolation technique. A visual examination reveals that the Lally method results in a continued downward slope for the RBA replication model curve, whereas the SAPN method restores the upward slope for the curve.

The numerical results for the curve assessments are presented below in Table 3.6. When considering the outcomes for the un-weighted tests, the lowest sum of squared errors is obtained for the curve which has been extrapolated using the SAPN method. Similarly, for the weighted tests, the lowest weighted sum of squared errors has been recorded for the RBA replication model curve that has been extrapolated using the SAPN technique. Therefore, the empirical evidence suggests that, over the November-December measurement period for United Energy, the best fit is derived by extrapolating using the linear regression method that is inherent in the SAPN approach.

The findings about the best fit of the curve can be derived by using only a narrow sample of bonds for curve testing. Nonetheless, we also present, for the purposes of comparison, the test results that are obtained when a broader sample of bonds is employed in the quantitative assessment process. The results from the tests involving a larger number of bonds are also presented in Table 3.6. For illustrative purposes, the broader sample of bonds has also been shown as a scatter plot in Figure 3.3. The application of a broader bond sample leads to another set of findings, but does not alter the conclusions that can be drawn.

In his recent (October 2015) report prepared for the AER, Lally (2015b) has criticized the application of curve testing methods. He has specifically remarked, several times throughout the report, that:

The goodness of fit test proposed by CEG and others (which involves selecting bonds in accordance with particular criteria) in order to choose between the RBA and BVAL curves, and also between competing extrapolation methods, conflates the merits of those extrapolation methods with the merits of competing criteria for selecting bonds.

The comments made by Lally would have no standing if they were levelled at ESQUANT in the current context. The reason is that, firstly, ESQUANT is not currently using curve testing to select between alternative third party indicator series for measuring the cost of debt. ESQUANT is applying curve testing to gain further insight into the merits (or otherwise) of different extrapolation methods. Secondly, when producing its primary test results, ESQUANT has used a confined sample of bonds which matched the sample that was used to generate the RBA replication model curve in the first instance.

Increment from extrapolation (bppa) and impact on 10-year spread								
		Lally method (swap rates only)	Lally method (swap rates and CGS yields)	SA Power Networks (SAPN) method				
	Units							
RBA replication basis points model, spread-to- swap at a 10-year target tenor (effective tenor of 9.15 years)		247.53	247.53	247.53				
RBA replication bppa model, increment from 9.15 to 10 years		-3.991	-7.343	4.143				
Resulting 10-year spread	basis points	244.12	241.27	251.06				
Resulting 10-year yield	per cent	5.46	5.43	5.53				
		Limited bond sample (satisfies RBA selection criteria)						
Sum of squared errors of the extrapolation (SSE).		1,335,433	1,489,464	1,042,099				
Weighted SSE (using Gaussian kernel weights at a 10-year tenor, and the sizes of the issue amounts).		2,214.54	2,239.69	2,199.08				
Complete available bond sample (BBB rated bonds only)								
Sum of squared errors of the extrapolation (SSE).		3,205,853	3,943,934	2,128,856				
Weighted SSE (using Gaussian kernel weights at a 10-year tenor, and the sizes of the issue amounts).		1,917.74	1,951.29	1,910.57				

Table 3.6: The impact of the Lally and SAPN extrapolation methods: Results from empirical tests of goodness-of-fit, using a bond sample which matches the RBA selection criteria

Source: ESQUANT analysis. Results from CEG RBA replication model, updated by ESQUANT. Under the South Australia Power Networks (SAPN) method, a slope is calculated by fitting a straight line through the observed credit spreads and known tenors.

Figure 3.2: RBA replication model: Results from extrapolation using the Lally (CGS yields) method and the SAPN extrapolation method. Curve testing using a narrow sample of bonds

Source: CEG RBA replication model, updated by ESQUANT. The bonds shown in the chart are those which satisfy the selection criteria set by the RBA. The same sample of bonds has been used to produce the smoothed Gaussian kernel curve that is shown.

3.3.1.1 Conclusions regarding goodness-of-fit tests

The Gaussian kernel method has, on a number of occasions, over the past 13 months, produced counterintuitive results. The application of local constant smoothing by the RBA has delivered values for the 10 year spread-to-swap which are below the values for the 7-year spread-to-swap. There are no intrinsic term structure factors which should contribute to such an outcome. For instance, none of the Nelson-Siegel yield curves that have been estimated by ESQUANT show evidence of such a phenomenon. In the recent past, there has similarly been no evidence from other third party indicator series, of inverted yield curves between 7-years and 10-years. The Bloomberg BBB rated BVAL curve does not present a downward slope between the 7-year tenor and the 10-year tenor, when examining spreads-to-swap, and nor for that matter does the BBBAUDBMK credit curve produced by Thomson Reuters. Thus, the downward slope in the spread-to-

swap between the 7-year tenor and the 10-year tenor appears to be an artefact of the methodology applied by the RBA.

Lally (2015b) has described the occurrence of the downward slope as being a "highly unusual" feature¹⁵. However, he appears to have stepped away from a detailed discussion of the issue. For example, he has neglected to mention the recent evidence from RBA Table F3, even though most of the data would have been available for him to consider.

For most of the past 13 months, the published RBA spreads-to-swap at a 10-year tenor have been below those at a 7-year tenor. From December 2014 to February 2015, as has already been mentioned, the 10-year spread-to-swap was markedly less than the 7-year spread-to-swap. From July 2015 to October 2015, the 10-year spread was marginally below the 7-year spread, although the gap then widened in November 2015. The RBA has not demonstrated that these outcomes are in any way supported by the underlying term structures of the yields on corporate bonds.

The Lally extrapolation method accentuates the observed anomalies and therefore produces perverse results.

ESQUANT's earlier analysis found that the application of the SAPN extrapolation method produced a lower root mean squared error (RMSE) than did the application of other extrapolation approaches¹⁶. A further advantage of the SAPN method is the apparent ease with which it can be implemented.

 15 Lally (2015b), section 2, page 8.

¹⁶ Diamond, N.T. and Brooks, R. (2015a), section 12, page 30.

Figure 3.3: RBA replication model: Results from extrapolation using the Lally (CGS yields) method and the SAPN extrapolation method. Curve testing using a broad sample of bonds

Source: CEG RBA replication model, updated by ESQUANT.

4 Summary of outputs from the third party indicator series

4.1 Harnessing the results from the data vendors and information providers

The third party indicator series that ESQUANT has examined in this report are the Bloomberg BVAL BBB rated curve, the measures of corporate bond spreads for non-financial corporations from the Reserve Bank of Australia (RBA), and the Thomson Reuters BBB rated corporate credit curve, BBBAUDBMK.

A consideration of the components of the different series has revealed that there is no universal or unambiguous method for selecting a bond sample. The bond samples used by Bloomberg, the RBA and Thomson Reuters (TR) all differ. The most definitive conclusion that can be drawn is that there are advantages to the use of broader samples of bonds.

Table 4.1 below presents a summary of the data from the Bloomberg BVAL curve, and the TR BBBAUD credit curve in respect of the November-December averaging period that was nominated by United Energy. The bond yields are shown on a semi-annual basis.

Averages over the period from 13/11/2015 to 10/12/2015									
Tenor	Units	6	7	8	9	10	15		
Bloomberg BVAL BBB yields	per cent	n/a	5.03	5.22	5.41	5.54	5.91		
Interpolated end-of-day swap rates from ADSWAP series	per cent	2.68	2.78	2.87	2.95	3.02	3.28		
Bloomberg BVAL BBB spreads-to-swap	basis points	n/a	225.45	235.38	245.97	252.71	263.42		
Reuters BBBAUDBMK yields	per cent	4.62	4.88	5.18	5.52	5.85	n/a		
Reuters BBBAUDBMK spreads-to-swap	basis points	193.79	209.75	231.65	256.67	283.58	n/a		

Table 4.1: Summary of credit spread data over United Energy's measurement period: Bloomberg BVAL BBB rated series and Reuters BBBAUD credit curve.

Source: Bloomberg and Thomson Reuters

The Bloomberg BVAL BBB rated curve provides a 10-year yield of 5.5440 per cent over the reference period, while the BBBAUD series from Thomson Reuters shows that the 10-year yield was 5.8528 per cent. An arithmetic average of the two sets of results delivers a 10-year yield of 5.6984 per cent.

The results from the previous section can also be incorporated into the analysis. The RBA does not prepare daily measures of corporate credit spreads, and its outputs are only available for the penultimate or final business day of the month. Accordingly, the results from the RBA replication model (originally developed by CEG, and then updated by ESQUANT) can be used in place of the published series. The 10-year yield from the RBA replication model, when extrapolated using the SA Power Networks method is 5.5275 per cent.

An arithmetic average of the two third party indicator series, and of the extrapolated yield from the RBA replication model, delivers a 10-year yield of 5.6414 per cent. This value, expressed on a semi-annual basis, can be transformed into an annual equivalent rate, producing a 10-year yield of 5.72 per cent.

The AER has applied an arithmetic mean of two of out of three third party indicator series in its recent determinations for regulated energy businesses. The AER method has been given impetus by a theoretical analysis undertaken by Lally (2014a) which attempted to show that combining two data series would assist in bringing down the mean squared error (MSE). However, Lally simply assumed that each of the component data series would be unbiased¹⁷. Lally (2014a) did not perform empirical analysis.

An average of the published measures provides useful corroborative evidence, at this time, of the results from the application of yield curves and other empirical methods. However, an average of the third party

 17 Lally (2014a), section 2.2, pages 21-22.

indicator series will not always be optimal. ESQUANT does not provide an unequivocal endorsement of such an approach.

5 List of References

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Appendix B

AER information request United Energy - Number 032 Return on debt

To: Jeremy Rothfield **From:** Neil Diamond **Subject:** AER information request United Energy - #032 Return on debt **Date:** 21st September 2015

1 Background

In its draft decision for Jemena Gas Networks (JGN), the AER has adopted the method, described below, for estimating the return on debt for a benchmark efficient entity¹:

- Adopting a 10-year term for the return on debt with a BBB+ credit rating.
- Applying a simple average of independent third party data from the Reserve Bank of Australia (RBA) and Bloomberg as follows:
	- **–** The RBA broad BBB rated 10 year curve (the RBA curve²) extrapolated to better reflect a 10 year estimate, and interpolated to produce daily estimates.
	- The Bloomberg broad BBB rated 7 year BVAL curve (the BVAL curve³) extrapolated to 10 years.

The estimates of the cost of debt which are prepared by the RBA, and published as Table F3, are derived using a Gaussian kernel smoother, which is known to exhibit bias. ESQUANT (2014) suggested that local linear smoothing could remove the bias to first order, while Lally (2014) suggested an alternative method based on extrapolating the 7 year and 10 year estimates provided by the RBA. Finally the South Australian Power Networks (SA Power Networks, 2014) suggested another method based on a linear regression of the 3, 5, 7 and 10 year estimates provided by the RBA.

Diamond and Brooks (2015) evaluated the three methods. The three methods were shown to be linear smoothers, to be unbiased to first order, and expressions for the bias and variance of the three methods were given. Specifically, (Diamond and Brooks, Appendix D, 2015) for the Lally method the bias to second order is given by

Bias =
$$
\frac{G''(10)}{2} \times \sum_{i=1}^{N} u_i(\sigma) (T_i - 10)^2
$$

while the variance is given by

$$
\text{Variance} = \text{Variance}(\varepsilon_i) \times \sum_{i=1}^{N} u_i(\sigma)^2
$$

where $G(T_i)$ is the spread curve at a tenor of T_i years, $u_i(\sigma)$ is the weight of the *i*th bond for the Lally method, and ε_i is the error from the model

$$
S_i = G(T_i) + \varepsilon_i.
$$

Additionally, the Root Mean Square Error (RMSE) is given by

RMSE =
$$
\sqrt{\text{Bias}^2 + \text{Variance}}
$$
.

Similar results apply to Local Linear Smoothing and the South Australian Power Networks method. The AER has recently asked for some clarification, and this is the subject of this note.

³The Bloomberg ticker for this curve is: BVCSAB07.

¹AER (2014), Draft decision, Jemena Gas Networks (NSW) Ltd, Access Arrangement 2015-20, Attachment 3: Rate of return, Australian Energy Regulator, November 2014; page 3-9.

²The RBA refers to this curve as "Non-financial corporate BBB-rated bonds".

2 AER Question

UED relies on the following report in relation to its proposed return on debt methodology:

Esquant, Evaluation of methods for extrapolating Australian corporate credit spreads published by the RBA, 27 March 2015

Esquant's report contains root mean square error (RMSE) formulas for each of the three extrapolation methods examined. These formulas are intended to be for the spread (DRP) rather than the yield. Each such RMSE formula has a bias term common to all three methods (curvature of the true curve at 10 years), a bias multiplier peculiar to the method, a variance term common to all three methods (standard deviation of the residuals around the true curve), and a variance multiplier peculiar to the method. The empirical estimates of the two multiplier terms are for the spread but the other two terms seem to be taken from Nelson-Siegel curves for the bond yield rather than the spread. So, Esquant seem to have inserted parameters relating to yield into a formula for the spread.

We request that UED:

- 1. Confirm whether our above understanding of the Esquant methodology is correct, specifically in relation to whether Esquant have inserted parameters relating to yield into a formula for the spread?
- 2. Provide a brief justification for this approach?

3 Response

We can confirm that the AER's understanding of the ESQUANT methodology is correct. ESQUANT obtained values from a Nelson-Siegel curve which was applied to data on bond yields rather than to data on the spreads-to-swap.

The values used were the second derivative of the yield function (which measures the rate of change of the slope, and was recorded at 10 years), and the standard deviation of the regression residuals (which was assessed using the standard error of the regression). Thus, ESQUANT obtained estimates of the bias of the true function, and estimates of the variance of the true function from a Nelson-Siegel curve that was fitted to yield data rather than to spread data. However, the practical implication of using yields rather than spreads is almost negligible from the perspective of root mean squared error. As is explained over the remainder of the report, the use of yield data rather than spread data has only a moderate effect on the bias term, but has almost no effect on the variance term. In terms of the magnitude of the respective variables, the variance is larger than the square of the bias. Thus, the variance is of greater significance when considering the overall root mean squared error. The consequences of using yield data rather than spread data when working out the root mean squared error are therefore barely discernible.

A relevant consideration is that there are sound reasons for estimating Nelson-Siegel curves using data on yields rather than on spreads. The Nelson-Siegel model is a model for yields, not spreads. Our view is that it is better to fit the model to yields and to then subtract the corresponding risk-free rate. Evidence from the literature indicates that if the yields follow a Nelson-Siegel model, and the swap rates follow a Nelson-Siegel model, then the difference between the two only follows a Nelson-Siegel model if the non-linear parameter is the same for both models, a restrictive and unnecessary assumption.

Indeed, it should be noted that Diebold and Rudebusch (2013, p. 100-102) showed that Nelson-Siegel yield curves are closed under conversion to spreads,

"That is, if two term structures of yields $y_t^1(\tau)$ and $y_t^2(\tau)$ follow DNS⁴ with the same λ^5 , then the term structure of *spreads* also follows DNS."

In addition, since the base interest rates at the various terms to maturity for the bonds in the sample are estimated using linear interpolation, conversion to spreads introduces an additional source of vari-

⁵The non-linear parameter in the Nelson-Siegel model.

⁴Dynamic Nelson-Siegel.

ability. The base interest rates may be either swap rates or the yields on Commonwealth Government Securities (CGS).

4 Notation

In this report, a comparison will be made between the swap rates that are reported by Bloomberg (ADSWAP series) and the swap rates, at longer tenors, that are estimated using extrapolation methods.

The notation used in this report is as follows:

- S_i = Spread of the *i*th bond (measured in percent, %)
- Y_i = Yield of the *i*th bond (measured in percent, %)
- R_i = The swap rate with a tenor that corresponds to the remaining term to maturity of the *i*th bond (%)
- T_i = Remaining term to maturity of the *i*th bond (years). T_i is also the effective tenor for an estimate of the yield or spread.
- $S_L(T)$ = Estimated Spread at target tenor T using the Lally Method (%)
- $Y_L(T)$ = Estimated Yield at target tenor T using the Lally Method (%)
- $R_L(T)$ = Swap rate at target tenor T, estimated using the Lally Method (%)

$$
S_{LL}(T)
$$
 = Estimated Spread at target tenor *T* using Local Linear Smoothing (%)

- $S_{SA}(T)$ = Estimated Spread at target tenor T using the South Australian Power Networks Method (%)
	- $G(t)$ = Spread vs. maturity curve
	- $H(t)$ = Yield vs. maturity curve
	- $K(t)$ = Swap vs. maturity curve

For a corporate bond, the observed spread over swap rates is typically measured or recorded in basis points. However, these values can be converted into per cent for analytical purposes.

5 The three methods of smoothing are linear

In Diamond and Brooks (2015), three methods of smoothing are compared: the Lally Method (Lally, 2014), Local Linear Smoothing (see, for example Hastie et al., 2009), and the South Australian Power Networks Method (SA Power Networks, 2014).

For the Lally method, the estimate of the spread at 10 years was shown to be

$$
S_L(10) = \sum_{i=1}^{N} u_i(\sigma) S_i
$$

with the weights given by

$$
u_i(\sigma) = (1+a)w_i(10;\sigma) - aw_i(7;\sigma).
$$

where S_i is the spread of the ith bond, $w_i(7;\sigma)$ and $w_i(10;\sigma)$ are the weights from Gaussian smoothing multiplied by the issue weights, with target tenors 7 and 10 years, respectively, and a is given by

$$
a = \frac{10 - E(10)}{E(10) - E(7)}
$$

where E(7) and E(10) are the effective tenors of the Gaussian smoothers for 7 and 10 years respectively. The RBA (Arsov et al. 2013) uses $\sigma = 1.5$.

The estimates of the spreads with the other two methods are also *linear* weighted averages:

$$
S_{LL}(10) = \sum_{i=1}^{N} l_i(10; \sigma) S_i
$$

$$
S_{SA}(10) = \sum_{i=1}^{N} v_i(\sigma) S_i
$$

with the weights formulae being slightly more complicated than for the Lally method.

6 Bias with Smoothing of Spreads

The yield of bond i is given by:

$$
Y_i = S_i + R_i
$$

where R_i is the base interest rate for the *i*th bond, given by linearly interpolating the Bloomberg swap rates (from the Bloomberg ADSWAP series) or by linearly interpolating the yields on CGS, which are provided by the RBA's Table F16. For the Lally method, (the other methods give analogous results)

$$
S_L(10) = \sum_{i=1}^{N} u_i(\sigma) S_i
$$

=
$$
\sum_{i=1}^{N} u_i(\sigma) (Y_i - R_i)
$$

=
$$
\sum_{i=1}^{N} u_i(\sigma) Y_i - \sum_{i=1}^{N} u_i(\sigma) R_i
$$

=
$$
Y_L(10) - R_L(10)
$$

where $Y_L(10)$ is the estimated yield at a 10 year term to maturity, and $R_L(10)$ is the estimated swap rate (or CGS yield) at 10 years maturity, with both values obtained by using the Lally method. This shows that we can get the estimated spread at 10 years by applying the Lally method to the spreads, or, alternatively, by applying the Lally method to the yields and applying the Lally method to the swap rates (or CGS yields) and then taking the difference.

To obtain an expression for the bias, the expected value of $S_L(10)$ needs to be calculated. It is given by

$$
E[S_L(10)] = \sum_{i=1}^{N} u_i(\sigma) E(Y_i) - \sum_{i=1}^{N} u_i(\sigma) E(R_i)
$$

\n
$$
= \sum_{i=1}^{N} u_i(\sigma) H(T_i) - \sum_{i=1}^{N} u_i(\sigma) E(R_i)
$$

\n
$$
= \sum_{i=1}^{N} u_i(\sigma) \left(H(10) + H'(10)(T_i - 10) + \frac{H''(10)}{2} (T_i - 10)^2 + \text{higher order terms} \right) - \sum_{i=1}^{N} u_i(\sigma) E(R_i)
$$

\n
$$
= H(10) \sum_{i=1}^{N} u_i(\sigma) + H'(10) \sum_{i=1}^{N} u_i(\sigma) (T_i - 10) + \frac{H''(10)}{2} \sum_{i=1}^{N} u_i(\sigma) (T_i - 10)^2 - \sum_{i=1}^{N} u_i(\sigma) E(R_i) + \text{higher order terms}
$$

\n
$$
\approx \left(H(10) + \frac{H''(10)}{2} \sum_{i=1}^{N} u_i(\sigma) (T_i - 10)^2 \right) - \left(\sum_{i=1}^{N} u_i(\sigma) E(R_i) + K(10) - K(10) \right)
$$

and hence

$$
E[S_L(10)] - H(10) + K(10) \approx \left(\frac{H''(10)}{2} \sum_{i=1}^N u_i(\sigma) (T_i - 10)^2\right) - \left(\sum_{i=1}^N u_i(\sigma) E(R_i) - K(10)\right)
$$

$$
E[S_L(10)] - S(10) \approx \left(\frac{H''(10)}{2} \sum_{i=1}^N u_i(\sigma) (T_i - 10)^2\right) - \left(\sum_{i=1}^N u_i(\sigma) E(R_i) - K(10)\right)
$$

and therefore an expression for the bias is

Bias
$$
\approx \left(\frac{H''(10)}{2}\sum_{i=1}^{N} u_i(\sigma)(T_i - 10)^2\right) - \left(\sum_{i=1}^{N} u_i(\sigma)K(T_i) - K(10)\right)
$$
 (1)

since $E(R_i) = K(T_i)$, where T_i is remaining term to maturity of the *i*th bond.

The first composite term on the right hand side of Equation 1 corresponds to the expression that was used in Diamond and Brooks (2015). In that report, the authors fitted a Nelson-Siegel curve to the yields and obtained the second derivative of the fitted curve for a remaining term to maturity of ten years. The second composite term on the right hand side of Equation 1 is the bias that results from using an estimate of the swap rate (or base interest rate) instead of actual, reported swap rates.

The difference between the first and second composite terms on the right hand side of Equation 1 is a measure of the bias of the relevant method when using spreads rather than yields.

Figure 1 shows a plot of the actual swap rates, for vanilla interest rate swaps, as reported by Bloomberg for 30th January 2015. Bloomberg publishes actual swap rates at tenors of 1, 2, . . . , 10, 12, 15, 20, 25, and 30 years. Under the ADSWAP series, swap rates are recorded at increments of one year, from a one year remaining term to maturity to a 10-year remaining term to maturity. An interpolated cubic spline can be fitted through the points. The cubic spline can be reasonably presumed to provide the correct representation of the curvature.

In order to obtain estimated swap rates at tenors corresponding to the remaining terms to maturity of bonds in the dataset, the rates were simply read off the cubic spline curve. The weights formulae for the three extrapolation methods are known, and so the following expression can be evaluated:

$$
\sum_{i=1}^{N} u_i(\sigma) K(T_i).
$$

The actual, reported swap rate at a 10-year tenor is then subtracted from the expression shown above so as to deliver an estimate of the "bias correction term":

$$
\sum_{i=1}^{N} u_i(\sigma)K(T_i) - K(10).
$$

The calculated values for the bias, obtained for the end of the month using Equation 1 are shown in Table 1, in respect of the period from November 2013 to January 2015. The bias correction terms are also shown. Note that the absolute values of the bias correction terms obtained under the three extrapolation methods are relatively small. The largest value to be reported is 0.15% which has been calculated using the SA Power Networks extrapolation method for 29th November 2013.

Figure 1: Bloomberg Swap rates for 30th January 2015, with linear interpolation and cubic spline.

7 Expression for the Variance

In section 6, an expression for the bias was derived and presented. In this section an expression for the variance is obtained. We use the models

$$
S_i = G(T_i) + \varepsilon_i
$$

\n
$$
Y_i = H(T_i) + \eta_i
$$

\n
$$
R_i = K(T_i) + \tau_i
$$

 $= H(T_i) + \eta_i - K(T_i) - \tau_i$

 $\varepsilon_i = \eta_i - \tau_i$

 $S_i = Y_i - R_i$

 $= G(T_i) + \varepsilon_i$

Then

where

and

$$
Var(\varepsilon_i) = Var(\eta_i) + Var(\tau_i) - 2Cov(\eta_i, \tau_i).
$$
\n(2)

The η_i were estimated from the regression residuals that were obtained by fitting the Nelson-Siegel curve to data on bond yields. In order to obtain an estimate of the variance for base interest rates, $Var(\tau_i)$, linear interpolation was applied to produce swap rates at tenors corresponding to the remaining terms to maturity of corporate bonds in the dataset used for the analysis. The τ_i were estimated by taking the difference between the swap rates estimated using the cubic spline function and the swap rates obtained by linear interpolation. Once the η_i and τ_i were estimated, the sample variances and sample covariance were calculated, and these values were then combined according to Equation 2 in order to get an estimate of $Var(\varepsilon_i)$. A degrees of freedom adjustment was made⁶. Note that $Var(\varepsilon_i) \approx$ Var(η_i) since the τ_i are very small.

Table 2 gives the variance calculations for the end of the month from November 2013 to January 2015.

Table 2: Variance Calculations for Local Linear Smoothing ($\sigma = 2.4$), the Lally extrapolation method, and the SA Power Networks extrapolation approach. The standard deviation of the error terms, $sd(\epsilon_i)$, is obtained for each month using the calculations presented in section 7.

⁶The sample variance of the regression residuals needs to be multiplied by $(n-1)/(n-k)$ where k is the number of parameters estimated in the Nelson-Siegel model and n is the number of data points.

8 RMSE

The results for bias in Table 1 and the results for variance in Table 2 were combined to calculate the RMSE for the three methods for each month from November 2013 to January 2015. The values for RMSE are displayed in Table 3. The results only differ from those given in Table 9 of Diamond and Brooks (2015) at the third decimal point. A graphical display of the RMSE is given in Figure 2, which is almost identical to that shown in Figure 5 of Diamond and Brooks (2015).

Bias			Variance			RMSE			
	Local Linear	Lally	SA	Local Linear	Lally	SA	Local Linear	Lally	SA
Nov ₁₃	-0.041	-0.033	-0.081	0.067	0.075	0.045	0.262	0.277	0.228
Dec13	-0.035	-0.027	-0.067	0.069	0.078	0.047	0.265	0.280	0.226
Jan14	-0.068	-0.059	-0.111	0.071	0.080	0.047	0.274	0.289	0.244
Feb ₁₄	-0.037	-0.029	-0.061	0.047	0.054	0.031	0.220	0.234	0.186
Mar14	-0.012	-0.008	-0.027	0.053	0.061	0.033	0.230	0.248	0.184
Apr ₁₄	-0.027	-0.023	-0.048	0.062	0.064	0.039	0.250	0.254	0.203
May14	-0.013	-0.012	-0.013	0.062	0.065	0.038	0.249	0.254	0.196
Jun14	-0.022	-0.023	-0.037	0.042	0.046	0.029	0.207	0.216	0.174
Jul ₁₄	-0.023	-0.024	-0.050	0.058	0.065	0.041	0.243	0.257	0.208
Aug14	-0.022	-0.022	-0.044	0.057	0.065	0.041	0.240	0.256	0.207
Sep14	-0.010	-0.009	-0.026	0.044	0.050	0.035	0.211	0.223	0.188
Oct14	-0.012	-0.010	-0.015	0.043	0.049	0.033	0.208	0.222	0.183
Nov ₁₄	0.005	0.007	0.026	0.037	0.043	0.029	0.193	0.209	0.173
Dec14	0.038	0.042	0.086	0.040	0.048	0.032	0.204	0.223	0.199
Jan15	0.027	0.029	0.056	0.051	0.063	0.042	0.228	0.252	0.213

Table 3: The results for Bias, Variance, and RMSE for three extrapolation methods: Local Linear Smoothing ($\sigma = 2.4$), the Lally extrapolation method, and the SA Power Networks extrapolation approach.

9 Conclusions

The results that were originally reported in ESQUANT (2015) withstand scrutiny and can be used with confidence.

Expressions for the bias and variance using spreads rather than yields were derived for the three extrapolation methods and these were applied to the data used in Diamond and Brooks (2015).

The bias term is now calculated completely using both yield and base rate components. The overall result for the bias is derived using a bias multiplier (which uses weights that are unique to the particular extrapolation method); the second derivative of the slope of the true yield curve; and a bias correction factor (which takes account of the slope of the curve for swap rates).

The variance term depends on the variance of the residuals from the Nelson-Siegel yield curve and the deviations of the linearly interpolated swap rates from the swap rates estimated using a cubic spline. These components were combined and then a multiplier, dependent on the extrapolation method, was applied.

Although the results for the bias were slightly different when using spreads rather than yields, the more important variance term was little changed, and therefore the RMSE altered by only a very small margin.

Figure 2: Comparison of RMSE for the Lally Method, SA Power Networks Method, and Local Linear Smoothing from November 2013 to January 2015. The results are partly underpinned by the variance of the true spread curve, by the second derivative of the Nelson-Siegel yield curve (evaluated at a 10-year term to maturity), and by a bias correction factor.

10 References

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Appendix C

Images of the Thomson Reuters BBB Rating AUD Credit Curve (Corporate Cash Credit Curve).

C.1 A sample of the data and the images that were sourced for the BB-BAUDBMK credit curve

The images of the Thomson Reuters BBB rated credit curve that are shown in this appendix represent a sample of the images that were captured by ESQUANT. The BBBAUDBMK credit curve is produced on a real-time basis, and live images were retrieved by ESQUANT on consecutive days during and after the third averaging period for United Energy. The credit curve and its constituents were viewed using the Thomson Reuters Eikon application. The third averaging period for United Energy covered the business days from 13th November 2015 to 10th December 2015.

According to the Thomson Reuters publication, 'Asia Credit Curves Guide', the Asian credit curves, with the exception of the AUD curves, are constructed with real time pricing from the Thomson Reuters Pricing Service (TRPS). The AUD curves source Thomson Reuters SuperRICs featuring contributions from quality domestic Australian price makers.

The images or snapshots of the BBBAUDBMK credit curve that are shown in this appendix were taken on 14/11/2015, 17/11/2015, 18/11/2015, 19/11/2015, 20/11/2015, 14/12/2015, and 31/12/2015.

Although the BBBAUDBMK credit curve is produced on a real-time basis, and is updated continuously, end of day values can be sourced from Thomson Reuters Eikon, and its Excel interface. The end-of-day values are produced for business days. The values that were used in the calculations for the third averaging period for United Energy were the end-of-day values for the relevant business days. The end of day values have not been reproduced in this appendix. The figures that are shown in this appendix, for selected days, do not necessarily coincide exactly with the end of day values that have been factored into the analysis undertaken for this report, (refer to Appendix A, Analysis of third party indicator series including credit curves from Thomson Reuters).

BBB RATING AUD CREDIT CURVE | Corporate Cash Credit Curve RIC: 0#BBAUDBMK=

BOND CONSTITUENTS

«« First | « Prev | Next» Coupon Maturity Bid **Bid Yield** Ask Yield Benchmark Spread Swap Spread Asset Swap Spread ISIN Name Ask WOOLWORTH 03/16 22-Mar-2016 101.257 101.274 3.028 87.4 6.75 2.978 100.5 89.8 AU3CB0172039 DAIWA 05-Dec-2016 173.9 170.6 XS0857206782 3.80 99.946 100.266 3.851 3.538 186.8 **UED 04/17** AU3CB0192599 11-Apr-2017 103,631 103,700 6,25 3,558 3,508 153,8 145,1 146,1 HOLCIM FI 07/17 $3,541$ 6.00 18-Jul-2017 103,938 104,130 3.425 152.1 144.5 144.3 AU3CB0196699 CROWN GRP 07/17 3.596 AU3CB0196848 5.75 18-Jul-2017 103,447 103,529 3,546 157.6 150.0 149.4 **BOFA 08/18** 4.50 23-Aug-2018 102.525 102.780 3.531 3.435 141.2 138.3 137.4 AU3CB0208775 AAPT 11/18 5.75 01-Nov-2018 100,044 100,179 5,732 5,682 361.6 357.0 352.3 AU3CB0215457 LEND LEAS 11/18 5.50 103,266 4.242 215.9 215.4 AU3CB0208494 13-Nov-2018 103,493 4.322 221.3 ANGLO AME 11/18 AU0000AOMHA7 5.75 27-Nov-2018 97.015 97.147 6,859 6,809 475.0 468.7 454.9 WOOLWORTH 03/19 3,863 3,813 161,7 165,2 AU3CB0191815 $6,00$ 21-Mar-2019 106,631 106,793 175.4 EMIRATES 05/19 08-May-2019 209.1 AU3CB0220861 5.75 104,482 104,889 4.345 4.221 212.9 206.6 CROWN GRP 11/19 100,356 100,538 4,352 4.50 18-Nov-2019 4,402 218.6 199.8 197.0 AU3CB0225324 BOFA 03/20 4 2 5 05-Mar-2020 101 609 101 955 3839 3752 162.3 1400 1374 AU3CB0223675 HOLCIM FI 03/20 3.75 19-Mar-2020 99,356 99,755 3.912 3,811 169.6 146.8 142.1 AU3CB0228286 APT PIPEL 07/20 7.75 22-Jul-2020 115,824 116.055 4.004 3.954 164.4 151.9 163.3 AU3CB0155133 OPH FINAN 07/20 5.75 29-Jul-2020 108.013 108,236 3,866 3.816 150.6 137.8 141.1 AU3CB0211647 CONNECTEA 09/20 5.75 02-Sep-2020 107.610 107836 3 9 8 7 3 9 3 7 162.7 148.8 1520 AU3CB0212967 BRIS AIRP 10/20 6.00 21-Oct-2020 109,256 109.490 3.914 3.864 155.4 139.9 144.5 AU3CB0214823 AURIZON N 10/20 5.75 28-Oct-2020 106,200 106,428 4.342 4.292 198.2 182.4 185.7 AU3CB0215119 WESFARMER 11/20 366 18-Nov-2020 99.599 99 801 3 7 4 9 3704 138.9 1224 118.3 AU3CB0229565 PERTH AIR 03/21 5.50 25-Mar-2021 105.222 106.093 4.393 4.215 197.1 182 B 185.4 AU3CB0219681 ALISTRAL IA 12/21 4.50 17-Dec-2021 101.677 101.946 4 188 4 138 $160A$ 153.8 151.2 ALISCR0226264 EMIRATES 02/22 475 18-Feb-2022 100.503 100 935 4655 4.575 2071 198.5 1944 AU3CB0227411 ASCIANO F 05/25 5.25 19-May-2025 97.570 97,930 5.583 5.533 267.4 260.1 251.7 AU3CB0229680

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OVERVIEW

CURVE CHART $\begin{array}{c|c}\n\hline\n\multicolumn{1}{r}{\textbf{0#BBBAUDBMK=}}\n\end{array}$ $\frac{1}{3}$ $\frac{1}{2}$ $\frac{1}{3}$ \overline{ab} $\overline{\mathbf{1}}$ ΔV

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Appendix D

Terms of Reference

JOHNSON WINTER & SLATTERY

L A W Y E R S

Partner: Anthony Groom +61 8239 7124 Email: Anthony.groom@jws.com.au Our Ref: B1505 Doc ID: 67303906.1

4 January 2016

Dr Neil Diamond Esquant Statistical Consulting 5 Everage Street MOONEE PONDS VIC 3039

Dear Dr Diamond

2016-2020 Price Determination

We act for United Energy (**UE**) in relation to the Australian Energy Regulator's (**AER**) review of United Energy's regulatory proposal under the National Electricity Law for the period 2016 to 2020.

UE wishes to engage you to prepare an expert report relating to cost of debt in connection with UE's revised regulatory proposal.

This letter sets out the matters which UE wishes you to address in your report and the requirements with which the report must comply.

Terms of Reference

UE is required to submit a regulatory proposal under the National Electricity Rules for consideration by the AER. In reviewing this proposal the AER's discretion is regulated by the National Electricity Objective in section 7 of the National Electricity Law, the revenue and pricing principles in section 7A of the National Electricity Law and the specific requirements of the National Electricity Rules.

The AER's decision in respect of the allowed rate of return is also made having regard to Rate of Return Guidelines published by the AER under Chapter 6 of the National Electricity Rules.

The AER released its Preliminary Decision on 29 October 2015. The approach to rate of return in that decision is generally consistent with that taken by the AER in decisions for the New South Wales electricity distributors between April and June 2015.

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Opinion

In this context, UE wishes to engage you to prepare an expert report which:

- 1. Considers the different models that have been put forward for the transition to a trailing average, portfolio return on debt.
- 2. Reviews and, where appropriate, responds to matters that were raised in the 29 October 2015 Preliminary Decision, and the final decisions for New South Wales electricity distributors noted above, regarding the available methods for estimating the rate of return on debt over particular reference intervals.

The matters to be considered will include (but will not be limited to):

- (a) Theoretical frameworks or conceptual specifications, including the term structure of interest rates, and the spreads on corporate debt. The term structure would distinguish between spot rates, yields, and, potentially, forward rates.
- (b) Methods for implementing the theoretical frameworks. Empirical techniques or models that can be used to estimate the term structure of interest rates, and then produce results for the yields on corporate debt at different tenors, or terms to maturity.
- (c) Methods that make use of the available yield data for corporate bonds.
- (d) Sources of data for bond prices, yields, and other variables, such as credit ratings.
- (e) Parametric versus non-parametric methods for deriving estimated yields or spreads.
- (f) The use of aggregate indices, such as third party measures, which convey information about the cost of debt.
- (g) The need to apply extrapolation methods to third party measures of the cost of debt.
- (h) Any specific considerations that may apply to annual updates of the rate of return on debt.
- (i) A consideration of whether the AER's proposed approach to the rate of return on debt would result in the best estimate of the return on debt that contributes to the achievement of the allowed rate of return objective, and that meets the requirements of clause 6.5.2 of the National Electricity Rules; and
- (j) An assessment of whether an estimate of the return on debt that would be obtained using the approach adopted by the AER would produce a result consistent with the achievement of the National Electricity Objective and the Revenue and Pricing Principles.
- 3. In light of your opinion on the above matters and on any other matters that you consider relevant, and having regard to the AER's objective of implementing a trailing average method in future periods, please:

- (a) Recommend a method for estimating the rate of return on debt for the forthcoming regulatory period that best satisfies the National Electricity Law and the National Electricity Rules; and
- (b) Apply this method to estimate the return on debt for the first year of the forthcoming regulatory period (2016 to 2020) for UE.

In preparing your report, please:

- 1. Consider the theoretical and empirical support for different return on debt estimation methods.
- 2. Consider any comments raised by the AER and other regulators on return on debt estimation.
- 3. Examine reports that have been prepared by advisors for the AER, such as Chairmont Consulting and Dr Martin Lally.
- 4. Use robust methods and data, where relevant.
- 5 Use the final determination averaging period of 13th November 2015 to 10th December 2015 (inclusive) to estimate any prevailing parameter estimates that are needed to calculate the rate of return on debt. The results for other relevant averaging periods should also be examined.

Use of Report

It is intended that your report will be submitted by UE to the AER with its response to the Preliminary Decision. The report may be provided by the AER to its own advisers. The report must be expressed so that it may be relied upon both by UE and by the AER.

The AER may ask queries in respect of the report and you will be required to assist in answering these queries. The AER may choose to interview you and, if so, you will be required to participate in any such interviews.

The report will be reviewed by UE's legal advisers and will be used by them to provide legal advice as to its respective rights and obligations under the National Electricity Law and National Electricity Rules.

If UE was to challenge any decision ultimately made by the AER, that appeal will be made to the Australian Competition Tribunal and your report will be considered by the Tribunal. UE may also seek review by a court and the report would be subject to consideration by such court. You should therefore be conscious that the report may be used in the resolution of a dispute between the AER and UE. Due to this, the report will need to comply with the Federal Court requirements for expert reports, which are outlined below.

Compliance with the Code of Conduct for Expert Witnesses

Attached is a copy of the Federal Court's Practice Note CM 7, entitled "*Expert Witnesses in Proceedings in the Federal Court of Australia*", which comprises the guidelines for expert witnesses in the Federal Court of Australia (**Expert Witness Guidelines**).

Please read and familiarise yourself with the Expert Witness Guidelines and comply with them at all times in the course of your engagement by UE.

In particular, your report should contain a statement at the beginning of the report to the effect that the author of the report has read, understood and complied with the Expert Witness Guidelines.

Your report must also:

- 1 contain particulars of the training, study or experience by which the expert has acquired specialised knowledge;
- 2 identify the questions that the expert has been asked to address;
- 3 set out separately each of the factual findings or assumptions on which the expert's opinion is based;
- 4 set out each of the expert's opinions separately from the factual findings or assumptions;
- 5 set out the reasons for each of the expert's opinions; and
- 6 otherwise comply with the Expert Witness Guidelines.

The expert is also required to state that each of the expert's opinions is wholly or substantially based on the expert's specialised knowledge.

It is also a requirement that the report be signed by the expert and include a declaration that "*[the expert] has made all the inquiries that [the expert] believes are desirable and appropriate and that no matters of significance that [the expert] regards as relevant have, to [the expert's] knowledge, been withheld from the report*".

Please also attach a copy of these terms of reference to the report.

Terms of Engagement

Your contract for the provision of the report will be directly with UE. You should forward your account for the work performed directly to UE.

Please sign a counterpart of this letter and return it to us to confirm your acceptance of the engagement.

Yours faithfully

Juneon Witchers Statter

Enc: Federal Court of Australia Practice Note CM 7, "Expert Witnesses in Proceedings in the Federal Court of Australia"

……………………………………………………

Signed and acknowledged by Dr Neil Diamond on behalf of ESQUANT Statistical Consulting

5/1/2016

Date ……………………………………

FEDERAL COURT OF AUSTRALIA *Practice Note CM 7* **EXPERT WITNESSES IN PROCEEDINGS IN THE FEDERAL COURT OF AUSTRALIA**

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

Commencement

1. This Practice Note commences on 4 June 2013.

Introduction

- 2. Rule 23.12 of the Federal Court Rules 2011 requires a party to give a copy of the following guidelines to any witness they propose to retain for the purpose of preparing a report or giving evidence in a proceeding as to an opinion held by the witness that is wholly or substantially based on the specialised knowledge of the witness (see **Part 3.3 - Opinion** of the *Evidence Act 1995* (Cth)).
- 3. The guidelines are not intended to address all aspects of an expert witness's duties, but are intended to facilitate the admission of opinion evidence¹, and to assist experts to understand in general terms what the Court expects of them. Additionally, it is hoped that the guidelines will assist individual expert witnesses to avoid the criticism that is sometimes made (whether rightly or wrongly) that expert witnesses lack objectivity, or have coloured their evidence in favour of the party calling them.

Guidelines

1. General Duty to the Court²

- 1.1 An expert witness has an overriding duty to assist the Court on matters relevant to the expert's area of expertise.
- 1.2 An expert witness is not an advocate for a party even when giving testimony that is necessarily evaluative rather than inferential.
- 1.3 An expert witness's paramount duty is to the Court and not to the person retaining the expert.

¹ As to the distinction between expert opinion evidence and expert assistance see *Evans Deakin Pty Ltd v Sebel Furniture Ltd* [2003] FCA 171 per Allsop J at [676].

²The "*Ikarian Reefer*" (1993) 20 FSR 563 at 565-566.

2. The Form of the Expert's Report³

- 2.1 An expert's written report must comply with Rule 23.13 and therefore must
	- (a) be signed by the expert who prepared the report; and
	- (b) contain an acknowledgement at the beginning of the report that the expert has read, understood and complied with the Practice Note; and
	- (c) contain particulars of the training, study or experience by which the expert has acquired specialised knowledge; and
	- (d) identify the questions that the expert was asked to address; and
	- (e) set out separately each of the factual findings or assumptions on which the expert's opinion is based; and
	- (f) set out separately from the factual findings or assumptions each of the expert's opinions; and
	- (g) set out the reasons for each of the expert's opinions; and
	- (ga) contain an acknowledgment that the expert's opinions are based wholly or substantially on the specialised knowledge mentioned in paragraph (c) above⁴; and
	- (h) comply with the Practice Note.
- 2.2 At the end of the report the expert should declare that "[the expert] has *made all the inquiries that* [the expert] *believes are desirable and appropriate and that no matters of significance that* [the expert] *regards as relevant have, to* [the expert's] *knowledge, been withheld from the Court*."
- 2.3 There should be included in or attached to the report the documents and other materials that the expert has been instructed to consider.
- 2.4 If, after exchange of reports or at any other stage, an expert witness changes the expert's opinion, having read another expert's report or for any other reason, the change should be communicated as soon as practicable (through the party's lawyers) to each party to whom the expert witness's report has been provided and, when appropriate, to the Court⁵.
- 2.5 If an expert's opinion is not fully researched because the expert considers that insufficient data are available, or for any other reason, this must be stated with an indication that the opinion is no more than a provisional one. Where an expert witness who has prepared a report believes that it may be incomplete or inaccurate without some qualification, that qualification must be stated in the report.
- 2.6 The expert should make it clear if a particular question or issue falls outside the relevant field of expertise.
- 2.7 Where an expert's report refers to photographs, plans, calculations, analyses, measurements, survey reports or other extrinsic matter, these must be provided to the opposite party at the same time as the exchange of reports⁶.

³ Rule 23.13.

⁴ See also *Dasreef Pty Limited v Nawaf Hawchar* [2011] HCA 21.

⁵ The *"Ikarian Reefer"* [1993] 20 FSR 563 at 565

⁶ The *"Ikarian Reefer"* [1993] 20 FSR 563 at 565-566. See also Ormrod *"Scientific Evidence in Court"* [1968] Crim LR 240

3. Experts' Conference

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

> J L B ALLSOP Chief Justice 4 June 2013

