Benchmarking Credit ratings

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Executive summary

1. CEG was asked to provide an empirical assessment of the determinants of credit ratings for the owners of regulated assets. One of the key questions we have been asked to address is whether there is evidence that gas transmission pipeline operators tend to have lower credit ratings than other similar regulated businesses.

2. We have addressed this question by analysing a dataset maintained by SNL Financial of 507 United States privately owned gas and electricity transmission and distribution businesses. Of this population, 244 have credit ratings with one of the three major credit ratings agencies and provide a basis upon which to undertake quantitative analysis.

3. The key economic conclusions drawn our analysis is that gas transmission pipelines have consistently lower credit ratings than other businesses in our sample and that this conclusion is very unlikely to be a result of chance.

4. This is a conclusion that can be drawn by comparing the average credit rating/financial leverage of gas pipelines with the average credit rating/financial leverage for non-pipeline businesses. It is also supported by statistical testing. However, there are good reasons to believe that standard statistical testing underestimates how much lower a gas pipeline's credit ratings is relative to an otherwise similar non-gas pipeline.

5. Based on the evidence in this report, we consider that the best estimate is that gas transmission pipelines should be assumed to have a credit rating that is at least one notch lower than otherwise similar electricity or gas network businesses.

6. In our sample of 244 United States privately owned gas and electricity transmission and distribution operating businesses with credit ratings we have identified 25 gas transmission pipeline firms. These 25 firms have slightly lower credit ratings than the remainder of firms. The median and mean credit rating for a gas pipeline is BBB while the median and mean credit rating for all other operating companies is BBB+.

7. However, this slightly lower credit rating is misleading as an indicator of the difference in 'like for like' credit risk because it does not account for other factors that are known to influence credit rating. For example, it does not account for factors one might expect to have an impact on credit rating such as:

   - financial leverage;
   - the maturity profile of existing debt obligations;
   - the size of the business; and
   - the volatility of profitability for the business.

8. The table below describes the difference between the median and mean of potential proxies for these explanatory variables. A credit rating of 15 is equivalent to a Standard & Poor's BBB+ credit rating and an increase/decrease of one unit is equivalent to one notch higher/lower credit rating (e.g., BBB/A- is represented by 14/16).

Summary statistics – gas transmission pipelines and other gas and electricity network businesses

	Credit rating	Debt to total assets (%)	Debt to unlevered free cash flow	Recurring EBITDA margin volatility	Total assets ($m)	Average debt term (years)
All excluding gas transmission pipelines (219 businesses)						
Median	15.00	50%	10.54	1.12	5,565	18.24
Mean	14.82	51%	14.49	1.55	12,145	17.51
Gas transmission pipelines (25 businesses)						
Median	14.00	36%	5.19	0.63	2,749	15.46
Mean	14.16	36%	5.40	0.96	3,509	16.36

Source: SNL Financial, CEG analysis

9. The results reported in the table above show that despite having significantly lower average gearing and EBITDA margin volatility, suggesting that they should be lower credit risk than other businesses in the sample, gas transmission pipeline businesses were assigned a riskier average credit rating (about one notch lower).

10. This provides strong support for a conclusion that there is some unobserved characteristic of gas transmission pipeline businesses that lowers their credit ratings relative to other gas and electricity network businesses. There are a number of potential explanations for this difference. However, these propositions cannot easily be tested because it is difficult to collect statistics to proxy the factor(s) in question.

11. We have also tested the hypothesis that gas transmission pipelines have systematically lower credit ratings than other gas and electricity network businesses using formal statistical analysis. The table below shows results of implementing ordinary least squares regression using gearing, weighted average debt term and a gas transmission pipeline dummy variable as explanatory factors.

Ordinary least squares regression model results

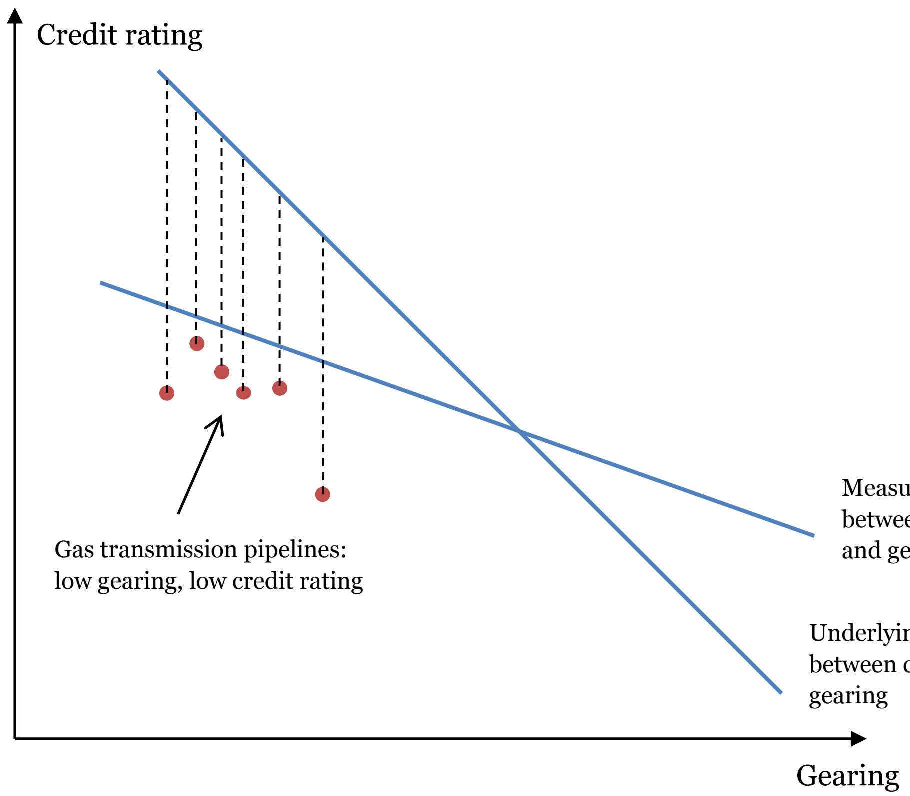
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	15.07	0.66	22.96	0.0000
Gearing	-2.10	1.13	-1.86	0.0647
W.A.debt.term	0.04	0.01	3.11	0.0011
Gas.pipeline	-0.89	0.42	-2.14	0.0337

Source: SNL Financial, CEG analysis

12. The interpretation of this regression is consistent with prior economic intuition. The results are consistent with our *a priori* expectations and interpretation of the summary statistics reported in the previous table above.

13. However, we note that the magnitude and significance of the gearing term is lower than would be expected. This is likely explained by the fact that firms with high base levels of credit risk (e.g., firms whose operations are naturally high risk without any gearing) tend to adopt more conservative gearing than do firms with low levels of base credit risk. Consequently, the impact of leverage of credit rating risk is masked in the sample.

14. An important implication of this is that the gas pipeline dummy variable will, because gas pipelines have lower than average gearing, tend to be underestimated. The reason why this is so can be illustrated in graphically. In the below figure there are two lines drawn describing the relationship between gearing and credit rating. The shallow sloped line is the regression line through all of the available data. The steeper line is the true relationship – the relationship that would be observed if one could hold constant the natural/base level of credit risk in the sample (i.e., adjust for the above described inverse relationship between natural (ungeared) credit risk and the ultimate choice of gearing by a company).



15. The gas pipeline observations are represented on the graph consistent with their actual position in the data set – with lower than predicted credit rating and lower than average gearing. It can easily be seen that the regression dummy variable (approximately the average distance between the pipeline dots and the regression line) will underestimate the true dummy variable (approximately the average distance between the pipeline dots and the higher line representing the 'underlying' relationship between credit rating and gearing holding the base/natural level of credit risk constant).

16. We proceed to test the statistical properties of the above regression by testing for robustness to:

- heteroscedasticity in the error terms conditional on the independent variables (noting that OLS regressions assume homoscedastic error terms);
- outliers in the sample;
- the possibility that credit ratings have only an ordinal (not a linear cardinal) relationship to each other. That is, the possibility that moving from BBB+ to A- involves a different quantitative change than moving from, say, A- to A etc.;
- the inclusion of different variables in the regression. This includes variables intended to capture the size of the business, alternative measures of financial leverage and variables intended to capture the volatility of profitability/cash-flow; and

- the possibility that the relationship between credit rating response and the explanatory variables is not linear.

17. The robustness testing does not reveal that a simple linear model is an unreasonable fit to the data. Our robustness tests support the finding of the simple linear model that gas transmission pipelines are associated with credit ratings of more than approximately one notch lower than other gas and electricity network businesses once other factors are controlled for.

18. However, given the above described reasons for believing the gas pipeline dummy variable will be underestimated (in absolute terms) the best estimate of the impact on credit rating is a more than one notch reduction in credit rating.

1 Introduction

19. CEG has been commissioned by Dampier Bunbury Pipeline (DBP) to provide an empirical assessment of the determinants of credit ratings for the owners of regulated assets. We have been asked to investigate how risks involved in the provision of reference services might influence a gas transmission pipeline business' credit rating and how credit ratings for these businesses compare on average to those of other regulated electricity and gas network businesses.

20. The United States provides an obvious starting point for an analysis of this type. It contains a large number of gas transmission pipeline businesses and excellent information about these and other gas and electricity utilities from which to conduct this analysis.

21. We have sourced data on 507 entities identified by SNL Financial as privately owned United States gas and electricity transmission and distribution operating businesses. Of these companies 244 had credit ratings issued by either Standard & Poor's, Moody's and/or Fitch. The relatively sparse coverage of credit ratings for these entities can be attributed to the fact that most of them are subsidiaries of other businesses and do not have or do not require standalone credit ratings of their own.

22. The focus of this report is to explain variation in credit rating in terms of variation in possible explanatory variables. Variables that we investigate include:

- industry of operation – in particular whether the entity operates a gas transmission pipeline or another electricity or gas utility;
- financial leverage – the extent to which the entity funds its capital through debt as opposed to equity;
- weighted average term of debt on issue;
- variability in the entity's profitability; and
- size of the entity.

23. We have tested the robustness of our proposed regression and investigated alternative models and methods of identifying the effect of these explanatory variables on credit ratings.

24. The remainder of this report is set out as follows:

- **Section 2** introduces the dataset of United States operating companies that we have sourced from SNL Financial.
- **Section 3** provides an analysis and interpretation of that data without the use of formal statistical analysis; and

- **Section 4** proposes a simple regression model that attempts to estimate the explanatory factors for an entity's credit rating. We discuss the robustness tests of our proposed regression model and the interpretation of these. We investigate why gearing does not have as great an effect on credit rating as might be expected.

2 SNL Financial dataset

25. We have sourced information from SNL Financial which includes data from United States Federal Energy Regulatory Commission (FERC) and the United States Securities and Exchange Commission (SEC) filings.

26. Our core dataset consists of 507 privately owned gas and electricity transmission and distribution operating businesses. 244 of these have credit rating data. The list consists of FERC-filing businesses (in SNL's "Regulated Energy Companies" dataset), less:

- Allegheny Generating Company, Ameren Generating Company and System Energy Resources; and
- Public Power and Electric Cooperative businesses.

27. The first three companies are excluded because they are primarily electricity generation companies.

28. Public Power businesses are omitted because they are not privately owned. Government-owned businesses and are likely to have high credit ratings independent of their other characteristics such as debt profile, gearing and industry.

29. Electric cooperatives are composed of many businesses joined to form a cooperative, making them unsuitable for comparison to other businesses. Moreover, many electric cooperatives are owners of significant electricity generation facilities, rendering their comparability to privately owned gas and electric network businesses even more tenuous.

30. In the following sub-sections we summarise the data that we have collected from SNL and used in our analysis in this report.

2.1 Credit ratings

31. We collected Standard and Poor's, Moody's and Fitch long-term corporate credit ratings from SNL Financial. Each rating was assigned a value according to the scale designated in Table 1. A single ratings value was then selected for each business, preferring S&P, followed by Moody's then Fitch, in order of data completeness.

Table 1: Credit rating values and comparability scale

S&P	Moody's	Fitch	Assigned value
AAA	Aaa	AAA	22
AA+	Aa1	AA+	21
AA	Aa2	AA	20
AA-	Aa3	AA-	19
A+	A1	A+	18
A	A2	A	17
A-	A3	A-	16
BBB+	Baa1	BBB+	15
BBB	Baa2	BBB	14
BBB-	Baa3	BBB-	13
BB+	Ba1	BB+	12
BB	Ba2	BB	11
BB-	Ba3	BB-	10
B+	B1	B+	9
B	B2	B	8
B-	B3	B-	7
CCC+	Caa1	CCC	6
CCC	Caa2		5
CCC-	Caa3		4
CC	Ca		3
C			2
D	C	DDD	1

2.1.1 Gas transmission pipeline dummy

32. Based on the nature of its operations, SNL classifies each energy network company in the dataset into one of the following regulatory industries: Diversified Utility, Wholesale Gen/Trans, Electric Utility, Gas Utility, Gas Pipeline, Public Power or Electric Cooperative, with the latter two being excluded from our dataset.

33. We define a gas transmission pipeline variable as a dummy variable which is equal to one for all businesses classified as gas pipelines and zero for all other businesses.

2.1.2 Measures of gearing

34. The gearing variable was calculated as total debt over total debt and equity from SNL's Total Debt/Total Equity field.

35. Debt over unlevered FCF is defined by SNL as “Average total debt as a multiple of recurring unlevered free cash flow” where free cash flow is “available prior to the servicing of interest payments”.

2.1.3 Weighted average debt term

36. Weighted average debt term (W.A. debt term) is the average term of debt issued by a business, weighted by the value of each debt issue. We sourced details on the current debt issued by businesses in our core dataset from SNL. From this, we calculated the average debt term for each business, weighted by Liquidation of Principal Value.

2.1.4 Measures of business size

37. We sourced three measures of business size from SNL, being:

- total operating revenue;
- total assets (balance sheet); and
- total revenue (including non-recurring).

2.1.5 Measures of earnings volatility

38. As proxies for measures of earnings volatility we sourced from SNL across each year in the period 1996 to 2012:

- recurring EBITDA;
- recurring EBITDA margin (as a percentage of operating revenue); and
- adjusted cash flows from operations (before the effect of changes in allowances for funds used for construction and changes in working capital).

39. As a measure of their volatility, we took the variance of each of these fields over 1996-2012 and scaled them by the absolute value of their average over this period.

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3 Description and interpretation of data

40. Of the sample of 244 privately owned gas and electricity transmission and distribution businesses with credit ratings we have identified 25 gas transmission pipeline firms. These 25 firms have, on average, slightly lower credit ratings than the remainder of firms. The median and mean credit rating for a gas transmission pipeline is BBB while the median and mean credit rating for all other operating companies was BBB+.

41. However, this slightly lower credit rating is a misleading as an indicator of the difference in 'like for like' risk because it does not account for other factors that are known to influence credit rating. For example, it does not account for factors one might expect to have an impact on credit rating such as:

- financial leverage;
- the maturity profile of existing debt obligations;
- the volatility of profitability for the business; and
- the size of the business.

42. Table 2 below describes the average level of these variables for gas transmission pipelines and other companies.

Table 2: Summary statistics – gas transmission pipelines and other gas and electricity network businesses

	Credit rating	Debt to total assets (%)	Debt to unlevered free cash flow	Recurring EBITDA margin volatility	Total assets ($m)	Average debt term (years)
All excluding gas transmission pipelines (219 businesses)						
Median	15.00	50%	10.54	1.12	5,565	18.24
Mean	14.82	51%	14.49	1.55	12,145	17.51
Gas transmission pipelines (25 businesses)						
Median	14.00	36%	5.19	0.63	2,749	15.46
Mean	14.16	36%	5.40	0.96	3,509	16.36

Source: SNL Financial, CEG analysis

43. It is clear from this table that there are material differences, on average, between gas pipelines and other businesses in the sample. Gas pipelines tend to have materially lower financial leverage on both of the two measures presented. They also have materially lower volatility in EBITDA margin.[1] They are significantly

[1] Calculated as the variance in EBITDA margin from 1996 to 2012 divided by the (absolute) value of the mean of the EBITDA margin over that time.

smaller on average than other gas and electricity network businesses. The average term of debt issuance for gas transmission pipelines is slightly shorter on average than the rest of the sample.

44. On the basis of a comparison of financial leverage we would expect to see gas transmission pipelines have a materially higher credit rating than other businesses in our sample. The fact that they have a slightly lower credit rating strongly suggests that there is something else about the gas pipelines in our sample that makes them higher risk. Similarly, when accounting for differences in variability of EBITDA margin we would expect gas pipelines to have a higher credit rating than the other firms in the sample – other things equal.

45. Lower credit ratings for gas pipelines, despite lower financial leverage and lower variability in profits, might conceivably be explained by the fact that gas pipelines are smaller than other businesses - to the extent that 'size' provides some sort of proxy for the diversity of customer base (which we might expect to reduce credit rating risk). However, for this to be the case 'size' would have to be a very powerful determinant of credit rating. This is intuitively unlikely – and this intuition is confirmed in our statistical analysis at section 4.3.4 below.

46. The results reported in Table 2 above provide strong support for a conclusion that there is some unobserved characteristic of gas transmission pipeline businesses that lowers their credit ratings relative to other gas and electricity network businesses. There are a number of potential explanations for this difference. For example:

- gas transmission pipelines may tend to face higher counterparty risk with their customers than do other energy network businesses (e.g., because gas pipelines tend to sell a greater percentage of their output to industrial customers including electricity generators); and/or
- the 'long skinny' nature of many gas pipelines may mean that technological risks (e.g., devastating interruption on the pipeline or at the gas field) are higher than for assets that involve more 'meshed' networks (such as electricity and gas distribution and electricity transmission).

47. However, these propositions cannot easily be tested because it is difficult to collect statistics to proxy the factor(s) in question. For instance, there is no accessible metric for customer counterparty risk that can be gathered consistently across all businesses in our sample. Similarly, we have no quantifiable metric for technological risks faced by different businesses.

48. Nonetheless, based on the summary statistics in Table 2 a strong conclusion can be reached that gas pipelines can be expected to have a credit rating that is several notches lower than an otherwise similarly geared utility (gas and electric distribution and electric transmission).

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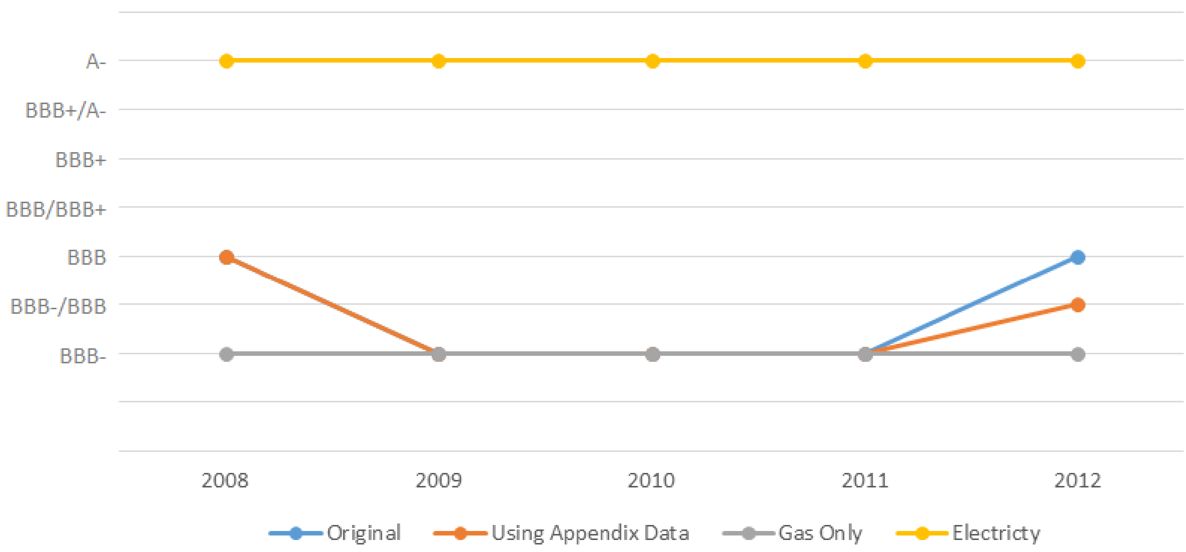
3.1 Consistency with ERA results

49. The ERA Explanatory Statement finds a difference between the credit ratings of gas network businesses generally and mixed or electricity-only network businesses. Based on the data reported by the ERA in Appendices 8 and 10 to its explanatory statement, the difference between average credit rating for gas only businesses and electricity only businesses was consistently two and a half or 3 notches between 2008 and 2012.

50. However, we note that that there appears to be a minor error in the ERA's presentation of the data in Figure 10 in the ERA's report. This figure shows results regarding the ERA's Sample 3, i.e. gas and electricity companies, excluding those that are government or parent owned. In the graph below the ERA reported results for gas companies are replicated in the blue line labelled "Original." This is coincident with (and therefore obscured by) the "Using Appendix Data" in Figure 1 below in all years except 2012. In 2012 the Using Appendix Data observation is below the "Original" – suggesting an inconsistency between Figure 10 and the ERA data reported in its Appendix 10. Based on the data in that appendix the 2012 median credit rating is half way between BBB- and BBB.

51. Moreover, we note that the original ERA 'gas pipeline' calculation includes diversified gas and electric utilities. If these are removed the 'gas only' observations are always BBB-. These facts are reflected the figure below.

Figure 1: Median credit ratings benchmarked by the ERA



Source: ERA, CEG analysis

4 Regression model and diagnostics

52. Based on the *a priori* reasoning set out in section 3 above we define the following specification for an econometric regression model to estimate credit rating:

$$Credit\ rating_i = \beta_0 + \beta_1(Gearing_i) + \beta_2(Debt\ term_i) + \beta_3(Gas\ Pipeline_i) + u_i$$

53. In implementing this specification, we have assumed that each credit rating can be assigned a cardinal numerical value. Specifically, we assume that a Standard & Poor's BBB credit rating has a value of 14 and each credit rating notch higher has a cardinal value one unit higher and vice versa for credit rating notches that are lower. A full description of how we have used credit ratings information is set out in section 2.1 above.

54. Although the equation above excludes potential explanatory variables such as business size and volatility of returns, alternative regression models are investigated in more detail at section 4.3 below.

4.1 Simple linear regression

55. Table 3 below shows the results of a simple ordinary least squares implementation of this specification.

Table 3: Ordinary least squares regression model results

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	15.07	0.66	22.96	0.0000
Gearing	-2.10	1.13	-1.86	0.0647
W.A.debt.term	0.04	0.01	3.11	0.0011
Gas.pipeline	-0.89	0.42	-2.14	0.0337

Source: SNL Financial, CEG analysis

56. The interpretation of this regression is consistent with prior economic intuition. It is also consistent with the expectations that support our interpretation of the results of Table 2 above.

57. The negative coefficient on the gearing variable suggests that, other things constant, as financial leverage rises credit rating falls. However, the strength of the gearing relationship is significantly weaker than might be expected. The estimated coefficient of -2.10 suggests that the difference between 0% gearing and 100% gearing (in the extreme), holding other factors constant, is limited to just over two credit ratings notches. This does not appear to represent a realistic estimate of the effect of gearing on credit rating. We discuss at section **Error! Reference source**

not found. below why this coefficient may be underestimated (in absolute terms) in the regression results.

58. The positive coefficient on the weighted average debt term suggests that, other things constant, reliance on longer term debt increases credit rating. Firms that issue long term debt will need to refinance on average a lower proportion of their overall debt funding in any given year. Other things being equal, this would be expected to reduce the exposure of the business to high interest rates in the short to medium term and reduce the likelihood of default over that period. Although the coefficient is strongly significant, it is also reasonable low, such that the difference between a firm issuing only short term debt and a firm issuing 20 year debt (holding other factors constant) is estimated to be less than a single credit rating notch.

59. The negative coefficient on the gas pipeline dummy variable suggests that, holding financial leverage and the term of debt issued constant, gas transmission pipelines tend to have lower credit ratings. The size of the coefficient, at -0.94, indicates that gas transmission pipelines with the same characteristics as other electricity and gas network businesses would be expected to have credit ratings almost a whole notch lower – although, as discussed in the next section, this is very likely an underestimate.

60. The estimated coefficients on debt term and the gas transmission pipeline dummy variable are statistically significant at the 5% level. This means that, provided the assumptions underlying this calculation hold true, a null hypothesis that these variables have no effect on credit rating can be rejected with a confidence level of 95%. The coefficient on gearing is significant at the 10% level.

61. Of course, the level of statistical significance is not the only factor that is relevant when assessing a regression coefficient. Under the assumptions of ordinary least squares, a regression coefficient provides the best linear unbiased estimate of the relationship and this remains true whether or not the estimate is statistically significantly different to zero at a given significance level. It does not follow that because a coefficient is not statistically significantly different to zero at any particular significance level that the correct alternative assumption is that the true value of the coefficient is zero.

4.2 Why the gas pipeline dummy is underestimated

4.2.1 Surprisingly small coefficient on dummy variable

62. Based on the analysis in section **Error! Reference source not found.** above we would expect to see a gas pipeline dummy of at least -2 – suggesting that gas transmission pipelines can be expected to have a credit rating at least two notches lower than non-gas transmission pipelines with the same financial leverage. This is because we observe that even though gas transmission pipelines have lower credit

ratings despite having much lower average financial leverage than other businesses in the sample.

63. One might have expected that adjusting for differences in financial leverage alone would have given rise to a 'like for like' gas transmission pipeline credit rating being at least 2 notches lower than other businesses. For example, increasing the leverage of a gas transmission pipeline business from 36% to 50% (to match that of the non-gas transmission pipeline businesses) could have been expected to depress the gas transmission pipeline's 'like for like' credit rating to be several notches below the other businesses.

64. However, econometric regression modelling provides a surprisingly small estimate of the difference in credit rating associated with being a gas transmission pipeline – only around one credit rating notch. This implies, for example, that if a business that were not a gas transmission pipeline had a credit rating of BBB then an otherwise similar gas transmission pipeline would be expected to have a credit rating of BBB-.

4.2.2 Regression estimates underestimate true coefficient on gearing

65. The reason we do not observe a larger (absolute) dummy variable is because there is only a relatively weak relationship in the data between financial leverage and credit rating – much weaker than we might expect based on *a priori* reasoning. For example, the regression results reported in Table 3 above suggest that if gearing increases from 20% to 70% then credit rating will drop by only around one credit rating notch (half of -2.10 = -1.05 which represents slightly more than a fall of one credit rating notch).

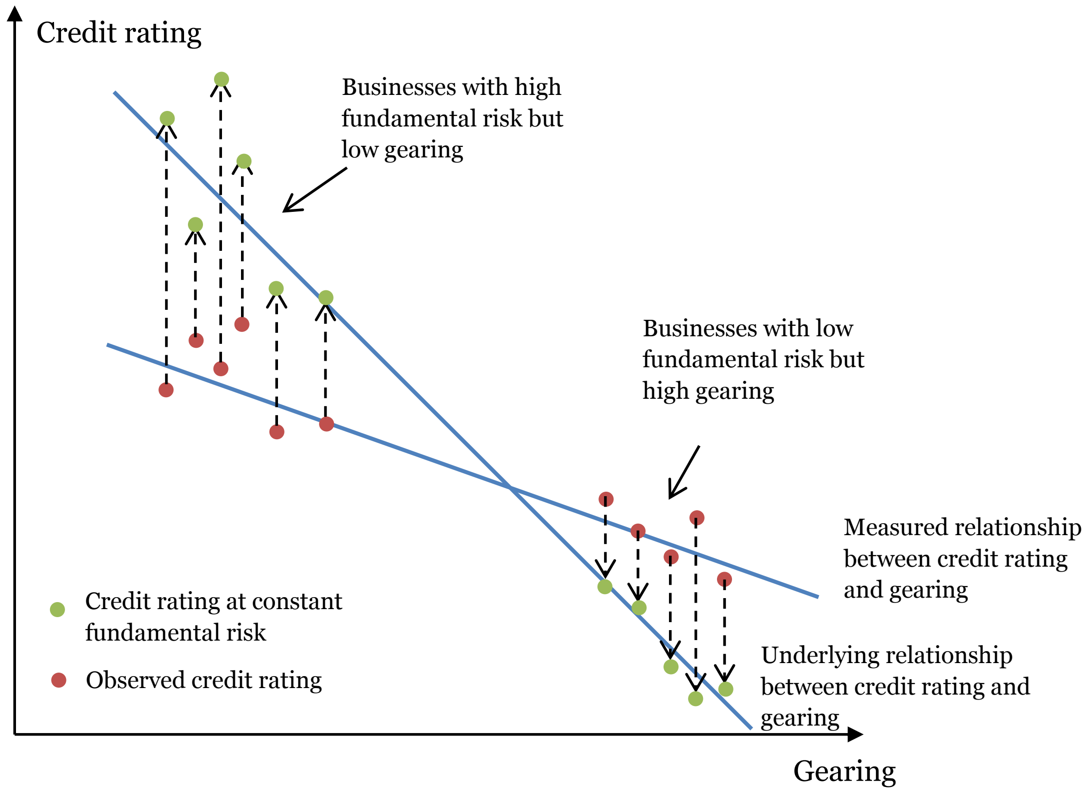
66. In our view this is not likely to be a realistic estimate of the impact on a firm's credit rating of more than tripling their gearing - from a level that most would regard as "conservative" to a level that most would regard as "aggressive". A better estimate would be that such an increase in gearing would give rise to a significant reduction in credit rating.

67. The reason that the regression coefficient gives a smaller estimate is, in our view, very likely explained by the fact that our regression does not include all of the factors that might determine credit rating risk. There is some unobservable base (natural/ungeared) level of credit risk for each firm.

68. Moreover, the level of gearing adopted by a firm is likely to be inversely related to the level of base level of credit risk. That is, firms that have low base level credit risk tend to adopt higher leverage and firms that have high base level credit risk tend to adopt lower leverage. Consequently, the impact of leverage of credit rating risk is masked in the sample. It appears 'as if' leverage has a relatively small impact on credit rating because we are unable to hold these unobservable factors constant.

69. This phenomenon is illustrated in Figure 2 below. This shows the regression estimate based on the observed credit rating observations (orange dots) making no adjustment to each observation for the level of (unobservable) base level credit risk. However, if firms with high levels of base level credit risk tend to have low gearing and *vice versa* then the true relationship between gearing and credit rating, holding base level risk constant, is steeper. This is illustrated in the graphic by shifting the low gearing (high base credit risk) observations up and relative to the higher gearing (low base credit risk) observations. The relationship between credit rating and gearing holding base credit risk is given by the steeper regression line through the adjusted (green) observations.

Figure 2: Illustration of role of unobservable confounding factor



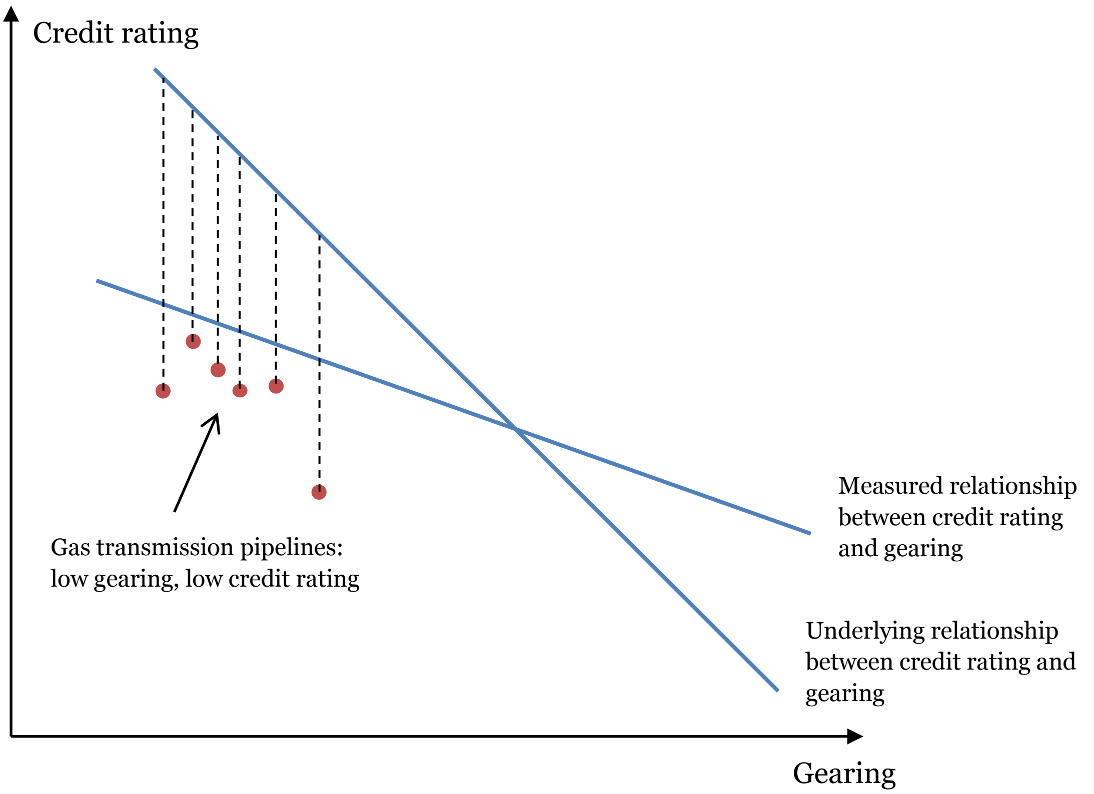
4.2.1 Underestimate the true coefficient on gearing leads to underestimation of the transmission pipeline dummy variable

70. If we were able to control for these unobservable factors then we would be likely to estimate a more negative (and more realistic) coefficient for financial leverage. This would then be associated with a higher (and more statistically significant) coefficient on the gas transmission pipeline dummy variable.

71. This is because the average absolute residual on (lowly geared) gas pipeline businesses would be higher the more negative the coefficient on gearing. Given that the dummy variable is set in the regression to minimise the absolute/squared residuals for gas pipelines this will result in a higher dummy coefficient. Since the coefficient will be higher but its standard error unchanged it will have a higher statistical significance.

72. The reason why this is so can also be illustrated in graphically. In the below figure there are two lines drawn describing the relationship between gearing and credit rating. The shallow sloped line is the regression line through all of the available data. The steeper line is the true relationship – the relationship that would be observed if one could hold constant the natural/base level of credit risk in the sample (i.e., adjust for the above described inverse relationship between natural (ungeared) credit risk and the ultimate choice of gearing by a company).

Figure 3: Illustration of impact on dummy variable



73. The gas pipeline observations are represented on the graph consistent with their actual position in the data set – with lower than predicted credit rating and lower than average gearing. It can easily be seen that the regression dummy variable (approximately the average distance between the pipeline dots and the regression line) will underestimate the true dummy variable (approximately the average distance between the pipeline dots and the higher line representing the 'underlying'

relationship between credit rating and gearing holding the base/natural level of credit risk constant).

4.3 Robustness testing

74. In this section we review the proposed linear regression model for its robustness to relaxing some of the key assumptions of ordinary least squares. We estimate:

- standard errors that are robust to the presence of heteroscedasticity;
- coefficient estimates using MM estimators and least absolute deviation that are robust to the presence of outliers in the data;
- an ordinal credit rating response regression model to test the assumption that credit ratings can be represented by a cardinal response variable as assumed above;
- alternative models with different variable inclusions/exclusions to tests whether the model proposed above performs well in comparison to other models; and
- non-parametric smoothed functions to assess whether the assumption of a linear relationship between credit ratings and the explanatory variables is reasonable.

75. Generally we find that the results of the linear regression model on these data are robust to the issues raised.

4.3.1 Robust standard errors

76. Ordinary least squares estimators are the best (most efficient) linear unbiased estimators under a number of assumptions. One of these assumptions is that the disturbance terms are homoscedastic – i.e., that they have constant variance across all observations.

77. If the disturbance terms are heteroscedastic this will not cause the estimated coefficients to be biased but it will give rise to biased estimates of the standard errors. Moreover the direction of this bias may not be known, making statistical inference invalid.

78. We have re-estimated the regression model at Table 3 using White's standard errors. This technique is robust to the presence of heteroscedastic disturbances. The results of this regression are shown in Table 4 below.

Table 4: Regression model using robust standard errors

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	15.07	0.69	21.91	0.0000
Gearing	-2.10	1.30	-1.61	0.1096
W.A.debt.term	0.04	0.01	3.62	0.0004
Gas.pipeline	-0.89	0.44	-2.05	0.0414

Source: SNL Financial, CEG analysis

79. The robust standard errors estimated in Table 4 above are similar to those in Table 3. The gearing coefficient is no longer significant at the 10% level due to an increase in its estimated standard error, but debt term and the gas transmission pipeline dummy remain significant at the 5% level. Overall, the results of Table 4 suggest that heteroscedasticity does not significantly impair ordinary least squares estimation in this dataset.

4.3.2 Robust regressions

80. Ordinary least squares regression can be sensitive to the presence of outliers, particularly in the explanatory variables. A researcher may want to estimate whether a relationship is sensitive to outliers and may even want to adopt a regression estimate that gives less weight to outliers. This could be because the outlier may be due to measurement error or the researcher may simply be interested in the 'normal' relationship between variables (i.e., without giving material weight to a small number of unusual observations), Various methods have been developed to implement alternative methods that are robust to (not materially affected by) the presence of outliers.

81. MM estimators are a class of robust estimator with high breakdown points[2] (50%) and high efficiency (95% of ordinary least squares). They utilise multiple iterations of maximum likelihood techniques that iteratively reweight the observations and are resistant to outliers under a range of unfavourable scenarios. MM estimators are described as "perhaps now the most commonly employed robust regression technique".[3]

82. Table 5 below shows the results of re-estimating our proposed regression model with robust MM estimators and robust standard errors.

2 The breakdown point is the smallest percentage of discrepant data that the estimator can tolerate without producing an arbitrary result.

3 Andersen, *Modern methods for robust regression*, 2008, p. 56

Table 5: Regression model using robust standard errors

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	14.85	0.63	23.40	0.0000
Gearing	-1.68	1.12	-1.50	0.1335
W.A.debt.term	0.04	0.01	3.58	0.0003
Gas.pipeline	-0.92	0.41	-2.24	0.0252

Source: SNL Financial, CEG analysis

83. The robust MM coefficient estimates in Table 5 remain similar to those estimated using ordinary least squares. The coefficient on gearing is even lower, at -1.68, and less significant again than in Table 4 above.

84. We also estimate least absolute deviation estimators. This technique minimises the sum of absolute deviations, rather than squared deviations as applied in ordinary least squares.

85. Although least absolute deviation is commonly cited as an example of a robust estimation technique, under many circumstances it does not perform well and MM estimation is to be preferred. As Andersen states:[4]

> *Although LAV1 is less affected than OLS by unusual y values, it fails to account for leverage… and thus has a breakdown point BDP = 0. Moreover, LAV estimates have relatively low efficiency… about 64% efficiency. The combination of low breakdown point and low efficiency makes LAV less attractive than other robust regression methods…*

86. It is also important to note that the standard error estimates for least absolute deviation coefficient estimates depends upon what methodology is selected. Table 6 below shows the results of least absolute deviation regression under the assumption of independent and identically distributed deviations.

Table 6: Regression model using least absolute deviation, iid

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	15.04	0.71	21.20	0.0000
Gearing	-2.34	1.22	-1.92	0.0566
W.A.debt.term	0.05	0.02	3.32	0.0011
Gas.pipeline	-1.05	0.45	-2.32	0.0214

Source: SNL Financial, CEG analysis

[4] Ibid, p. 48

87. The results of least absolute deviation are similar to the ordinary least squares regression estimates in Table 3 above. All coefficients are significant at the 5% level, except gearing which is significant at the 10% level.

88. However, we note that the significance of the gearing and gas transmission pipeline coefficients depends upon the assumptions made in the calculation of standard errors.

4.3.3 Ordinal regression on credit ratings

89. The linear regression model proposed above represents credit ratings with cardinal numbers. BBB is represented with 14, BBB+ with 15 etc. This representation assumes that the credit rating dependent variable is linear – that each successive increment in credit ratings category has the same quantitative value.

90. Since it is known that credit rating is an ordinal variable, whether this proposition is reasonable can be tested by a more general proportional-odds logistic regression model. This model is:

$$logit\big(Pr(y \le k|x)\big) = \zeta_k - \eta$$

where the logit transformation is given by:

$$logit(p(x)) = log\left(\frac{p(x)}{1 - p(x)}\right)$$

91. This ensures that the estimated probabilities lie between 0 and 1, y is the credit rating response variable with k levels, x are the explanatory variables, ζ is a k-length vector of credit rating response thresholds and η is the estimated linear predictor of the explanatory variables.

92. One way to think about the model is to imagine that there is an unobserved (or latent) response variable for each company. If this response variable for a particular company is less than ζ_1, then the company has the first credit rating; if the response variable is between ζ_1 and ζ_2 , then the company has the second credit rating; and so on.

93. Table 7 below shows the results of this ordinal regression model.

Table 7: Ordinal regression model results

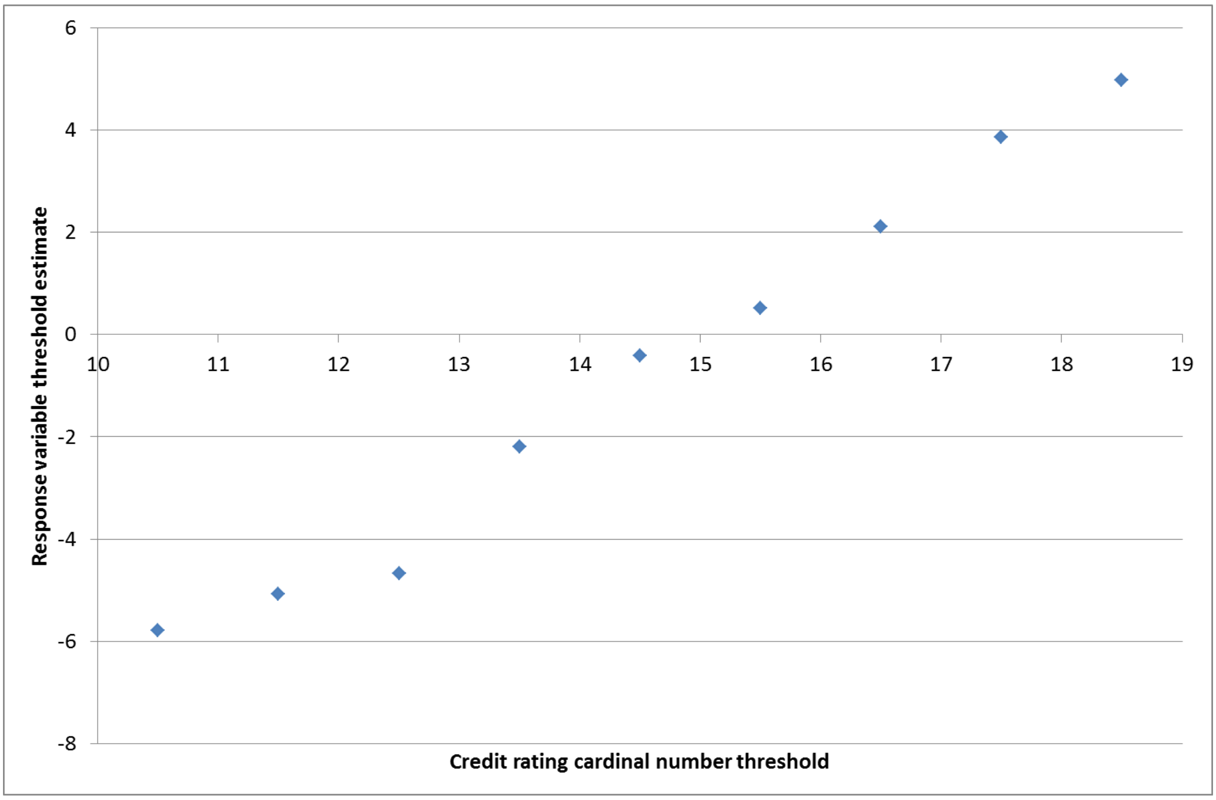
	Estimate	Std. Error	t value	Pr(>|t|)
Gearing	-2.76	1.64	-1.68	0.09
W.A.debt.term	0.06	0.02	3.14	0.00
Gas.pipeline	-1.44	0.62	-2.31	0.02
Credit rating 10|11	-5.78	1.38	-4.20	0.00
Credit rating 11|12	-5.08	1.18	-4.31	0.00
Credit rating 12|13	-4.67	1.11	-4.22	0.00
Credit rating 13|14	-2.19	0.95	-2.29	0.02
Credit rating 14|15	-0.42	0.93	-0.45	0.65
Credit rating 15|16	0.52	0.94	0.55	0.58
Credit rating 16|17	2.11	0.96	2.19	0.03
Credit rating 17|18	3.86	1.09	3.53	0.00
Credit rating 18|19	4.98	1.36	3.65	0.00

Source: SNL Financial, CEG analysis

94. The results in Table 7 indicate broadly similar results to ordinary least squares, but with each of the coefficients on explanatory variables being greater in magnitude, and the associated standard errors also being higher.

95. Figure 4 below shows these values plotted against the cardinal credit rating values. The results suggest that a straight line fit is appropriate and support the assumption that credit ratings could be accurately characterised as having a linear cardinal relationship to each other.

Figure 4: Thresholds for ordinal regression



Source: SNL Financial, CEG analysis

96. Interpreting the coefficients for a proportional-odds logistic regression model is more involved than for an ordinary least squares regression model. Appropriate interpretations based on the coefficient estimates shown in Table 7 are:

- gas transmission pipeline companies are, other things equal, 4.2 times more likely to have a lower credit rating than non-gas pipeline companies.[5] This result is statistically significant at the 5% level. This means that gas transmission pipeline companies have an 81% probability of having a lower credit rating than an otherwise similar[6] non-gas transmission pipeline company. This result does not point to the magnitude of how large the expected difference would be;
- a company with an average debt term that is 10 year longer than another company is, other things constant, 1.9 times more likely to have a higher credit rating.[7] This result is statistically significant at the 5% level; and

5 1/exp(-1.44) = 4.2

6 That is, a company that has the same gearing and weighted average term of debt but which is not a gas transmission pipeline.

7 exp(10*0.0622) = 1/9

- a company that had gearing that is 20% higher than another company is, other things constant, 1.7 times more likely to have a lower credit rating.[8] This result is statistically significant at the 10% level.

4.3.4 Alternative regression models

97. We have investigated alternative models using a variety of potential variables for inclusion and exclusion.

98. Using groups of variables defined in Table 8 below, we considered models with the variables from group A and group B, and combinations of variables from groups C, D and E with at most one variable from each of these groups included. All variables from groups D and E, and 'Debt over re-levered RCF' from group C were logged with base 2 in order to reduce the skewed nature of the distribution of these variables.

99. The combinations considered amount to a total of 48 possible alternative models.

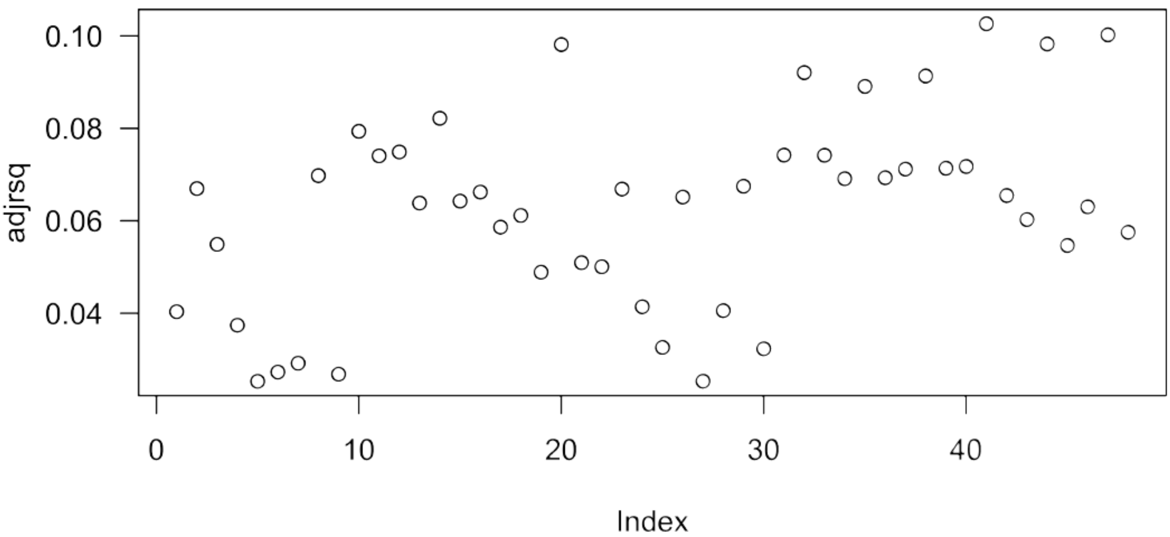
Table 8: Groups of variables considered

Group	Variables
A	Gas pipeline
B	Weighted average debt term
C	Debt over debt plus equity Debt over re-levered RCF
D	Operating revenue total Total assets Total revenue
E	Recurring EBITDA margin Recurring EBITDA margin variance Adjusted cashflows from operations variance

100. Of the models tested, eight performed moderately well with an adjusted R-squared of above 0.08. Figure 5 below shows graphically how these models R-squared compared to other specifications tested.

8 $1/\exp(0.2*-2.7647) = 1.7$

Figure 5: Adjusted R-square for 48 fitted models



101. The full details for the eight highest R-squared models are shown at Appendix A below. The regression results for the best performing model are reproduced at Table 9 below.

Table 9: Alternative regression model 1

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	14.68	0.68	21.67	0.0000
Gas.pipeline	-0.94	0.42	-2.25	0.0255
W.A.debt.term	0.05	0.01	3.26	0.0013
debt.over.debt.plus.equity	-1.35	1.17	-1.16	0.2489
log2ofRecurring.EBITDA.margin.variance	-0.16	0.07	-2.14	0.0339

Source: SNL Financial, CEG analysis

102. The results indicate that adding proxies for company size does not improve the regression results. Proxies for company size were statistically insignificant and the explanatory power (in terms of adjusted R squared) of the relationship did not improve with the addition of a size proxy.

103. However, adding a measure of the variability in profits did improve the regression results in terms of adjusted R squared. The best performing proxy for variability in profits was the variability in EBITDA margin and this was highly statistically significant in all regressions.

104. The gas transmission pipeline variable and the weighted average debt term variable coefficients were largely stable in magnitude and significance across the various alternative regression models. However, the coefficient on gearing materially

reduced in magnitude and significance when the variability in EBITDA margin was introduced. This suggests a degree of collinearity between these variables.

4.3.5 Generalised additive models

105. We have generally assumed a particular linear form for the relationship between explanatory factors and credit ratings. If the true underlying relationship were in fact not well represented by this linear relationship, estimating a regression would give rise to a specification error which could cause mis-estimation of the coefficients and render statistical inference invalid.

106. To check this assumption, we have implemented generalised additive models[9] as a method that does not impose a particular functional form on the data but lets the data "speak for itself". It implements non-parametric smoothing functions implemented in piecewise polynomial functions which allow for a very wide array of possible forms.

107. We have further imposed monotonicity constraints on these functional forms. This is consistent with *a priori* reasoning that of our continuous explanatory variables, we would expect the effect of gearing, debt term and variation in profits to have monotonic effects on credit ratings.

108. Figure 6 and Figure 7 below show the smoothed non-parametric functions based on the model proposed at Table 3 above. In general, we find that debt term and margin variance are well explained by a straight line fit but that gearing has some non-linear characteristics. These may contribute to our difficulty in finding strongly significant coefficients on gearing.

9 See for example Wood, *Generalized Additive Models: An Introduction with R*, 2006.

Figure 6: Non-parametric monotonic smoothed fit for gearing

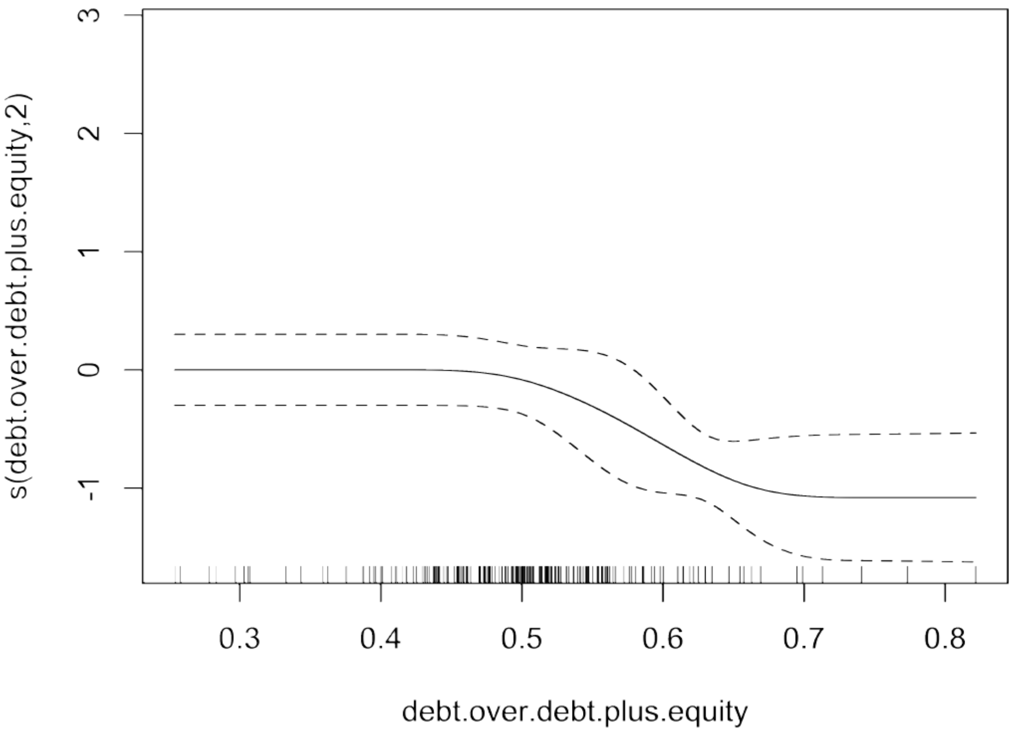
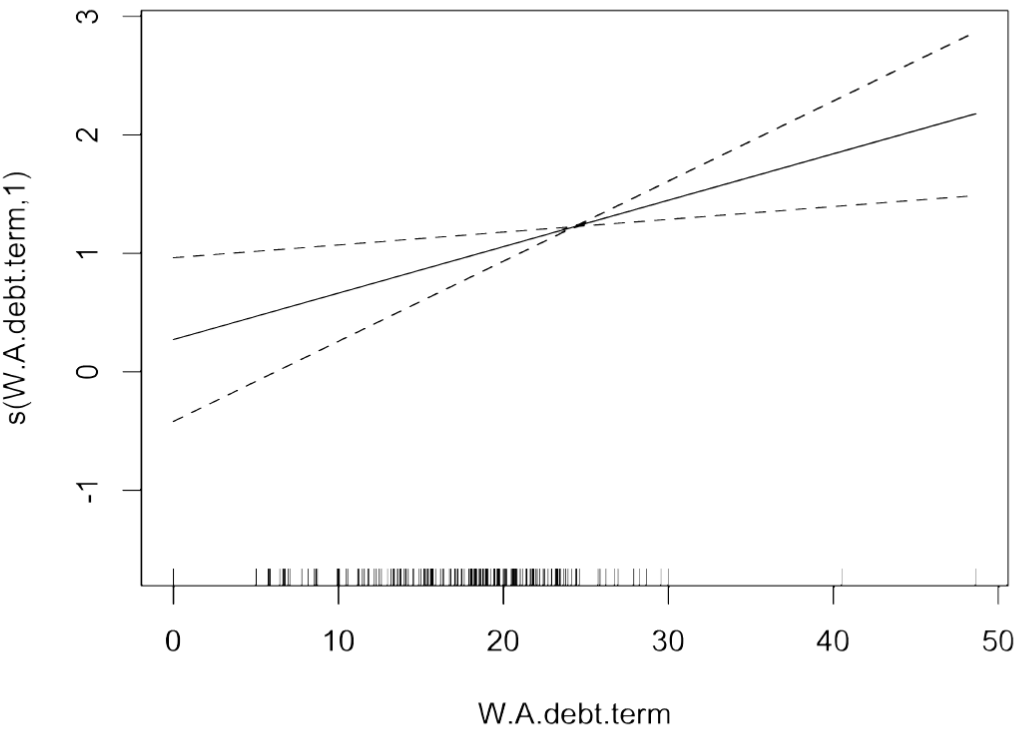


Figure 7: Non-parametric monotonic smoothed fit for debt term



Appendix A Alternative regression models

Table 10: Alternative regression model 1

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	14.68	0.68	21.67	0.0000
Gas.pipeline	-0.94	0.42	-2.25	0.0255
W.A.debt.term	0.05	0.01	3.26	0.0013
debt.over.debt.plus.equity	-1.35	1.17	-1.16	0.2489
log2ofRecurring.EBITDA.margin.variance	-0.16	0.07	-2.14	0.0339

Source: SNL Financial, CEG analysis

Table 11: Alternative regression model 2

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	13.85	0.58	23.93	0.0000
Gas.pipeline	-0.82	0.45	-1.82	0.0705
W.A.debt.term	0.05	0.02	3.17	0.0018
og2ofDebt.over.Unlevered.FCF	-0.02	0.13	-0.15	0.8786
log2ofRecurring.EBITDA.margin.variance	-0.25	0.09	-2.81	0.0056

Source: SNL Financial, CEG analysis

Table 12: Alternative regression model 3

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	12.29	1.40	8.67	0.0000
Gas.pipeline	-0.75	0.42	-1.77	0.0778
W.A.debt.term	0.05	0.01	3.45	0.0007
debt.over.debt.plus.equity	-1.81	1.20	-1.51	0.1328
log2ofOperating.Revenue..Total	0.12	0.06	1.96	0.0513
log2ofRecurring.EBITDA.margin.variance	-0.14	0.07	-1.95	0.0532

Source: SNL Financial, CEG analysis

Table 13: Alternative regression model 4

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	12.83	1.37	9.34	0.0000
Gas.pipeline	-0.89	0.42	-2.14	0.0341
W.A.debt.term	0.05	0.01	3.42	0.0008
debt.over.debt.plus.equity	-1.66	1.18	-1.41	0.1613
log2ofTotal.Assets	0.09	0.06	1.55	0.1241
log2ofRecurring.EBITDA.margin.variance	-0.15	0.07	-2.06	0.0406

Source: SNL Financial, CEG analysis

Table 14: Alternative regression model 5

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	12.71	1.34	9.46	0.0000
Gas.pipeline	-0.81	0.42	-1.91	0.0578
W.A.debt.term	0.05	0.01	3.41	0.0008
debt.over.debt.plus.equity	-1.10	1.18	-1.44	0.1515
log2ofTotal.Revenue	0.10	0.06	1.69	0.0934
log2ofRecurring.EBITDA.margin.variance	-0.15	0.07	-2.08	0.0393

Source: SNL Financial, CEG analysis

Table 15: Alternative regression model 6

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	11.57	1.53	7.23	0.0000
Gas.pipeline	-0.64	0.46	-1.39	0.1660
W.A.debt.term	0.05	0.02	3.26	0.0014
log2ofDebt.over.Unlevered.FCF	-0.07	0.13	-0.50	0.6191
log2ofOperating.Revenue..Total	0.12	0.08	1.49	0.1372
log2ofRecurring.EBITDA.margin.variance	-0.24	0.09	-2.58	0.0108

Source: SNL Financial, CEG analysis

Table 16: Alternative regression model 7

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	12.43	1.53	8.13	0.0000
Gas.pipeline	-0.78	0.45	-1.75	0.0828
W.A.debt.term	0.05	0.02	3.22	0.0016
log2ofDebt.over.Unlevered.FCF	-0.06	0.13	-0.42	0.6750
log2ofTotal.Assets	0.07	0.07	1.01	0.3147
log2ofRecurring.EBITDA.margin.variance	-0.24	0.09	-2.70	0.0078

Source: SNL Financial, CEG analysis

Table 17: Alternative regression model 8

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	12.24	1.51	8.08	0.0000
Gas.pipeline	-0.71	0.46	-1.56	0.1215
W.A.debt.term	0.05	0.02	3.21	0.0016
log2ofDebt.over.Unlevered.FCF	-0.06	0.13	-0.47	0.6384
log2ofTotal.Revenue	0.08	0.07	1.15	0.2503
log2ofRecurring.EBITDA.margin.variance	-0.24	0.09	-2.69	0.0081

Source: SNL Financial, CEG analysis