THE PREDICTIVE POWER OF S&P GLOBAL RATINGS IN 19-MONTH COMPANY DEFAULT LIKELIHOODS

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Abstract

Credit Ratings have long been a critical tool used by both financial market and business participants to assess a company's ability to repay its debts. This thesis analyses the ability of S&P Global credit ratings as assigned on 2024-04-01 in predicting the likelihood of a company default occurring over the 19-month between the former date and 2025-10-22 in 3 model types – linear, polynomial, and sigmoid. This thesis also assesses the contributions of selected company financial metrics, geographic location, and industrial sector, when added to these models. The best default predictive performance of credit ratings was observed in the sigmoid model. Among the assessed selected variables, two significantly increased the model's performance in addition to the credit ratings, namely the debt/EBITDA ratio and whether the company was registered as being in the 'Materials' sector.

Key words: Credit rating, S&P Global, default predictability, polynomial model, sigmoid model, rating inputs

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1. INTRODUCTION

Credit ratings (CRs) are an integral part of modern finance. Companies from all industries operate under stress from competition, rising costs, market movement and other factors. A crucial source of financial support for both daily operations and long-term strategic initiatives is debt financing. The cost of that financing is strongly influenced by credit ratings, a tool to quantify a company's ability to manage and repay debt into a single, easy to understand value. Reports issued by agencies such as S&P, Moody's, Fitch, and KBRA provide investors and lenders with independent assessments of the risks associated with their credit. So far, S&P has issued over 1 million credit ratings (S&P, 2025, d).

Rating decisions from established rating agencies (RAs) are not only descriptive but are also carry strongly influential in themselves. This influence is so great that not only do corporations and corporate investors pay attention to the results, but even some of the most economically powerful nations find themselves adjusting their behaviours to obtain a more favourable rating (Basu and Sun, 2022). An example of this is seen in the recent downgrade of the nation of France, which triggered large market and governmental response. The French Minister of the Economy subsequently stated that "it was now the collective responsibility of the government and parliament to adopt a budget that meets this [5.4 per cent] target before the end of 2025" (Klasa, 2025).

Additionally, debt investors (including both asset managers in fixed-income markets, and participants in private markets) increasingly rely on ratings when making investment decisions, primarily due to convenience and the absence of comparable alternatives (Baghai, Becker and Pitschner, 2021). Regulatory requirements under the CRR (Capital Requirements Regulation) II and CRR III have further increased the reliance of regulated entities, including banks, on externally assessed credit ratings (Rump et al., 2023).

Rating agencies (RAs) have long faced criticism for the damage that inaccurate rating results can have on financial markets due to their tremendous influence on investor behaviour. Inflated ratings of structured finance products, for example, played a significant role in the 2008 financial crisis (Benmelech and Dlugosz, 2010).

There has been extensive research on the predictability of defaults from credit ratings, and accuracy of rating agencies. Researchers have found that the 'issuer-pays' model of RAs (where the entity seeking a credit rating pays an RA for an assessment) embeds inherent conflicts of interest in both structured finance and corporate ratings provided by major RAs (Coffee, 2011) (Beatty et al., 2019).

Becker and Milbourn (2011) analysed the impact of competition amongst RAs on the quality of credit ratings. It was found that intensified competition, particularly following the expansion of Fitch, further weakened the rating quality of S&P and Moody's. Beatty et al. (2019) found that Moody's and Fitch recalibrated municipal bond ratings to obtain higher fees. Further studies have examined more issues in the rating practices of RAs: the rating bias towards geographically closer issuers (Jaggi and Tang, 2016), positive adjustments on RA's main models to improve ratings of collateralised debt obligations (Griffin and Tang, 2012), rating analysts inflating ratings on their future employers (Cornaggia, Cornaggia and Xia, 2016), and how regulatory reliance on RAs introduced by the SEC in 1975 inflated investment-grade ratings (Behr, Kisgen and Taillard, 2018).

Various attempts have been made to improve the state of credit ratings. In 2009 increased pressure from regulatory bodies and investors on the three main rating agencies led to improvements in the timeliness, accuracy, and volatility of issued ratings (Cheng and Neamtiu, 2009). Researchers have also suggested that governmental bodies should balance market tools, reduce regulatory reliance on credit ratings, and apply more scrutiny to the portfolios of institutional investors (Calabria and Ekins, 2012) (White, 2010). Additionally, there have been calls for greater transparency and refinement of rating methodologies of RAs (Bolger, 2011) (Cash, 2025).

As rating agencies continue to gain further significance in the global economy, regulators, researchers and market participants are increasingly aware of the importance of rating accuracy. This thesis supplements the existing evaluations of the accuracy and usefulness of credit ratings. This thesis assesses the ability of S&P Global credit ratings assigned on 2024-04-01 in predicting the likelihood of a company defaulting by 2025-10-22, and tests for over- or underweighting of financial metrics of the issuer. S&P ratings are chosen due to the more readily accessible credit ratings and financial metrics of issuers, and S&P being the single largest RA today.

This thesis first investigates the numeric distributions of issuer financial metrics, with the dataset split based on credit rating on 2024-04-01, and status of whether the company has defaulted by 2025-10-22. This was done as an initial assessment of which isolated financial metrics dominate the decision of assigning credit rating, and the likelihood of defaulting.

This thesis then fits several models to obtain predictions of the default probability from credit rating and additional metrics, called ‘control variables’. These control variables consist of financial metric data, but also ‘switch variables’, which are used to inform the fit on less numeric attributes, specifically geographic location and sector in which the company operates.

The tested models were a multilinear fit of CR and control variables, a polynomial of CR and linear addition of the control variables, and finally a sigmoid function of CR and linear addition of the control variables. These models are used to assess the ability of credit ratings to accurately predict default likelihood, and test which control variables are not sufficiently accounted for in S&P’s credit rating calculations. These models were a fit over credit rating range of D to BBB-, as ratings higher than this all showed a 0% likelihood of defaulting with a large dataset, and were therefore not of interest to the model.

This analysis is limited by a few attributes. The analysis only had access to 785 issuer observations in the range D to BBB- and is particularly limited in data size at the lowest credit rating values. Additionally, the method of gathering data meant that companies which have an evolving credit throughout the period, were only included in the data sample if they included a bankruptcy during the period of 2024-04-01 to 2025-10-22, this affects the interpretation of the default probability.

2. DATA AND VARIABLES

2.1 Gathered Data

This analysis sources data primarily from the S&P Capital IQ database (S&P Capital IQ, 2025c), which provides the financial metrics of issuers alongside long-term credit ratings. Where historical S&P ratings were missing in older versions of the S&P database, relevant observations were supplemented using Refinitiv data.

S&P Capital IQ was selected as it is the only available source that offers both the financial performance figures at the start of the observation period and the corresponding latest issuer credit ratings. Although the Fixed Income Securities Database (FISD) contains a larger pool of recorded defaults, it does not include the necessary historical financial statements. Other major rating datasets, such as those provided by Moody's or Fitch, were not accessible due to the absence of institutional subscriptions at the Stockholm School of Economics.

2.2 Definition of Default

For the purpose of this thesis, the term 'default' encompasses both confirmed bankruptcies—defined as CC, SD, or D ratings, or bankruptcy events recorded by S&P where the issuer's rating was subsequently withdrawn—and situations judged to be economically equivalent to default, namely an issuer being assigned a CCC or CCC− rating and a negative outlook.

This approach follows S&P Global's Long-Term Issuer Credit Ratings definitions (S&P Global, 2025b). The three ratings that explicitly denote default or its near-certainty are CC – default is regarded as virtually certain; SD – selective default; D – general default.

In addition, this thesis treats CCC and CCC− ratings with a Negative Outlook as indicative of near-default conditions. Although CCC is formally classified as merely "vulnerable", issuers in this category remain dependent on favourable business, financial, or economic conditions to avoid default. A Negative Outlook exacerbates this risk and, in practice, brings the issuer closer to CC-level distress.

For the regression analysis, the default status of a company on 2025-10-22 is defined as the term '*Y*'. A company which is defaulted is assigned a value of *Y*=1, otherwise the issuer is assigned a value of *Y*=0.

2.3 Credit Rating Range and Observation Period

The full dataset includes issuer ratings from AAA to D. No issuer rated BBB or above defaulted during the observation window. Accordingly, the analytical focus is restricted to the BBB− to D spectrum, where default risk is most relevant, to avoid this less interesting upper credit region from disrupting the models.

The observation period spans 19 months, from 2024-01-01 to 2025-10-22. The end time is chosen to maximize relevance to the current market conditions by using the most recent available data. The time period of 19 months is chosen to be comparable to the typical 'grace period' applied by rating agencies. These periods, usually one to two years, define the time allowed for an issuer to execute commitments such as deleveraging, post-acquisition integration, or operational efficiency improvements. For example, the public rating report for Euronext conditioned its rating stability on the successful integration of its acquisition target within two years (Raposo and Edwards, 2019), while the base-case scenario for Core & Main's issuer rating also applied a two-year horizon (C. Lopez and S. Austin, 2025). As most issuer ratings are reviewed annually, an interval slightly exceeding 18 months is consistent with established industry practice. The end date, 22 October 2025, reflects the most recent bankruptcy data available from S&P Global at the time of data extraction.

2.4 How Rating Agencies Balance Inputs

The methodologies employed by major rating agencies (RAs), including S&P, combine quantitative analysis with qualitative judgement. Ratings are therefore the outcome of a structured but discretionary process drawing on hundreds of data points. S&P's corporate criteria framework (Figure 1) outlines how more than eleven categories of information feed into a final issuer rating. A similar multi-factor construction is evident in Moody's scorecard-based methodology (Moody's, 2024), seen in Figure 2.

Commonly considered financial indicators include leverage ratios such as debt/EBITDA, interest-coverage metrics including EBIT/interest expense, cash-flow

measures, and assessments of business size, diversification, cyclicality, and exposure to sectoral or geographic risk (S&P Global, 2025a; Moody's, 2024).

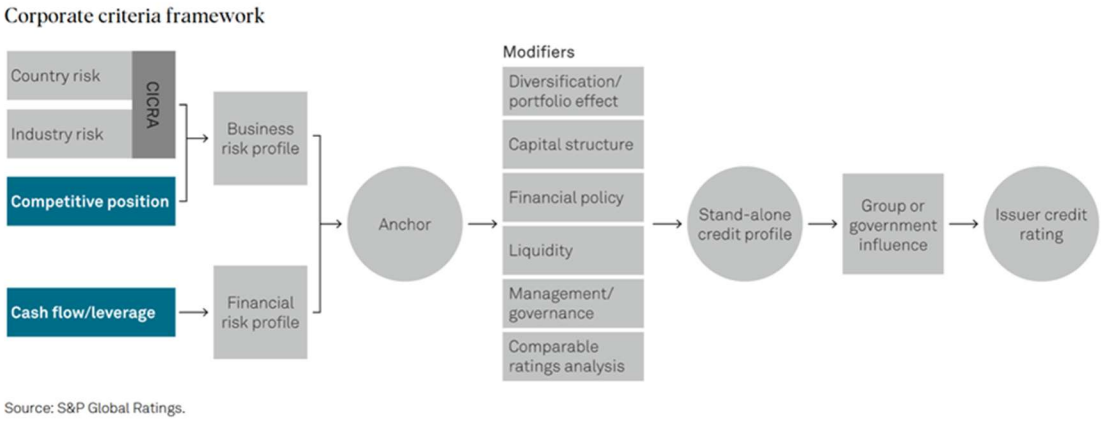


Figure 1: A high-level view of S&P Global rating considerations (S&P Global, 2024)

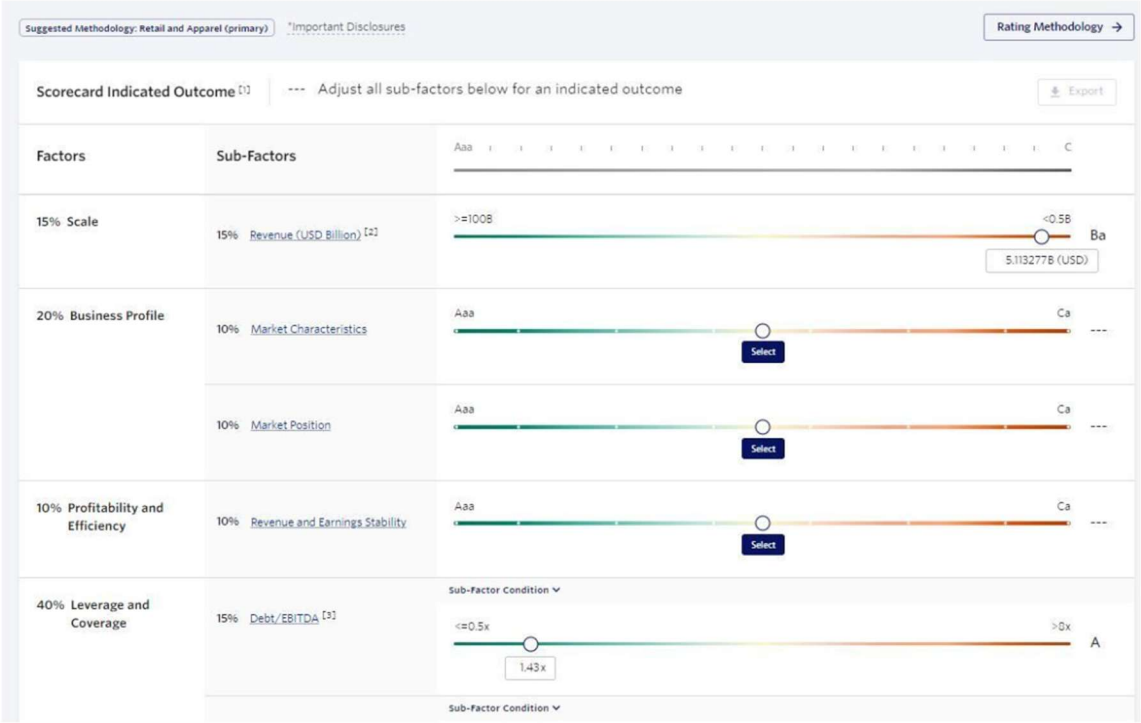


Figure 2: An example of Moody's scorecard used for calculating credit ratings. (Moody's, 2024)

These inputs interact and partially offset one another. A demonstration using energy-sector issuers after controlling rating score, country, date, and outlook in Figure

3 shows that larger issuers (by revenue and scale) are afforded greater tolerance for weaker profit margins or higher leverage.

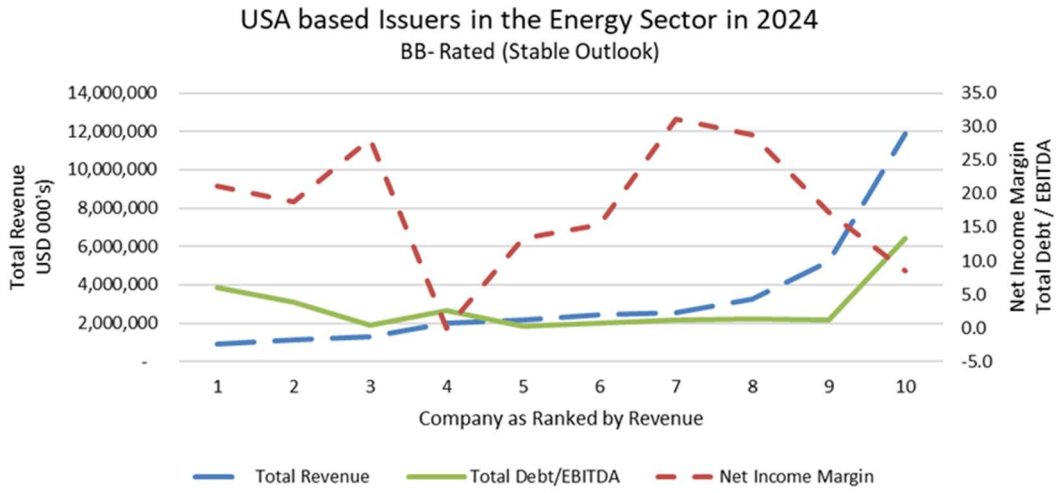


Figure 3: A visual demonstration of the interaction among the three main rating inputs

Such interactions enable rating agencies to form a comprehensive view of creditworthiness but also introduce scope for biases or unintended weighting distortions across inputs. Identifying whether such distortions exist requires careful selection of control variables.

2.5 Control Variable Selection

To reduce multicollinearity and preserve explanatory clarity, only the most representative financial metric from each category is included. Many quantitative inputs—such as EBITDA, operating leases, and pension liabilities—are internally adjusted by rating agencies (S&P Global, 2019; Kraft, 2015). For consistency, all metrics used in the regressions are therefore taken directly from S&P's adjusted dataset, and no publicly reported financials are manually added.

Profitability. Net profit margin is used instead of EBITDA margin, as net profit more directly reflects the issuer's capacity to generate economic returns after accounting for interest, taxes, and depreciation. EBITDA, though widely cited for comparability, obscures these effects and is therefore a weaker proxy for underlying profitability in this context.

Cash flow. Net profit margin also serves as a proxy for cash-flow generation. Traditional cash-flow indicators, such as free cash flow, are highly correlated with

profitability metrics and would exacerbate multicollinearity. Changes in net working capital offer a lower-correlation alternative but suffer from substantial data gaps: 64% of BBB− to D issuers lack this variable in the extracted data (2,298 missing values out of 3,603 raw observations).

Leverage. Total debt/EBITDA is preferred over net debt/EBITDA purely for reasons of data availability. Net debt/EBITDA would ordinarily be superior as it captures cash-adjusted leverage and is emphasized in S&P reports, but 94% of observations were missing in the raw extraction. By contrast, total debt/EBITDA was available for 43% of observations.

Capital intensity. Net property, plant and equipment (PP&E) is included as a proxy for capital expenditure and is widely available.

Several variables commonly used by rating agencies—FFO/debt, EBIT/interest expense, dividends, and rating outlook—were excluded because bulk extraction was not possible for a sufficiently large proportion of issuers.

Sector-specific metrics (e.g., customer retention, ARR, or FFO as a stand-alone measure) were also excluded to avoid excessive model complexity given the limited dataset.

After filtering for variable availability, re-introducing bankrupt issuers whose ratings had been withdrawn, and excluding outdated ratings (those reviewed before 2024-04-01), the final analyzable sample contains 1,252 issuers between BBB− and D. Of these, 785 issuers either maintained a constant rating or transitioned into bankruptcy or near-bankruptcy during the observation period. Issuers receiving a new non-default rating after 1 April 2024 were excluded because the relevant initial rating could not be automatically retrieved.

2.6 Display of Control Variables

The selected variables are presented across two summary tables – Tables 1 and 2. Table 1 defines each variable and reports its data source for both the polynomial and sigmoid regression models. Table 2 provides descriptive statistics for the ones listed in Table 1.

TABLE1
VARIABLE DEFINITIONS

Variable	Date	Source	Definition
Long Term Issuer Rating Raw	1st April 2024 & 22nd October 2025	S&P Capital IQ & Refinitiv	Long term rating assigned to issuers, ranging from BBB- to D. Screening method from S&P Capital IQ (old version): Entity Credit Rating_Issuer Credit Rating_Local Currency LT. According to S&P, the rating is a 'forward looking opinion' about the issuer's creditworthiness and ability to meet its financial commitments
Long Term Issuer Rating	1st April 2024 & 22nd October 2025	Computed	Ratings distributed evenly between 0 and 1 in ascending order
IQ_TOTAL_REV_FY2023	Year End 2023	S&P Capital IQ	Total revenue of the issuer in 1,000 USD
IQ_TOTAL_REV_FY2023 (Log)	Year End 2023	Computed	Log value of Revenue
IQ_NPPE_FY2023	Year End 2023	S&P Capital IQ	Net property, plants and equipments calculated by S&P in 1,000 USD
IQ_NPPE_FY2023 (Log)	Year End 2023	Computed	Log value of NPPE
IQ_NI_MARGIN_FY2023	Year End 2023	S&P Capital IQ	Net profit margin calculated by S&P in 1,000 USD
IQ_DEBT_TO_EBITDA_FY2023	Year End 2023	S&P Capital IQ	Total debt/EBITDA calculated by S&P in 1,000 USD
GEO_EU	Latest Record in 2025	S&P Capital IQ	Europe
GEO_AP	Latest Record in 2025	S&P Capital IQ	Asia-Pacific
GEO_NA	Latest Record in 2025	S&P Capital IQ	United States and Canada
GEO_ME	Latest Record in 2025	S&P Capital IQ	Middle East
GEO_AF	Latest Record in 2025	S&P Capital IQ	Africa
GEO_LA	Latest Record in 2025	S&P Capital IQ	Latin America
Sector	Latest Record in 2025	S&P Capital IQ	Sectors that issuers operate in, including 'Materials', 'Financials', 'Industrials', 'Consumer Staples', 'Utilities', 'Consumer Discretionary', 'Health Care', 'Real Estate', 'Information Technology', 'Energy', 'Communication
Default	Latest Record in 2025	Computed	Dummy variable if the issuer received D, SD, CC rating, or CCC, CCC- ratings with negative outlook, or was reported as bankruptcy during the observation period

NOTES: This table lists the definitions for the variables used in the analyses

TABLE2
VARIABLE DEFINITIONS

Variable	Mean	Standard Deviation	Median	Observations
Long Term Issuer Rating (As of 1st Apr 2024)	0.81	0.17	0.83	785
Long Term Issuer Rating (As of 22nd Oct 2025)	0.80	0.20	0.83	785
IQ_TOTAL_REV_FY2023 (in 1,000 USD)	7,153,308	13,731,263	2,996,363	785
IQ_NPPE_FY2023 (in 1,000 USD)	3,837,954	9,297,245	1,356,000	785
IQ_NI_MARGIN_FY2023	5.06	22.05	4.48	785
IQ_DEBT_TO_EBITDA_FY2023	4.74	5.72	3.61	785
Default (1 as default, 0 as non-default)	0.04	0.20	0.00	785

NOTES: This table lists the definitions for the variables used in the analyses

3 INITIAL OBSERVATION OF THE DEFAULT PATTERN

Table 3 provides a statistical overview of the dataset to provide an initial assessment of whether particular control variables are under- or overweighted in S&P rating calculations. For each credit rating, the values of a set of control parameters are compared between the full dataset and the subset of companies that defaulted. This comparison is done by using either the mean of the variables (log or normal form). This is done for the set of control variables, namely Profit_Margin_FY2023, Revenue_FY2023, and Debt/EBITDA_FY2023. The dataset is binned by credit rating, from BBB- to D.

The dataset in B- and CCC+ had the highest number of bankrupt issuers, meaning observations in these 2 categories carry more weight. In the B- category, issuers that declared bankruptcy had a better performance in the 3 financial metrics – profit margin, revenue, and leverage. Looking more closely at the underlying data, issuers from different sectors show different characteristics. For example, B- graded issuers in the materials sector who later default have a 3 times greater mean revenue and leverage than the means of the whole B- default sample. In the CCC+ category, defaulted companies had performed worse on revenue and leverage metrics than the total CCC+ population. Within the category, issuers in the real estate sector consistently have worse performance in the 3 mentioned metrics when compared to peers from other sectors.

Defaulted companies with ratings above B- are not focused on in this section due to a very limited number of bankrupt companies that can be used for comparisons, resulting in a large statistical uncertainty.

In this initial observation it was noted that issuers in different industries can have different means of financial metrics for the same rating, confirming that sector is an important factor in analysing the default probability.

There is not an obvious sign that defaulted issuers performed consistently worse on financial metrics, suggesting that at this level credit rating does a good job at capturing the influence of financial metrics. To further assess the credit rating accuracy, the next section analyses the sample data by performing fits of multivariate models to the data.

TABLE 3
RATING OBSERVATION

Rating			Mean of Net Profit Margin FY2023			Exp of Mean of Revenue FY2023 (Log)			Mean of Debt/EBITDA FY2023		
	1st Apr 2024	22nd Oct 2024		Total population	Bankrupt population		Total population	Bankrupt population		Total population	Bankrupt population
BBB-	205	205	BBB-:	7.99	N/A	BBB-:	4,770,815	N/A	BBB-:	4.41	N/A
BB+	140	139	BB+	8.93 >	-6.49	BB+	4,654,703 <	14,138,897	BB+	4.96 <	25.78
BB	131	131	BB	6.53	N/A	BB	3,061,671	N/A	BB	4.16	N/A
BB-	110	108	BB-	5.92 <	10.89	BB-	2,914,378 >	1,526,540	BB-	4.28 <	5.78
B+	84	83	B+	3.67 >	-28.37	B+	1,843,398 >	1,122,177	B+	4.07 >	3.65
B	52	50	B	-1.07 >	-30.55	B	1,538,833 >	536,228	B	5.78 <	14.08
B-	37	26	B-	-6.67 <	-6.05	B-	1,395,462 <	3,070,978	B-	8.01 >	7.66
CCC+	18	10	CCC+:	-9.45 <	-8.91	CCC+:	1,164,765 >	1,029,529	CCC+:	6.92 <	8.46
CCC	3	11	CCC	-29.43 <	-13.01	CCC	768,203 >	589,718	CCC	6.56 >	4.29
CCC-	0	2	CCC-:	N/A	N/A	CCC-:	N/A	N/A	CCC-:	N/A	N/A
CC	1	5	CC	8.66 =	8.66	CC	3,455,121 =	3,455,121	CC	3.06 =	3.06
SD	1	3	SD	4.77 =	4.77	SD	3,021,000 =	3,021,000	SD	3.19 =	3.19
D	3	12	D	-60.64	-60.64	D	1,249,792 =	1,249,792	D	6.08 =	6.08
Total	785	785									

NOTES: This table uses three selected variables listed in Table 1

Revenue normalisation: $10^{mean(log_{10}Revenue)}$

4 MODELS AND FIT RESULTS

4.1 Modelling and Fitting

The goal of modelling is to produce an accurate prediction of default probability (P) on or before 2025-10-22 (t+19), given a measurement of input parameters at 2024-04-01 (t). Additional financial metrics (**Controls**), also measured at t, are added as a sum of linear terms, coupled with a vector of associated parameters (**β**). For a generic credit rating function, $F(\mathrm{CR}_t)$, the predicted probability is expressed as the sum of a baseline credit-rating component and a multilinear adjustment derived from the control variables:

$$P_{t+19} = F(\mathrm{CR}_t) + \boldsymbol{\beta} \cdot \mathbf{Controls}_t \tag{1}$$

The model parameters are optimised in a model fit implemented using the *lmfit* python package. This is done by quantifying the 'default status' (Y) of every company as Y=0 when a company has not defaulted within the outlined period, and Y=1 if the company has defaulted within the outlined period. The difference between the modelled prediction and the data (Δ) is quantified as a sum of the squared differences between the predicted P_{t+19} value and the Y value for every data point:

$$\Delta = \sum_{i=1}^{N} (P_{t+19}^{i} - Y^{i})^2 \tag{2}$$

The value Δ is then minimised through variance of the parameters, called fit parameters. Fits are performed both with and without the presence of the control variables to assess the significance of the extra information provided to the overall model through inclusion of these control variables. Uncertainties reported on fit parameters are calculated using the *lmfit* standard error calculation functionality.

4.2 Polynomial Model

The first class of trialled models used a form of the credit rating function, $F_{\mathrm{poly}}(\mathrm{CR}_t)$ built out of polynomial sums of the credit ratings and polynomial fit parameters, p, where for a given polynomial set:

$$F_{\mathrm{poly}}(\mathrm{CR}_t) = \sum_{j=1} p_j \, \mathrm{CR}_t^j \tag{3}$$

A demonstration of this function would be the polynomial set, j ∈ [3, 1, 0], which would produce a form: $F_{\mathrm{poly}}(\mathrm{CR}_t) = p_3 \mathrm{CR}_t^3 + p_1 \mathrm{CR}_t + p_0$. The initially used

polynomial model is the most basic form of the model – where the set is j ∈ [1, 0] – called the 'linear' model:

$$F_{\text{lin}}(\text{CR}_t) = p_1 CR_{\text{t}} + p_0 \tag{4}$$

The result of the fitted linear model, both with and without the control variable term (**β·controls**) is seen in Figure 4.

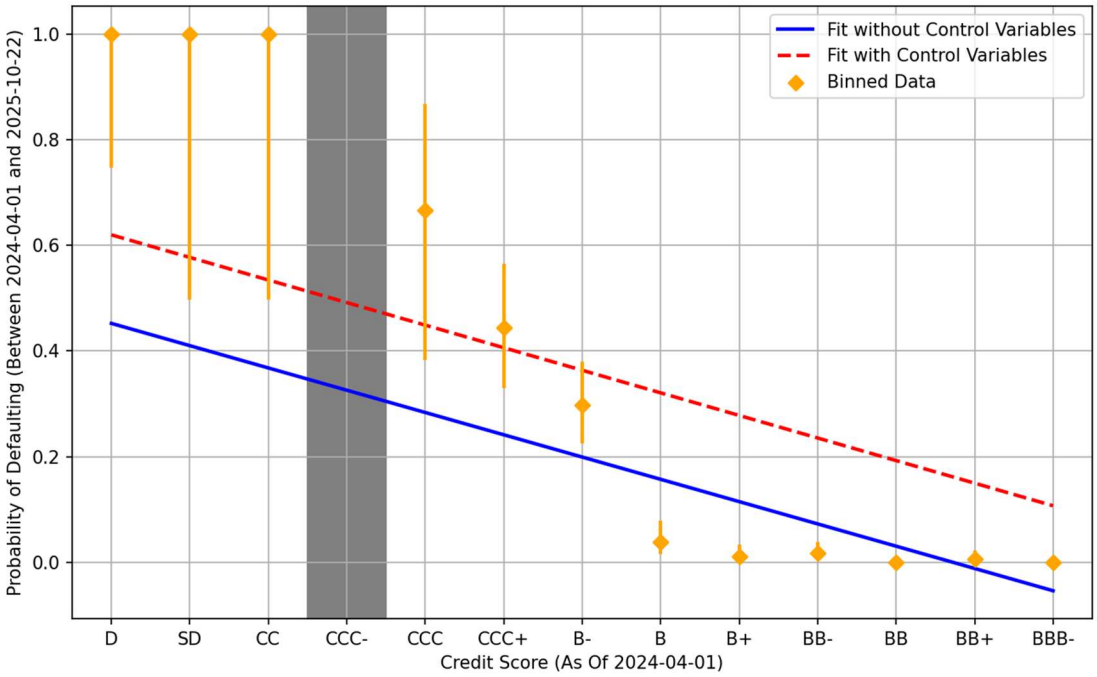


Figure 4: A linear polynomial ($j \in [1, 0]$) model of predicted P_{t+19} against CR. Fits performed with and without control variables are presented, with the control-including fit displayed post integration of the control variables. Geography and sector controls are not included in the 'with controls' fit.

Fit R^2 (without controls) = 19.83%
Fit R^2 (with controls) = 20.93%

Figure 4 shows the result of fitting the linear CR model for prediction of P_{t+19} and provides a demonstration of the general fit-and-data plotting format used in this section. The fit performed without the inclusion of any control parameters (CR dependence only) is shown in the solid blue line. The fit which includes both CR and control variables is seen as the dashed red line, post-integration of control variables for the 1D representation. The probability of a company defaulting over the analysed period, as observed in the dataset, is presented in bins according to credit rating. The vertical orange bars at each datapoint show the statistical uncertainty on the true default likelihood. This uncertainty is defined as the range in which the true default likelihood

has a 68% of being located for each bin. The uncertainties are calculated using the Wilson (Score) formula for calculating binomial uncertainties. This method of uncertainty calculation was chosen due to its good performance even under low dataset sizes, and when observed probabilities are near 0 or 1. Fits featuring the geographic location and sector controls are not displayed on the fit graphs unless specified. Presence of a grey band spanning the height of the page shows an absence of data.

The linear model correctly captures the dependence of the default probability on credit rating. Figure 4 shows (seen in an increase of the value of the R^2 fit parameter), an improved fit when the control variables are included, with many values of control variable parameters, β_i, that are measured to be non-zero with a strong significance score. This improved fit, however, is likely enabled by the poor quality of the initial model (seen both in the low R^2 value and through visual inspection of data-model differences on Figure 4). The measurements of these β_is therefore cannot be used to draw conclusions about the ability of credit rating alone to predict default likelihood.

The model is given more predictive power by adding higher polynomial orders. Demonstrative fits up to the polynomial power 3 are shown in Figures 5-8.

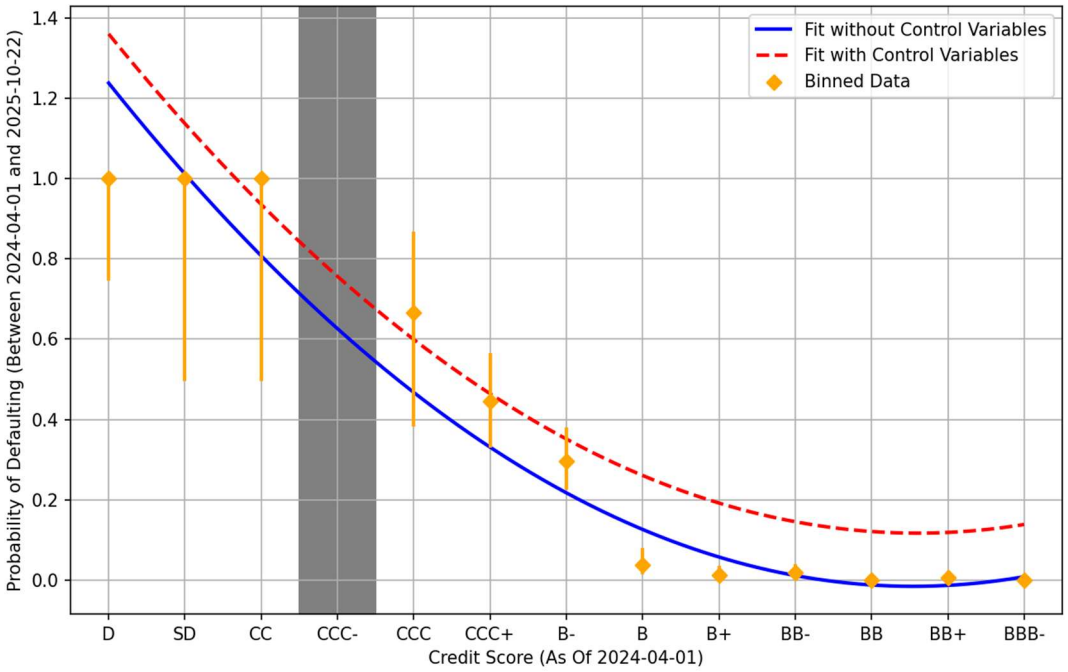


Figure 5: A polynomial $j \in [2, 1, 0]$ model of predicted P_{t+19} against CR_t. Fits performed with and without control variables are presented, with the control-including fit displayed post integration of the control variables. Geography and sector controls are not included in the 'with controls' fit. Fits detailed in table 4.

Fit R^2 (without controls) = 34.28%
Fit R^2 (with controls) = 34.80%

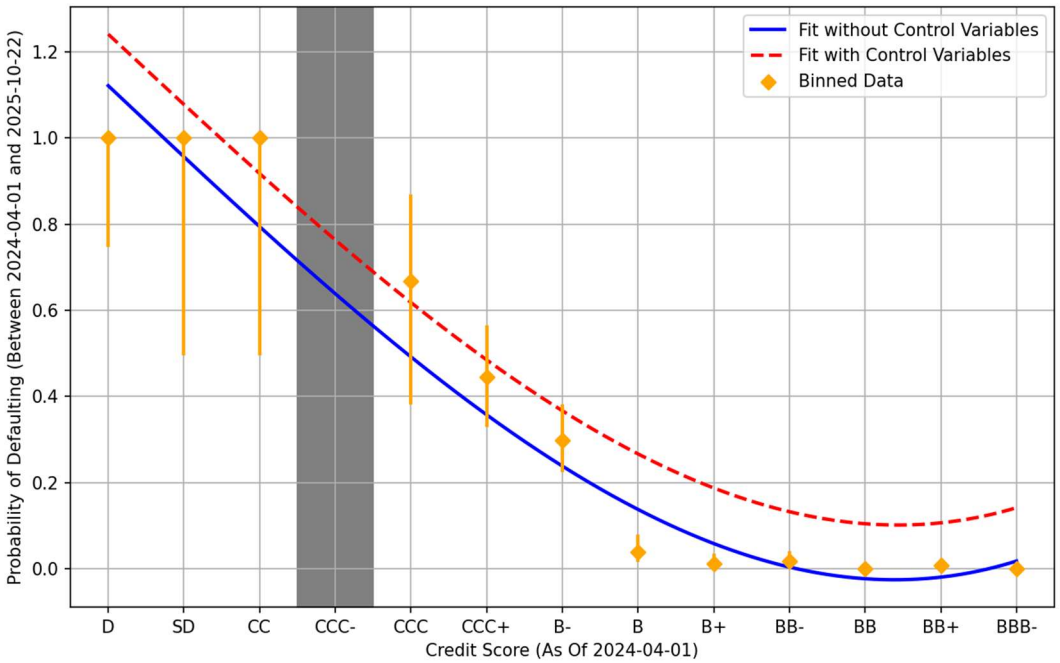


Figure 6: A polynomial $j \in [3, 1, 0]$ model of predicted P_{t+19} against CR_t. Fits performed with and without control variables are presented, with the control-including fit displayed post integration of the control variables. Geography and sector controls are not included in the 'with controls' fit.

Fit R^2 (without controls) = 35.00%
Fit R^2 (with controls) = 34.50%

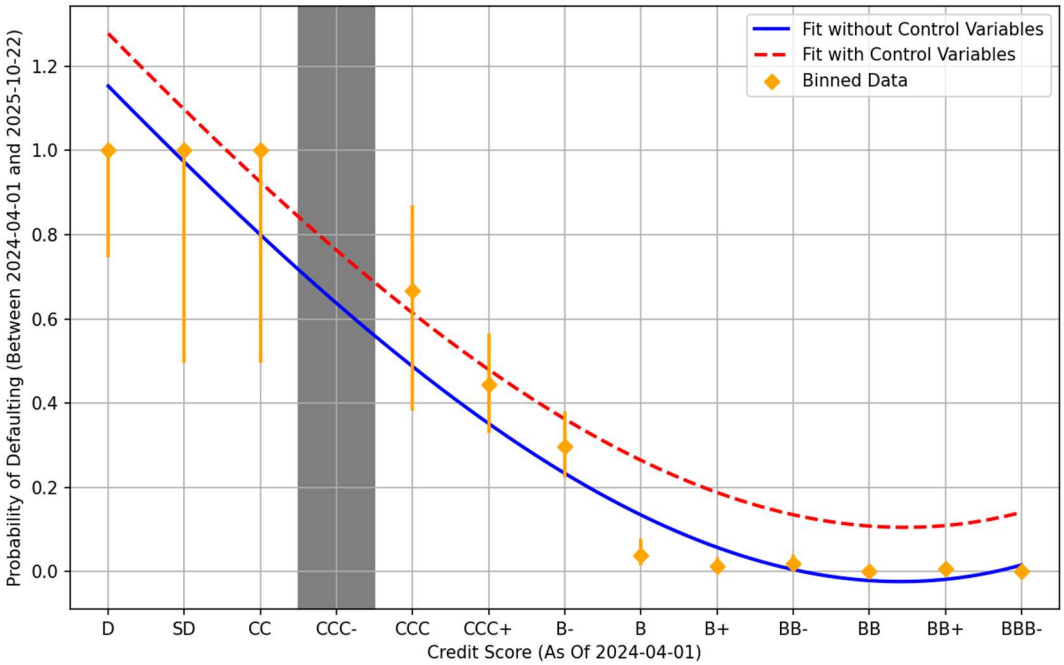


Figure 7: A polynomial $j \in [3, 2, 1, 0]$ model of predicted P_{t+19} against CR_t. Fits performed with and without control variables are presented, with the control-including fit displayed post integration of the control variables. Geography and sector controls are not included in the 'with controls' fit.

Fit R^2 (without controls) = 34.52%
Fit R^2 (with controls) = 35.02%

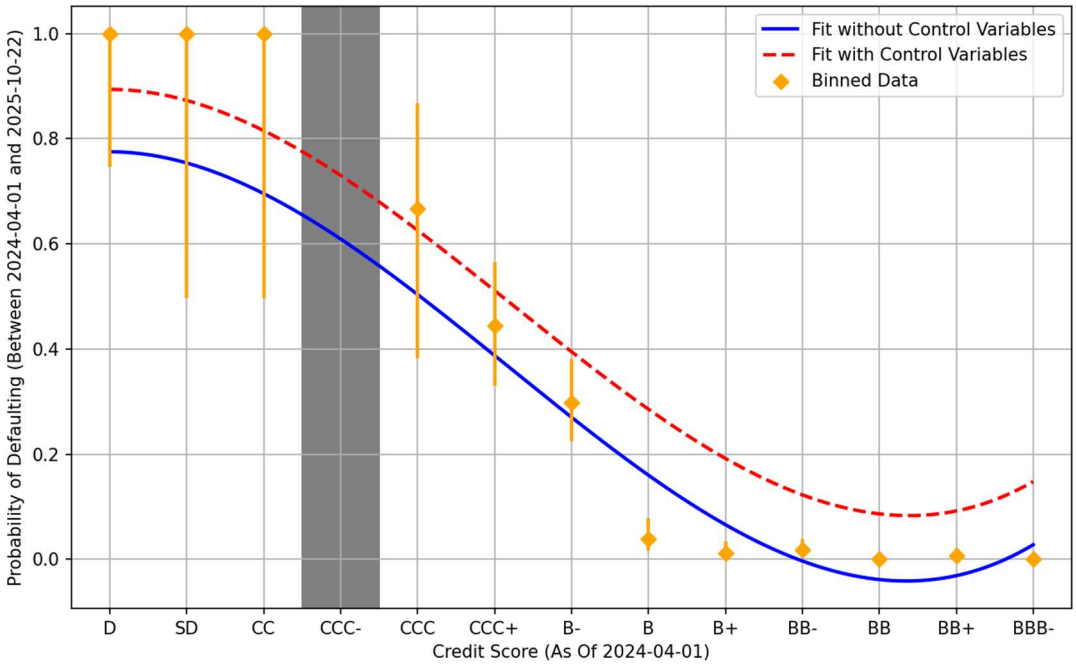


Figure 8: A polynomial $j \in [3, 2, 0]$ model of predicted P_{t+19} against CR_t. Fits performed with and without control variables are presented, with the control-including fit displayed post integration of the control variables. Geography and sector controls are not included in the 'with controls' fit.

Fit R^2 (without controls) = 32.24%
Fit R^2 (with controls) = 32.74%

Inclusion of the $j = 2$ order substantially improves the fit, improving both the visual agreement between the model and data, but also increasing the value of the fit R^2 by a substantial margin. R^2 is improved by 14.45% in the without controls fit, and by 13.87% in the fit with controls. Inclusion of polynomial orders up to $j = 3$ does improve the fit slightly, increasing R^2 value by 0.24% in the case of the without controls fit, and 0.22% in the cast of the with controls fit. These improvements are however minor when compared to the improvement observed when moving from a linear to quadratic model. The model $j \in [2, 1, 0]$ is therefore chosen as the focus model out of the polynomial models.

Detailed fit results for the $j \in [2, 1, 0]$ polynomial models, are shown in tables 5 and 6. Table 5 details the fit results of the models shown in Figure 5, where the 'with controls' model does not include a parameter describing whether the company is in the materials sector. Table 6 details the fit results of the models shown in Figure 9, where the 'with controls' model does include this materials sector parameter.

As seen in Tables 5 and 6, credit rating offers a strong predictor of default likelihood. The polynomial parameters having highly significant p-values shows this causal relationship is extremely strong. Visual inspection of the plots and measurement of R^2 values indicate a strong agreement between the data and fit model.

The only control variables found to have fit parameters with significant p-values are the materials sector switch variable, and the debt/EBITDA ratio. An increasing debt/EBITDA ratio increases the likelihood of defaulting, even when considered alongside the credit rating. This implies that calculations of the credit rating underweight the importance of the debt/EBITDA ratio.

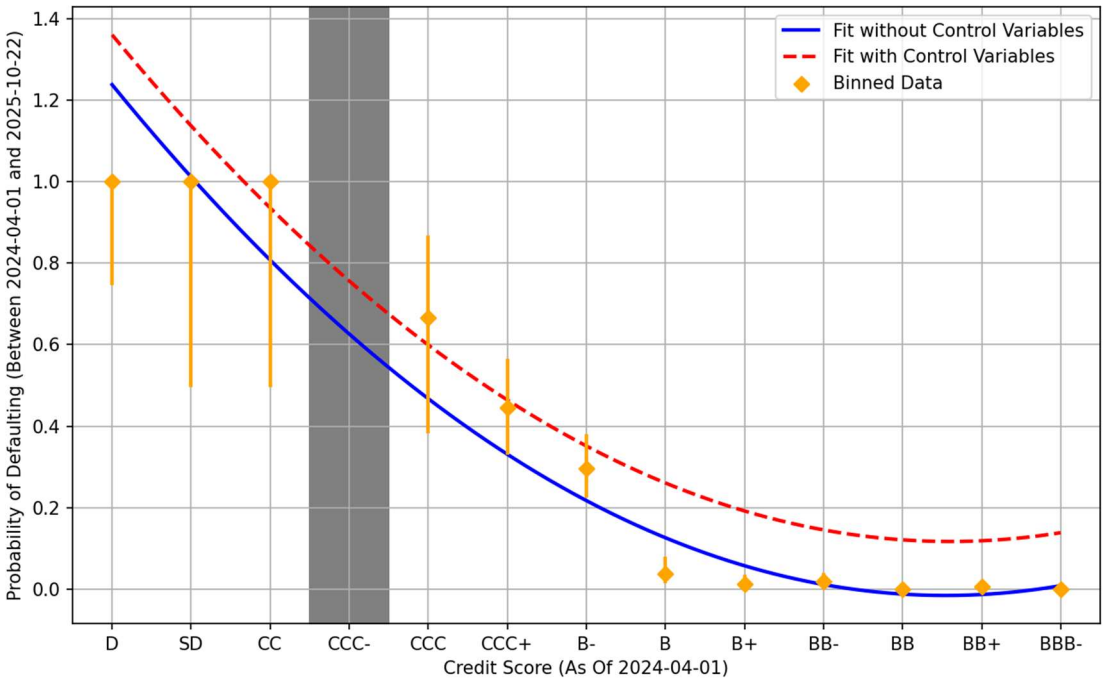


Figure 9: A polynomial $j \in [2, 1, 0]$ model of predicted P_{t+19} against CR_t. Fits performed with and without control variables are presented, with the control-including fit displayed post integration of the control variables. The control variable describing whether a company is classified as being in the 'Materials' sector is included. Fits detailed in table 5.

The parameter value, β, associated with the materials sector switch variable (0.0510 ± 0.0181) suggests that companies considered to be in the materials sector had a 5.1% higher probability of going bankrupt than a similar company outside of this sector. This is likely to be a strongly time-dependent parameter and could perhaps be due to the sector's vulnerabilities to the effects of tariffs, inflation, rising energy prices, and supply chain disruptions.

TABLE 4

Regression output without controls

Variables	Parameters	Fit Result		Fit Parameter Uncertainty	Uncertainty / Fit Value	Not-Zero Significance (p)
CR²	poly2	1.62	±	0.12	7.63%	0.000
CR	poly1	-2.85	±	0.18	6.38%	0.000
Intercept	poly0	1.24	±	0.07	5.32%	0.000

Fit R^2: 34.28%

Regression output with controls, without switch

Variables	Parameters	Fit Result		Fit parameter uncertainty	Uncertainty / Fit Value	Not-Zero Significance (p)
CR²	poly2	1.61	±	0.13	7.77%	0.0000
CR	poly1	-2.84	±	0.18	6.50%	0.0000
Intercept	poly0	1.20	±	0.10	8.69%	0.0000
(IQ_TOTAL_REV_FY2023) (Log)	beta0	0.05	±	0.04	82.59%	0.2260
(IQ_NPPE_FY2023) (Log)	beta1	-0.03	±	0.05	198.17%	0.6138
(IQ_NI_MARGIN_FY2023)	beta2	0.01	±	0.12	1319.89%	0.9396
(IQ_DEBT_TO_EBITDA_FY2023)	beta3	0.25	±	0.11	44.98%	0.0262

Fit R^2: 34.78%

Correlation Matrix:

	p2	p1	p0	β0	β1	β2	β3
p2	1.00	-0.98	0.53	-0.01	-0.08	0.11	0.00
p1	-0.98	1.00	-0.52	-0.04	0.05	-0.16	0.01
p0	0.53	-0.52	1.00	-0.03	-0.31	-0.70	-0.29
β0	-0.01	-0.04	-0.03	1.00	-0.46	0.07	0.10
β1	-0.08	0.05	-0.31	-0.46	1.00	0.07	-0.09
β2	0.11	-0.16	-0.70	0.07	0.07	1.00	0.22
β3	0.00	0.01	-0.29	0.10	-0.09	0.22	1.00

TABLE 5

Regression output without controls

Variables	Parameters	Fit Result		Fit Parameter Uncertainty	Uncertainty / Fit Value	Not-Zero Significance (p)
CR²	poly2	1.62	±	0.12	7.63%	0.0000
CR	poly1	-2.85	±	0.18	6.38%	0.0000
Intercept	poly0	1.24	±	0.07	5.32%	0.0000

Fit R^2: 34.28%

Regression output with controls, with Materials

Variables	Parameters	Fit Result		Fit parameter uncertainty	Uncertainty / Fit Value	Not-Zero Significance (p)
CR²	poly2	1.59	±	0.12	7.84%	0.0000
CR	poly1	-2.81	±	0.18	6.54%	0.0000
Intercept	poly0	1.18	±	0.10	8.77%	0.0000
(IQ_TOTAL_REV_FY2023) (Log)	beta0	0.06	±	0.04	72.83%	0.1698
(IQ_NPPE_FY2023) (Log)	beta1	-0.05	±	0.06	107.84%	0.3538
(IQ_NI_MARGIN_FY2023)	beta2	0.02	±	0.12	533.08%	0.8512
(IQ_DEBT_TO_EBITDA_FY2023)	beta3	0.28	±	0.11	40.26%	0.0130
(SECTOR Materials)	beta4	0.05	±	0.02	35.42%	0.0047

Fit R^2: 35.46%

Correlation Matrix:

	p2	p1	p0	β0	β1	β2	β3	β4
p2	1.00	-0.98	0.53	-0.01	-0.07	0.11	-0.01	-0.05
p1	-0.98	1.00	-0.52	-0.04	0.04	-0.16	0.01	0.05
p0	0.53	-0.52	1.00	-0.03	-0.29	-0.70	-0.30	-0.05
β0	-0.01	-0.04	-0.03	1.00	-0.46	0.07	0.10	0.06
β1	-0.07	0.04	-0.29	-0.46	1.00	0.06	-0.10	-0.15
β2	0.11	-0.16	-0.70	0.07	0.06	1.00	0.23	0.04
β3	-0.01	0.01	-0.30	0.10	-0.10	0.23	1.00	0.09
β4	-0.05	0.05	-0.05	0.06	-0.15	0.04	0.09	1.00

The model $j \in [2, 1, 0]$ including the control variable was also performed separately for each geographic and industrial sector control variable, to assess the significance of each of these variables. The results of these significance determining tests are seen in Table 6, from which it is concluded that the only one of these control variables of significance is whether the company is registered as being in the materials sector. Fits were performed separately due to the extremely high correlation caused by how these control variables are constructed.

TABLE 6
Values, Uncertainties, and P-values of parameters associated with switch variables when individually added to a $j \in [2, 1, 0]$ polynomial model.

Control Variable Type	Control Variable	Parameter Value	Parameter Uncertainty	P value
Geography	Europe	0.009	0.014	0.503
Geography	Asia-Pacific	-0.037	0.024	0.133
Geography	USA and Canada	-0.017	0.012	0.154
Geography	Middle East	-0.080	0.061	0.189
Geography	Africa	-0.020	0.049	0.688
Geography	Latin America and Carribean	0.063	0.059	0.285
Sector	Materials	0.051	0.018	0.005
Sector	Financials	-0.041	0.031	0.183
Sector	Industrials	0.018	0.015	0.240
Sector	Consumer Staples	-0.011	0.024	0.637
Sector	Utilities	-0.015	0.023	0.510
Sector	Consumer Discretionary	-0.002	0.016	0.883
Sector	Health Care	0.027	0.027	0.305
Sector	Real Estate	-0.004	0.026	0.880
Sector	Information Tehcnology	-0.016	0.025	0.535
Sector	Energy	-0.024	0.020	0.227
Sector	Communication Services	-0.038	0.022	0.079

Despite the evident strength of the $j \in [2, 1, 0]$ polynomial model, there are major issues with this model. Polynomial models frequently produce impossible default probability values (values above 1.0, or below 0.0). The used dataset has a far greater number of companies with credit ratings in the upper end of the assessed range (around BBB-), where the observed default probabilities is close to 0 and has minimal variance. The shape of polynomial functions makes them particularly vulnerable to having the model behaviour in the more relevant region (lower credit scores) dominated by the higher-rating region, due to its greater data density. The predictive power of the polynomial model can also not be improved without adding more parameters.

Due to these factors, the sigmoid model is introduced and used to model the default likelihoods.

4.3 Sigmoid Model

Issues with the polynomial model motivate adoption of a more useful functional form. A sigmoid model is chosen due to its visual similarity to the shape of the binned default probability, and its ability to 'contain' the data dense higher-credit region due to its plateau-transition-plateau shape.

The total model still follows the form outlined in equation (1), but the CR based function now takes the form $F_S(\mathrm{CR}_t)$, where a, b, c are new fit parameters that define the sigmoid shape:

$$F_S(\mathrm{CR}_t) = \frac{a}{1+ e^{-b(\mathrm{CR}_t - c)}} \tag{5}$$

The fitted sigmoid models are shown in Figures 10 and 11. Figure 10 shows the fitted sigmoid model both with and without control variables, but without the materials sector switch variable. These fits are detailed in table 7. Figure 11 shows the fitted sigmoid model with and without control variables, where the materials sector switch variable is included in the control variables. These fits are detailed in Table 8. The fitted sigmoid parameters show a p-value of effectively 0, the fits have an R^2 value greater than that achieved in the polynomial models, and model is visually compatible with the data. This all shows that the sigmoid provides a suitable base model.

The same two control variables – debt/EBITDA ratio and material sector status – are found to have significant p-values in this sigmoid model. This agreement between the polynomial and sigmoid models reinforces the idea that the credit rating fails to fully account for the significance of the debt/EBITDA ratio. This also reinforces the idea that credit rating either fails to consider risks inherent in the materials sector, or that the period used in this analysis was a particularly unpredictable year for companies operating in this sector.

There are no significant concerns around multicollinearity between the parameters associated with the control variables, with a maximum pairwise correlation magnitude of 0.69, and most correlations below 0.25.

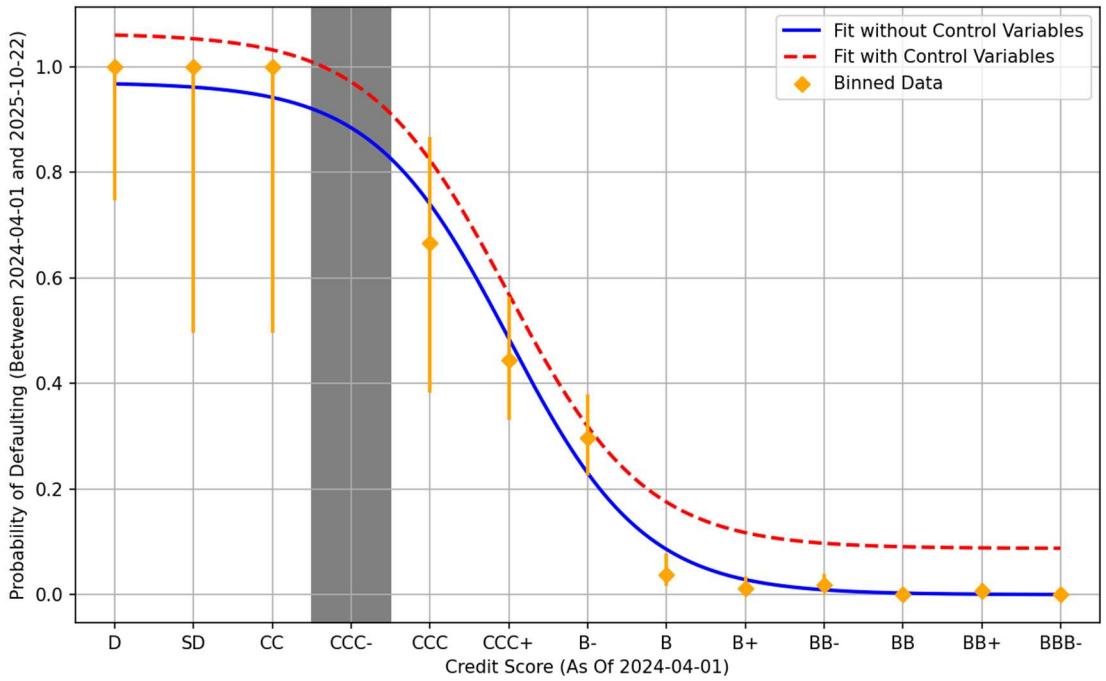


Figure 10: A sigmoid model of predicted P_{t+19} against CR_t. Fits performed with and without control variables are presented, with the control-including fit displayed post integration of the control variables. The control variable describing whether a company is classified as being in the 'Materials' sector is not included. Fits detailed in table 9

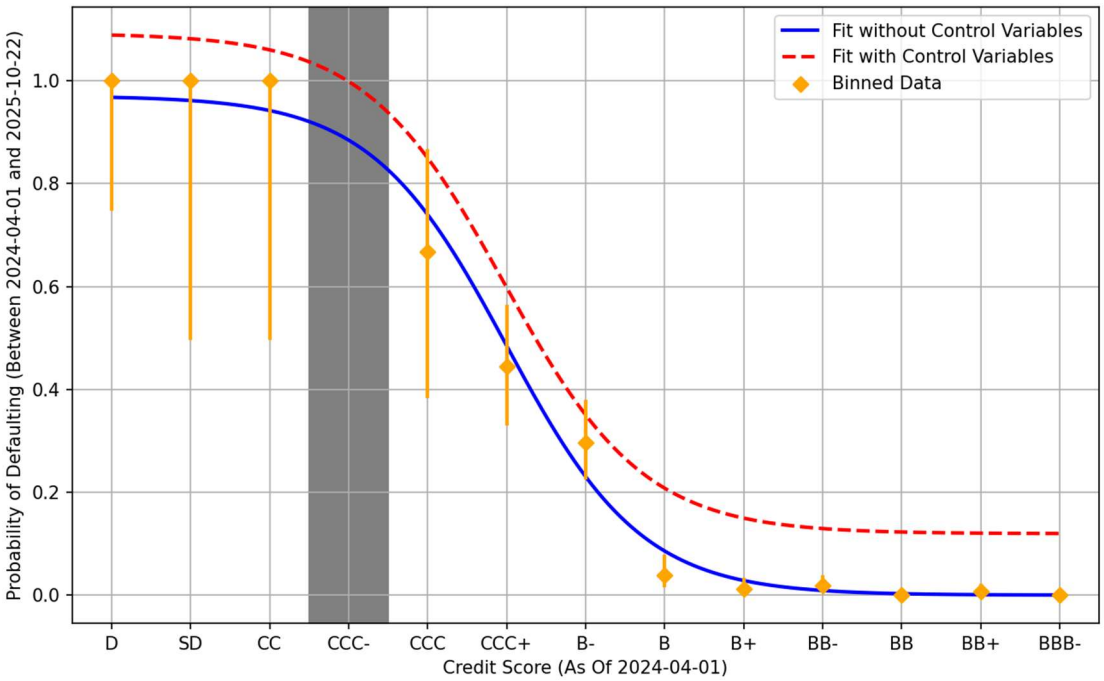


Figure 11: A sigmoid model of predicted P_{t+19} against CR_t. Fits performed with and without control variables are presented, with the control-including fit displayed post integration of the control variables. The control variable describing whether a company is classified as being in the 'Materials' sector is included. Fits detailed in table 10.

TABLE 7
Regression output without controls

Variables	Parameters	Fit Result		Fit Parameter Uncertainty	Uncertainty / Fit Value	Not-Zero Significance (p)
	a	0.97	±	0.07	7.30%	0.0000
	b	-13.98	±	1.49	10.62%	0.0000
	c	0.42	±	0.01	3.45%	0.0000

Fit R^2: 37.83%

Regression output with controls, without switch

Variables	Parameters	Fit Result		Fit parameter uncertainty	Uncertainty / Fit Value	Not-Zero Significance (p)
	a	0.98	±	0.07	7.46%	0.0000
	b	-13.72	±	1.63	11.86%	0.0000
	c	0.41	±	0.01	3.56%	0.0000
(IQ_TOTAL_REV_FY2023) (Log)	beta0	0.05	±	0.04	87.59%	0.2536
(IQ_NPPE_FY2023) (Log)	beta1	-0.02	±	0.05	257.66%	0.6979
(IQ_NI_MARGIN_FY2023)	beta2	-0.05	±	0.04	86.45%	0.2474
(IQ_DEBT_TO_EBITDA_FY2023)	beta3	0.20	±	0.10	52.89%	0.0587

Fit R^2: 38.24%

Correlation Matrix:

	a	b	c	β0	β1	β2	β3
a	1.00	0.44	-0.78	0.08	-0.07	-0.01	-0.02
b	0.44	1.00	-0.64	0.11	-0.01	-0.15	-0.04
c	-0.78	-0.64	1.00	0.00	0.06	-0.02	-0.07
β0	0.08	0.11	0.00	1.00	-0.54	-0.09	0.06
β1	-0.07	-0.01	0.06	-0.54	1.00	-0.69	-0.22
β2	-0.01	-0.15	-0.02	-0.09	-0.69	1.00	-0.19
β3	-0.02	-0.04	-0.07	0.06	-0.22	-0.19	1.00

TABLE 8
Regression output without controls

Variables	Parameters	Fit Result		Fit Parameter Uncertainty	Uncertainty / Fit Value	Not-Zero Significance (p)
	a	0.97	±	0.07	7.30%	0.0000
	b	-13.98	±	1.49	10.62%	0.0000
	c	0.42	±	0.01	3.45%	0.0000

Fit R^2: 37.83%

Regression output with controls, with Materials

Variables	Parameters	Fit Result		Fit parameter uncertainty	Uncertainty / Fit Value	Not-Zero Significance (p)
	a	0.97	±	0.07	7.48%	0.0000
	b	-13.62	±	1.61	11.86%	0.0000
	c	0.41	±	0.01	3.59%	0.0000
(IQ_TOTAL_REV_FY2023) (Log)	beta0	0.05	±	0.04	77.75%	0.1984
(IQ_NPPE_FY2023) (Log)	beta1	-0.04	±	0.05	115.09%	0.3849
(IQ_NI_MARGIN_FY2023)	beta2	-0.04	±	0.04	99.64%	0.3156
(IQ_DEBT_TO_EBITDA_FY2023)	beta3	0.23	±	0.10	46.57%	0.0318
(SECTOR Materials)	beta4	0.05	±	0.02	35.63%	0.0050

Fit R^2: 38.86%

Correlation Matrix:

	a	b	c	β0	β1	β2	β3	β4
a	1.00	0.44	-0.78	0.08	-0.07	-0.01	-0.02	-0.02
b	0.44	1.00	-0.65	0.12	-0.02	-0.15	-0.04	0.03
c	-0.78	-0.65	1.00	0.00	0.06	-0.02	-0.07	-0.01
β0	0.08	0.12	0.00	1.00	-0.54	-0.09	0.07	0.05
β1	-0.07	-0.02	0.06	-0.54	1.00	-0.69	-0.23	-0.17
β2	-0.01	-0.15	-0.02	-0.09	-0.69	1.00	-0.19	0.05
β3	-0.02	-0.04	-0.07	0.07	-0.23	-0.19	1.00	0.09
β4	-0.02	0.03	-0.01	0.05	-0.17	0.05	0.09	1.00

The significance of each of the switch variables is again assessed by performing a separate fit for each switch variable with the non-switch control variables, and the fitted CR function. The results of these significance-testing fits are seen in Table 9. Similar to the polynomial case, the only switch variable identified as being significant was the material sector switch variable. This fit value also produced a similar value to that of the polynomial model, predicting that a company classified as being in the materials sector had a 4.95% higher chance of going bankrupt, all else being equal, compared with a similar company outside this sector.

TABLE 9
Values, Uncertainties, and P-values of parameters associated with switch variables when individually added to the sigmoid model.

Control Variable Type	Control Variable	Beta Value	Parameter Uncertainty	P value
Geography	Europe	0.006	0.013	0.626
Geography	Asia-Pacific	-0.033	0.024	0.160
Geography	USA and Canada	-0.015	0.012	0.200
Geography	Middle East	-0.089	0.060	0.501
Geography	Africa	-0.018	0.048	0.705
Geography	Latin America and Carribean	0.064	0.059	0.281
Sector	Materials	0.049	0.018	0.005
Sector	Financials	-0.033	0.030	0.265
Sector	Industrials	0.018	0.015	0.217
Sector	Consumer Staples	-0.013	0.023	0.584
Sector	Utilities	-0.021	0.022	0.341
Sector	Consumer Discretionary	-0.005	0.015	0.740
Sector	Health Care	0.031	0.026	0.234
Sector	Real Estate	-0.011	0.025	0.650
Sector	Information Technology	-0.015	0.025	0.528
Sector	Energy	-0.017	0.020	0.374
Sector	Communication Services	-0.033	0.021	0.115

Despite the better performance of the sigmoid model, there is an issue concerning the sigmoid model when it is combined with the linear control terms. A sigmoid term is bound between the range of 0 and 1, but the addition of the control variables can push this outside of this probability range. To mitigate this issue, a probit specification is adopted, ensuring that predicted probabilities remain within the [0,1] range. This approach aligns with the methodology presented in Becker, Bos and Roszbach (2020).

5. CONCLUSIONS

This thesis concludes that the S&P Global ratings are strong predictors of company default likelihood, and that these ratings generally incorporate key company metrics. This is the case with both financial metrics (revenue, profitability, debt/EBITDA ratio, and capital expenditure) and less-quantifiable metrics (geographic location and industry sector).

Although in both polynomial and sigmoid models, the S&P global ratings overall are a very strong predictor of bankruptcy probability, the ratings are also found to have under-weighted the impact of debt/EBITDA ratio, and sector-specific risks of the materials industry. The risks associated with the materials sector is likely to be time dependent.

6. FURTHER WORK

The analysed data sample lacks rated companies that experience a change in credit rating over the analysed period, but do not default. The analysed data sample only includes companies that either held a constant credit rating over the period of 2024-04-01 to 2025-10-22 or defaulted during this period. This weakens the usefulness of the observed default likelihoods model.

This thesis specifically uses the dates 2024-04-01 and 2025-10-22 in its analysis of 19-month default likelihood. Included in this period was a global trade war, geopolitical conflicts, and a high cost of debt, and global supply chain disruptions. This is particularly expected to affect the usefulness of the geographic location and industrial sector variables.

The current probability models suffer from production of non-valid probabilities (outside the 0, 1 range). To address this, the polynomial model should be adjusted to a probit regression, containing the model outputs to a range of [0, 1].

To summarise, a more comprehensive analysis should incorporate companies with changing credit over the studied period into the data. It additionally should perform this analysis over a set of distinct periods, as to account for time dependent effects, and convert to a probability-valid model with a range of 0 to 1.

7. Use of Large Language Models disclaimer

AI tools such as Large Language Models (ChatGPT, Gemini, Claude) were used for improvements in grammar, code debugging, and information searching. All responses were confirmed with further research. All analysis was conducted independently.

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