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Credit Risk Modeling for European Utility Companies: A Hybrid Approach

by

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Abstract

Assessing credit risk for European utility companies is difficult due to the limited number of defaults and differences in data availability between firms. This thesis develops a hybrid framework to estimate one-year Probability of Default for a portfolio of European utilities, combining a market-based structural model for publicly traded companies with a financial ratio-based scoring model for private companies. The firms are segmented according to listing status and business focus (trading vs. non-trading), and the model is calibrated with industry benchmarks to increase interpretability. The proposed methodology uses the Merton structural model for firms with equity market data and a tailored financial scorecard inspired by Altman's Z-score and credit rating agency criteria for firms without market data. The financial score is mapped to PDs using a calibrated sigmoid function for conventional utility businesses and a conservative, interval-based assessment for energy trading firms. All modeling is implemented in Python, employing K-Nearest Neighbors imputation to address missing data and ensure a complete analysis. The result is an integrated PD estimation tool suited to the unique characteristics of the utility sector. This framework fills a gap in the literature by providing a unified, sector-specific approach to default risk modeling, with clear motivation and contribution: it offers a practical solution for credit risk evaluation across both public and private entities in an industry where traditional models fall short.

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1 Introduction

Credit risk, the likelihood that a borrower may default on their obligations, is a fundamental part of financial risk management. It is of particular significance for banks, investors, regulators, and policy makers in sectors that combine systemic importance with capital intensity. The European energy and utility sector is a prime example, as these companies provide essential services in energy production, distribution, and infrastructure management while operating with substantial leverage, making accurate credit evaluation important.

The industry is currently navigating significant challenges, with a shift towards renewable energy transition, heightened geopolitical risks, and increasing decarbonization requirements. European utilities must maintain aging infrastructure, but also finance large-scale investments in clean energy to comply with the changing regulatory demands. These factors collectively increase credit risk exposure, even among historically stable firms.

Despite these pressures, defaults remain remarkably rare in the European utility sector, thanks in part to regulated income streams and frequent government involvement.

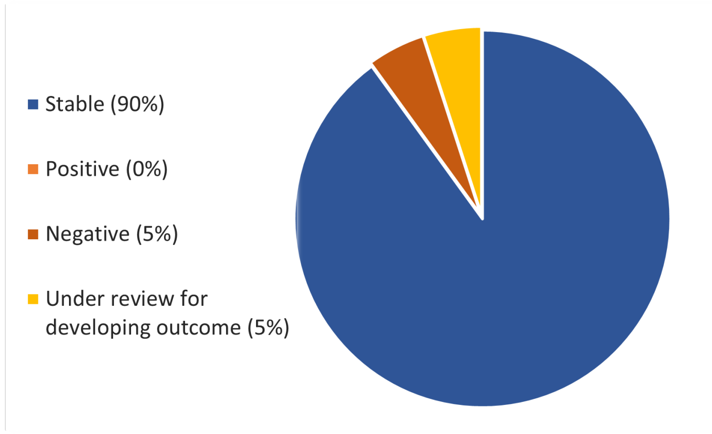

Figure 1: Distribution of rating outlooks as of Jan 2021. Source: Scope Ratings (39 European utilities rated by Scope) (GmbH 2021).

Even during the peak of the COVID-19 pandemic, when economic uncertainty was at its highest, the majority of European utilities were assigned a stable outlook. As shown in Figure 1, 90% of companies covered by Scope Ratings were assessed with a stable outlook in January 2021, indicating confidence in the sector's ability to withstand macroeconomic stress.

However, this rarity of default events limits the effectiveness of traditional Probability of Default models, which depend on extensive historical data. The challenge is compounded by the presence of many private and unlisted firms in the sector, which lack the market data necessary for equity-based Probability of Default models. From now on, the term Probability of Default will be abbreviated as PD.

These limitations show the need for tailored PD models that can be applied to public and private companies, offer clear interpretation, and utilize financial statement data rather than relying exclusively on market signals or external credit ratings. This thesis addresses this gap by developing a dual methodology, applying structural models to public companies while creating financial scorecards for private and subsidiary firms. This approach aims to provide a robust and consistent framework for assessing credit risk across the full spectrum of the European utility sector.

A fundamental challenge in credit risk assessment for European utility companies is the lack of a unified, transparent framework for estimating the PD. This is caused by two key issues: defaults are historically rare, largely due to government involvement, stable regulatory environments, and the monopolistic characteristics of many utilities. On top of that, many firms are either privately owned or operate as subsidiaries within larger corporate groups, and therefore lack publicly traded equity. According to Scope Ratings, these stable, regulated cash flows and the potential for state support can materially reduce default risk, complicating attempts to compare creditworthiness using traditional methods (Scope Ratings GmbH 2024).

The consequences of inaccurate credit risk models in this sector could have a substantial effect. If credit risk is calculated inaccurately, it can result in credit ratings that are either too high or too low, causing lenders to lose confidence, leading to limited access to financing (Cantor and Mann 2007). These effects are particularly problematic for utilities, which rely on steady access to capital to maintain and upgrade essential infrastructure. Credit rating downgrades caused by environmental risks have already led to higher financing costs for utilities and made it harder for them to secure funding for future projects (Pearce 2025).

Most established credit risk models either rely on market-based inputs or extensive default history. For European utilities, both data sources are often either unavailable or insufficient. This becomes especially problematic in mixed portfolios that contain public companies, subsidiaries, and private companies, where no single modeling approach works reliably for all.

To address these limitations, this thesis puts forward a hybrid framework that combines market-based structural models for firms with available market information and tailored financial ratios for those without. By combining these methods, the aim is to provide PD estimates that are consistent, meaningful, and sector-appropriate, even when defaults are rare or market signals are missing.

This thesis analyzes a portfolio of 37 European utility companies spanning the electricity, gas, and water sectors. The portfolio of companies and their financial data was provided by the partnering company Energy Quant Solutions, and is based on fiscal year 2024. The sample includes public corporations, privately held firms, and subsidiaries of larger corporate groups, reflecting a range of ownership structures and regulatory environments. The analysis uses only financial data sourced from publicly available or company-reported filings, and it deliberately excludes broader macroeconomic indicators, forward-looking projections, and country-specific regulatory factors such as tariffs and climate policies, as including these would require more extensive data and modeling capacity than is available in this study.

The modeling framework operates under defined practical constraints. For the public companies that have sufficient market data, a structural modeling approach is used to estimate default risk. For private companies and subsidiaries without such data, a financial score based on accounting ratios is calculated. Missing values are handled through an imputation method to ensure full coverage of the companies in the dataset. While these simplification choices support consistency, they may introduce estimation uncertainty, which is discussed in later sections.

This thesis does not aim to replicate internal rating-based (IRB) systems or comply with Basel regulatory standards (Basel Committee on Banking Supervision 2025). Rather, the goal is to construct a transparent, academically robust framework for estimating default probabilities in a sector where traditional modeling assumptions are frequently undermined by scarce data and rarity of defaults.

1.1 Credit Risk Fundamentals

Credit risk is defined as the potential that a bank borrower or its equivalent will fail to meet its obligations under agreed terms. Managing credit risk is one of the core responsibilities of financial institutions and is essential to their long-term success (Basel Committee on Banking Supervision 2000). The goal of credit risk management is to maintain risk within acceptable limits while achieving a solid return on capital. This involves monitoring both individual exposures and the portfolio as a whole, and understanding how credit risk interacts with other types of risk in the institution.

A PD is the likelihood that a borrower will default within a given time period, usually one year. Under the Internal Ratings-Based (IRB) approach in Basel II, banks are required to estimate PDs for their credit exposures. These PDs are used to calculate regulatory capital requirements and influence the degree to which risk weight is applied to each asset (Basel Committee on Banking Supervision 2006).

The Basel Committee emphasizes that the PD estimates must be conservative and reflect a long-term average, including periods of financial stress. To avoid underestimation, Basel imposes minimum PD values, often referred to as PD floors. For example, for certain corporate exposures, a minimum PD of 0.03% is required (Basel Committee on Banking Supervision 2006).

There are several ways to estimate PD, each with different strengths and data requirements.

One method is the use of structural models. These models assume that a company defaults when its asset value falls below the value of its liabilities, with the Merton model being a well-known example (see Section 4.2). Structural models are most appropriate for listed firms with available market data.

Another widely used approach is credit scoring, which refers to statistical models that estimate default risk based on historical financial data and borrower characteristics. Altman's Z-Score (see Section 4.6) and logistic regression models are classic examples. These methods are especially common for corporate borrowers when market-based data is unavailable.

In recent years, machine learning models have been introduced to improve the accuracy of PD predictions. However, these models often operate as 'black boxes', which means that it is difficult to explain how they make decisions. Because of this, the European Banking Authority (EBA) has warned that machine learning models used for regulatory purposes must be transparent and understandable. The EBA guidelines emphasize that complexity should not limit the interpretability of a model by banks or supervisors (European Banking Authority 2021).

1.2 Credit Risk in the Utility Sector

European utilities are generally capital-intensive companies that operate long-lasting infrastructure assets, including electricity grids, gas pipelines, and power plants. These companies often function as natural monopolies or under strict regulatory oversight, benefiting from stable and predictable cash flows. Their infrastructure, such as electricity grids and gas pipelines, typically requires a high upfront investment, making them economically difficult to duplicate. This naturally limits competition, resulting in monopoly-like market structures.

European utilities typically carry substantial long-term debt to finance infrastructure projects. Scope Ratings highlights that compared to power generators, grid and network operators tend to exhibit lower earnings volatility, more stable cash flows due to regulated tariffs, and more spread out capex (Scope Ratings GmbH 2024). Capex (capital expenditure) refers to money spent on long-term assets such as infrastructure or equipment.

The ongoing energy transition also adds another layer of complexity to credit risk profiles. According to the European Central Bank, firms that set emission reduction targets tend to achieve greater emission reduction than those that do not. Furthermore, firms with more ambitious and forward-looking goals are often linked to better credit ratings, suggesting that markets view proactive climate strategies more favorably (ECB/ESRB Project Team on Climate Risk Monitoring 2021).

Government ownership and support also play a role in utility credit profiles. In several European markets, utilities are partially or fully state-owned, and Scope Ratings highlight that those that are government-backed can receive capital injections or guarantees during financial distress, and this support often translates into increased credit rating (Scope Ratings GmbH 2024).

In summary, the credit risk of European utilities is influenced by their capital intensity, stable revenues under regulation, and differences between business models. Climate transition strategies and the level of government ownership also affect credit ratings, making support and policy alignment important factors.

2 Literature Review

European utility companies typically operate in a low default, regulated environment, which poses a unique challenge for credit risk modeling. The main problem in estimating the PD in this scenario is the lack of historical default data. As stated in Kiefer (2006): *"The problem in default probability estimation for low-default portfolios is that there is little relevant historical data information. No amount of data processing can fix this problem."* In practice, banks and regulators must often resort to conservative assumptions [1] or expert opinion to compensate for data scarcity. This limitation means regular statistical models may be unreliable when applied to utility portfolios, where actual defaults are extremely rare. For perspective, infrastructure companies, including utilities, have long-term default rates under 1%, much lower than other business sectors (S&P Global Ratings 2023). This creates a gap between what risk managers need (default probability estimates despite limited data) and what current modeling techniques can reliably provide under these conditions.

A different challenge exists for privately owned utility companies in Europe. Since many of these utilities aren't publicly traded, they lack market data like stock prices that advanced default probability models typically use.

There is limited research on default risk for privately held companies. Duan et al. (2018) observe that when private firms default, it is typically viewed as a business matter rather than a subject for academic study. They note that there is very little academic research on this topic, and that the few studies that do exist are predominantly conducted by industry practitioners rather than academics, with many remaining proprietary and not publicly available. Duan et al. further highlight that even when financial statements from private utility companies are accessible, critical market information such as stock prices is often missing, limiting the ability to assess up-to-date credit risk. In their study, they estimate the probability of default for private companies in South Korea by first deriving a market-based credit risk proxy, distance-to-default, from a sample of similar public firms. They build a regression model that links the distance-to-default of public firms to their financial ratios and macroeconomic indicators, and then apply this model to private firms to estimate their implied risk. This estimated risk measure is then fed into a forward intensity model to generate default probabilities over various time horizons. Their findings show that this approach significantly outperforms traditional models such as the Altman Z-score.

Bitetto and Filomeni (2023) examine whether market-based data from listed firms im-

[1] Conservative assumptions in the context of credit risk means assuming worse outcomes than historically observed.

proves default prediction for unlisted Micro, Small, and Medium-sized Enterprises (MSMEs). They calculate a proxy for Merton's PD using market data from comparable public firms, matched through an original clustering and dimensionality reduction approach. The resulting PDs are combined with accounting data in predictive models. They show a significant improvement in model performance, both in F1-score and AUC, when market information is included. This supports the use of market-implied risk measures to enhance credit assessments for private firms.

Blümke (2020) addresses the methodological challenge of calibrating PDs in portfolios with few or no defaults, proposing a Bayesian estimation framework that produces stable, conservative PDs while preserving rating rank order. This is directly relevant for sectors like utilities, where the lack of default history complicates standard PD calibration methods.

Finally, Benli and Yetgin (2021) provide a case study on a regulated gas utility, comparing market-based and agency-based approaches to PD estimation. Their results highlight significant discrepancies between methodologies and support the development of hybrid frameworks that reflect both market conditions and regulatory fundamentals.

In conclusion, private utility companies face practical challenges due to the absence of transparent risk indicators. Additionally, researchers have not adequately explored default probability modeling for these firms, partly due to data limitations and dependence on confidential industry information.

3 Data

This chapter describes the dataset that was used in the credit risk modeling framework, including its sources, structure, and key characteristics. It also outlines the preprocessing steps taken to ensure the data was clean, consistent, and ready for analysis across both public and private European utility companies.

3.1 Data Sources

The primary financial data were sourced from Energy Quant Solutions and EnBW, who provided standardized financial statements for 32 European utility companies for the fiscal year 2024. To address the underrepresentation of publicly traded firms in the original set, where only 3 of the 32 were listed, 5 additional public companies were incorporated, bringing the total to 37.

To facilitate model calibration and benchmarking, external PD estimates were obtained for available firms using Bloomberg Terminal's Default Risk (DRSK) scores [2].

In addition to internal financial data, the model retrieves external market information from Yahoo Finance using the yfinance API. These variables were used for the public companies to calculate market-based default probabilities with the Merton model, to normalize data across currencies, and to obtain parent company revenue when adjusting subsidiary default risk. The key external variables retrieved are listed in Table 1. The following subsection elaborates on how each variable is utilized in the modeling framework.

Table 1: Market Variables Retrieved from Yahoo Finance

Variable Name
Market Capitalization
Daily Closing Stock Prices
Total Revenue
Foreign Exchange Rates

3.2 Dataset Description

Market data for publicly traded companies was collected using the yfinance Python library. Daily historical stock prices were retrieved to calculate equity volatility, typically

[2] Bloomberg's Default Risk (DRSK) model uses a hybrid methodology combining market-based signals with company fundamentals to estimate credit risk, offering both timeliness and stability during market volatility (Bloomberg L.P. 2023).

using a one-year window (252 trading days) before the analysis date. This volatility is a key input in the Merton model, which estimates market-based probabilities of default. Market capitalization figures were also obtained; these represent the total market value of a company's outstanding shares and are calculated by multiplying the share price by the number of shares in circulation (Fernando 2025). In cases where a company in the dataset was a subsidiary and only subsidiary-level financials were available, yfinance was used to collect total revenue data for the parent company, but only if the parent was also part of the dataset. This allowed for more accurate adjustments to the subsidiary's probability of default, ensuring it better reflects the financial strength of the broader corporate group. Foreign exchange rates were also collected to convert all monetary values into euros, ensuring consistency across firms operating in different currency zones. The risk-free rate r, used in the Merton model, is set to 3.037%, based on the 12-month euro area yield in 2024 (European Central Bank 2024).

In addition to the market data collected for public companies, a set of core financial statement variables was extracted from the dataset provided by Energy Quant Solutions and EnBW. These variables were available for all companies in the sample and served as the foundation for the financial scoring and credit risk modeling applied throughout the thesis. The key financial metrics used are summarized in Table 2.

Variable	**Description**
Net Cash Flow from Operating Activities	Cash generated from a company's regular business operations.
EBIT (Earnings Before Interest and Taxes)	A company's profit before interest and tax expenses.
Total Revenue	All income earned from selling goods or services.
Total Current Assets	Assets expected to be used or converted into cash within one year.
Current Liabilities	Debts or obligations that are due within one year.
Total Capital	The total amount of capital a company uses to finance its operations, including debt and equity.
Total Debt	The total amount of money a company owes to lenders.
Total Equity	The value of the company owned by its shareholders after subtracting liabilities.
Retained Earnings	Profits kept in the company instead of being paid out as dividends.

Table 2: Key financial variables used in the analysis

To better reflect differences in data availability and business risk, the companies were divided into three modeling groups: public companies, private trading companies, and private non-trading companies. Public companies, which have available market data, were assessed using the Merton structural model. Private companies, which lack such market data, were split into trading and non-trading firms to capture differences in operational characteristics and financial behavior. This segmentation ensured that each group could be evaluated using a method appropriate to its data profile and risk structure.

Trading companies primarily buy and sell energy products such as electricity, gas, and carbon certificates. They are active market participants who seek to profit from price fluctuations, with a strong focus on short-term trading and risk management. Many are subsidiaries of large international energy groups.

In contrast, non-trading companies include utilities and energy producers whose core activities involve generating electricity or gas, distributing it through networks, and supplying it to households and businesses. These firms typically have more stable revenues and often operate under government regulation.

The full company list and corresponding segmentation are provided in Appendix B.

This classification is important for the credit risk model because trading and non-trading companies have very different financial structures and risk levels.

3.3 Data Cleaning and Preprocessing

The quality and reliability of a credit risk model are fundamentally dependent on the integrity of the underlying data. Since the dataset was provided in a standardized format by Energy Quant Solutions, all companies shared the same column structure. Minor checks were still performed to confirm the presence of key fields, particularly the company name, which serves as the main identifier. Any missing or unexpected values were noted to maintain consistency throughout the analysis.

Monetary values in the provided financial statements were already reported in euros and consistently formatted. However, for the additional public companies that were manually added to the dataset, currency symbols and formatting (e.g., commas, parentheses for negatives) were standardized, and all figures were converted to euros using exchange rates for fiscal year 2024. Any values that could not be converted were assigned as missing (NaN) to maintain consistency.

To address missing values in key financial variables, a K-Nearest Neighbors (KNN) imputation method is applied. This approach estimates missing values by identifying the most similar companies based on existing financial metrics. Before imputation, all variables are scaled to prevent features with larger magnitudes from dominating the distance calculations. After imputation, the data is inverse-transformed back to its original scale. This method maintains the relative structure and correlations of the financial variables and is particularly well suited for structured financial datasets.

Finally, as the original financial dataset was reported in millions of euros, all monetary values were converted to full currency units by multiplying by 1,000,000. This was done to match the scale of market data retrieved from Yahoo Finance, which was reported in base currency units, ensuring consistency across all inputs used in the modeling process.

4 Methodology

This chapter outlines the credit risk modeling framework developed for the thesis, including the construction of a financial score and the mapping of that score to a PD. Each component is tailored to reflect the characteristics and data availability of different segments in the European utility sector.

4.1 Overall Modeling Framework

The framework is applied to the dataset discussed in Sector 3. The modeling process consists of two main components, company segmentation and PD estimation, detailed below:

4.1.1 Company Segmentation and Financial Scoring:

Companies in the sample were grouped to their public or private status and their primary operational focus (energy trading or non-trading). Subsidiaries were also identified for later adjustments. Each company received a composite financial score (0-100), calculated as the weighted sum of key financial ratios and the choice of the specific ratios and the weighting logic applied depended on the company's main operational focus and is detailed in Section 4.3.

4.1.2 PD Estimation:

Public Companies: For publicly traded companies, PDs were estimated using the Merton model, which uses market-based inputs to derive a firm's distance-to-default and convert it into a one-year probability of default. The model and its assumptions are described in detail in Section 4.2.

Private Non-Trading Firms: For private non-trading companies, PDs were estimated by mapping the financial score to a default probability using a calibrated sigmoid function. This mapping was benchmarked against available Bloomberg DRSK PD values to ensure consistency with market-based credit risk measures. The calibration process is detailed in Section 4.4.

Private Trading Firms: For private trading companies, PDs were assigned using fixed intervals based on financial score ranges. This method was selected due to the limited availability of benchmark PDs and the structurally higher uncertainty associated with trading-focused business models. The intervals were defined conservatively, drawing on available reference data to ensure that the resulting risk estimates are both reasonable and consistent with industry standards. Further details are provided in Section 4.4.

All modeling was performed in Python, using the following libraries: `pandas` and `numpy` for data processing, `scipy.stats` and `scipy.optimize` for modeling and optimization, `sklearn` for imputation and scaling, `yfinance` for market data, and `matplotlib` and `seaborn` for visualization. The resulting framework provides a transparent, adaptable, and segment-sensitive method for assessing credit risk in the European utility sector.

4.2 Merton Model

The Merton model, developed by Robert C. Merton (Merton 1974), is a structural credit risk framework and forms a theoretical foundation for modeling PD based on the dynamics of the firm's assets. This method is used widely by analysts and investors to gain insights into how capable a company is at meeting its financial obligations, therefore weighing the possibility of a company entering default. Based on option pricing theory (Black and Scholes 1973), the model treats a company's stock equity as a call option on its assets, with the strike price equivalent to the face value of its debt. Default is assumed to occur at the maturity of the debt if the firm's asset value falls below the debt obligation.

To estimate default risk, the Merton model utilizes several observable inputs: the market value of equity (E), the volatility of equity returns (σ_E), the book value of debt (D), the risk-free interest rate (r), and the time to debt maturity (T). Since the firm's total asset value (V_A) and its volatility (σ_A) are not directly observable, these are estimated by simultaneously solving the following system of two non-linear equations:

$$E = V_A N(d_1) - De^{-rT} N(d_2) \tag{1}$$

$$\sigma_E = \frac{V_A N(d_1)}{E} \sigma_A \tag{2}$$

where $N(\cdot)$ is the cumulative standard normal distribution function. The terms d_1 and d_2 are given by:

$$d_1 = \frac{\ln(V_A/D) + (r + \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}} \tag{3}$$

$$d_2 = d_1 - \sigma_A \sqrt{T} \tag{4}$$

Since both the asset value (V_A) and its volatility (σ_A) are unknown, the system defined by Equations 1 and 2 must be solved numerically. In this case, the Newton-Raphson method is applied to iteratively estimate the asset value V_A. The procedure begins with an initial guess ($V_A = E+D$), and iteratively updates this value to minimize the difference between the left- and right-hand sides of Equation 1, using the observed market value of equity E and equity volatility σ_E. At each iteration, the derivative of the equity value function with respect to V_A is used to compute the adjustment step, following the Newton-Raphson update rule. Once V_A converges to a stable solution, the asset volatility σ_A is recovered from Equation 2. This ensures that the model's implied equity value and equity volatility are consistent with observed market data. Once both V_A and σ_A are estimated, these values can be used to calculate the distance-to-default, which forms the basis for the PD in the Merton model, defined as:

$$d_2 = \frac{\ln(A/F) + (r - \sigma_a^2/2)T}{\sigma_a\sqrt{T}} \tag{5}$$

where A is the asset value, F is debt, r is the risk-free rate and σ_a is the asset volatility. The PD is then: $N(-d_2)$, with N representing the cumulative normal distribution.

Given the availability of market data for many large European utility companies, and the ability to estimate firm asset values and volatilities using equity data, the Merton model remains a widely used tool for assessing default risk in this sector. However, for companies where such data is unavailable, such as private firms or subsidiaries, alternative approaches must be used.

While the Merton model remains widely used for estimating default risk, it has known limitations, particularly in low-volatility, low-default sectors. Multiple studies have shown that it tends to produce unrealistically low probabilities of default for financially stable firms, often clustering near zero and failing to reflect meaningful risk variation (Reisz and Perlich 2004; Jessen and Lando 2013). To address this, several extensions have been proposed. First-passage models such as Black–Cox allow for default to occur at any time the firm's asset value breaches a threshold, while other formulations incorporate stochastic volatility or alternative capital structures (Black and Cox 1976). These approaches improve flexibility and typically yield more realistic default estimates in settings where traditional assumptions do not hold.

4.3 Financial Score Construction

A key component of the PD estimation framework for private companies is the creation of a quantitative financial score. This score provides a consistent way to rank firms by financial strength, based on its reported financial statements. Scaled from 0 to 100, a higher financial score signals a stronger financial position and lower credit risk.

The financial score is built in two main steps:

1. **Individual Financial Ratios:** A carefully selected set of financial ratios is calculated for each company using its reported financial data. The ratios used are:

   - Funds From Operations (FFO) to Net Debt
   - Interest Coverage (EBIT to estimated interest expense)
   - Equity Ratio (Total Equity to Total Capital)
   - Current Ratio (Current Assets to Current Liabilities)

   Where FFO to Net Debt captures cash flow coverage of debt, Interest Coverage measures the ability to service debt from earnings, Equity Ratio reflects capital structure strength, and Current Ratio indicates short-term liquidity. Each financial ratio is converted to a score between 0 and 100 based on how it ranks compared to the rest of the companies in the dataset. For instance, if a company's FFO/Net Debt ratio is higher than 80% of the other companies, it gets a score of 80 for that ratio. Since all selected ratios in this model reflect stronger financial health when their values are higher, the percentile ranking lines up directly with financial strength. This makes it easier to compare across different ratios and helps limit the impact of outliers.

2. **Segmented Financial Score:** After each company's financial ratios are scored, they are combined into the overall financial score using a weighted average. The weights are tailored to reflect the company's core operations, as the financial characteristics and risk factors differ significantly between traditional utility businesses and energy trading companies.

   - **Non-Trading Utility Weights:** For companies primarily engaged in regulated or conventional utility operations, such as generation, distribution or integrated utility services, the weights are based on the Moody's methodology for regulated gas and electric utilities (Moody's Investors Service 2017), with some adjustments due to some specific data limitations, specifically the absence of a consistent retained cash flow (RCF) metric. This approach is built around the principles of long-term financial stability, the ability to service substantial debt, and the maintenance of a solid capital structure. Within this framework, Funds from Operations to Net Debt, stands out as the most critical factor, given the heavy debt loads that are typical for capital-intensive utilities. In addition, equal emphasis is placed on both Interest Coverage and Equity Ratio. Consistent interest coverage is indicative of stable underlying earnings, which is essential for meeting ongoing debt obligations. Similarly, a strong equity foundation increases a utility's ability to withstand financial shocks and contributes to sustaining a stable and durable capital structure. Overall, the weighting scheme is designed to capture the financial characteristics most important to the long-term stability and creditworthiness of non-trading private utility companies.

- **Trading/Market Weights:** The financial ratio weights in the 'Trading/Market' segment are deliberately structured to reflect the different risk profile of trading companies. Liquidity, measured by Current Ratio, is emphasized as the most critical factor, with both S&P Global (S&P Global Ratings 2017) and Moody's (Moody's Investors Service 2025) highlighting it as the key factor of creditworthiness for commodity traders. S&P Global not only regards liquidity as integral but may also directly cap a trader's Stand-Alone Credit Profile (SACP) if liquidity is insufficient. Moody's similarly describes liquidity as 'paramount', noting that ratings can be significantly affected by liquidity shortfalls.

  Capital strength, captured by Equity Ratio is also given substantial weight, as S&P Global, includes financial leverage and capital strength as key factors in their evaluation of commodity traders, while Moody's, uses measures such as Debt/Book Capitalization to assess leverage. Their rationale for this emphasis is that trading companies often exhibit characteristics of both corporate and financial institutions, requiring a robust equity foundation to absorb potential trading losses and maintain solvency.

  Interest Coverage is another important metric, as it demonstrates consistent debt servicing capacity despite potential earnings volatility. This aligns with S&P Global's focus on profitability and track record (S&P Global Ratings 2017), as well as Moody's assessment of performance stability within its broader business profile analysis (Moody's Investors Service 2025). Consistent interest coverage is an essential measure of financial resilience for trading companies during periods of market fluctuation.

  While Funds from Operations (FFO) to Net Debt is a standard metric in credit analysis, its relative weight is intentionally lower in this context. While both Moody's and S&P consider FFO-based ratios in their frameworks, the practical realities of trading companies call for a different emphasis. In this sector, immediate liquidity is often far more critical than longer-term cash flow measures, as frequent and sometimes dramatic swings in working capital can make FFO an unreliable indicator of true financial health. Fitch Learning also points out the limitations of relying solely on cash flow metrics for traders, given the volatility in the sector (Fitch Learning 2025). Thus, greater emphasis is placed on liquidity and interest coverage, which better captures a trading firm's resistance to shifting market conditions.

Table 3 presents the weights assigned to each ratio for both segments, where the sum of weights for each equals 100%.

Table 3: Financial Ratio Weights for Score Calculation (%)

Financial Ratio	**Non-Trading Utility Weight**	**Trading/Market Weight**
FFO/Net Debt	50.0	15.0
Interest Coverage	25.0	20.0
Equity Ratio	25.0	25.0
Current Ratio	0.0	40.0
Total	**100.0**	**100.0**

By tailoring the scoring approach to different segments and using percentile rankings, the financial score effectively accounts for both data outliers and the specific financial characteristics in various parts of the European utility sector. This score is then used as one of the main inputs for estimating the PD for private companies.

4.4 PD Mapping and Calibration

Once the financial score for each private company and the initial PD for public companies have been determined, these values are mapped to final, calibrated PDs using segment-specific mapping functions. For public companies, the final PD is taken directly from the Merton Model output. For private companies, the financial score is mapped to a PD estimate using approaches tailored to each company segment, as outlined below.

Given the absence of sufficient default data in the European utility sector, and the historically low observed default rates, a calibrated PD range was applied, with a minimum of 0.0001% and a maximum of 5%.

This upper bound reflects a conservative approach suitable for portfolios with limited default observations. The Basel Committee on Banking Supervision, for example, suggests applying an upper bound to PD estimates in cases of data scarcity to support more reliable risk estimates. (Basel Committee on Banking Supervision 2005).

Industry benchmarks further support this calibration and show that one-year PDs for speculative-grade obligors rarely exceed 5%. For example, data compiled by the NAIC based on Moody's historical defaults indicates that B1-rated firms have an average 1-year PD of 2.7%, and B2-rated firms approximately 4.5% (Johnson et al. 2020).

Given that the companies in this study are predominantly utilities with stable cash flows and historically low default rates, a ceiling of 5% is likely to be conservative. This threshold prevents the model from assigning higher PDs than those typically seen for similarly risky firms in the broader market, helping avoid overstating credit risk in a low-default environment.

4.4.1 Private Non-Trading Utility Companies:

For private companies primarily engaged in non-trading utility operations, the financial score is mapped to a PD using a calibrated sigmoid function. A sigmoid function was selected due to its S-curve shape, which closely reflects how default risk typically behaves: at the extremes, small changes in financial scores have a small effect on PD, while mid-range scores are more sensitive and result in bigger PD shifts. Functions like linear and logistic regression were not selected since linear regression assumes a constant relationship between financial strength and default risk, which doesn't reflect the reality that risk changes more dramatically at certain points. Logistic regression, while related to the sigmoid curve, requires clear default or non-default outcomes to train the model, and such data was not available in this case. Instead, the calibrated sigmoid function was preferred since it can be directly fitted to the benchmark PDs from DRSK. The function takes the form:

$$\text{Mapped\_PD} = \text{PD}_{\text{floor}} + \frac{\text{PD}_{\text{ceiling}} - \text{PD}_{\text{floor}}}{1 + e^{k\cdot(\text{Financial Score}-m)}}$$

where:

- PD_{floor} is the minimum allowable PD. (0.0001%)
- $\text{PD}_{\text{ceiling}}$ is the maximum allowable PD before a company is considered in or near default. (5%)
- k represents the steepness of the sigmoid curve.
- m is the midpoint of the sigmoid curve, representing the financial score at which the PD is halfway between the floor and ceiling.

The parameters k (steepness) and m (midpoint) for the sigmoid mapping function were calibrated empirically using a sample of 9 private non-trading companies. For these firms, both the financial score values and external PD estimates, sourced from a Bloomberg database, were available. The calibration process involved optimizing k and m to maximize the coefficient of determination (R^2, better outlined in Section 4.5), outputting the best statistical fit between the financial score and the Bloomberg DRSK PDs. The final calibrated parameters $m = 10.72$ and $k = 0.064$ are used in the model for private non-trading utilities.

Since only nine non-trading firms in the dataset had Bloomberg DRSK PD values, the sample was too small to support any out-of-sample validation or holdout testing of the sigmoid mapping. Attempting to split such a limited dataset into training and test sets would not have produced meaningful results. Therefore, the calibration was carried out using the entire available sample, focusing on achieving a smooth and interpretable fit. To avoid overfitting, the sigmoid function was deliberately kept simple, with just two parameters: midpoint and steepness. The fitted curve was then visually examined to ensure it behaved plausibly across the full range of financial scores. In future research, access to a larger set of benchmark PDs or external ratings could enable more thorough validation methods, such as sensitivity analyses or cross-validation.

4.4.2 Private Trading/Market Companies:

Private energy trading companies exhibit risk profiles vastly different from vertically integrated or regulated utilities. These trading firms typically have low levels of fixed assets, experience significant earnings volatility, and are highly sensitive to short-term liquidity risks. Given the limited availability of default and benchmark data for these private entities, a continuous calibration approach, like the one used for the non-trading firms, was not feasible without risking overfitting. Instead, an interval-based mapping was used, where financial scores are mapped to fixed PD values across five predefined ranges. The PD intervals are:

Financial Score Range	**Assigned PD**
$80 \leq$	0.5% (0.0050)
$60 \leq \text{Score} < 80$	1.5% (0.0150)
$40 \leq \text{Score} < 60$	3.0% (0.0300)
$20 \leq \text{Score} < 40$	4.5% (0.0450)
< 20	5.0% ($\texttt{PD}_{\texttt{ceiling}}$)

This method is consistent with regulatory guidance from The Basel Committee and European Banking Authority, both of which explicitly permit assigning PDs based on score or rating intervals in low-default portfolios (Basel Committee on Banking Supervision 2005; European Banking Authority 2017).

To maintain model reliability in a low-default environment and avoid overfitting, a fixed PD floor and an interval mapping structure are applied for private trading firms. The minimum PD of 0.5% is assigned to the strongest companies in this segment, reflecting ongoing uncertainty in the trading sector, even among the top performers. This approach is consistent with industry practices such as Fitch Ratings, which applies a 0.5% one-year PD floor to highly rated commercial exposures to avoid understating risk in volatile sectors (Ratings 2024). The use of set PD intervals (1.5%, 3.0%, and 4.5%) follows regulatory expectations around low-default portfolios. The Prudential Regulation Authority (PRA), for instance, requires internal models to assign exposures to a limited set of PD bands rather than using a continuous probability scale. This interval approach improves model reliability by reducing the impact of limited or noisy default data (Bank of England, Prudential Regulation Authority 2022).

4.4.3 Subsidiary PD Adjustments:

All subsidiaries identified in the dataset are private trading arms of larger public parent companies. For these cases, the PD is adjusted by taking a weighted average of the subsidiary's PD and the parent company's PD, where the weight is based on the subsidiary's revenue share to the parent. This method is based on the idea that revenue share serves as a reasonable proxy for economic exposure within a corporate group. MSCI, for example, uses a company's revenue distribution to estimate its economic exposure in global investing and risk analysis contexts (MSCI 2018). This adjustment aims to reflect the financial and operational links between the parent and subsidiary, which can influence credit risk. For subsidiaries whose parent companies are not public or not included in the dataset, no adjustment was made due to the lack of reliable parent company information.

The objective of this comprehensive PD mapping and calibration process is to produce consistent and accurate PD estimates for different types of companies within the portfolio, leveraging the most relevant information available for each segment while keeping all estimates on the same scale and within safe and cautious limits.

4.5 Coefficient of Determination (R^2)

To assess the goodness of fit between the calibrated sigmoid mapping and the observed PD, the R-squared score (R^2) is used. This metric quantifies how well the predicted

PDs from the fitted sigmoid function explain the variance in the actual (DRSK) PDs obtained from Bloomberg's DRSK model. The R^2 score is useful in regression settings, as it provides a normalized measure of model performance ranging from 0 to 1, where higher values indicate better explanatory power.

The R^2 score is computed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

where y_i is the observed PD, $\hat{y}_i$ is the predicted PD from the sigmoid function, $\bar{y}$ is the mean of the observed PDs, and n is the number of data points used in the calibration.

4.6 Altman Z-Score Model

To support the model validation, a recognized external benchmark is incorporated to compare against the custom financial score. The Altman Z"-Score, a variation of the original Z-Score adapted for private non-manufacturing firms, serves this role. While it is not used directly in the PD estimation, it provides a valuable reference point for assessing how well our approach differentiates between financially stronger and weaker firms within the dataset.

When market data is scarce or nonexistent, credit risk assessment must rely on firm-intrinsic information, chiefly financial statements. One of the most established tools in this regard is Altman's Z-Score model, which pioneered the use of multiple discriminant analysis on financial ratios to predict corporate bankruptcy (Altman 1968). Altman's original model (Z-score) was developed for publicly traded manufacturing firms.

It combines five financial ratios weighted by coefficients to produce a single score that classifies companies according to their bankruptcy risk:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \tag{7}$$

Where:

- X_1 = Working Capital/Total Assets (measure of liquidity)
- X_2 = Retained Earnings/Total Assets (measure of cumulative profitability)
- X_3 = Earnings Before Interest and Taxes/Total Assets (measure of operating efficiency)

- X_4 = Market Value of Equity/Book Value of Total Liabilities (measure of leverage)
- X_5 = Sales/Total Assets (measure of asset turnover)

Companies above a certain threshold score are deemed "safe", those below a lower threshold are in "distress", and the intermediate range is a gray zone indicating uncertainty. The Z-Score's simplicity and relatively good performance made it a cornerstone of credit risk modeling.

Over time, Altman's framework was adapted for different types of firms. The Z'-Score modified the original formula to consider privately held companies by removing the reliance on market equity value and replacing it with book equity since private firms lack market capitalization data (Altman, Marco, and Varetto 1994). Later, Altman introduced the Z"-Score for non-manufacturing and emerging market firms, which excludes the Sales/Total Assets ratio to better suit industries where asset turnover is not an indicator of default risk (Altman 2005). In the Z"-Score, four ratios are used: Working Capital/Total Assets, Retained Earnings/Total Assets, EBIT/Total Assets, and Book Equity/Total Liabilities, with different cut-off values being applied to interpret financial health:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \tag{8}$$

For non-U.S. and emerging market companies, Altman added a constant term of 3.25 to standardize the scores, where a score of zero becomes equivalent to a bond rating of D (default).

Generally, for Z", a score above roughly 2.6 suggests a low likelihood of distress, while a score below about 1.1 indicates a high risk of bankruptcy, with values in between being ambivalent. These adaptations allowed the Altman model to remain relevant across various sectors and company types.

However, subsequent studies by Grice and Ingram (2001) pointed out that the model's accuracy can deteriorate over time or when applied to new contexts. They recommend periodic re-estimation or recalibration of the discriminant coefficients to reflect contemporary economic conditions and industry structures. These observations suggest that while Altman's approach is a useful baseline, it should be adjusted for specialized applications.

The main reason for including the Altman Z"-Score in our analysis is to provide a widely recognized, external reference point against which our custom financial score and the resulting PD model. This comparison allows us to assess how well our financial score differentiates between stronger and weaker companies, compared to a well-established distress prediction model, specifically within our portfolio of European utility and trading companies. It also highlights any improvements offered by our model, which uses segment-specific ratios and customized weights (as detailed in Section 4.3) to better reflect the different financial structures and risk factors of the sectors.

Despite the Z”-Score's adaptation for non-manufacturing private firms, our decision to develop a custom financial scoring model is also motivated by several limitations to the Altman Z-Score model, which underline the potential advantages of a tailored approach.

To start, the Z”-Score's coefficients are based on historical data, which may not perfectly reflect the current European market conditions or the specific characteristics of highly specialized energy trading companies compared to regulated utilities. There were also complications when applying the Z”-Score to our dataset due to the lack of retained earnings data for some of the private companies in the dataset, which is essential for calculating the X2 ratio (Retained Earnings / Total Assets). Although we used standardized data imputation methods to address the missing data (Section 4.7), we are relying on these imputed values for the Z”-Scores's X2 ratio. Therefore, the benchmark scores for companies with incomplete data are influenced by the patterns found in similar companies, which could affect how consistent and reliable the Z”-Score is as a comparison tool. Another important limitation is that the Z”-Score only classifies firms into categories of different risk, instead of offering a detailed PD, which is the primary output of our model. By comparing our financial score against the Altman Z”-Score and recognizing these limitations, we aim to highlight both the need and the advantages of our customized approach to estimating default probabilities.

4.7 K-Nearest Neighbors (KNN) Imputation

Missing data is a common issue in financial datasets, especially for private firms where reporting may be inconsistent or incomplete. The choice of KNN imputation over simpler methods like mean, median, or mode imputation is driven by its ability to use the relationships between the multiple variables within the dataset. Financial variables are often correlated, for example, a company's revenue might be related to its total assets or operating expenses. KNN imputation attempts to capture these interdependencies by identifying companies (neighbors) with similar values based on their available data to estimate the missing value. In this study, we use five nearest neighbors (K=5), which represents a reasonable balance given the dataset's size of 37 companies. This ensures that each imputation is based on a meaningful but not overly broad comparison group, preserving local patterns in the data.

To illustrate how this works in practice: if a company's 'Current Liabilities' is missing, but it has similar values to other firms in terms of 'Total Revenue', 'Total Assets', and 'EBIT', KNN imputation finds the most similar companies based on these features and averages their 'Current Liabilities' values to fill in the missing one. This multivariate approach leverages the structure of the dataset, rather than relying solely on the distribution of the missing variable itself.

This approach is further supported by Batista and Monard (2002), whose research shows that KNN imputation significantly outperforms mean imputation, especially in datasets with correlated variables. Their findings indicate that KNN better preserves the data's internal structure and improves the accuracy of the modeling results, making it especially relevant for financial applications involving interdependent balance sheet and income statement items.

5 Results

The following section presents the results, along with a discussion and the model´s limitations.

5.1 Public Companies - Merton Model Output

This subsection focuses on the publicly listed companies for which the PD was estimated using the Merton Model. The results are compared against Bloomberg´s DRSK benchmark to evaluate how well the model reflects the actual market-implied credit rating.

Company Name	Financial Score	Merton PD (%)	DRSK PD (%)	Difference (%)
EVN AG	73.0	0.0001	0.001 16	0.000 16
Shell plc	69.6	0.0001	0.0028	0.0018
CEZ	54.7	0.0001	0.000 345	0.000 655
Engie SA	50.7	0.0001	0.0069	0.0059
Enel SpA	41.9	0.0001	0.0053	0.0043
Iberdrola	41.2	0.0001	0.002 19	0.001 19
E.ON	34.5	0.0001	0.014 06	0.013 06
EDP Renováveis	27.7	0.0258	0.5741	0.5481

Table 4: Comparison of Merton PD and Benchmark PD for Public Companies, Ranked by Financial Score

The comparison between the Merton model and Bloomberg's DRSK PDs for the public companies in our portfolio reveals notable differences in how these models distinguish credit risk. As shown in Table 4, the Merton model assigns a PD floor (0.0001%) for seven of the eight firms in the sample, with only EDP Renováveis exceeding this floor (0.0258%). This is not because the model estimates were exactly identical, but because predicted PDs fell below the predefined floor set in our framework to avoid unrealistic near-zero values. As a result, the output is clustered at the lower bound, limiting the model's ability to distinguish relative credit quality among firms with stable financial profiles.

As discussed in Section 4.2, this limitation is well-documented in the literature, particularly for low-volatility, low-default sectors such as regulated utilities. In contrast, EDP Renováveis stands out as an exception, with a significantly higher Merton PD (0.0258%), reflecting its weaker financial standing and greater exposure to market volatility.

While the Merton model remains useful for establishing a baseline assessment of credit risk, its limited output differentiation highlights the importance of supplementing it with additional metrics that reflect firms' financial structures. In this dataset, the financial score provides a more distinct ranking across companies, indicating that relying solely on market-based measures does not adequately capture differences in credit quality within a portfolio of public utilities.

5.2 Private Non-Trading Companies - Model Comparison

This section analyzes the calibration of the financial scoring model against the market-based PD benchmark (DRSK) and compares its performance with the Altman Z"-Score.

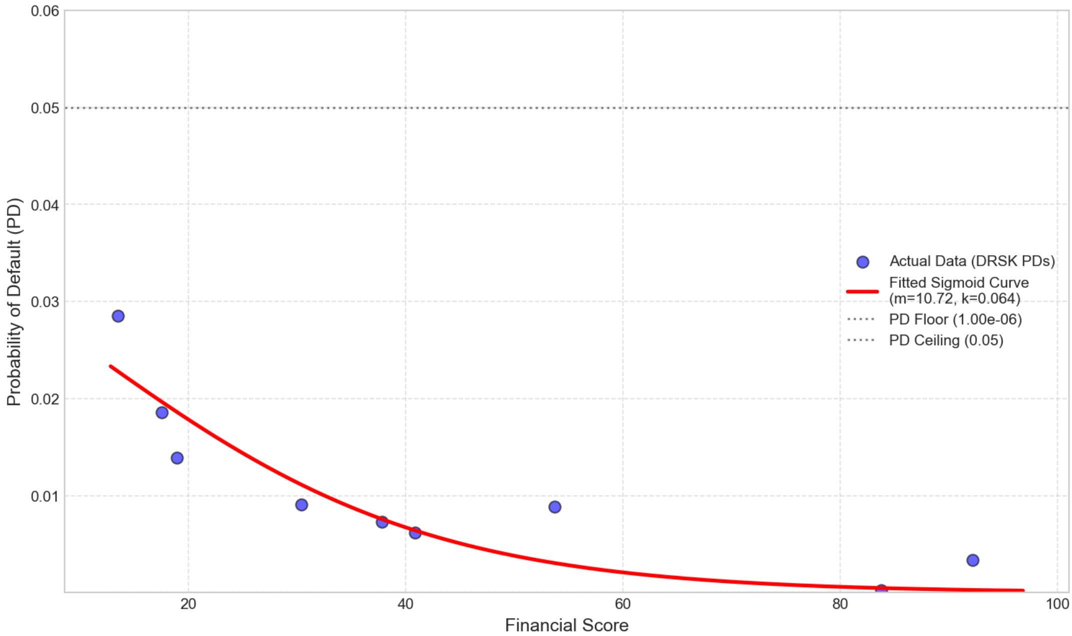

Figure 2: The sigmoid function fit for the non-trading utilities with Financial Score

The custom financial score shows a much stronger correlation with Bloomberg's DRSK 1-year PD for non-trading private utility firms compared to the Altman Z"-Score, as shown in Figures 2 and 3. The sigmoid fit based on the financial score achieves an R^2 of 0.8246, compared to just 0.2834 for the Z"-Score. This gap highlights the clear difference in how effectively the two models capture credit risk variation across firms. In practical terms, an R^2 of 0.82 means the financial score explains 82% of the variation in benchmark PDs, indicating that it aligns closely with the market's own assessment of risk. By contrast, the Z"-Score accounts for less than 30% of the variance, suggesting it fails to capture the majority of risk differentiation. While the Z"-Score was designed for non-manufacturing

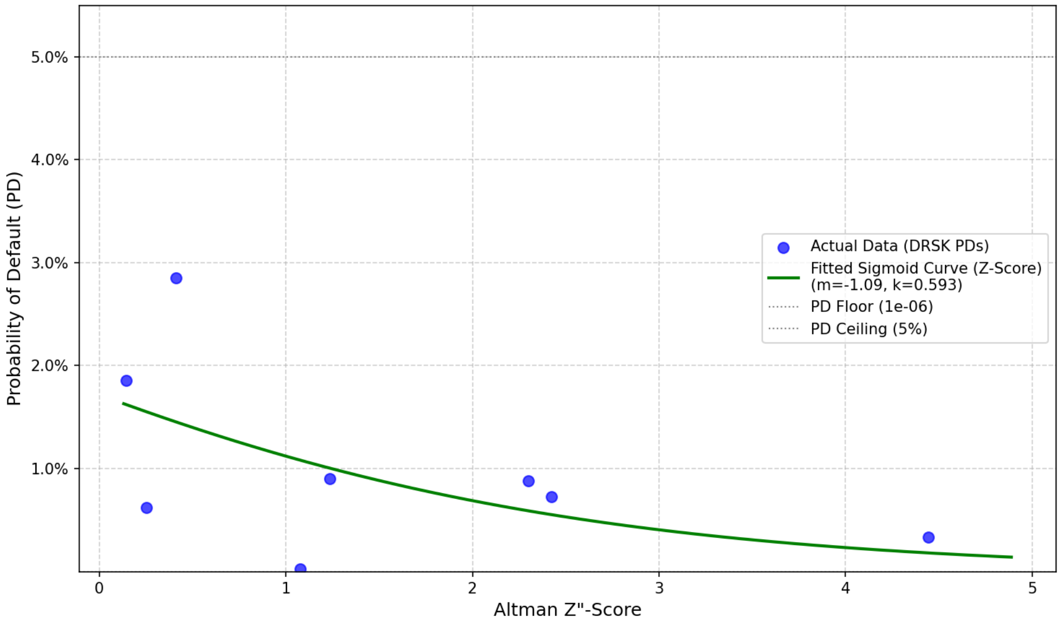

Figure 3: The sigmoid function fit for the non-trading utilities with Altman-Z scores

private firms, it still carries assumptions that don't translate well to capital-intensive, regulated utilities.

Part of the performance gap may also come from the limitations of the data. Retained earnings had to be estimated for several firms using KNN imputation, which added noise to the Z"-Score calculations. The financial score, on the other hand, was tailored for this sector and built using ratios that reflect actual credit drivers for utilities like debt servicing capacity, capital structure, and liquidity, meaning its strong performance isn't just due to statistical calibration but reflects a better fit with the realities of the sector.

Overall, these results reinforce the value of building sector-specific models. The financial score outperforms a classic benchmark not because it's more complex, but because it's more relevant. That makes it a stronger foundation for credit assessment when conventional models fall short.

5.3 Private Trading Companies and Subsidiaries

This section presents the PD mapping strategy used for private energy trading firms and trading subsidiaries of public companies.

Figure 4 shows the assigned PD against financial score for private trading utility firms and subsidiaries, based on the interval mapping strategy outlined in Section 4.4.

As shown in the figure, the mapped PDs decrease consistently as financial score increases, confirming that the interval mapping behaves as expected. Although the mapping was

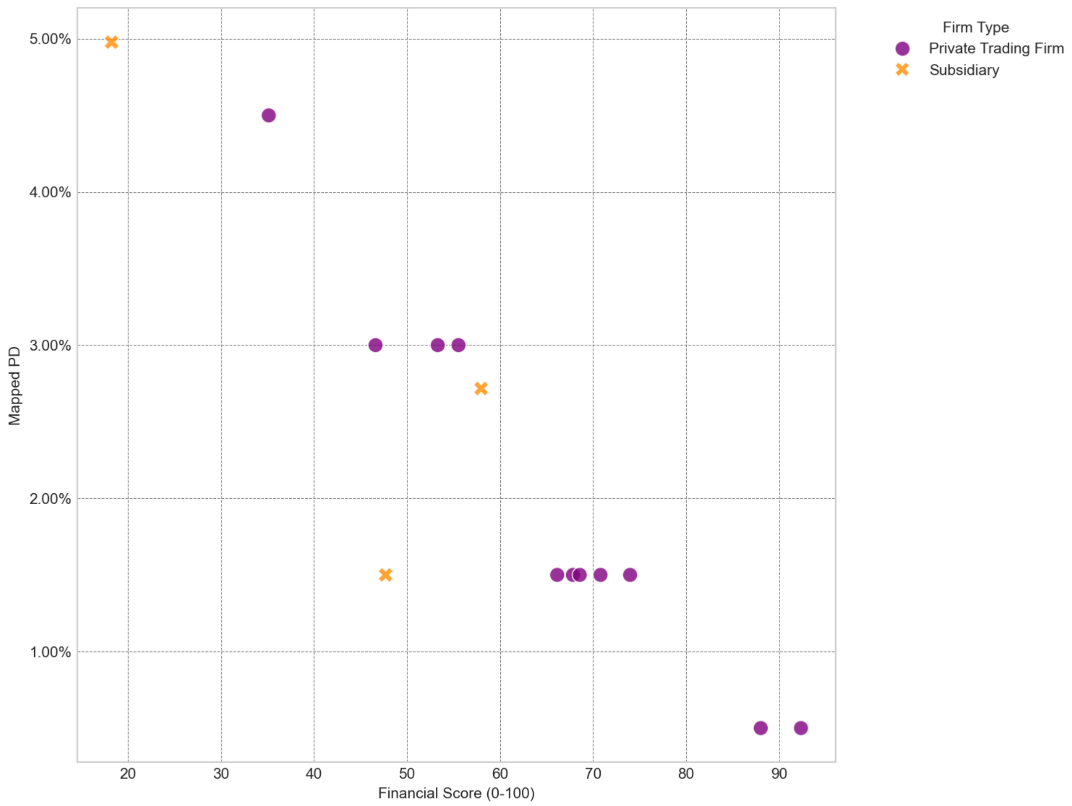

Figure 4: The trading firms mapping with Mapped PD against financial score

not fitted to actual defaults or benchmark PDs, the goal was to apply a transparent and consistent ranking framework across firms, rather than to estimate precise default probabilities. Given the absence of sufficient data for calibration in this segment, a simple interval mapping is more appropriate than attempting to fit a statistically unstable and possibly overfitting curve.

The figure is mainly intended to confirm that subsidiaries are incorporated in the analysis and to assess whether the mapping framework remains consistent when their PDs are adjusted. By adjusting their PDs through a revenue-weighted average with their public parent, the model maintains their position within the expected risk tiers. This adjustment method effectively captures the financial relationship between parent and subsidiary, while preserving the integrity of the original financial score method. While this approach is not intended for highly detailed credit prediction, the method is transparent and aligns with industry practices for low-default portfolios.

5.4 Model Limitations

While the developed credit risk model offers a tailored and transparent approach for assessing the PD for companies in the European utility and energy trading sectors, its outputs are subject to several important limitations. These stem from both data-related constraints and methodological choices and should be carefully considered when interpreting results.

5.4.1 Data Quality and Availability

The model's reliability is highly dependent on the quality and completeness of the input data. While the primary dataset was provided by Energy Quant Solutions, retained earnings were manually added for companies where reliable data could be found.

For private firms with incomplete financial data, K-Nearest Neighbors (KNN) imputation was used. While this method attempts to estimate missing values based on similarity to other firms, it inevitably introduces estimation noise. Its effectiveness depends on the quality and representativeness of the data available for neighboring firms, as well as the extent of missingness.

For publicly traded companies, market data such as share prices and market capitalization is sourced via the yfinance API, which may be subject to lags or data interruptions compared to real-time feeds. Additionally, the model is based exclusively on 2024 financial statements. This ensures a consistent time frame, but it also means the analysis may not reflect material changes in financial condition since 2024. As with any point-in-time analysis, the results are inherently backward-looking.

5.4.2 Methodological Assumptions

The selection and weighting of financial ratios are based on theoretical considerations and domain knowledge but are not derived through empirical optimization against large historical default datasets. The weights are static and do not adjust to evolving economic or sector conditions, which may limit predictive accuracy over time.

The financial score itself is based on percentile ranks within the sample. This means a firm's score is influenced by changes in the peer group, even if its financials remain unchanged.

The mapping of financial scores to PDs for private firms uses either a sigmoid function for the non-trading entities or fixed interval mapping for the trading entities. The sigmoid mapping assumes a continuous relationship with benchmark calibration, while the interval approach uses step changes, where small score differences can result in disproportionately large PD differences.

Both mapping techniques impose PD floors and ceilings to prevent extreme values, but this may also understate risk in cases of severe financial distress. Subsidiaries are adjusted based on revenue proportion and the parent company's PD, reflecting financial connection and common risk practices. However, this simplified approach does not account for legal ring-fencing, strategic importance, or parent willingness to intervene, and assumes the parent's PD is both available and reliable.

5.4.3 Scope and External Validity

The model is designed specifically for the European utility and energy trading sectors. The choice of financial ratios, weighting schemes, and calibration benchmarks is not necessarily transferable to other sectors or geographies without significant modification. The model also does not explicitly incorporate country-specific risks such as political or legal instability, nor does it incorporate qualitative factors like management quality, governance, competitive environment, or ESG considerations, which are often used in credit analysis.

5.4.4 Model Validation and Technical Considerations

While the model offers transparency and sector-specific segmentation, its layered structure for the different types of firms adds complexity. This can make the understanding and interpretation of individual PD outcomes difficult without examining the entire calculation framework.

6 Conclusion

This thesis set out to develop a practical and transparent approach to estimating one-year default risk for European utility companies, a sector where standard credit models struggle due to the rarity of defaults and limited data, especially for private firms. To address this, a hybrid framework was developed, combining a market-based Merton model for public companies with a custom financial scoring system for private firms and subsidiaries. The financial score draws on ratios relevant to the sector, and for non-trading companies, it was calibrated against Bloomberg DRSK data to map credit strength to PDs. For trading companies, a conservative interval-based mapping based on the financial score was used instead, due to limited benchmark data.

The primary contribution of this thesis lies in adapting and integrating established methodologies to the unique conditions of the European utility sector. This includes implementing a sector-specific weighting in the financial scoring process, ensuring transparent PD mapping despite data limitations, and introducing a practical approach for factoring in parent-subsidiary relationships in risk assessment. Together, these elements form a transparent and implementable framework, offering a valuable alternative in contexts where standard credit models fall short.

The model is not intended to mirror internal bank models or comply with regulatory standards. Its goal is rather to offer a sector-specific framework that is clear and usable in real-world credit assessment. The approach is streamlined where necessary, for example, through KNN Imputation for missing data and setting minimum thresholds to prevent unrealistic PD values, yet it still accommodates the specific characteristics of different company segments.

There are, however, several limitations to this approach. The model is static, therefore relying solely on financial data from 2024, and does not account for macroeconomic shocks, forward-looking measures, or qualitative factors such as governance and ESG risks. Calibration is also limited by the small sample of available benchmark PDs. The findings, however, demonstrate that with careful segmentation and conservative assumptions, a functional and transparent PD estimation framework can still be built in a low-default environment.

Future work could extend the model beyond one-year default probabilities to longer time frames, such as five- or ten-year risk estimates. This would allow for a more strategic, long-term view of credit risk, especially relevant for infrastructure-heavy sectors like utilities. Dynamic modeling over time could incorporate macroeconomic scenarios or simulated financial trajectories to reflect potential changes in credit profiles. Given the limited default history in the sector, calibration could rely on external benchmark curves or rating transition data. These extensions would further strengthen the model's applicability without sacrificing its transparency or sector relevance.

Overall, the framework developed in this thesis fills a practical gap in credit risk assessment for regulated sectors like energy, where data is limited and default rates are low. It offers a usable approach for analysts and institutions needing transparent, tailored models in environments where standard tools fall short.

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A AI Statement

For this thesis, we used the AI-based tools ChatGPT, Gemini, and Cursor. ChatGPT was used to improve the clarity and flow of our writing. It helped rephrase and refine technical explanations, but all content was critically reviewed and written by us. It also helped us to format and fix coding errors in Overleaf. Gemini was used to support our understanding of complex concepts used and discussed in this thesis. It was used strictly for conceptual clarification and did not generate any content included in the thesis. Cursor was used as an AI-assisted coding environment to help implement, debug, and document the Python code used for the modeling framework. These tools were used to assist with editing, coding, and conceptual understanding, but all modeling decisions, interpretation of results, and written content were independently developed by us.

B Company List

Public Companies
CEZ
E. ON
EDP Renováveis
EVN AG
Enel SpA
Engie SA
Iberdrola
Shell plc

Table 5: List of companies that are publicly traded on stock exchanges.

Private Trading Companies
ACT Commodities Group B.V
Axpo Solutions AG
Cheniere Marketing International LLP
Enel Global Trading S.p.A.
GO2-markets GmbH
InCommodities A/S
Nordic Green Power AS
Oekostrom Handels GmbH
SET Swiss Energy Trading AG
SKS HANDEL AS
STX Commodities B.V.
Shell Energy Europe Limited
Shell Global LNG Limited
Socar Trading SA

Table 6: Private companies primarily engaged in energy and commodity trading.

Private Non-Trading Companies
Alpiq AG
EDF
ENTEGA AG
Elektrizitätswerk des Kantons Schaffhausen AG
Energie Steiermark Business GmbH
Enerparc AG
Estra Energie S.R.L.
Groupe E S.A.
Linz AG
SFE Produksjon AS
SHB Schwäbisch Haller Beteiligungsgesellschaft mbH
Stadtwerke Ettlingen GmbH
Stadtwerke Köln GmbH
Städtische Werke Nürnberg GmbH
Trianel GmbH

Table 7: Private companies not primarily engaged in market trading, including utilities and producers.