White paper

An update on the performance of LSEG StarMine Credit Risk Models

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LSEG DATA & ANALYTICS

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Abstract

This paper provides a performance update on StarMine's suite of credit risk models, covering the period from January 2021 through November 2025. Building on our earlier work analysing model performance from 2011 to 2020, this study reaffirms the strong and consistent predictive power of all four StarMine credit risk models: the Structural Credit Risk Model (SCR), SmartRatios Credit Risk Model (SRCR), Text Mining Credit Risk Model (TMCR), and the Combined Credit Risk Model (CCR). Each model has remained effective in forecasting credit risk amid the post-pandemic recovery and a prolonged high-interest-rate environment. StarMine Combined Credit Risk Model (CCR), which synthesises outputs from SCR, SRCR, and TMCR, continues to deliver the most accurate results, significantly outperforming the Altman Z-score in predicting default or bankruptcy within a one-year horizon.

Introduction

Over the past decade, global credit markets have faced a shifting landscape, marked by a historic low-rate environment, a global pandemic, and a sharp pivot to rising rates and inflation. Through these economic phases, the importance of accurate and timely credit risk assessment has only grown.

This paper provides an updated performance analysis of StarMine's suite of credit risk models, covering the period from January 2021 through November 2025. The suite includes three distinct models, Structural Credit Risk Model (SCR) [1], SmartRatios Credit Risk Model (SRCR) [2], Text Mining Credit Risk Model (TMCR) [3], each designed to capture different dimensions of default and bankruptcy risk, and a Combined Credit Risk Model (CCR) [4], that intelligently combines the output from the three models to generate our best estimate of public company credit risk.

We assess how these models have performed across the post-2020 period, shaped by the COVID-19 pandemic, supply-chain disruptions, and a global tightening cycle. This paper builds on previous performance evaluation that assessed the performance from 2011 to 2020. We find that the StarMine credit risk models have continued to deliver strong predictive performance, reaffirming their value in today's complex credit landscape.

Coverage universe

StarMine's suite of credit risk models covers the global universe of publicly listed companies, including financial institutions, an area often excluded by traditional credit risk models. Each model draws on distinct data inputs, so individual coverage varies based on data availability. The Combined Credit Risk Model (CCR) offers the broadest reach, as it combines the output from the three stand-alone models and only requires input from one of the underlying models to generate a score.

As of November 2025 (see **Figure 1** for coverage over time):

- Combined Credit Risk Model (CCR) covered over 50,000 public companies.
- SmartRatios Credit Risk Model (SRCR) covered over 48,000.
- Structural Credit Risk Model (SCR) covered over 43,000.
- Text Mining Credit Risk Model (TMCR) covered over 34,000.

This broad and layered coverage ensures that the StarMine models remain applicable across a wide spectrum of industries, regions, and market capitalisations. The design enables both depth through complementary data inputs, and breadth, through CCR's union-based scoring approach.

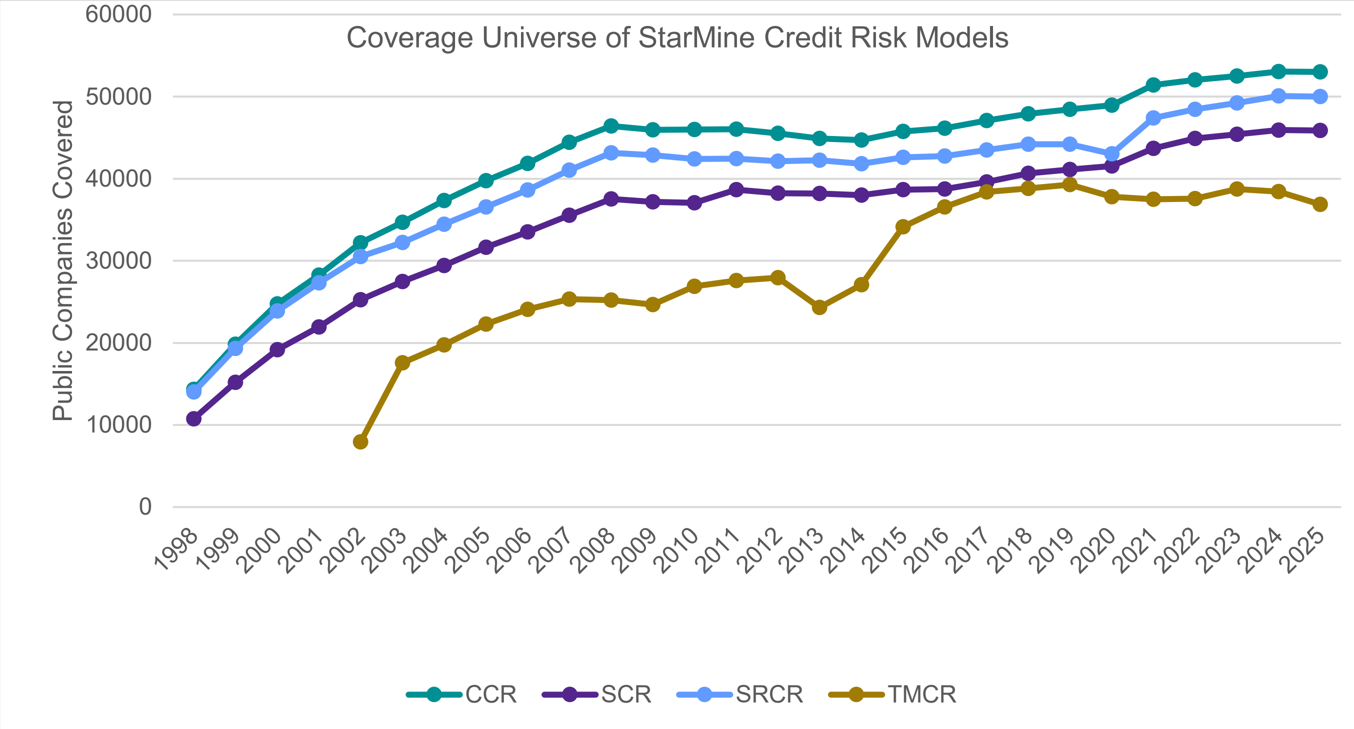

Figure 1. *Coverage universe of the four StarMine credit risk models from 1998-2025.*

Performance measures and benchmark

To evaluate the performance of the StarMine credit risk models, we use the Area Under the Receiver Operating Characteristic Curve (AUC) as our primary metric. AUC values range from 0 to 1, where a value of 0.5 indicates a model with no predictive power (equivalent to random guessing), a value of 1 indicates perfect discrimination between defaulters and non-defaulters, and a value of 0 means the model is wrong every time it makes a prediction (perfectly incorrect).

As in previous analyses, we construct Cumulative Accuracy Profiles (CAP) to compute the AUC. A CAP curve plots the cumulative percentage of actual positive outcomes (defaults) captured by the model as you move through the ranked list of entities (companies) from highest predicted risk to lowest. Full details of the calculation methodology are available in the StarMine Structural Credit Risk Model white paper [1].

In addition to AUC, we assess model performance using a “danger zone” capture rate, which is the proportion of default events that occur within the bottom quintile (20%) of model scores. This metric provides an intuitive sense of how well the model identifies the riskiest firms.

We also compute the Altman Z-score [5] as a benchmark. Still widely used today, the Altman Z-score was developed using discriminant analysis to assess bankruptcy risk, based on a study of 66 U.S. manufacturing firms (33 bankrupt and 33 solvent) from 1946 to 1965. Altman evaluated 22 financial ratios and identified five key indicators representing profitability, leverage, liquidity, solvency, and activity to construct a linear scoring model. The resulting Z-score formula is:

$$Z = \frac{3.3 * EBIT}{Total\ Assets} + \frac{0.999 * Net\ Revenue}{Total\ Assets} + \frac{0.6 * Market\ Cap}{Total\ Liabilities} + \frac{1.2 * Working\ Capital}{Total\ Assets} + \frac{1.4 * Retained\ Earnings}{Total\ Assets}$$

Altman proposed the following interpretation:

- **Z > 3.0**: Low risk of bankruptcy
- **Z < 1.8**: High risk of financial distress
- **1.8 ≤ Z ≤ 3.0**: Grey area; warrants further analysis

It is important to note that the Altman Z-score was developed for manufacturing firms and is generally not applicable to financial institutions.

Performance of StarMine Structural Credit Risk model (SCR)

StarMine SCR is our proprietary extension of the structural default-prediction framework introduced by Robert Merton [6]. The Merton distance-to-default model builds on the Black–Scholes option-pricing framework and models a company's equity as a call option on its assets. In this framework, the probability of default (PD) is the probability that the option expires worthless. As a result, the model provides an estimate of the likelihood that a corporation will go bankrupt or default on its obligations within a given time horizon. StarMine SCR employs a one-year forecast horizon.

The performance of StarMine SCR has remained strong and broadly stable over time, both in terms of AUC and the fraction of default events captured in the bottom quintile of model scores**. Table 1** shows that SCR consistently outperformed the Altman Z-score by a wide margin across all historical windows examined. Because the models look one year ahead, the evaluations from January 2021 to November 2025 come from forecasts made one year earlier.

Area Under the Curve

	StarMine SCR	Altman Z-score	Difference
January 1999 – December 2011	0.89	0.78	0.11
January 2012 – June 2021	0.91	0.82	0.09
January 2021 – November 2025	**0.87**	**0.75**	**0.12**
January 1999 – November 2025	0.90	0.79	0.11

Fraction of default events captured in the bottom quintile

	StarMine SCR	Altman Z-score	Difference
January 1999 – December 2011	82.7%	62.3%	20.4%
January 2012 – June 2021	86.8%	70.7%	16.1%
January 2021 – November 2025	**78.0%**	**70.3%**	**7.7%**
January 1999 – November 2025	84.0%	68.2%	15.8%

***Table 1**. Comparative performance of StarMine SCR and the Altman Z-score from January 2021 to November 2025. Historical data from earlier periods are incorporated from previous model update publications.*

We further break down performance by region and sector in **Table 2**. StarMine SCR delivered its strongest results in North America, Developed Europe, and Emerging Markets. We observed that numerous sectors outperformed the Altman Z-score benchmark by substantial margins.

January 2021 – November 2025

	StarMine SCR	Altman Z-score	Difference
All Regions and Sectors	0.87	0.75	0.12
By Region			
North America	0.93	0.69	0.24
Developed Europe	0.90	0.74	0.16
Developed Asia	0.78	0.73	0.05
Emerging Markets	0.88	0.74	0.14
By Sector			
Energy	0.92	0.79	0.13
Basic Materials	0.83	0.73	0.10
Industrials	0.85	0.74	0.11
Consumer Cyclicals	0.92	0.70	0.12
Consumer Non-Cyclicals	0.96	0.77	0.19
Healthcare	0.85	0.75	0.10
Technology	0.85	0.68	0.17
Telecommunications Services	0.96	0.79	0.17
Utilities	0.97	0.95	0.02

***Table 2**. AUC of StarMine SCR versus the Altman Z-score, by region and sector, from January 2021 to November 2025. We note that, in contrast to prior studies [8], due to the limited number of default events, Japan is not reported separately and is incorporated within the Developed Asia region. Similarly, the default counts for the Telecommunication Services and Utilities sectors were found insufficient for meaningful statistical inference.*

Figure 2 compares the AUC of StarMine SCR versus the Altman Z-score by region, year, and sector between January 2021 and November 2025.

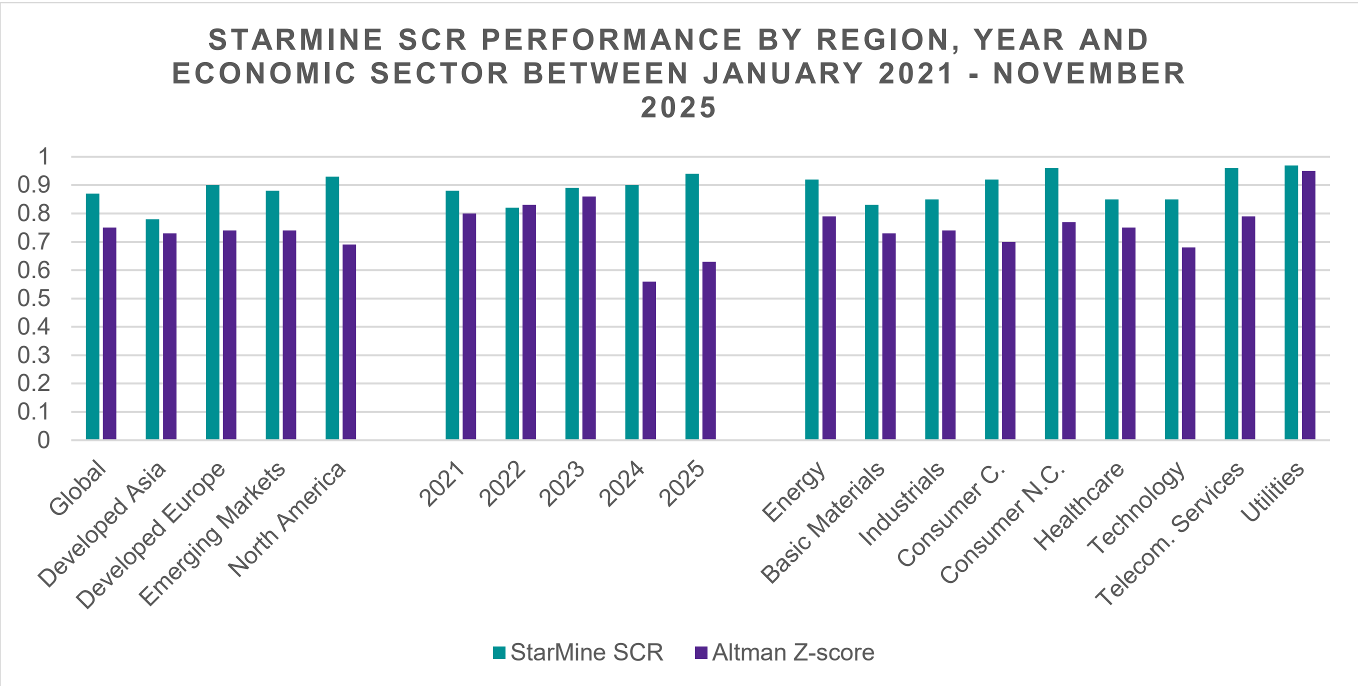

***Figure 2.** AUC of StarMine SCR versus the Altman Z-score from January 2021 to November 2025, decomposed by region, year and sectors.*

Performance of StarMine SmartRatios Credit Risk model (SRCR)

StarMine SRCR analyses a broad set of accounting ratios that are predictive of credit risk. It blends information from both reported financials and forward-looking analyst estimates through StarMine's proprietary SmartEstimates [7]. These ratios, together with industry-specific metrics, are combined in a framework that assigns greater weight to the indicators most relevant for each sector. This approach ensures that sector-specific drivers of financial distress are appropriately captured in the final score.

Table 3 reports the performance summary of StarMine SRCR versus Altman Z-score over all public companies scored by both models globally in different periods.

AUC

	StarMine SRCR	Altman Z-score	Difference
January 1999 – December 2011	0.86	0.76	0.10
January 2012 – June 2021	0.86	0.81	0.05
January 2021 – November 2025	0.81	0.75	0.06
January 1999 – November 2025	0.85	0.78	0.07

Fraction of default events captured in the bottom quintile

	StarMine SRCR	Altman Z-score	Difference
January 1999 – December 2011	75.8%	57.2%	18.6%
January 2012 – June 2021	75.7%	70.4%	5.3%
January 2021 – November 2025	60.6%	69.7%	(9.1)%
January 1999 – November 2025	74.5%	65.1%	9.4%

Table 3. *Comparative performance of StarMine SRCR and the Altman-Z Score from January 2021 to November 2025. Historical data from earlier periods are incorporated from previous model update publications.*

We further break down performance by region and sector in **Table 4**, and **Figure 3** compares the AUC for StarMine SRCR versus Altman Z-score by region, year and sector between January 2021 and November 2025. The performance of StarMine SRCR was adversely impacted in the 2021 to 2023 period, as the efficacy of the fundamental ratio driven signals temporarily weakened amid elevated macroeconomic volatility and as businesses transitioned to a higher interest rate regime. The performance of StarMine SRCR recovered by 2024 as firms returned to more grounded and consistent forward-looking statements.

January 2021 – November 2025

	StarMine SRCR	Altman Z-score	Difference
All Regions and Sectors	0.81	0.75	0.06
By Region			
North America	0.84	0.69	0.15
Developed Europe	0.83	0.74	0.09
Developed Asia	0.74	0.72	0.02
Emerging Markets	0.86	0.74	0.12
By Sector			
Energy	0.80	0.76	0.04
Basic Materials	0.77	0.73	0.04
Industrials	0.88	0.73	0.15
Consumer Cyclicals	0.86	0.70	0.16
Consumer Non-Cyclicals	0.85	0.78	0.07
Healthcare	0.84	0.75	0.09
Technology	0.87	0.68	0.19
Telecommunications Services	0.79	0.78	0.01
Utilities	0.62	0.95	(0.33)

Table 4. *AUC of StarMine SRCR versus the Altman Z-score, by regions and sectors from January 2021 to November 2025. We note that, in contrast to prior studies [8], due to the limited number of default events, Japan is not reported separately and is incorporated within the Developed Asia region. Similarly, the default counts for the Telecommunication Services and Utilities sectors were found insufficient for meaningful statistical inference.*

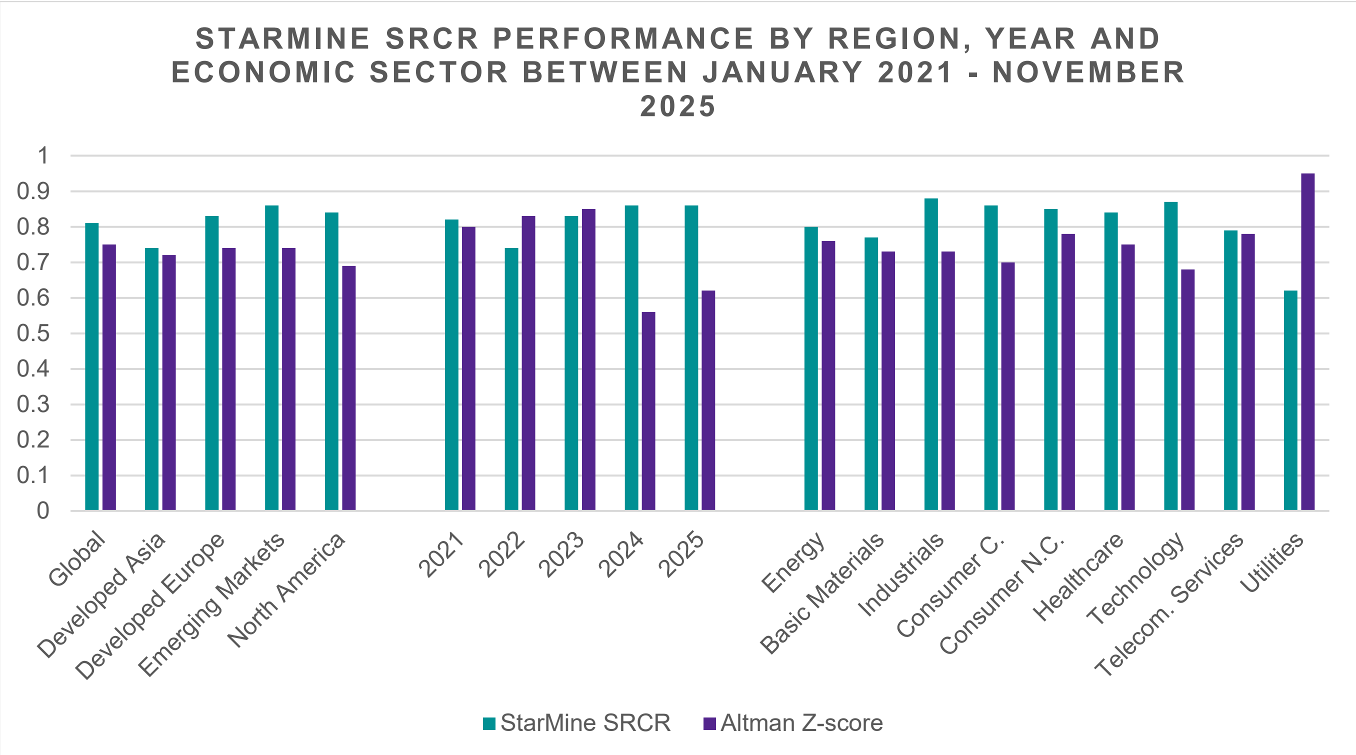

Figure 3. *AUC of StarMine SRCR versus the Altman Z-score from January 2021 to November 2025, broken down by region, year and sectors.*

Performance of StarMine Text Mining Credit Risk model (TMCR)

StarMine TMCR assesses the default risk of publicly traded companies by systematically evaluating the language in Reuters news, StreetEvents conference call transcripts, corporate filings (10-K, 10-Q and 8-K) and select research documents from participating brokers to predict which firms are likely to come under financial distress, and which are likely to thrive. For more details regarding the data availability in each region, please review the TMCR model whitepaper [3]. **Table 5** summarises the overall performance of StarMine TMCR (for observations with coverage on three or more StarMine TMCR components) versus the Altman Z-score. Performance of StarMine TMCR remained essentially unchanged throughout the years both in terms of AUC as well as the fraction of default events captured in the bottom quintile. StarMine TMCR consistently outperformed the Altman Z-score, gaining the widest margin between January 2021 and November 2025 compared to previous model performance updates.

AUC

	StarMine TMCR	Altman Z-score	Difference
January 2004 – December 2011	0.91	0.82	0.09
January 2012 – June 2021	0.90	0.85	0.05
January 2021 – November 2025	0.86	0.76	0.10
January 2004 – November 2025	0.90	0.82	0.08

Fraction of default events captured in the bottom quintile

	StarMine TMCR	Altman Z-score	Difference
January 2004 – December 2011	86.4%	70.5%	15.9%
January 2012 – June 2021	85.1%	77.2%	7.9%
January 2021 – November 2025	76.7%	69.2%	7.5%
January 2004 – November 2025	84.3%	74.1%	10.2%

Table 5. *Comparative performance of StarMine TMCR and the Altman Z-score from January 2021 to November 2025. Historical data from earlier periods are incorporated from previous model update publications.*

Table 6 breaks down AUC of StarMine TMCR (for observations with coverage on three or more StarMine TMCR components) versus the Altman Z-score by region and sector. StarMine TMCR consistently performed better in North America, as the U.S. financial filings and North American event-transcript coverage are the most comprehensive. Technology and Consumer Cyclicals are among the top performing sectors of StarMine TMCR.

January 2021 – November 2025

	StarMine TMCR	Altman Z-score	Difference
All Regions and Sectors	0.86	0.76	0.10
By Region			
North America	0.85	0.73	0.11
Ex-North America	0.79	0.81	(0.02)
Sector			
Energy	0.86	0.92	(0.06)
Basic Materials	0.90	0.96	(0.06)
Industrials	0.85	0.75	0.10
Consumer Cyclicals	0.93	0.71	0.22
Consumer Non-Cyclicals	0.86	0.74	0.12
Healthcare	0.86	0.74	0.12
Technology	0.91	0.67	0.23
Telecommunications Services	0.73	0.95	(0.22)
Utilities	0.99	0.97	0.02

Table 6. *AUC of StarMine TMCR versus the Altman Z-score, by regions and sectors from January 2021 to November 2025. We note that, in contrast to prior studies [8], due to the limited number of default events, Japan is not reported separately and is incorporated within the Developed Asia region. Similarly, the default counts for the Telecommunication Services and Utilities sectors were found insufficient for meaningful statistical inference.*

Figure 4 compares the AUC of StarMine TMCR versus the Altman Z-score by region, year and sector between January 2021 and November 2025.

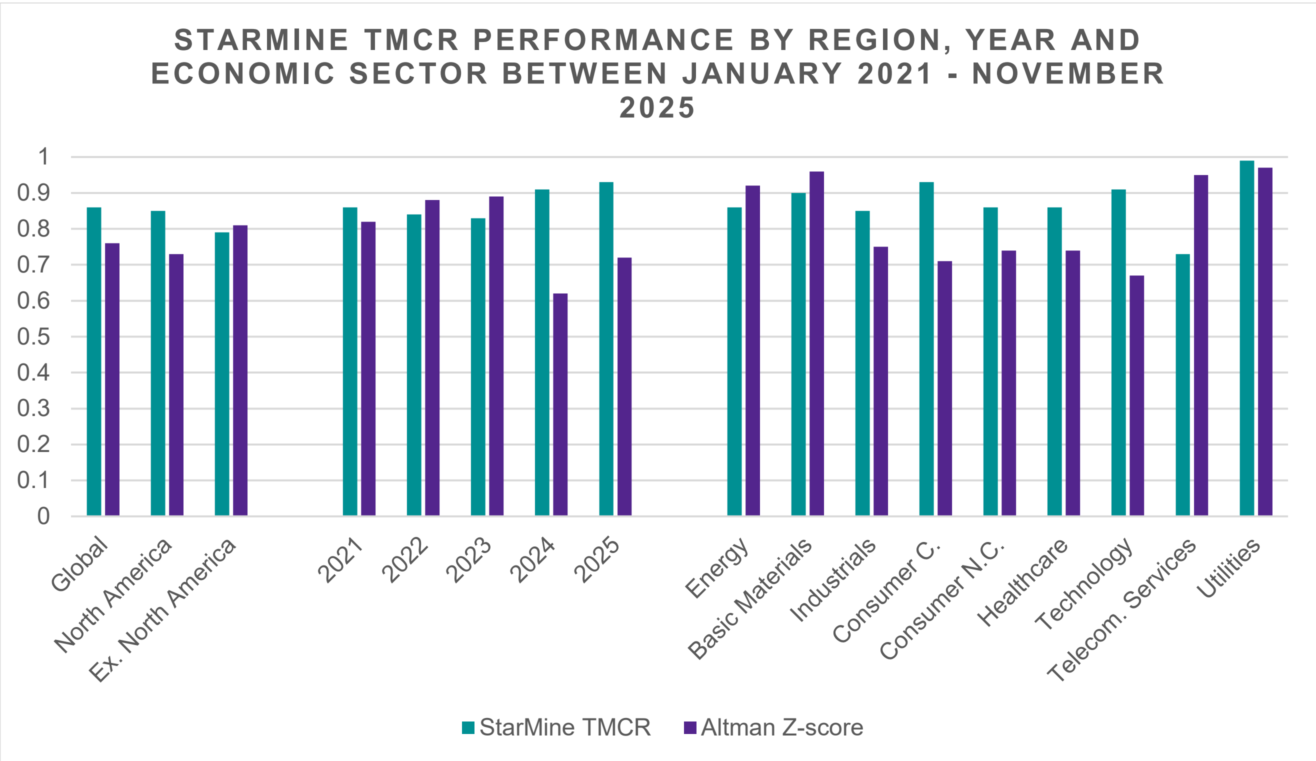

Figure 4. *AUC of StarMine TMCR versus the Altman Z-score from January 2021 to November 2025, broken down by region, year and sectors.*

Performance of StarMine Combined Credit Risk model (CCR)

StarMine CCR has the largest scored public company universe among all StarMine credit risk models. It intelligently combines the power of StarMine's three credit risk models, SCR, SRCR, and TMCR, to generate our single, final estimate of public company credit risk.

Table 7 summarises the overall performance of StarMine CCR versus the Altman Z-score. Performance of StarMine CCR remained essentially unchanged throughout the years both in terms of AUC as well as the fraction of default events captured in the bottom quintile. StarMine CCR consistently outperformed the Altman Z-score by a wide margin.

AUC

	StarMine CCR	Altman Z-score	Difference
January 1999 – December 2011	0.91	0.76	0.15
January 2012 – June 2021	0.91	0.81	0.10
January 2021 – November 2025	0.87	0.75	0.12
January 1999 – November 2025	0.90	0.78	0.12

Fraction of default events captured in the bottom quintile

	StarMine CCR	Altman Z-score	Difference
January 1999 – December 2011	85.7%	57.5%	28.2%
January 2012 – June 2021	85.9%	70.3%	15.6%
January 2021 – November 2025	76.7%	70.2%	6.5%
January 1999 – November 2025	85%	65.1%	19.9%

Table 7. *Comparative performance of StarMine TMCR and the Altman Z-score from January 2021 to November 2025. Historical data from earlier periods are incorporated from previous model update publications.*

Table 8 breaks down AUC of StarMine CCR versus the Altman Z-score by region and sector. StarMine CCR consistently performed better in Emerging Markets, North America and Developed Europe. Consumer Cyclicals, Consumer Non-Cyclicals and Technology were among the top performing sectors of StarMine CCR.

January 2021 – November 2025

	StarMine CCR	Altman Z-score	Difference
All Regions and Sectors	0.87	0.75	0.12
By Region			
North America	0.92	0.69	0.23
Developed Europe	0.88	0.74	0.14
Developed Asia	0.76	0.72	0.04
Emerging Markets	0.90	0.74	0.16
By Sector			
Energy	0.89	0.77	0.12

Basic Materials	0.83	0.73	0.10
Industrials	0.88	0.72	0.16
Consumer Cyclicals	0.91	0.69	0.22
Consumer Non-Cyclicals	0.95	0.77	0.18
Healthcare	0.87	0.75	0.12
Technology	0.89	0.69	0.20
Telecommunications Services	0.94	0.78	0.16
Utilities	0.94	0.95	(0.01)

Table 8. *AUC of StarMine CCR versus the Altman Z-score, by regions and sectors from January 2021 to November 2025. We note that, in contrast to prior studies [8], due to the limited number of default events, Japan is not reported separately and is incorporated within the Developed Asia region. Similarly, the default counts for the Telecommunication Services and Utilities sectors were found insufficient for meaningful statistical inference.*

Figure 5 compares the AUC of StarMine CCR versus the Altman Z-score by region, year and sector between January 2021 and November 2025.

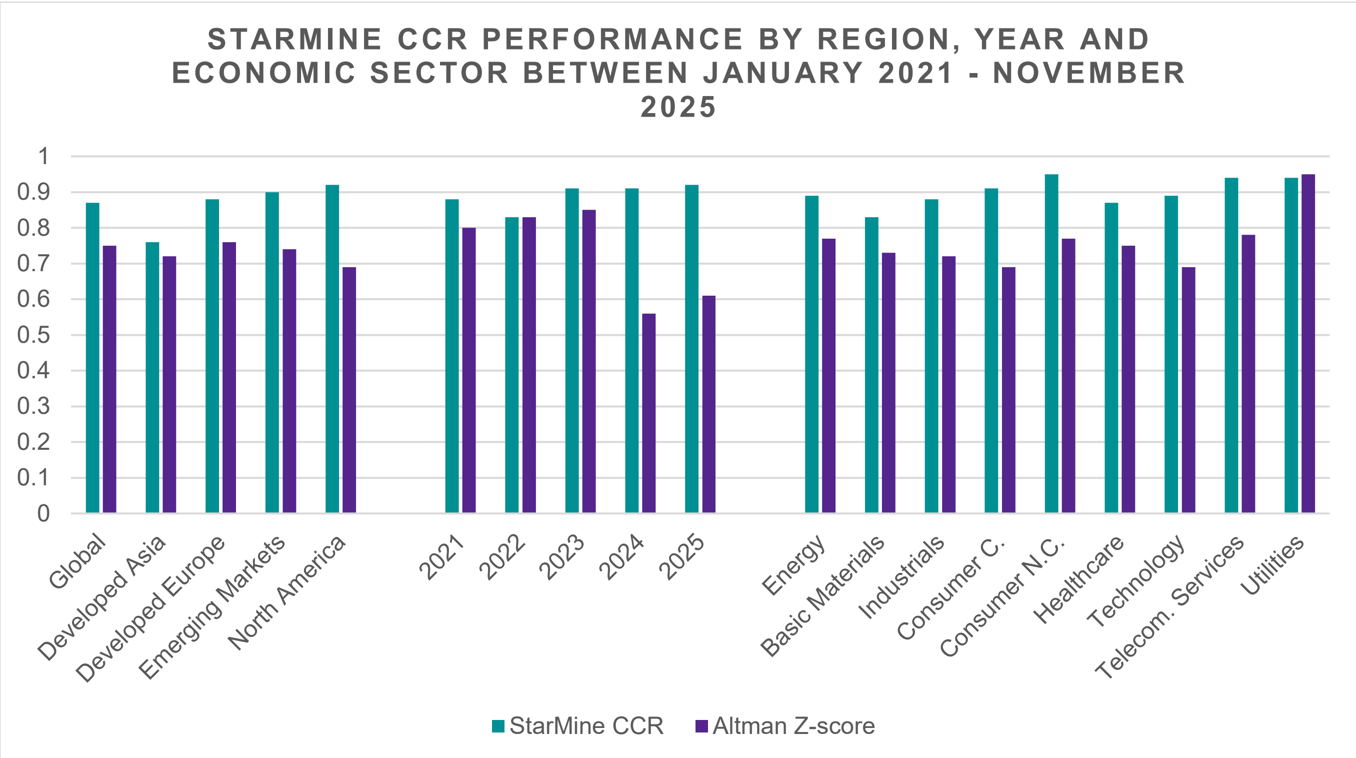

Figure 5. *AUC of StarMine TMCR versus the Altman Z-score from January 2021 to November 2025, broken down by region, year and sectors.*

A case study on StarMine ratings versus agency ratings

Many investors are accustomed to the letter rating scales commonly employed by the rating agencies. By examining the historical distribution of agency ratings on a common universe of companies, we map StarMine default probabilities to letter ratings such that the distribution of StarMine ratings is consistent with the distribution of agency ratings. This ensures that a difference in rating between StarMine and a rating agency is due to differences in assessment of credit risk, rather than simply differences in distributions of ratings.

Once StarMine default probabilities are mapped to letter ratings, a natural question arises: “What happens when the agency rating and the StarMine rating differ significantly? Who follows whom?” To examine this, **Table 9** summaries the result from a case study using StarMine CCR over the period from January 1999 to November 2025.

The results in **Table 9** show that whenever agency rating and StarMine CCR model implied ratings differ by six or more notches, our definition of a significant divergence representing roughly 15% of observations, in at least 70% of the times agency ratings remain unchanged over next 12 months. However, if the agency ratings do move, it is found to move towards StarMine CCR implied rating at least 81% of the time over the next 12 months. Therefore, when a material disagreement occurs, agency ratings are five to six times more likely to move toward the StarMine CCR rating than away from it. This behaviour suggests that StarMine CCR can serve as a useful leading indicator of agency rating changes, analogous to the well-established relationship between the StarMine SmartEstimate and earnings surprises [7].

Change in agency rating	Move towards StarMine CCR rating	Move away from StarMine CCR rating	% of movers that move towards StarMine CCR rating	No change	Move towards StarMine CCR rating more often than move away
in the next one month	2.94%	0.48%	85.74%	96.64%	6.13x
in the next three months	8.10%	1.43%	84.99%	90.46%	5.66x
in the next six months	14.92%	2.81%	83.77%	82.66%	5.30x
in the next 12 months	23.89%	5.44%	81.45%	70.65%	4.39x

Table 9. *When the agency rating differs significantly from the StarMine CCR rating, the agency rating ends up moving towards the StarMine CCR rating in more than 81% of the cases. The sample set represents all global companies with both StarMine CCR and agency rating data available over the period from January 1999 to November 2025.*

Discussion

The comparative performance of the StarMine credit risk models from 2021 to 2025 highlights key differences in how each model captures credit risk, particularly during periods of market disruption and recovery.

Structural Models: SCR & SRCR

During and after the COVID-19 pandemic, the **SCR** and **SRCR** models, both structurally driven and reliant on market fundamentals, tended to overpredict defaults, especially in the 2021- 2022 forecast horizon. This overprediction is largely attributable to the exceptional market volatility in 2020-2021, when equity valuations and asset dynamics were distorted. These models, by design, could not fully account for the unprecedented scale of fiscal stimulus and policy intervention, which temporarily decoupled fundamental signals from actual default outcomes.

Similarly, **SRCR** underperformed during this period due to ongoing uncertainty in corporate fundamentals as businesses adjusted to pandemic-era operations, shifting government incentives, and long-term risk restructuring. Like SCR, its structural nature made it less responsive to short-term policy-induced market distortions.

Text-Based Model: TMCR

In contrast, the **TMCR** model, based on textual analysis of corporate disclosures and analyst reports, performed strongly in 2021. It benefited from rich, differentiated language as companies communicated outlooks in an uncertain environment. As noted by Loughran and McDonald (2011) [9], sentiment-based signals tend to be most effective in bifurcated markets.

Although performance dipped in 2022, it rebounded by 2024 as market sentiment normalised, and firms returned to more grounded forward-looking statements.

Combined Model: CCR

The **CCR** model maintained a stable and strong performance throughout the period. By combining multiple model types, it offers a diversified view of credit risk and demonstrated resilience even during periods of heightened economic stress.

Key insights

The overall analysis from 2021 to 2025 shows a clear distinction:

- **Structural models** (SCR, SCRC) are more sensitive to fundamental financial indicators.
- **Text-based models** (TMCR) offer a near real-time view of market sentiment.
- **Hybrid models** (CCR) balance both, showing the highest consistency and robustness.

As noted by S&P Global (2022) [10], global default rates remained below long-term averages during and after the pandemic, despite record rating downgrades—underscoring the stabilising role of fiscal support. Similarly, an IMF working paper (2021) [11] observed that public distance-to-default measures improved not due to operational resilience, but due to government-induced balance sheet support.

Data limitations

By 2023, all models had largely returned to pre-pandemic performance levels, signalling the normalisation of market conditions. However, limitations in the dataset remained a challenge. Insufficient data for certain countries such as Japan and sectors such Telecommunication Services and Utilities during this period constrained the robust statistical analysis.

Conclusion

In the 2021-2025 period, StarMine's suite of credit risk models demonstrated strong performance, with each model offering distinct advantages across varying market conditions.

- **Structural models** such as **SCR** and **SRCR** performed well under normal market conditions but were more prone to overprediction during periods of extreme fiscal intervention, such as the COVID-19 pandemic.
- The **TMCR** model, driven by sentiment extracted from corporate disclosures and analyst reports, excelled in volatile and uncertain environments where market language diverged from financial fundamentals.
- The **CCR** model, which integrates the complementary signals of all component models, proved to be the most robust across sectors and regions, offering resilience during both stable and stressed periods.

Across the full period, **StarMine credit models consistently outperformed the benchmark Altman Z-score** in predicting one-year default or bankruptcy risk across more than 50,000 public companies globally.

The top performer, **StarMine CCR**, achieved an **average AUC of 0.87** and **captured 76.7%** of default events in the bottom quintile of scores, compared to **0.75 AUC** and **70.2%** capture for the Altman Z-score.

This sustained outperformance confirms the **continued effectiveness of StarMine models** as tools for:

- Assessing credit and counterparty risk.
- Informing equity selection and portfolio risk management.
- Supporting fixed-income security selection and valuation.

As credit markets continue to evolve, the **diversified architecture of the StarMine model suite** - combining structural, market, and sentiment-based approaches - positions it well to deliver **reliable, forward-looking credit risk insights** in both normal and stressed conditions.

Current StarMine credit-model scores are available in LSEG Workspace platform and as daily data feeds. Historical point-in-time scores are also available for those who wish to backtest the models.

Acknowledgement

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