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Robustness analysis in an augmented credit rating for SMEs

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Executive Summary

Small and Medium-sized Enterprises (SMEs) play a crucial role in economic systems, driving employment and growth. As the regulatory emphasis on sustainability increases, alongside the mandatory production of sustainability reports for listed SMEs, the need for comprehensive credit rating models, incorporating both financial and Environmental, Social, and Governance (ESG) criteria, has become critical.
To address these factors, this policy brief presents key insights from the study "*Robustness analysis in an augmented credit rating for Small and medium-sized enterprises*", by S. Angilella, M. Doumpos, S. Mazzù, M.R. Pappalardo, and C. Zopounidis (2025). The study proposes an augmented credit rating methodology for SMEs, using the sigma-mu efficiency analysis, proposed by Greco et al. (2009), and enhanced by Angilella et al. (2024).
A key contribution of this study is an extended robustness analysis of both the sample composition and evaluation criteria, to ensure the model's reliability in identifying financial and ESG factors that contribute to SMEs' risk exposure.
The empirical analysis, conducted on 569 listed SMEs from Refinitiv Eikon (2018–2022) and supported by these robustness checks, confirms that variations in these elements have minimal impact on final benchmark ratings, which are based on the classification systems of major rating agencies. This brief summarizes the study's methodology, key findings, and policy recommendations offering deeper insights into the financial stability, resilience and long-term sustainability of SMEs.

Context and Importance of the Issue

SMEs, which account for 99.8% of European enterprises, are vital to the economy but face challenges in sustainability reporting due to financial constraints, lack of expertise, and insufficient regulatory incentives. While the European Commission's Corporate Sustainability Reporting Directive (CSRD) mandates ESG reporting for listed SMEs by 2027, non-listed ones remain largely unregulated. Despite this, strong ESG performance is increasingly a prerequisite for securing funding and maintaining business partnerships. To support sustainable growth, there is the need for a comprehensive methodology that integrates financial and ESG indicators into a unified evaluation tool. The proposed "augmented credit rating" model addresses this need by accounting for uncertainty and variability in stakeholder preferences, providing investors and policymakers a more holistic and adaptive assessment of SME creditworthiness.

Figure 1 illustrates the distribution of the dataset used for this study, which includes 569 SMEs observed over five years (2,845 observations), by size, sector and country of incorporation. The sample is well distributed across size categories, with the largest proportion (39.19%) classified as medium-sized. The healthcare sector dominates the sample (48.68%), followed by energy (13.71%) and information technology (12.13%). Geographically, the sample is skewed toward the U.S. (71.88%), due to better data availability, stricter reporting requirements, and the historical focus of Refinitiv (our source of data) on US markets (ESMA, 2022).

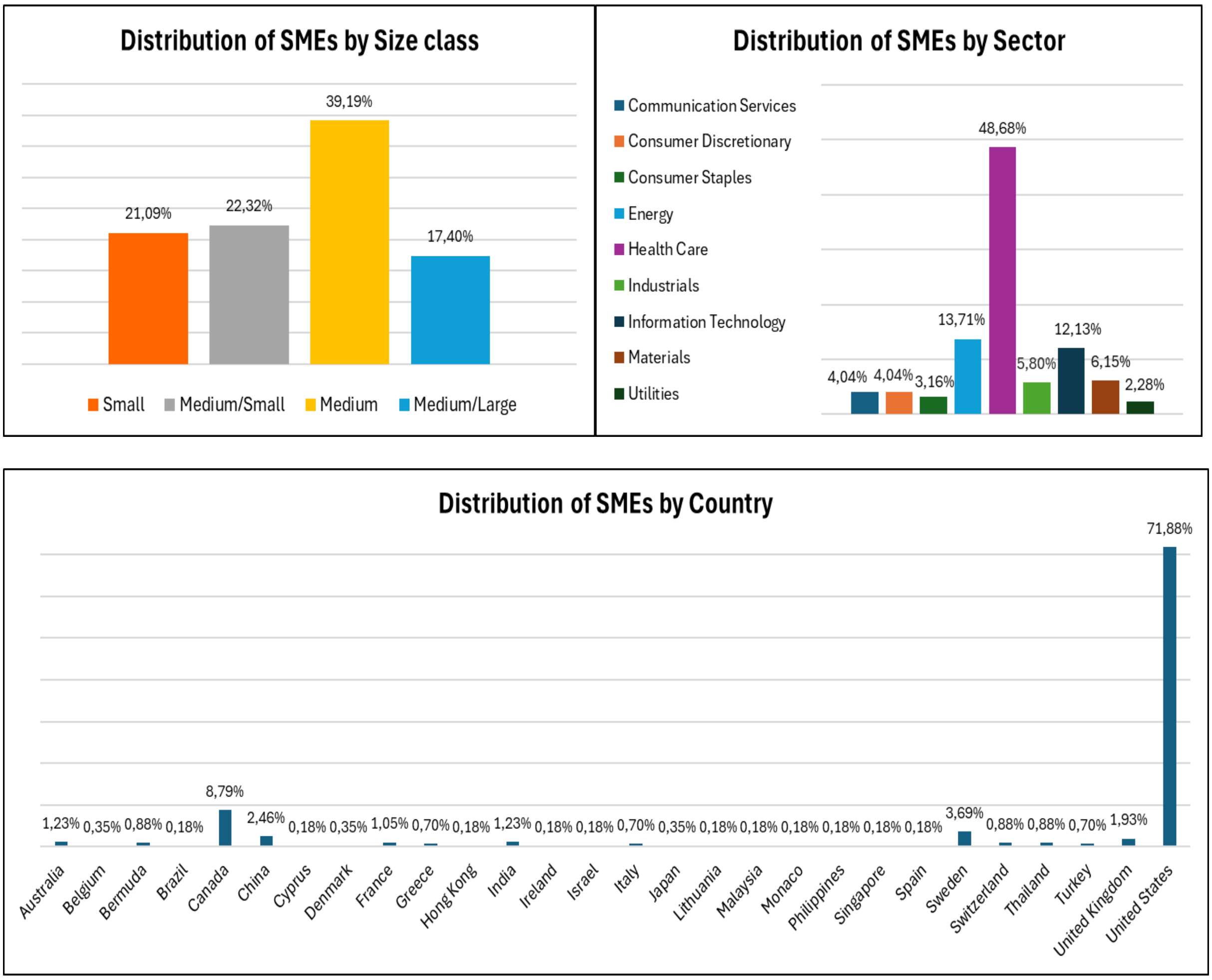

Figure 1.: Distribution of SMEs by size, sector and country.

Methodology and key findings

This study proposes an augmented credit rating methodology that combines multi-criteria efficiency analysis with robustness testing to classify SMEs into risk categories and evaluate the model's stability to changes in sample composition and evaluation criteria. Key steps involve:

1. **Score generation and classification:** SMEs are evaluated using sigma-mu efficiency analysis, yielding normalized efficiency scores ($\bar{s_x}$). These scores are then grouped into risk categories using the Freedman-Diaconis formula (Freedman and Diaconis, 1981), which determines optimal classification thresholds on the scores' distribution.
2. **Credit Risk Categorization:** Each SME a_x is assigned to a credit risk class C_p with the rule:
$$a_x \in C_p \Leftrightarrow b_{p-1} \leq \bar{s_x} < b_p$$
where $1 \geq b_1 > b_2 \cdots > b_q \geq 0$ are the classification thresholds.
3. **Robustness testing** performed on:
    a) **Sample composition:** the study generates 100 random subsamples of SMEs, with sizes ranging from 25% to 90% of the full dataset. The ratings from each subsample are compared to the benchmark ratings of the full dataset to assess stability.
    b) **Evaluation criteria:** Factor analysis is conducted to identify the most influential financial and ESG indicators. Two sets of criteria, "*Trial 1*" and "*Trial 2*," are used to examine how sensitive the ratings are to different variable selections.
4. **Stability measurement:** Bhattacharyya Coefficient (BC) (Bhattacharyya, 1943) is used to assess how similar the distribution of ratings in each subsample is to the benchmark model. A coefficient closer to 1 indicates higher robustness and stable performance of the classification model across various samples and criteria.

The key findings of this study focus on:

1. **SME Credit Rating Distribution:** In Trial 1, the annual distribution of SMEs across rating classes do not exhibits a perfectly symmetrical bell shape but instead show a slight positive skewness. Most SMEs fall within the B- to BB- range, indicating a moderate level of credit risk. Extreme ratings (AAA to A and CCC to D) are rare, reflecting that few SMEs have extremely high or low risk (Figure 2).

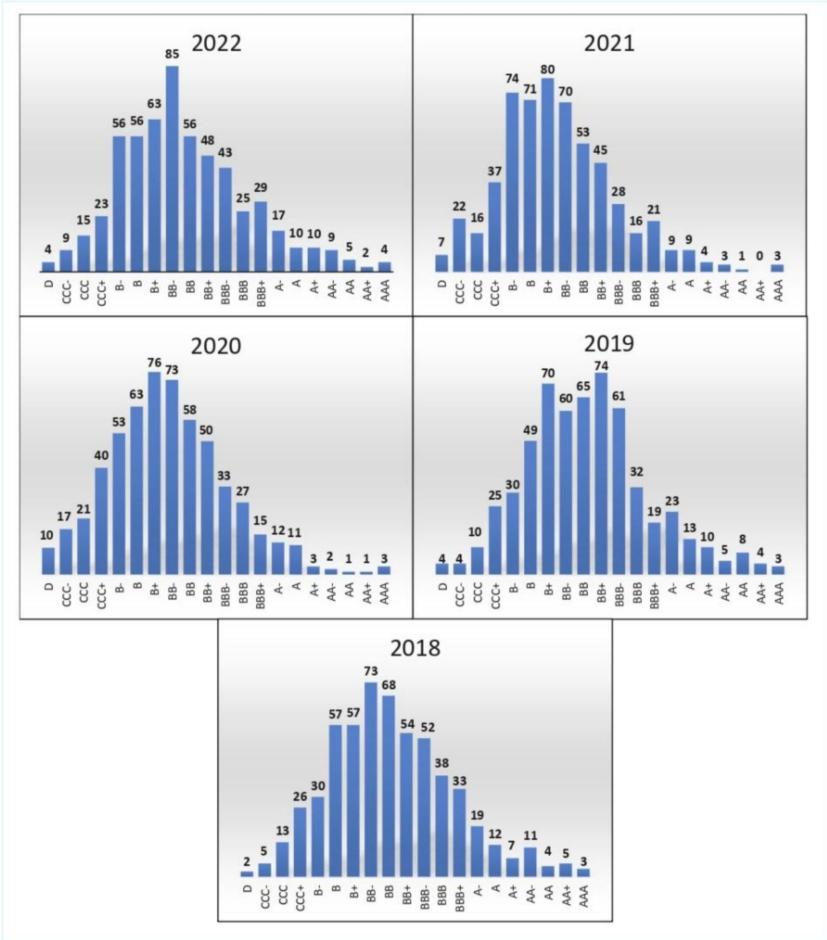

Figure 2:: Distribution of SMEs by rating class based on the bin intervals for Trial 1 across years.

Robustness of the Model: The robustness testing of 100 subsamples using different sample sizes (25%, 50%, 75%, and 90%) show that in Trial 1, almost all subsamples (99 out of 100), generated using 25% of the sample, exhibit strong similarity to the benchmark distribution (Table 1, left side). A different pattern emerges in Trial 2 where few subsamples (30 out of 100) generated using 25% of the sample fall within the highest similarity class 0.95 ≤ BC < 1, while a larger share (52 out of 100) lies in the range 0.90 < BC ≤ 0.95 (Table 1, right side), pointing to greater deviations from the benchmark distribution, potentially influenced by factors such as country trends or sector-specific risks. Furthermore, the BC summary statistics in Table 2 supports the stability and reliability of the proposed methodology across different sample sizes, especially in Trial 1, with consistently high average BC values ($0.9745 \leq \mu_{BC} \leq 0.9985$) and low standard deviations ($0.0019 \leq \sigma_{BC} \leq 0.0107$).

Table 1:: Distribution of the 100 subsamples created using 25%, 50%, 75% and 90% of the total sample across similarity classes based on BC values in Trial 1 and Trial 2, 2022.

	Trial 1				Trial 2			
	Subsample				Subsample			
BC Range	25%	50%	75%	90%	25%	50%	75%	90%
[0.95, 1)	*99*	*100*	*100*	*100*	*30*	*74*	*95*	*98*
[0.90, 0.95)	*1*	*0*	*0*	*0*	*52*	*24*	*5*	*2*
[0.75, 0.90)	*0*	*0*	*0*	*0*	*16*	*1*	*0*	*0*
[0, 0.75)	*0*	*0*	*0*	*0*	*2*	*0*	*0*	*0*

Table 2:: Summary statistics of the BC across the 100 subsamples created using 25%, 50%, 75% and 90% of the total sample in Trial 1 and Trial 2, 2022.

	Trial 1				Trial 2			
BC Summ	Subsample				Subsample			
Statistic	25%	50%	75%	90%	25%	50%	75%	90%
Min	0.9497	0.9780	0.9862	0.9915	*0.7169*	*0.8945*	*0.9142*	*0.9196*
Mean	0.9745	0.9902	0.9958	0.9985	*0.9266*	*0.965*	*0.9849*	*0.9937*
Max	0.9912	0.9985	0.9991	0.9997	*0.9927*	*0.9985*	*0.9993*	*0.9998*
St. Dev.	0.0107	0.0046	0.0032	0.0019	*0.0469*	*0.0250*	*0.0206*	*0.0145*

1. **Stability Across Trials**: A comparison between Trial 1 and Trial 2 reveals minimal rating variations for most SMEs in 2022, with 75.92% of SMEs experiencing rating shifts within 0–4 notches. Only 1.76% of SMEs display significant changes (greater than 10 notches), indicating a high level of consistency between the two trials (Figure 3 and Table 3).

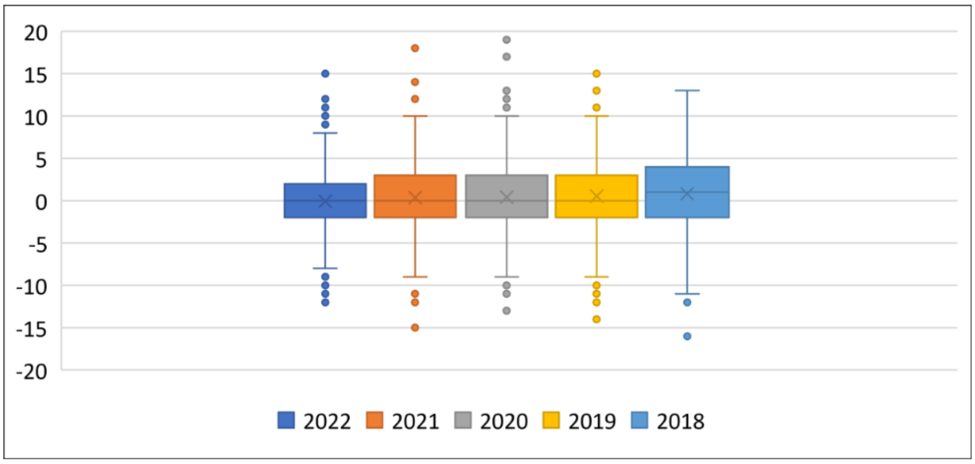

Figure 3:: Year-to-Year rating variation between Trial 1 and Trial 2.

Table 3:: Percentage variation of rating notches between the two trials by year.

Notches difference	*2022*	*2021*	*2020*	*2019*	*2018*	*Mean*
0-4	75.92%	79.09%	74.87%	74.17%	67.31%	74.27%
5-10	22.32%	19.68%	22.85%	24.08%	30.23%	23.83%
>10	1.76%	1.23%	2.28%	1.76%	2.46%	1.90%

Policy Options and Analysis

Option 1: Integrate ESG factors into credit rating models

- Analysis: the study highlights that adopting ESG practices helps SMEs mitigate risks, access better financing opportunities and gain competitive advantages. The proposed sigma-mu efficiency analysis, which combines financial data with ESG criteria, offer a more comprehensive assessment of SME creditworthiness.
- Policy Implications:
  - ESG factors help identify long term risks that traditional financial metrics may overlook.
  - Integrating ESG factors enhances the predictive power of credit ratings, allowing regulators and investors to detect those non-financial risks that may compromise a firm's long-term stability and competitiveness.

Option 2: Promote robust, stakeholder-inclusive credit ratings for SMEs

- Analysis: The proposed methodology employs Stochastic Multi-Attribute Acceptability Analysis (SMAA) (Lahdelma et al., 1998; Lahdelma and Salminen, 2001) to address uncertainty in stakeholder preferences regarding criteria weights. This allows the model to reflect a wide range of potential perspectives. Robustness testing across sample sizes and evaluation criteria further confirms the model's high stability and reliability effectively accounting for varying stakeholder views.
- Policy Implications:
  - Regulators can encourage its adoption in sectors where stakeholder interests are different, such as in public-private partnerships or SME financing.
  - By incorporating different perspectives, this model can reduce errors in risk evaluation and contribute to greater overall financial system stability.

Option 3: Develop a Publicly Available ESG-Financial Benchmarking Platform for SMEs

- Analysis: The study highlights that, while the European CSRD mandates ESG reporting for listed SMEs by 2027, non-listed SMEs remain largely unregulated. As a result, many SMEs lack insight into how their ESG and financial performance compare to peers, creating a gap in comprehensive ESG credit ratings.
- Policy Implications:
  - A benchmarking platform based on the proposed models could help SMEs compare their ESG and financial performance with others, promoting transparency and providing reliable data for better decision-making and improved access to finance.
  - The platform would encourage SMEs to voluntarily assess and enhance their ESG practices, without waiting for regulatory mandates.

Recommendations

1. **Strengthening ESG integration in Credit Rating Models**
   - Regulatory and financial institutions should encourage the adoption of ESG-inclusive models, like the proposed sigma-mu efficiency analysis, to improve SME credit evaluations.
   - Revise regulatory guidelines to incorporate ESG factors, enabling banks to make more responsible lending decisions that account for environmental, social, and long-term risk considerations.
2. **Enhance stakeholder representation in credit rating methodologies**
   - Create rating systems where different people and organizations (such as banks, companies, regulators) can take part, so that SME credit scores are more equitable, comprehensive, and reliable.
   - Promote the use of SMAA to reflect diverse stakeholder preferences in credit risk models.
3. **Build an accessible ESG-Financial benchmarking platform**
   - Develop a publicly available benchmarking platform to help SMEs compare ESG and financial performance.
   - Foster public-private partnerships to ensure data reliability, user accessibility, and long-term platform sustainability.

Implementation Considerations

1. **Support Data Collection and Model Adoption**
   - Create simple ESG reporting tools and clear instructions that match SME needs.
   - Offer training and technical assistance to help SMEs and credit analysts apply the proposed model effectively.
2. **Ensure Inclusivity and Transparency in Rating Processes**
   - Establish stakeholder engagement mechanisms to define relevant criteria and preferences in credit models.
   - Introduce checks, such as regular audits, to ensure the rating system remains fair, unbiased and credible.
3. **Enable secure and flexible digital infrastructure**
   - Make the benchmarking tool simple to use, secure, and flexible to future regulations.
   - Ensure strong data protection and regularly update the system to keep it accurate and reliable.

Conclusion

With sustainability becoming increasingly important in finance, SMEs must evolve to stay competitive and secure the funding they need. To provide a more accurate and forward-looking assessment of SME creditworthiness, this policy brief introduced an augmented credit rating approach that integrates financial and ESG factors. The model's reliability and flexibility are demonstrated through various tests on sample composition and evaluation criteria. This helps investors, financial institutions, and governments make more informed and responsible decisions. Encouraging the use of these models, along with inclusive processes and easily accessible comparison tools, can drive long-term economic growth, strengthen SMEs' resilience, and align financial practices with sustainability goals.

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