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The Omega Score, a novel SME default predictor developed by Altman et al. (2022), combines indicators related to financial ratios, payment behavior, management and employees variables that play an important role in predicting SME defaults. Built with machine learning techniques and rich dataset information, the Omega Score can be used to categorize an SME into one of the following three groups: Healthy, Moderate-risk, and High-risk. The Omega Score can be leveraged by financial institutions to reduce lending errors and minimize loan defaults, support policymakers in implementing effective restructuring policies, assist credit analytics firms in assessing creditworthiness, assist investors in allocating funds, and asset managers to support decision-making processes.

Keywords: Omega Score; Default prediction modeling; small and medium-sized enterprises; machine- learning techniques

Introduction

The prediction of SME default risk holds a significant place in the management and finance literature (Altman, 1968; Altman et al., 2017). Improving SME default prediction can generate several benefits for a variety of stakeholders. For lenders, it can minimize potential non-performing loans, reduce their default risk, and maximize profits on credit activities. Improving SME default prediction can also help financial institutions reduce lending errors and minimize loan defaults.

Moreover, effective SME default predictors can support policymakers in implementing effective restructuring policies. They can assist credit analytics firms in accurately assessing creditworthiness and provide valuable insights for investors in allocating funds. Asset managers can also use these predictors as a tool to support decision-making processes and select appropriate firms for their portfolios. Effective SME default predictors can also support public and private investors in allocating funds, and entrepreneurs to access funds (Altman, 2017).

Altman et al. (2022) use a combination of machine learning techniques and an early event to classify an SME as defaulted[1] to develop a new SME default predictor – the Omega Score - which combines traditional financial ratios and payment behavior variables with management- and employee-related variables such as the change in management, the firing ratio, and the mean employee tenure.

As the analysis suggested, the inclusion of management- and employee-related variables improves the SME predictive accuracy as these groups of variables entail a set

[1] An SME is deemed in default when its bank account is blocked for a period of 30 or 60 days due to their inability to fulfill payment obligations to creditors, including suppliers, financial institutions, and the government.

of information that is not captured by financial indicators and payment behavior variables in the assessment of SME defaults.

Management- and employee-related variables exert an incremental role in predicting SME defaults, even in presence of indicators coming from financial statements, creditworthiness analysis, and a number of potential controls. Out of the 164 variables analysed in Altman et al. (2022), 8 of the most significant variables were selected, which allow for an accurate prediction of financial difficulties experienced by SMEs.

The Omega Score specific formula for the 60-day blockage takes the following form:

Omega Score = Set 1{0.003 * Days of debtors' change - 0.328 * Retained earnings / Total assets – 0.617 * Quick ratio – 0.695 * Surplus dummy} +

Set 2{0.621 * Number of short creditor payment defaults} +

Set 3{0.626 * Firing ratio - 0.029 * Mean employee tenure} +

Set 4{0.395 * Change in management}

Omega Score Groups = Alpha (Omega Score ≤ 0.007) – Healthy SME

Beta (Omega Score > 0.007 & Omega Score ≤ 1.626) – Moderate risk SME

Gamma (Omega Score > 1.626) – High-risk SME

Omega Score specific formula for the 30 days blockage takes the following form:

Omega Score = Set 1{0.154 * Days of clients' change - 0.299 * Personnel costs/gross profit – 0.585 * Quick ratio + 0.002 * Days of debtors' change – 0.594 * Surplus dummy} +

Set 2{0.798 * Number of short creditor payment defaults}

+

Set 3{0.583 * Firing ratio - 0.029 * Mean employee tenure}

Omega Score Groups = Alpha (Omega Score ≤ 0.564) – Healthy SME

Beta (Omega Score > 0. 564 & Omega Score ≤ 0.931) – Moderate risk SME

Gamma (Omega Score > 0.931) – High-risk SME

The variables mentioned above can be transformed into logically formulated questions to assess the firm with which one intends to conduct business. These inquiries can assist the entrepreneur in enhancing their risk assessment process. Specifically, every business decision made by the entrepreneur can be evaluated by simulating its impact on the evaluation model, such as the Omega Score. Despite the common wisdom of conducting case-by-case assessments for complex decisions, particularly those within business environments, the responses presented in Table 1 are grounded upon the analysis of a large sample of SMEs, on which the development of the Omega Score is grounded.

Table 1. Interpreting the Omega Score

Question		Responses Interpreting the Omega Score
1	How does the reporting of a profit/loss in the income statement affect default risk?	Positive business performance is associated with a lower likelihood of financial difficulties.
2	What is the trend of the ratio of retained earnings to total assets?	A higher ratio is associated with a lower likelihood of financial distress, as it suggests that a firm can generate more retained earnings with a given amount of assets.
3	What is the trend of the *current ratio*?	The current ratio, calculated as the ratio of current assets minus inventories to current liabilities, provides information on the firm's ability to meet its short-term obligations without selling inventory. A higher ratio is often indicative of a lower probability of financial difficulties.
4	What is the trend *of days payables outstanding*?	This metric shows the average number of days a firm needs to settle its obligations to suppliers. A lower coefficient indicates more regular and faster payments and a lower likelihood of financial difficulties, while a higher coefficient is associated with a higher probability of financial distress.
5	If the firm has a history of *broken promises to creditors*?	The existence of previous blockages is associated with higher likelihood of future financial difficulties.
6	What is the trend *of employee turnover in the firm*?	Is the number of people leaving the firm growing? Higher employee turnover is associated with a higher likelihood of financial distress. If the number of employees leaving the firm is growing, this can indicate financial distress, even if the total number of employees remains the same. Employee turnover can be caused by various factors, such as unsatisfactory working conditions, poor hiring practices, or a lack of confidence in the firm's future.
7	What is the *average seniority of employees in the firm*?	A longer average tenure of employees is associated with a lower probability of financial difficulties.

8	Has the firm changed a member of management in the last two years?	Even if in some cases a change in management can be positive, such as when bankruptcy plans or pre-bankruptcy settlements remove ineffective managers, the departure of managers can also be a negative sign and raise concerns, such as the firm's inability to retain key personnel or a lack of confidence in its future. Similarly to *the turnover of employees in the firm*, more negative interpretations are possible, for example, the departure of managers could be attributed to a perceived lack of growth opportunities or to the firm's inability to retain them. Overall, as our formula suggests, a change in management is generally associated with increased financial difficulties.

The study by Altman et al. (2022) has significant implications for creditors, entrepreneurs, and managers of SMEs, as well as potential investors, policymakers, and rating agencies evaluating SME default risks. Small entrepreneurs can use the Omega Score to gauge the default risk of new SME clients and to monitor their ongoing relationships with existing customers and key suppliers. Early identification of financial difficulties allows creditors to reduce credit exposure to high-risk firms, either by reducing payment terms or by requesting immediate payment upon delivery, thus preventing a contagion in the supply chain and benefiting all stakeholders in the economy.

Banks and rating agencies should incorporate qualitative variables related to human capital into their internal rating models. Governments can benefit from the study in several ways. Firstly, the Omega Score can be used to predict default in SME tax credits, allowing governments to estimate expected tax revenue in a probabilistic manner. Secondly, the model can be used to screen for default risk in SMEs and set up procedures for preventing default and establishing appropriate rescue plans.

The early identification of high-risk SMEs is especially relevant in EU countries where debtors consider business bankruptcy a personal failure, causing a fear of failure that discourages early reporting (Danaux, 2016). Preventive measures taken at early stages of SME financial difficulties can have positive effects for all stakeholders, increasing the probability of resolving the crisis and keeping the SME active (Cultrera, 2020). Several European countries have developed dedicated tools to support SMEs in difficulty, such as “Early Warning” in Denmark, “TEAM U” in Germany, “Dyzo” or “Ced-W” in Belgium, and “Early Warning Europe” founded by seven European countries in 2016. The Omega Score and the suggested procedure for developing an SME default model can be valuable tools in early identification of SMEs at high risk of financial difficulties.

The next sections of this paper are organized as follows. First, we briefly discuss the theoretical background related to default predictors, then we illustrate how the Omega Score has been developed, also providing additional considerations on default definition. After that, we discuss each of the four components of the Omega Score and how the simultaneous incorporation of different types of variables increases the predictive power of the Omega Score. We end up with few concluding remarks and summarizing key potential implications of our work.

Theoretical background

Over the years, many articles propose variations of the original Altman Z-Score[2], with the aim of improving its predictive power. For instance, to further enhance default prediction accuracy, some scholars have integrated financial indicators with variables related to payment behavior. This new group of variables has proven to be significant, adding relevant (and non-overlapping) information that increases the predictive power of default predictors that are based solely on financial indicators. This supports the notion

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[2] . The first version of the Z Score comprehended five financial ratios: Working Capital/Total Assets, Retained Earnings/Total Assets, EBIT/Total Assets, Market Value Equity/BV of Total Debt and Sales/Total Assets (Altman, 1968).

that default processes are gradual, with creditors' promises being broken prior to actual default. As an example, Norden and Weber (2010) found in their study that credit line usage and cash flows in a borrower's checking accounts provide banks with additional information on default risks.

Studies on default predictions have consistently shown that credit information plays a crucial role in debt contracting and has a direct impact on a firm's default risk. For example, Laitinen (1999) and Back (2005) found empirical support for their hypothesis that integrating financial and non-financial information in default predictive models increases their predictive power in their analyses of Finnish firms. Similarly, Turetsky and McEwen (2001) found in their analysis of US firms that payment delays are positively associated with higher default risk. Wilson, Summers, and Hope (2000) also found in their analysis of UK firms that integrating credit-related variables with financial information significantly increases default prediction accuracy compared to default models that adopt financial figures only. In fact, past payment dynamics are important in predicting future payments (and related default risks) for several reasons. For example, a firm with a bad reputation regarding past payment dynamics can lead financial institutions to claim back granted loans and ask for more financial guarantees before granting additional loans. As a result, firms with a bad reputation about past payment dynamics may have more difficulties accessing funds, which increases their likelihood of default. Moreover, when financial institutions have information about a firm's recent payment history, they can rely on this information, in addition to financial statement analysis (which is often available only several months after the end of the financial year), to assess solvency. These arguments and empirical relationships are not limited to large corporations and have also been supported in the study of SMEs (e.g., Ciampi, 2015; Ciampi, Cillo, & Fiano, 2018).

Interestingly, Balcaen and Ooghe (2006) noted in their review that default predictions were mainly based on univariate models, risk index models, MDA (Multiple Discriminant Analysis) models, and conditional probability models. Despite some scholars discussing the potential of alternative techniques (e.g., Agarwal & Taffler, 2008; Bauer & Agarwal, 2014; Campbell et al., 2008), the Z-Score and its derivatives continue to be widely adopted as the prevailing or supporting tool for default predictions (Altman et al., 2017).

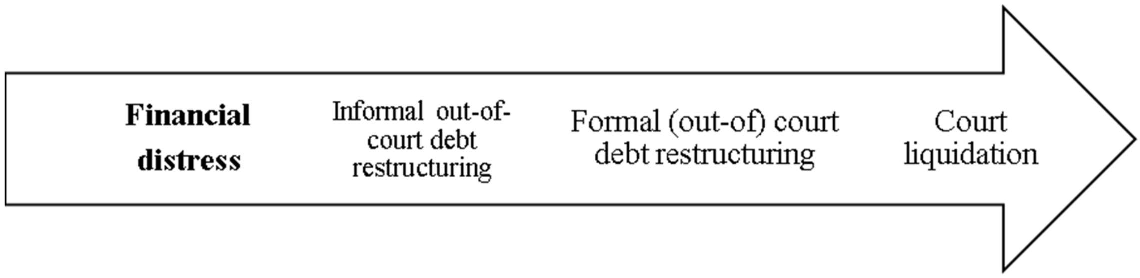
Building on these premises, and considering the limited attention given to SMEs compared to large corporations, Altman et al. (2022) developed a novel and accurate SME default predictor: the Omega Score, which simultaneously incorporates financial ratios, payment behavior, management and employees variables.

How the Omega Score has been developed

We employed two alternative dependent variables to capture SME default events. The blockage date, which is either 30 or 60 days after a payment violation, was used to construct our SME default indicators and to create a timely history of creditor payment defaults. An SME bank account becomes blocked when the debtor fails to repay debts to creditors, such as suppliers, banks, or the government, on the due date.

Our SME default definition encompasses defaults to bank loans, as well as default payments to suppliers and taxes, and is defined earlier than the Basel III criteria. This enables us to be an earlier indicator of financial difficulties in bank-firm relationships and in commercial transactions and tax credits from the government perspective, giving additional time for a rescue plan, for suppliers to adjust their strategies, or for banks to estimate their risk exposures earlier. This definition of default is similar to the "Unlikely to Pay" loan classification by banks, but it also includes events associated with defaults in commercial relationships.

Figure 1. Timeline of a usual firm unwillingly starting bankruptcy



Note: A pessimistic scenario is outlooked. A firm might cease operations also due to financial distress, unfavorable economic conditions, or different factors.

The analysis included 164 variables. To simulate a real-time out-of-sample prediction exercise, we divided the training and test samples by years, with the test sample being in later years. We employed the least absolute shrinkage and selection operator (LASSO) method, which performs regularization and variable selection, to select the most important predictors (Tibshirani, 1996; Coad & Srhoj, 2020). We ran LASSO on financial indicators only, financial indicators and payment behavior variables, financial indicators, management, and employee-related variables, and all variables together, tracking prediction performance metrics each time. The final list of variables selected when using all variables was used to build an Omega Score using discriminant analysis.

The independent variables were divided into four main groups: financial indicators, payment behavior variables, management-related variables, and employee-related variables. The first group was based on administrative data on SMEs' financial information for the period 2014-2019 from FINA, including 87 different variables related to balance sheets, income statements, interest rate risk exposure, liquidity, and financial leverage (Altman et al., 2017; Giannozzi et al., 2013). The second group consisted of six payment behavior variables, including the number of times a firm had a bank account blocked and the duration of the blockage. The third group consisted of 33 management-related variables, such as management board gender composition, manager age, management experience, and changes in management. The fourth group consisted of 21 employee-related variables, such as the mean employee tenure, firing and hiring ratio, share of work contracts (full and part time), and share of higher-educated employees.

Eight categories of control variables were also considered: internationalization, innovation, relational capital/public contract and political connections, firm size, age, industry, region, and year. In total, 17 variables were considered as potential controls, including firm demographics, exports, export and import intensity, firm age, investments in R&D, intangible assets, sector, and region, as well as variables related to relational capital/public contract and political connections.

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The four components of the Omega Score

The importance of financial indicators and payment behavior variables in the academic debate has been well-established. Financial indicators have been deemed crucial for effective default predictions as they reflect a firm's operations and financial stability (Altman et al., 2017). Meanwhile, payment behavior variables have been discussed in the context of the gradual process of default, highlighting the impact of a poor debt reputation or broken creditor promises on the overall default risk (Norden & Weber, 2010).

However, recent advances in machine learning techniques have shown that management and employee-related variables also play a significant role in the Omega Score, adding to its predictive power. Management-related variables, such as board composition and CEO influence, are central to the strategic direction of a firm and can impact its survival chances, particularly in the case of small and medium-sized enterprises (SMEs) (Aguilera et al., 2008; Dowell et al., 2011). Employee-related variables, such as employee turnover and diversity, can also have a significant impact on a firm's performance and long-term viability (Zhang, 2020; Gardner, 2005). Recent studies show that the recruitment of qualified personnel is one of the most critical issues in business contexts (Duke Fuqua School of Business, 2022), and employee turnover has been indicated as a non-negligible variable determining default risk (Securities and Exchange Commission, 2019).

It is important to note that neither management nor employee-related variables can be captured solely by financial indicators and payment behavior variables, as they provide information on the link between firms and their management boards, as well as the recruitment and retention of qualified personnel. The simultaneous incorporation of these four groups of variables is likely to further improve SME default risk models.

The simultaneous incorporation of variables to increase the predictive power of the Omega Score

The results reported by Altman et al. (2022) demonstrate improvement in the prediction performance of financial indicators when enriched with payment behavior variables and employee and management-related variables. The improvement is likely due to the fact that similar accounting numbers can indicate diverse situations for SMEs.

This is particularly the case for SMEs, for which one does not have market, but only accounting variables, which do not capture information on investors' expectations of a firm's prospects. SME default, as shown by Altman et al. (2022), is typically a gradual process where defaulted SMEs have already failed to fulfil previous obligations and have managed to rectify those failures.

Employee and management-related variables provide additional information that is not observable in accounting data and are related to factors such as the firm's "future thinking" and employee satisfaction with the work environment. If employees are dissatisfied or do not see a positive future for the firm, they may leave, and this information is captured by these variables. Thus, Altman et al. (2022) show improvement in the prediction performance metrics. Specifically, employee tenure and the employee fire ratio are shown to improve prediction, though it is important to note that the employee fire ratio is not the same as a change in employment. For example, an SME with ten employees can have a high fire ratio but no change in the number of employees if in two consecutive years the firm has ten employees, but these ten are completely different individuals in each year.

The Omega Score also shows that a step-down from a key member of management in SMEs is usually a negative sign for the firm, which may indicate that the management member does not see a positive future for the SME or that the SME has difficulty retaining management. These findings should be interpreted with caution, keeping in mind that the event being predicted is SME default, which is not bankruptcy, but an early warning of financial difficulties.

Conclusions

Altman et al. (2022) has demonstrated that incorporating both management and employees' characteristics in models with financial ratios and payment behaviour can enhance small and medium-sized enterprises (SMEs) default predictions, thereby reducing lending errors and minimizing potential non-performing loans. Their results show that the share of terminated work contracts, employee tenure, and changes in management significantly and incrementally improve SME default prediction.

The Omega Score, introduced in the study of Altman et al. (2022), serves as an effortless indicator of SME health and can be used by lenders, creditors, governments, and the SMEs themselves to calculate the probability of default in commercial transactions, bank loans, and tax liabilities. Also, Altman et al. (2022) contribute to the ongoing discussion about the need to revamp banks' internal rating models, by prioritizing qualitative variables such as the expertise of managers and employees, their skills, and overall human and relational capital. These variables play a crucial role in strengthening SMEs' resilience in crisis and their ability to thrive in a highly competitive business environment.

However, it should be noted the study of Altman et al. (2022) is not free from limitations. Most importantly results are based on several administrative datasets and 167 variables, but stemming from a single country. Nonetheless, the study's objective was to identify the added value of a large number of non-financial variables in SME default prediction, and to propose a methodology combining LASSO, MDA, and machine learning techniques to improve model accuracy. The findings on the importance of human capital can be tested in other countries as SMEs in different regions share the importance of human capital. In any event, the Omega Score can be replicated or re-calibrated using different national data, and the BIS definition of "*Unlikely to Pay*" loans provides European banks with a similar early definition of default as used in Altman et al. (2022).

Video materials

Research minute
A one-minute video introduction with Professor Edward I. Altman reflecting on the full paper published in the *Journal of Small Business Management*.
https://vimeo.com/776562515

Interview on developing Omega Score

A 24-minute video interview with Professor Edward I. Altman on developing Omega Score for SME default prediction.
https://www.youtube.com/watch?v=a7YrrSeKPzU&t=7s

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