The Relationship Between Risk Management And Firm Efficiency in the Georgian Manufacturing Industry: A Data Envelopment Analysis Approach

Vakhtang Berishvili [1]

[1] *Caucasus University*
1 Paata Saakadze St, Tbilisi, 0102, Georgia

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Corresponding Author:
Vakhtang Berishvili

Abstract. This study explores the relationship between corporate risk management (RM) practices and firm efficiency in the Georgian manufacturing sector—an area where empirical evidence remains scarce. While the theoretical value of RM is widely recognised, its measurable impact on how firms use resources to produce economic outputs has received limited attention, particularly in emerging economies.

The research applies a two-stage analytical approach. In the first stage, the researchers assessed the relative efficiency of 105 Georgian manufacturing firms in 2021 using Data Envelopment Analysis (DEA) under both Constant Returns to Scale (CCR) and Variable Returns to Scale (BCC) models, in both input- and output-oriented forms. The researchers tested seven model specifications that incorporated financial indicators such as assets, expenses, equity, debt, and income. A specialised two-stage DEA further separated operational efficiency (transforming resources into sales) from financial efficiency (turning sales into profit).

In the second stage, efficiency scores were regressed on comprehensive RM disclosure scores (ranging from 0 to 10) derived from the ISO 31000 and COSO ERM frameworks. The analysis found no statistically significant relationship between RM scores and DEA-based efficiency measures across any of the tested models.

The DEA results revealed significant heterogeneity in performance, with a wide dispersion of efficiency scores across the sample. The two-stage DEA indicated that, on average, firms were less efficient at converting sales into net income than at generating sales from initial inputs. However, overall, the findings suggest that within Georgia's manufacturing industry, formal risk management systems—at least as reflected in disclosure quality—do not have a clear or direct link to short-term operational or financial efficiency.

Keywords: Manufacturing industry companies' efficiency; Risk management; Data envelopment analysis; Efficient use of resources.

INTRODUCTION

In today's uncertain global business environment, firms' ability to identify, assess, and respond to risks has become essential for maintaining sustainable performance. Events such as the 2008 global financial crisis, the COVID-19 pandemic and recent geopolitical disruptions have increased firms' vulnerability if risk management (RM) is weak or reactive. For manufacturing companies with significant capital investment needs and complex supply chains, strong risk management practices may be vital for maintaining stability and competitiveness.

Although RM is in focus of both corporate strategies and academic research, its direct impact on firm efficiency remains unclear. Traditional financial indicators, like return on assets or profitability margins, measure performance outcomes but not the efficiency with which firms transform resources into results. Data Envelopment Analysis (DEA) provides a robust framework to fill this gap. The authors of [1] introduced DEA, which enables researchers to evaluate the relative efficiency of firms (decision-making units, DMUs) without estimating production functions. It assesses efficiency by comparing single or multiple inputs and outputs simultaneously, determining which firms operate on the "best practice frontier" or how "far" they are from it.

This study employs DEA to assess the relative efficiency of manufacturing firms in Georgia using both the CCR and BCC [1, 2] models, under both input- and output-oriented assumptions.

Despite the extensive use of DEA in performance measurement across industries and regions, little research has examined its relationship with firms' risk management practices. Most prior studies have focused on financial institutions (e.g., banks or insurance companies) or on developed economies, where data availability and governance frameworks are stronger [3]. Research on manufacturing efficiency primarily examines technological or productivity factors; this creates a clear empirical gap - particularly in the context of emerging markets - regarding whether firms that invest in RM actually demonstrate better efficiency.

Existing literature provides mixed evidence on the relationship between RM and firm performance. Some studies argue that RM enhances decision-making and resource allocation, thereby improving performance and long-term value creation [4, 5]. Others report non-significant or even negative relationships, suggesting that excessive control and bureaucratic risk procedures may reduce quick-response capability and innovation [6]. Therefore, empirical evidence from distinct industrial and institutional contexts remains necessary to clarify the true impact of RM systems. The novelty of this research lies in its integration of DEA-based efficiency analysis with firm-level RM assessment in the manufacturing sector of an emerging economy.

This study, therefore, has two aims: first, to measure the operational efficiency of Georgian manufacturing firms using DEA; and second, to test whether firms with stronger RM systems, as measured by RM scores based on disclosures, are more efficient. The main question is:

Do Georgian manufacturing firms with stronger risk management systems exhibit higher operational efficiency compared to those with weaker risk management practices?

The study contributes to both academic and applied areas by assessing how governance and management systems influence firm efficiency in emerging economies.

Literature Review

Data Envelopment Analysis (DEA) emerged as a widely used nonparametric frontier analysis method for measuring the relative efficiency of comparable decision-making units (DMUs) that convert inputs into outputs. The classic CCR model, introduced by authors [1], established DEA's linear programming approach and the concept of an efficient frontier against which DMUs are assessed. A DMU sitting on the frontier is considered technically efficient and is assigned a score of 1, while others are assigned scores between 0 and 1, indicating their distance from the frontier [1]. Building on CCR, the BCC model dropped the constant returns-to-scale assumption and allowed variable returns to scale, recognising that internal and external factors affecting DMUs may vary. This distinction enables separating pure technical efficiency (managerial performance) from scale efficiency (the effect of unit size) [2]. The methods have expanded further (e.g., slack-based measures (SBM) that directly account for input/output slacks, directional/RDM approaches to accommodate negative data, and super-efficiency variants for ranking frontier units) [7].

DEA can be implemented in either input orientation (minimising inputs for a given output level) or output orientation (maximising outputs for given inputs). The orientation chosen should reflect managerial control: firms able to adjust inputs (cost reduction) are suited to input-orientation; those constrained in inputs but seeking to increase outputs (sales/profits) are suited to output-orientation [8]. Practical applications often run both orientations and both CCR/BCC models to test robustness [9].

While DEA is robust for measuring nonparametric efficiency, several methodological caveats and refinements are needed for applied researchers.

First, when outputs (or inputs) can be negative or include undesirable measures, directional distance functions and RDM or modified SBM approaches are preferable because they avoid ad hoc data shifting [10].

Second, a common empirical practice is the "two-stage" approach: estimate DEA efficiency scores at stage one, then regress those scores on environmental or managerial variables (stage two) to identify determinants of efficiency [11].

For modelling efficiency scores (which are proportions bounded in (0,1)), econometric methods appropriate for fractional responses are recommended: authors [12] fractional logit provides a direct approach to model conditional means constrained to (0,1) and is widely used in DEA second-stage analysis when scores include values strictly within the interval.

DEA has been applied extensively to manufacturing sectors at the firm, plant, and industry levels to evaluate efficiency and productivity change (Malmquist index) [13] and to identify best-practice frontiers. Recent industry-level and firm-level DEA studies show that manufacturing efficiency varies widely across countries and subsectors and that efficiency estimates are sensitive to model specification (inputs/outputs chosen, orientation, returns to scale) [14]. Empirical DEA work in manufacturing often selects inputs such as total assets, labour, operating expenses, and capital, and outputs such as sales, value added, EBIT or net income [15]. Multi-model testing (e.g., running alternative I/O specifications and comparing CCR/BCC and orientations) is a recommended robustness strategy because DEA scores can change substantially with different variable choices [9].

The literature linking risk management to firm financial performance is extensive. Meta-analytical and empirical studies show consistent but heterogeneous evidence: many studies find a positive association between formal Enterprise RM (ERM) practices and performance measures (ROA, market value, lower cost of capital), but results vary by institutional context, industry, firm size, and the exact ERM measures used [16]. Recent papers argue that ERM enhances value primarily through improved strategic decision making, reduced volatility, and better capital allocation - mechanisms that can improve efficiency as measured by DEA [17]. Several empirical investigations in emerging and transition economies report positive links between ERM and firm-level performance, frequently conditional on complementary capabilities (e.g., information systems, governance) and moderated by supply-chain resilience or technology adoption. Thus, the hypothesis that stronger RM systems are associated with higher technical or profit efficiency is supported in principle, although empirical magnitudes and significance vary [18].

Relatively few papers have directly linked DEA efficiency scores with risk management indicators. Typical approaches estimate DEA efficiencies and then employ second-stage regressions to test whether governance or risk variables explain cross-DMU differences [19]. A specific strand of the literature examines manufacturing firms' disclosures and risk governance practices: several country-level studies find that firms with more structured risk reporting or board-level risk committees tend to exhibit better operational metrics (e.g., cost control, asset turnover) and, in some cases, better frontier-efficiency scores. However, results are context-dependent - industry structure, regulation and firm heterogeneity matter; this motivates the present country-focused (Georgia) manufacturing application: local institutional features may condition how RM translates into observable efficiency gains.

Based on the literature review, the researchers developed several aspects of the research design.

First, because DEA scores are model-sensitive, running multiple I/O specifications and both CCR/BCC and input/output orientation offers robustness checks and richer interpretation.

Second, when linking efficiency to managerial variables (here: Risk Management score), researchers should use second-stage methods appropriate for fractional dependent variables (e.g., fractional logit or beta regression) [11, 12].

Third, two-stage or network DEA formulations are valuable when production occurs sequentially (resources-sales-profit), which aligns with the multi-stage tests conducted.

Finally, local-context studies (country- or industry-specific) add value because ERM effects on efficiency are moderated by governance, market, and regulatory regimes [20, 21].

The two most widely recognised ERM standards are ISO 31000:2018 and the COSO ERM Integrated Framework (2017). Both outline how to design and implement effective risk management systems and emphasise embedding risk management into decision-making processes [22, 23]. The COSO ERM Framework introduces 20 principles, grouped into five components: Governance and Culture, Strategy and Objective-Setting, Performance, Review and Revision, and Information, Communication, and Reporting. Similarly, ISO 31000:2018 defines eight guiding principles—including integration, customisation, inclusivity, and continual improvement—as the foundations of effective risk management. Both frameworks highlight the importance of top management support and risk culture in successful ERM implementation [24]. The Chief Risk Officer (CRO) also plays a crucial role; research shows CRO presence is a key determinant of ERM adoption [5, 25, 26]. For instance, authors [27] found that 86.3% of firms with established ERM frameworks had a CRO. Additionally, establishing a Risk Management Committee (RMC) strengthens oversight compared to assigning this role solely to the Audit Committee. The RMC enhances board effectiveness in managing risk and fosters more sophisticated monitoring practices [28].

METHOD

Overview of the Analytical Approach. This study employs Data Envelopment Analysis (DEA) to evaluate companies' relative efficiency based on financial measures, followed by a fractional logit regression to examine the relationship between efficiency scores and firms' Risk Management (RM) scores. The methodology quantifies how effectively companies convert their available financial resources into performance outcomes and examines whether this effectiveness is systematically related to their disclosure of risk management practices. The analytical process consisted of two main stages:

1) DEA efficiency estimation across seven different model specifications, and

2) Regression analysis of the efficiency results against risk management scores.

The researchers performed the DEA computations in both R and Python to ensure computational reliability and reproducibility. They used R to run DEA models across multiple input–output configurations and Python to validate and verify the results. The researchers also conducted regression analyses in R using the betareg package, which is suitable for modelling data in the 0-1 range.

Data and Variables. The researchers obtained Risk Management disclosure scores by analysing the financial statements and management reports of first- and second-category manufacturing firms in Georgia for 2021, which are available on the official website at https://reportal.ge. The analysis was based on ISO 31000:2018 and the COSO ERM Integrated Framework. The methodology applied may be reviewed in the authors' paper [16]. Scores range from 0 to 10. The researchers used the same sources to obtain financial data for the inputs and outputs in the DEA analysis.

The final dataset includes 105 companies operating within the selected industry scope. However, due to data limitations and negative financial values (e.g., firms reporting losses in a given indicator), the number of decision-making units (DMUs) differs slightly across datasets. In each DEA test, companies with negative input or output values were excluded to maintain the theoretical assumptions of the DEA framework. As a result, the number of DMUs analysed in each test varies.

DEA models can be oriented either toward inputs or outputs, depending on the managerial context:

1) Input-oriented models focus on minimising input usage while maintaining the same level of output. This perspective is appropriate when firms are constrained in their ability to expand production, but can potentially optimise internal efficiency by reducing waste or resource use.

2) Output-oriented models, conversely, focus on maximising output for a given level of input. This orientation is relevant when firms have fixed resources but seek to enhance performance outcomes, such as revenue or profit.

The financial indicators used in this study include Net Income, EBIT (Earnings Before Interest and Taxes), Sales Revenue, Operating Expenses, Total Assets, Equity, and Debt. The researchers selected these variables to capture the main aspects of financial performance and resource utilisation. And capital structure. Each DEA model used a distinct combination of these indicators to reflect alternative perspectives on operational and economic efficiency.

In total, the researchers constructed seven datasets (models) as follows:

Model 1: Inputs – Operating Expenses, Total Assets; Output – Sales Revenue (105 DMUs).

Model 2: Inputs – Operating Expenses, Total Assets; Output – EBIT (86 DMUs).

Model 3: Inputs – Operating Expenses, Total Assets; Output – Net Income (89 DMUs).

Model 4: Inputs – Sales Revenue, Total Assets; Output – Net Income (89 DMUs).

Model 5: Inputs – Equity, Debt; Output – Net Income (89 DMUs).

Model 6: Input – Total Assets; Output – Net Income (89 DMUs).

Model 7: Inputs – Operating Expenses, Total Assets; Outputs – Sales Revenue, Net Income (89 DMUs).

The seventh model was further analysed using a two-stage DEA to understand better the transformation of inputs into intermediate and final outputs.

Data Envelopment Analysis (DEA) Model. For each dataset, the researchers constructed the corresponding DEA model by defining input and output matrices. They then calculated efficiency scores for all DMUs under both CCR and BCC models, using both input- and output-oriented specifications.

The DEA computations were carried out in R, using the Benchmarking and deaR packages. Each DEA run generated an efficiency value for every DMU.

Two-Stage DEA. To further explore the transformation process between intermediate and final performance stages, a two-stage DEA was applied to the seventh dataset. In this model, Operating Expenses and Total Assets serve as initial inputs; Sales Revenue serves as an intermediate output (which also serves as an input to the second stage); and Net Income is treated as the final output.

The first stage evaluates how efficiently companies convert financial resources (Operating Expenses and Total Assets) into Sales Revenue. This stage captures operational efficiency—namely, how effectively companies manage costs and assets to generate revenue. In the second stage, the researchers assess how efficiently firms convert generated sales revenue into net income; this reflects financial efficiency, or how effectively firms transform revenue into bottom-line profitability after deducting operating and non-operating expenses.

The researchers estimated each stage separately under both CCR and BCC assumptions and for both input- and output-oriented versions. The resulting efficiency scores from the second stage were used in the regression analysis as the dependent variable, as this stage most directly represents the firm's ability to convert operational outcomes into financial performance.

Regression Analysis. After obtaining DEA efficiency scores for each dataset, the following analytical step aimed to determine whether companies' Risk Management (RM) performance is systematically associated with their efficiency. The underlying hypothesis is that firms with more developed risk management systems are more efficient in resource allocation, cost control, and performance optimisation.

Since DEA efficiency scores are bounded between 0 and 1, traditional linear regression (OLS) is inappropriate because it may violate the normality and heteroscedasticity assumptions. Therefore, a fractional logit regression model, as proposed by Papke and Wooldridge (1996), was used.

The fractional logit model uses the logistic function to model the conditional mean of efficiency scores as a function of the independent variable (RM score). A positive coefficient implies that higher risk management performance is associated with greater efficiency. The researchers assessed coefficient significance using p-values and considered values below 5% to be statistically significant.

RESULTS AND DISCUSSION

DEA Analysis. The researchers conducted the efficiency analysis using seven input–output configurations that represent various perspectives on firm performance. They evaluated each dataset using both the CCR (constant returns to scale) and BCC (variable returns to scale) models under both input- and output-oriented approaches. The results showed firm-level efficiency scores ranging from 0 to 1, indicating each firm's relative performance along the efficient frontier formed by the best-performing firms in the sample.

Across all seven datasets, efficiency scores varied meaningfully among companies, indicating heterogeneity in operational performance. While several firms operated near the efficiency frontier, many others exhibited significant inefficiency, highlighting structural and managerial disparities within the sector.

However, only minor differences were observed between the CCR and BCC models. Similarly, results from input-oriented and output-oriented models were broadly consistent, suggesting that most firms' relative efficiency rankings are not highly sensitive to whether the focus is on cost minimisation or output maximisation. Examples of some results are shown in Table 1.

Table 1 – Example of some results of different DEA models

Dataset 1				
Company_N	CCR_in	BCC_in	CCR_out	BCC_out
9	1	1	1	1
14	1	1	1	1
35	1	1	1	1
52	1	1	1	1
57	1	1	1	1
67	0.8306	1	0.8306	1
22	0.8001	1	0.8001	1
73	0.7796	1	0.7796	1
36	0.7009	1	0.7009	1
53	0.6668	1	0.6668	1
68	0.6340	1	0.6340	1
72	0.2744	1	0.2744	1
93	0.2385	1	0.2385	1
69	0.6992	0.9680	0.6992	0.9723
78	0.7489	0.9530	0.7489	0.9553
45	0.8179	0.9495	0.8179	0.9520
41	0.8975	0.9403	0.8975	0.9448
7	0.8181	0.9366	0.8181	0.9405
3	0.6950	0.9257	0.6950	0.9387
19	0.5484	0.9186	0.5484	0.9354
Dataset 5				
Company_N	CCR_in	BCC_in	CCR_out	BCC_out
9	1	1	1	1
53	1	1	1	1
57	1	1	1	1
78	0.9455	1	0.9455	1
17	0.8252	1	0.8252	1
27	0.7946	1	0.7946	1
3	0.7915	1	0.7915	1
67	0.4997	1	0.4997	1
10	0.4529	1	0.4529	1
69	0.3540	1	0.3540	1
68	0.3070	1	0.3070	1
52	0.2638	1	0.2638	1
63	0.4493	0.8518	0.4493	0.9376
45	0.4955	0.8144	0.4955	0.8516
7	0.4901	0.7220	0.4901	0.7882
12	0.0524	0.7132	0.0524	0.0544
39	0.4917	0.7034	0.4917	0.7793
60	0.5762	0.6260	0.5762	0.5849
25	0.5826	0.6131	0.5826	0.5858
32	0.5352	0.6109	0.5352	0.7626
Dataset 7				
Company_N	CCR_in	BCC_in	CCR_out	BCC_out

9	1	1	1	1
14	1	1	1	1
35	1	1	1	1
52	1	1	1	1
57	1	1	1	1
67	0.8306	1	0.8306	1
36	0.7009	1	0.7009	1
3	0.6950	1	0.6950	1
53	0.6668	1	0.6668	1
68	0.6340	1	0.6340	1
44	0.2865	1	0.2865	1
69	0.6992	0.9680	0.6992	0.9723
78	0.7489	0.9530	0.7489	0.9553
45	0.8179	0.9495	0.8179	0.9520
41	0.8975	0.9403	0.8975	0.9448
7	0.8181	0.9366	0.8181	0.9405
81	0.7023	0.9157	0.7023	0.9390
19	0.5484	0.9186	0.5484	0.9354
63	0.5134	0.8436	0.5134	0.9342
8	0.6860	0.9051	0.6860	0.9123

In the two-stage DEA applied to the seventh dataset, the first stage measured the effectiveness with which companies converted their inputs (Operating Expenses and Total Assets) into intermediate outputs (Sales Revenue). In the second stage, the researchers evaluated how efficiently firms transformed those revenues into net income. The results revealed a noticeable decline in efficiency between the first and second stages. This pattern suggests that many firms are relatively capable of generating sales from their available resources, yet face difficulties turning those sales into actual profits. Such findings are consistent with multi-stage production processes, in which inefficiencies tend to compound as operations progress from production to financial outcomes.

Regression Analysis. To examine the relationship between firms' efficiency and their Risk Management (RM) scores (research by Berishvili and Mamedova [16]), fractional regression models were employed. Efficiency scores derived from the DEA were used as dependent variables, with the RM score (ranging from 0 to 10) as the independent variable. Separate regressions were estimated for all DEA efficiency measures (input/output, CCR/BCC).

Across all models, the estimated coefficients for the RM score were not statistically significant at conventional levels ($p > 0.05$). The results showed no consistent pattern in coefficient direction: most models produced optimistic estimates, whereas some produced pessimistic forecasts. This finding suggests that the efficiency differences identified through DEA are not systematically associated with variations in firms' risk management scores.

The two-stage DEA regression results followed a similar pattern. Stage 2 efficiencies regressed on the RM score were not significantly associated. The regression results are presented in Table 2.

Table 2 – Regression results

Dataset	DEA model	Coefficient	Std_Error	p_value
1	CCR_in	0.0654	0.0529	0.2168
	BCC_in	-0.0392	0.0537	0.4646
	CCR_out	0.0654	0.0529	0.2168
	BCC_out	-0.0219	0.0548	0.6887
2	CCR_in	0.0430	0.0592	0.4674

Dataset	DEA model	Coefficient	Std_Error	p_value
	BCC_in	0.0446	0.0662	0.5006
	CCR_out	0.0430	0.0592	0.4674
	BCC_out	0.0503	0.0671	0.4533
3	CCR_in	0.0497	0.0593	0.4020
	BCC_in	0.0595	0.0659	0.3670
	CCR_out	0.0497	0.0593	0.4020
	BCC_out	0.0750	0.0673	0.2649
4	CCR_in	0.0456	0.0622	0.4639
	BCC_in	0.0158	0.0664	0.8125
	CCR_out	0.0456	0.0622	0.4639
	BCC_out	0.0176	0.0682	0.7968
5	CCR_in	0.0456	0.0633	0.4712
	BCC_in	0.1283	0.0676	0.0579
	CCR_out	0.0456	0.0633	0.4712
	BCC_out	0.1306	0.0686	0.0569
6	CCR_in	0.0346	0.0547	0.5265
	BCC_in	0.0320	0.0639	0.6169
	CCR_out	0.0346	0.0547	0.5265
	BCC_out	0.0552	0.0651	0.3968
7	CCR_in	0.0332	0.0570	0.5600
	BCC_in	0.0505	0.0573	0.3785
	CCR_out	0.0332	0.0570	0.5600
	BCC_out	0.0584	0.0568	0.3045
Two stage	Stage2_CCR_in	0.0346	0.0547	0.5265
	Stage2_BCC_in	0.0320	0.0639	0.6169
	Stage2_CCR_out	0.0346	0.0547	0.5265
	Stage2_BCC_out	0.0552	0.0651	0.3968

CONCLUSIONS

This study examined whether risk management practices influence firm efficiency in Georgia's manufacturing sector. Using several DEA models and a two-stage approach, the study examined how effectively firms convert resources into desired outcomes and whether these efficiencies are linked to their risk management systems.

The analysis revealed apparent differences in efficiency across firms, showing that performance varies widely within the industry. However, the regression results showed no statistically significant relationship between firms' RM disclosure scores and their DEA-based efficiency ratios. The coefficients were inconsistent in direction (some were negative) and were not crucial in any of the tested models.

These findings suggest that at least within the observed sample, risk management systems do not directly translate into higher operational or financial efficiency; this does not mean that risk management lacks value. Its benefits may lie in areas not captured by the DEA, such as resilience during crises, long-term risk-adjusted performance, or improved stakeholder confidence.

The results of this study highlight the complexity of business processes: managerial system components do not directly translate into measurable efficiency outcomes, at least in Georgia's emerging economy. Future studies may examine a larger time span, include additional variables, or employ longitudinal designs to capture the delayed effects of RM practices on performance.

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