ANALYSIS OF THE EFFECT OF CREDIT RISK AND OPERATIONAL RISK ON FINANCIAL PERFORMANCE WITH GOOD CORPORATE GOVERNANCE AS A MODERATING VARIABLE IN THE MANAGEMENT OF SUGARCANE FARMERS' RECEIVABLES AT PT PABRIK GULA CANDI BARU

[1]**Doni Ali Rizki** (Master of Management, Faculty of Business, Law, and Social Sciences, Universitas Muhammadiyah Sidoarjo, Indonesia)
E-mail: doniariz1985@gmail.com

[2]**Wisnu Panggah Setiyono** (Master of Management, Faculty of Business, Law, and Social Sciences, Universitas Muhammadiyah Sidoarjo, Indonesia)
E-mail: wisnu.setiyono@umsida.ac.id

[2]**Rita Ambarwati S** (Master of Management, Faculty of Business, Law, and Social Sciences, Universitas Muhammadiyah Sidoarjo, Indonesia)
E-mail: ritaambarwati@umsida.ac.id

Keywords: corporate governance, credit risk, financial performance, operational risk, sugar industry.

Received : 03 August 2026
Revised : 09 August 2026
Accepted: 21 August 2026
©2026The Author(s): This is an open-access article distributed under the terms of theCreative Commons Attribution 4.0 International.

ABSTRACT
Analysis of the Effect of Credit Risk and Operational Risk on Financial Performance with Good Corporate Governance as a Moderating Variable in the Management of Sugarcane Farmers' Receivables at PT Pabrik Gula Candi Baru. This study examines the association of credit risk and operational risk with financial performance, and the moderating role of a governance implementation index (GCGI), at a sugar mill that finances its partner farmers. Monthly secondary data from January 2023 to December 2025 (36 observations) were analyzed with moderated time-series regression that controls for the milling season and a time trend, using Newey-West standard errors, and were then subjected to robustness checks (HC3, wild bootstrap, influence diagnostics, and alternative specifications). Credit risk is proxied by the payment shortfall against the annual collection target, operational risk by negative gross profit margin, and governance by the share of eight documented governance milestones that have been implemented. Operational risk is significantly and negatively associated with net profit margin and return on assets in every specification, whereas credit risk and GCGI show no significant direct association. The negative association of operational risk is weaker at higher

ISSN-E: : 2808-1714 (online media)
https://jurnal.stiedarulfalahmojokerto.ac.id/ index.php/jurnal_IJE

GCGI, but this moderation is only partially robust: it holds for return on assets under most specifications, not for net profit margin, and it depends heavily on a single extreme month (December 2025). Because the operational-risk proxy overlaps mechanically with profit margin and governance is observed as a single step after 2024, the findings are indicative rather than causal.

I. INTRODUCTION

The sugar industry links sugarcane cultivation, farmer partnerships, milling, and the marketing of products. Consequently, the performance of a sugar company is determined not only by its ability to generate revenue, but also by its ability to manage risk along the business chain. Risks related to farmer financing, raw material quality, production process disruptions, cost efficiency, and changing market conditions can affect overall company performance (Maharani et al., 2024; Permadhi et al., 2025; S. V. C. et al., 2024; Sahara et al., 2025; Surjanto & Ariefianto, 2025).

At PT Pabrik Gula Candi Baru, the partnership with sugarcane farmers encompasses receivables management and financing support. This condition gives rise to Credit Risk, particularly related to payment attainment and the uncertainty of receivable recovery. On the other hand, the company faces Operational Risk associated with processing efficiency, the quality of the sugarcane received, and disruptions during the milling season. The company's risk management documents place these risks within monitoring and control activities (Dwirayani, 2025; Maharani et al., 2024; Sahara et al., 2025).

Farmer receivable balances fluctuated considerably over 2023–2025. In April 2025, the balance reached approximately IDR 527.56 billion, far above other months, whereas in July 2025 a negative balance of approximately IDR 13.47 billion was recorded, which still requires journal tracing or reclassification. According to the company's internal explanation, the April 2025 surge is suspected to be related to farmers' economic activities, including land purchases; supporting documents still need to be attached, so this figure is treated as a business condition that requires further tracing rather than as a data error. Because the monthly balances contain both events, the receivable balance is not entered directly into the model. Credit Risk is measured from the realization of receivable payments against the annual target, which is available for all 36 months (see the Method section). These dynamics highlight the importance of receivables management that is oriented toward payment attainment as well as toward information quality and transaction control.

Operating revenue also fluctuates in line with the seasonal nature of sugar production and sales; in 2025, the highest monthly revenue was recorded in October, at IDR 216.52 billion. High revenue does not necessarily imply high profitability, because the final result is also determined by the cost of goods sold and other expenses. Company profit is likewise dynamic: in 2023, the company recorded losses in February, March, and December; in 2024, losses occurred in April and May; and in 2025, positive profit was recorded in 8 of the 12 months, with losses in January, February, July, and December. Profit is far smaller than operating revenue, which indicates that profit margins are relatively thin amid operating cost pressures and farmer financing risk. Therefore, financial

performance in this study is examined through Net Profit Margin (NPM) and Return on Assets (ROA) so that the relationships among risk, revenue, costs, profit, and asset utilization can be examined more comprehensively.

Risk and performance are also inseparable from the production cycle. Operational records show production in May–October 2023, June–November 2024, and June–November 2025. Differences between months with production records and months without them may affect revenue, costs, and efficiency indicators. Therefore, the milling season is included as a control variable so that the relationship between risk and performance does not merely capture changes that coincide with the production cycle.

Conceptually, credit risk is regarded as one determinant of profitability because it relates to the potential for default, delays in settling receivables, and the effectiveness of current asset management (Jamil et al., 2024; Komite Nasional Kebijakan Governance [KNKG], 2022; Utami et al., 2022). Operational risk relates to the possibility of loss resulting from weaknesses in internal processes, human resources, information systems, or external factors that affect operational activities. Effective risk management enables a company to identify, evaluate, and control sources of risk so that decision quality and performance stability can be maintained (Kalia & Gill, 2023; Mutaz et al., 2021). In addition, Good Corporate Governance (GCG) is important because oversight mechanisms, accountability, internal control, and clarity of responsibility can influence how a company recognizes and responds to risk; the magnitude of this influence still needs to be tested in the context and period under study (Hazzaa et al., 2022; KNKG, 2022; Utami et al., 2022). In this study, GCG is considered not only as a factor that may be directly related to performance, but also as a variable that potentially alters the relationships among credit risk, operational risk, and financial performance.

The verifiable Risk Maturity Index (RMI) assessment shows annual values of 1.47 in 2023 and 2.06 in 2024. The 2025 value found in certain documents is still a simulation, and a verifiable monthly numerical RMI series is not available. Therefore, the annual RMI is neither interpolated nor repeated as a monthly value. As an alternative, this study constructs a Governance Implementation Index (GCGI) from dated evidence of governance implementation. The GCGI measures the progress of implementing documented governance components, not the level of risk management maturity; it is therefore not identical to the RMI and takes a value of zero in months without dated documents even though RMI assessments had been conducted.

The state of the art of this study lies at the intersection of risk management, financial performance, corporate governance, and the characteristics of the sugar agroindustry. Studies on governance, risk management, efficiency, and performance have developed for public companies and the banking sector (Amar & Ahjadi, 2025; Hazzaa et al., 2022; Jamil et al., 2024; Junaidi & Hanggraeni, 2024; Kaban et al., 2025; Kalia & Gill, 2023; Maulydia & Setiawati, 2025; Metana & Meiranto, 2023; Pebiana et al., 2024; Rahmah & Mahastanti, 2026; Utami et al., 2022), whereas studies on sugarcane have mostly highlighted financing, productivity, and farmer partnership relationships (Dwirayani, 2025; Maharani

et al., 2024; Permadhi et al., 2025; Sahara et al., 2025). These two bodies of literature provide a relevant conceptual foundation, but they do not by themselves explain how the credit risk of farmer receivables and operational risk relate to the profitability of sugar companies when governance is tested as a moderator on monthly data.

The research gap of this study encompasses three aspects. First, a contextual gap: sugar companies that depend on farmer partnerships and the milling-season cycle differ from the banking sector, which has been the main context of risk–performance research (Amar & Ahjadi, 2025; S. V. C. et al., 2024). Second, an analytical gap: monthly observations require a model that accounts for temporal dynamics and the production season, rather than merely relationships among variables without temporal controls. Third, a measurement gap: governance assessments in prior studies are generally self-assessment scores or periodic indices (Maulydia & Setiawati, 2025; Pebiana et al., 2024) that are not available as monthly series for non-financial companies. This study addresses these gaps by constructing a governance implementation index based on dated documentary evidence, separating it from the credit risk proxy, and testing its relationship with performance through moderated time-series regression.

The novelty of this study lies in applying a risk–performance model to the management of sugarcane farmer receivables in a sugar company using a monthly unit of observation. Credit Risk and Operational Risk are tested together, GCG is positioned as a moderator, and the milling season and a time trend are included as control variables. In terms of measurement, GCG is operationalized through the GCGI, which is based on traceable implementation evidence, without converting the annual RMI into an artificial monthly series. Its contribution is therefore an empirical test appropriate to the company's context and the limits of data availability, not a claim that the GCGI is identical to the RMI.

The grand theory of this study is Enterprise Risk Management (ERM), which views risk as an integral part of the process of achieving organizational objectives and of decision-making (Committee of Sponsoring Organizations of the Treadway Commission [COSO], 2017; International Organization for Standardization [ISO], 2018). Within this framework, Credit Risk and Operational Risk are positioned as sources of uncertainty that can affect Financial Performance, whereas GCG is viewed as a governance mechanism that supports oversight, control, and risk management (Kalia & Gill, 2023; KNKG, 2022). From this perspective, the study tests whether governance implementation is not only directly related to performance but also alters the strength of the relationship between risk and performance (Amar & Ahjadi, 2025; Kaban et al., 2025; Maharani et al., 2024; Maulydia & Setiawati, 2025; Mutaz et al., 2021). Figure 1 presents the conceptual framework of the study.

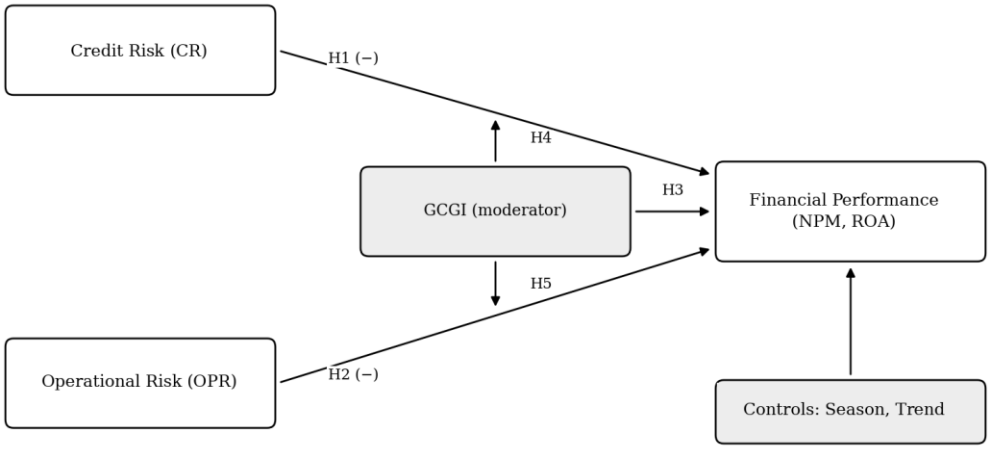


Figure 1. Conceptual Framework of the Study

This study aims to obtain empirical evidence on the effects of Credit Risk, Operational Risk, and the GCGI on Financial Performance, and to test whether the GCGI moderates the relationship between each risk and performance. Unmanaged Credit Risk ties up cash flow and burdens profit, and is therefore expected to reduce financial performance (H1) (Amar & Ahjadi, 2025; Maulydia & Setiawati, 2025; Mohammad et al., 2026). Operational Risk, reflected in cost-of-goods inefficiency, depresses margins and is therefore expected to reduce performance (H2) (Kaban et al., 2025); because its proxy is based on gross margin, this relationship is partly accounting-based and is interpreted as an association. The direct effect of GCG on performance may operate through risk control and is not always visible in monthly profit measures (Kalia & Gill, 2023); H3 is therefore formulated without a direction. Because GCG functions to strengthen oversight and control over risk, GCG is expected to weaken the negative effect of each risk on performance (H4 and H5), consistent with the moderation frameworks in risk–performance studies (Amar & Ahjadi, 2025; Maulydia & Setiawati, 2025; Mohammad et al., 2026; Naibaho & Mayayogini, 2023). Because the GCGI has been documented only since September 2024, the moderation test is read as a difference in the slope of the risk–performance relationship between the periods before and after the documented implementation of governance. The research hypotheses are as follows.

H1: Credit Risk has a negative effect on Financial Performance.
H2: Operational Risk has a negative effect on Financial Performance.
H3: GCG has an effect on Financial Performance.
H4: GCG weakens the negative effect of Credit Risk on Financial Performance.
H5: GCG weakens the negative effect of Operational Risk on Financial Performance.

II. RESEARCH METHOD

This study uses a quantitative approach with an explanatory-associative design to examine the relationship of Credit Risk and Operational Risk with Financial Performance, as well as the role of Good Corporate Governance as a

moderating variable. Because the data are arranged in chronological order, the analysis uses time-series regression with the month as the unit of observation. The observation period from January 2023 to December 2025 yields 36 monthly observations. The analysis is conducted for two measures of financial performance, namely Net Profit Margin (NPM) as the primary outcome and Return on Assets (ROA) as a robustness check of the results.

The data used are secondary data from monthly financial statements, risk management presentations, production and operational records, available Risk Maturity Index (RMI) assessment documents, and documents evidencing governance implementation. Financial data were used to construct revenue, cost of goods sold (COGS), net profit, total assets, and receivable balances. Year-to-date (YTD) receivable payment data and their annual targets were used to construct the Credit Risk proxy, whereas decision documents, meeting minutes, memos, and risk management implementation reports were used to construct the GCGI. Data without a traceable source were neither imputed nor constructed on the basis of assumptions. The complete monthly data and the list of evidence for the GCGI components are presented in the appendix to the first author's thesis.

Each variable is constructed using an explicit formula or measurement rule so that it can be traced and replicated (Table 1). Credit Risk (CR) is proxied as the shortfall in receivable payment attainment relative to the annual target; a higher value indicates that payment attainment is further from the target.

$$CR_t = 1 - \min(\text{Payment YTD}_t / \text{Annual Target}_t, 1) \quad (1)$$

A higher CR indicates a larger shortfall in receivable payment attainment relative to the annual target. This measure is a proxy for payment *shortfall* and not a measure of NPL or receivable *aging*. For illustration, in February 2023, YTD receivable payments were recorded at IDR 0.50 billion against an annual target of IDR 5.20 billion, so CR = 1 − min(0.50/5.20; 1) = 0.903846. This example clarifies the application of the formula and does not change the definition of CR.

Operational Risk (OPR) is proxied from gross-margin inefficiency. Gross Profit Margin (GPM) = (Revenue − COGS)/Revenue is given a negative sign so that a higher OPR value indicates a lower GPM.

$$OPR_t = -GPM_t = -(Revenue_t - COGS_t) / Revenue_t \quad (2)$$

This indicator is an operational risk proxy oriented toward COGS efficiency because it is available monthly throughout the study period. It does not cover all dimensions of operational risk; *downtime* and sugarcane quality data are not fully available for all 36 months and were therefore not included in the model. Because NPM equals GPM minus other expenses relative to revenue, OPR and NPM overlap in accounting terms; an OPR coefficient on NPM approaching −1 is a consequence of this relationship and does not automatically indicate a separate risk effect.

GCG is operationalized as the Governance Implementation Index (GCGI), a cumulative index calculated from eight governance components (G1–G8) that have documentary evidence and traceable implementation dates.

$$GCGI_t = (\text{number of components implemented up to month } t / 8) \times 100 \quad (3)$$

The index is cumulative: components that have been implemented continue to be counted in subsequent months. The GCGI is not an RMI value and is not constructed by interpolating or repeating the annual RMI value.

Consequently, the GCGI is zero before September 2024 because dated documents do not yet exist, not because governance did not exist. The available RMI is annual and does not provide a verified monthly numerical series for the entire period.

Table 1. Operational Definitions of Research Variables

Variable	Operational definition	Formula / rule	Role
Credit Risk (CR)	Shortfall in farmer receivable payment attainment relative to the annual target; source: 2023–2025 risk management presentations	Equation (1); ratio 0–1	Independent
Operational Risk (OPR)	Negative GPM as a proxy for gross margin inefficiency; source: monthly financial statements	Equation (2); ratio	Independent
GCGI	Cumulative index of governance implementation based on 8 dated *milestones*; source: 2024–2025 risk management presentations along with evidence of decrees, minutes, and FGDs	Equation (3); index 0–100	Moderator
NPM	Ratio of net profit to revenue	NPM_t = Net $Profit_t$ / $Revenue_t$	Primary dependent
ROA	Ability of assets to generate net profit	ROA_t = Net $Profit_t$ / Total $Assets_t$	Dependent (robustness test)
Milling Season (Season)	*Dummy* 0/1 variable that distinguishes months with production records from months without production records; source: One Book 2023–2025 and production data	$Season_t$ = 1 if production records exist; 0 otherwise	Control
Time Trend (Trend)	Deterministic time index to capture tendencies throughout the period and to reduce the risk of confounding the trend with the GCGI implementation pattern	$Trend_t$ = 1, 2, …, 36	Control

Source: Compiled by the researchers based on documents of PT Pabrik Gula Candi Baru and the literature review (2026).

For the Season variable, a value of 0 does not automatically prove that there was no production activity whatsoever; it means that there is no production row in the source used. Production records are available for May–October 2023, June–November 2024, and June–November 2025.

Before estimation, the data were verified by checking the consistency of the revenue, COGS, net profit, total assets, and receivable components; reconciling the 2025 profit components; assessing extreme values based on transaction context; and constructing CR, Season, and the GCGI from their sources. The column labeled profit/loss in the 2025 source file has values identical to operating revenue for January–October 2025, namely IDR 857,335,913,725, and was therefore not treated as net profit; monthly profit for

January–June 2025 was derived from changes in the available cumulative profit values. The annual RMI was not interpolated into monthly values. Values that could not be verified were not filled with artificial numbers, and extreme observations were not removed without substantive and documentary justification.

The analysis begins with descriptive statistics, followed by stationarity tests (ADF and KPSS), a multicollinearity test (VIF), residual autocorrelation tests (Durbin–Watson, Breusch–Godfrey, and Ljung–Box), and a heteroscedasticity test (Breusch–Pagan). The moderated regression model in Equation (4) is then estimated separately for NPM and ROA; the interaction coefficients are used to test the moderating effect.

$$Y_t = \alpha + \beta_1 CR_t + \beta_2 OPR_t + \beta_3 GCGI_t + \beta_4 (CR_t \times GCGI_t) + \beta_5 (OPR_t \times GCGI_t) + \beta_6 Season_t + \beta_7 Trend_t + \varepsilon_t$$

In Equation (4), Y_t is the financial performance in month t (NPM or ROA), α is the constant, β_1–β_7 are the regression coefficients, and ε_t is the error term. The coefficient β_4 is used to test H4 and β_5 is used to test H5. Before the interaction terms are formed, CR, OPR, and the GCGI are centered on their means (*mean-centering*). The ROA model uses the same specification as the NPM model and is estimated separately to determine whether the pattern observed for NPM also appears when performance is measured relative to assets.

Both models are estimated using Ordinary Least Squares (OLS), and inference uses Newey–West HAC *standard errors* with a lag of 2 to accommodate possible heteroscedasticity and residual autocorrelation. The time trend is included because the implementation of the GCGI develops cumulatively, so that temporal changes are not directly interpreted as governance effects. With 36 observations, HAC inference is indicative and is read together with the limitations described in the Results and Discussion section.

Because the sample is small (n = 36) and the GCGI is step-shaped, robustness tests were conducted on the interaction coefficients, namely: (1) alternative inference consisting of HAC with the t distribution, HC3 *standard errors*, and Rademacher *wild bootstrap* (4,000 replications); (2) influence diagnostics using *leverage*, Cook's distance, and re-estimation without the most influential observation; (3) alternative specifications consisting of a *dummy* variable for the period after September 2024 in place of the GCGI, an additional ln(revenue) control, OPR lagged by one month, and the annual RMI as an alternative moderator (the 2025 value is a simulation); and (4) residual normality tests (Jarque–Bera and Shapiro–Wilk) and the decomposition NPM = −OPR − X, with X = GPM − NPM, to assess the accounting overlap between OPR and NPM.

Hypotheses are assessed based on the sign of the coefficient and the p-value with Newey–West HAC *standard errors*. H1 tests the relationship between CR and performance; H2 tests the relationship between OPR and performance; H3 tests the direct relationship between the GCGI and performance; H4 tests the CR × GCGI interaction coefficient (β_4); and H5 tests the OPR × GCGI interaction coefficient (β_5). A hypothesis is considered statistically supported if the p-value is < 0.05 and the direction of the coefficient is consistent with the hypothesis. Decisions are read by taking time-series diagnostics and proxy limitations into

account; results that are significant in the main model but do not survive the robustness tests are declared to be supported only to a limited extent.

III. RESULTS AND DISCUSSION

A. Descriptive Statistics and GCGI Profile

All figures in this section are calculated from the 36-month dataset constructed in the Method section. Table 2 shows the basic characteristics of the variables across the 36 observations. The GCGI equals 0 in 20 months (median 0), so its distribution forms two groups, namely before and after September 2024.

Table 2. Descriptive Statistics of Research Variables

Variable	N	Mean	Std. Dev.	Min	Median	Max
CR	36	0.517771	0.359461	0	0.494444	1
OPR	36	−0.062090	0.071505	−0.209166	−0.063206	0.189909
Season	36	0.500000	0.507093	0	0.500000	1
NPM	36	0.001818	0.076040	−0.267657	0.012185	0.117826
ROA	36	0.002492	0.004581	−0.003377	0.001283	0.015431
GCGI	36	34.375000	41.979481	0	0	100

Source: Compiled by the researchers from the research dataset (2026). OPR = RO_GPM_Risk.

The GCGI consists of eight components with documentary evidence and verifiable implementation dates, namely the risk management guidelines, risk discussions by the Board of Commissioners, the risk identification memo, Board of Directors involvement through risk management FGDs, the Risk Monitoring Committee, the Audit Committee, the Internal Audit Unit (SPI), and the Three Lines Model/PIC. Its value is 0 before September 2024, then 12.5 in September 2024, 37.5 in October, 50 in November, 75 in December 2024 and January 2025, 87.5 from February 2025, and 100 from November 2025. The zero values for January 2023–August 2024 (20 of 36 months) mean that dated documentary evidence is not yet available, not that governance did not exist: RMI assessments had been conducted, and their value rose from 1.47 (2023) to 2.06 (2024). Accordingly, the GCGI measures the documentation of implementation, not governance maturity, and is separate from the RMI. Because its value is step-shaped and rises after September 2024, the OPR × GCGI interaction is read as a difference in slope before and after the period of documented implementation, which cannot be fully separated from changes in other conditions in the same period, for example the increase in revenue in 2025.

B. Stationarity, Multicollinearity, and Residual Diagnostic Tests

Table 3. Stationarity Test Results

Variable	ADF p	KPSS p	Conclusion
NPM	0.000064	0.100	Stationary
ROA	0.012427	0.100	Stationary
CR	0.004940	0.100	Stationary
OPR	0.479960	0.100	Mixed evidence/caution
GCGI	0.9659	0.014*	Level follows implementation stages; time trend controlled

Source: Compiled by the researchers from the research dataset (2026).

Table 3 shows that NPM, ROA, and CR are stationary. OPR shows mixed evidence (the ADF test does not reject a unit root, whereas the KPSS test does not reject stationarity), and the GCGI is non-stationary because it develops in stages. Therefore, the risk of spurious regression is taken into account, the time trend is controlled, and inference uses HAC. The VIF values range from 1.332 to 6.148 (CR 1.857; OPR 1.454; GCGI 5.377; CR × GCGI 1.459; OPR × GCGI 1.389; Season 1.332; Trend 6.148). The GCGI and the time trend have relatively higher VIFs because GCGI implementation develops cumulatively throughout the period; all values are below 10, so they do not indicate extreme multicollinearity.

Table 4. Autocorrelation and Heteroscedasticity Test Results

Model	DW	BG p	BP p	LB1 p	LB2 p
NPM	2.149	0.302	0.210	0.540	0.233
ROA	2.298	0.014	0.146	0.346	0.011

Source: Compiled by the researchers from the research dataset (2026).

Table 4 shows that the NPM model exhibits no indication of autocorrelation according to Breusch–Godfrey (p = 0.302) or Ljung–Box at lag 2 (p = 0.233). In the ROA model, there is an indication of serial correlation at lag 2 according to Breusch–Godfrey (p = 0.014) and Ljung–Box (p = 0.011). The Breusch–Pagan test shows no significant heteroscedasticity in either the NPM model (p = 0.210) or the ROA model (p = 0.146). Given these time-series characteristics, final inference uses Newey–West (HAC) *standard errors* with a lag of 2, and the time trend is included explicitly because the GCGI develops in stages during the study period.

C. Main Model Estimation Results (H1 and H2)

Table 5. Time-Series Regression and GCGI Moderation Estimation Results

Variable	NPM β	NPM p HAC	ROA β	ROA p HAC
Constant	−0.056106	0.124805	+0.002455	0.137352
CR	−0.003718	0.907964	+0.000539	0.753170
OPR	−0.687802	<0.001	−0.041334	<0.001
GCGI	−0.000492	0.144526	−0.000010	0.474242
CR × GCGI	−0.001279	0.142514	−0.000013	0.650104
OPR × GCGI	+0.005379	0.009	+0.000548	<0.001
Season	+0.030009	0.008551	+0.002506	0.005037
Trend	+0.001804	0.268731	−0.000091	0.217734

Source: Compiled by the researchers from the research dataset (2026). CR, OPR, and GCGI are mean-centered; n = 36.

The model is estimated with centered CR, OPR, and GCGI, the CR × GCGI and OPR × GCGI interactions, the milling-season control, and a deterministic time trend, using the same specification for NPM and ROA. The model explains 45.6% of the variance in NPM and 63.1% of the variance in ROA (R^2 = 0.456 and 0.631; Adjusted R^2 approximately 0.320 and 0.539, respectively; n = 36; 7 regressors).

H1 is not supported. The Credit Risk coefficient is not significant for either NPM or ROA. This finding applies only to the proxy used: the cumulative payment *shortfall* declines mechanically throughout the course of the year and returns to a high level at the start of each year, so it does not capture arrears or receivable quality. This result cannot be interpreted to mean that the credit risk of farmer receivables has no effect on performance. Substantively, this relationship may also be influenced by payment cycles, the timing of revenue recognition, and the seasonal character of the sugar industry (Maharani et al., 2024; Mutaz et al., 2021; Sahara et al., 2025).

H2 is supported. Operational Risk, proxied by a risk-oriented measure derived from GPM, has a negative and significant effect on both NPM and ROA, and remains significant across all robustness-test specifications ($p < 0.05$ in all specifications in Table 7, including HC3 and OPR lagged by one month). This means that lower COGS efficiency is associated with a decline in Financial Performance. Because OPR and NPM are both constructed from income statement components, NPM = −OPR − X, where X = GPM − NPM (the ratio of other expenses to revenue). In the X model, the OPR coefficient is −0.312 (p = 0.005), so the OPR coefficient in the NPM model (−0.688) equals −1 minus that coefficient: approximately 69% of a change in gross margin is passed through to

net margin at the mean GCGI (34.4), and the remainder is absorbed by other expenses. A coefficient approaching −1 at GCGI 0 (approximately −0.873) is thus a consequence of the accounting relationship. This result is read as an association for the proxy used, not as evidence of causality, and its magnitude depends on the GCGI, as shown by the *simple slopes* in Table 6 (Kaban et al., 2025; Maulydia & Setiawati, 2025).

This finding is managerially relevant because company documents place COGS inefficiency, sugarcane quality, and milling stoppage hours as part of operational risk. Controlling process and cost efficiency is thus an important area for maintaining company profitability during the study period (Sahara et al., 2025; Surjanto & Ariefianto, 2025). The milling-season coefficient is positive and significant in both the NPM model ($p = 0.009$) and the ROA model ($p = 0.005$), whereas the time trend is not significant in either NPM ($p = 0.269$) or ROA ($p = 0.218$). These results indicate that the seasonal character of production needs to be controlled when explaining the performance of sugar companies, and that, after risk, governance, and the milling season are accounted for, there is no significant general linear tendency over the observation period.

D. GCGI Moderation (H3, H4, and H5)

H3 is not supported because the GCGI coefficient is not significant for NPM ($p = 0.145$) or ROA ($p = 0.474$). H4 is likewise not supported because the CR × GCGI interaction is not significant for NPM ($p = 0.143$) or ROA ($p = 0.650$); the coefficient is even negative, opposite to the hypothesized direction. In the main model (HAC lag 2), the OPR × GCGI interaction is positive and significant for NPM ($\beta = 0.005379$; $p = 0.009$) and ROA ($\beta = 0.000548$; $p < 0.001$), which means that the negative slope of the relationship between Operational Risk and Financial Performance is weaker at higher GCGI levels. *The simple slopes* in Table 6 show that at GCGI 0 the OPR coefficient is approximately −0.873 for NPM and approximately −0.0602 for ROA, whereas at GCGI 87.5 they are approximately −0.402 and −0.0122, respectively. However, the robustness tests in the following subsection show that this finding is not as strong as it appears in the main model. H5 is therefore supported only to a limited extent: for ROA, the positive interaction is consistent and significant in most specifications, whereas for NPM significance appears only under HAC inference and disappears under HC3 and the *wild bootstrap*, and when December 2025 is excluded.

Table 6. *Simple Slope* Analysis of H5

DV	GCGI	OPR Coefficient	SE HAC	p HAC
NPM	0	−0.872722	0.132972	<0.001
NPM	87.5	−0.402016	0.152812	0.009
ROA	0	−0.060172	0.008578	<0.001
ROA	87.5	−0.012221	0.004659	0.009

Source: Compiled by the researchers from the research dataset (2026).

Table 6 shows that the slope of the relationship between Operational Risk and performance becomes less negative at higher GCGI levels. Because GCGI 0 covers the 20 months before September 2024 and GCGI 87.5–100 covers only months in 2025, this difference mainly indicates lower performance sensitivity in the period after the documented implementation of governance. Whether the difference originates from governance, from the increase in the scale of revenue and assets in 2025 (average total assets rose from IDR 449.8 billion to IDR 912.0 billion), or from other changes in conditions cannot be distinguished with these data.

E. Robustness Tests

Table 7 compares the OPR × moderator interaction coefficients across various specifications. For ROA, the interaction remains positive in all specifications and is significant in most of them (HAC, HC3 with p = 0.042, conventional OLS, scale control, lagged OPR, and annual RMI), but the *wild bootstrap* p-value (0.090) is above 0.05 and the effect is no longer significant once December 2025 is excluded (HAC, p = 0.071). For NPM, significance appears only under HAC-based inference, including with the scale control and the period *dummy* variable; the interaction is not significant under HC3 (p = 0.407), the *wild bootstrap* (p = 0.340), conventional OLS (p = 0.144), and lagged OPR (p = 0.279), and its coefficient approaches zero without December 2025 (β = −0.0004; p = 0.925). In contrast, the main OPR coefficient remains negative and significant (p < 0.05) in all specifications.

Table 7. Robustness Tests of the OPR × Moderator Interaction Coefficient

Specification (OPR × moderator coefficient)	NPM β	NPM p	ROA β	ROA p
Main model (HAC lag 2, normal distribution)	0.005379	0.009	0.000548	<0.001
HAC lag 2, t distribution	0.005379	0.014	0.000548	<0.001
Standard error (HC3)	0.005379	0.407	0.000548	0.042
Wild bootstrap (HC3, 4,000 replications)	0.005379	0.340	0.000548	0.090
Conventional OLS	0.005379	0.144	0.000548	0.005
Excluding December 2025, HAC lag 2 (t)	−0.000389	0.925	0.000365	0.071
Excluding December 2025, HC3	−0.000389	0.955	0.000365	0.403
Excluding December 2025, *wild bootstrap*	−0.000389	0.952	0.000365	0.363
Moderator *dummy* (post-Sep 2024), HAC (t)	0.481920	0.026	0.049889	<0.001
Moderator *dummy* (post-Sep 2024), HC3	0.481920	0.434	0.049889	0.094
Additional ln(revenue) control, HAC (t)	0.005840	0.008	0.000566	<0.001
OPR lagged 1 month, HAC (t)	0.003201	0.279	0.000524	0.003

Specification (OPR × moderator coefficient)	NPM β	NPM p	ROA β	ROA p
Annual RMI as moderator, HAC (t)*	0.837859	0.009	0.074279	0.003

Source: Compiled by the researchers from the research dataset (2026). The scale of β in the period *dummy* and RMI rows differs from that of the GCGI. *The 2025 RMI is a simulation, not an official assessment.

The main cause is a single observation. December 2025 has the highest GCGI (100), the highest OPR (GPM −19.0% because COGS exceeded revenue), *leverage* of 0.86, and a Cook's distance of 0.81 in the NPM model (threshold 4/n = 0.111) and 0.33 in the ROA model. Because the right tail of the GCGI distribution is supported by only two months (November and December 2025), the slope at high GCGI is strongly influenced by that month, and the *simple slopes* in Table 6 must be read with this in mind.

A more consistent pattern is seen in the sample split. Before September 2024 (n = 20), the OPR coefficient is −0.803 ($p < 0.001$) for NPM and −0.0555 ($p < 0.001$) for ROA. After September 2024 (n = 16), the coefficient for NPM declines to −0.131 and is not significant ($p = 0.177$), whereas for ROA it becomes −0.0094 and remains significant ($p < 0.001$). The NPM model residuals are not normally distributed (Jarque–Bera $p < 0.001$; Shapiro–Wilk $p < 0.001$), whereas the ROA model residuals show mixed results (Jarque–Bera $p = 0.129$; Shapiro–Wilk $p = 0.033$); normality-based inference is therefore read with caution and the *wild bootstrap* is reported for comparison.

F. Summary of Hypothesis Testing

Table 8. Summary of Hypothesis Testing

Hypothesis	Result	Decision
H1: CR → FP	Not significant for NPM (negative direction) or ROA (positive direction)	Not supported
H2: OPR → FP	Negative and significant for NPM and ROA	Supported (survives robustness tests)
H3: GCG → FP	GCGI is not significant for NPM or ROA	Not supported
H4: CR × GCG → FP	Interaction is not significant for NPM or ROA	Not supported
H5: OPR × GCG → FP	Positive and significant interaction in the main model (HAC); does not hold for NPM and is sensitive for ROA (Table 7)	Limited support (ROA); does not survive testing (NPM)

Source: Compiled by the researchers from the research dataset (2026). FP = Financial Performance.

G. Discussion in Relation to Previous Studies

The direction of the H5 finding for ROA is consistent with the moderation frameworks in studies of the banking sector (Amar & Ahjadi, 2025; Maulydia & Setiawati, 2025) and with the finding of Naibaho and Mayayogini (2023) that GCG can strengthen the relationship between risk and performance in non-financial companies in Southeast Asia. However, moderation in this study appears only for Operational Risk and not for Credit Risk (H4), does not hold for NPM, and depends on a single influential observation; because the GCGI is documented as a single step after September 2024, the consistency of direction does not yet prove a governance effect. The non-significance of Credit Risk is consistent with the finding of Mohammad et al. (2026) that the relationship between credit risk and performance depends on the measure used; the CR proxy here is the cumulative payment *shortfall* that moves with the calendar of the current year, not a measure of arrears or receivable quality. The absence of a direct GCGI effect (H3) is consistent with the idea that the benefits of governance are more visible in risk control than in monthly profit (Kalia & Gill, 2023). Differences in context (a single sugar agroindustry company, monthly data) from the reference studies, which are generally based on banking and panel data, also limit direct comparison.

H. Limitations

This study has several limitations, so its results should not be over-generalized:

- The 36 observations from a single company limit generalizability and statistical power.
- The CR proxy is the cumulative payment *shortfall* (not receivable *aging* or NPL), so its value declines mechanically throughout the course of the year.
- The OPR proxy is based on GPM because *downtime* and sugarcane quality data are incomplete for the 36 months; OPR and NPM share overlapping income statement components, so their relationship is partly mechanical.
- The GCGI is based on internal evidence, is cumulative, and equals zero in 20 months because dated documents are absent, even though the RMI rose from 1.47 to 2.06 in 2023–2024; the GCGI is not an official RMI score and is step-shaped, so its moderating effect cannot be separated from changes in conditions after September 2024.
- The OPR and GCGI series are non-stationary in the ADF test, the NPM model residuals are not normally distributed, and HAC inference with n = 36 tends to be overly optimistic compared with HC3 and the *wild bootstrap* (Table 7); therefore, all conclusions about moderation are indicative.
- The April 2025 surge in the receivable balance and the July 2025 negative balance still require tracing of journals or supporting documents; neither value is used in the model because CR is constructed from realized receivable payments.
- The moderation results depend on a single influential observation, namely December 2025 (GCGI 100; GPM −19.0% because COGS exceeded revenue). Without that observation, the interaction for NPM approaches zero and for ROA is no longer significant under robust inference

IV. CONCLUSION

The results show that the Credit Risk proxy (the *shortfall* in receivable payments relative to the annual target) has no significant effect on Financial Performance in the period January 2023–December 2025, so H1 is not supported. Operational Risk, proxied by negative GPM, is negatively and significantly associated with NPM and ROA in all specifications, so H2 is supported; this relationship is partly accounting-based because the proxy and NPM are constructed from the same income statement components. The GCGI has no significant direct effect (H3 is not supported) and does not moderate the relationship between Credit Risk and performance (H4 is not supported). The moderating effect of the GCGI on the Operational Risk relationship (H5) is supported only to a limited extent: for ROA, the positive interaction persists in most specifications, whereas for NPM it does not persist under robust inference or after December 2025 is excluded. The stronger pattern is a lower sensitivity of performance to Operational Risk in the period after September 2024. The model explains 45.6% of the variance in NPM and 63.1% of the variance in ROA (Adjusted R^2 of approximately 32.0% and 53.9%).

Theoretically, these findings are consistent with the idea in the ERM framework that the role of governance is visible in changes in the strength of the risk–performance relationship rather than in direct effects. However, with a single company, 36 observations, a step-shaped GCGI, and dependence on a single influential month, these findings are indicative and do not yet prove a causal effect. Practically, the company needs to monitor gross margin and cost-of-goods efficiency monthly as early indicators of profitability pressure, document governance implementation with clear dates so that its impact can be evaluated, and improve the recording and reconciliation of farmer receivable balances (including the April 2025 surge and the negative value in July 2025) so that credit risk can be measured from arrears and receivable age.

Future research is advised to extend the observation period so that the GCGI has more variation after implementation, to use more direct credit risk indicators such as receivable *aging* and non-performing receivables, to supplement GPM with *downtime* and sugarcane quality data, to use the official RMI series when available as an alternative measure of GCG, and to add similar companies so that governance effects can be distinguished from changes in scale and period conditions.

Acknowledgments

This article was prepared from the first author's Master of Management thesis at Universitas Muhammadiyah Sidoarjo. The authors express their gratitude to the management of PT Pabrik Gula Candi Baru for making available the financial data, risk management documents, and production data and for their willingness to explain and verify those data, and to the Master of Management Study Program at Universitas Muhammadiyah Sidoarjo for academic support during the research.

V. REFERENCES

Amar, S. S., & Ahjadi, B. T. (2025). Role of credit risk, market risk, liquidity risk, and operational risk on banking financial performance with good corporate governance as a moderating variable. *International Journal of Innovative Research and Scientific Studies, 8*(3), 5001–5015.

Committee of Sponsoring Organizations of the Treadway Commission. (2017). *Enterprise risk management: Integrating with strategy and performance*.

Dwirayani. (2025). The effectiveness of people's business credit (KUR) in sugarcane farming in West Java Province. *Agrisocionomics, 9*(3).

Hazzaa, O. T., Abdullah, D. F., & Dhahebi, A. M. (2022). Review on the role of corporate governance and internal control system on firms' financial performance. *Asian Journal of Accounting Perspectives, 15*(1).

International Organization for Standardization. (2018). *ISO 31000:2018 Risk management – Guidelines*.

Jamil, P. C., Yulyanti, S., & Prabowo, A. (2024). Enterprise risk management (ERM) and corporate value in Indonesia. *KIAT, 35*(1).

Junaidi, W., & Hanggraeni, D. (2024). Revealing the impact of ERM and ESG disclosures on the performance of non-financial public companies in Indonesia. *Eduvest, 4*(11).

Kaban, E., et al. (2025). Analysis of the influence of corporate governance and enterprise risk management COSO on firm performance with the mediation role of operational efficiency. *International Journal of Accounting and Business Society, 33*(3).

Kalia, A., & Gill, S. (2023). Corporate governance and risk management: A systematic review and synthesis for future research. *Journal of Advances in Management Research, 20*(3), 409–461.

Komite Nasional Kebijakan Governance. (2022). *Indonesian general guidelines for public sector governance (PUGSPI)*.

Maharani, D., Kusnadi, N., & Fariyanti, A. (2024). The impact of credit constraint on productivity and technical efficiency of sugarcane in Indonesia. *Jurnal Manajemen dan Agribisnis, 21*(1).

Maulydia, D. S., & Setiawati, R. I. S. (2025). Analyzing the impact of risk profile on financial performance in banks: Moderating effect of good corporate governance. *Optimum, 15*(2), 272–281.

Metana, A. O., & Meiranto, W. (2023). Pengaruh enterprise risk management disclosure dan intellectual capital terhadap nilai perusahaan. *Diponegoro Journal of Accounting, 12*(1).

Mohammad, R., Nour, A., & Al-Atoot, S. M. (2026). Risk and reward: Unraveling the link between credit risk, governance and financial performance in banking industry. *Journal of Islamic Marketing, 17*, 486–508.

Mutaz, Hernawati, E., & Maulana, A. (2021). Pengaruh enterprise risk management terhadap kinerja keuangan perusahaan. *Equity, 24*(2).

Naibaho, E. A. B., & Mayayogini, N. M. C. (2023). The impact of risk management on firm performance: Corporate governance as moderating variable. *Media Ekonomi dan Manajemen, 38*(1), 129–146.

Pebiana, M., et al. (2024). The effect of self assessment good corporate governance and risk management on financial performance. *Jurnal Ilmiah Akuntansi Universitas Pamulang, 12*(2), 232–248.

Permadhi, D., et al. (2025). Analisis usahatani tebu rakyat (TR) kategori tanaman PC (plant cane) pada lahan tegal di Provinsi Jawa Timur. *Indonesian Sugar Research Journal, 5*(2), 75–88.

Rahmah, S. A., & Mahastanti, L. A. (2026). Do risk disclosure and firm value drive Indonesian bank stock returns? *Review of Management and Entrepreneurship, 10*(1).

Sahara, D., et al. (2025). Partnerships between sugarcane factories and farmers: Performance, waste management, and perception analysis. *Agro Ekonomi, 36*(2).

Surjanto, V., & Ariefianto, M. D. (2025). Rent-seeking in sugar industry: Evidence from financial accounting data. *Research World Agricultural Economics, 6*(2), 211–224.

S. V. C., Uppard, J., & R. H. R. (2024). Risk management in agriculture. In *Agri-business management in agripreneurship* (pp. 128–155).

Utami, D., et al. (2022). Does enterprise risk management affecting firm value? The Indonesian non financial firm case. *Webology, 19*(2).