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Research Article

Optimización estocástica mediante modelos de riesgo GARCH-Cox para mitigar la quiebra de las pymes agrícolas en las economías emergentes

Stochastic optimization via GARCH-Cox hazard modeling to mitigate agricultural SME failure in emerging economies

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Resumen: Los modelos tradicionales de dificultades financieras, diseñados en contextos de altos ingresos y baja volatilidad, no captan la exposición conjunta de las pymes agrícolas a choques de precios y variaciones climáticas. Este estudio desarrolla un marco de optimización de supervivencia estocástica que integra un modelo GARCH(1,1)–GJR de varianza condicional con un modelo de riesgos proporcionales de Cox dependiente del tiempo, incorporando el riesgo agroclimático heteroscedástico en la probabilidad de quiebra. Se emplearon datos longitudinales de 205 pymes agrícolas registradas en la Superintendencia de Compañías del Ecuador en Quevedo, Los Ríos, zona bananera y cacaotera con volatilidad de precios superior al 34 % anualizado; el modelo se estimó sobre 80 empresas entre 2021 y 2025. A partir de condiciones KKT se identificó un umbral crítico de apalancamiento (Zoc = −0,2263) y un límite de diversificación (σ* = 0,312), bajo los cuales la quiebra aumenta no linealmente. Los resultados evidencian que 43 empresas (53,75 %) se ubican en alto riesgo, y que el riesgo condicional crece 2,14 por cada unidad de reducción en utilidades retenidas. El modelo aporta reglas de decisión aplicables a la gestión agroalimentaria y al análisis de supervivencia financiera no gaussiana.

Palabras clave: Empresas agrícolas, gestión de riesgos, modelos económicos, economía agrícola, econometría.

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Abstract:

Traditional models of financial distress, designed in high-income, low-volatility contexts, fail to capture the combined exposure of agricultural SMEs to price shocks and climate variations. This study develops a stochastic survival optimization framework that integrates a GARCH (1,1)–GJR conditional variance model with a time-dependent Cox proportional hazards model, incorporating heteroscedastic agroclimatic risk into the probability of bankruptcy. Longitudinal data were used from 205 agricultural SMEs registered with the Superintendency of Companies of Ecuador in Quevedo, Los Ríos, a banana- and cocoa-growing region with price volatility exceeding 34% annualized; the model was estimated for 80 firms between 2021 and 2025. Based on KKT conditions, a critical leverage threshold (Zoc = −0.2263) and a diversification limit (σ* = 0.312) were identified, below which bankruptcy increases non-linearly. The results show that 43 companies (53.75%) are at high risk, and that conditional risk increases by 2.14 for every unit decrease in retained earnings. The model provides decision rules applicable to agri-food management and non-Gaussian financial survival analysis.

Keywords: Agricultural enterprises, risk management, economic models, agricultural economics, econometrics.

1. Introduction

The prediction of business failure constitutes one of the most enduring problems in corporate finance, yet its theoretical architecture remains anchored to assumptions of distributional normality and institutional stability that systematically misrepresent the risk environment of agricultural small and medium-sized enterprises (SMEs) in emerging economies (Altman et al., 2022; Ciampi et al., 2021; Kovacova et al., 2022). This disjunction between canonical bankruptcy theory and the operational reality of agro-SMEs is nowhere more apparent than in Los Ríos, Ecuador, where enterprises engaged in banana and cacao cultivation face a trifecta of compounding stressors: government-mandated support price ceilings that suppress upside revenue volatility while leaving downside exposure structurally uncapped, seasonal climate shocks documented to reduce crop yields by up to 40% in El Niño years, and credit markets characterized by collateral illiquidity and asymmetric information (Baselga-Pascual et al., 2022; Figini & Giudici, 2022).

The intellectual genealogy of failure prediction traces from Beaver's (1966) univariate ratio tests through Altman's (1968) seminal Z-score—a linear discriminant function that, for all its parsimony, encodes an implicit assumption of elliptically distributed financial ratios—to Ohlson's (1980) logistic transformation, which relaxed the equal-covariance constraint but retained the cross-sectional, single-period structure that forecloses dynamic volatility modeling (Ashraf et al., 2022; Diez-Esteban et al., 2022).

The subsequent three decades witnessed an efflorescence of machine-learning extensions (Siddiqui et al., 2023; Barboza et al., 2023), yet these approaches, while improving predictive accuracy on benchmark datasets, rarely address the theoretical problem of endogenous agroclimatic shocks or provide the interpretable decision boundaries that SME managers require (Li et al., 2022; Muñoz-Izquierdo et al., 2022).

We identify three specific lacunae in the extant literature that this paper resolves. First, no published model formally integrates conditional heteroskedasticity, the stylized empirical feature of commodity-linked SME financial ratios, into the failure hazard function, creating systematic underestimation of left-tail risk in high-volatility agricultural contexts (Blanco-Oliver et al., 2023; Calabrese & Osmetti, 2022). Second, the treatment of endogeneity in failure studies remains perfunctory: the established finding that financial distress and managerial decision-making are jointly determined (Hernandez Tinoco et al., 2023; Liang et al., 2022) demands instrumental variable correction, yet fewer than 15% of studies reviewed by Arora et al. (2023) implement such correction for agricultural firms. Third, existing thresholds from Altman-type models calibrated on North American or European manufacturing data yield substantial classification error when applied to tropical agribusinesses, where the ratio of biological assets to total assets can exceed 60% and where weather-driven revenue discontinuities violate the stationarity assumptions embedded in static discriminant functions (Ouenniche et al., 2023; Ptak-Chmielewska, 2021).

We develop and estimate a Stochastic Survival Optimization (SSO) model that addresses each lacuna. The core theoretical contribution is a dynamic failure probability function in which the conditional hazard rate is parameterized by a GARCH(1,1)–GJR process governing the volatility of key financial ratios, and in which the optimal capital structure, defined as the leverage allocation that maximizes expected firm survival duration, is solved analytically through KKT conditions. Empirically, we exploit a panel of 205 agricultural SMEs in the Quevedo metropolitan area, applying factor-reduced discriminant analysis (Altman, 1968; Correa-Mejía & Lopera-Castaño, 2022) on 40 financial and non-financial variables to construct composite latent constructs that serve as covariates in the Cox hazard regression (Rodríguez-Valencia et al., 2023; Sun et al., 2023).

Quevedo represents a theoretically compelling data-generating environment—not a case study in the colloquial sense, but a high-dimensional volatility laboratory. The city anchors Ecuador's second-largest agricultural export corridor, generating approximately USD 1.4 billion annually in banana-cacao output while simultaneously exhibiting the highest SME failure turnover rate in Los Ríos. The confluence of institutional underdevelopment, biological production cycles, and international commodity price pass-through creates a regime of non-Gaussian financial dynamics that stress-tests conventional failure models in ways that manufacturing or service-sector datasets cannot (Muthoni et al., 2023; Bismark et al., 2023). By developing our framework in this context and demonstrating its out-of-sample stability, we produce a model with direct applicability to the broader universe of tropical agro-SMEs in the Global South (Camacho-Miñano & Campa-Planas, 2021; Kliestik et al., 2021).

The remainder of the paper is organized as follows. Section 2 presents the theoretical model, formal derivations, and sensitivity analysis. Section 3 describes the empirical methodology and identification strategy. Section 4 reports estimation results. Section 5 discusses implications relative to the contemporary literature. Section 6 translates model outputs into managerial decision rules. Section 7 concludes

1.2. Theory and analytical model

Theoretical foundations and model primitives

We begin from first principles by modeling the agricultural SME as an entity whose survival depends on the intertemporal alignment of cash-flow generation capacity and debt service obligations under stochastic agroclimatic conditions. Let the state space of firm (i) at time (t) be described by the vector:

$\Omega_{it} = \{X1_{it}, X2_{it}, X3_{it}, X4_{it}, X5_{it}, \xi_t\}$

where $X1_{it} = Working\ Capital/Total$ Assets (liquidity buffer), $X2_{it} = Retained\ Earnings/Total\ Assets$ (accumulated resilience), $X3_{it} = EBIT/Total\ Assets$ (operational efficiency), $X4_{it} = Total\ Equity/Total\ Liabilities$ (solvency coverage), $X5_{it} = Net\ Sales/Total\ Assets$ (asset utilization), and ξ_t is an agroclimatic shock process capturing the exogenous commodity price and rainfall disturbances specific to Los Ríos.

Agroclimatic shock process and garch specification

We model the shock process through a GJR-GARCH(1,1) specification that allows for leverage effects—the empirically documented finding that negative commodity price shocks generate disproportionately larger volatility responses than equivalent positive shocks (applicable to banana export prices subject to FOB Guayaquil fluctuations):

$$\xi_t = \mu_\xi + \varepsilon_t, \quad \varepsilon_t = z_t \cdot \sqrt{(h_t)}, \quad z_t \sim i.i.d.\,N(0,1)$$

$$h_t = \omega + \alpha \cdot \varepsilon^2_{(t-1)} + \gamma \cdot \varepsilon^2_{(t-1)} \cdot I[\varepsilon_{(t-1)} < 0] + \beta \cdot h_{(t-1)}$$

where h_t is the conditional variance of the agroclimatic shock, $\omega > 0, \alpha \geq 0, \beta \geq 0, \alpha + \gamma/2 + \beta < 1$ (stationarity condition), and $I[\cdot]$ is the indicator function capturing asymmetric (leverage) effects when $\gamma > 0$. Under this specification, a climatic disruption generating $\varepsilon < 0$ (crop yield shortfall) transmits into financial ratios with amplified persistence relative to positive shocks.

The survival optimization problem

Define the survival probability of firm i over horizon T as:

$$S_i(T) = exp\{-\int_0^T \lambda_i(t \mid \Omega_{it})\, dt\}$$

where $\lambda\_i(t \mid \Omega\_it)$ is the conditional failure hazard rate. The firm's financial management problem is to choose leverage allocation L_it and portfolio diversification vector d_it so as to maximize expected survival duration subject to operational and regulatory constraints.

Formally, the Stochastic Survival Optimization (SSO) problem is:

$$max\_\{L, d\}\ E[T\_i \mid \Omega\_i0] = \int{}_0\hat{}\infty\ S\_i(t)\, dt$$

Subject to:

$$(C1): L\_it \leq \bar{L} - regulatory\ leverage\ ceiling\ (Superintendencia\ constraint)$$

$$(C2): \sigma\_p(d\_it) \leq \sigma * - portfolio\ volatility\ constraint$$

$$(C3): X3\_it \geq X3\_min - minimum\ operational\ efficiency\ threshold$$

$$(C4): d\_it \in \Delta\hat{}K - portfolio\ simplex\ (K\ productive\ subsectors)$$

1.1.2.4. KKT Equilibrium conditions and theorem 1

Forming the Lagrangian:

$$\mathcal{L} = E[T\_i] - \mu_1(L\_it - \bar{L}) - \mu_2(\sigma\_p - \sigma *) - \mu_3(X3\_min - X3\_it) - \lambda^{\mathrm{T}}(1 - \Sigma d\_k)$$

We derive the following equilibrium theorem:

Theorem 1 (Optimal Survival-Leverage Boundary). Under the GJR-GARCH agroclimatic shock process h_t satisfying the stationarity condition, there exists a unique critical leverage threshold $Z * \_oc$ such that:

$$Z * \_oc = (n\_s \cdot Z\_s + n\_w \cdot Z\_w) / N$$

where n_s and n_w denote the number of strong and weak firms, Z_s and Z_w are group centroids of the discriminant function, and N is total sample size. Firms with $Z > Z * \_oc$ satisfy the first-order survival condition; firms with $Z \leq Z * \_oc$ violate it.

Proof sketch. The expected survival time $E[T\_i]$ is a decreasing, convex function of the hazard $\lambda\_i(t)$. Under the Cox proportional hazard parameterization $\lambda\_i(t) = \lambda\_0(t) \cdot exp(\beta' X\_it)$, the gradient $\partial E[T_i]/\partial L_$it is monotonically negative for $L\_it > \bar{L}$. Applying the KKT stationarity condition to constraint C1 yields the unique interior solution $Z * \_oc = -0.2263$ under our empirical parameterization. Complementary slackness confirms that $\mu_1 > 0$ only when the leverage constraint binds.

Lemma 1: Portfolio diversification threshold

Lemma 1 (Diversification Boundary). Under the portfolio constraint C2, the optimal diversification volatility satisfies $\sigma * = 0.312$ when the GJR leverage parameter $\hat{\gamma} = 0.218$. For $\sigma\_p > \sigma *$, the marginal contribution of additional diversification to $E[T\_i]$

is strictly positive; for $\sigma\_p \leq \sigma *$, the constraint is inactive and further concentration increases failure hazard nonlinearly.

Proof. The portfolio variance $\sigma^2\_p = d^{\mathrm{T}}\Sigma d$, where Σ is the variance-covariance matrix of sub-sector returns. Differentiating the Lagrangian with respect to d and setting equal to zero yields $d * = (2\mu_2\Sigma)^{-1}\lambda$. Substituting the empirical Σ estimated from Quevedo agro-sector data (2021–2025) produces $\sigma * = 0.312$.

Sensitivity analysis under external shocks

We perform a comparative statics analysis of $Z * \_oc$ with respect to two external shock parameters: (a) an agroclimatic shock θ_c that reduces EBIT/Total Assets by Δ and (b) an international commodity price shock θ_p that increases revenue volatility $\sigma(X5)$. Formally:

$$\partial Z * \_oc/\partial\theta\_c = -(\partial Z\_w/\partial\theta\_c \cdot n\_w + \partial Z\_s/\partial\theta\_c \cdot n\_s) / N < 0$$

$$\partial Z * \_oc/\partial\theta\_p = -(\partial Z\_w/\partial\theta\_p \cdot n\_w + \partial Z\_s/\partial\theta\_p \cdot n\_s) / N < 0$$

Both partial derivatives are strictly negative, indicating that external shocks shift the critical threshold leftward, expanding the set of firms classified as weak. A one-standard-deviation agroclimatic shock (Δ = 0.18 in EBIT ratio terms) reduces $Z * \_oc$ by 0.094, reclassifying an estimated 6–8 additional firms from strong to weak in the Quevedo panel. This sensitivity result has direct implications for risk-adjusted capital buffer requirements.

2. Materials and methods

Sample and data architecture

We constructed a longitudinal panel from the administrative financial records of 205 agricultural SMEs registered under ISIC 4.0 Section A (Agriculture, Livestock, and Forestry, Divisions 01–02) with the Superintendencia de Compañías, Valores y Seguros del Ecuador (SCVS) in Quevedo, covering fiscal years 2021–2025. After excluding firms with fewer than three consecutive years of complete financial reporting and winsorizing extreme ratio values at the 1st and 99th percentiles, we retained a working sample of 80 firms, consistent with the sample size criteria established by Ptak-Chmielewska (2021) for hazard model estimation in SME contexts. The target population parameters are summarized in Table 1.

Table 1
Research Design Technical Specifications

Parameter	Specification
Target Population	Agricultural SMEs, Quevedo, Los Ríos
Data Source	SCVS Ecuador Administrative Registry (2021–2025)
Population (N)	205 firms

Parameter	Specification
Estimation Sample (n)	80 firms (stratified, discretionary sampling)
Sampling Error	10% (one-tailed)
Confidence Level	90%; Z = 1.645; p = q = 0.50
Panel Length	5 years (2021–2025)
Failure Events Observed	43 firms (53.75% of sample)

Note: (Authors, 2026).

GARCH-Based conditional volatility estimation

We estimated the GJR-GARCH(1,1) model on the time series of each financial ratio composite ($X1 - X5$) using quasi-maximum likelihood (QML) with Bollerslev-Wooldridge robust standard errors, which maintain consistency under non-normality of standardized residuals, a crucial robustness feature given that agro-sector ratio distributions exhibit significant excess kurtosis ($\hat{\kappa} = 4.73$ for $X3$, $EBIT/Total\ Assets$). The conditional variance estimates $\hat{h}_t$ were then extracted and incorporated as time-varying covariates in the Cox proportional hazard regression (Chen et al., 2022; Ciampi et al., 2021).

The QML log-likelihood is:

$$l(\theta) = -½\, \Sigma_t\, [log(\hat{h}_t) + \varepsilon^2_t / \hat{h}_t]$$

with parameters $\theta = (\omega, \alpha, \gamma, \beta)$ estimated via Broyden-Fletcher-Goldfarb-Shanno (BFGS) numerical optimization. Convergence diagnostics reported in Section 4 confirm that all five ratio-specific GARCH models achieved convergence within 150 iterations.

Cox proportional hazard specification

The conditional failure hazard function takes the partial likelihood form of Cox (1972), extended to accommodate time-varying GARCH-augmented covariates:

$$\lambda_i(t \mid X_i(t)) = \lambda_0(t) \cdot exp(\beta_1 X1_{it} + \beta_2 X2_{it} + \beta_3 X3_{it} + \beta_4 X4_{it} + \beta_5 X5_{it} + \delta \hat{h}_{it})$$

where $\lambda_0(t)$ is the unspecified baseline hazard, β_k are ratio-specific coefficients, and δ captures the additional marginal hazard contribution of GARCH-estimated conditional volatility $\hat{h}_{it}$. The partial likelihood, which eliminates $\lambda_0(t)$ without requiring its parametric specification, is:

$$PL(\beta, \delta) = \Pi_{\{i:\, event\}} [exp(\beta' X_i(t_i)) / \Sigma_{\{j \in R(t_i)\}}\, exp(\beta' X_j(t_i))]$$

where $R(t_i)$ is the risk set at failure time t_i. We handled tied failure times using the Breslow (1974) approximation, appropriate given the low tie frequency in our panel (maximum 3 ties per period).

Endogeneity correction via instrumental variables

The potential endogeneity of the solvency ratio $X4$ ($Total\,Equity/Total\,Liabilities$) with respect to the failure outcome arises because firms anticipating distress may engage in strategic recapitalization, inflating equity in the pre-failure period and biasing Cox coefficients downward (Hernandez Tinoco et al., 2023). We addressed this through a two-stage residual inclusion (2SRI) approach following Terza et al. (2022). The instrument for $X4$ was the province-level agricultural credit disbursement index from Banco del Estado, which influences firm capital structure through credit supply but is exogenous to individual firm failure decisions. First-stage F-statistics ($F = 34.2, p < 0.001$) confirm instrument strength, satisfying the relevance criterion; the Sargan-Hansen J-statistic ($J = 1.34, p = 0.247$) supports exclusion restriction validity.

Discriminant function estimation

Parallel to the Cox specification, we estimated the Altman-framework discriminant function using confirmatory factor analysis to construct composite scores from the 80-firm sample. Kaiser-Meyer-Olkin (KMO) adequacy statistics and Bartlett sphericity tests (reported in Section 4) confirmed factor solution stability across all five composite variables. The linear discriminant function takes the form:

$$Z\_i = -1.43 + 0.007 \cdot RC\_i + 0.776 \cdot ACP\_i + 0.128 \cdot ALP\_i$$

where *RC* = Current ratio composite, *ACP* = Working capital composite, and *ALP* = Liquidity pressure composite, derived from the factor-analytic reduction of 40 financial indicators. The cut-score $Z * \_oc = -0.2263$ was computed as the weighted centroid between group means, consistent with Theorem 1.

3. Results

3.1. Descriptive statistics and factor structure validation

Table 2 reports the KMO adequacy statistics and Bartlett sphericity tests for each of the five Altman composite variables. All KMO values exceed the conventional threshold of 0.75, and all Bartlett chi-square statistics are significant at $p < 0.001$, confirming that the inter-ratio correlation matrices are suitable for factor extraction.

Table 2

Factor Adequacy Statistics for Composite Financial Indicators (n = 80)

Composite	Financial Ratio	KMO	Bartlett χ²	df	p-value	% Var. Explained
X1	Working Capital / Total Assets	0.791	501.92	79	< 0.001	56.89%
X2	Retained Earnings / Total Assets	0.815	379.20	79	< 0.001	71.04%
X3	EBIT / Total Assets	0.812	322.46	79	< 0.001	68.32%

Composite	Financial Ratio	KMO	Bartlett χ^2	df	p-value	% Var. Explained
X4	Total Equity / Total Liabilities	0.864	803.82	79	< 0.001	67.45%
X5	Net Sales / Total Assets	0.834	618.37	79	< 0.001	64.18%

Note: (Authors, 2026).

3.2. GARCH conditional variance estimates

Table 3 presents GJR-GARCH (1,1) parameter estimates for the five ratio composites. The leverage parameter γ is statistically significant for X3 (EBIT ratio, $\hat{\gamma} = 0.218$, $p < 0.01$) and $X1$ (working capital ratio, $\hat{\gamma} = 0.163$, $p < 0.05$), confirming that negative agroclimatic shocks generate disproportionate conditional variance in operational profitability, the mechanism theorized in Section 2. Persistence parameters ($\alpha + \gamma/2 + \beta$) range from 0.84 to 0.92, indicating high but stationary volatility dynamics.

Table 3

GJR-GARCH (1,1) parameter estimates for financial ratio composites

Ratio	ω ($\times 10^{-4}$)	α	γ (leverage)	β	Persistence	ARCH-LM (p)
X1: WC/TA	0.312**	0.092**	0.163*	0.748***	0.921	0.318
X2: RE/TA	0.284**	0.071*	0.089	0.801***	0.916	0.421
X3: EBIT/TA	0.419***	0.113***	0.218**	0.724***	0.946†	0.287
X4: EQ/TL	0.238**	0.083**	0.074	0.812***	0.932	0.534
X5: Sales/TA	0.291**	0.068*	0.097	0.789***	0.906	0.412

Note. $***\ p < 0.001$; $**\ p < 0.01$; $*\ p < 0.05$; † persistence marginally exceeds stationarity threshold for $X3$; see robustness checks in supplemental material. ARCH-LM = p-value from Engle (1982) LM test for remaining autocorrelation in squared residuals (Authors, 2026).

3.3. Cox Proportional hazard estimates

Table 4 reports the Cox partial likelihood estimates with and without the GARCH volatility augmentation. The inclusion of GARCH conditional variance ($\delta = 1.847, p < 0.001$) substantially improves model fit ($\Delta LR = 18.42, df = 1, p < 0.001$), confirming the theoretical proposition that agroclimatic volatility carries information about failure hazard beyond that captured by ratio levels alone.

Table 4

Cox Proportional Hazard Model Estimates (n = 80 firms; 43 failure events)

Covariate	Model 1 (Base)		Model 2 (GARCH-augmented)	
	$\hat{\beta}$	Hazard Ratio	$\hat{\beta}$	Hazard Ratio

Covariate	Model 1 (Base)		Model 2 (GARCH-augmented)	
X1: Working Capital/TA	-2.341***	0.096	-2.189***	0.112
X2: Retained Earnings/TA	-2.143***	0.117	-2.014***	0.133
X3: EBIT/TA	-1.876***	0.153	-1.724***	0.178
X4: Total Equity/TL	-1.514**	0.220	-1.438**	0.237
X5: Net Sales/TA	-0.892*	0.410	-0.834*	0.434
ĥ_it (GARCH Variance)	—	—	1.847***	6.342
Log-Likelihood	-187.32		-178.11	
Concordance Index	0.763		0.812	

Note. Standard errors are clustered at the firm level. $*** \ p < 0.001$; $** \ p < 0.01$; $* \ p < 0.05$. Model 2 endogeneity correction applied to X4 via 2SRI (first-stage $F = 34.2$). Convergence achieved in all GARCH models within 150 iterations using BFGS optimization (Authors, 2026).

3.4. Discriminant classification and cut-score

Applying Theorem 1, we computed $Z*\_oc = -0.2263$. The discriminant functions for the two groups produced group centroids $Z\_strong = -0.7566$ $(n = 37;\ 46.25\%)$ and $Z\_weak = +0.2301$ $(n = 43;\ 53.75\%)$. Of firms classified as strong $(Z > Z*\_oc)$, 57.5% exhibit conditional failure probability below 0.15 over the five-year horizon; of firms classified as weak $(Z \leq Z*\_oc)$, 64.1% exhibit conditional failure probability exceeding 0.50. The overall classification accuracy rate was 78.3% (hold-out cross-validation), exceeding the Altman Z-score benchmark of 72.1% reported by Altman et al. (2022) on comparable SME samples.

Table 5

Discriminant Classification Summary

Classification	n	% of Sample	Mean Z-Score	P(Failure ≥ 0.50)	P(Failure < 0.15)
Strong (Z > Z*_oc)	37	46.25%	−0.7566	16.2%	57.5%
Weak (Z ≤ Z*_oc)	43	53.75%	+0.2301	64.1%	8.4%
Full Sample	80	100%	−0.2263	42.3%	34.7%

Note: (Authors, 2026).

4. Discusión

The finding that GARCH-augmented conditional volatility carries an independent hazard contribution $(\delta = 1.847,\ HR = 6.342)$ demands a substantive reinterpretation of how we understand bankruptcy risk in agricultural firms. Canonical models treat the levels of financial ratios as the causal mechanism; our results indicate that the second-moment dynamics of those ratios—the speed and asymmetry with which ratio volatility responds to shocks—contain approximately 18% additional explanatory power over and above ratio levels $(\Delta AIC = 14.24$ in favor of Model 2). This finding extends the theoretical framework of Blanco-Oliver et al. (2023), who established that distress probability is sensitive to ratio trend dynamics but stopped short of formalizing the volatility channel through a GARCH specification.

The leverage asymmetry captured by the GJR parameter $\hat{\gamma} = 0.218$ for $EBIT/Total\ Assets$ deserves particular theoretical attention. This coefficient implies that a downward shock to operational profitability—the characteristic response to a frost or flooding event in the cacao-banana corridor—generates 21.8% more persistent volatility than an equivalent upward shock. This asymmetry cannot be accommodated by standard logistic regression models and explains, at least partially, why models calibrated on upward-skewed training periods systematically underestimate failure risk in the subsequent stress period (Diez-Esteban et al., 2022; Ouenniche et al., 2023). Unlike previous studies that treated agricultural SME failure as a static cross-sectional event, we demonstrate through the time-varying Cox specification that the pathway to failure is better understood as a dynamic volatility accumulation process, with the critical threshold crossed not at a single point but over a trajectory of compounding variance.

The classification result, 53.75% of Quevedo agro-SMEs operating in the high-failure zone, is substantially higher than the 30-35% distress rate reported for manufacturing SMEs in comparable Altman-framework studies (Altman et al., 2022; Kovacova et al., 2022). We attribute this differential to three institutional mechanisms specific to the Los Ríos agrarian context: (1) the banana price support program (Precio de Sustentación del Banano) creates a price floor that, while protecting revenue in normal years, simultaneously discourages ex ante hedging behavior, leaving firms structurally underprepared for episodes when market prices drop below the support level; (2) the predominance of biological assets in firm balance sheets generates accounting-timing mismatches between revenue recognition and biological growth cycles that inflate $X1$ and $X2$ ratios in years of plantation expansion while suppressing $X3$, a pattern that masks underlying distress in the Altman framework but is captured by the volatility trajectory in our GARCH specification; and (3) the concentrated bank credit market in Los Ríos Province means that liquidity shocks cannot be absorbed through credit market access, forcing immediate operational contraction (Camacho-Miñano & Campa-Planas, 2021; Muthoni et al., 2023).

Our cut-score $Z*\_oc = -0.2263$ diverges markedly from Altman's canonical manufacturing threshold of +1.81 (gray zone boundary) and from the agricultural sector threshold of $+0.73$ proposed by Camacho-Miñano & Campa-Planas (2021) for Spanish agro-cooperatives. This divergence is not a limitation but a finding: it empirically confirms that direct cross-sector transplantation of failure thresholds produces systematic misclassification in tropical agro-SMEs and validates the theoretical necessity of context-specific calibration. The sensitivity analysis in Section 2.6 further demonstrates that a one-standard-deviation agroclimatic shock shifts $Z*\_oc$ leftward by 0.094, indicating that the threshold is not a static scalar but a regime-dependent boundary that should be updated dynamically as ξ_t evolves (Ashraf et al., 2022; Li et al., 2022).

The endogeneity correction via the 2SRI instrument (provincial credit disbursement) addressed a heretofore neglected source of bias in the agricultural failure literature. Prior studies relying on OLS or standard MLE frameworks confound capital structure decisions with anticipated distress, producing attenuated coefficient estimates for solvency ratios (Hernandez Tinoco et al., 2023; Rodríguez-Valencia et al., 2023). The corrected coefficient on X4 ($\beta = -1.438$ versus uncorrected -1.287) indicates a 11.7% downward bias in the uncorrected specification—material enough to alter classification decisions for firms near the cut-score.

Relative to the machine-learning literature on SME failure (Siddiqui et al., 2023; Barboza et al., 2023), our framework sacrifices predictive accuracy (concordance index 0.812 versus reported AUROCs of $0.87 - 0.93$ for gradient boosting) in exchange for theoretical interpretability and managerial actionability. The KKT-derived equilibrium conditions produce closed-form threshold rules that can be monitored monthly by firm controllers and communicate the mechanism of distress—not merely its probability. We argue, following Muñoz-Izquierdo et al. (2022), that interpretability is not a second-order consideration in the SME context but a primary determinant of model adoption: a threshold that a manager cannot understand or operationalize generates zero policy value regardless of its statistical performance.

4.1. Implications for agricultural finance theory

Our findings contribute to a broader reconceptualization of agricultural financial theory in three respects. First, they empirically establish that the Modigliani-Miller capital structure irrelevance proposition, which underlies much of the normative finance advice directed at SMEs, fails under biologically constrained cash flow uncertainty: when the variance of the EBIT ratio follows a GJR process with significant asymmetry, the cost of capital is endogenously determined by the direction of shocks, not merely their magnitude (Sun et al., 2023; Liang et al., 2022). Second, they validate the portfolio constraint embedded in Lemma 1: firms operating below the diversification boundary $\sigma * = 0.312$ face a nonlinearly increasing failure hazard, suggesting that crop diversification policy (e.g., intercropping banana with cacao and piñón) has a mathematically determinate optimal boundary beyond which additional diversification yields diminishing survival benefits (Bismark et al., 2023; Chen et al., 2022). Third, the high persistence parameters ($\hat{\alpha} + \hat{\gamma}/2 + \beta \approx 0.90$) imply that financial ratio volatility in this ecosystem behaves as a near-integrated process, meaning that shocks accumulate rather than dissipate, a regime that requires risk buffers to be sized against the long-run unconditional variance, not the short-run conditional variance that conventional stress-testing employs (Figini & Giudici, 2022; Calabrese & Osmetti, 2022).

Managerial Insights: Decision Rules for Agricultural SME Managers

We translate the mathematical results of Sections 2 through 5 into a set of operationally actionable decision rules calibrated to the Quevedo agrarian context. These rules are grounded in the equilibrium conditions of the SSO model and are designed to be computable from standard annual financial statements without requiring econometric software.

Decision Rule 1 — Solvency monitoring (Theorem 1): Compute the monthly discriminant score Z using equation $(2)/(3)$ from the empirical discriminant functions. If Z falls below $Z*\_oc = -0.2263$ for two consecutive quarters, activate the Capital Reinforcement Protocol: suspend non-essential capital expenditure, initiate renegotiation of short-term liabilities, and engage the local SCVS restructuring program. The two-quarter condition provides a buffer against transient ratio fluctuations while ensuring timely intervention before irreversible liquidity depletion.

Decision Rule 2 — Volatility alert threshold (GARCH Channel): Monitor the 12-month rolling standard deviation of $X3$ $(EBIT/Total\ Assets)$. If $\sigma(X3)$ exceeds 0.18 (one standard deviation of the Quevedo panel shock distribution), increase retained earnings retention by a minimum of 15 percentage points of net profit, redirecting resources from dividend distribution or owner withdrawals. This rule operationalizes the sensitivity result $\partial Z*\_oc/\partial\theta\_c < 0$: when the agroclimatic shock intensifies, the survival boundary shifts, requiring proactive reserve accumulation.

Decision Rule 3 — Portfolio diversification (Lemma 1): Maintain productive crop allocation such that the Herfindahl-Hirschman Index (HHI) of revenue by crop type does not exceed $HHI\_max = 0.45$, which corresponds empirically to the $\sigma * = 0.312$ portfolio volatility boundary. Firms exceeding $HHI > 0.45$ should initiate inter-season transition to at least two primary crops, targeting 30-40% cacao/banana revenue balance where agroclimatic conditions permit.

Decision Rule 4 — Leverage Ceiling (Constraint C1): Total liabilities should not exceed 2.3× total equity (corresponding to $X4 = 0.435$). Firms approaching this ceiling—particularly in Q1 (harvest season) when accounts payable spike—should pre-arrange revolving credit lines with Banco del Pacífico's PYME agricultural desk or BanEcuador to prevent leverage breaches that would trigger the KKT shadow price $\mu_1 > 0$ condition, indicating that the leverage constraint is binding and survival probability is actively being suppressed.

Decision Rule 5 — Early Warning Score Card: Integrate Rules 1–4 into a monthly 5-point scorecard: assign 1 point for each of $Z > Z*\_oc$; $\sigma(X3)\_12m < 0.18$; $HHI < 0.45$; $X4 < 2.3$; $and\ X1 > 0.15$ (positive working capital ratio). A scorecard total below 3/5 for two consecutive months constitutes a Board-level early warning signal requiring external financial review.

5. Conclusiones

This paper develops a Stochastic Survival Optimization framework that, for the first time in the agricultural SME literature, formally integrates GJR-GARCH conditional heteroskedasticity into a Cox proportional hazard failure model and derives analytically tractable KKT equilibrium conditions for optimal financial management under agroclimatic volatility. We apply the framework to 80 agricultural SMEs in Quevedo, Ecuador—a data environment that concentrates the institutional, biological, and climatic complexity characteristic of tropical agribusiness in the Global South.

The core empirical findings are three-fold. First, GARCH-augmented conditional volatility carries a hazard ratio of 6.342 $(p < 0.001)$ independent of ratio levels, establishing that the second-moment dynamics of financial ratios are theoretically irreducible in agricultural failure modeling. Second, the KKT-derived cut-score $Z * \_oc = -0.2263$ classifies 53.75% of Quevedo agro-SMEs as high-failure-risk, a substantially higher rate than comparable manufacturing benchmarks, reflecting the institutional specificities of Los Ríos Province. Third, the GJR leverage asymmetry parameter $\hat{\gamma} = 0.218$ confirms that negative agroclimatic shocks generate nonlinearly larger volatility persistence than positive shocks, necessitating asymmetric risk-buffering strategies.

The theoretical contributions of this paper extend across three dimensions: (1) a formal mathematical proof of the optimal survival-leverage boundary as a function of group discriminant centroids and sample composition; (2) a Lemma establishing a closed-form portfolio diversification threshold $\sigma * = 0.312$ tied to the GJR leverage parameter; and (3) a comparative statics framework showing that both agroclimatic and commodity price shocks shift the failure boundary leftward, with immediate implications for dynamic capital buffer policy.

We acknowledge three limitations that future research should address. First, our panel covers 2021–2025, a period that includes the long-haul covid-19 shock of 2021; while we included year fixed effects, disentangling pandemic effects from secular agroclimatic trends requires a longer time series. Second, the instrument for endogeneity correction—provincial credit disbursement—may be correlated with regional economic conditions that also affect failure risk, a concern that future work might address using natural experiments in agricultural credit policy. Third, the model has been calibrated exclusively on banana-cacao SMEs; its portability to coffee, rice, or tilapia aquaculture firms in Ecuador requires separate validation.

Future research should pursue three extensions. The integration of satellite-derived climate indices (NDVI, precipitation anomaly) as real-time inputs to the GARCH shock process would transform the framework from a backward-looking diagnostic into a forward-looking early warning system. The application of the SSO framework to SME panels across multiple Latin American agricultural provinces would test whether the equilibrium boundary $Z * \_oc$ is region-specific or exhibits structural stability across comparable tropical agrobusiness ecosystems. Finally, the translation of the decision rules developed in Section 6 into a software tool integrated with the SCVS reporting platform would provide the institutional channel through which the model's theoretical contributions yield maximum social value.

CONFLICTO DE INTERESES

“Los autores declaran no tener ningún conflicto de intereses”.

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