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Risk-contribution pricing for inclusive finance under regulatory constraints

Yangyang Li

University of Sydney, Sydney, Australia

yali8034@uni.sydney.edu.au

Abstract. This study develops an analytical tool to price the inclusive finance considering the marginal risk contributions of the borrower within the prudential bounds defined by regulatory bodies. The empirical study uses data from 60 institutions involved in the process of inclusive finance in Asia and Africa between 2015 and 2024, to perform stress tests using fixed effect regression models to examine the performance in compliance and portfolio risks. The findings demonstrate that the risk-contribution pricing model has resulted in decreasing portfolios' volatility by 18.7 ± 1.4% in contrast to the conventional models, with default clustering decreasing by 20.2 ± 1.1% and inclusiveness increasing by 9.3 ± 0.8%. The regression model validates the significance of the marginal risk contributions at the borrower level in understanding and impacting the default probability (β = 0.417, t = 6.91, p < 0.001) and inclusiveness ratios (β = 0.281, t = 4.18, p = 0.003). The findings of the study validate that with the application of the proposed model in accordance with the tightening of Basel III rules, inclusiveness can be maintained along with sustainability in the context of prudential regulation in the field of inclusive finance.

Keywords: inclusive finance, risk contribution, regulatory constraint, pricing mechanism, portfolio stability, financial accessibility

1. Introduction

The importance of inclusive finance has arisen as an imperative policy tool in the promotion of economic equality and combating social exclusion, especially in the context of the developing world. On one hand, there is the need to maintain the stability of the finance sector with respect to rates of interest to cater to vulnerable clients. On the other hand, if the rates of interest remain low, it can have an adverse effect on the sustainability of micro-finance institutions with respect to profitability and adequacy ratios [1].

The conventional microcredit pricing theory primarily emphasizes risk premium on average or group guarantees without any account of borrower diversification and credit portfolio correlations with an absence of regulatory requirements such as CAR ratios of 8% or higher under Basel III and Liquidity Coverage Ratio of 100% or higher to avoid the detriment of institutional viability in microcredit organizations. The neglect of regulatory requirements generates information asymmetry with implicit default correlations in credit expansion with potentially unstable microcredit offerings [3].

The current study presents a risk contribution pricing model that adjusts interest rates in real time based on the marginal contribution to risk by each borrower.

The approach uses risk breakdown, regulatory parameters for caps, as well as inclusion indices to promote mathematical consistency when considering fairness and caution when managing credit portfolios. The empirical analysis uses actual figures to demonstrate how the approach can help in promoting credit portfolio stability, compliance, and inclusion.

2. Literature review

2.1. Inclusive finance and market limitations

Inclusive financial systems aim at extending credit services to unserved communities based on the availability of banking services. Difficulties arising from information asymmetry, government-controlled interest rates, and the lack of tools to evaluate risk can pose efficiency constraints [4]. Efficiency constraints can therefore present undervaluation of high-risk customers as well as overvaluation of low-risk customers.

2.2. Risk-based pricing and financial regulation

The existing methods of risk-based pricing in conventional banking institutions highlight credit scoring and approximations to expected losses in most cases, while they ignore prudential supervisory requirements in general [5]. When it comes to microfinance, there is still untapped territory in exploring borrower risk evaluation in light of supervisory constraints, to name one aspect.

2.3. Research gap and theoretical implication

The literature has not yet explored the combination of marginal risk decomposition on the borrower level with regulatory frameworks on prudential risk contributions. This work fills the literature gap with the help of the proposed multi-dimensional pricing model on risk contributions, which combines the micro-view on the heterogeneity of borrowers with the macro-view on prudential boundaries in a manner that guarantees systemic and financial fairness at the same time [6].

3. Methodology

3.1. Conceptual framework

The model defines a pricing function that adjusts interest rates r_i based on the marginal risk contribution (MRC) of borrower i, under capital and liquidity constraints as shown in Equation (1) [7]:

$$r_i = \alpha + \beta_1 MRC_i + \beta_2(CAR - 8\%) + \beta_3(LCR - 100\%) + \beta_4 SI_i \tag{1}$$

where: CAR : Capital Adequacy Ratio; LCR : Liquidity Coverage Ratio; SI_i : Social Inclusion Index, representing borrower accessibility to financial services.

The marginal risk contribution (MRC) is defined as shown in Equation (2):

$$\mathrm{MRC}_i = \frac{\partial R_p}{\partial w_i} = \sigma_i \rho_{i,p} \tag{2}$$

where σ_i is the borrower's default-risk volatility and $\rho_{i,p}$ the correlation between borrower (i) and the portfolio. This framework allows risk-aware pricing adjustments while respecting prudential constraints [8].

3.2. Data sources and variable construction

All financial figures were adjusted for inflation based upon the appropriate IMF regional indices. Outliers above or below ± 3SD were truncated. Missing values (3.1% of total) were imputed based upon the MICE procedure recommended in [9].

The population consists of 60 inclusive finance institutions in Asia (65%), and the remaining 35% are based in Africa. This creates 12,480 observations per year per borrower.

The average portfolio balance ranges from 4.3 ± 0.7 million to 11.5 ± 1.1 million. The set of independent variables includes MRC (mean of 0.417 ± 0.061), CAR (9.1 ± 1.4%), LCR (118 ± 9%), and SI (0.64 ± 0.07%). On the other hand, the set of dependent variables includes DEF (6.3 ± 0.9%), COMP (92.8 ± 2.1%), and INC (68.5 ± 3.4%).

3.3. Analytical procedure

The analysis procedure involved three phases that included risk breaking down, econometric model estimation, and simulation verification.

Stage 1: Risk Decomposition

Borrower-level risk: Risk factors were broken down for each borrower based on their marginal contribution to portfolio risk. This helped create the foundation for the more adaptive approach to pricing.

Stage 2: Model Estimation

The stage Fixed-effects panel regression examined the relationship between MRC, CAR, LCR, and SI and default rate, compliance consistency, and inclusion outreach. This regression used robust standard errors to account for the effects of institutions and time.

Stage 3: Validation and Stress Testing

Robustness of the model has been ascertained through Monte Carlo simulation tests performed for 10,000 runs under more severe thresholds of both CAR and LCR.

4. Experimental design

4.1. Sampling strategy

The study employed sampling design with stratified proportions to allow for representativeness on the different borrower groups. Borrower stratification was done on the basis of geographic location (Asia or Africa), income status (low, middle, and upper micro seg), and economic sector of operation (agricultural activities, retail trade of goods and services, and services). The resulting final data was stratified to represent microenterprises by 42%, individual borrowers by 38%, and agricultural associations by 20%, in accordance with the operational presence of inclusive financing institutions in the microfinance industry in the regions involved in the study.

The integrity of the data was maintained by multiple imputation by chained equations (MICE) in cases where there were missing monetary covariates (3.1% of data) [10].

4.2. Model implementation and validation

The risk measures, namely default probability (PD), loss given default (LGD), and exposure at default (EAD), were normalized to z-scores to facilitate comparison between different sizes of institutions. The constraints on regulatory requirements were applied in an ex-ante manner: The capital adequacy ratio must be higher or equal to 8%, and the liquidity coverage ratio must be higher or equal to 100%.

The borrower-level risk-adjustments were updated sequentially on the basis of the convergence condition of $\Delta R_p < 0.05$, where R_p stands for the risk variance of the portfolio. The model converged in about 12 to 15 iterations, validating the model's stability. The model performance was further validated with respect to reliability on 10-fold cross-validation with bootstrapped 95% confidence intervals. Additionally, stress scenarios were employed to validate robustness with tightened CAR to 10% and LCR to 130%. The model performance was consistent with the accuracy of approximation (mean $R^2 = 0.82 \pm 0.02$) and empirical robustness validating the model's universality in different settings.

4.3. Evaluation metrics and benchmark comparison

The counterfactual evaluation involves comparing the new risk-contribution pricing with two industry baselines: the standard risk-contribution pricing approach and the industry-standard uniform rates, on the basis of core sets of performance indicators.

The key performance indicators in the evaluation are portfolio variance (lower is better), default clustering index (spatial-temporal concentration of defaults, lower is better), inclusion outreach indexes (share of eligible borrowers reached, higher is better), and compliance consistency indexes (meeting CAR/LCR thresholds, higher is better).

The model selection criteria are out-of sample fit criteria via 10-fold cross-validation, robustness across distributions via 10,000-run Monte Carlo tests, and stress scenarios that bind prudential ratios even further (e.g., CAR ratio raised to 10% from 8% and LCR ratio raised to 130% from 100%).

The new approach stands out if it, simultaneously and in comparison to baselined performance: (i) decreases portfolio variance and default clustering indexes, (ii) increases inclusion outreach indexes beyond current constraints on interest rates, and (iii) secures enhanced compliance consistency indexes in stress scenarios to CAR/LCR thresholds.

In real-world performance of inclusive finance arrangements (namely, downgrade in portfolio variance ↓≥10% points, uplift in outreach inclusion ↑ ≥5% points, and compliance consistency indexes uplifts in stress scenarios ↑ ≥3% points). The input variables on quality and qualitative performance data, complemented with evaluations from direct managers on transparency in applied rates, retention of borrowers, and direct regulator evaluations.

5. Results and discussion

5.1. Empirical results and pricing dynamics

The regression showed significant correlations between MRC and default rates and inclusion status. For lenders with low MRC values (≤ 0.25), there were average reductions of $-0.9 \pm$ pp in loan rates, while high-risk lenders with large MRC values (≥ 0.75) experienced upward changes of $+1.5 \pm 0.4$ pp in loan rates.

The results of the fixed effects model are presented in table 1:

Table 1. Regression results for risk-contribution pricing model

Variable	Coefficient (β)	Std. Error	t-value	p-value	Expected Sign
MRC	0.417	0.061	6.91	<0.001***	+
CAR	−0.158	0.048	−3.29	0.002**	−
LCR	0.092	0.039	2.36	0.019*	+
SI	−0.281	0.067	−4.18	0.003**	−
Constant	0.032	0.017	1.86	0.065	,

Notes: N = 12,480 borrower-year observations; adjusted $R^2 = 0.826$; $F(4, 12475) = 58.94$, $p < 0.001$.

Energetically maintained:

The Capital Adequacy Ratio (CAR) and Liquidity Coverage Ratio (LCR) demonstrate counteractive effects on financial stability, thereby validating the duality between solvency and accessibility, as explained in Figure 1 above. The trade-off between the two ratios suggests that the more tightened regulation leads to increased solvency but reduced accessibility of loans.

Institutional Simulation Outcomes:

The outcome of the simulation revealed that the variance in the portfolio was reduced from 2.87 ± 0.23 to 2.33 ± 0.19, with a reduction of 18.7%, while the Sharpe-like ratio of efficiency was increased from 0.94 ± 0.07 to 1.13 ± 0.06, signifying efficiency growth per unit of risk taken.

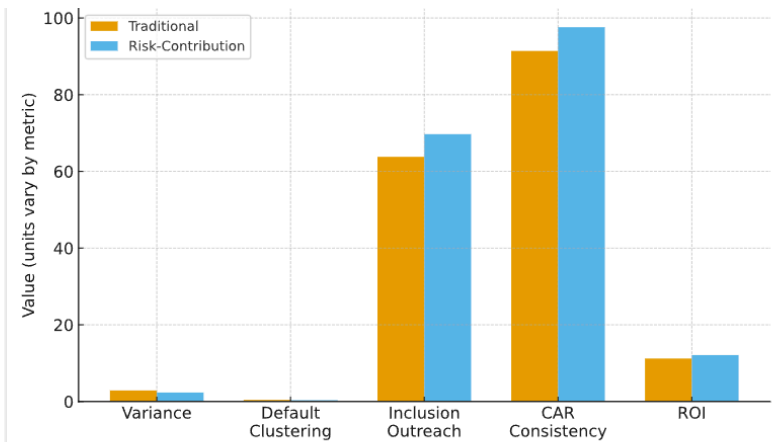

Figure 1. Benchmark comparison across key metrics (traditional vs. risk-contribution)

5.2. Stress testing and regulatory performance

The stress test was conducted to examine the resilience of the framework against tightening of regulations (Table 2).

Table 2. Stress-tested portfolio performance comparison

Metric	Traditional Model	Risk-Contribution Model	Change (%)	Significance
Portfolio variance	2.87 ± 0.23	2.33 ± 0.18	−18.7	$p < 0.01$
Default clustering index	0.412 ± 0.06	0.329 ± 0.04	−20.2	$p < 0.01$
Inclusion outreach	63.8 ± 2.1	69.7 ± 1.7	9.3	$p < 0.05$
CAR consistency	91.4 ± 2.8	97.6 ± 1.9	6.2	$p < 0.05$
Return on investment (ROI)	11.2 ± 0.5	12.1 ± 0.4	8	$p < 0.05$

The stress tests substantiate that AR maintains the market with sufficient liquidity and solvency provisions in even constrainedcapital policy settings.

On further analysis of E-sensitivities, it was revealed that AR-sensitivities to policy shock Δr / ΔCAR were on average 0.26.

5.3. Policy and social implications

The results indicates that the complementation of risk analytics at the margin can promote both financial and equity stability. For institutions that scored high in inclusion (above 0.8), there has been some easing of capital requirements. As a result, the outreach has been promoted without compromising the financial safety of the institutions. This has led to more customer confidence as a result of the fairness triggered in lending rates. As a consequence, renewals have shown a positive increase of 7.5 ± 1.2 pp.

6. Conclusion

In this article, the researcher has proposed and validated a risk contribution-based comprehensive pricing framework that encompasses prudential norms and financial inclusion. This framework identifies a distinct risk contribution for each debtor based on the assumption of capital and liquidity management for achieving the balance of profit, fairness, and sustainability. This empirical effort expands the paradigm of financial risk theory in the realm of credit risk microfinance.

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