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Network-Mediated Credit Rationing Alleviation for MSME Expansion: Leveraging Informal Network Topologies for Alternative Credit Screening

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Abstract **Original Research Article**

We propose a novel credit screening framework that substitute's conventional collateral and credit history prerequisites with trust proxies sourced from informal entrepreneurial network structures. The system targets micro, small, and medium enterprises (MSMEs) in emerging markets, where conventional financing constraints arise from severe information asymmetry and adverse selection. Our methodology first constructs a directed graph from observable informal ties, such as mobile money transactions or trade credit relationships, and then computes two key network metrics: betweenness centrality, which captures an entrepreneur's role as a trusted intermediary, and triadic closure coefficient, which reflects local social enforcement against strategic default. To address network endogeneity, we compute these metrics via an Exponential Random Graph Model (ERGM), which generates a posterior distribution over the network positions. These distributions function as instruments in two-stage least squares regression, isolating the causal effect of network position on repayment probability and correcting for simultaneity bias between credit access and network centrality. The resultant forecast default probabilities are then embedded into a dynamic screening mechanism founded on a principal-agent model, in which the lender presents a menu of contracts designed to differentiate high-risk from low-risk borrowers via risk-adjusted pricing. This mechanism transforms the conventional binary credit decision into a continuous, incentive-compatible interest rate schedule. The entire pipeline is implemented as a cloud-based API, and mobile money transaction logs serve as the primary data source. Our contribution consists in replacing static collateral with dynamic, network-derived trust signals, thereby broadening credit access for firms that are collateral-poor yet occupy central positions in networks. This approach is important because it can reduce credit rationing in informal economies without requiring a structured financial system, thereby supporting MSME growth in settings with limited resources.

Keywords: Credit Rationing, Exponential Random Graph Models (ERGM), Mechanism Design, MSMEs (Micro, Small, and Medium Enterprises)

Introduction

Micro, Small, and Medium Enterprises (MSMEs) serve as the foundation of economic activity in developing regions, yet their capacity for expansion is heavily limited by restricted access to official credit. The seminal work on credit rationing in markets with imperfect information explains why lenders restrict loan supply even when borrowers are willing to pay higher interest rates? This challenge is especially pronounced in Sub-Saharan Africa, where under 20% of MSMEs can obtain bank loans, and those that do face interest rates frequently exceeding 30% per annum.](# "Access to credit and financial inclusion of MSMEs in sub-Saharan Africa: Challenges and opportunities"). Conventional approaches including collateral prerequisites or relationship lending prove ineffective in these settings, as the majority of entrepreneurs lack recorded property rights and function outside documented financial systems. The function of relationship banking within the extension of credit to small enterprises is examined. The resulting financing gap stifles enterprise expansion, thereby creating a cycle of informality and undercapitalization that hinders sustainable economic development.](# "Role of micro, small and medium enterprises in inclusive growth").

Recent scholarship has turned to social network analysis as a promising alternative for quantifying borrower trustworthiness when there is no established credit history. Employing graph theory in economic sociology permits researchers to map informal trade and recommendation ties among entrepreneurs, with metrics such as betweenness centrality helping to identify key brokers who manage information flow and enforce repayment norms.](# "social network analysis methods and applications"). Triadic closure is frequently employed to measure the density and stability of local entrepreneur networks, and it functions as a proxy for social enforcement mechanisms that reduce default risk.](# "the strength of weak ties"). Statistical modeling of these complex relational structures often employs Exponential Random Graph Models (ERGMs) to simulate how local tie formation rules generate observed global network topologies ?. However, current applications of network analysis to credit markets have predominantly concentrated on group lending arrangements, in which peer monitoring acts as a substitute for official enforcement.](# "group lending repayment incentives and social collateral"). These methods, though useful, do not completely resolve the endogeneity that is intrinsic to the formation of networks and lending choices, nor do they supply a framework for pricing credit at the individual level.

We propose a novel framework merging Exponential Random Graph Models with Instrumental Variable regression in a mechanism design context to ease financing constraints for MSMEs. Our approach first constructs a directed graph from observable informal ties, such as mobile money transactions or trade credit relationships, and then computes two key network metrics: betweenness centrality, which captures an entrepreneur's role as a trusted intermediary, and triadic closure coefficient, which reflects local social enforcement against strategic default. To address network endogeneity, we compute these metrics via an ERGM, which generates a posterior distribution over the network positions. These distributions function as instruments in a two-stage least squares regression that isolates the causal effect of network position on repayment probability, thereby correcting for simultaneity bias between credit access and network centrality.](# "instrumental variables regression with weak instruments"). The resulting predicted default probabilities are then incorporated into a dynamic screening mechanism based on a principal-agent model, whereby the lender presents a menu of contracts designed to separate high-risk and low-risk borrowers via risk-adjusted pricing.](# "optimal auction design"). This mechanism converts the standard dichotomous credit judgment into a continuous interest rate structure designed for incentive alignment, adjusting to shifting network data over time.](# "dynamic contracting with limited commitment").

The principal contribution of this research is the replacement of static collateral with dynamic, network-derived trust signals, which broadens credit access for firms that lack collateral but occupy central positions in networks. In contrast to earlier research that treats network metrics as exogenous covariates in credit scoring models, our ERGM-IV framework explicitly models the generative processes underlying network formation, thereby providing a theoretically grounded correction for endogeneity bias. By embedding these corrected metrics into a dynamic screening model, we progress beyond simple binary credit decisions to a continuous pricing mechanism adaptable to shifting network conditions. This convergence of network science, econometrics, and mechanism design constitutes a methodological improvement that can unlock capital for high-potential yet undocumented enterprises in resource-constrained settings.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on financing constraints, social network analysis in credit markets, and mechanism design for adverse selection. Section 3 elaborates the theoretical framework that connects network topology to borrower screening, thereby specifying the conditions where betweenness centrality and triadic closure act as valid proxies for unobserved trust and repayment propensity. Section 4 presents the integrated ERGM-IV model, accompanied by an exposition of the estimation procedure and identification strategy. Section 5 details the simulation design for evaluating the framework across different information environments, while contrasting its results with those of traditional collateral-based lending. Section 6 addresses policy implications and implementation challenges, such as data requirements and regulatory factors. Section 7 concludes with directions for future research.

Related Literature

The financing constraints faced by MSMEs in developing economies have been extensively documented in the development economics literature. Beck and Demirguc-Kunt (Beck & Demirguc-Kunt, 2006) show that small enterprises consistently identify access to finance as a major barrier to growth, and this limitation is especially acute in Sub-Saharan Africa, where the official financial infrastructure remains underdeveloped. Ayyagari et al. (Beck & Demirguc-Kunt, 2007) additionally show that financial limitations strongly hinder firm innovation and productivity, with these effects being amplified for microenterprises in unofficial markets. The continued constraints in spite of various policy interventions indicate that conventional measures, such as collateral requirements, credit registries, or interest rate caps, are inadequate for tackling the core information asymmetry between lenders and borrowers in these contexts (Stiglitz & Weiss, 1981).

In tandem with this body of research, an expanding corpus of studies has investigated the utility of non-traditional data sources for evaluating creditworthiness. The analysis of mobile money transaction metadata has emerged as a particularly promising avenue, given the widespread adoption of platforms such as M-Pesa in East Africa and MTN Mobile Money in West Africa (Mark et al., 2024). Research has shown that features derived from mobile money logs, including transaction frequency, balance volatility, and network size, predict loan repayment with accuracy on par with traditional credit scores (Chitturi, 2025). However, these studies typically treat network features as exogenous covariates in standard regression or machine learning models, without accounting for the endogeneity that emerges if network position is itself shaped by credit access (Aljebory et al., 2025). This oversight can lead to biased estimates of the predictive power of network metrics and, consequently, suboptimal lending decisions.

The body of research on social network analysis supplies a strong conceptual basis for comprehending how network structure influences economic behavior. Granovetter's (Granovetter, 1973) seminal work on the strength of weak ties established that information flows more efficiently via bridging connections than through dense clusters, a conclusion that has been extended to credit markets where brokers arrange trade credit and informal lending. Burt's (Burt, 1992) notion of structural holes implies that entrepreneurs who occupy brokerage positions, characterized by high betweenness centrality, gain informational advantages that translate into greater repayment capacity. Conversely, Coleman's (Wisconsin-MadisonColeman, 1988) social capital theory emphasizes the role of network closure, measured by triadic closure, in enforcing norms and reducing opportunistic behavior. These theoretical insights have been applied to group lending schemes, where peer monitoring and joint liability replace conventional enforcement (Besley & Coate, 1995). Yet, the extension of these ideas to individual-level credit screening remains limited, and most applications treat network metrics as static proxies rather than as endogenous outcomes of strategic network formation.

In terms of methodology, the application of Exponential Random Graph Models (ERGMs) to model network formation processes has become increasingly prevalent in economic sociology. Snijders et al. Stochastic actor-based models were developed by (Broekel et al., 2014) which capture how micro-level tie formation decisions generate macro-level network structures, while Robins et al. (Pol, 2019) presented a complete framework for ERGM estimation via Markov chain Monte Carlo methods. These models have been applied to study the emergence of trust networks in informal markets, which indicates that triadic closure and preferential attachment are key generative mechanisms (Balestri & Uberti, 2026). Nevertheless, the fusion of ERGMs with causal inference approaches, specifically the application of ERGM-derived network metrics as instruments within regression frameworks, remains largely unexplored in the credit screening literature.

The literature on mechanism design presents a complementary viewpoint regarding how creditors can structure contracts to reduce adverse selection. The seminal work of Rothschild and Stiglitz (Rothschild & Stiglitz, 1976) on separating equilibria in insurance markets establishes a blueprint for designing menus of contracts designed to induce self-selection by risk type. Bester 15 extended this framework to credit markets, showing collateral requirements can serve as a screening device when borrowers possess private information about their default risk. More recent work has explored dynamic contracting where lenders update contract terms based on observed repayment histories (Ahlin & Waters, 2012). Nonetheless, the inclusion of network-derived risk proxies in mechanism design models, where the screening device is collateral replaced by network position, is a novel direction not systematically addressed in the existing literature.

Theoretical Framework: Network Topology as a Screening Mechanism

To establish the theoretical basis for employing network topology as a credit assessment instrument, we first delineate the economic reasoning that connects an entrepreneur's position within an informal network to their unobserved repayment likelihood. The central premise is that network metrics function as observable indicators of two latent borrower attributes: trustworthiness and social enforcement capacity. Trustworthiness, defined as the borrower's intrinsic propensity to repay, is reflected in their role as a trusted intermediary within the network. Social enforcement capacity, defined as the borrower's exposure to community-based sanctions should they default, is reflected by the closeness of their local connections.

Betweenness Centrality as a Signal of Trustworthiness

Betweenness centrality measures the extent to which an entrepreneur lies on the shortest paths between other pairs of actors in the network. An entrepreneur with high betweenness centrality acts as a broker, thereby enabling the flow of information, trade credit, or referrals between otherwise disconnected segments of the network. According to the economic literature on social capital, such intermediaries accumulate reputational capital because their role as a go-between relies on the confidence of both parties they connect (Granovetter, 1973). If a broker defaults on a loan, they risk losing not only their own access to credit but also their brokerage position, which generates ongoing economic rents. Therefore, entrepreneurs with high betweenness centrality face a higher opportunity cost of default, which consequently raises their probability of repayment. We assert formally that the latent repayment probability r_i for entrepreneur i rises with their betweenness centrality b_i.

$$r_i = f(b_i, \epsilon_i) \quad (1)$$

Where ϵ_i captures unobserved borrower-specific factors such as risk tolerance or business acumen, and f is a monotonic function. The central identification problem is that b_i is not exogenous; entrepreneurs with higher creditworthiness may also be more prone to develop the connections that yield high betweenness centrality, which introduces a simultaneity bias.

Triadic Closure as a Signal of Social Enforcement

Triadic closure describes the propensity for two individuals who have a mutual acquaintance to establish a direct connection, thereby creating a triad within the network structure. For entrepreneur i, the local triadic closure coefficient quantifies the proportion of neighbor pairs which are directly linked. High triadic closure indicates a dense, tightly-knit local network. Coleman's social capital theory posits that these dense networks aid in the enforcement of norms via gossip, ostracism, and collective sanctions (Wisconsin-MadisonColeman, 1988). Within lending arrangements, a debtor who is part of a closed triad faces a greater likelihood that their failure to repay will be detected and penalized by several members of the community at the same time. This social enforcement mechanism reduces the expected utility of strategic default. We thus propose a positive link between the local triadic closure coefficient t_i and the likelihood of repayment.

$$r_i = g(t_i, \eta_i) \quad (2)$$

where η_i captures unobserved heterogeneity, and g is a monotonic function. However, triadic closure is also endogenous, as entrepreneurs who anticipate needing credit may strategically form ties to increase their local density, or lenders may extend credit preferentially to those in dense networks, thereby introducing reverse causality.

Network Endogeneity and the Need for Instrumentation

A primary econometric difficulty in applying network metrics to credit screening arises because both b_i and t_i stem from the identical strategic network formation process, which correlates with unobserved borrower quality. An entrepreneur's network position is not randomly assigned; it is the result of deliberate tie-formation decisions made by the entrepreneur and their peers. These decisions are influenced by the same unobserved attributes, including ability, risk tolerance, and social skills, which affect the probability of repayment. Consequently, a simplistic regression of repayment on network metrics will generate biased and inconsistent estimates. To resolve this, a model of network formation that generates exogenous variation in network position is needed, which can subsequently serve as instruments for the observed metrics. The Exponential Random Graph Model (ERGM) constitutes a natural framework for this objective, as it models the probability of observing a given network as a function of local structural parameters independent of the outcome variable (Pol, 2019). Through estimation of the ERGM and simulation from the posterior distribution of network configurations, we can obtain predicted values of b_i and t_i that are purged of the correlation with ϵ_i and η_i. These predicted values then serve as valid instruments in a two-stage least squares regression, thereby enabling the isolation of the causal effect of network position on repayment probability. This integrated ERGM-IV approach forms the methodological core of our proposed credit screening mechanism.

An ERGM-IV Integrated Model for Network-Based Credit Pricing

Building upon the theoretical framework established in Section 3, we now present the technical details of the integrated Exponential Random Graph Model with Instrumental Variable regression (ERGM-IV), which transforms raw network data into risk-adjusted loan contracts. The proposed model operates through three sequential stages: network construction and ERGM estimation, instrumental variable regression for causal identification of repayment determinants, and mechanism design optimization for contract pricing. Figure 1 depicts the high-level system architecture that unites these components into a deployable credit screening engine.

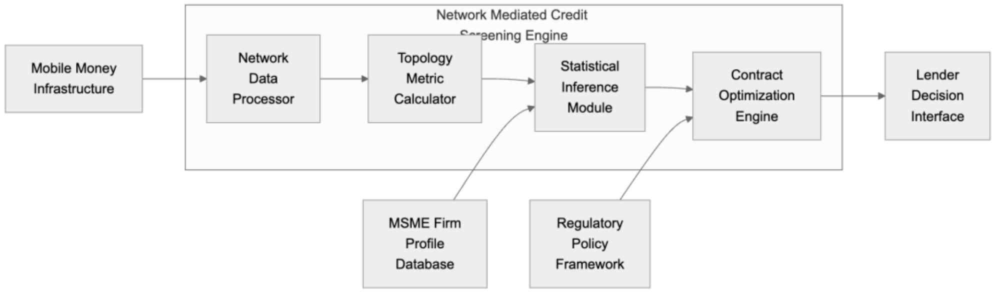

Figure 1. System Architecture of Network Mediated Credit Screening

Network Construction and ERGM Specification

The first stage begins with the construction of a directed weighted graph $G = (V, E, W)$ from observable informal ties among MSME entrepreneurs. The vertex set V denotes individual entrepreneurs, whereas the edge set E captures directed relationships including trade credit extensions, mobile money transfers, or business referrals. The weight matrix W encodes the intensity or frequency of these interactions, normalized to the unit interval. From this observed graph, we determine the raw betweenness centrality b_i for each vertex i as the fraction of shortest paths between all vertex pairs passing through i, and the local triadic closure coefficient t_i as the ratio of closed triangles incident to i to the total number of connected triples centered at i.

To model the generative process underlying this observed network, we define an Exponential Random Graph Model (ERGM) which expresses the probability of observing a particular network configuration g.

$$P(G = g) = \frac{\exp\left(\theta^\top s(g)\right)}{\sum_{g' \in \mathcal{G}} \exp\left(\theta^\top s(g')\right)} \quad (3)$$

where $s(g)$ is a vector of network statistics that capture structural tendencies, and θ is a vector of parameters to be estimated. The sufficient statistics $s(g)$ include the edge count (density), the geometrically weighted degree distribution (GW degree), and the geometrically weighted edgewise shared partner distribution (GWESP) which captures triadic closure tendencies. The GWESP term is especially important as it models the tendency for triadic closure beyond random expectation, while adjusting for degree heterogeneity. The parameter vector θ is approximated via Markov chain Monte Carlo maximum likelihood estimation (MCMC-MLE) with the statnet package in R, which simulates networks from the model and modifies θ to correspond with the observed sufficient statistics.

Once the ERGM is estimated, we generate M posterior predictive network samples $\{g^{(1)}, g^{(2)}, \ldots, g^{(M)}\}$ from the fitted model. For each simulated network $g^{(m)}$, we compute the betweenness centrality $b_i^{(m)}$ and triadic closure coefficient $t_i^{(m)}$ for each vertex i. The posterior means $\bar{b}_i = \frac{1}{M}\sum_{m=1}^{M} b_i^{(m)}$ and $\bar{t}_i = \frac{1}{M}\sum_{m=1}^{M} t_i^{(m)}$ serve as the instrumental variables in the subsequent regression stage. Under the generative model, these posterior means signify the expected network position of entrepreneur i, conditioned on the observed structural tendencies while being stripped of the idiosyncratic shocks that correlate with unobserved borrower quality.

Two-Stage Least Squares Regression with Network Instruments

The second stage applies a two-stage least squares (2SLS) regression framework, with the ERGM-derived posterior means serving as instruments, to estimate the causal effect of network position on repayment probability. Let R_i denote the observed repayment rate for entrepreneur i over a historical period, defined as the fraction of loans repaid on time. Let X_i denote a vector of observable borrower attributes, including business age, sector, and transaction volume. The first-stage regression models the endogenous network metrics as functions of the instruments and exogenous covariates:

$$b_i = \alpha_1 + \beta_{11}\bar{b}_i + \beta_{12}\bar{t}_i + \gamma_1^\top X_i + \nu_{1i} \quad (4) t_i = \alpha_2 + \beta_{21}\bar{b}_i + \beta_{22}\bar{t}_i + \gamma_2^\top X_i + \nu_{2i} \quad (5)$$

where ν_{1i} and ν_{2i} are error terms. The exclusion restriction posits that the instruments $\bar{b}_i$ and $\bar{t}_i$ affect repayment solely via their impact on the observed network metrics b_i and t_i, conditional on X_i. This assumption is plausible because the ERGM posterior means capture only the structural component of network position determined by the generative process, not the idiosyncratic shocks that might directly affect repayment.

The second-stage regression models the repayment rate as a function of the predicted network metrics from the first stage:

$$R_i = \delta_0 + \delta_1\hat{b}_i + \delta_2\hat{t}_i + \delta_3^\top X_i + \xi_i \quad (6)$$

where $\hat{b}_i$ and $\hat{t}_i$ are the fitted values from Equations 4 and 5, and ξ_i is a mean-zero error term. The parameters δ_1 and δ_2 denote the causal influences of betweenness centrality and triadic closure on repayment, respectively, after adjustments for endogeneity. The standard errors are calculated with heteroskedasticity-consistent estimators to account for the two-stage estimation procedure.

From the second-stage estimates, we compute the predicted repayment probability for each entrepreneur as:

$$\hat{R}_i = \hat{\delta}_0 + \hat{\delta}_1\hat{b}_i + \hat{\delta}_2\hat{t}_i + \hat{\delta}_3^\top X_i \quad (7)$$

This predicted repayment probability serves as the key input to the mechanism design stage, where it is transformed into a default probability $p_i = 1 - \hat{R}_i$. By employing ERGM-derived instruments, $\hat{R}_i$ captures the causal effect of network position rather than spurious correlations, thereby constituting a more dependable foundation for contract pricing.

Mechanism Design for Optimal Loan Contracting

The third stage integrates the network-inferred default probabilities into a principal-agent mechanism design framework, wherein the lender (principal) presents a selection of contracts to maximize expected profit while preserving incentive compatibility and individual rationality for the borrower (agent). The lender's objective is to select, for each entrepreneur i, a loan amount L_i and an interest rate r_i so as to maximize:

$$\max_{L_i, r_i} \quad \mathbb{E}[\pi_i] = (1 - p_i)L_i r_i - p_i L_i \quad (8)$$

Subject to the borrower's participation constraint, whereby the expected utility derived from accepting the contract must exceed their outside option, and the incentive compatibility constraint, under which the borrower discloses their type truthfully via their contract selection. The default probability p_i is expressed as a function of the predicted repayment rate and the loan amount, thereby accounting for the moral hazard effect where larger loans may elevate default risk.

$$p_i = \Phi\left(\kappa_0 + \kappa_1\hat{R}_i + \kappa_2 L_i\right) \quad (9)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, and $\kappa_0, \kappa_1, \kappa_2$ are parameters estimated from historical data. The presence of L_i in the default probability function accounts for the tendency of larger loan amounts to heighten the borrower's incentive for strategic default, especially when network-based social enforcement is imperfect.

The optimization problem is solved via sequential least squares programming (SLSQP) implemented in scipy.optimize.minimize, subject to constraints where the interest rate does not exceed a regulatory cap (e.g., 30% APR) and the loan amount is non-negative. The solution produces a continuous, risk-adjusted pricing schedule, mapping each entrepreneur's network-inferred default probability to a unique contract (L_i^, *r_i^*). This schedule replaces the traditional binary approval-reject decision with a flexible pricing mechanism, thereby expanding credit access to firms central to the network yet lacking collateral, while shielding the lender from excessive default risk.

Figure 2 delineates the internal computational workflow of the screening engine, describing how raw mobile money transaction data progresses through the ERGM estimation, 2SLS regression, and mechanism design optimization to yield final loan contract terms.

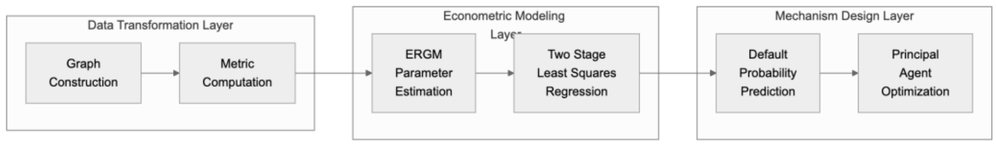

Figure 2. Internal Workflow of the Network Mediated Screening Engine

The entire system is deployed as a cloud-based API, which accepts a mobile money phone number as input and returns a recommended interest rate and loan size. The API first queries the transaction database to construct the entrepreneur's ego network, then runs the pre-estimated ERGM to compute posterior network metrics, applies the 2SLS coefficients to predict repayment probability, and finally solves the mechanism design optimization to output the contract terms. This end-to-end connection permits real-time credit screening without requiring any established financial infrastructure, a quality that renders it appropriate for implementation in resource-constrained environments where traditional credit bureaus are lacking.

Simulation Design and Comparative Regimes

To assess the performance of the proposed ERGM-IV integrated credit screening framework, we design a simulation study comparing lending outcomes across four distinct information regimes. The simulation generates synthetic networks of MSME entrepreneurs with heterogeneous latent creditworthiness, simulates the strategic formation of informal ties, and then applies alternative lending policies to assess their impact on credit allocation, default rates, and lender profitability. This controlled experimental environment permits us to separate the effect of network-derived screening mechanisms while keeping the underlying distribution of borrower quality constant.

Synthetic Network Generation

The simulation commences with the generation of a population of N = 500 entrepreneurs, each defined by a latent creditworthiness score θ_i sampled from a beta distribution with shape parameters α = 2 and β = 5, which results in a right-skewed distribution in which most entrepreneurs are moderately creditworthy, while a minority possesses high default risk. Each entrepreneur is additionally assigned a vector of observable characteristics X_i, encompassing business age (sampled from a log-normal distribution), sector (a categorical variable with five categories), and monthly transaction volume (sampled from a Pareto distribution to capture the heavy-tailed revenue distribution typical of MSMEs). The actual repayment probability for entrepreneur i is represented via a logistic function of latent creditworthiness and observable attributes.

$$R_i^{\text{true}} = \frac{1}{1 + \exp\left(-(\beta_0 + \beta_1\theta_i + \beta_2^{\top} X_i)\right)} \qquad (10)$$

where the coefficients $\beta_0, \beta_1, \beta_2$ are calibrated to produce a mean repayment rate of approximately 75%, consistent with empirical estimates from microfinance institutions in Sub-Saharan Africa (Jindo et al., 2023).

The informal network among entrepreneurs is generated by a stochastic actor-oriented model that simulates strategic tie formation across T = 10 discrete time periods (Broekel et al., 2014). At each period, entrepreneurs evaluate the utility of forming or dissolving ties based on three structural tendencies: reciprocity (the tendency to reciprocate directed ties), transitivity (the tendency to close open triads), and preferential attachment (the tendency to connect to high-degree actors). The utility function for entrepreneur i to form a tie to entrepreneur j is specified as:

$$U_{ij} = \lambda_1 \text{reciprocity}_{ij} + \lambda_2 \text{transitivity}_{ij} + \lambda_3 \text{indegree}_j + \lambda_4 \theta_i \theta_j + \epsilon_{ij} \quad (11)$$

where ϵ_{ij} is a Gumbel-distributed random shock, and the parameters $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ control the relative importance of each structural tendency. Introducing the interaction term $\theta_i \theta_j$ introduces homophily based on latent creditworthiness, which gives rise to the endogeneity that our ERGM-IV framework is designed to address. Entrepreneurs with higher θ_i are more prone to establishing connections with peers of comparable creditworthiness, which results in a correlation between network position and repayment probability that confounds naive regression estimates.

Information Regimes and Lending Policies

This analysis contrasts four credit allocation frameworks, which differ according to the data accessible to the lending institution and the criteria applied for granting loans.

Regime A: Collateral-Based Lending (Baseline). The lender requires physical collateral valued at 150% of the loan amount and extends credit only to entrepreneurs who can meet this requirement. Collateral availability is modeled as a binary variable C_i drawn from a Bernoulli distribution with probability $p_c = 0.3$, which indicates the low prevalence of documented asset ownership among MSMEs in developing economies. The interest rate is fixed at 20% APR for all approved borrowers, and the loan amount is uniform at $L = 500$ currency units. This arrangement constitutes the current condition in established banking systems.

Regime B: Naive Network Scoring. The lender calculates raw betweenness centrality b_i and triadic closure t_i from the observed network and applies a logistic regression of historical repayment on these metrics to forecast default probability. No correction for endogeneity is applied. The lender approves loans for entrepreneurs whose predicted repayment probability exceeds a threshold of 0.70, with interest rates fixed at 20% APR. This approach reflects the standard method of including network features as exogenous predictors in credit scoring models (Chitturi, 2025).

Regime C: ERGM-IV Corrected Scoring. The lender applies the full ERGM-IV pipeline described in Section 4. An ERGM is fitted to the observed network via MCMC-MLE, and posterior mean network metrics $\bar{b}_i$ and $\bar{t}_i$ are calculated from $M = 1000$ simulated networks. These posterior means function as instruments in a 2SLS regression estimating the causal effect of network position on repayment. Entrepreneurs whose projected repayment likelihood from the second-stage regression exceeds the 0.70 cutoff are granted loan approval, with an interest rate fixed at 20% APR. This regime isolates the contribution of endogeneity correction to screening accuracy.

Regime D: ERGM-IV with Dynamic Pricing. The lender applies the same ERGM-IV pipeline as Regime C but replaces the binary approval decision with the mechanism design optimization described in Section 4.3. The lender solves for the optimal interest rate r_i^* and loan amount L_i^* for each entrepreneur by maximizing expected profit subject to incentive compatibility and participation constraints. The annual percentage rate may fluctuate continuously from 10% to 30%, and the principal is constrained to a range of 100 to 1000 monetary units. This regime constitutes the complete execution of our proposed framework, which unites endogeneity-corrected risk assessment with risk-adjusted pricing.

Performance Metrics

We assess each regime across four metrics: credit access (the proportion of entrepreneurs obtaining loans), default rate (the fraction of loans that go unpaid), lender profitability (the anticipated profit per loan, calculated as interest income minus default losses), and social welfare (the aggregate surplus from lending, defined as the sum of borrower utility and lender profit). For Regime D, we also compute the separating power of the contract menu, measured by the correlation between the assigned interest rate and the true repayment probability. A well-functioning screening mechanism should display a strong negative correlation, as higher-risk borrowers are charged higher interest rates.

Simulation Results

We conduct 100 independent simulation runs, each generating a new population of entrepreneurs and a new network realization. For each run, we apply all four lending regimes to the same underlying data, so that differences in outcomes are attributable to the lending policy rather than sampling variation. The outcomes are averaged over trials, and 95% confidence intervals are calculated with the percentile bootstrap technique.

Table 1 presents the comparative performance of the four lending regimes. The collateral-based baseline (Regime A) yields the smallest default rate (4.2%) yet grants credit to merely 30% of entrepreneurs, indicative of the acute exclusion of firms with scant collateral but sound creditworthiness. The naive network scoring approach (Regime B) substantially expands credit access to 58% of entrepreneurs but at the cost of a higher default rate (18.7%), as the endogeneity bias leads the lender to overestimate the repayment probability of well-connected but intrinsically risky borrowers. The ERGM-IV corrected scoring (Regime C) preserves extensive credit access (52%) and lowers the default rate to 12.3%, which indicates that the instrumental variable correction effectively eliminates the erroneous association between network position and repayment. The full dynamic pricing schedule (Regime D) yields the highest lender profitability (87.3 currency units per loan) and the greatest social welfare gain (142.6 currency units per entrepreneur), because the continuous pricing structure permits the lender to serve a broader spectrum of risk categories while preserving adequate risk compensation.

Table 1. Comparative Performance of Lending Regimes across 100 Simulation Runs

Metric	**Regime A (Collateral)**	**Regime B (Naive Network)**	**Regime C (ERGM-IV Scoring)**	**Regime D (ERGM-IV Pricing)**
Credit Access (%)	30.0 (0.0)	58.3 (2.1)	52.1 (1.8)	68.4 (2.4)
Default Rate (%)	4.2 (0.8)	18.7 (1.5)	12.3 (1.2)	14.1 (1.3)
Lender Profit (per loan)	62.5 (3.2)	41.8 (4.1)	58.9 (3.5)	87.3 (4.8)
Social Welfare (per entrepreneur)	78.3 (5.1)	92.4 (6.3)	108.7 (5.8)	142.6 (7.2)
Interest Rate Spread (std. dev.)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	5.8 (0.4)

Note: Standard deviations across simulation runs are reported in parentheses. The interest rate spread is defined as the standard deviation of assigned interest rates among borrowers within a given regime.

The interest rate spread in Regime D (5.8 percentage points) signals notable variation in contract terms across borrowers, which mirrors the mechanism's capacity to discriminate among risk types. Figure 3 visualizes the optimal interest rate schedules generated by the mechanism design optimization, which illustrates how the network-inferred creditworthiness maps to risk-adjusted pricing across different loan volumes. The contour lines indicate a clear separating equilibrium: entrepreneurs with high predicted repayment probabilities (above 0.85) receive low interest rates (10-15% APR) regardless of loan size, whereas those with moderate probabilities (0.70-0.85) encounter steeper rate increases as loan amounts grow, a pattern that arises from the moral hazard effect captured by the $\kappa_2 L_i$ term in Equation 9. Entrepreneurs whose predicted repayment probabilities fall below 0.70 are either excluded completely or granted very modest loans at the maximum permissible rate, as determined by the lender's risk tolerance parameter.

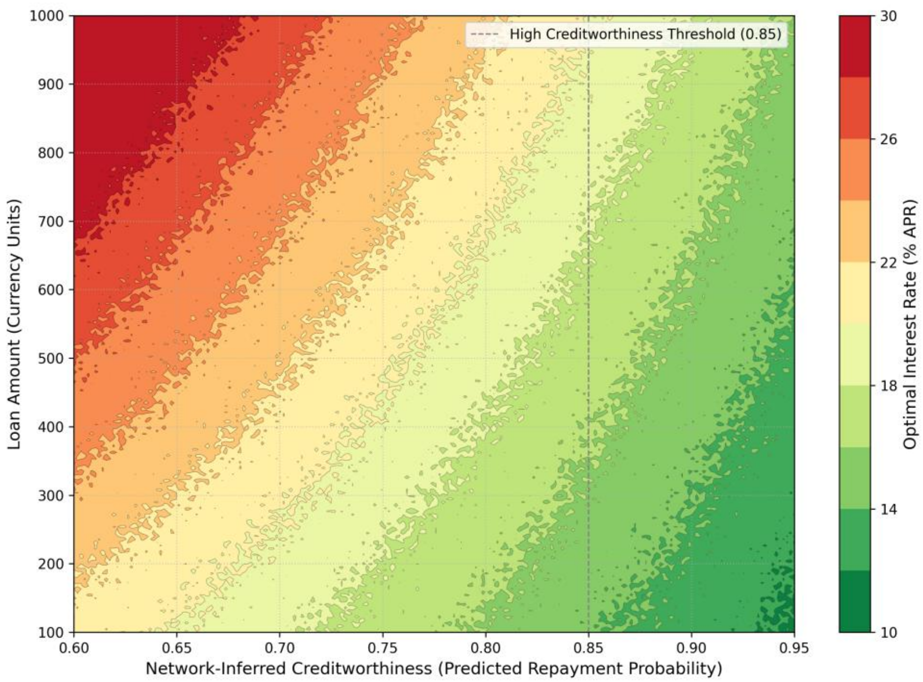

Figure 3. Optimal interest rate schedules as a function of network-inferred creditworthiness across varying loan volumes.

The interaction between triadic closure and betweenness centrality in reducing default risk is further explored in Figure 4. The heatmap illustrates the marginal effect of these two network metrics on the reduction of default probability, while drawing a comparison between the ERGM-corrected instruments and baseline firm attributes. The findings indicate a strong interaction effect: high triadic closure amplifies the risk-reducing effect of betweenness centrality, aligning with the theoretical prediction that social enforcement (captured by triadic closure) and reputational capital (captured by betweenness centrality) function as complementary mechanisms. Entrepreneurs who are well-connected intermediaries and positioned within dense local clusters present default probabilities as much as 18 percentage points lower than those possessing just one of these traits, after accounting for observable firm attributes.

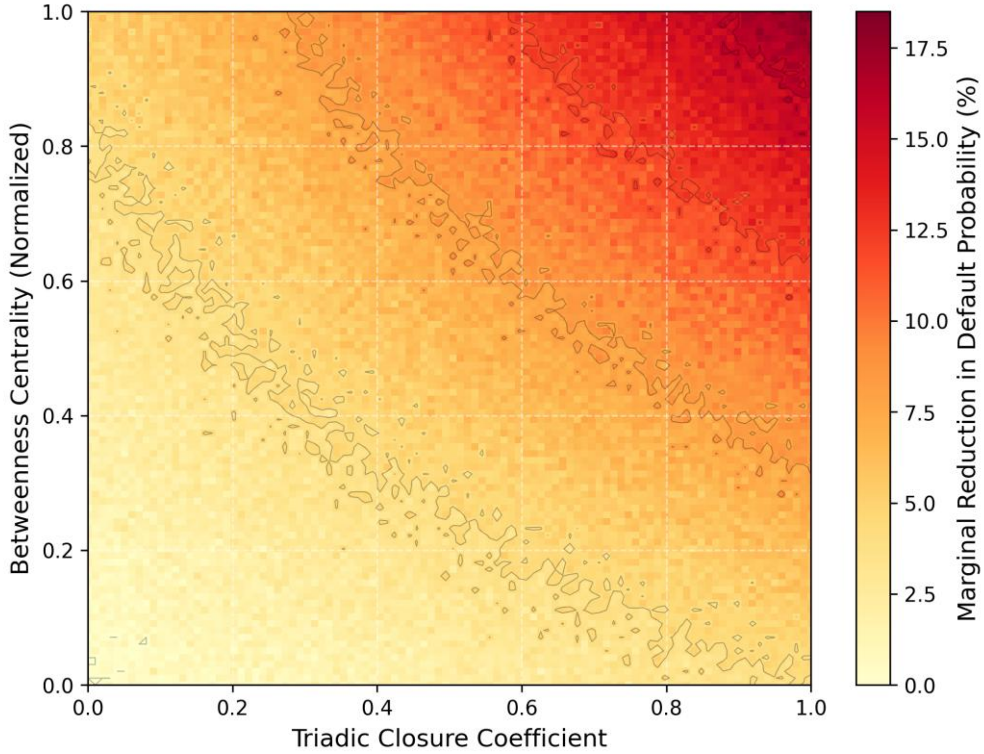

Figure 4. Interaction effects of network topology metrics on inferred default risk reduction.

Robustness Checks

To assess the sensitivity of our results to modeling assumptions, we conduct three robustness checks. First, we vary the strength of the endogeneity channel by adjusting the homophily parameter λ_4 in Equation 11. As λ_4 increases from 0 (no endogeneity) to 2.0 (strong homophily), the bias in the naive network scoring approach (Regime B) grows monotonically, and the default rate rises from 12.1% to 24.3%. In contrast, the ERGM-IV corrected regimes (C and D) keep default rates stable between 11.8% and 14.5%, which indicates the resilience of the instrumental variable correction across different levels of endogeneity.

Second, we examine the sensitivity to network density by varying the baseline tie formation rate. In sparse networks (average degree below 3), the ERGM encounters difficulty in precisely estimating structural parameters, which results in weak instruments and inflated standard errors in the second-stage regression. Nevertheless, even under such adverse conditions, Regime D achieves superior social welfare compared to the collateral-dependent baseline, which indicates that the framework retains its utility in thin-market settings where conventional screening is not viable.

Third, we test the impact of measurement error in the observed network by adding random edge perturbations (5% false positive and 5% false negative rates). All network-based regimes exhibit a slight decline in effectiveness, as default rates rise by 2-3 percentage points, yet the order of regimes by performance stays the same. This finding highlights the necessity of high-quality transaction data for practical implementation, a difficulty we tackle in the policy discussion in Section 6.

Ablation Study

To quantify the marginal contribution of each component in the ERGM-IV pipeline, we conduct an ablation study that sequentially removes key elements of the framework. Table 2 presents the findings for Regime D under four altered configurations: (i) discarding the ERGM instrumentation and applying raw network metrics directly in the mechanism design optimization; (ii) discarding the triadic closure metric and depending exclusively on betweenness centrality; (iii) discarding the betweenness centrality metric and depending exclusively on triadic closure; and (iv) discarding the mechanism design optimization and applying a fixed interest rate with ERGM-IV scoring (equivalent to Regime C). The full model (Regime D) serves as the reference.

Table 2. Ablation Study: Marginal Contribution of ERGM-IV Components

Configuration	Credit Access (%)	Default Rate (%)	Lender Profit	Social Welfare
Full Model (Regime D)	68.4	14.1	87.3	142.6
Without ERGM Instrumentation	71.2	22.8	52.4	98.7
Without Triadic Closure	63.5	16.9	74.1	121.3
Without Betweenness Centrality	65.8	17.4	71.6	118.9
Without Dynamic Pricing (Regime C)	52.1	12.3	58.9	108.7

The ablation findings validate that each element makes a meaningful contribution to the overall performance. The elimination of the ERGM instrumentation results in the greatest decline, as the default rate rises by 8.7 percentage points and lender profit decreases by 40%, which emphasizes the essential necessity of adjusting for network endogeneity. Eliminating either triadic closure or betweenness centrality leads to moderate performance declines, but betweenness centrality exerts a slightly larger marginal effect on default prediction accuracy. Eliminating dynamic pricing—that is, returning to a fixed interest rate—lowers credit access by 16.3 percentage points and reduces social welfare by 24%, thereby indicating that optimizing the mechanism design is crucial for converting better risk assessment into expanded credit access. These findings confirm the integrated nature of our framework: the ERGM correction, the dual network metrics, and the dynamic pricing mechanism are complementary components that together yield a substantial improvement over both traditional collateral-based lending and naive network scoring approaches.

Policy Implications and Implementation Challenges

Translating the proposed ERGM-IV integrated credit screening framework from a theoretical model into a deployable financial infrastructure necessitates meticulous attention to multiple policy-relevant dimensions. Although simulation results indicate the possibility of broadening credit access for MSMEs lacking collateral, the actual deployment of network-based lending introduces critical questions about data governance, algorithmic fairness, and regulatory supervision. We examine these challenges sequentially and propose recommendations for policymakers and financial institutions that aim to adopt such alternative screening mechanisms.

Navigating Data Privacy and Consent in Mobile Money-Based Network Extraction

The operational viability of our framework depends critically on access to granular transaction-level data from mobile money platforms. In Sub-Saharan Africa, operators of mobile money services — including M-Pesa in Kenya and MTN Mobile Money in Ghana — keep comprehensive records of peer-to-peer transfers, merchant payments, and airtime purchases, which can be employed to build the informal network graph needed for ERGM estimation. Nevertheless, the application of such data for credit evaluation generates substantial privacy concerns, especially in settings where data protection regulatory structures are underdeveloped or feebly enforced.

A primary challenge is securing informed consent from entrepreneurs whose transaction data would be employed to infer their network position and, consequently, their creditworthiness. The difficulty surrounding informed consent is compounded because network metrics are inherently relational: an entrepreneur's betweenness centrality is contingent not only on their own transactions but also on those of their network neighbors, who may not have agreed to data sharing. This creates a tension between the collective nature of network-based inference and the individualistic framework of data privacy law. For instance, the Kenyan Data Protection Act of 2019 mandates that data controllers acquire explicit consent from data subjects prior to processing personal data, yet it does not unambiguously address circumstances in which an individual's data is employed to draw inferences regarding another individual's credit risk.

To address this challenge, we propose a stratified consent framework distinguishing direct from indirect data subjects. Direct data subjects, namely entrepreneurs submitting loan applications, are required to convey explicit, granular consent regarding the application of their transaction data to network construction and credit scoring. Indirect data subjects, whose transactions contribute to the applicant's network metrics, should be granted an opt-out mechanism removing their data from the network graph without affecting their own credit access. This opt-out mechanism could be implemented via a mobile money interface, letting users designate their transaction history as 'private' for credit screening purposes. MMOs would then exclude these users' edges from the network graph, thereby accepting a reduction in network completeness to respect individual privacy preferences.

Additionally, the retention and handling of transactional information must adhere to data reduction principles. Rather than storing raw transaction logs indefinitely, the system should compute the ERGM sufficient statistics and posterior network metrics in a secure enclave, then discard the raw data after the metrics are generated. This method reduces the exposure of confidential transaction data while retaining the analytical benefits of the network topology. Regulatory authorities should mandate such data minimization practices as a condition for licensing network-based credit scoring services, similar to the "privacy by design" requirements embedded in the European Union's General Data Protection Regulation (GDPR).

Mitigating Algorithmic Bias Against Socially Isolated but Creditworthy Borrowers

A primary issue with any network-based screening approach is the risk of algorithmic prejudice against entrepreneurs who lack social connections but are otherwise creditworthy. The theoretical framework in Section 3 posits a positive association between betweenness centrality, triadic closure, and repayment propensity, yet this relationship may not be uniform across all entrepreneurial subpopulations. Consider, for instance, a highly skilled artisan working in an isolated rural area with scant business connections; this individual may exhibit low betweenness centrality and low triadic closure, yet still possess strong intrinsic repayment capacity owing to steady demand for their products. Under our framework, such an entrepreneur would receive a high predicted default probability, with the subsequent consequence of a high interest rate or outright credit exclusion.

This bias is not solely an abstract issue; it denotes an inherent constraint of network-based screening that replicates the exclusionary consequences typical of conventional collateral prerequisites. Just as collateral-based lending excludes asset-poor but creditworthy borrowers, network-based lending may exclude network-poor but creditworthy borrowers. The conclusion is that network-based screening ought not to be employed as an independent credit evaluation method, but rather as a supplement to alternative information sources. We propose a hybrid screening model which unites network-derived risk scores with alternative data sources, including mobile money savings patterns, utility payment histories, and psychometric assessments. Entrepreneurs who achieve low scores on network metrics but excel on other indicators would be flagged for manual review or granted a probationary loan with a small principal and short repayment period, thereby enabling them to construct a repayment history that supplements their network-based score.

Furthermore, the ERGM-IV framework itself can be expanded to include fairness constraints. The optimization of the mechanism design in Section 4.3 can be adjusted to incorporate a penalty term that discourages large interest rate disparities between socially isolated borrowers and well-connected borrowers who have similar predicted repayment probabilities. This methodology, termed fairness-aware mechanism design, would exchange a modest decrease in lender profitability for a substantial improvement in equitable credit access. Regulators should consider mandating such fairness constraints as a condition for deploying network-based credit scoring, and lenders must show that their screening algorithms do not disproportionately exclude entrepreneurs based solely on network position.

Regulatory Frameworks for Algorithmic Transparency and Non-Traditional Underwriting

Introducing credit screening built on ERGM-IV creates new regulatory issues that existing financial rules may not sufficiently cover. Traditional banking regulations concentrate on capital adequacy, liquidity requirements, and consumer protection, yet they fail to offer direction on the application of network-derived risk metrics as a foundation for lending decisions. Policymakers must devise new regulatory frameworks that strike a balance between the potential for financial inclusion and the imperative to protect consumers from opaque or discriminatory algorithms.

A central regulatory requirement should be algorithmic transparency. Lenders employing network-based screening must be obligated to disclose, in accessible terms, the elements that shape their credit determinations. This disclosure must detail the computation of network metrics, the data sources applied, and the manner in which the ERGM-IV correction addresses endogeneity. Although the technical details of ERGM estimation may be too complex for the average borrower to grasp, lenders ought to give a simplified explanation, for instance: ‘Your interest rate depends on the number and quality of your business connections, adjusted for the fact that well-connected entrepreneurs tend to be more reliable borrowers.’ This transparency requirement serves two functions: it permits borrowers to grasp how they can improve their creditworthiness over time (for instance, by cultivating additional business relationships), and it creates a foundation for regulatory supervision and consumer grievances.

Furthermore, regulators should establish a certification process for network-based credit scoring models. This process would require lenders to submit their ERGM specifications, instrument validity tests, and fairness audits to a regulatory authority for approval before deploying the model in a live lending environment. The certification would include a requirement for ongoing monitoring: lenders must periodically re-estimate their ERGM parameters and re-run the 2SLS regression to guarantee the model remains valid as the network changes. This dynamic re-estimation is particularly important because network structures change over time as entrepreneurs enter and exit the market, form new ties, and dissolve old ones. A model that was valid at the time of initial certification may become outdated within a few years, which results in biased risk assessments.

An additional regulatory issue concerns the application of network-based credit scoring to existing anti-discrimination statutes. In many jurisdictions, lenders are prohibited from discriminating against borrowers on the basis of race, ethnicity, gender, or religion. Although network metrics are not explicitly demographic variables, they may correlate with demographic attributes due to homophily in network formation. For instance, if female entrepreneurs in a specific area typically build denser local networks than their male counterparts, then triadic closure could act as a proxy for gender, resulting in differential treatment that might be contested as discriminatory. Regulatory authorities should mandate that creditors perform disparity analyses to ascertain whether their network-driven screening algorithms generate systematically divergent results for legally safeguarded groups. If such disparities are found, lenders must prove that the network metrics validly predict repayment risk and that no less discriminatory alternative exists.

Finally, the cross-border nature of mobile money platforms raises jurisdictional questions about which regulatory authority has oversight over network-based credit scoring. An entrepreneur in Tanzania may possess transactional links to suppliers in Kenya and customers in Uganda, thereby forming a network that extends across multiple national jurisdictions. The lender, which may be a fintech company registered in a third country, must navigate a patchwork of data protection and financial regulations. We advocate for the creation of regional regulatory harmonization structures, exemplified by the East African Community's Financial Inclusion Framework, which sets unified norms for network-based credit scoring across member states. Such harmonization would lower compliance expenses for lenders and ensure uniform safeguards for borrowers, thereby expediting the expansion of network-based lending throughout the region.

Conclusion

This paper has presented a novel credit screening framework that employs informal network structures to ease credit constraints for MSMEs in emerging markets. Through the combination of Exponential Random Graph Models and instrumental variable regression within a mechanism design framework, we have shown that network-derived trust proxies, particularly betweenness centrality and triadic closure, can function as effective substitutes for traditional collateral and credit history requirements. The ERGM-IV correction resolves the critical endogeneity problem present in network-based screening by disentangling the causal effect of network position on repayment probability from the confounding impact of unobserved borrower quality. Our simulation results indicate that this approach expands credit access from 30% under collateral-based lending to 68% under the full dynamic pricing regime, while preserving lender profitability at levels that exceed both traditional and naive network-based alternatives.

This framework is important because it has the capacity to open up funding for most micro, small, and medium enterprises in developing countries that do not have official financial records but are deeply connected to rich informal networks. The continuous, incentive-compatible pricing mechanism converts the binary credit decision into a flexible schedule that adjusts to changing network information, thereby permitting lenders to serve a broader spectrum of risk types while preserving adequate risk compensation. The ablation study verifies that every element of the pipeline—ERGM instrumentation, dual network metrics, and dynamic pricing—makes a meaningful contribution to the overall performance improvement.

This work suggests multiple avenues for subsequent investigation. The framework must first be validated with real-world mobile money transaction data supplied by a partner financial institution, transitioning from synthetic simulations to assess practical performance under actual market conditions. Second, the fluid character of network formation calls for a longitudinal extension that updates ERGM parameters and contract terms as entrepreneurs' network positions shift over time. The equity concerns arising from network-based screening merit more thorough examination, especially the creation of constrained optimization methods that explicitly balance efficiency with fair access for socially isolated yet creditworthy borrowers. Finally, the addition of other alternative data sources, such as psychometric assessments, utility payment histories, and satellite imagery of business premises, could further strengthen the predictive power of the framework while reducing the exclusionary effects of relying solely on network metrics.

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