



Article

The Signalling Trap: How Crisis Lending Reinforced Informal MSME Exclusion in Indonesia's Financial System

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Abstract

This study examines access to Indonesia's subsidised credit programme, *Kredit Usaha Rakyat* (KUR), during the COVID-19 pandemic using signalling theory. Based on logit regression of survey data from 2361 micro and small enterprises (MSEs), the study analyses how borrower characteristics were associated with loan approval across the Super Micro, Micro, and Small KUR schemes. The results show that prior credit history was the strongest observed signal of creditworthiness during the crisis. Previous receipt of KUR was associated with a 5 percentage-point higher probability of loan approval. Scheme-level estimations indicate heterogeneous signalling mechanisms. Prior credit history was positively associated with access to Micro KUR (15 p.p) and negatively associated with access to KUR Super Mikro that targeted non-bankable SMEs, whereas access to Small KUR was more strongly associated with collateral-based signals, particularly land ownership. The findings further indicate that borrowers lacking prior credit experience or formal assets were less likely to obtain KUR during the pandemic, suggesting that crisis-period lending created a "signalling trap" that stabilised liquidity while perpetuating exclusion. The study recommends reforms to KUR that incorporate hybrid risk assessment mechanisms, capacity-building, decentralised guarantees, and pathways to formalisation.

Keywords: microfinance; KUR; crisis lending; SMEs; signalling theory

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1. Introduction

Micro, Small, and Medium Enterprises (MSMEs) are the backbone of Indonesia's economy, accounting for over 99% of businesses, 97% of employment, and 61% of GDP ([Ministry of MSMEs, 2024](#)). Yet many struggle to grow, mainly due to limited access to formal finance ([Adam & Lestari, 2017](#); [OECD, 2017](#); [TNP2K, 2022](#)). According to [OJK \(2021\)](#) around 80% of MSMEs cannot obtain bank credit because of insufficient collateral, informality, and weak credit histories. Consequently, MSMEs face constraints in expanding production, adopting new technology, and hiring skilled workers, which ultimately reduces their productivity and competitiveness ([Adam et al., 2021](#); [Burger et al., 2015](#)).

To address financial constraints, the government launched KUR a subsidised credit programme designed to expand MSMEs' access to affordable finance (Adam et al., 2021; OJK, 2020). KUR operates through three distinct schemes—Super Micro, Micro, and Small—each targeting different firm profiles with varying loan ceilings and eligibility criteria. Although KUR has promoted financial inclusion for over two decades, its effectiveness under crisis conditions remains less understood. During the COVID-19 pandemic, KUR was proposed to serve as both an economic stabilisation instrument and a prudential lending programme. At the same time, banks became more risk-averse and increasingly relied on alternative borrower assessments, like credit history and business formality, rather than physical collateral alone (Adam & Lestari, 2023). These conditions likely altered how lenders evaluated borrower credibility and determined credit eligibility. This tension, between the policy mandate for broad inclusion and lenders' need to manage risk, raises a fundamental question: Under crisis conditions, which borrower characteristics are associated with access to a government-backed credit programme, and do these patterns vary across scheme tiers?

Studies on crisis-period credit allocation have largely focused on firms with stronger formal signals such as audited financials, established credit ratings, and documented performance records that leaving the MSME segment underexplored (Bańkowska et al., 2020; Bräuning et al., 2022; Zhang et al., 2023). Research does establish that informal MSMEs tend to face tighter credit conditions during downturns (Aditya & Amri, 2023; Bach et al., 2021; Colombo et al., 2013; Grover & Pereira-López, 2023) and that lenders generally respond to uncertainty by placing greater emphasis on verifiable signals (Berger & Udell, 2006; Stiglitz & Weiss, 1981). However, they pay limited attention to how crises reshape lenders' screening logic within government-backed programmes serving highly informal firms. Most studies implicitly treat financial exclusion as a stable structural problem and assume that the determinants of credit access remain constant across normal and crisis periods. Consequently, existing research provides limited insight into how heightened uncertainty changes the signals lenders prioritise when evaluating MSME borrowers.

This gap in the literature is particularly consequential in the context of Indonesia's KUR programme, where many applicants lack conventional collateral and formal financial records. Consequently, lenders rely more heavily on alternative signals, including business legality, bookkeeping practices, sectoral characteristics, and prior banking relationships. During crisis periods, however, the reliability of these signals may shift as banks attempt to balance rising credit risk with the programme's financial inclusion mandate, creating tension between social-policy objectives and prudential lending considerations.

This research is built on conventional policy evaluation by offering a theory-driven empirical analysis that addresses existing gaps. Drawing on signalling theory (Spence, 1973), we examine which borrower characteristics were associated with credit access, and whether these associations varied by scheme design. We introduce the concept of a "signalling trap" to describe a condition in which over-reliance on formal, verifiable signals—a predictable response to crisis-induced uncertainty—inadvertently narrows access within an inclusion-oriented programme. Rather than claiming that signals shifted during the pandemic, we ask what signal-dependence looked like during the crisis and whether its distributional consequences were consistent across schemes.

The analysis draws on a cross-sectional survey of 2361 MSEs across eight regions, covering both KUR recipients and non-recipients during the COVID-19 pandemic. Two contributions follow, first, we provide scheme-level evidence on the factors associated with KUR access during a systemic crisis to show that the signals associated with approval differ substantially across Super Micro, Micro, and Small KUR and, second, we extend signalling theory into the context of government-backed crisis lending, showing how a mechanism

designed to reduce information asymmetry can function as a structural screening device under heightened uncertainty.

This paper is organised as follows. Section 2 reviews the MSME finance literature and develops a signalling-based framework to analyse crisis-era credit access. Section 3 describes the methodology and datasets, based on nationally representative surveys across eight regions. Section 4 presents the logit results and supporting evidence, identifying key signals shaping loan approvals. Section 5 interprets the findings. Section 6 discusses limitation of the study and Section 7 presents the conclusion.

2. Literature Review

Understanding MSME access to KUR during the COVID-19 pandemic requires examining how crises reshape lender behaviour under heightened uncertainty. During systemic shocks, lenders tend to rely more heavily on observable and verifiable borrower characteristics to manage risk, potentially altering the mechanisms through which MSMEs gain access to credit. This creates a fundamental tension within government-backed lending programmes between financial inclusion objectives and prudential risk management. To analyse these dynamics, this section reviews the literature on MSME financing constraints, crisis-era tensions between financial inclusion and risk management, and signalling theory in microcredit markets.

2.1. MSME Financing Constraints and Crisis-Era Lending

Limited access to formal finance remains one of the main constraints facing MSMEs in developing countries. Existing studies consistently identify inadequate collateral, business informality, and weak financial records as key barriers to credit access (Amer & Selwaness, 2022; Banerjee & Duflo, 2013; Beck & Demirguc-Kunt, 2006; Burger et al., 2015; Harrison et al., 2022). Because lenders depend on verifiable information to reduce uncertainty, firms lacking formal documentation or asset ownership are often excluded from formal credit markets (Demirguc-Kunt et al., 2017). This exclusion limits business expansion, productivity growth, and long-term sustainability (Adam et al., 2025; Burger et al., 2015).

The literature also highlights the importance of “soft” information in lending decisions. Credit history, repayment records, and bank–firm relationships frequently function as proxies for borrower reliability, particularly when collateral is limited (Ayyagari et al., 2017; Berger & Udell, 2006; Smith & Henderson, 2018). These studies align closely with signalling theory (Spence, 1973), in which lenders rely on observable and verifiable signals to infer borrower quality under information asymmetry. However, most of this literature assumes relatively stable economic conditions and pays limited attention to how systemic crises may alter the credibility and predictive value of borrower signals.

The COVID-19 pandemic intensified these constraints. MSMEs experienced severe declines in demand, disruptions in supply chains, and heightened liquidity pressures (Arslan et al., 2020; Bartik et al., 2020). Under these conditions, lenders became more risk-averse and increasingly prioritised borrowers with stronger formal indicators of credibility, such as established repayment histories, business legality, and stable financial records. More formalised and digitally adaptable firms were generally better able to maintain operations and preserve lender confidence during the crisis (Adam & Lestari, 2023; Baldwin & Weder, 2020). These developments suggest that crises do not merely intensify existing financial exclusion, but may also reshape the criteria through which inclusion itself is determined.

2.2. KUR and the Tension Between Inclusion and Risk Management

In response to the COVID-19 pandemic, the Indonesian government expanded credit restructuring and subsidised lending programmes to protect MSME liquidity and financial

stability. Policy measures included loan moratoriums, interest subsidies, liquidity support for banks, and government guarantees aimed at preventing widespread business failure and supporting firm recovery. Within the National Economic Recovery (PEN) programme, KUR became a central instrument, receiving IDR 66 trillion to support 4.7 million MSMEs affected directly or indirectly by the crisis (Adam & Lestari, 2023; Purnagunawan et al., 2022). During this period, KUR served both as a social stabilisation mechanism and as a prudential lending programme, creating tensions between broad financial inclusion and lender risk management.

Although KUR was designed to support “non-bankable” MSMEs, evidence suggests that access during the pandemic disproportionately favoured relatively lower-risk firms. (Suryahadi et al., 2021) show that banks continued prioritising borrowers with stable financial records and stronger business profiles, while riskier but potentially viable firms, including more innovative enterprises, often remained excluded because of stricter collateral and screening requirements. This pattern highlights a fundamental tension between financial inclusion and lender risk aversion in government-backed lending. Even under public credit guarantees, banks may remain reluctant to lend to highly uncertain borrowers during systemic crises, raising broader questions about the extent to which guarantee schemes can alter bank behaviour under heightened economic uncertainty (Beck et al., 2018; Gropp et al., 2019).

This tension is particularly important because KUR operates through different schemes, namely Super Micro, Micro, and Small KUR, each with distinct borrower requirements and financing characteristics (Adam & Lestari, 2017). Smaller schemes often rely more heavily on behavioural and relational information, while larger schemes place greater emphasis on legality, asset ownership, and formal business capacity (Adam & Lestari, 2023; Purnagunawan et al., 2022). Consequently, crisis conditions may amplify differences in access across schemes and unintentionally favour firms with stronger formal signals. Yet existing studies generally aggregate KUR into a single category, providing limited insight into how crisis-era lending dynamics vary across programme tiers and regional contexts. Understanding how crisis conditions reshaped access across KUR schemes requires first examining what factors associated with credit eligibility under normal conditions that the signals lenders use and how they vary by scheme tier.

2.3. The KUR Program and Credit Eligibility Determinants

In Indonesia, the KUR program seeks to integrate MSMEs into the formal financial system. However, eligibility criteria appear uneven across tiers. Evidence suggests that asset ownership—particularly land—significantly increases the likelihood of Micro and Small KUR approval, reflecting banks’ continued preference for collateral despite the program’s partial guarantee scheme. At the same time, Micro KUR is frequently extended without physical collateral, relying instead on credit history and borrower profiling. This differentiation across Super Micro, Micro, and Small schemes may generate a de facto two-tier structure that favours more formal, asset-owning enterprises. The effectiveness of KUR’s affirmative targeting—especially during the pandemic—remains insufficiently examined.

From lenders’ perspectives, credit eligibility is shaped by socio-demographic factors (Karlan & Zinman, 2009; Noviarini et al., 2021; Potrich et al., 2015), business characteristics (Chandrayanti et al., 2019), and credit history which Berger and Udell (2006) and Barslund and Tarp (2008) identify credit history is identified as the strongest predictor in microcredit, as it reduces information asymmetry. This finding is consistent with (Spence, 1973) signalling theory, where a borrower’s track record functions as a credibility signal to lenders.

However, Karlan and Zinman (2009) warn that excessive reliance on credit history can exclude new but potentially innovative firms. This concern is relevant in Indonesia’s

KUR scheme. Super Micro KUR is often extended to businesses without a formal track record, while Small KUR places greater weight on legal status and asset ownership. The contrast underscores the need to examine how banks reconcile financial inclusion with risk management. Yet little is known about how the relative weight of these signals shifts during systemic crises, particularly across scheme tiers within a single government-backed programme.

2.4. Signalling Theory in Microcredit

Signalling theory (Spence, 1973) explains how borrowers communicate credibility to lenders under conditions of imperfect information. In microcredit markets, signals such as repayment history, business legality, bookkeeping practices, and prior banking relationships help lenders assess borrower quality when direct verification is costly or collateral is limited. These signals are especially important in microfinance and KUR lending because small loan sizes constrain the feasibility of intensive screening procedures (Armendáriz De Aghion & Morduch, 2005).

Before the pandemic, repayment history functioned as one of the most reliable signals in KUR lending. It reduced information asymmetry, lowered screening costs, and substituted for physical collateral, particularly for micro and informal enterprises (Adam & Lestari, 2017; Barslund & Tarp, 2008; Charles & Mori, 2017). Previous repayment performance also served as a behavioural indicator of borrower discipline and future repayment capacity (Banerjee & Duflo, 2013).

However, systemic crises can weaken the reliability of these conventional signals. During the COVID-19 pandemic, business disruptions affected firms regardless of their prior repayment discipline or operational quality. Accordingly, pre-crisis repayment records may no longer have reflected actual borrower viability under crisis conditions (Adam & Lestari, 2023). At the same time, lenders continued relying on familiar and institutionally accepted indicators because these signals remained administratively efficient and defensible within formal banking procedures. This condition may eventually trigger a signalling trap.

The signalling trap is defined as a condition in which lenders continue relying on previously reliable borrower signals even after systemic external shocks have weakened their predictive value. The concept differs from traditional adverse selection and credit rationing models (Stiglitz & Weiss, 1981), in which lenders lack sufficient information to distinguish creditworthy borrowers from risky borrowers before lending occurs. In contrast, the signalling trap arises when lenders possess observable signals but persist in relying on them despite their declining reliability under crisis conditions.

The signalling trap also differs from broader theories of financial exclusion, which primarily emphasise structural constraints such as poverty, informality, and limited collateral (Beck & Demirguc-Kunt, 2006). Rather than focusing solely on borrower disadvantage, the signalling trap highlights institutional and behavioural rigidity in lender decision-making. Even when alternative screening approaches may better capture borrower viability during crises, lenders may persist with familiar criteria to minimise operational uncertainty, bureaucratic risk, and reputational exposure. This tendency may persist even within government-backed lending programmes intended to support vulnerable firms.

The concept of the signal trap is analytically similar to two closely related fields of study: credit rationing theory and financial exclusion. Credit rationing theory (Stiglitz & Weiss, 1981) explains why lenders may withhold credit even from willing borrowers due to adverse selection resulting from information asymmetry. Meanwhile, research on financial exclusion documents the structural barriers that prevent certain groups from accessing the formal financial system. The signaling trap differs from both in a specific and consequential way, namely it describes a situation where mechanisms designed to overcome these barriers

actually reproduce exclusion through their reliance on signals. This is not a market failure in the conventional sense, but rather an institutional paradox: inclusion-oriented lending inadvertently narrows access precisely because crisis conditions limit the range of signals lenders are willing to accept.

A crisis alters how lenders interpret signals from borrowers. Under normal circumstances, lenders can rely on various indicators such as collateral, business performance, and sector stability to assess creditworthiness. Systemic shocks like a pandemic disrupt this by rendering many of these indicators unreliable simultaneously. As a result, lenders faced with rising uncertainty narrow their focus to any signals that can still be verified, and the most common is formal credit history. This raises the bar for borrowers who lack such a track record—not because they are less creditworthy, but because they cannot generate signals that lenders are willing to trust in crisis conditions. The result is a structural shift in which fewer borrowers can distinguish themselves as low-risk, while many creditworthy companies that lack visible information are treated as no different and denied access. Crisis lending thus risks reinforcing the very exclusion it aims to address.

Under a separating equilibrium, lenders can use past credit history as a low-cost, high-accuracy signal, since only borrowers with genuinely stronger repayment capacity are likely to have maintained a positive track record. Systemic shocks disrupt this relationship: borrowers who were creditworthy before the crisis (type H) may now appear observationally similar to those who were always higher risk (type L), as both groups experience comparable disruptions in income, cash flow, and operational continuity. However, most importantly, lenders do not always abandon this signal as its discriminatory power weakens. Because credit history remains administratively verifiable and institutionally accepted—even though its correlation with post-crisis business survival has declined—lenders continue to treat credit history as a condition for access. The result is a pooling effect where borrowers without prior credit history are treated as indistinguishable from high-risk borrowers, regardless of their actual post-crisis business survival, while those with prior history continue to be approved largely based solely on the strength of that record. This is the structural core of the signaling trap: the resilience of signal-based screening rules whose fundamental discriminatory function has been disrupted by the very shocks the program aims to address.

This pooling dynamic has direct implications for signalling costs and credit allocation. As uncertainty increases, reliance on standardised and verifiable signals intensifies, raising the effective cost of signalling for borrowers lacking formal credentials. As a result, signalling no longer functions solely as a mechanism for information disclosure but evolves into a form of structural screening that reinforces pooling equilibrium, where many eligible business actors still fail to obtain credit, leading to credit rationing (Galema, 2020; Jin & Zhang, 2019). Ultimately, this condition contributes to persistent financial exclusion driven by information asymmetry and inappropriate signalling mechanisms (Peng et al., 2026; Williams, 2025).

Consequently, government guarantees do not necessarily eliminate exclusionary dynamics during crises and may instead reinforce conservative screening practices that favour previously bankable firms over newly vulnerable but potentially viable MSMEs. In this context, the signalling trap extends signalling theory beyond static sender–receiver models by showing how the informational value of borrower signals can deteriorate under systemic shocks even as lenders continue relying on them. This perspective provides a dynamic, crisis-contingent refinement of signalling theory by distinguishing between stable and disrupted informational environments. Thus, crisis-era government credit programmes may expand overall lending while still systematically excluding informal and higher-risk MSMEs.

Building on the preceding literature review, this study develops an integrated analytical framework to examine how crisis conditions reshaped MSME access to government-backed credit (Figure 1). The framework operationalises the signalling trap by analysing how lenders increasingly relied on formal borrower signals—including repayment history, business legality, financial records, collateral ownership, and profitability—during the COVID-19 crisis despite the declining reliability of these indicators under systemic shocks. As economic uncertainty and information asymmetry intensified, lenders became more risk-averse and differentiated lending decisions more strongly according to the strength and formality of borrower signals across KUR schemes.

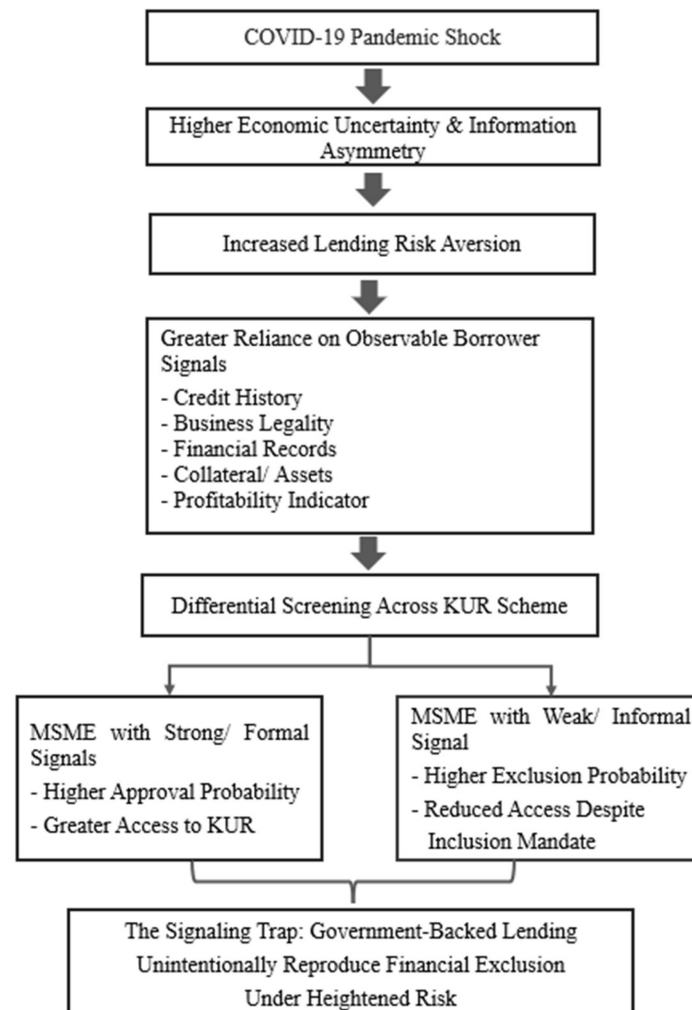


Figure 1. Analytical framework.

The framework further explains how institutional factors, particularly risk aversion and bureaucratic defensibility, reinforced lenders' continued reliance on familiar and institutionally recognised signals even when their predictive value weakened during the crisis. Consequently, MSMEs with stronger formal signals were more likely to obtain KUR access, while informal or weakly documented but potentially viable firms faced greater exclusion despite the programme's inclusion mandate.

Analytically, the framework distinguishes between screening (lenders' ex ante use of borrower information), signalling (borrowers' disclosure of attributes), and institutional constraints (bureaucratic procedures and guarantee scheme design), thereby addressing conceptual ambiguities identified in prior studies. This framework provides the analytical basis for interpreting the empirical findings in the following sections, particularly how

crisis-period screening practices may unintentionally reproduce financial exclusion within government-backed credit programmes.

3. Methods

3.1. Research Design

This study uses a cross-sectional survey design to analyze the factors associated with access to KUR among Micro, Small, and Medium Enterprises (MSEs) in Indonesia during the COVID-19 pandemic. MSEs are defined as productive businesses that are classified based on the scale of assets and annual turnover based on Law Number 20 of 2008, with this study focusing on micro and small enterprises as the dominant beneficiaries of KUR.

Data were sourced from one of the largest KUR-distributing banks in Indonesia, selected based on its extensive MSME customer base and its prominent role in implementing the KUR program through various financing schemes, including Super Micro KUR, Micro KUR, and Small KUR. Access to this customer base allowed for the identification of both KUR recipients and non-recipients within the formal banking ecosystem, consistent with the cross-sectional design.

3.2. Sampling Framework

The sample was constructed using a mix of sampling strategies: purposive sampling-referral-based and random sampling, both with geographic stratification to ensure broad regional and sectoral representation. Geographic coverage was determined based on eight major regional banking offices: Palembang, DKI Jakarta, Yogyakarta, Malang, Denpasar, Banjarmasin, Manado, and Jayapura. Sampling weights were derived from the national distribution of KUR disbursement by island in 2019, the most recent pre-pandemic year available, to approximate the structural distribution of KUR recipients prior to COVID-19-related policy adjustments. The sample was further stratified by sector to reflect the national composition of KUR recipients: trade (59.21%), agriculture and fisheries (23.27%), manufacturing (7.00%), construction (0.05%), and other sectors (10.51%) ([The Coordinating Ministry for Economic Affairs, 2020](#)). The sample also includes both urban and rural enterprises to capture spatial heterogeneity in credit access.

The sample comprises two groups. The first consists of MSEs that received KUR from the partner bank during the pandemic period, identified directly from the bank's customer database. The second consists of MSEs that did not receive KUR from the partner bank during the same period, selected through random sampling from the bank's broader service areas. Members of this group may have previously received KUR—from this or other institutions—but were not active KUR recipients during the observation period. Neither group therefore represents MSEs entirely excluded from the formal financial system; both were already operating within the formal banking ecosystem. This design allows for direct comparison of the characteristics associated with KUR receipt in 2020 while controlling for basic financial system access. Consequently, the findings should be interpreted as evidence of signal-based differentiation among MSEs already connected to the formal banking system, rather than as evidence of exclusion from the financial system *per se*.

Respondents were purposively selected from MSE meeting two criteria: (1) they are the primary owner or manager of the enterprise, and (2) the business was actively operating at the time of the survey. Data collection was conducted from May to July 2022 through *face-to-face interviews* using structured questionnaires administered by trained enumerators to ensure consistency across sites. All participants provided verbal informed consent prior to interview and were free to withdraw at any point. Survey responses were anonymised at the point of data collection and no personally identifiable information is

reported in this study. The study was conducted in accordance with the ethical principles of the National Research and Innovation Agency (BRIN). A total of 2500 respondents were initially collected; following validation and data cleaning, 2361 observations were retained as the final analytical sample.

While the sampling design does not support claims of full national statistical representativeness, the geographic and sectoral stratification ensures sufficient variation across schemes, regions, and enterprise types to support meaningful analysis of KUR access patterns during the pandemic.

3.3. Variables

The dependent variable in this study is a binary variable denoting whether an MSME received KUR during the pandemic. It is coded as 1 if the firm obtained KUR in 2020, regardless of the specific loan scheme, and 0 otherwise. To identify the factors that influenced banks' decisions to disburse KUR during this period, we classified the explanatory variables into six broad categories: socio-demographic characteristics, business attributes, business performance, asset ownership, capital structure, and credit history.

Socio-demographic characteristics were represented by a continuous variable for the owner's age and binary variables for gender, marital status, and education level (see Table 1). Business attributes included the duration of business operations (continuous) and the legal status of the enterprise (binary). Business performance was measured using the natural logarithms of current profit and household income, along with binary indicators capturing the use of internet marketing and technology in business operations.

Table 1. Variables' Operational Definitions.

No	Variable	Definition
Dependent Variable		
	KUR during pandemic	Received KUR in 2020 = 1
	KUR scheme during pandemic	Received Super Micro KUR = 1, Received Micro KUR = 2, Received Small KUR = 3
Socio-demographic		
	Age	Years
	Gender	Male = 1
	Marital status	Married = 1
	Education	Above secondary level = 1
Business Characteristics		
	Business tenure	Years
	Business legality	Licensed = 1
Asset Ownership		
	Land	Owns certified land = 1
	Vehicle	Owns vehicle = 1
Capital Structure		
	Initial self-financing	Yes = 1
Business Performance		
	Profit	Log of current profit
	Household income	Log of current income

Table 1. *Cont.*

No	Variable	Definition
	Internet use for marketing	Yes = 1
	Technology use	Semi-automated/automated = 1
	Subsidized Credit History	
	Previous KUR	Received KUR before 2020 = 1
	Confounding Variables	
	Location	Urban = 1
	Sector	Trade = 1, Manufacturing = 2, Services = 3, Agriculture/Fisheries/Livestock = 4, Construction = 5

Asset ownership was assessed through binary variables to indicate whether the business owned certified land or motor vehicle, both of which are commonly used as collateral in credit applications. Capital structure was measured by binary indicators of whether the initial capital originated from self-financing, allowing us to evaluate the potential role of non-bank credit access in influencing bank credit access. Finally, control variables were included for business sector and geographic location, with urban areas coded as 1 and rural areas as 0.

Although the survey was administered in 2022, respondents were explicitly asked to recall their business conditions and financial situation during the pandemic period (2020–2021). This ensures that both the dependent variable KUR receipt in 2020 and the explanatory variables refer to the same reference period during the pandemic.

However, several potentially relevant determinants of credit access, including entrepreneurial orientation, informal social networks, lender-specific screening practices, financial literacy, and local institutional conditions, could not be directly observed or adequately measured in the survey. The omission of these unobserved factors may contribute to residual confounding and omitted variable bias, thereby limiting the extent to which the estimated relationships can be interpreted.

3.4. Statistical Analysis

To examine the predictors of KUR access during the COVID-19 pandemic, this study employs a logit regression model. The dependent variable is binary, taking the value of one if an enterprise received KUR in 2020 and zero otherwise. Average Marginal Effects (AME) are reported to facilitate interpretation of each variable's association with the probability of KUR receipt. Robust standard errors are applied to address heteroskedasticity. Although the survey was administered across eight regional offices, the small number of primary sampling units precludes reliable cluster-robust inference (Cameron & Miller, 2015), thus region cluster-robust specifications were not used as the primary approach.

To complement the logit analysis and provide additional evidence on the association between prior credit history and KUR access during the pandemic, propensity score matching (PSM) is employed using the potential outcomes framework (Rosenbaum & Rubin, 1983). Specifically, the average treatment effect on the treated (ATET) is estimated using one-to-one nearest-neighbour matching without replacement, implemented via the `teffects psmatch` command in Stata. The treatment variable is defined as having received KUR prior to the pandemic (at aggregate level), and the outcome variable is KUR receipt during the pandemic.

Three sets of estimations are presented. The first examines KUR access in the full sample using logit, comparing a fully specified model against alternative specifications.

The second replicates this approach across KUR scheme subgroups to assess whether associations vary by scheme. The third presents PSM estimates for both the full sample and scheme subgroups as a robustness check on the logit findings. All analyses were conducted in Stata version 17.

4. Results

This section empirically evaluates the signalling framework developed in Section 2. As illustrated in Figure 1, the analysis examines three interrelated propositions. First, crisis conditions were associated with increased lender reliance on formal and observable borrower signals. Second, the signalling value of borrower characteristics varied across KUR schemes according to loan size and perceived risk. Third, stronger reliance on formal signals was associated with the relative exclusion of informal MSEs despite KUR's inclusion mandate. The findings are therefore interpreted as empirical associations that align with the proposed signalling framework and suggest differential screening dynamics during the crisis period.

4.1. Descriptive Analysis

The survey collected responses from 2361 respondents across eight regions in Indonesia (Table 2). A majority of respondents (57.53%) were from Java, while 42.47% were from other regions. The largest shares came from DKI Jakarta (20.16%) and DIY (4.31%). Outside Java, the highest proportions were recorded in Palembang (9.87%) and Denpasar and Manado, each 9.15%. In terms of residence, 61.12% of respondents lived in urban areas and 38.88% in rural areas.

Table 2. Sample Distribution by Province.

No	Provinces	Freq.	Percent
1	Palembang	233	9.87
2	DKI Jakarta	476	20.16
3	DIY	431	18.25
4	Malang	451	19.10
5	Denpasar	216	9.15
6	Banjarmasin	167	7.07
7	Manado	216	9.15
8	Jayapura	171	7.24
Total		2361	100

By sector, Table 3 shows that the sample is heavily concentrated in the trade sector (47.4%), indicating that commercial activities dominate the surveyed businesses. Agriculture and fisheries account for 22.66%, while manufacturing (13.68%) and services (13.26%) contribute nearly equal shares, reflecting moderate representation of secondary and tertiary activities. Construction has the smallest share (3.01%), suggesting limited participation from infrastructure-related enterprises in the sample.

Table 3. Sample Distribution by Sectors.

Sector	Freq.	Percent
Trade	1119	47.4
Manufacture	323	13.68
Services	313	13.26
Agriculture and Fisheries	535	22.66
Construction	71	3.01

The survey indicates that 65.99% of respondents received KUR during the pandemic, while 34.01% did not (Table 4). Of the 1519 beneficiaries, 59.97% accessed Micro KUR, 26.6% Super Micro, and 13.43% Small schemes. Prior to 2020, 40.36% of 2361 respondents had previously obtained KUR, borrowing between one and seven times. Women comprised 55.53% of respondents, highlighting female inclusion in the program and their central role in household income and local economic activity. Most respondents were household heads (62.26%), married (87.97%), and educated above secondary school (70.31%).

Table 4. Descriptive Statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
Received KUR during the pandemic	2361	0.66	0.47	0	1
Received KUR before 2020	2361	0.4	0.49	0	1
Age	2361	42.87	10.36	14	79
Gender	2361	0.44	0.5	0	1
Marital status	2361	0.88	0.33	0	1
Education	2361	0.7	0.46	0	1
Location	2361	0.61	0.49	0	1
Sector	2361	2.2	1.32	1	5
Business duration	2281	11.56	8.60	1	69
Business legality	2361	0.46	0.5	0	1
Initial self-capital	2361	0.64	0.48	0	1
Profit (million)	2361	4.95	10.2	0.05	250
Household income (million)	2361	6.76	10.4	300	300
Online marketing	2361	0.24	0.42	0	1
Technology use	2361	0.15	0.35	0	1
Land ownership	2361	0.41	0.49	0	1
Vehicle ownership	2361	0.77	0.42	0	1

Respondents had operated their businesses for an average of 11.5 years, suggesting KUR primarily serves established MSMEs, although only 46.38% possessed formal licenses. Most relied on self-financed start-up capital (64%), while just 3% used non-bank loans. Asset ownership was widespread: 42% owned land and 77% vehicles, commonly pledged as collateral. Average monthly profit was IDR 4.95 million, with household income at IDR 6.76 million. Job creation remained limited, with fewer than one paid worker per firm. Technology adoption was modest: 15% used semi-automated tools and 24% engaged in online marketing (Table 3).

In terms of business duration, more than half of the respondents (approximately 56%) have been in business for 10 years or less, while the remainder have more than 10 years of business experience. The largest group consists of businesses with an operating duration of approximately 5–8 years, indicating a predominance of MSEs that have passed the initial stages of business development. This variation in business duration reflects the varying levels of business maturity among respondents, ranging from relatively new to more established businesses, which can influence their capacity and opportunities to access KUR financing.

These descriptive patterns (Table 4) indicate substantial structural informality among Indonesian MSEs during the pandemic period. Although many firms had operated for more than a decade, fewer than half possessed formal business legality, and most relied primarily on self-financing rather than formal financial institutions. This pattern is particularly important because signalling theory suggests that under heightened uncertainty, firms lacking formal and verifiable indicators of creditworthiness are more likely to face exclusion from formal lending systems.

4.2. Crisis Conditions Increased Dependence on Formal Signals

To examine which borrower characteristics were associated with KUR access during the pandemic, Table 5 presents Average Marginal Effects from logit estimation across six model specifications to capture the patterns of relationships and shifts in the determinants of KUR uptake before and during the pandemic. The complete logit estimation results are reported in Appendix A. Column (1) shows the baseline model prior to the pandemic, while Columns (2) through (7) test the consistency of these relationships during the pandemic by gradually incorporating control variables: excluding credit history in Column (2), including the credit history variable in Column (3), disaggregating by KUR scheme in Columns (4) through (6), and incorporating the gender interaction effect in Column (7). Through a comparison between Column (1) and Column (3), a structural shift is evident in the indicators strongly associated with credit acceptance due to the crisis shock.

Table 5. Marginal Effects of Factors Associated with KUR Recipients by Scheme Allocation.

Var.	Before Pandemic		Pandemic				
	KUR All	KUR All	KUR All	KUR Super-Micro	KUR Micro	KUR Small	KUR All Interaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	−0.000 (0.001)	−0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Marital status	0.100 *** (0.034)	0.040 (0.030)	0.035 (0.030)	−0.014 (0.035)	−0.008 (0.042)	0.025 (0.033)	0.036 (0.030)
Education	−0.046 * (0.024)	−0.085 *** (0.023)	−0.082 *** (0.023)	−0.021 (0.025)	−0.005 (0.029)	0.023 (0.020)	−0.081 *** (0.023)
Business tenure	0.002 * (0.001)	0.000 (0.001)	−0.000 (0.001)	−0.003 * (0.001)	0.001 (0.002)	0.002 (0.001)	−0.000 (0.001)
Business legality	−0.004 (0.022)	0.037 * (0.021)	0.036 * (0.021)	−0.028 (0.023)	−0.028 (0.027)	0.058 *** (0.020)	0.035 * (0.021)
Asset ownership: land	0.082 *** (0.023)	0.073 *** (0.021)	0.068 *** (0.021)	−0.082 *** (0.025)	0.023 (0.028)	0.057 *** (0.020)	0.069 *** (0.021)
Asset ownership: vehicle	0.036 (0.027)	0.045 * (0.025)	0.043 * (0.025)	0.048 * (0.029)	−0.044 (0.034)	−0.004 (0.025)	0.042 * (0.025)
Profit (ln)	0.038 *** (0.012)	−0.005 (0.011)	−0.007 (0.011)	−0.030 ** (0.013)	−0.008 (0.015)	0.041 *** (0.012)	−0.007 (0.011)
Household income (ln)	−0.008 (0.016)	−0.053 *** (0.015)	−0.052 *** (0.015)	−0.031 * (0.018)	−0.008 (0.020)	0.024 * (0.013)	−0.052 *** (0.015)
Internet use for marketing	0.001 (0.028)	−0.011 (0.026)	−0.011 (0.026)	0.026 (0.029)	−0.051 (0.034)	0.024 (0.024)	−0.010 (0.026)
Automated machine	−0.036 (0.034)	0.006 (0.031)	0.008 (0.031)	−0.018 (0.035)	0.035 (0.040)	−0.016 (0.028)	0.008 (0.031)
Trade	0.229 *** (0.071)	0.102 * (0.059)	0.090 (0.059)	0.073 (0.077)	−0.153 * (0.088)	0.091 (0.075)	0.089 (0.059)
Manufacture	0.265 ***	0.109 *	0.095	0.076	−0.118	0.058	0.094

Table 5. Cont.

Var.	Before Pandemic			Pandemic			
	KUR All	KUR All	KUR All	KUR Super-Micro	KUR Micro	KUR Small	KUR All Interaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(0.075)	(0.063)	(0.063)	(0.081)	(0.093)	(0.078)	(0.063)
Services	0.192 **	0.050	0.041	0.056	−0.192 **	0.142 *	0.040
	(0.076)	(0.064)	(0.063)	(0.083)	(0.093)	(0.076)	(0.063)
Agriculture	0.176 **	−0.019	−0.028	0.029	−0.100	0.076	−0.029
	(0.074)	(0.061)	(0.061)	(0.081)	(0.092)	(0.077)	(0.061)
Construction	-	-	-	-	-	-	-
Initial self-financing	−0.059 ***	−0.208 ***	−0.204 ***	0.047 **	−0.095 ***	0.044 **	−0.203 ***
	(0.022)	(0.021)	(0.021)	(0.023)	(0.027)	(0.020)	(0.021)
Rural/urban	−0.019	−0.029	−0.028	−0.008	0.015	−0.009	−0.030
	(0.023)	(0.022)	(0.022)	(0.025)	(0.029)	(0.020)	(0.022)
Sex	0.017	0.015	0.013	−0.059 **	0.048 *	0.010	0.013
	(0.022)	(0.021)	(0.021)	(0.024)	(0.027)	(0.018)	(0.021)
KUR before pandemic			0.055 ***	−0.156 ***	0.132 ***	0.022	0.055 ***
			(0.020)	(0.023)	(0.026)	(0.018)	(0.020)
KUR pandemic*women							0.087 ***
							−0.027
KUR pandemic*men							0.018
							0.03
Constant							4.914 ***
							−1.056
N	2153	2153	2153	1392	1392	1392	2153

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This adjustment pattern can first be observed from the perspective of entrepreneurs' socio-demographic characteristics. The education variable consistently shows a significant positive association, both before and during the pandemic. This indicates that a higher level of formal education remains one of the indicators of an entrepreneur's personal capacity that is strongly correlated with the conditional probability of credit approval across various economic situations. Conversely, marital status, which had a significant relationship before the crisis, lost its statistical relevance during the pandemic and no longer was associated with the probability of KUR approval.

In addition to individual personal characteristics, a starkly contrasting shift in assessment criteria occurred regarding formal credit history and business financial performance. Amid the pandemic, credit history emerged as the variable with the strongest and most dominant positive association within the model. Business owners with a recorded KUR history prior to the pandemic had a 5.5 percentage point (pp) higher probability of receiving KUR again in 2020 (Column 3). Regarding financial performance indicators, while net profit had a significant positive relationship before the pandemic, the focus of this relationship shifted to revenue during the pandemic, with a negative coefficient. This pattern indicates that during the crisis, KUR allocation was more concentrated on businesses with lower revenue scales. Consistent with this shift, the revenue change variable (d_income)

showed a positive relationship of 5.6 pp, reflecting a tendency for greater credit allocation to businesses experiencing revenue declines due to the crisis.

In line with the financial aspects, operational characteristics and business risk management also show a shift in the pattern of relationships. While business tenure was closely linked to credit eligibility before the crisis, during the pandemic this variable lost its significance and was replaced by business license ownership as the primary administrative prerequisite. From the perspective of banking risk management, tightening is reflected in the physical collateral variable; whereas before the pandemic only land collateral showed a significant relationship, during the pandemic vehicle collateral ownership also demonstrated a significant relationship. Conversely, alternative indicators such as market share and technology adoption consistently failed to show statistically significant relationships across all models.

Finally, the spatial configuration of sectoral relationship patterns also underwent changes in tandem with shifts in the distribution of KUR disbursements across economic sectors. Before the pandemic, the agriculture, trade, and services sectors (Sectors 1, 3, and 4) exhibited a significant positive relationship with the likelihood of receiving KUR compared to the reference sector. However, during the pandemic, all coefficients for these sectors reversed to become significantly negative. This phenomenon indicates a shift in the concentration of KUR disbursements, which were massively redirected to the manufacturing industry (Sector 5), which was deemed more resilient during the crisis.

To address structural selection bias, where 2020 loan recipients are inherently more likely to be creditworthy, this study employs Propensity Score Matching (PSM) based on the Average Treatment Effect on the Treated (ATET) (Table 6). Matching covariates include socio-demographic and business characteristics measured in the pre-pandemic period: age, sex, marital status, education, rural location, business tenure, business legality, pre-pandemic household income, pre-pandemic land asset ownership, sectoral classification, and primary capital source. This specification ensures that matching is performed on pre-treatment characteristics, reducing the influence of selection bias on the estimated association.

Table 6. Propensity Score Matching Estimates of the Association Between Prior Credit History and KUR Access During the Pandemic (ATET).

Variable	KUR Pandemic	KUR Pandemic Super Micro	KUR Pandemic Micro	KUR Pandemic Small
KUR before pandemic	0.0628 ** (0.0271)	−0.153 *** (0.0313)	0.121 *** (0.0346)	0.0319 (0.0228)
Observations	2263	1461	1461	1461

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

Covariate balance was assessed using standardised mean differences and variance ratios before and after matching. After matching ($n = 1846$; 923 treated, 923 control), all covariates achieved standardised differences below 0.10, indicating adequate balance. PSM estimations are conducted separately for the full sample and for each KUR scheme subgroup (Super Micro, Micro, and Small KUR), with results reported in (Table 5).

Estimation results in the All Model show an ATET coefficient of 0.063, which is statistically significant ($p = 0.018$; $\alpha = 5\%$). This means that, after initial characteristics were controlled for, business owners with a KUR history had a 6.35 percentage point higher probability of regaining access to KUR during the 2020 pandemic compared to the group without a history. When analyzed by financing scheme, contrasting heterogeneity in the impact was found. In the KUR Micro scheme, the effect of credit history increased to 0.121 and remained significant ($p = -0.035$; $\alpha = 1\%$), where super micro-businesses with a history had a 15.3 percentage point lower chance of obtaining emergency capital. Conversely,

under the KUR Small scheme, this effect was not statistically significant ($p = 0.23$). These findings confirm that the credit signaling mechanism proved robust in mitigating banking information asymmetry during the crisis, with its influence operating exclusively and more strongly in the Micro segment compared to the Small segment.

4.3. Scheme Design Altered the Weighting of Borrower Signals

Table 5, coll. (4)–(7) presents disaggregated estimation results by credit scheme. The disaggregated estimates in Columns (4), (5), and (6) indicate that the characteristics relevant to credit approval vary significantly depending on the credit limit of the scheme accessed. In Column 4, unlike other schemes, business operators under the Super Micro Scheme with a history of past credit actually exhibit a significant negative relationship, meaning they have a 15.6 percentage point lower probability of receiving the Super Micro KUR. This pattern aligns with the scheme's characteristics, which are targeted at new borrowers. Instead, the likelihood of approval under this scheme shows a strong association with physical prerequisite variables such as business tenure, land collateral, and vehicle collateral.

In the Micro segment, neither physical indicators nor business financial performance (such as profit and assets) show a statistically significant relationship. Conversely, the likelihood of loan approval relies exclusively on the variable of prior KUR history, with a probability advantage of up to 13 percentage points. Once prior borrowing history is included, nearly all socio-demographic and business performance variables become statistically irrelevant, revealing the clearest evidence of crisis-era signalling dependence. This pattern suggests that, amid heightened uncertainty, lenders relied overwhelmingly on repayment track records as the most direct, credible, and low-cost predictor of future repayment behaviour, outweighing indirect indicators like education or asset ownership.

Meanwhile, for the Small Scheme (Column 6), as the credit limit increases, the variable of past credit history loses its significance. The probability of approval under the Small Scheme shows a stronger relationship with conventional business capacity indicators such as net profit margin, business tenure, legal status of permits, and collateral value. Business legality, land ownership, and profit were associated with a 5.1 p.p, 6.3 p.p, and 4.6 p.p higher likelihood of allocation to this scheme, respectively. These findings suggest that as loan size and risk exposure increased, lenders relied on a cumulative portfolio of formal signals, reflecting a more conventional commercial lending logic with stricter screening standards. In this context, legal status signalled institutional legitimacy and business permanence, land ownership served as high-quality collateral that mitigated default risk, and profitability indicated repayment capacity and stable cash flow. Together, these characteristics formed a comprehensive profile of high creditworthiness associated with approval for larger loan sizes.

Through the interaction model in Column (7), evidence of gender-based asymmetry in relationship patterns during the crisis was found. The relationship between past credit history and the probability of KUR approval during the pandemic operates asymmetrically: for female business owners, having a credit history indicates a very strong positive association, with a 9.9 percentage point higher probability of receiving KUR (Column 7). Conversely, for male entrepreneurs, the relationship with the credit history variable shrinks to 2.6 percentage points and is not statistically significant.

4.4. The Emergence of a Signalling Trap

The findings suggest that the COVID-19 pandemic shifted KUR lending from a primarily inclusion-oriented programme toward a more signal-dependent allocation system. Under heightened uncertainty, banks increasingly prioritised observable indicators that

reduced lending risk and administrative uncertainty, particularly prior repayment history, business legality, collateral ownership, and profitability.

Because these signals were more commonly possessed by MSEs already integrated into formal financial systems, the lending process generated what this study conceptualises as a “signalling trap.” Firms most in need of support during the crisis were often the least able to provide the formal signals required to access subsidised credit. Hence, crisis lending partially reinforced existing structural divides between formal and informal enterprises.

This dynamic does not necessarily imply intentional exclusion by lenders. Rather, it reflects the interaction between crisis-induced risk management and persistent structural informality within Indonesia’s MSE sector. Faced with heightened uncertainty, financial institutions rationally shifted toward safer and more verifiable borrower profiles. However, this adaptive lending behaviour simultaneously narrowed effective access for highly informal firms whose economic vulnerability was not matched by institutional visibility within the formal financial system.

Several institutional features of KUR may also help explain why exclusionary dynamics became more pronounced during the crisis period. First, subsidised interest rate ceilings may have reduced incentives for lenders to undertake costly screening of highly informal borrowers. Second, although the government guarantee scheme covered 70–85% of defaults, lenders still faced residual risk and administrative costs, potentially encouraging greater reliance on easily verifiable indicators of repayment capacity. Third, the rigid categorisation of Super Micro, Micro, and Small KUR created threshold effects in which firms exceeding the Super Micro ceiling could face difficulties accessing larger loans if they lacked the formal signals typically associated with higher lending categories. Taken together, these institutional features may have reinforced a more signal-dependent allocation process during the pandemic.

However, these institutional interpretations should be treated with caution. A full empirical demonstration of a signalling trap would ideally require longitudinal data tracking the same firms across multiple lending cycles, together with an identification strategy capable of addressing endogeneity. The present cross-sectional analysis therefore provides empirical associations consistent with a trap mechanism rather than definitive causal evidence. Accordingly, the “signalling trap” is best understood as a conceptual heuristic grounded in observed signal–access asymmetries, which future panel-based research should examine more directly.

5. Discussion

The findings suggest that the COVID-19 crisis reshaped Indonesia’s KUR programme beyond short-term liquidity support. Heightened uncertainty increased lenders’ reliance on conventional borrower signals, may have contributed to uneven inclusion across enterprise groups and regions. As access became more dependent on formal credit histories, collateral, and business legality, existing structural inequalities appeared to be further embedded within crisis lending dynamics. These patterns raise important questions about how government-backed financial inclusion programmes can balance risk management with broader goals of inclusive and transformative MSME development during periods of systemic disruption.

5.1. Crisis Lending and the Signalling Trap

In small-scale credit markets, information asymmetry is typically reduced through observable indicators such as credit history, collateral, and business legality. During the pandemic, however, these indicators became increasingly rigid screening tools. This finding aligns with crisis-lending literature showing that financial institutions tend to

tighten lending standards during periods of uncertainty, even within government-backed inclusion programmes (Bańkowska et al., 2020; Bräuning et al., 2022). Our findings extend this literature by showing that exclusion during crises arises not only from reduced credit supply, but also from changes in how lenders prioritise borrower signals.

Among KUR recipients, prior credit history was associated with a higher likelihood of allocation to Micro KUR, while business legality and land ownership were strongly associated with allocation to Small KUR. The fact that recipients were repeat borrowers further reflects the importance of relationship lending during the crisis period. Although reliance on verifiable signals helped reduce information asymmetry and accelerate credit disbursement, it simultaneously disadvantaged informal and first-time MSEs lacking observable indicators of creditworthiness. Thus, crisis-era financial inclusion programmes may unintentionally favour firms already integrated into formal financial systems, thereby reinforcing pre-existing inequalities in access to finance.

This dynamic was particularly visible in Small KUR, where collateral and legal status operated as strict screening mechanisms directing larger and more transformative loans toward firms with stronger formal credentials. By contrast, asset-poor but potentially viable enterprises were more likely to be excluded. These findings contribute to the MSE finance literature by showing that formality became increasingly valuable during the crisis period. Under normal conditions, informality may limit borrowing capacity. During crises, however, the absence of formal signals becomes far more consequential as lenders prioritise verifiability and administrative certainty.

These findings also extend the existing literature on MSME credit access. While prior studies have separately shown that collateral, prior credit history, and informality are associated with financing outcomes, this study demonstrates how a single policy intervention (KUR) functioned as three distinct signalling regimes during the crisis period. Specifically, the same programme applied inverse signalling (Super Micro), pure track-record signalling (Micro), and cumulative formal-signal stacking (Small) across loan tranches. This scheme-based institutional differentiation, rather than differences across lenders or borrower groups, constitutes the study's primary analytical contribution.

However, these cross-scheme comparisons remain correlational rather than causal. Differences in borrower composition across schemes, including unobserved firm quality, borrower risk profiles, or lender assignment rules, may partly account for the observed heterogeneity. In the absence of random assignment to loan tiers or a discontinuity design around scheme thresholds, the notion of "distinct signalling regimes" should be interpreted as a descriptive characterization of observed approval patterns, rather than definitive evidence of differing lender screening mechanisms.

Taken together, the findings extend signalling theory by showing that signalling under crisis conditions can evolve from a mechanism for reducing information asymmetry into a mechanism of access control. Rather than merely differentiating borrower quality, lenders may exclude firms unable to provide verifiable signals altogether, creating a "signalling trap" that reinforces informality and financial exclusion. In this context, signalling is no longer a neutral market mechanism but an institutional filtering process that tends to privilege already formalised firms. This pattern raises the possibility that crisis-response lending may shift from broad financial inclusion toward selective access based on verifiable status rather than productive potential. However, because our data do not directly observe lender decision-making processes, these interpretations remain suggestive rather than definitive.

5.2. KUR Access and Structural Inequality

The signalling dependence that intensified during the pandemic also produced uneven inclusion across enterprise groups and regions. Formal, Java-based MSMEs with

established credit profiles were more likely to access larger and more transformative KUR schemes. Although Java accounted for 58% of KUR loans while representing 56% of the national population, disparities were more pronounced in Small KUR, where firms in Java were 34% more likely to gain access than those in Eastern Indonesia.

These patterns reflect broader inequalities in banking infrastructure, formalisation rates, and institutional connectivity across Indonesia. Enterprises in economically advanced regions are better positioned to generate the formal signals required by lenders, while firms in peripheral regions face overlapping disadvantages related to informality, weaker financial access, and limited administrative visibility. The findings therefore support regional development literature (e.g., Beck et al., 2018; Lämmermann, 2020) showing that nationwide credit programmes can reproduce spatial inequality when implementation depends heavily on existing financial ecosystems.

Although Super Micro KUR expanded access for unlicensed businesses, its low loan ceiling ($\leq$ IDR 10 million) limited its capacity to support business expansion, positioning the scheme primarily as survival financing. Inclusion gains, including women accounting for 55.53% of recipients, were also not accompanied by significant technological upgrading or digital market integration. Credit provision therefore remained focused on static risk indicators rather than long-term productivity enhancement.

These findings suggest that KUR functioned more effectively as a short-term liquidity stabilisation instrument than as a mechanism for structural transformation during the pandemic. Expanding access to microcredit alone was insufficient to promote enterprise upgrading when borrowers remained concentrated in low-value and low-productivity activities. Rather than reducing inequality, crisis lending partially reinforced segmentation between formal and informal enterprises and between economically advanced and peripheral regions which consistent with broader concerns that emergency credit expansion tends to prioritise administratively verifiable borrowers over structurally disadvantaged ones. Given that our analysis does not establish causality between regional disparities and lending decisions, alternative explanations, such as differences in demand-side borrower characteristics, cannot be ruled out.

5.3. Policy Implications

Repositioning KUR toward transformative financial inclusion could be supported by policies that reduce signalling barriers, strengthen enterprise capabilities, expand regional access, accelerate formalisation, and integrate finance with broader business development support. These implications are derived from our observed associations and existing literature. They should be tested in future research with causal designs.

First, credit assessment could be enhanced by moving beyond conventional indicators such as collateral and repayment history by incorporating alternative data, including digital transactions, utility payments, and supplier contracts. This recommendation follows from the finding that MSEs lacking formal credit histories faced systematic disadvantages in accessing Micro and Small KUR. Hybrid risk-assessment models would reduce information asymmetry and allow lenders to evaluate enterprise viability using broader behavioural and transactional signals.

Second, KUR could be more effective if integrated with subsidised digital and financial capacity-building programmes. Training in bookkeeping, digital literacy, e-commerce, and online marketing would strengthen MSEs' technological adoption, financial management, and market reach. This recommendation is directly linked to the finding that digital integration among KUR recipients remained relatively weak despite large-scale crisis lending. Beyond improving business resilience, stronger digital capabilities would also help firms generate verifiable financial records that support future creditworthiness and

long-term scaling. Evidence on the causal impact of such training on credit outcomes is still limited.

Third, reducing regional disparities might be supported by strengthening decentralised lending through regional guarantees and targeted incentives for microfinance institutions (MFIs), particularly in underserved regions outside Java. The findings show that firms in agrarian and fisheries-based regions faced lower probabilities of accessing larger KUR schemes. Because local MFIs often possess superior soft information about informal borrowers, expanding decentralised financial intermediation could partially compensate for the absence of formal signals required by commercial banks. Partial portfolio guarantees would further reduce lender risk and encourage broader outreach to excluded enterprises.

Fourth, KUR could be piloted in conjunction with simplified business licensing and formalisation support. Integrating credit approval with streamlined digital registration systems would lower bureaucratic barriers and help informal enterprises obtain legal status. This recommendation reflects the finding that business legality significantly increased access to Small KUR, where larger and more transformative financing was concentrated. Accelerating formalisation would therefore strengthen MSEs' institutional visibility, improve future access to finance, and support long-term business expansion.

Fifth, future KUR frameworks might consider integrating credit provision with technology adoption, skills upgrading, and market integration strategies. The findings indicate that emergency lending alone did not substantially improve productivity transformation or enterprise competitiveness. Consequently, crisis-response financing could benefit from incorporating measurable development-oriented indicators, including digital adoption, employment generation, business upgrading, and long-term formalisation. Aligning finance with broader enterprise development policies would strengthen MSEs not merely as recipients of liquidity support, but as drivers of sustainable and inclusive economic growth.

6. Limitation

This study has three main limitations. First, although survey questions explicitly referenced pandemic-era conditions, retrospective self-reporting of financial variables, particularly profit and household income introduces the possibility of recall bias that may not be uniformly distributed across KUR recipients and non-recipients. This concern is partially mitigated by two observations: these variables are not statistically significant in the fully specified models, and variables less susceptible to recall bias such as asset ownership, employment, and technology use yield consistent results.

Second, the cross-sectional observational design precludes causal inference. Unobserved factors such as entrepreneurial orientation, informal networks, managerial quality, and local institutional conditions may jointly influence both firm characteristics and KUR access. The PSM analysis provides partial reassurance that the core association between prior credit history and KUR access is not driven by observable selection alone, though unobserved confounders cannot be ruled out.

Third, the purposive sampling approach, which targeted enterprises already within the formal banking ecosystem, limits external validity. The findings likely understate exclusion among the most marginalised MSEs, and uneven regional coverage constrains the generalisability of scheme-level and regional comparisons.

7. Conclusions

This study examined the determinants of MSMEs' access to Indonesia's KUR program during the COVID-19 pandemic, focusing on how crisis conditions reshaped lending behaviour across the Super Micro, Micro, and Small schemes. Drawing on signalling

theory, it analysed which borrower characteristics functioned as credible indicators of creditworthiness under heightened uncertainty.

The findings suggest that the pandemic increased banks' reliance on conventional, verifiable signals, particularly among the sampled borrowers and provinces covered in this study, creating patterns of exclusion for informal and first-time borrowers. Access determinants varied across schemes, indicating a tiered risk structure. For Micro KUR, prior credit history was the only significant predictor, increasing approval probability by 8%, suggesting that banks relied heavily on established repayment records during the crisis period. Small KUR required a wider set of formal signals, including business legality, land ownership, and profitability, reflecting stricter screening for larger loans. Super Micro KUR was more accessible to asset-poor and unlicensed firms, although the evidence suggests that it functioned primarily as short-term survival support rather than long-term business expansion financing. Overall, the observed approval patterns in the sampled data were more strongly associated with repeat, formal, and Java-based borrowers, although these relationships should be interpreted cautiously given the study's sampling and contextual limitations.

Theoretically, this study extends signalling theory into the context of systemic crisis. The findings are consistent with the possibility that, under heightened uncertainty, signalling functions more narrowly as a restrictive screening mechanism for reducing information asymmetry. Rather than relying on multiple indicators, lenders may concentrate their assessment on a smaller set of historically verifiable signals, especially prior credit history. However, this interpretation remains associative rather than causal, as the cross-sectional design cannot fully determine whether these patterns reflect lender behaviour, borrower composition, or broader institutional constraints during the pandemic. The findings nevertheless point to a potential structural tension in government-backed crisis lending between the goals of rapid disbursement and inclusive access.

Furthermore, the concentration of KUR expansion in Java, particularly in the Small KUR scheme, suggests that institutional capacity and risk mitigation considerations may have outweighed efforts to equalise access across regions during the crisis period. While the study does not directly measure institutional decision-making, the regional concentration observed in the sample indicates the possibility that crisis-era lending mechanisms may reinforce existing regional disparities.

These findings have several policy implications. If KUR is to evolve from emergency liquidity support into a more inclusive development instrument, policy reforms may need to reduce excessive dependence on conventional borrower signals. This paper therefore proposes five policy directions. First, adopting hybrid risk assessments that combine alternative and traditional data. Second, linking credit access to capacity-building through subsidised training. Third, promoting decentralised lending with regional guarantees and incentives for MFIs. Fourth, simplifying formalisation through KUR-linked licensing support. Fifth, aligning credit access with skills, technology, and market integration to strengthen MSME resilience in post-pandemic recovery.

However, the study's conclusions should be interpreted in light of several limitations. First, the purposive sampling approach limits external validity, as the findings may not fully generalise beyond the sampled provinces and recruitment channels. Although sampling weights based on pre-pandemic KUR disbursement data were applied, some borrower groups, regional dynamics, and unobserved heterogeneity may remain underrepresented. Second, the cross-sectional design identifies associations rather than causal effects, particularly given the time gap between the 2020 crisis and data collection. The analysis therefore cannot fully address potential endogeneity arising from omitted variables, self-selection into loan schemes, unobserved borrower characteristics, or reverse causality between

prior access to finance and current business characteristics. Third, the study focuses on enterprises that survived at least two years before the pandemic, potentially underrepresenting younger MSEs facing different credit constraints. Moreover, because the analysis is grounded in Indonesia's institutional and pandemic context, the findings may not be directly transferable to other countries or credit systems. Accordingly, the study should be viewed primarily as providing descriptive, theory-informed evidence on crisis-era lending patterns rather than definitive causal evidence of lender behaviour.

Future research should therefore employ broader probability-based and longitudinal designs to better capture the evolution of credit access across regions, sectors, and enterprise age groups. Further investigation into the interaction between KUR, digitalisation, gender dynamics, and regional disparities would deepen understanding of inclusive finance. Comparative analysis of similar government-backed lending programmes could also help assess whether the signalling patterns observed in this study are specific to Indonesia's KUR system or reflect broader features of crisis-era credit policy.

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Data Availability Statement: The authors do not have permission to share data.

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Appendix A. Logit Estimation Results

VARIABLES	Before Pandemic			Pandemic			
	KUR All	KUR All	KUR All	KUR Super-Micro	KUR Micro	KUR Small	KUR All Interaction
Age	0.006 (0.005)	0.008 (0.005)	0.007 (0.005)	−0.001 (0.007)	−0.003 (0.006)	0.008 (0.009)	0.007 (0.005)
Marital status	0.429 ***	0.196	0.169	−0.082	−0.036	0.227	0.176

VARIABLES	Before Pandemic		Pandemic				
	KUR All	KUR All	KUR All	KUR Super-Micro	KUR Micro	KUR Small	KUR All Interaction
	(0.145)	(0.145)	(0.145)	(0.202)	(0.183)	(0.306)	(0.145)
Education	−0.196 *	−0.413 ***	−0.402 ***	−0.119	−0.021	0.211	−0.397 ***
	(0.103)	(0.114)	(0.114)	(0.144)	(0.126)	(0.181)	(0.114)
Business tenure	0.011 *	0.000	−0.000	−0.015 *	0.004	0.014	−0.000
	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.010)	(0.006)
Business legality	−0.016	0.179 *	0.177 *	−0.159	−0.122	0.533 ***	0.170 *
	(0.095)	(0.100)	(0.100)	(0.133)	(0.118)	(0.181)	(0.101)
Asset ownership: land	0.353 ***	0.357 ***	0.333 ***	−0.467 ***	0.101	0.521 ***	0.335 ***
	(0.098)	(0.105)	(0.105)	(0.144)	(0.123)	(0.182)	(0.105)
Asset ownership: vehicle	0.155	0.220 *	0.210 *	0.275 *	−0.194	−0.038	0.206 *
	(0.114)	(0.120)	(0.121)	(0.167)	(0.146)	(0.229)	(0.121)
Profit (ln)	0.162 ***	−0.025	−0.035	−0.174 **	−0.036	0.372 ***	−0.036
	(0.050)	(0.053)	(0.053)	(0.074)	(0.064)	(0.109)	(0.053)
Household income (ln)	−0.033	−0.257 ***	−0.256 ***	−0.175 *	−0.034	0.222 *	−0.254 ***
	(0.067)	(0.072)	(0.073)	(0.103)	(0.086)	(0.122)	(0.073)
Internet use for marketing	0.005	−0.054	−0.053	0.147	−0.220	0.217	−0.050
	(0.121)	(0.127)	(0.128)	(0.169)	(0.150)	(0.217)	(0.128)
Automated machine	−0.152	0.030	0.041	−0.106	0.152	−0.142	0.040
	(0.145)	(0.150)	(0.150)	(0.200)	(0.173)	(0.258)	(0.150)
Trade	0.977 ***	0.495 *	0.439	0.416	−0.667 *	0.830	0.437
	(0.307)	(0.287)	(0.287)	(0.442)	(0.384)	(0.685)	(0.287)
Manufacture	1.132 ***	0.530 *	0.465	0.433	−0.513	0.527	0.458
	(0.323)	(0.308)	(0.309)	(0.466)	(0.406)	(0.718)	(0.309)
Services	0.819 **	0.245	0.199	0.318	−0.836 **	1.298 *	0.196
	(0.327)	(0.310)	(0.310)	(0.476)	(0.409)	(0.702)	(0.310)
Agriculture	0.755 **	−0.093	−0.136	0.166	−0.434	0.693	−0.141
	(0.316)	(0.297)	(0.297)	(0.465)	(0.400)	(0.704)	(0.297)
Construction	-	-	-	-	-	-	-
Initial self-financing	−0.253 ***	−1.011 ***	−0.998 ***	0.268 **	−0.412 ***	0.398 **	−0.994 ***
	(0.097)	(0.110)	(0.111)	(0.133)	(0.120)	(0.185)	(0.111)
Rural/urban	−0.082	−0.141	−0.137	−0.048	0.063	−0.086	−0.145
	(0.097)	(0.106)	(0.105)	(0.144)	(0.125)	(0.182)	(0.106)
Sex	0.071	0.071	0.065	−0.335 **	0.207 *	0.092	0.198
	(0.094)	(0.100)	(0.101)	(0.137)	(0.118)	(0.169)	(0.123)
Previous KUR			0.268 ***	−0.892 ***	0.573 ***	0.200	0.425 ***
			(0.100)	(0.139)	(0.116)	(0.163)	(0.137)
Constant	−3.874 ***	4.857 ***	4.988 ***	4.629 ***	2.255 *	−13.512 ***	4.914 ***
	(0.990)	(1.048)	(1.055)	(1.594)	(1.310)	−1.966	(1.056)
Observations	2153	2153	2153	1392	1392	1392	2514

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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