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Lemons in the Labour Market: Information Asymmetry, Adverse Selection, and Credit Exclusion in India's Gig Economy

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Abstract

India's gig economy is projected to grow from 7.7 million workers in FY2020–21 to 23.5 million by 2029–30, yet the overwhelming majority of platform workers remain excluded from formal credit markets. The mechanism is informational, not financial: traditional credit-scoring systems cannot interpret the data that gig workers produce. Drawing on Akerlof's (1970) model of adverse selection and Spence's (1973) signaling theory, this paper argues that India's gig credit market exhibits the structural properties of a lemons market, where lenders unable to distinguish creditworthy from non-creditworthy informal borrowers either price credit beyond reach or exit altogether. Two existing data sources, Unified Payments Interface (UPI) transaction histories and e-Shram registration records, are identified as credible, low-cost signals capable of resolving this failure. Using secondary data from NITI Aayog, the Reserve Bank of India, the Ministry of Labour and Employment, and recent NBER empirical work, the paper proposes a dual-pillar policy framework: institutionalising platform behavioural data as an alternative underwriting input through the Unified Lending Interface (ULI), and mandating e-Shram registration for gig aggregators to establish formal worker identity. The central finding is that the infrastructure required to correct this market failure is already operational; what is missing is the institutional commitment to integrate it.

Keywords: information asymmetry, gig economy, credit exclusion, UPI, e-Shram, Akerlof, Spence, Unified Lending Interface, financial inclusion, India

1. Introduction

India's informal economy is not a residue of underdevelopment. Informality is the labour market's structural baseline: over 90 percent of the total workforce engages in non-standard employment arrangements (ILO, 2020), and within that vast informal sector, platform-based gig work has emerged as its fastest-growing layer. Delivery executives for Swiggy and Zomato, ride-hailing drivers for Ola and Uber, freelancers on Urban Company: these workers are economically active, digitally integrated, and increasingly essential to the daily functioning of urban India. The formal financial system, by and large, does not know they exist.

The scale of this oversight is not trivial. NITI Aayog (2022) estimates 7.7 million gig workers in FY2020–21, constituting 1.5 percent of total employment. The Economic Survey 2023–24 projects 23.5 million by

2029–30. Yet formal credit denial rates among this cohort remain near-universal. Gig workers receive income through irregular digital credits from multiple platforms rather than a single monthly salary. Their income is real, though volatile. Their work is documented, but on proprietary platform systems that banks do not recognise. The salary slips, Form 16 records, and employer letters that Indian credit assessment requires are simply not part of their financial footprint, even though the underlying economic behaviour can be observed.

The argument of this paper is straightforward: the exclusion is informational, not financial. Using Akerlof's (1970) theory of adverse selection, we model the gig credit market as one in which lenders, unable to separate reliable from unreliable informal borrowers, either price credit beyond reach of both or withdraw entirely. The problem is not that gig workers are bad credit risks; it is that lenders have no way of identifying which ones are not. We then apply Spence's (1973) signalling framework to locate the resolution: UPI transaction histories and e-Shram registration records satisfy the conditions for credible, low-cost signals that would enable lenders to make that distinction.

Two research questions organise the analysis. First, do UPI data and the e-Shram registry function as Spencian signals with sufficient credibility to restore a separating equilibrium in the gig credit market? Second, what institutional mechanisms are necessary to transmit these signals to lenders at scale? Section 2 reviews the theoretical and empirical literature. Section 3 describes the structure of India's gig economy and the mechanics of credit exclusion. Section 4 applies the theoretical frameworks. Section 5 presents the quantitative evidence. Sections 6 and 7 cover policy implications and methodological considerations, respectively. Section 8 concludes.

2. Literature Review

2.1 Information Asymmetry and the Lemons Problem

Akerlof's 'The Market for Lemons' (1970) remains the theoretical starting point. Akerlof showed that when one side of a transaction holds private information about quality that the other cannot verify, markets do not just clear imperfectly; they can collapse entirely. In his used car example, sellers know whether their vehicle is a reliable 'peach' or a defective 'lemon.' Buyers, unable to distinguish between them, bid at average quality. This pricing pushes high-quality sellers out of the market, lowering average quality further and inviting more exits. Akerlof called this spiral adverse selection. The paper earned him a share of the 2001 Nobel Prize in Economics.

The credit market translation is direct. Banks are buyers of loan risk; borrowers who know their own creditworthiness are the sellers. When lenders cannot assess informal borrowers (no CIBIL score, no pays lip, no institutional reference), they face a textbook Akerlof problem. They either deny credit to the entire informal population or set rates high enough to cover expected default across it. Both responses exclude the creditworthy gig worker who would repay reliably but cannot demonstrate it. Stiglitz and Weiss (1981) formalized this mechanism as credit rationing. Because lenders cannot observe borrower quality, they may refuse to lend at any interest rate rather than raise rates indefinitely, since higher rates select for riskier borrowers. The gig credit market exhibits exactly this structure.

2.2 Signaling and Separating Equilibria

Spence's 'Job Market Signaling' (1973) provides the resolution. In labour markets where employers cannot observe worker quality before hiring, Spence showed that high-productivity workers can credibly signal their type through educational credentials, provided one condition holds: the cost of obtaining the credential must be inversely related to true quality. If acquiring a degree is cheap for productive workers

and prohibitively expensive for unproductive ones, the signal is self-enforcing: only the genuinely productive will invest in it. This produces what Spence called a separating equilibrium, in which different quality types receive appropriately differentiated treatment.

Applying this to gig credit requires identifying signals that are passively generated by creditworthy borrowers, verifiable by lenders, and difficult to fabricate. UPI transaction data and e-Shram registration satisfy all three conditions, as developed in Section 4. A related literature on credit signaling, including work by Bester (1985) on collateral as a screening device and de Meza and Webb (1987) on adverse selection in competitive credit markets, reinforces the intuition that the key to market correction is not eliminating asymmetry but creating mechanisms through which high-quality types can credibly distinguish themselves. The UPI-e-Shram bundle is precisely such a mechanism.

2.3 Digital Finance, Transaction Data, and Credit Inclusion

The empirical literature connecting digital payment infrastructure to credit access is growing, and its findings are directly relevant here. Ghosh et al. (2024), in the most rigorous study to date, find that high-UPI adoption regions in India experienced four percent higher credit access for new-to-credit borrowers and eight percent higher access for subprime borrowers relative to low-adoption areas. Their NBER working paper treats UPI as a form of digital public infrastructure that enables authenticated financial transaction data, tackling the twin problems of absent credit bureau ratings and absent transaction histories that this paper identifies as the structural cause of gig worker exclusion.

The international precedent is instructive. Jack and Suri (2011) showed that M-Pesa transaction data in Kenya could substitute for formal credit history in extending small loans to previously excluded borrowers, a finding that has since influenced fintech lending models across sub-Saharan Africa. The Indian UPI-ULI architecture operates at a far greater scale and with a stronger state infrastructure, and the argument of this paper is partly that India is better positioned than any prior context to execute this kind of informational correction.

The gig-specific literature is thinner but consistent. Flourish Ventures (2020) surveyed platform workers across five emerging economies and found that income irregularity, not income absence, was the primary barrier to financial product access, a distinction that maps cleanly onto the Akerlof framing. Murthy and Deshpande (2022), writing for CGAP, concluded that platform-side data integration was the most effective route to formal credit access for this population. The Boston Consulting Group (2021) estimated that India's gig workforce had a largely unmet credit demand of approximately USD 8 billion annually, a gap that conventional underwriting models are structurally incapable of filling.

This paper sits at the intersection of these three bodies of work: adverse selection theory, digital infrastructure and credit, and gig worker financial inclusion. The contribution is to synthesize them into a coherent analytical framework and to show that India's existing digital infrastructure already meets the theoretical conditions for market correction, without requiring new data sources or new institutions.

3. The Indian Gig Economy: Scale, Structure, and Credit Exclusion

3.1 Scale and Structural Growth

India's gig economy has grown faster than most conventional employment categories. NITI Aayog (2022) sets the FY2020–21 baseline at 7.7 million workers, comprising 2.6 percent of the non-agricultural workforce. Sood and Singh (2023) document growth from 2.52 million in 2011–12 to 6.8 million in 2019–20, a compound annual growth rate of 16.78 percent. Third-party estimates placed active workers at roughly 12 million by 2024–25, and the Economic Survey 2023–24 projects 23.5 million by 2029–30,

equivalent to 4.1 percent of total livelihoods. The global context matters: the gig economy was valued at $556.7 billion in 2023 and is projected to reach $1,847 billion by 2032 (PMC, 2025). The platform-mediated work model is not India-specific, but the scale of India's informal baseline makes the financial exclusion problem particularly acute here.

The skill composition of this workforce is worth noting. NITI Aayog (2022) classifies 47 percent of gig labour as medium-skilled, 31 percent as low-skilled, and 22 percent as high-skilled, with the low-skilled and high-skilled shares both rising at the expense of the middle. This polarization matters for credit policy: the workers most financially vulnerable, those in low-skilled delivery and ride-hailing, are also those least likely to have any formal documentation of their income, and most dependent on the alternative signals this paper proposes.

Table 1: Growth of India's Gig Workforce (2011–30)

Period	Estimated Workers	CAGR	Source
2011–12	2.52 million	N/A	Sood & Singh (2023)
2019–20	6.80 million	16.78%	Sood & Singh (2023)
2020–21	7.70 million	13.2% (est.)	NITI Aayog (2022)
2024–25 (est.)	12.00 million	11.7% (est.)	PMC (2025)
2029–30 (proj.)	23.50 million	11.8% (proj.)	Economic Survey 2023–24

Note: CAGR figures are approximate. Projections from Economic Survey 2023–24 and PMC (2025).

3.2 The Mechanics of Credit Exclusion

Platform workers face near-universal rejection from formal credit institutions, and the reason is structural rather than behavioral. Gig workers accumulate income through irregular digital transfers across multiple platforms. They cannot produce salary slips, Form 16 tax records, or employer letters, the documentary artefacts that Indian credit assessment frameworks treat as proxies for creditworthiness. Their CIBIL scores are either absent or so thin as to be analytically useless. For many, formal borrowing has simply never occurred.

The financial consequences are significant. Unable to access institutional credit, gig workers turn to informal moneylenders, platform-affiliated micro-credit schemes, or family networks, channels that charge effective annual rates of 18 to 30 percent, compared with 10 to 15 percent through formal institutions (Banerjee & Duflo, 2007; National Economic Forum, 2025). Fair Work India (2023) documented monthly incomes of between ₹15,000 and ₹20,000 among delivery and ride-hailing workers, an income level that would, by standard debt-service coverage ratios, comfortably support moderate loan repayments. The problem is not repayment capacity; it is the absence of any mechanism through which that capacity can be verified.

The exclusion is self-perpetuating. A 2024 NITI Aayog study found that 90 percent of gig workers hold no savings (Drishti IAS, 2025). Credit exclusion prevents the accumulation of financial buffers; the absence of buffers makes workers more susceptible to income shocks; heightened vulnerability reinforces the lender's assessment of default risk, which in turn sustains the exclusion. Without structural intervention at the informational level, this cycle does not break.

3.3 The e-Shram Dimension

The e-Shram portal, launched in August 2021 as a National Database of Unorganized Workers linked to Aadhaar, represents the state's most significant attempt to bring informal workers into formal institutional view. Cumulative registrations reached 305.8 million by January 2026, with 1.23 crore new registrations in 2024 alone, averaging 33,700 daily enrolments (Ministry of Labour and Employment, 2025). The 2025–26 Union Budget formally extended e-Shram eligibility to platform workers, a meaningful policy recognition that gig workers constitute a distinct category within the unorganized workforce.

Despite this scale, gig worker penetration within e-Shram is shallow. Fewer than 729,000 gig workers had registered by July 2024, a penetration rate below six percent of the estimated 12 million active workers (Business Today, 2024). The gap reflects awareness constraints and the historically voluntary nature of registration. Two developments are beginning to change this: the Ministry of Labour and Employment's September 2024 notification mandating that gig aggregators register themselves and their workers through API integration (Nishith Desai Associates, 2024), and the extension of eligibility in the FY2025–26 budget. The mandatory aggregator requirement is the more consequential of the two, converting e-Shram from a voluntary database into a structural feature of the gig economy's formal architecture, and in doing so, establishing the identity foundation that the signaling framework requires.

4. Theoretical Framework: Applying Akerlof and Spence to Gig Credit

4.1 The Gig Credit Market as a Lemons Market

To apply Akerlof's adverse selection model, partition the informal borrower population into two types. Creditworthy gig workers, those with stable platform income, consistent digital payment histories, and low default probability, are the 'peaches.' Non-creditworthy informal borrowers, with volatile income and high default risk, are the 'lemons.' Borrowers know which type they are; lenders, in the absence of formal documentation or credit history, cannot determine it.

Lenders respond rationally: they price credit against the average default risk of the pooled informal population. Creditworthy gig workers, whose actual risk is lower than this average, find formal credit prohibitively expensive relative to what they would access if their creditworthiness were legible. They exit, not by choice but by exclusion. Their exit raises the average risk of the remaining pool, which justifies further rate increases, which drive further exits. The equilibrium is a market increasingly dominated by high-risk borrowers, serviced at rates designed for them. Stiglitz and Weiss (1981) showed that in such markets, lenders may prefer not to raise rates at all, opting instead for outright credit rationing. Both outcomes, prohibitive rates and outright denial, characterize the experience of gig workers seeking institutional credit.

This is not a theoretical abstraction. RBI data consistently shows the persistence of informal borrowing at elevated rates among low-income demographics (RBI, 2019–2024). The RBI's decision to pilot unsecured lending to gig workers in December 2024, specifically because traditional underwriting methods were inadequate, constitutes an institutional acknowledgment of the failure this framework diagnoses.

4.2 UPI Data and e-Shram as Spencian Signals

A credible signal, in Spence's (1973) framework, requires two properties: it must be observable by the uninformed party, and it must be differentially costly, cheap for high-quality types to produce and prohibitively expensive for low-quality types to replicate. The joint signal proposed in this paper, UPI transaction history paired with e-Shram registration, satisfies both conditions.

Consider UPI data first. A gig worker receiving consistent weekly credits from Zomato or Ola, with regular outflows to utilities, groceries, and household expenses, generates a financial behavioral profile structurally indistinguishable from that of a formal-sector employee. Critically, this profile is produced passively: the worker does nothing beyond ordinary economic activity to create it. The NPCI's cryptographic authentication infrastructure ensures that the transaction record is tamper-resistant. Fabricating a convincing three-year UPI history, with realistic income patterns, merchant diversity, and seasonal variation, is not a realistic option for a fraudulent applicant. The signal is cheap for genuine creditworthy borrowers and prohibitively costly to fake. Spence's separation condition holds.

E-Shram adds the identity dimension. Aadhaar-linked and maintained by the state, it provides a verified formal identity that financial institutions can access. On its own, this would be insufficient as a credit signal; identity does not imply repayment capacity. But paired with UPI behavioral data, it closes the loop: one signal speaks to financial conduct, the other to authenticated identity. Together they provide what no individual platform data point could offer alone, a joint signal bundle that reduces the informational asymmetry at the root of the Akerlof failure.

It is worth acknowledging where the analogy to Spence strains. In Spence's original model, the signal is deliberately acquired; education is chosen specifically to communicate type. UPI data is not chosen in this sense: it is a by-product of participation in the digital economy. This makes it, in some respects, a stronger signal than Spence's education credential: precisely because it is generated without strategic intent, it is harder to game. The theoretical precedent for this interpretation exists in the screening literature, where Stiglitz (1975) distinguishes between signals chosen for communicative purposes and characteristics that reveal type as a by-product of other activity. UPI data falls into the latter category.

Figure 1: Conceptual Framework, From Market Failure to Separating Equilibrium

MARKET FAILURE (Akerlof)	MARKET CORRECTION (Spence via UPI + e-Shram)
The lender cannot observe the borrower's quality	UPI history reveals income regularity and financial behavior
No formal documentation exists for gig income	Passively generated data substitutes for traditional documentation
Lender pools all informal borrowers at average risk	Separating equilibrium: creditworthy workers distinguished by signal bundle
Creditworthy workers excluded; informal rates prevail	Formal credit accessible; debt servicing cost declines
Transmission channel: None	Transmission channel: Unified Lending Interface (ULI) + Account Aggregator

Source: Authors' conceptual framework, drawing on Akerlof (1970) and Spence (1973).

4.3 The Unified Lending Interface as Transmission Infrastructure

Identifying the right signals is necessary but not sufficient. The signals must be transmittable to lenders in a verified, standardized, and privacy-compliant manner. This is the role of the Unified Lending Interface (ULI), developed by the Reserve Bank Innovation Hub and operational in pilot phase since August 2023.

ULI provides a digital public infrastructure layer through which lenders access verified financial and non-financial data via a plug-and-play API, replicating in the credit domain the interoperability that UPI created in payments (RBI, 2024). By December 2024, it had facilitated over 600,000 loans worth ₹27,000 crore, including ₹14,500 crore to 160,000 MSME borrowers across 36 onboarded lenders (Business Standard, 2024).

The December 2024 RBIH-Vivifi Finance pilot applied this architecture explicitly to gig workers, using platform earnings histories, activity data, and behavioral signals as underwriting inputs in place of conventional credit scores (APAC News Network, 2024; Inc42, 2024). This is the closest real-world approximation of the framework proposed in this paper. When extended broadly through ULI, it converts the theoretical separating equilibrium into operational lending practice.

5. Quantitative Evidence

5.1 The Credit Gap

The credit gap facing India's gig workers is large in absolute terms and tractable in theoretical terms. Ghosh et al. (2024) find that the average fintech loan facilitated through UPI-linked infrastructure was ₹27,778, roughly seven times average rural monthly expenditure, indicating substantial unmet demand at income levels consistent with gig worker earnings. Regions with high UPI adoption saw four percent higher credit access for new-to-credit borrowers and eight percent higher access for subprime borrowers relative to low-adoption regions. This establishes a causal relationship between digital transaction infrastructure and credit market expansion, not merely correlation.

BCG and the Michael and Susan Dell Foundation (2021) estimated the annual unmet credit demand of India's gig workforce at approximately USD 8 billion. If gig workers currently servicing informal debt at 18–30 percent annually were to access formal credit at 10–15 percent, the interest savings per worker would range from ₹8,000 to ₹30,000 annually depending on loan size, a meaningful welfare gain for workers whose median monthly incomes are in the ₹15,000–20,000 range (Fair Work India, 2023).

5.2 UPI at Scale

The data infrastructure underpinning the signaling proposal is not hypothetical. Annual UPI transaction value reached ₹246.8 lakh crore in FY2024, with volume growing from 1,079 crore transactions in 2019 to 17,221 crores in 2024. By August 2025, UPI processed over 20 billion transactions monthly, representing 85 percent of India's total digital retail payment volume (Kotak Mutual Fund, 2025). The platform has onboarded 300 million individual users and 50 million merchants since its 2016 launch (Ministry of Finance, 2024). The NPCI's expansion of per-day transaction limits to ₹10 lakh for verified merchant categories, and the active piloting of UPI data for real-time credit scoring via ULI, indicate the system is already transitioning toward higher-value financial operations.

Table 2: UPI Scale Indicators (Selected Years)

Year	Transaction Volume (crore)	Approx. Value
FY2019	1,079	N/A (baseline)
FY2024	17,221	₹246.8 lakh crore
Aug 2025 (monthly)	>2,000/month	₹24.85 lakh crore/month

Sources: Ministry of Finance (2024); Kotak Mutual Fund (2025).

5.3 e-Shram: Coverage and Demographic Relevance

E-Shram is, by registration count, the world's largest database of unorganized workers. Registrations totalled 305.8 million by January 2026 and 309.7 million by July 2025 (Ministry of Labour and Employment, 2025; IMPRI, 2025). The five states with the highest registration, Uttar Pradesh (83 million), Bihar (30 million), West Bengal (26 million), Madhya Pradesh, and Maharashtra, correspond to the primary labour supply sources for tier-1 city gig platforms, which strengthens the demographic fit.

The registrant profile is directly relevant to gig credit policy: 53.8 percent female, 58.8 percent aged 18 to 40 (IMPRI, 2025). This is the active gig worker demographic. The integration of e-Shram with the myScheme platform, the UMANG mobile application, and the mandatory aggregator API requirement from September 2024 has established the technical architecture for the portal to function as a validated identity signal in lender credit assessment workflows.

6. Policy Implications

The theoretical diagnosis and empirical evidence converge on two institutional pathways, neither of which requires building new systems. Both leverage infrastructure already operational at scale.

6.1 Institutionalizing Platform Data Through ULI

The first pathway is the systematic use of ULI to transmit platform behavioral data, UPI transaction histories, platform earnings records, and activity data to lenders as alternative underwriting inputs. ULI provides the consent-based, API-standardized channel through which this data can flow from financial information providers to lenders in a verified, privacy-compliant manner (RBI, 2024). The RBIH-Vivifi Finance pilot demonstrates proof of concept: platform-generated behavioral signals can substitute for conventional credit scores. Expanding that pilot across all ULI-onboarded lenders would represent a decisive correction of the Akerlof informational failure.

The Account Aggregator (AA) framework provides the complementary consent architecture. As of December 2024, the AA framework had processed over 140 million consent requests, with approximately 7 to 8 percent of the Indian population registered as consent-givers and nearly 600 financial institutions in the network (Sahamati, 2024; Precisa, 2025). Monthly growth in the framework runs at approximately 13 percent. Research on thin-file and low-income borrowers indicates that the AA architecture enables income verification and credit assessment for workers whose incomes were previously invisible to formal lenders (Advances in Consumer Research, 2025). The open banking market, underpinned by this infrastructure, generated USD 1,595 million in revenue in 2024 and is projected to reach USD 8,254 million by 2030, at a CAGR of 31.8 percent (Precisa, 2025).

6.2 Mandatory e-Shram Integration

The second pathway addresses the identity component of the informational problem. The September 2024 notification from the Ministry of Labour and Employment, mandating that gig aggregators register both themselves and their workers on e-Shram through API integration, is the pivotal policy instrument (Nishith Desai Associates, 2024). Full enforcement converts e-Shram from a voluntary registry into a structural component of the gig economy's formal architecture, and simultaneously elevates e-Shram registration from an optional credential to a mandatory, Aadhaar-verified identity signal accessible to lenders.

When platform-generated behavioral data via ULI is paired with Aadhaar-anchored identity via e-Shram, the joint signal bundle is both verifiable and asymmetrically costly to produce. A creditworthy gig worker generates it as a by-product of working within the formal digital economy. A fraudulent applicant with

poor credit history cannot replicate it without sustained, authentic platform activity and biometric identity verification. The Spencian separating equilibrium becomes achievable.

The welfare stakes are material. If the 23.5 million projected gig workers by 2029–30 access formal credit at institutional rates rather than informal ones, interest savings per worker range from ₹8,000 to ₹30,000 annually. At scale, this amounts to a substantial reallocation of economic surplus toward workers who are already producing value but are structurally prevented from retaining it.

7. Methodology, Limitations, and Ethical Considerations

7.1 Methodological Approach

The paper employs a qualitative-analytical methodology combining applied theoretical modelling with secondary data analysis. The theoretical contribution is the application of Akerlof's adverse selection model and Spence's signaling framework to the specific institutional context of India's gig credit market, a synthesis not present in the existing literature in this form. Quantitative evidence is drawn from official government publications, peer-reviewed and working paper research, and credible industry analyses. All statistical claims are sourced; no data is fabricated or extrapolated beyond published sources.

7.2 Limitations

Three limitations are worth acknowledging directly. First, the paper relies exclusively on secondary data. Primary evidence, particularly surveys of gig workers and interviews with lenders and platform operators, would significantly strengthen the causal claims, especially regarding how lender behaviour actually changes in response to alternative data inputs. Future research should incorporate direct investigation of the RBIH-Vivifi Finance pilot and similar programmes.

Second, the theoretical argument assumes that the cost asymmetry between high- and low-quality borrowers is sufficiently large to prevent a pooling equilibrium. The paper argues this condition holds for UPI and e-Shram signals, but formal modelling of the threshold cost differential required for separation is beyond its scope. Whether a genuine separating equilibrium obtains in practice, rather than a partial or unstable one, is an empirical question that pilot programme evaluation should address.

Third, the framework is specific to urban platform workers in the organized gig sector. The vast majority of informal workers, those who are not platform-affiliated and generate no UPI or e-Shram footprint, face comparable or worse credit exclusion without access to the proposed signals. The analysis should not be read as a general solution to India's informal credit problem; it addresses an important but bounded subset of it.

7.3 Ethical Considerations

The use of behavioral data for credit assessment raises ethical concerns that the policy framework must confront rather than bracket. The Account Aggregator consent architecture provides a structural safeguard, but informed consent in practice, particularly among workers with lower digital literacy, requires more than a consent prompt embedded in a platform agreement. Workers may authorize data sharing without understanding its scope or implications.

There is also a risk that algorithmic credit models trained on UPI data will encode rather than correct existing structural inequalities. If historical transaction patterns reflect income disparities shaped by caste, gender, or geography, models trained on them may reproduce those disparities under the guise of neutral assessment. Regulatory frameworks governing alternative credit scoring, particularly on model explainability, bias auditing, and grievance mechanisms, are currently underdeveloped relative to the pace

of technical deployment. Closing this gap is not incidental to the policy framework; it is a precondition for its legitimacy.

8. Conclusion

India's gig economy does not have a credit risk problem. It has an information problem. The roughly 12 million workers currently driving, delivering, and servicing urban India through digital platforms are economically productive and, for the most part, financially reliable. The credit system simply cannot read them.

The Akerlof-Spence framework developed in this paper provides both a diagnosis and a coherent direction for resolution. The diagnosis: lenders, unable to distinguish creditworthy from non-creditworthy informal workers, treat them identically and price credit accordingly, excluding a population that would largely repay. The resolution: UPI transaction histories and e-Shram registration records satisfy the conditions for credible, low-cost signals that can restore a separating equilibrium, transmitted to lenders at scale through ULI's API infrastructure.

What makes this argument more than theoretical is that the infrastructure is already operational. UPI processed over 20 billion transactions monthly by August 2025. ULI has facilitated ₹27,000 crore in loans. E-Shram holds over 305 million registrations. The September 2024 aggregator mandate is moving platform workers toward formal registration. The gig worker credit pilot is running. The question is not whether the tools exist; it is whether the institutional commitment to integrate them follows.

If it does, the distributional consequences are real. Formal credit at institutional rates instead of informal moneylender rates would represent a meaningful transfer of economic surplus to workers who are already contributing substantially to the urban economy. The informational barrier that excluded them was not inevitable. Neither is its persistence.

References:

1. Advances in Consumer Research. (2025). The transformative impact of the account aggregator framework on financial inclusion in India: A multi-sectoral study of MSMEs, microfinance, and personal lending. ACR Journal. https://acr-journal.com/article/the-transformative-impact-of-the-account-aggregator-framework-on-financial-inclusion-in-india-a-multi-sectoral-study-of-msmes-microfinance-and-personal-lending-1852/
2. Akerlof, G. A. (1970). The market for 'lemons': Quality uncertainty and the market mechanism. Quarterly Journal of Economics, 84(3), 488–500. https://doi.org/10.2307/1879431
3. APAC News Network. (2024, December 30). RBI Innovation Hub introduces digital unsecured loans for gig workers. Retrieved from https://apacnewsnetwork.com
4. Banerjee, A. V., & Duflo, E. (2007). The economic lives of the poor. Journal of Economic Perspectives, 21(1), 141–167. https://doi.org/10.1257/jep.21.1.141
5. Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. American Economic Review, 75(4), 850–855.
6. Boston Consulting Group & Michael & Susan Dell Foundation. (2021). Unlocking the potential of the gig economy in India. BCG.
7. Business Standard. (2024, December 26). Over 600k loans worth Rs 27,000 cr disbursed on ULI platform: RBI report. Retrieved from https://www.business-standard.com

8. Business Today. (2024). Gig workers and e-Shram registration. Retrieved from https://www.businesstoday.in
9. de Meza, D., & Webb, D. C. (1987). Too much investment: A problem of asymmetric information. Quarterly Journal of Economics, 102(2), 281–292. https://doi.org/10.2307/1885064
10. Drishti IAS. (2025). Transforming India's gig economy. Retrieved from https://www.drishtiias.com/daily-updates/daily-news-editorials/transforming-india-s-gig-economy
11. Economic Survey 2023–24. (2024). Ministry of Finance, Government of India.
12. Fair Work India. (2023). Fair Work India ratings 2023. Fairwork Foundation.
13. Flourish Ventures. (2020). The digital hustle: Gig worker financial lives under pressure. Flourish Ventures.
14. Ghosh, S., Vallee, B., & Zeng, Y. (2024). Breaking barriers to financial access: Cross-platform digital payments and credit markets (NBER Working Paper No. 33259). National Bureau of Economic Research. https://doi.org/10.3386/w33259
15. ILO. (2020). World employment and social outlook 2020: Trends. International Labour Organization.
16. ILO. (2023). Expansion of the gig and platform economy in India: Opportunities for employer and business member organizations. International Labour Organization.
17. IMPRI Impact and Policy Research Institute. (2025, August 10). Digitizing informality: A policy update on the e-Shram portal, 2021. Retrieved from https://www.impriindia.com
18. Inc42. (2025, January 2). RBI Innovation Hub pilots unsecured loan offerings for gig workers. Retrieved from https://inc42.com
19. Jack, W., & Suri, T. (2011). Mobile money: The economics of M-PESA (NBER Working Paper No. 16721). National Bureau of Economic Research. https://doi.org/10.3386/w16721
20. Kotak Mutual Fund. (2025, November 21). India's UPI journey: From disruption to digital transformation. Retrieved from https://www.kotakmf.com
21. Ministry of Finance, Government of India. (2024, December 14). UPI achieves 15,547 crore transactions worth ₹223 lakh crore from January to November 2024. Press Information Bureau.
22. Ministry of Labour and Employment, Government of India. (2025, February 4). Over 30.58 crore workers registered on the e-Shram portal, including 1.23 crore new registrations in 2024. Press Information Bureau. Retrieved from https://ddnews.gov.in
23. Murthy, G., & Deshpande, R. (2022). How can financial services support a platform work? Insights from five emerging markets (CGAP Focus Note). CGAP.
24. National Economic Forum. (2025, March 17). Lending labyrinth: Is India's credit system a path to prosperity or peril? Retrieved from https://nationaleconomicforum.org
25. Nishith Desai Associates. (2024, October 8). Registration of gig workers and platform aggregators on the e-Shram portal. Retrieved from https://www.lexology.com
26. NITI Aayog. (2022). India's booming gig and platform economy: Perspectives and recommendations on the future of work. Government of India. https://www.niti.gov.in/sites/default/files/2022-06/25th_June_Final_Report_27062022.pdf
27. OpenGov Asia. (2025, February 4). e-Shram: Connecting India's unorganized workforce. Retrieved from https://archive.opengovasia.com
28. PMC / National Institutes of Health. (2025). Rise of the gig economy and its health toll on workers. PubMed Central. Retrieved from https://pmc.ncbi.nlm.nih.gov/articles/PMC12318557/

29. Precisa. (2025). Account aggregator integration: Future of consent-based financial data access. Retrieved from https://precisa.in/blog/account-aggregator-integration-financial-data-access/
30. Reserve Bank of India. (2019–2024). National strategy for financial inclusion 2019–2024. RBI.
31. Sahamati. (2024, December). Reconciling the account aggregator and consent manager frameworks. Retrieved from https://sahamati.org.in
32. Sood, A., & Singh, R. (2023). The gig economy in India: Growth, challenges, and policy implications. International Journal of Research and Innovation in Applied Science, 8(4). https://rsisinternational.org/journals/ijrias/
33. Spence, M. (1973). Job market signaling. Quarterly Journal of Economics, 87(3), 355–374. https://doi.org/10.2307/1882010
34. Stiglitz, J. E. (1975). The theory of 'screening,' education, and the distribution of income. American Economic Review, 65(3), 283–300.
35. Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. American Economic Review, 71(3), 393–410.
36. The New Indian Express. (2024, December 9). UPI enables expansion of credit among underserved borrowers: Study. The New Indian Express Economics Bureau.