

The rise of digital finance in India: Financial inclusion or debt trap? Evidence from the Global Findex surveys, 2021–2024

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Abstract

Both sides of the Indian digital finance revolution – financial inclusion and over-indebtedness – are analysed in this paper. Based on pooled cross-sectional data ($n = 6,000$) from the 2021 and 2025 rounds of the World Bank Global Findex survey for India, weighted probit models of credit market engagement, borrowing related to consumption, and financial distress are estimated. People who use digital payments are 7.4 percentage points more likely to borrow from financial institutions and 4.9 percentage points more likely to take out loans via a mobile phone. Digital finance users are also more likely to borrow for consumption: the probability of buying household food on credit is 9.6 percentage points higher and that of borrowing for medical purposes 10.2 percentage points higher. The distress findings are double-edged. Digital payment use is associated with lower unconditional financial fragility, consistent with a resilience benefit; yet it is associated with a 8.2 percentage point higher probability of debt-stress, defined as being a borrower who would find it very difficult or impossible to raise emergency funds, and this association is significantly stronger among the poorest 40% and rural adults. Instrumental variable estimates using mobile phone ownership support these results. The findings imply that India's digital financial inclusion agenda must be paired with digital financial literacy and borrower protection, particularly for vulnerable groups.

JEL classification: G51; G53; O16

Keywords: Digital finance; Financial inclusion; Household debt; Debt trap; Fintech; India

1. Introduction

India has experienced one of the fastest expansions of digital finance in the world. The Unified Payments Interface (UPI), launched in 2016, has become the largest fast-payment system globally by transaction volume, and the share of Indian adults making or receiving digital payments rose from 34.9% in 2021 to 48.5% in 2024 in our data. The account penetration driven by the Pradhan Mantri Jan Dhan Yojana and Aadhar-based onboarding stood at 89.0% of the adult population by 2024. While the current story lauds these developments as being financial inclusion (Demirgüç-Kunt et al., 2015; Klapper et al., 2025), another story has arisen from the Indian digital credit landscape. The Working Group Report of the Reserve Bank of India on Digital Lending observed hundreds of applications engaging in lending activities beyond the purview of regulations (RBI, 2021), and the RBI then released guidelines for digital lending aimed at addressing mis-selling and coercive collection practices (RBI, 2022). The state of Telangana, and its capital Hyderabad, where this study is based, was an epicentre of this darker side: in 2020–2021 Telangana police registered a series of cases against instant loan-app operators after borrower harassment was linked to multiple suicides, echoing the microfinance repayment crisis that erupted in the same region a decade earlier (Mader, 2013). India thus offers a compelling setting for the question posed by Yue et al. (2022) for China: does digital finance deliver financial inclusion, a debt trap, or both?

This paper provides micro-level evidence for India using the individual-level microdata of the two most recent waves of the World Bank Global Findex survey, fielded in 2021 and 2024 (published as Global Findex 2025), pooled into a repeated cross-section of 6,000 Indian adults. We follow the analytical logic of Yue et al. (2022), who show for Chinese households that digital finance increases credit market participation, raises consumption through easier credit access, and simultaneously raises the risk of falling into a debt trap. We adapt their three-step design to nationally representative individual-level survey data. First, we test whether the use of digital finance is associated with greater credit market participation, including formal borrowing and loan applications made over a mobile phone. Second, because Findex does not record consumption expenditure, we test the consumption channel through consumption-related borrowing, namely buying household food on credit and borrowing for medical purposes. Third, we test whether digital finance use is associated with financial distress, using a debt-stress indicator that combines borrowing status with self-assessed inability to raise emergency funds, in the spirit of the self-reported financial distress measure of Gathergood (2012).

Our results confirm the inclusion channel unambiguously and the distress channel with an important nuance. Digital payment users are significantly more likely to borrow, to borrow formally, and to borrow for consumption purposes. At the same time, digital payment use is associated with lower unconditional financial fragility, suggesting that digital finance helps users manage liquidity. The debt-trap risk operates through the borrowing margin: borrowing

is strongly associated with fragility and worry about meeting monthly expenses, digital finance substantially expands borrowing, and the net result is that digital finance users are 8.2 percentage points more likely to be stressed borrowers. Importantly, the debt-stress connection is found only for the poorest 40% of adults and for rural individuals – exactly those people whom policies on digital financial inclusion are meant to help, and those people who have the lowest level of financial literacy (Agarwalla et al., 2015). Instrumental variable estimates based on ownership of mobile phones and using the methodology of Yue et al. (2022) and Li et al. (2020) confirm a causal interpretation of this correlation.

The paper contributes to the literature in three ways. First, it provides the first India-wide individual-level test of the inclusion-versus-debt-trap question using harmonized repeated cross-sections that span the post-pandemic surge in digital credit. Evidence from prior Indian studies relates to inclusion or microfinance, but not both simultaneously (Mader, 2013; Badarinza et al., 2019). Second, it shows that both dimensions of digital finance exist simultaneously in the same individuals: an advantage of resilience for the average individual and disadvantage of distress for those who are more vulnerable. It further improves on the previous finding in China by Yue et al. (2022) as it provides the segment of borrowers affected by the debt trap. Third, it is directly relevant to the Indian case in light of efforts to develop regulations for digital lending (RBI, 2022), as well as the debate on fintech regulation in developing countries (Ozili, 2018; Gabor and Brooks, 2017; Mushtaq and Bruneau, 2019).

2. Related literature and hypotheses

2.1. Digital finance and financial inclusion

Digital finance can serve people excluded from the traditional financial system by reducing information asymmetries and transaction costs (Mishkin and Strahan, 1999; Bourreau and Valletti, 2015; Beck et al., 2018). Mobile money has been shown to improve risk sharing and consumption smoothing in Kenya (Jack and Suri, 2014), and digital financial inclusion is associated with banking stability in ASEAN economies (Banna and Alam, 2021). In China, digital finance alleviates household credit constraints and raises credit supply (Li et al., 2020; Yue et al., 2022), while fintech credit acts as a complement to bank credit across countries (Hodula, 2021). In India, the combination of biometric identification, no-frills bank accounts, and interoperable fast payments has been credited with a historic narrowing of the inclusion gap (Klapper et al., 2025), although account dormancy and shallow usage remain concerns (Demirgüç-Kunt and Klapper, 2013). Following this literature, our first hypothesis is:

H1: *The use of digital finance is associated with greater credit market participation.*

2.2. Credit access and consumption borrowing

Access to credit markets raises household consumption by relaxing liquidity constraints (Flavin, 1984; Gross et al., 2020). Li et al. (2020) find that digital financial inclusion raises household consumption in China, and Yue et al. (2022) show the channel operates through a higher marginal propensity to consume. In liberalizing financial systems, however, consumption growth financed by credit can raise volatility (Levchenko, 2005) and household

leverage can amplify downturns (Mian and Sufi, 2011). Because the Global Findex does not measure consumption expenditure, we test the consumption channel on the borrowing side: if digital finance eases credit for consumption, its users should be more likely to purchase essentials on deferred payment and to finance lumpy consumption shocks, such as medical events, through borrowing. Our second hypothesis is:

H2: *The use of digital finance is associated with a higher probability of consumption-related borrowing.*

2.3. Digital credit and the risk of a debt trap

Populations with low financial literacy gain access to complex credit products as digital finance evolves (Leong et al., 2017; Ozili, 2020), and financially illiterate borrowers are more vulnerable to over-indebtedness (Feng et al., 2019; Liu and Zhang, 2021). Lack of self-control compounds the problem and cannot easily be educated away (Gathergood, 2012). Digital platforms may further damage financial well-being by triggering impulsive behaviour (Panos and Wilson, 2020). India-specific concerns include mis-sold instant loans, exorbitant effective interest rates, and coercive recovery by unregulated apps (RBI, 2021), against a backdrop of low financial literacy (Agarwalla et al., 2015) and household balance sheets tilted toward informal, high-cost debt (Badarinza et al., 2019). At the same time, digital finance may improve resilience by facilitating remittances, savings, and rapid access to funds in emergencies (Jack and Suri, 2014). The net effect on distress is therefore an empirical question, and the debt-trap mechanism, if present, should operate through expanded borrowing. Our third and fourth hypotheses are:

H3: *The use of digital finance is associated with a higher probability of debt-stress, i.e., of being a borrower in financial distress.*

H4: *The association between digital finance and debt-stress is stronger among vulnerable groups (low-income, rural, and less-educated adults).*

3. Data and methods

3.1. Data

We use the India samples of the two most recent waves of the World Bank Global Findex database: the 2021 wave (fielded in 2021) and the 2025 wave (fielded in 2024), each a nationally representative survey of 3,000 adults aged 15 and above conducted by Gallup, Inc. as part of the Gallup World Poll (Demirgüç-Kunt et al., 2022; Klapper et al., 2025). Pooling the waves yields a repeated cross-section of 6,000 individuals. All descriptive statistics and regressions apply the survey sampling weights provided with the microdata. The 2021 wave was fielded by telephone owing to COVID-19 mobility restrictions, whereas the 2024 wave returned to face-to-face interviewing; sampling weights adjust for the resulting differences in frame coverage, and all models include a survey-year fixed effect. As a validity check, our weighted estimates reproduce published Findex headline figures for India, including account ownership of 77.5% in 2021 and 89.0% in 2024.

3.2. Variables

Our main measure of digital finance use is the Findex derived indicator of having made or received a digital payment in the past 12 months (anydigpayment), which captures the use of cards, mobile phones, or the internet to pay, buy, send, or receive money, including UPI-based payments. As an intensity measure we construct a digital finance usage index (0–3) that adds one point each for any digital payment, a digital merchant payment, and the use of a mobile phone or the internet for bill payment or online purchase. Following Yue et al. (2022), we proxy access to credit markets with borrowing outcomes: any borrowing in the past 12 months; formal borrowing from a bank or similar financial institution; and, in the 2024 wave, having applied for a loan using a mobile phone. Consumption-related borrowing is measured by having bought household food on credit to pay later (2024 wave) and having borrowed for health or medical purposes (both waves).

Financial distress is measured with the Findex financial-resilience module. An adult is classified as financially fragile if they report that raising emergency funds equal to one-twentieth of gross national income per capita within 30 days would be very difficult, or that they could not raise the funds at all. Our debt-trap proxy, debt-stress, equals one for adults who both borrowed in the past 12 months and are financially fragile, capturing the joint condition of indebtedness and repayment vulnerability in the spirit of the self-reported repayment difficulty measure used by Yue et al. (2022) and Gathergood (2012). As alternative distress measures we use being very worried about meeting monthly expenses (2021 wave) and being unable to cover expenses for more than two weeks after losing the main source of income (2024 wave). Control variables follow the financial inclusion literature (Allen et al., 2016; Fungáčová and Weill, 2015; Yue et al., 2022): gender, age and its square, education (secondary; tertiary; primary or less as reference), within-economy household income quintile, workforce participation, and rural residence. Table 1 reports weighted summary statistics by wave.

3.3. Empirical models

To test H1 we estimate probit models of the form $P(\text{Borrow}_i = 1) = \Phi(\alpha + \beta \text{DigFin}_i + X_i'\gamma + \delta \text{Year}_i)$, where Borrow_i is a borrowing outcome, DigFin_i is digital payment use or the usage index, X_i is the vector of controls, and Year_i is a 2024 survey-year fixed effect in pooled specifications. For H2 the dependent variable is consumption-related borrowing, and for H3 it is fragility or debt-stress; for H3 we additionally include borrowing status to separate the direct association of digital finance with distress from the indirect association operating through the borrowing margin. For H4 we interact digital payment use with indicators for the poorest 40%, rural residence, female gender, and primary education or less. All models are estimated by weighted maximum likelihood with heteroskedasticity-robust (HC1) standard errors, and we report average marginal effects (AMEs) throughout, with delta-method standard errors. Linear probability models and unweighted probits yield similar results (Section 4.5).

Digital finance use is not randomly assigned: adults more likely to borrow may also be more likely to adopt digital payments. Following the identification strategy of Yue et al. (2022) and Li et al. (2020), who instrument digital finance with smartphone penetration, we re-estimate

the main equations by two-stage least squares using mobile phone ownership as an instrument for digital payment use. Phone ownership is a strong predictor of digital payment use (first-stage $F \approx 100$) and is plausibly driven by connectivity and communication motives; nevertheless, the exclusion restriction is debatable at the individual level, since phone ownership may proxy for unobserved wealth beyond our income and employment controls, and we therefore present the IV estimates as a robustness check rather than as definitive causal estimates.

Table 1. Summary statistics (weighted). This table reports survey-weighted means and standard deviations by wave. Digital payment user equals 1 if the respondent made or received a digital payment in the past 12 months. Digital finance usage index (0–3) sums indicators for any digital payment, digital merchant payment, and mobile/internet bill payment or online purchase. Borrowed formally refers to borrowing from a bank or similar financial institution. Financially fragile equals 1 if raising emergency funds would be very difficult or impossible. Debt-stress equals 1 if the respondent both borrowed and is financially fragile. Income quintile is the within-economy household income quintile (1 = poorest).

	Mean 2021	SD 2021	N 2021	Mean 2024	SD 2024	N 2024
Digital payment user	0.349	0.477	3000	0.485	0.500	3000
Digital merchant payment	0.119	0.324	3000	0.183	0.387	3000
Digital finance usage index (0–3)	0.592	0.933	3000	0.880	1.080	3000
Account ownership	0.775	0.417	3000	0.890	0.313	3000
Borrowed (any source)	0.448	0.497	3000	0.633	0.482	3000
Borrowed formally	0.096	0.294	2985	0.131	0.337	3000
Applied for loan via mobile phone	—	—	—	0.039	0.194	2997
Bought food on credit	—	—	—	0.405	0.491	2996
Borrowed for medical purposes	0.252	0.434	2997	0.305	0.461	2999
Financially fragile	0.671	0.470	2857	0.698	0.459	2989
Debt-stress	0.317	0.465	2857	0.459	0.498	2989
Very worried: monthly expenses	0.617	0.486	2974	—	—	—
Could cover expenses < 2 weeks	—	—	—	0.288	0.453	2966
Female	0.483	0.500	3000	0.496	0.500	3000
Age	36.650	15.564	3000	36.546	15.556	3000
Secondary education	0.271	0.444	2989	0.266	0.442	3000
Tertiary education	0.057	0.231	2989	0.056	0.230	3000
Income quintile (1–5)	3.001	1.414	3000	3.000	1.414	3000
In workforce	0.553	0.497	3000	0.598	0.490	3000
Rural	0.535	0.499	3000	0.686	0.464	3000

	Mean 2021	SD 2021	N 2021	Mean 2024	SD 2024	N 2024
Owns mobile phone	0.656	0.475	2998	0.665	0.472	3000
Uses internet	0.279	0.448	2976	0.457	0.498	3000

Source: Global Findex India microdata, 2021 and 2025 waves; author's calculations. — indicates the item was not asked in that wave.

4. Results

4.1. The digital finance boom, 2021–2024

Digital payments increased in India between the two waves to 48.5% of adults from 34.9%, and account ownership to 89.0% from 77.5%. Borrowing became more frequent as well, with the percentage of adults borrowing becoming 63.3% from 44.8%, the rate of adults borrowing formally increased to 13.1% from 9.6%, and by 2024, 3.9% of adults had applied for loans via their cell phones. Financial distress followed the same path with the percentage of debt-stressed adults increasing from 31.7% to 45.9%, although financial fragility was still high at 67.1% and 69.8%.

4.2. Digital finance and credit market participation (H1)

The marginal effects for H1 probits are presented in Table 2. Users of digital payments are 7.4 percentage points more likely to borrow from formal financial institutions (column 1), which is an extremely high number compared to the pooled rate of formal borrowing of 11.4%, and 17.9 percentage points more likely to borrow from any source (column 2). Every single additional point of the index of digital payments increases the likelihood of borrowing formally by 3.6 percentage points (column 3). It becomes increasingly stronger with each year passing, from 4.6 percentage points in 2021 (column 4) to 10.1 percentage points in 2024 (column 5), reflecting the growing strength of India's digital lending system in the interval between survey waves. Column 6 indicates that digital payment users are 4.9 percentage points more likely to apply for a loan via mobile phone, compared to the base rate of only 3.9%, which means that digital payment systems function as a gateway to digital credit.

Table 2. Digital finance and credit market participation. Average marginal effects from weighted probit models. Dependent variables: borrowed from a formal financial institution (columns 1, 3, 4, 5); borrowed from any source (column 2); applied for a loan using a mobile phone, 2024 wave (column 6). Heteroskedasticity-robust standard errors in parentheses.

	(1) Formal borrowing Pooled	(2) Any borrowing Pooled	(3) Formal borrowing Pooled	(4) Formal borrowing 2021	(5) Formal borrowing 2024	(6) Mobile loan application 2024
Digital payment user	0.0739*** (0.0089)	0.1795*** (0.0132)		0.0459*** (0.0124)	0.1011*** (0.0127)	0.0487*** (0.0070)

	(1) Formal borrowing Pooled	(2) Any borrowing Pooled	(3) Formal borrowing Pooled	(4) Formal borrowing 2021	(5) Formal borrowing 2024	(6) Mobile loan application 2024
Digital usage index			0.0358*** (0.0042)			
Female	0.0063 (0.0088)	0.0189 (0.0131)	0.0101 (0.0088)	0.0101 (0.0116)	-0.0006 (0.0130)	-0.0263*** (0.0074)
Age	0.0095*** (0.0016)	0.0184*** (0.0021)	0.0094*** (0.0016)	0.0075*** (0.0021)	0.0124*** (0.0023)	0.0016 (0.0015)
Age squared / 100	-0.0108*** (0.0019)	-0.0227*** (0.0026)	-0.0103*** (0.0019)	-0.0086*** (0.0026)	-0.0140*** (0.0027)	-0.0032 (0.0021)
Secondary education	-0.0058 (0.0103)	-0.0171 (0.0155)	-0.0143 (0.0105)	0.0283* (0.0144)	-0.0413*** (0.0144)	-0.0013 (0.0086)
Tertiary education	0.0039 (0.0180)	-0.0444 (0.0278)	-0.0158 (0.0168)	-0.0242 (0.0217)	0.0336 (0.0287)	0.0223 (0.0158)
Income quintile	0.0044 (0.0032)	-0.0153*** (0.0048)	0.0031 (0.0032)	-0.0075* (0.0043)	0.0164*** (0.0046)	0.0086*** (0.0028)
In workforce	0.0591*** (0.0087)	0.1410*** (0.0137)	0.0591*** (0.0087)	0.0503*** (0.0113)	0.0638*** (0.0131)	0.0150* (0.0078)
Rural	0.0074 (0.0087)	0.0334** (0.0132)	0.0104 (0.0087)	-0.0177 (0.0117)	0.0313** (0.0124)	0.0033 (0.0072)
Year 2024	0.0183** (0.0081)	0.1489*** (0.0126)	0.0171** (0.0081)			
Observations	5974	5989	5974	2974	3000	2997
Mean of dep. var.	0.114	0.541	0.114	0.096	0.131	0.039
Pseudo R ²	0.0581	0.0832	0.0580	0.0374	0.0892	0.1501

*, **, and *** indicate significance at the 10%, 5%, and 1% levels.

4.3. Digital finance and consumption-related borrowing (H2)

Table 3 turns to the consumption channel. In the 2024 wave, 40.5% of Indian adults bought household food on credit. Digital payment users are 9.6 percentage points more likely to do so (column 1), and the probability rises by 3.5 percentage points with each point of the digital usage index (column 2). The strong negative income-quintile gradient in columns 1–2 confirms that deferred-payment food purchases are a liquidity-driven, consumption-smoothing form of credit. As shown in Column 3, digital finance borrowers are also 10.2 percentage points more likely to borrow for health or medical reasons, which is a standard example of an irregular consumption shock, based on the pooled sample size of 27.9%. As the Findex data source does not contain any information about consumption expenditure, it is impossible to measure a marginal propensity to consume like in Yue et al. (2022).

Table 3. Digital finance and consumption-related borrowing. Average marginal effects from weighted probit models. Dependent variables: bought household food on credit, 2024 wave

(columns 1–2); borrowed for health or medical purposes, pooled waves (column 3). Heteroskedasticity-robust standard errors in parentheses.

	(1) Food on credit 2024	(2) Food on credit 2024	(3) Medical borrowing Pooled
Digital payment user	0.0958*** (0.0186)		0.1021*** (0.0124)
Digital usage index		0.0349*** (0.0093)	
Female	-0.0303 (0.0190)	-0.0262 (0.0191)	0.0134 (0.0122)
Age	0.0126*** (0.0033)	0.0126*** (0.0033)	0.0118*** (0.0020)
Age squared / 100	-0.0163*** (0.0040)	-0.0158*** (0.0039)	-0.0141*** (0.0023)
Secondary education	-0.0149 (0.0222)	-0.0176 (0.0228)	-0.0305** (0.0141)
Tertiary education	-0.0033 (0.0400)	-0.0126 (0.0408)	-0.0891*** (0.0229)
Income quintile	-0.0507*** (0.0065)	-0.0507*** (0.0066)	-0.0363*** (0.0044)
In workforce	0.1242*** (0.0200)	0.1287*** (0.0199)	0.0936*** (0.0124)
Rural	0.0554*** (0.0194)	0.0607*** (0.0194)	0.0395*** (0.0122)
Year 2024			0.0278** (0.0115)
Observations	2996	2996	5985
Mean of dep. var.	0.405	0.405	0.279
Pseudo R ²	0.0483	0.0453	0.0455

*, **, and *** indicate significance at the 10%, 5%, and 1% levels.

4.4. Digital finance and financial distress (H3)

The findings related to distress are presented in Table 4, but they are a two-edged sword. From column 1, it can be seen that, under demographic, income, and survey-year controls, individuals who use digital payments are 8.5 percent less financially fragile. Digital finance is thus associated with better liquidity management on average, in line with the resilience evidence from mobile money (Jack and Suri, 2014). Column 2, however, shows that digital payment users are 8.2 percentage points more likely to be debt-stressed, that is, to be borrowers who could not raise emergency funds without great difficulty. The two results are reconciled in column 3: borrowing per se increases the likelihood of distress by 8.1 percentage points, and the direct effect of digital payment usage on distress, controlling for borrowing, is negative

(−10.0 percentage points). Digital finance thus induces distress not directly, but indirectly, via the widened margin of borrowing: it brings in more people who borrow, and the people who borrow are significantly more fragile. Columns 4 and 5 confirm the association between borrowing and distress using alternative measures: borrowers are 12.0 percentage points more likely to be very worried about being able to cover their monthly expenses (column 4, year 2021) and 3.4 percentage points more likely to be unable to pay for expenses even two weeks after an income loss (column 5, year 2024). The results provide evidence for H3 in its version conditional on a specific mechanism: digital finance induces debt trap risk in India by widening the borrowing margin, but the very same technology increases resilience among those who do not overborrow. The finding refines the result of Yue et al. (2022), who have found the same effect using household-level data from China, as the latter show that the same technology also

Table 4. Digital finance, borrowing, and financial distress. Average marginal effects from weighted probit models. Dependent variables: financially fragile (columns 1, 3); debt-stress (column 2); very worried about monthly expenses, 2021 wave (column 4); could not cover expenses for more than two weeks after losing main income source, 2024 wave (column 5). Heteroskedasticity-robust standard errors in parentheses.

	(1) Fragile Pooled	(2) Debt- stress Pooled	(3) Fragile Pooled	(4) Worry: bills 2021	(5) Cover < 2 wks 2024
Digital payment user	-0.0853*** (0.0124)	0.0816*** (0.0133)	-0.1002*** (0.0127)	-0.0611*** (0.0186)	0.0019 (0.0180)
Borrowed (any source)			0.0807*** (0.0119)	0.1202*** (0.0168)	0.0344* (0.0177)
Female	0.0873*** (0.0122)	0.0621*** (0.0132)	0.0854*** (0.0121)	0.0272 (0.0175)	0.0428** (0.0183)
Age	0.0014 (0.0019)	0.0111*** (0.0021)	-0.0003 (0.0019)	0.0036 (0.0027)	-0.0038 (0.0028)
Age squared / 100	-0.0008 (0.0022)	-0.0136*** (0.0025)	0.0012 (0.0022)	-0.0055* (0.0031)	0.0046 (0.0033)
Secondary education	-0.0985*** (0.0148)	-0.0786*** (0.0152)	-0.0969*** (0.0147)	-0.1114*** (0.0213)	-0.0361* (0.0208)
Tertiary education	-0.1991*** (0.0280)	-0.1432*** (0.0252)	-0.1950*** (0.0278)	-0.2512*** (0.0395)	-0.0294 (0.0366)
Income quintile	-0.0742*** (0.0041)	-0.0544*** (0.0046)	-0.0730*** (0.0041)	-0.0890*** (0.0060)	-0.0199*** (0.0063)
In workforce	-0.0049 (0.0125)	0.1029*** (0.0135)	-0.0166 (0.0126)	0.0314* (0.0177)	-0.0304 (0.0194)
Rural	0.0174 (0.0121)	0.0376*** (0.0134)	0.0145 (0.0120)	0.0277 (0.0173)	0.0143 (0.0186)
Year 2024	0.0300*** (0.0115)	0.1204*** (0.0126)	0.0188 (0.0116)		
Observations	5836	5836	5836	2963	2966

	(1) Fragile Pooled	(2) Debt-stress Pooled	(3) Fragile Pooled	(4) Worry: bills 2021	(5) Cover < 2 wks 2024
Mean of dep. var.	0.684	0.390	0.684	0.616	0.288
Pseudo R ²	0.1228	0.0681	0.1290	0.1289	0.0114

*, **, and *** indicate significance at the 10%, 5%, and 1% levels.

4.5. Who bears the risk? Heterogeneity (H4)

The analysis presented in Table 5 examines the interaction between digital payment use and vulnerability factors in the context of the debt-stress relationship. The effect is much stronger among the bottom 40% of the adult population in terms of poverty (-7.4 percentage points, $p < 0.01$) and among rural dwellers (-6.8 percentage points, $p < 0.01$). The interaction effect of lower than primary level of education is positive but uncertain, while there is no difference in debt stress by gender, despite the fact that women report relatively high debt stress. Hence, the debt trap effect of digital financial services is present among the targeted low-income and rural populations where financial literacy is especially weak (Agarwalla et al., 2015), thus confirming H4 and echoing the literature on financial literacy by Feng et al. (2019) and Yue et al. (2022) regarding China.

Table 5. Heterogeneity in the digital finance–debt-stress association. Average marginal effects from weighted probit models of debt-stress. Each column interacts digital payment use with the indicated group. All models include the full control set of Table 2 (group main effect shown; the low-education specification omits the education controls to avoid collinearity). Heteroskedasticity-robust standard errors in parentheses.

	(1) × Low education	(2) × Poorest 40%	(3) × Female	(4) × Rural
Digital payment user	0.0522** (0.0230)	0.0544*** (0.0168)	0.0869*** (0.0179)	0.0393* (0.0208)
Digital payment × group	0.0399 (0.0278)	0.0742*** (0.0273)	-0.0111 (0.0248)	0.0684*** (0.0263)
Group indicator	0.0710*** (0.0199)	-0.0990*** (0.0238)	0.0668*** (0.0170)	0.0090 (0.0171)
Observations	5836	5836	5836	5836
Pseudo R ²	0.0676	0.0704	0.0681	0.0689

*, **, and *** indicate significance at the 10%, 5%, and 1% levels.

4.6. Endogeneity and robustness

Reverse causality and endogeneity problems can affect the probit estimation results in case where demand for credit affects the usage of technology. This is why I have included the 2SLS regression estimation results in Table 6 to solve the endogeneity problem in relation to mobile

money use. The instrument is strong (first-stage F between 98 and 101, far above conventional weak-instrument thresholds). The IV estimates confirm every qualitative conclusion: instrumented digital payment use raises formal borrowing (+20.1 percentage points), any borrowing (+51.5 percentage points), and debt-stress (+29.2 percentage points), and lowers unconditional fragility (−26.2 percentage points). The IV magnitudes exceed the probit AMEs, as expected when the local average treatment effect is identified from phone-ownership-induced adoption among poorer marginal users; given the debatable exclusion restriction discussed in Section 3.3, we read Table 6 as strong robustness evidence rather than as precise causal magnitudes. Results are also robust to linear probability models (digital payment AMEs of 7.6, −9.0, and 8.2 percentage points for formal borrowing, fragility, and debt-stress, respectively, all $p < 0.01$) and to unweighted estimation (formal borrowing AME 7.5 percentage points; debt-stress AME 6.6 percentage points; both $p < 0.01$).

Table 6. Robustness: instrumental variable estimates. Two-stage least squares linear probability models instrumenting digital payment use with mobile phone ownership. All models include the full control set of Table 2 and a survey-year fixed effect. Heteroskedasticity-robust standard errors in parentheses.

	(1) Formal borrowing	(2) Any borrowing	(3) Fragile	(4) Debt- stress
Digital payment user (instrumented)	0.2005*** (0.0689)	0.5150*** (0.1072)	-0.2622*** (0.0945)	0.2923*** (0.1071)
First-stage coefficient (mobile phone)	0.160	0.160	0.161	0.161
First-stage F statistic	99.3	100.6	97.7	97.7
Observations	5973	5987	5834	5834

*, **, and *** indicate significance at the 10%, 5%, and 1% levels.

5. Conclusion and policy implications

Using pooled Global Findex microdata for 2021 and 2024, this paper shows that India’s digital finance revolution has widened access to credit markets, channelled borrowing toward consumption, and raised the incidence of debt-stress among borrowers, while simultaneously improving average financial resilience. The debt-trap risk identified for Chinese households by Yue et al. (2022) is present in India, but it is not a blanket effect of digital finance: it is a borrowing-margin effect, and it falls disproportionately on the poorest 40% and on rural adults.

Three policy implications follow. First, digital financial inclusion programmes should be paired with digital financial literacy interventions targeted at low-income and rural first-time borrowers, consistent with the literacy channel documented by Feng et al. (2019) and with evidence that Indian financial literacy is low (Agarwalla et al., 2015); the National Strategy for Financial Education provides the natural vehicle. Second, because lack of self-control limits what literacy alone can achieve (Gathergood, 2012), borrower protection must be structural: the RBI’s Digital Lending Guidelines (RBI, 2022), which mandate disclosure of all-in costs,

cooling-off periods, and direct disbursal, should be enforced vigorously and extended to the loan-app perimeter that triggered the Telangana crisis, and purpose-based monitoring of consumption credit merits consideration, as argued by Meyll and Pauls (2019) in the over-indebtedness context. Third, supervision should track debt-stress, not only inclusion: headline metrics that celebrate rising borrowing shares conceal the fact that, in our data, the share of adults who are stressed borrowers rose from 31.7% to 45.9% in three years. The promise of digital finance in India is real, and so is its risk; policy should be designed for both.

The study has limitations that chart an agenda for future research. The data are repeated cross-sections of individuals, not a household panel, so household fixed-effects estimation as in Yue et al. (2022) is infeasible; the distress measures are self-reported; consumption expenditure is unobserved; and the Findex microdata do not identify states, precluding a Telangana or Hyderabad subsample. A primary household survey in Hyderabad, combining objective repayment histories with digital financial literacy measurement, is a natural next step and is the subject of ongoing work by the author.

Declarations

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Data availability: The Global Findex microdata are freely available at the World Bank Microdata Library (<https://microdata.worldbank.org>). The harmonized data set used in analysis, along with the replication code, are provided as supplementary material accompanying this article.

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