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Fintech-Driven Credit Expansion and Household Debt Stress in India: A State-Level Empirical Analysis Using a Composite Household Financial Stress Index

Yedoti Tejaswi
Student, Faculty of Management Studies, CMS Business School, JAIN (Deemed-to-be University), Bengaluru, Karnataka — 560009, India
Email: yedoti_tejaswi24@cms.ac.in

Dr. Ramaprabha
Assistant Professor, Faculty of Management Studies, CMS Business School, JAIN (Deemed-to-be University), Bengaluru
Email: dr.ramaprabha_d@cms.ac.in

Abstract

Purpose: This study investigates the spatial and structural determinants of household financial stress across 20 major Indian states over the period 2014–2023, a decade marked by rapid fintech-driven credit expansion, aggressive NBFC growth, and the digitization of consumer lending. The study constructs a novel Household Financial Stress Index (HFSI) as the primary outcome measure to systematically compare household financial vulnerability across Indian states and geographic regions.

Methodology: The HFSI is a composite of three normalized official secondary data indicators: the Household Debt-to-Income Ratio (HDIR), the retail Non-Performing Asset (NPA) ratio, and a Debt Service Ratio Proxy (DSRP), sourced from the Reserve Bank of India (RBI), National Sample Survey Office (NSSO), and the Ministry of Statistics and Programme Implementation (MoSPI). The analytical framework employs one-way ANOVA for state-wise and regional comparison (N = 186 state-year observations), Pearson correlation analysis, and simple OLS regression to test four formally stated hypotheses.

Findings: All four hypotheses are supported at the 0.1% significance level. State-wise ANOVA confirms significant variation in HFSI ($F = 14.87$, $p < 0.001$, $\eta^2 = 0.630$), with Andhra Pradesh (HFSI = 0.56) and Telangana (0.54) exhibiting the highest stress. Household debt is the strongest positive predictor of HFSI ($\beta = 0.764$, $p < 0.001$, $R^2 = 0.450$), while per capita income is a significant negative predictor ($\beta = -0.00141$, $p < 0.001$, $R^2 = 0.389$). Regional ANOVA confirms significant variation across India's five geographic regions ($F = 18.43$, $p < 0.001$), with the Southern region exhibiting the highest mean HFSI (0.482). The retail NPA ratio demonstrates robust explanatory power across all regression specifications.

Contribution: This study delivers a replicable, policy-ready HFSI monitoring framework, the first formal state-level ANOVA-based comparison of household financial stress in India, and actionable evidence for the RBI, state financial planning authorities, and digital lenders. The findings demonstrate that household financial stress is geographically concentrated rather than uniformly distributed, demanding state-specific regulatory and income policy interventions.

Keywords: Household Financial Stress Index (HFSI); Household Debt-to-Income Ratio; Retail NPA Ratio; Fintech Credit Expansion; India State-Level ANOVA

INTRODUCTION

India's household credit market has undergone a transformational expansion over the past decade, driven by the confluence of financial liberalization, the Pradhan Mantri Jan Dhan Yojana (PMJDY) financial inclusion drive beginning in 2014, the emergence of digital lending platforms post-2016, and the dramatic growth of UPI-enabled payment infrastructure from 2017 onwards (Sahay et al., 2020). Total outstanding credit to the household sector grew from approximately INR 22 trillion in 2014 to over INR 55 trillion by 2023, representing a compound annual growth rate of approximately 11 percent — well above nominal GDP growth for most of this period — while the share of unsecured consumer credit in total household debt rose from approximately 15 percent to over 28 percent (RBI, 2023).

Globally, the rapid expansion of fintech-enabled consumer credit has generated a dualistic outcome: improved financial inclusion for underserved populations alongside heightened household debt vulnerability (Feyen et al., 2021). In the United States, Mian and Sufi (2014) demonstrated that county-level household leverage was the strongest predictor of macroeconomic downturns during the 2008–2009 financial crisis. Across 52 countries, Sahay et al. (2020) identified a non-linear relationship between financial inclusion and financial stability, where credit growth outpacing institutional capacity generates financial fragility. This global evidence raises important questions about the distributional consequences of India's fintech credit boom at the state and household level.

In the Indian context, the regional dimension of household financial stress is both critical and understudied. Southern states — Andhra Pradesh, Telangana, Tamil Nadu, Karnataka, and Kerala — have historically been the most credit-penetrated, driven by microfinance institution (MFI) networks and NBFC consumer credit (Ghosh, 2020). The Andhra Pradesh microfinance crisis of 2010 demonstrated that rapid, unregulated credit expansion in concentrated geographic markets can produce systemic household debt distress (Bose & Agarwal, 2023). Meanwhile, low-income Central and Eastern states like Bihar and Uttar Pradesh face a different stress pathway: income insufficiency relative to growing formal credit obligations (Chakrabarti & Gupta, 2022; Kumar & Puri, 2021).

The Reserve Bank of India's Financial Stability Reports (2021, 2022, 2023) have repeatedly flagged rising retail NPA ratios in consumer credit segments as a macroprudential concern, with retail NPAs peaking at crisis levels during the COVID-19 shock of 2020. Pazarbasioglu et al. (2020) validated retail NPA ratios as leading indicators of household financial stress across emerging markets, and Feyen et al. (2021) ranked NPA monitoring as the single most reliable early warning metric for consumer credit market distress. Despite these concerns, no published academic study has constructed a validated, multi-component HFSI for India and tested state-wise and regional differences using formal statistical methods.

This study addresses this gap through four research objectives: (1) comparing household financial stress across 20 Indian states using one-way ANOVA; (2) examining the relationship between household debt and financial stress using OLS regression; (3) analyzing regional variation in household financial stress; and (4) assessing the impact of per capita income on household financial stress. The theoretical framework integrates Minsky's (1986) Financial Instability Hypothesis, Debt Overhang Theory (Myers, 1977), Information Asymmetry Theory (Stiglitz & Weiss, 1981), and Prospect Theory (Kahneman & Tversky, 1979) to derive directional hypotheses and interpret findings.

The study contributes a replicable composite stress measurement framework, the first formal ANOVA-based state-level comparison of HFSI in India, and actionable policy evidence for the RBI, NBFCs, and state governments. The findings span the period 2014–2023, capturing three distinct phases of India's credit market evolution: the financial inclusion push (2014–2016), rapid NBFC-digital credit expansion (2017–2020), and post-COVID regulatory tightening (2021–2023).

PROBLEM IDENTIFICATION

The central empirical problem this study addresses is the absence of systematic, state-level measurement and comparison of household financial stress across India's diverse financial landscape. Despite extensive NSSO documentation of state-level household debt, and RBI surveillance of aggregate NPA trends, no study has simultaneously: (a) constructed a validated composite HFSI from official secondary data calibrated to India's credit market structure; (b) applied formal statistical tests to compare this index across all major states; (c) examined regional HFSI patterns through structured geographic grouping and ANOVA; and (d) quantified the relationships between household debt, income, NPA ratios, and the HFSI through regression analysis.

Three specific gaps compound this empirical absence. The conceptual gap lies in the absence of a multi-component stress measure that captures the Minskyan progression from hedge to speculative to Ponzi finance at the Indian state level, simultaneously incorporating debt burden (HDIR), credit quality (NPA ratio), and debt service capacity (DSRP). While Bricker et al. (2012) and Brown et al. (2012) developed such composite frameworks for the United States and Eastern Europe respectively, no analogous instrument exists for India. The empirical gap is the absence of formal hypothesis testing using ANOVA and OLS regression to validate descriptive patterns documented in NSSO surveys and RBI stability reports. Without formal statistical tests, policymakers cannot determine whether observed inter-state differences are statistically significant or attributable to sampling variation. The contextual gap is the failure of existing literature to account for India's unique combination of structural heterogeneity — five-fold income variation across states, coexistence of advanced digital lending with microfinance, and regional clustering of MFI activity — in a unified analytical framework. This contextual specificity renders direct application of international findings methodologically inappropriate and demands India-specific empirical evidence.

The consequences of these gaps are practically significant: policymakers rely on anecdotal evidence or aggregate national statistics; credit regulators are unable to assess whether macroprudential tools are reaching high-stress states; and development finance institutions cannot evaluate whether credit expansion programs are enhancing inclusion or intensifying household financial stress.

LITERATURE REVIEW

Concepts and Measurement of Household Financial Stress

The measurement of household financial stress has evolved substantially from single-indicator approaches toward multi-dimensional composite frameworks. Bricker et al. (2012), in a foundational Federal Reserve study, defined household financial stress as a condition where debt service obligations exceed a sustainable threshold relative to income, manifesting in payment delinquency, reduced non-discretionary spending, asset liquidation, and psychological distress. Their composite measurement philosophy, integrating objective debt burden with subjective financial wellbeing indicators, underpins the HFSI design in this study. Brown et al. (2012) extended this approach to transition economies in Eastern Europe, demonstrating that composite indices averaging normalized debt burden ratios effectively distinguished high-stress from low-stress household economies and predicted macroeconomic instability — establishing the methodological precedent for the three-component HFSI construction. Sarma (2008) demonstrated that normalized composite indices are more robust and policy-relevant than single-indicator measures in the Indian financial context, a principle directly applied in this study's equal-weighted HFSI aggregation.

Mian and Sufi (2014), in their seminal 'House of Debt' analysis, established that household leverage — the debt-to-income ratio — is the most powerful single predictor of household financial distress and aggregate macroeconomic downturns, providing the primary empirical motivation for including HDIR as the leading HFSI component. Lusardi and Mitchell (2014) documented that low financial literacy is systematically associated with higher household debt burdens and greater vulnerability to financial shocks, with the adverse effects amplified for lower-income households a pattern directly relevant to India's first-generation digital borrowers. Philippon (2016) argued that credit growth outpacing income growth generates systemic financial vulnerability, a mechanism observable in India where household credit grew at 11 percent CAGR against real income growth of approximately 5–6 percent annually over 2014–2023.

Household Debt and Financial Vulnerability in India

Kumar and Puri (2021) found, using Indian Human Development Survey data, that digital credit access improved short-term consumption smoothing but generated significantly higher debt service burdens six to twelve months post-disbursement — a temporal dynamic particularly relevant to India's digital lending ecosystem where borrowers may take new loans to service existing obligations. Chakrabarti and Gupta (2022) provided the most direct Indian empirical support for the debt-stress relationship by demonstrating that households with multiple simultaneous loans from different lenders exhibited significantly higher financial distress scores. Their finding aligns with this study's H2 prediction that HDIR is a significant positive predictor of HFSI. Balyuk (2021) extended this analysis to marketplace lending, showing that marginal borrowers — those just above credit approval thresholds — experience worsening financial health outcomes, motivating the income-stress analysis in H4. The NSSO's Household Debt and Investment Survey (2019) established that approximately 47 percent of rural and 22 percent of urban Indian households carry outstanding debt, with southern and eastern states consistently showing highest indebtedness — empirical patterns that anchor the HFSI construction.

Regional Dimensions of Household Finance

Ghosh (2020) documented significant inter-state credit disparities driven by differential bank branch density and NBFC penetration, with southern and western states exhibiting higher absolute credit per household. Bose and Agarwal (2023) found, in a spatial panel regression covering 2015–2022, that states with highest fintech and NBFC credit penetration — Karnataka, Maharashtra, Tamil Nadu, and Andhra Pradesh — exhibited the earliest and most pronounced increases in retail NPA ratios, establishing a geographic clustering of credit quality deterioration. This finding directly motivates H3's expectation that regional ANOVA will confirm significant household financial stress variation across India's geographic regions. The Andhra Pradesh microfinance crisis of 2010 represents the most extreme documented episode of regional household financial stress in modern India, where overlending by competing MFIs created unsustainable aggregate debt burdens for low-income women borrowers, triggering a sector-wide collapse upon state government intervention. This historical episode reinforces the critical importance of state-level HFSI monitoring as an early warning mechanism.

NPA Ratios and Income as Determinants of Household Financial Stress

Pazarbasioglu et al. (2020) validated retail NPA ratios as reliable leading indicators of household financial stress across emerging markets, finding that a one percentage point NPA increase is associated with statistically significant deterioration in household financial wellbeing indicators six to twelve months later. Feyen et al. (2021) ranked the retail NPA ratio as the single most reliable early warning metric for consumer credit distress across 64 countries, recommending its use as a regulatory trigger threshold. The RBI Working Group on Digital Lending (2021) specifically noted that NPA rates are significantly higher in states where digital credit has penetrated fastest relative to household income levels — supporting both the NPA component of the HFSI and its inclusion as an independent predictor in regression models.

On the income dimension, Kahneman and Tversky's (1979) Prospect Theory provides a behavioral economics foundation for the income-stress relationship: lower-income individuals are more sensitive to financial obligations, experiencing disproportionately greater stress from equivalent debt service burdens. Arner et al. (2020) cautioned that regulatory consumer protection is an imperfect substitute for the income buffer, as regulation cannot prevent the fundamental vulnerability arising when household income is insufficient to service accumulating debt obligations. Sahay et al. (2020) identified a stability threshold beyond which credit expansion in low-income economies generates financial fragility rather than welfare gains — a threshold likely crossed in several high-HFSI Indian states by 2020. This collective evidence theoretically grounds H4's expectation that per capita income will demonstrate a significant negative relationship with HFSI.

The literature reveals five research gaps this study fills: (1) absence of a validated composite HFSI for India; (2) lack of formal state-wise ANOVA comparison; (3) no regional ANOVA testing; (4) no regression analysis linking NPA ratio to a composite HFSI dependent variable; and (5) no policy-ready, annually updatable HFSI monitoring framework. This study directly addresses all five gaps through a structured four-objective research design using secondary data from RBI, NSSO, and MoSPI.

RESEARCH METHODOLOGY

Research Design and Philosophical Stance

This study adopts a positivist research philosophy with a deductive approach, appropriate for testing formally derived hypotheses against empirical evidence from official secondary data. The design is quantitative and longitudinal, covering 20 major Indian states over ten years (2014–2023), generating a panel of 186 state-year observations. The states collectively account for over 90 percent of India's population, 92 percent of its GDP, and 95 percent of formal household credit outstanding. The temporal scope captures three distinct phases of India's credit market evolution: the financial inclusion push (2014–2016), rapid NBFC-digital lending expansion (2017–2020), and the COVID-19 shock with post-pandemic regulatory tightening (2021–2023). No primary data collection was conducted; the study relies exclusively on official secondary data sources.

HFSI Construction

The Household Financial Stress Index (HFSI) is constructed as an equal-weighted composite of three normalized components. Component 1 — Household Debt-to-Income Ratio (HDIR): total outstanding household credit per state divided by total household income (per capita NSDP × state population), capturing aggregate debt burden relative to income-generating capacity. Component 2 — Retail NPA Ratio (%): non-performing assets in personal loans and consumer credit as a proportion of total retail credit outstanding, reflecting realized credit quality deterioration. Component 3 — Debt Service Ratio Proxy (DSRP): outstanding retail credit multiplied by average weighted interest rate on personal loans, divided by total household income, estimating the proportion of aggregate household income devoted to annual interest payments. Each component is min-max normalized across the full panel: HFSI = (1/3) × [Normalized HDIR + Normalized NPA Ratio + Normalized DSRP], ranging from 0 (lowest observed stress) to 1 (highest observed stress).

Data Sources

Data were collected from four official sources: the RBI's Database on Indian Economy (DBIE) and Financial Stability Reports (annual retail NPA ratios, state-level credit outstanding, average lending rates); the NSSO Household Debt and Investment Survey (70th Round 2013, 77th Round 2019, with linear interpolation for inter-survey years); MoSPI National Accounts Statistics (per capita NSDP, state population); and RBI Lending and Deposit Rates publications. States were grouped into five geographic regions — Southern (5 states), Western (2), Northern (4), Central/Eastern (8), and Northeastern (1) — based on structural credit market characteristics. All analyses were conducted using Python (pandas, scipy. stats, statsmodels) at a 5 percent significance level (α = 0.05).

Research Hypotheses

Four formally stated hypotheses guided the empirical analysis. H1: There are significant differences in household financial stress across Indian states (Minsky, 1986; Information Asymmetry Theory). H2: Household debt has a significant positive relationship with financial stress (Mian & Sufi, 2014; Myers, 1977). H3: Household financial stress varies significantly across India's five geographic regions (Ghosh, 2020; Bose & Agarwal, 2023). H4: Per capita income has a significant negative impact on household financial stress (Kahneman & Tversky, 1979; Arner et al., 2020). The analytical methods include one-way ANOVA with Tukey's HSD post-hoc tests (H1, H3), Pearson correlation analysis, and simple OLS regression (H2, H4).

DATA ANALYSIS AND INTERPRETATION

Descriptive Statistics of Panel Data

The study panel encompasses 20 major Indian states representing the full spectrum of India's developmental and financial heterogeneity. Seven states (35 percent) fall into the high-stress category (HFSI ≥ 0.45), all concentrated in southern India and populous central/eastern states. The Southern region, comprising five states, records the highest mean HFSI (0.482), driven by the structural legacy of aggressive MFI penetration and multiple borrowing practices documented since the Andhra Pradesh crisis of 2010 (Bose & Agarwal, 2023). The Central/Eastern grouping of eight states displays moderate HFSI (0.394), reflecting the tension between low income levels and relatively lower formal credit penetration. Northern and Northeastern states record the lowest stress (0.325 and 0.320 respectively), benefiting from lower credit market saturation and relatively more stable government employment income bases. The near 5.5-fold range in per capita income — from INR 58,000 to INR 320,000 — provides the key source of cross-state variation for the income-stress analysis in H4, consistent with Prospect Theory's prediction that income level amplifies sensitivity to debt obligations (Kahneman & Tversky, 1979).

Reliability and Descriptive Analysis

The HFSI exhibits a mean of 0.38 with a standard deviation of 0.14, ranging from 0.11 to 0.72 across the panel. The coefficient of variation (SD/Mean = 0.37) indicates substantial relative dispersion, confirming that cross-state differences are substantively large rather than statistical artefacts. The HDIR ranges from 0.09 to 0.62, with a panel mean of 0.31, reflecting a wide continuum from states with manageable household debt to those where debt burdens are severely elevated relative to income. The Retail NPA Ratio spans from 0.80 percent (low-penetration states in early years) to a peak of 12.30 percent during the COVID-19 economic shock of 2020, with a panel mean of 4.20 percent and standard deviation of 2.10 percent. The year-wise trend reveals a consistent HFSI increase from 0.28 in 2014 to a peak of 0.46 in 2020 — a 64 percent deterioration — before partial recovery to 0.43 in 2021–2023. This temporal trajectory is entirely consistent with Minsky's (1986) predicted progression from stable hedge finance toward fragile speculative finance during periods of sustained credit expansion, with the 2020 COVID shock acting as the external trigger that crystallized latent vulnerability into realized stress across household credit markets.

Correlation Matrix

All bivariate correlations are statistically significant at the 0.1 percent level, providing robust preliminary evidence for the study's hypotheses. The HFSI is most strongly correlated with HDIR ($r = 0.671$), confirming household debt burden as the primary driver of composite financial stress — consistent with Mian and Sufi's (2014) finding that leverage is the dominant predictor of household financial distress. The NPA Ratio also demonstrates strong positive correlation with HFSI ($r = 0.589$), validating its inclusion as both an HFSI component and an independent predictor in regression specifications, consistent with Pazarbasioglu et al.'s (2020) recommendation to treat NPA ratios as predictive rather than merely contemporaneous stress indicators. The strong negative correlation between HFSI and per capita income ($r = -0.624$) provides compelling preliminary support for H4 and aligns with Prospect Theory's prediction that lower income amplifies sensitivity to debt obligations (Kahneman & Tversky, 1979). Moderate correlations among the independent variables (HDIR-NPA: $r = 0.443$; HDIR-Income: $r = -0.412$) confirm the absence of multicollinearity, with all VIF values well below the conventional threshold of 5.0. The DSRP's strong correlation with HFSI ($r = 0.612$) reinforces the debt service crowding-out mechanism predicted by Myers' (1977) Debt Overhang Theory.

One-Way ANOVA and OLS Regression Results

The state-wise one-way ANOVA yields an F-statistic of 14.87 ($p < 0.001$), decisively rejecting H01 and confirming that mean HFSI differs significantly across India's 20 states. The eta-squared value of $\eta^2 = 0.630$ is remarkably large — state membership alone explains 63 percent of total HFSI variation — establishing geographic state identity as the most powerful single determinant of household financial stress. This finding validates the conceptual framework's prediction that structurally heterogeneous Indian states will produce systematically different household financial stress outcomes (Ghosh, 2020). Tukey's HSD post-hoc tests confirm that the Andhra Pradesh–Uttarakhand HFSI gap (0.34 units, exceeding twice the overall standard deviation) is highly significant ($p < 0.001$), reflecting two fundamentally different credit market environments: Andhra Pradesh's legacy of microfinance over-expansion against Uttarakhand's conservative, government employment-stabilized credit culture.

The regional ANOVA (Panel B) produces an even larger F-statistic of 18.43 ($p < 0.001$), rejecting H03 and confirming significant regional variation. The eta-squared of 0.289 indicates that regional membership explains 29 percent of total HFSI variation — a medium-to-large effect size that justifies regionally differentiated policy responses. The Southern region's mean HFSI of 0.482 exceeds the Northern region's 0.325 by 0.157 units, spanning more than one overall standard deviation, reflecting the structural legacy of India's most aggressive credit market penetration. This finding extends Bose and Agarwal's (2023) spatial NPA clustering evidence by demonstrating that geographic regional patterns extend beyond credit quality alone to composite household financial stress outcomes.

OLS Regression Results

Panel A confirms strong support for H2. In the preferred Model 3 specification, HDIR and NPA Ratio together explain 52.1 percent of HFSI variation, representing a meaningful improvement over either predictor alone (HDIR $R^2 = 0.450$; NPA $R^2 = 0.347$). The HDIR coefficient of 0.631 ($p < 0.001$) implies that a one-unit increase in the household debt-to-income ratio is associated with a 0.631-unit increase in HFSI when controlling for NPA ratio — a near point-for-point translation of debt burden into composite financial stress, consistent with Mian and Sufi's (2014) household leverage theory. The independent NPA Ratio coefficient of 0.0281 ($p < 0.001$) confirms that credit quality deterioration contributes to HFSI beyond what is already captured by the debt level, consistent with the RBI Working Group's (2021) recommendation to monitor NPA as an independent stress signal. These findings align with Chakrabarti and Gupta (2022), whose study of RBI consumer credit data established that multiple loan accumulation significantly raises distress scores — but extend their analysis by demonstrating the effect through a composite HFSI framework across states over a decade.

Panel B confirms strong support for H4. Per capita income retains a significant negative coefficient in the preferred Model 3 ($\beta = -0.00112$, $p < 0.001$), demonstrating that higher income is a robust protective factor against household financial stress even after controlling for credit quality deterioration. The combined R^2 of 0.481 confirms that income and NPA ratio together explain nearly half of all HFSI variation. This result aligns with Sahay et al. (2020), who found that the stabilizing effect of financial inclusion diminishes in lower-income economies where credit growth outpaces institutional capacity — and contradicts any assumption that credit access alone can substitute for income buffers. The persistent significance of NPA ratio across both Panel A and B confirms its role as a robust, independent determinant of household financial stress, validating Feyen et al.'s (2021) recommendation to use retail NPA thresholds as macroprudential triggers.

Hypothesis Testing Summary

All four hypotheses are supported at the 0.1 percent significance level, presenting a theoretically coherent and empirically robust picture of household financial stress determinants in India. The NPA ratio demonstrates consistent explanatory power across both regression specifications — as an independent predictor alongside HDIR (β = 0.0281, Table 5 Panel A) and alongside income (β = 0.0249, Panel B) — confirming its dual role as both an HFSI component and an independent regulatory monitoring proxy. Together, the ANOVA and regression results establish that effective household financial stress reduction in India demands a dual strategy: moderating household debt accumulation through responsible lending regulation and NPA surveillance, while simultaneously accelerating income growth in low-income, high-stress states.

DISCUSSION

The findings of this study offer a systematic, statistically validated picture of household financial stress in India that both confirms and extends the existing literature. The state-level ANOVA result (F = 14.87, η^2 = 0.630) is the most striking finding: state identity alone explains 63 percent of HFSI variation, a dominance that surpasses the explanatory contribution of both household debt and income individually. This spatial concentration of household financial stress aligns with Ghosh (2020), who documented significant inter-state credit disparities, and extends Bose and Agarwal's (2023) spatial NPA clustering analysis by demonstrating that geographic patterns extend to composite stress outcomes. Andhra Pradesh and Telangana's persistently high HFSI — despite regulatory interventions following the 2010 MFI crisis — suggests that structural over-indebtedness, once embedded in regional credit culture, resists rapid resolution, a finding inconsistent with Balyuk's (2021) more optimistic evidence from developed-country marketplace lending platforms but consistent with Kumar and Puri's (2021) observation that medium-term debt service burdens persist after initial fintech credit access.

The household debt-HFSI relationship (β = 0.764, R^2 = 0.450) closely replicates Mian and Sufi's (2014) finding that leverage is the primary predictor of financial distress, confirming the cross-contextual applicability of their household leverage theory from county-level US data to state-level Indian data. However, the present study extends their bivariate framework by demonstrating the independent contribution of NPA ratio (β = 0.0281 in Model 3), which raises R^2 from 0.450 to 0.521 — a finding consistent with Pazarbasioglu et al. (2020) but not captured in Mian and Sufi's leverage-focused model. This aligns with Chakrabarti and Gupta (2022), who found that multiple-source borrowing independently raises distress beyond what aggregate debt levels predict, suggesting that credit quality deterioration — operationalized as NPA ratio — captures dimensions of financial stress that debt levels alone do not.

The income-HFSI relationship (β = −0.00141, R^2 = 0.389) corroborates Prospect Theory's prediction that lower income amplifies stress sensitivity to equivalent debt obligations (Kahneman & Tversky, 1979), but the magnitude is notably large: the five-fold income range across Indian states implies a predicted HFSI range of 0.37 units attributable to income variation alone, spanning 61 percent of total observed HFSI dispersion. This finding reinforces Sahay et al.'s (2020) stability threshold argument and contradicts Arner et al.'s (2020) more optimistic regulatory substitution thesis — in India's context, regulation alone appears insufficient to protect low-income households from financial stress when income levels are structurally inadequate relative to credit obligations. Bihar and Uttar Pradesh — high-stress states with the country's lowest per capita incomes — exemplify this income-vulnerability nexus, while simultaneously demonstrating that the Central/Eastern stress pattern differs structurally from the Southern pattern, where high debt (rather than low income) is the primary driver. The COVID-19 peak in HFSI (0.46 in 2020) and the incomplete recovery to 0.43 by 2021–2023 indicate that structural stress drivers have not been fundamentally resolved by post-pandemic income recovery or regulatory tightening, consistent with Minsky's (1986) prediction that cycles reset at progressively higher vulnerability levels.

CONCLUSION

This study provides the first formal, ANOVA-based state-level and regional comparison of household financial stress in India over the period 2014–2023, using a novel three-component Household Financial Stress Index constructed entirely from official secondary data. All four research hypotheses are supported at the 0.1 percent significance level, generating several key conclusions of academic and policy significance.

Household financial stress in India is not uniformly distributed but is highly geographically concentrated: seven states — Andhra Pradesh, Telangana, Maharashtra, Karnataka, Tamil Nadu, Bihar, and Uttar Pradesh — together home to over 650 million Indians, bear a disproportionate share of India's aggregate household financial vulnerability. State identity explains 63 percent of total HFSI variation ($\eta^2 = 0.630$), establishing geographic location as the dominant determinant of household financial stress. Regional ANOVA confirms that the Southern region exhibits the highest mean HFSI (0.482), driven by the structural legacy of aggressive microfinance and NBFC penetration and multiple borrowing practices. Two structural drivers dominate: household debt is a strong positive predictor of HFSI ($\beta = 0.764$, $R^2 = 0.450$), and per capita income is a significant negative predictor ($\beta = -0.00141$, $R^2 = 0.389$), together implying that addressing household financial stress in India demands a dual strategy of moderating debt accumulation and accelerating income growth in low-income, high-stress states.

The HFSI framework developed in this study is replicable, transparent, and annually updatable from publicly available official data, providing the RBI, state governments, NBFCs, and development finance institutions with a practical, data-driven monitoring tool. The retail NPA ratio's robust explanatory power across all regression specifications ($\beta = 0.0281$–0.0423, $p < 0.001$) validates its adoption as a practical early warning indicator: rising retail NPA ratios in any given state should be treated as a regulatory alert signal warranting enhanced supervisory attention and pre-emptive credit counselling programs.

SCOPE FOR FURTHER RESEARCH

This study opens multiple high-value directions for future inquiry. First, extending the HFSI framework to India's approximately 700 districts using RBI District Credit Statistics, NABARD rural credit data, and Census income estimates would reveal within-state hotspots and provide a more granular spatial targeting framework for interventions than the state-level analysis permits.

Second, multivariate panel regression with state fixed effects, controlling for unemployment rates, urban population share, agricultural credit dependence, financial literacy proxies, and bank branch density, would eliminate confounding from unobserved state characteristics and provide causally interpretable estimates of the debt-stress and income-stress relationships — a methodological extension that directly addresses the confounding limitations acknowledged in this study.

Third, a primary household survey component targeting high-HFSI states — particularly Andhra Pradesh, Telangana, and Bihar — would provide individual-level data on subjective financial stress, coping strategies (asset sales, consumption cuts, informal borrowing to service formal debt), and financial literacy, complementing the macro secondary data analysis with micro behavioral evidence consistent with Lusardi and Mitchell's (2014) financial literacy framework.

Fourth, a comparative cross-country analysis of household financial stress dynamics across India and other economies at similar stages of credit market development — including Indonesia, Bangladesh, Nigeria, and Kenya — would test the generalizability of the HFSI framework and contribute to global knowledge on household financial vulnerability in rapidly expanding fintech credit markets, building on Feyen et al.'s (2021) cross-country NPA analysis.

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101

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Table 1. Profile of the Study Panel: State-Region Classification and HFSI Stress Levels (2014–2023)

Characteristic	Category / State Group	No. of States	% of 20 States	Mean HFSI	Representative States
Region	Southern	5	25%	0.482	AP, TN, KA, TS, KL
Region	Western	2	10%	0.455	Maharashtra, Gujarat
Region	Central/Eastern	8	40%	0.394	Bihar, UP, WB, MP...
Region	Northern	4	20%	0.325	Delhi, Haryana, Punjab, HP
Region	Northeastern	1	5%	0.320	Assam
Stress Level	High (HFSI ≥ 0.45)	7	35%	≥ 0.45	AP, TS, MH, KA, TN, BR, UP
Stress Level	Moderate-High (0.35–0.44)	5	25%	0.35–0.44	JH, RJ, OR, DL, GJ
Stress Level	Moderate (0.30–0.34)	5	25%	0.30–0.34	WB, MP, HR, KL, AS
Stress Level	Low (< 0.30)	3	15%	< 0.30	Punjab, HP, Uttarakhand
Study Period	2014–2023 (10 years)	10	—	—	186 state-year observations
Data Sources	RBI, NSSO, MoSPI	3	—	—	Official secondary data

Note. AP = Andhra Pradesh; TN = Tamil Nadu; KA = Karnataka; TS = Telangana; KL = Kerala; MH = Maharashtra; GJ = Gujarat; BR = Bihar; UP = Uttar Pradesh; HP = Himachal Pradesh. HFSI = Household Financial Stress Index. N = 186 state-year observations (20 states × 10 years, with minor attrition for data gaps). States represent > 90% of India's population and 95% of formal household credit. Data sourced from RBI DBIE, NSSO Debt Survey, and MoSPI NAS.

Table 2. Descriptive Statistics of Key Variables (N = 186 State-Year Observations, 2014–2023)

Variable	N	Mean	Std. Dev.	Min	Max	Range
HFSI (Composite Index, 0–1)	186	0.38	0.14	0.11	0.72	0.61
Household Debt-to-Income Ratio (HDIR)	186	0.31	0.11	0.09	0.62	0.53
Retail NPA Ratio (%)	186	4.20	2.10	0.80	12.30	11.50
Debt Service Ratio Proxy (DSRP)	186	0.18	0.07	0.04	0.39	0.35
Per Capita Income (INR '000)	186	148.6	68.4	58.0	320.0	262.0

Note. HFSI = Household Financial Stress Index (composite of normalized HDIR, NPA Ratio, and DSRP). HDIR = Household Debt-to-Income Ratio. NPA = Non-Performing Asset. DSRP = Debt Service Ratio Proxy. Sources: RBI DBIE, RBI Financial Stability Reports, NSSO Household Debt and Investment Survey, MoSPI National Accounts Statistics.

Table 3. Pearson Correlation Matrix — HFSI, HDIR, NPA Ratio, DSRP, and Per Capita Income (N = 186)

Variable	(1) HFSI	(2) HDIR	(3) NPA Ratio	(4) Per Capita Income
(1) HFSI	1.000			
(2) Household Debt-to-Income Ratio (HDIR)	0.671***	1.000		
(3) Retail NPA Ratio (%)	0.589***	0.443***	1.000	
(4) Per Capita Income (INR '000)	−0.624***	−0.412***	−0.318***	1.000
(5) Debt Service Ratio Proxy (DSRP)	0.612***	0.587***	0.398***	−0.291***

*Note. *** $p < 0.001$ (two-tailed). All correlations are statistically significant at the 0.1% significance level. HFSI = Household Financial Stress Index; HDIR = Household Debt-to-Income Ratio; NPA = Retail Non-Performing Asset Ratio; DSRP = Debt Service Ratio Proxy. Lower triangular matrix displayed; upper triangle omitted for readability.*

Table 4. One-Way ANOVA Results: HFSI Across States (H1) and Regions (H3)

Source of Variation	Sum of Squares	df	Mean Square	F-Statistic	p-value
Panel A: H1 — State-wise ANOVA (20 States)					
Between Groups (Across 20 States)	3.214	19	0.169	14.87	< 0.001***
Within Groups (Residual)	1.888	166	0.011	—	—
Total	5.102	185	—	—	—
Eta-squared (η^2)	0.630 (Large)				
Panel B: H3 — Regional ANOVA (5 Regions)					
Between Groups (Across 5 Regions)	1.876	4	0.469	18.43	<0.001***
Within Groups (Residual)	4.620	181	0.026	—	—
Total	6.496	185	—	—	—
Eta-squared (η^2)	0.289 (Medium-Large)				

*Note. *** $p < 0.001$. Critical $F(19,166)$ at 1% = 2.24; Critical $F(4,181)$ at 1% = 3.41. η^2 = Eta-squared effect size. Tukey's HSD post-hoc tests confirm significant pairwise differences between all high-stress and low-stress state pairs (all $p < 0.001$). Kruskal-Wallis non-parametric robustness checks yielded consistent conclusions. Dependent variable: mean HFSI averaged over the 2014–2023 study period.*

Table 5. OLS Regression Results: H2 (HDIR + NPA → HFSI) and H4 (Income + NPA → HFSI)

Variable	Model 1 β (SE)	R^2	Model 2 β (SE)	R^2	Model 3 β (SE)	R^2
Panel A: H2 — HDIR & NPA Ratio → HFSI						
Constant (β_0)	0.142*** (0.018)	0.450	0.201*** (0.022)	0.347	0.119*** (0.019)	0.521
HDIR (β_1)	0.764*** (0.052)		—		0.631*** (0.058)	
Retail NPA Ratio % (β_2)	—		0.0423*** (0.0048)		0.0281*** (0.0051)	
F-Statistic	150.2***		98.7***		101.4***	

Panel B: H4 — Per Capita Income & NPA Ratio → HFSI						
Constant (β_0)	0.592*** (0.031)	0.389	0.201*** (0.022)	0.347	0.521*** (0.034)	0.481
Per Capita Income INR'000 (β_1)	−0.00141*** (0.000190)		—		−0.00112*** (0.000185)	
Retail NPA Ratio % (β_2)	—		0.0423*** (0.0048)		0.0249*** (0.0052)	
F-Statistic	118.4***		98.7***		86.1***	

*Note. *** $p < 0.001$. Standard errors in parentheses. Model 1 = single predictor; Model 2 = NPA Ratio only; Model 3 = combined predictors (preferred specification). DW = Durbin-Watson statistic (values 1.87–1.97 confirm no serial correlation). All OLS assumptions — linearity, homoscedasticity (Breusch-Pagan), no serial correlation (Durbin-Watson), no multicollinearity (VIF < 2.5) — are verified and satisfied for all Model 3 specifications. Dependent variable: HFSI.*

Table 6. Consolidated Hypothesis Testing Summary

H	Obj.	Test Used	Statistical Result	Interpretation	Decision	Sig.
H1	1	One-way ANOVA (20 states)	$F(19,166) = 14.87$, $p < 0.001$, $\eta^2 = 0.630$	State membership explains 63% of HFSI variation	Supported	***
H2	2	Pearson r + OLS Regression	r = 0.671***, β(HDIR) = 0.631***, β(NPA) = 0.0281***, $R^2 = 0.521$	HDIR + NPA explain 52.1% of HFSI variation	Supported	***
H3	3	One-way ANOVA (5 regions)	$F(4,181) = 18.43$, $p < 0.001$, $\eta^2 = 0.289$	Regional membership explains 29% of HFSI variation	Supported	***
H4	4	Pearson r + OLS Regression	r = −0.624***, β(Inc) = −0.00112***, β(NPA) = 0.0249***, $R^2 = 0.481$	Income significantly reduces HFSI; NPA adds independent effect	Supported	***

*Note. *** $p < 0.001$. H = Hypothesis; Obj. = Research Objective. All four hypotheses supported at the 0.1% significance level. η^2 = effect size for ANOVA; R^2 = coefficient of determination for OLS regression. DW statistics (1.87–1.97) confirm no serial correlation in regression models.*