Banks and Inequality: Evidence from a Nationwide Branch Expansion Policy*

Ashish K. Sedai†, Mahmut Yasar‡, William Crowder§, Rikhia Bhukta¶

Abstract

We analyze the causal impact of a nationwide bank expansion policy on economic inequality in India using a regression discontinuity design (RDD). The findings reveal significant reductions in both consumption and wealth inequality, driven by economic growth and structural transformation. We document strong β-convergence in consumption and income, with middle-income households experiencing the largest relative gains, underscoring the role of financial access in accelerating upward mobility. Our results demonstrate that bank expansion fosters economic diversification, supporting non-agricultural development and narrowing regional disparities. This paper contributes to the literature by providing evidence on how large-scale financial inclusion policies reshape regional inequality dynamics and drive inclusive growth in developing economies.

Keywords: Bank Expansion, Economic Inequality, Financial Inclusion, Regression Discontinuity Design, β-Convergence, Structural Transformation, Wealth, Regional Disparities, Inclusive Growth.

JEL Codes: I3, O12, P43, D63

*We are grateful to Kim Fe Cramer for sharing the Master Office File, RBI, data which helped us construct the regression discontinuity design. We thank Shahe Emran and Nandini Gupta for discussions and their invaluable guidance in this research. We thank at International Growth Centre Conference, London School of Economics, 2023, Development Economics Conference at New York University, AD, 2023, Southern Economic Association Conference, New Orleans, 2023, Faculty Incubator Seminar, University of Texas at Arlington, 2023, Annual Conference on Economic Growth & Development, Indian Statistical Institute, Delhi, and Econometrics Society Conference, Indian Institute of Technology, Delhi, 2023 for their invaluable comments and suggestions.

†Corresponding author: Department of Economics, College of Business, University of Texas at Arlington, Email: ashish.sedai@uta.edu

‡Department of Economics, College of Business, University of Texas at Arlington

§Department of Economics, College of Business, University of Texas at Arlington

¶Department of Economic Sciences, Indian Institute of Technology, Kanpur

1 Introduction

The relationship between financial activity and inequality remains a subject of intense academic debate. While some scholars argue that financial deepening exacerbates inequality through unequal access to credit and financial services (Rajan and Zingales, 1998; Philippon and Reshef, 2012; Mian et al., 2019), others highlight its capacity to stimulate growth, investment, and employment, thereby fostering inclusive development (Burgess and Pande, 2005; Beck et al., 2007; Demirgüç-Kunt and Levine, 2009; Cramer, 2025). This debate is particularly salient in emerging economies, where informal networks, asymmetric information, and entrenched social and geographical disparities complicate the link between financial access and inequality (Karlan and Zinman, 2011; Jack and Suri, 2014; Lamba and Subramanian, 2020). Despite significant policy efforts to extend banking services, the distributive consequences of financial inclusion remain poorly understood, especially regarding its long-term effects on regional economic dynamics and convergence across diverse economic geographies.

This study advances the literature on large-scale financial inclusion and economic inequality by addressing critical gaps in scale, methodology, and measurement. Using the Reserve Bank of India's (RBI) 2005 bank Branch Authorization Policy (BAP), we shift the focus from household-level outcomes to district-level dynamics, aligning directly with the policy's goal of reducing regional disparities through expanded financial access. Unlike prior work (Gupta and Sedai, 2023; Cramer, 2025; Burgess and Pande, 2005), which emphasizes household welfare and urban-rural divides, our analysis highlights how the BAP shaped regional economic inequality and inter-district convergence. This meso-economic perspective captures systemic impacts that household-level studies often overlook.

A key contribution is the introduction of a novel β-convergence framework to evaluate whether underbanked districts experience catch-up growth relative to better-banked regions. This approach provides new insights into the long-term spatial effects of financial access, linking bank expansion to regional economic trajectories and addressing a critical gap in the literature. Additionally, by examining intra-district inequality across income terciles, we show that middle-income households gain disproportionately, driving reductions in inequality within districts.

Our study further extends the literature by incorporating wealth inequality as a core outcome, complementing existing studies that focus on short-term income or consumption measures. By analyzing asset accumulation and long-term economic resilience, we offer a more comprehensive view of financial inclusion's role in mitigating enduring disparities (Chancel et al., 2022). Together, these contributions provide a deeper understanding of how large-scale financial inclusion policies reduce disparities in consumption, income, and wealth, fostering inclusive growth at both regional and national levels.

India's economic inequality ranks among the highest globally, mirroring colonial-era disparities (Chancel et al., 2022), making it a pivotal case for examining entrenched structural divides and the role of financial inclusion in reshaping these disparities. Recent data reveal that the top 10% of the Indian population controls 77% of total national wealth, while the wealthiest 1% owns 53%. In stark contrast, the bottom 50% holds a mere 4.1% of the nation's wealth. Income disparities mirror this pattern, with the top 10% capturing 57% of national income compared to the bottom 50%, which accounts for only 13% (Chancel et al., 2022). Beyond aggregate inequality, stark inter-district inequalities persist in India, with infrastructural indices ranging from 0.44 to 0.90 and socio-economic development scores varying between 0.67 and 0.98, reflecting uneven development trajectories (Ohlan, 2013). These disparities highlight the urgency of investigating how financial inclusion policies influence inequality dynamics across spatial and temporal dimensions. Addressing this question is critical for understanding the extent to which financial inclusion serves as a catalyst for structural transformation and broad-based economic growth.

For our empirical analysis, we leverage a quasi-experiment: India's nationwide bank branch expansion program implemented by the Reserve Bank of India in 2005 (Young (2017)). The policy incentivized commercial banks to increase banks in 'underbanked' districts where the population-to-bank ratio was above the national average in 2005, which yields an RD design. It aimed to significantly boost financial inclusion across the country, leading to a 17% increase in bank branches in treated districts by 2010 (Cramer (2025)).[1] Using this policy, we employ two causal empirical strategies to separately analyze the impact of bank expansion on intra-district and inter-district inequality. For intra-district analysis, we utilize a *fuzzy* RD design, as ten districts of the 581 (as per the 2001 census) listed by the RBI as either banked or underbanked were not correctly identified by the cut-off.[2] The discontinuity analysis within optimal bandwidths allows us to isolate the Local Average Treatment Effects of bank branch expansion based on population density thresholds (Cattaneo and Titiunik (2022)). For inter-district inequality, we implement an integrated difference-in-differences (DID) β-convergence model, also supported by a difference in discontinuity model. This blended approach enables us to capture the convergence or divergence of consumption and income between treated and control districts over time. We also test for β-convergence within optimal bandwidths using a difference-in-discontinuity design.

[1]We are grateful to Kim Cramer for sharing the RBI MOF data and for her support in the empirical analysis of this paper.

[2]For details about the RBI policy implementation and the consequent fuzzy RD design, see Young (2017), Cramer (2025), and Gupta and Sedai (2023).

Our analysis is based on nationally representative panel and cross-sectional data sets covering a time frame from 2001-2015. We combine household surveys, census data, administrative records from various government agencies, and high-resolution satellite imagery to construct a multifaceted picture of financial activity and inequality. This rich dataset equips us to evaluate the real-world effects of bank branch expansion on both consumption and wealth inequality, both within and across districts, and identify channels through which the effects on inequality are mediated.

Our empirical findings show robust evidence of inequality reduction from bank branch expansion. Within treated districts, we observe a reduction in consumption and wealth inequality. Spatially, consumption and income, estimated using Machine Learning (ML) (Emran (2023)), converge between treatment and control groups, suggesting spillovers and reduction in inter-district inequality. Interestingly, in contrast to the existing literature, we find that large-scale bank expansion significantly favors the middle-income households rather than the rich or the poor households. This rise of middle-income household's consumption and income serves as the primary driver of the reduction in within-district inequality.

The reduction in inequality observed in treated districts can be attributed to several key mechanisms. First, there was a significant surge in Gross Domestic Product (GDP), accompanied by increases in night-light luminosity. This indicates robust economic growth, which is essential for examining the distributional impacts. Second, there was a notable structural shift from agricultural to non-agricultural employment, coupled with increased migration to treated districts. This shift provided the necessary productive capacity in previously underbanked areas. Third, we observed a reduction in earnings inequality, which was accompanied by perceptual shift in confidence in political institutions in treated districts, signifying a positive societal impact of increased financial access.

Six years post-policy, consumption inequality declined by 9.6% over the control group mean. Notably, wealth inequality witnessed a substantial 14.6% reduction after nine years. A conditional (β) convergence analysis to examine regional catch-up in consumption and income reveals strong and significant inter-district convergence in consumption (17.3%), and weaker convergence in household income (10%), between treatment and control groups. The weaker income convergence highlights structural barriers and delayed labor market responses, limiting the immediate income gains from financial inclusion. Reductions in intra and inter-district inequality are mediated by several factors. First, we observe a dynamic increase in the treated districts' GDP from 2007-2012, averaging 20% annually, compared to the control group, and we observe a significant increase in night-light luminosity in treated districts. This economic growth is reflected in rising incomes and earnings in treated districts, with predicted household income increasing by an average of 13.6% and earnings by 17.8%, over the control group mean. Importantly, increased bank presence drove structural employment changes, reducing agricultural employment by 6.1 percentage points while boosting non-agricultural employment by 5.5 percentage points. This shift, alongside an observed 11.5% reduction in earnings inequality, highlights the influence of large-scale financial inclusion policy in promoting structural change.

At the aggregate level, middle-income households captured a disproportionate share of the gains, with consumption increasing by 16.5% and income rising by 11.2%. Furthermore, middle-income households experienced more substantial increases in bank savings, access to bank loans, and workdays relative to both richer and poorer households. This concentrated benefit to the middle class was instrumental in reducing intra-district inequality. By emphasizing the upward mobility enabled for specific income groups, our findings provide critical insights for the design of financial inclusion policies that promote inclusive economic growth.

Beyond economic outcomes, our study reveals broader societal impacts. In treated districts, confidence in state government increased by 14.4 percentage points, public projects by 11.5 percentage points, and local leadership by 6.2 percentage points, all relative to the control group mean. Moreover, an influx of migrants (reaching 74% of the control mean) highlights the increased economic activity in treated districts.

The impacts of the policy exhibit significant variation across demographic and geographic segments. Urban regions experience greater reductions in inequality, while middle-income households, irrespective of rural-urban location, emerge as the primary beneficiaries. These findings underscore the policy's role in reducing regional economic inequality and increasing regional convergence by enabling greater economic participation among middle-income households and narrowing disparities within regions. The results highlight the necessity of addressing regional and income-based heterogeneity to design more equitable and effective financial inclusion strategies. The findings offer actionable insights for designing place-based policies that address regional and income-based heterogeneities, contributing to equitable and sustainable economic development.

Following the extensive RD robustness analysis of the policy in Cramer (2025) and Gupta and Sedai (2023), our results are backed by a similar array of RD robustness checks including second-order polynomials, alternative bandwidth selection methods, and placebo cutoff tests. Additionally, we conduct a donut hole test to ensure our results are not overly sensitive to observations close to the cutoff. These tests confirm the robustness of our findings, indicating that the observed effects are not driven by spurious factors.

2 Related Literature

Financial development plays a crucial role in advanced economies by enhancing economic opportunities and reducing inequality. Despite its importance, the existing literature on financial development has notable shortcomings. Many studies in advanced economies overlook the unique challenges faced by developing countries, such as informal networks and limited access to information. Additionally, while there is ample research on the effects of financial access on income inequality, there is a scarcity of studies exploring its impact on wealth inequality, particularly over the long term. Existing literature also highlights potential exacerbation in segmented markets ((Rajan and Zingales, 1998; Beck et al., 2004, 2007; Demirgüç-Kunt and Levine, 2009; Rajan and Ramcharan, 2011; Ashraf et al., 2017; Mumtaz and Theophilopoulou, 2017; Madsen et al., 2018; Heblich and Trew, 2019; Ait Lahcen and Gomis-Porqueras, 2021; Fischer and Huerta, 2021)). Beck et al. (2010) find that financial development not only curtails income inequality but also propels overall growth, with a significant 40% impact on minimizing inequality. This underscores the importance of understanding the mechanisms through which financial development affects economic outcomes.

Although studies in advanced economies provide valuable information, there is a noticeable dearth of empirical causal analysis on financial arrangements in developing countries ((Badarinza et al., 2019)). This gap underscores the need to explore the distributional impact of financial inclusion, particularly in emerging economies with distinct lending structures ((Banerjee et al., 2015; Barboni et al., 2022; Gupta and Sedai, 2023)). Understanding these dynamics is critical for formulating effective policy interventions.

Recent research has started to shed light on the distributional effects of financial development in emerging economies. Ji et al. (2023) show the impact of bank expansions in Thailand, revealing an inverted U-shaped pattern of decline in income inequality with bank expansions over a 20-year period. However, the context of a larger economy like India offers a unique opportunity to examine both consumption and wealth inequality more comprehensively, providing a wider understanding of the structural changes underlying these effects.

In emerging economies, the narrative of the distributional effects of bank expansions on outcomes shifts compared to advanced economies. Here, the "business finance channel" often assumes precedence over the "household demand channel" ((Gupta and Sedai, 2023)). This channel benefits households through employment generation and productive allocation of capital to credit-constrained firms, leading to increased household consumption and entrepreneurship. Studies in Brazil ((Fonseca and Matray, 2022)), Thailand ((Ji et al., 2023)), and Mexico ((Bruhn and Love, 2014)) have highlighted the positive effects of this channel on local income and employment, emphasizing its potential to uplift disadvantaged regions.

The "deposit/borrowing channel" of financial development also plays a crucial role in wealth accumulation ((Célerier and Matray, 2019; Mian et al., 2019)). However, its impact on reducing inequality depends on barriers to banking access, which tend to disadvantage poorer households ((Beck et al., 2010; Crawford et al., 2018; Bazillier et al., 2021)). In emerging economies, where the "business finance channel" and labor market effects are more pronounced, bank expansions could potentially favor the middle class, aligning with their workforce presence and entrepreneurial capacity in underserved areas. This unique middle-class-biased growth and inequality reduction are what we aim to explore further by examining the causal impact of RBI policy on consumption, income growth, and inequality in India.

Recent studies by Young (2017), Cramer (2025), Jiao and Mo (2023), and Gupta and Sedai (2023) shed light on the impacts of the 2005 RBI Branch Authorization Policy (BAP) in India. Young (2017) observed increased economic activity laying the foundation for distributional analysis, while Cramer (2025) found improved household health overall. Jiao and Mo (2023) find significant growth in manufacturing firms due to eased credit access, resulting in increased capital accumulation and employment in the formal sector.

Gupta and Sedai (2023) and our study assess the RBI's bank expansion policy but diverge in scope, methodology, and policy emphasis. Gupta and Sedai adopt a household-level framework, highlighting urban-rural disparities. They show that urban households benefited disproportionately through formal employment and consumption smoothing, offering insights into urban job creation but providing limited analysis of regional convergence or inter-district inequality—key objectives of the RBI policy.

In contrast, we adopt a district-level approach to assess inter-district inequality, focusing on economic disparities between advanced and underbanked districts. By examining β-convergence in consumption and income, we capture the structural catch-up growth of underbanked districts, providing a broader view of regional inequality and integration. This complements Gupta and Sedai's analysis, illustrating how financial inclusion fosters regional convergence across rural and urban populations.

Our results align with Gupta and Sedai (2023) on the urban gains from financial inclusion but extend the analysis to show significant reductions in rural inequality, driven by increased consumption among middle-class households. While their study highlights urban-rural disparities, we focus on intra-district inequality, demonstrating that middle-income households are central to narrowing these divides. By aggregating household data at the district level and incorporating inequality measures such as the Gini coefficient and the Theil index—absent from their analysis—we link class-specific improvements to broader patterns of economic inequality. This approach underscores how financial inclusion addresses inequality at multiple levels, fostering both regional and intra-district economic integration.

Our district-level focus also reveals the macroeconomic stability fostered by financial inclusion—dimensions overlooked in household-level studies. Leveraging data from nightlights and administrative records, we capture aggregate effects on regional inequality and inter-district convergence. These differences in focus, scope, and methodology underscore the complementarity of the two studies, offering a holistic view of the impacts of financial inclusion.

Existing literature on bank expansions and inequality in major emerging economies leaves unanswered questions, especially concerning long-term impacts. Do large-scale expansions reduce economic inequality within regions? Can they help poorer regions catch up? Concerns also arise about biased welfare gains distribution. Does this expansion benefit wealthier households more, leaving poorer ones behind? To answer these questions, our study disaggregates income and wealth inequality at district and household levels. Additionally, our β-convergence model examines if the policy led to mean convergence across treatment and control districts. We examine multiple channels in a causal framework: increased economic activity, structural change and labor income.

3 Data

Our empirical analysis relies on multiple datasets: (i) India Human Development Survey, panel data, 2004-05 and 2011-12; (ii) National Sample Survey, Consumption rounds, 2004 and 2009 (iii) Socioeconomic High-Resolution Rural-Urban Geographic data on Night-lights luminosity, 2000-2012; (iv) National Family Health Survey, 2014/2015; (v) RBI, Master Office File, 1996-2016; (vi) Population Census, 2001 and 2011; and (vii) ICRISAT district-level GDP data. These sources provide comprehensive insights crucial to our investigation.

3.1 Indian Human Development Survey (IHDS)

IHDS is India's largest household and individual panel survey; the first wave was conducted in 2004-05, and the second one in 2011-12 (Desai and Vanneman (2018)), with around 40,000 households in each wave. There is an 83% match of households across survey waves. The second wave, conducted six to seven years post-policy initiation, furnishes a substantial temporal span for evaluating the impact of the bank expansion policy on inequality metrics. The inaugural 2004/2005 wave establishes pre-policy benchmarks. After cleaning the IHDS data, we are able to merge 371 districts with the RBI MOF data without losing national representativeness. Gupta and Sedai (2023) and Cramer (2025) use the same number of districts from IHDS and show that it is comparable with other nationally representative and contemporary datasets like the National Sample Survey, the National Family Health Survey, and the population census. From IHDS, we create the Gini coefficient of total annual household consumption and earnings, and aggregate it at the district level, shown in Figure A1. Additionally, we aggregate data on employment–agriculture and non-agriculture at the district level. IHDS also provides unique data on confidence in institutions; specifically it asks households if they have 'a great deal of confidence', 'some confidence' or 'no confidence' that (i) the state government looks after people, (ii) local leaders (panchayat) properly implement public projects and (iii) politicians fulfill their promises. We create a dummy for each variable with a great deal of confidence coded as 1, and 0 otherwise.

Self-reported income data in our micro survey is prone to biases, including recall bias, social desirability bias, and reporting errors, which are further influenced by socioeconomic factors such as caste, religion, and geographic location. These distortions compromise the accuracy of income data, especially for marginalized groups. Moreover, annual income measures fail to capture within-year variations such as seasonality and liquidity constraints, which are particularly relevant for informal sector workers (Merfeld and Morduch, 2023). Moreover, income distributions measured at two points over six to seven years may obscure longer-term structural trends and fail to capture idiosyncratic uncertainty or demographic shifts (Aguiar and Bils, 2015; Abbott and Gallipoli, 2022). These challenges necessitate a more robust approach to accurately estimate income and account for the underlying biases inherent in self-reported data.

To address these issues, we use the adaptive Least Absolute Shrinkage and Selection Operator (LASSO) variable selection model, a machine learning technique that enhances flexibility and predictive accuracy. This method applies adaptive penalties to coefficients, enabling the selection of relevant predictors while allowing for nonlinear relationships and high-dimensional interactions, such as between caste and education or religion and geographic location. By incorporating baseline income, cumulative wealth (assets), and social characteristics, the adaptive LASSO model generates a more reliable income measure. The cross-validation results of the model are illustrated in Figure A2, and the selected coefficients are presented in Table A1, demonstrating the efficacy of this approach in mitigating biases and producing an income variable that better reflects socioeconomic realities.

3.2 National Family Health Survey, 2015, National Sample Survey, 2004, 2009, 2011, Population Census 2001, 2011

The advantage of NSS and NFHS is that they are extensive sample surveys (covering all districts in India). Based on NSS and NFHS, we can provide estimates for 575 and 580 districts, respectively, of the total of 581 districts in RBI MOF.[3] NFHS (2015-2016) provides us the wealth index by combining various household assets and services owned by the household. It is a composite and cumulative measure. The variable is based on a household's ownership of durable consumer items such as a television and car; dwelling characteristics such as flooring material; drinking water source; toilet facilities; and other characteristics related to wealth status. Each household asset for which information is collected is assigned a weight generated through principal component analysis. The resulting asset scores are standardized in relation to a standard normal distribution, and the standardized scores are used to define wealth quintiles. as: Lowest, Second, Middle, Fourth, and Highest. We use these quintile values averaged at the district level as our outcome measures. Since we measure the impact of the policy on wealth ten years later, we are able to determine the wealth effect over a relatively long time period.

3.3 Night-lights (2000–2012) and District GDP (2007-2013) Data

Night-light luminosity data is drawn from the Socioeconomic High-resolution Rural-Urban Geographic Data (SHRUG) (Asher et al. (2021)). Night-lights have been used as a log-linear proxy to measure economic welfare (Gibson et al. (2021); Prakash et al. (2019)). The data is extracted from the Defense Meteorological Satellite Program-Operational Line Scan (DMSP-OLS) program of the National Oceanic and Atmospheric Administration (NOAA). We subtract the district-level 'total night-lights' of 2005 from all other years (2000–2012) to compute the difference in night-lights, our outcome variable of interest.[4] District-level GDP data (current prices, base year=2004) in million (Rs.) is derived from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) data portal. ICRISAT's district-level data for India typically covers various agricultural and socio-economic indicators across 20 states in India, accounting for over 90% of India's GDP. A major drawback of the ICRISAT data is that it is not available for the pre-policy period and does not allow us to check for smoothness in district GDP before the RBI policy; however, on the positive side, the ICRISAT data allows us to measure the dynamic impact of the policy on district GDP over the years

[3] We lose data on 6 districts in NSS and MOF merge as the NSS data is collected using the 2001 census boundaries, which does not exactly match the RBI district names. NFHS data is available for 601,509 households. NSS number of households by round: (i) 2004 has 122,148, (ii) 2009 has 96,644 households, and (iii) 2011 has 96,767.

[4] Total night-light is a sum of pixels of the luminosity values [0-63] across the geographic unit; it is consistent across different satellite measures and time periods.

following the policy, thus allowing us to examine the lagged effects predicted by our model. For our analysis, we merge the difference in night-lights and the district-level GDP data with the RBI MOF to conduct the RD analysis.

4 Empirical Strategy

4.1 Regression Discontinuity Design

In 2005, the RBI introduced a branch expansion policy that incentivized scheduled commercial banks to open branches in underbanked districts.[5] Underbanked districts were identified by having a population-to-branch ratio higher than the national average, which facilitated the use of an RD design. The running variable in the RD design is the district population-to-bank branches ratio, and the cut-off is set at the national average of 14,780 people per branch (Cramer, 2025). Districts above the cut-off are treated (underbanked), and districts below the cut-off control (banked) districts. The McCrary (2008) density test checks for manipulation around the cut-off, as shown in Figure A3, along with the distribution of the running variable. The density plot shows no manipulation around the cut-off. The test also shows a similar number of districts to the left and right of the cut-off within the optimal bandwidth.

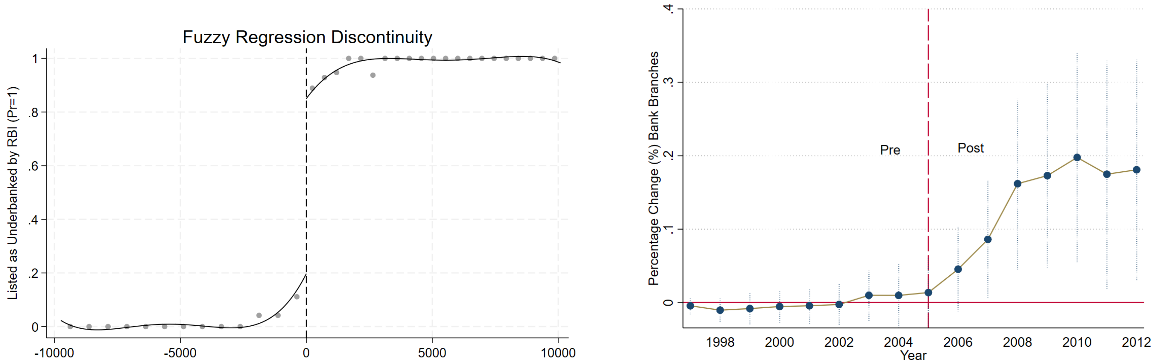
Panel (A) in Figure 1 shows the discontinuous jump in the probability of being underbanked (treated) at the cut-off. Panel (B) shows the percentage change in the number of bank branches pre and post policy. As shown in Panel (B), there is a 19% increase in bank branches in treatment districts in 2010. Post 2010/11, we observe a decline in the growth of bank branches which is explained by the easing of the regulation requiring setting up of branches in underbanked districts following the report of the committee on financial sector reforms in 2009/10 (Rajan (2015)). The robust RD design guides the size of the optimal bandwidth for each robust bias-corrected inference of the outcome variables (Calonico et al. (2020); Imbens and Kalyanaraman (2012)).

The following district-level regression shows our empirical model using non-parametric inference in RDD. Similar analyses are conducted for higher-order regressions:

$$Ineq_d = \tau_0 + \tau_1 Underbanked_d + \tau_2 BPopRatio_d + \tau_3 Treat * BPopRatio_d + L.Ineq_d + \epsilon_d \tag{1}$$

Equation 1 shows the RD equation. Here, d denotes the district. In the first stage, $Underbanked_d$ variable takes the value of 1 if the district is identified as underbanked, 0 otherwise. $BPopRatio_d$ is the district

[5] For details on the branch expansion policy design and the RD design, see Cramer (2025) and Gupta and Sedai (2023).



A: Fuzzy Discontinuity

B: Branch Expansion, Pre and Post Policy

Figure 1: Fuzzy Regression Discontinuity and Bank Branch Expansion.

Source: Authors' calculation, RBI MOF. Panel (A) shows the sample average within bins and polynomial fit of order 4. Panel (B) shows the increase in natural log of bank branches in treatment districts, pre and post policy. Confidence intervals with 5% level of significance. Data for Figure 1 was shared by Kim Fe Cramer.

population to bank branch ratio. $Treat_d$ variable takes the value 1 if the population-to-bank ratio is higher than the national average (14,780).[6] Following Abadie et al. (2023), standard errors are clustered at the district level. In the second stage, $Ineq_d$ shows the within-district inequality in consumption and living standards, and $Underbanked_d$ is the endogenous regressor. $L.Ineq_d$ controls for the lag value (pre-treatment) of district inequality. The first stage of the fuzzy RD design determines the treatment assignment based on the running variable, which is the district population-to-bank ratio (Cramer (2025)). Since the bank branch in a district in 2005 and the district population in 2001 (census) are used to create the running variable, we use these variables as covariates. The covariate-adjusted RD estimator remains consistent for the canonical fuzzy RD treatment effect, while offering a reduction in variance (Calonico et al. (2019)). To ensure the robustness of our empirical results, we perform a bandwidth selection sensitivity test. This involves varying the bandwidths around the optimal cut-off points and assessing the stability of our findings. Our results indicate that the observed effects on inequality reduction remain consistent across different bandwidth specifications, confirming the reliability of our empirical strategy. Notwithstanding the actual bandwidth size, the majority of the optimal bandwidths in our estimations fall in the range of ±6,000 relative to the cut-off.

There are some potential threats to identification namely, (i) political manipulation of district population to become an underbanked district, (ii) households migrating to treatment districts in anticipation of the treatment, (iii) national level public policies which could be strongly correlated to the BAP at the district level, and (iv) the IHDS sample, which does not cover all the districts in India, has more of either the

[6]This ratio was first developed by Cramer (2025).

treatment or control districts, thereby biasing the randomness of the treatment. To this effect, Gupta and Sedai (2023) and Cramer (2025) tested these possibilities and found that these issues do not confound the RDD. District population is taken from 2001, before the treatment; there is no significant migration into treatment districts before or at the time of the policy introduction. Major national public programs are not correlated with the roll-out of the BAP, and the IHDS sample does not bias the distribution of the districts identified by BAP. RDD estimates are robust to generic robustness tests: higher-order polynomials, placebo discontinuity tests, bandwidth multipliers, and bandwidth selectors.

4.2 Test for β-Convergence

Following Barro et al. (1991), Sala-i Martin (1996) and Young et al. (2008), we implement a β-convergence model in a Difference-in-Difference (DID) framework to examine if the policy led to conditional mean convergence in consumption and income across treatment and control districts. This methodological adaptation provides a structured way to evaluate whether a large scale regional bank expansion policy can promote catch-up growth in poorer regions, filling a notable gap in the literature on the impacts of financial inclusion on inter-regional economic inequality. Specifically, leveraging the panel data. we use the following linear DID model to measure additional treatment effects on regional convergence in economic growth:

$$\Delta \ln Y_{d,t} = \beta_0 + \beta_1 \ln Y_{d,t-1} + \beta_2 Treat_{d,t} + \beta_3 \ln Y_{d,t-1} * Treat_{d,t} + \lambda X_{d,t} + \gamma_r + \epsilon_{d,t} \tag{2}$$

In Equation 2, d and t denote districts and time, respectively. $\Delta \ln Y_{d,t}$ is the consumption or income growth from 2005 to 2012. $\ln Y_{d,t-1}$ represents the initial consumption or income level (2005), and $Treat_{d,t}$ is a categorical variable that determines the status of treatment (it takes value 1 if the district is underbanked (as per the RBI policy) and receives treatment, or it takes value 0 is the district is banked and does not receive the treatment). $X_{d,t}$ represents a vector of pre policy control variables namely: (i) household wealth aggregated at the district level and measured by possession of 0-30 durable assets including car, home, TV, fridge, bed, among others, (ii) household head's education aggregated at the district level, (iii) household poverty status (0/1) aggregated at the district level, and (iv) district level gini coefficients of consumption. Here, γ_r represents the region fixed effects to control for region-specific time-invariant unobserved factors, and $\epsilon_{d,t}$ is the error term.

Equations 1 and 2 analyze the impact of financial inclusion policies on inequality from two perspectives: within treated districts (Equation 1) and between districts (Equation 2). Equation 1 captures the effects of the policy on reducing inequality within treated districts. In contrast, Equation 2 focuses on β-convergence, examining whether underbanked districts (treated) are growing faster than better-banked (control) districts, thereby addressing inter-district inequality. This transition from within-district effects to inter-district convergence reflects the broader objective of financial inclusion policies, such as the RBI's bank expansion initiative, which aimed to reduce regional disparities. Equation 2 evaluates the policy's potential to enable poorer (underbanked) regions to catch up with developed ones, fostering regional economic convergence.

The coefficients of interest are β_1 and β_3. β_1 reflects the convergence rate across control group districts, while β_3 represents the differential convergence in consumption or income between treated and control groups. A negative β_1 suggests convergence among control districts, while a positive β_1 indicates divergence. A significant, negative β_3 implies that treated districts converged more than control districts, reducing consumption and income disparities. Using the district-wise population-to-bank ratio and panel data, we employ a difference-in-discontinuity design within the β-convergence model to examine if districts near the cut-off exhibit distinct convergence patterns compared to the full sample.

$$\Delta \ln Y_{d,t} = \beta_0 + \beta_1 \ln Y_{d,t-1} + \beta_2 \text{Treat}_{d,t} + \beta_3 \ln Y_{d,t-1} * \text{Treat}_{d,t} + \lambda X_{d,t} + \gamma_r + \epsilon_{d,t} \quad \forall \quad d \in \{-D, D\} \tag{3}$$

In Equation 3, $-D$ denotes districts with population-to-bank ratios to the left of the cut-off within the optimal bandwidth, while D represents ratios to the right. We use the optimal bandwidth from our main specification in Table 2 to test for convergence/divergence. The sever year time interval of the IHDS panel data allows us to study long-term convergence (Arunachalam and Shenoy (2017)).

A potential concern in analyzing the β-convergence model is the issue of division bias. This arises because the dependent variable $\Delta \ln Y_{d,t} = \ln Y_{d,t} - \ln Y_{d,t-1}$ includes $\ln Y_{d,t-1}$, which also appears as a regressor in the model. This overlap between the lagged outcome and the independent variable can result in an inflated correlation between the dependent and independent variables, especially in models with shorter time spans. However, by spanning the period from 2005 to 2012, our model focuses on capturing long-term dynamics rather than short-term fluctuations. Longer time spans, as noted by Islam (1995) and Mankiw et al. (1992), help attenuate division bias by diminishing the influence of transient shocks and measurement errors. Furthermore, we incorporate robust controls as discussed above, which help isolate the conditional convergence dynamics and reduce confounding.

$$\ln Y_{d,t} = \beta_0 + \gamma_1 \ln Y_{d,t-1} + \gamma_2 \text{Treat}_{d,t} + \gamma_3 \ln Y_{d,t-1} * \text{Treat}_{d,t} + \lambda X_{d,t} + \phi_r + \epsilon_{d,t} \tag{4}$$

To methodologically counter the division bias and the endogeneity concerns in our convergence estimates, we carry out two separate analysis to test the robustness. First, in contrast to the growth analysis in Equation 2, we conduct heterogeneous treatment effects analysis (Equation 4), which uses Log Consumption and Log Income post policy at the district level as the dependent variable, offers an alternative perspective on lagged effects and mitigates division bias arising from the inclusion of $\ln Y_{d,t-1}$ on both sides of Equation 2. A positive γ_1 in equation 4 indicates that districts with higher economic activity in the previous period tend to sustain higher economic activity in the current period. Notably, γ_1 in Equation 4 corresponds to $1 - \beta_1$ in Equation 2, reflecting the relationship between the growth and level models. While β_1 measures the convergence rate in growth ($\Delta \ln Y_{d,t}$), capturing how past levels reduce growth, γ_1 represents persistence in levels ($\ln Y_{d,t}$), inversely linked to β_1, highlighting their complementary dynamics. Similarly, a negative γ_3 in Equation 4, akin to the catch-up effect indicated by β_3 in Equation 2, underscores the impact of the bank expansion policy in reducing the persistence of unequal growth in consumption and income. This methodological refinement addresses division bias concerns in the convergence model.

A second robustness check addresses endogeneity concerns in the β-convergence model specified in Equation (2) by employing a two-stage least squares (2SLS) instrumental variable strategy. Specifically, we instrument $lnY_{d,t-1}$ with the logarithm of the mean outcome variable for the region-year, excluding the value of the district itself. This approach mitigates potential biases arising from reverse causality or omitted variables. Similar leave-one-out instruments have been employed in a range of studies to explore selection issues in diverse contexts, such as federal spending in the United States, corruption, and the effects of electricity and piped water in developing nations (see, for instance Levitt and Snyder Jr, 1997; Lamichhane and Mangyo, 2011; Bai et al., 2019; Dang and La, 2019; Sedai et al., 2021).This ensures that the instrument is not directly influenced by the district's individual outcome but captures broader regional trends, making it a valid and relevant proxy for the endogenous variable. Here, the interaction terms $\ln Y_{d,t-1} * \text{Treat}_{d,t}$ reinforces the role of the policy intervention in the convergence dynamics among treated districts relative to controls. These results substantiate the core hypothesis of β-convergence while mitigating biases stemming from omitted variables or measurement errors, thereby substantiating the findings of the growth convergence analysis.

5 Results

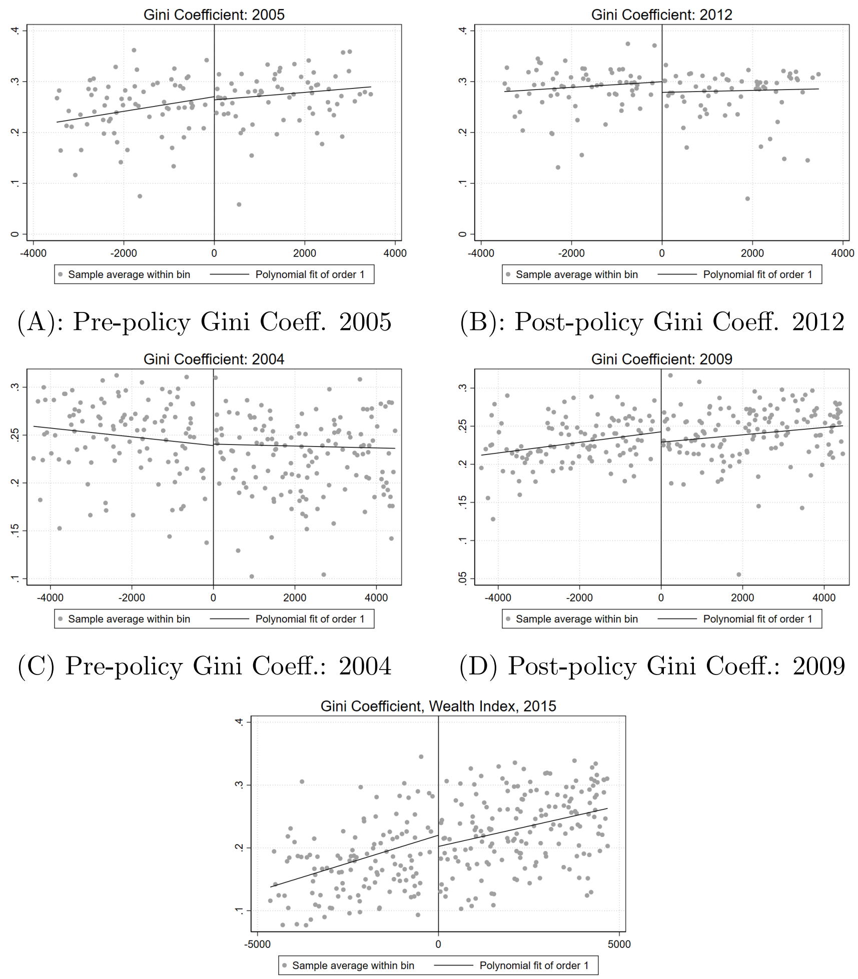
5.1 Descriptive Statistics

Table 1 shows the descriptive statistics from the IHDS panel. In the pre-policy period, underbanked areas exhibit elevated consumption inequality. Following the policy, consumption inequality remains stable in treated districts, in contrast to control districts where the Gini coefficient increases by 0.045. Underbanked districts also demonstrate lower income and consumption than their banked counterparts. A higher incidence of impoverished households characterizes treated districts. Moreover, underbanked areas experience lower business revenues relative to banked regions. Pre-policy, treated districts display relatively weaker economic conditions compared to control districts. In the post-policy phase, inequality diminishes, contributing to a convergence of outcomes between underbanked and banked districts. Table A2 presents descriptive statistics for consumption and living standards inequality using the NSS and NFHS cross-sectional data. Similar to the IHDS panel findings, both datasets reveal elevated inequality in underbanked districts. During the treatment period, the increase in consumption inequality is relatively milder in underbanked districts compared to banked ones. Subsequent sections will quantitatively assess the treatment's impact on consumption and living standards inequality.

5.2 Impact of Bank Expansion on Intra-district Inequality

Before the bank expansion program, there was statistically insignificant treatment effect on the level and log of the Gini coefficient of consumption inequality[7], as shown in columns 1 and 2 of Table 2, which indicates pre-policy smoothness. Six years after the policy, the Gini coefficient of consumption inequality was reduced by 0.025 units (8.9 percent reduction compared to the control mean) in treatment districts (column 3), significant at conventional levels. Log of consumption inequality reduced by 10.2 percent (column 4), showing robustness to change in the measurement of inequality. Additionally, using the panel structure of the IHDS data, we examine the difference in Gini from the pre (2005) to the post (2012) period and find a decline of 0.037 units in the difference in the Gini coefficient of consumption inequality in treated districts (column 5). Results in Table 2 clearly indicate a reduction in intra-district inequality. Table A3 shows pre-policy smoothness in consumption inequality in 2004, and a decline in consumption inequality similar to Table 2 when using the NSS data for 2011, specifically a significant 8.1 percent reduction in the natural log and quadratic measure of consumption inequality in treatment districts. Next, we examine treatment effects on wealth inequality from the NFHS data set. The NFHS, 2015, computed a wealth Index scale, which contains 11 items, viz. house type, source of lighting, toilet facility, the primary fuel for cooking, source of drinking water, separate room for cooking, ownership of the house, ownership of agricultural land, ownership of irrigated land, ownership of livestock, ownership of durable goods. These stock variables together account for the socio-economic status of households. As shown in column 1 of Table 3, 10 years after the policy, there is a 0.030 unit reduction in wealth inequality (compared to the control mean of 0.217). As shown in

[7] In section 6, we use Theil's index instead of Gini as an alternative measure of consumption inequality and show that our results hold.



(A): Pre-policy Gini Coeff. 2005 (B): Post-policy Gini Coeff. 2012

(C) Pre-policy Gini Coeff.: 2004 (D) Post-policy Gini Coeff.: 2009

(E): Post-policy Gini Coeff. 2015

Figure 2: RD plot on Bank Presence and Consumption Inequality

Source: Authors' calculation. Data for Panel (A) and (B): IHDS panel 2005 and 2012, Panel (C) and (D): NSS, 2004 and 2009, Panel (E): NFHS 2014-15. This figure shows pre-policy smoothness and post-policy discontinuity in household consumption and wealth inequality.

column 2, there is a significant reduction of 14.6% in the log of the wealth inequality index. To support the findings of reduced wealth inequality, in column 3, we show that the score of the wealth index significantly increased by 0.311 units in treatment districts, a 10.4% increase compared to the control mean of 2.985. The shift to wealth-based inequality measures captures long-term economic resilience and mobility, addressing a gap in prior studies that predominantly focus on short-term consumption and income metrics. This broader perspective aligns with recent calls for integrating wealth-based measures in inequality analyses.

Figure 2 shows the RD plot of consumption inequality at the household level in 2004 and 2005 (pre-policy) and in 2009 and 2012 (post-policy). Panels (A) and (C) show pre-policy smoothness. Within the optimal bandwidth, we do not see any significant jump in consumption inequality at the cut-off of the district population-to-bank branch ratio used to categorize treatment and control districts. In panels (B) and (D), we see a clear discontinuous decrease in consumption inequality at the cut-off, which signifies that the branch expansion policy reduced consumption inequality. Interestingly, we find that the decrease in consumption inequality is higher with the IHDS data as compared to NSS data. This is because IHDS is a panel data that allows us to control for pre-policy inequality levels. Similar to the sharp discontinuities found in the IHDS and NSS data with the treatment, panel (E) in Figure 2 shows the discontinuous decrease in wealth inequality in treatment districts.

Figure A4, using the NFHS data and ordinary least square regressions, shows the relationship between the levels of increase in bank branches between 2015 and 2005 (< 50, < 100, < 150 and < 200) on gini coefficient of the wealth index, separately for the treatment and control groups. We find the reduction in inequality higher in treatment districts and that there are insignificant impacts on wealth inequality at high levels of bank expansion. Additionally, Figure A5, using quantile regression, shows that the reduction in wealth inequality for treatment districts was lower at higher levels of wealth inequality, unlike the control group which shows a cyclical pattern. These findings resonate with the notion of diminishing marginal returns to financial access and underscore the importance of considering non-linear dynamics when assessing the long-term effects of such interventions.

Using the NSS data, Figure A6, Panels (A) and (B), capture district-level consumption inequality by underbankedness (treatment) in 2004 and 2011, respectively. This figure on aggregate shows a reduction in consumption inequality over time. Higher reductions are visible in districts which were at the middle of the inequality spectrum. Similar patterns of reduction of wealth inequality in treated districts are shown in Figure A5 and A7.

5.3 Impact of Banking Activity on β-Convergence Across Districts

In this section, we discuss the results from the DID β-convergence model (equation 2), DID β-convergence model within the optimal bandwidth (equation 3), heterogeneous treatment effects model (equation 4) and instrumental variable regressions in a β-convergence framework to analyze the effects of the bank expansion policy on convergence in consumption and income. Table 4 presents the results of the β-convergence models[8] in equation 2, examining the impact of the RBI bank branch expansion policy on convergence in consumption and income across districts.

[8] The β convergence, in general, refers to the tendency of poorer units (e.g., regions, countries, or in this case, districts) to grow faster than richer units, leading to a reduction in disparities over time (Sala-i Martin, 1996; Evans and Karras, 1996b,a).

Table 4 demonstrates evidence of economic convergence between poorer and richer districts, regardless of their treatment status, as reflected by the negative and statistically significant coefficients of $\ln Y_{d,t-1}$ (Lag Y). Districts with lower initial levels of income or consumption experienced faster growth rates, gradually reducing disparities over time (Sala-i Martin, 1996; Evans and Karras, 1996a,b). After the implementation of the policy, the rate of convergence accelerated between treated and control districts, suggesting that the policy played a catalytic role in enhancing the catch-up effect and fostering reductions in regional consumption and income inequalities. Specifically, the interaction term between lagged consumption and treatment in column 1 is negative and significant (-0.173, $p < 0.05$), indicating faster consumption convergence in treated districts. Similarly, column 2 shows a negative and significant interaction term for lagged income and treatment (-0.100, $p < 0.05$), providing evidence of income convergence. However, the evidence for income convergence is weaker compared to consumption. Robustness checks using the difference-in-discontinuity design in columns 3 and 4 confirm strong consumption convergence (-0.237, $p < 0.01$), and weaker income convergence (-0.107, $p < 0.05$). Treated districts had substantially lower consumption and income levels at the outset, as shown in Table 1; therefore, a negative coefficient on the interaction term reflects a catching-up to control districts due to the policy.

To address potential division bias in the growth convergence framework, as outlined in Section 4.2, we re-estimate the model in equation 2 by excluding the $\ln Y_{d,t-1}$ component from the dependent variable (as shown in equation 4). The positive and significant coefficients on $\ln Y_{d,t-1}$ as shown in Table A5 across all specifications reflect the persistence of consumption and income, indicating that higher initial levels of these variables are associated with sustained advantages over time. However, the negative and significant interaction terms between lagged outcomes and treatment suggest that the intervention tempers this persistence, resulting in stronger effects for districts with lower baseline consumption or income levels. This analysis reframes the findings not as evidence of convergence but as a demonstration of significant heterogeneous treatment effects, with a clearer and more pronounced impact on consumption than income. In Table A5, the interaction term for consumption (-0.173, $p < 0.05$) in column 1 shows a stronger and more statistically significant reduction in persistence compared to the weaker effect observed for income (-0.100, $p < 0.05$) in column 2. This pattern holds in the Difference-in-Discontinuity design, where the consumption effect (-0.239, $p < 0.01$) remains larger than that for income (-0.103, $p < 0.10$). The coefficients of the interaction terms in Tables 4 and A5 are similar, as γ_1 in equation 4 is defined as $1 + \beta_1$ in equation 2, reflecting the transition from growth to level equations. In other words, the 0.167 coefficient on L. Log Consumption in Table A5 is equivalent to $1 + (-0.833)$, the coefficient of L. Log Consumption in Table 4.

To address endogeneity concerns in the β-convergence model (equation 2), due to unobserved permanent or historical factors that affect both the pre and post policy consumption and income, we show the results from an instrumental variable regression (outlined in Section 4.2) in Table A6. The results in Table A6 validate the robustness of the β-convergence model using an instrumental variable approach. The significant negative coefficients for the interaction terms (L.Log Consumption*Treatment ($-0.298, p < 0.01$) and L.Log Income*Treatment(-0.082, $p < 0.10$)) confirm that the policy intervention accelerated convergence, with treated districts experiencing reduced persistence in consumption and income disparities compared to control districts. The strong first-stage results, including significant Sanderson-Windmeijer F-tests and Cragg-Donald Wald F-statistics, indicate the relevance and strength of the instruments. Notably, the results show a higher rate of convergence for consumption than for income, reinforcing the differential policy impacts on these two economic dimensions.

While Table 4 and A5 show convergence and reduced persistence, a closer inspection reveals that treated districts exhibit faster convergence in consumption compared to income. One plausible explanation rests in the differential responsiveness of consumption and income to policy changes. Improved financial access through bank expansion might directly fuel faster consumption growth in treated districts. People gain immediate opportunities to invest in their lives, adopt new technologies, and engage in broader spending patterns (Blinder (2007)). In contrast, income adjustments through wages and business growth often take longer to take root. This inherent time lag between consumption and income adjustments could be playing out in our observed convergence rates. Furthermore, initially, underbanked districts have more agrarian and less dynamic economic structure, as evident in Table 1. This inherent disadvantage, characterized by lower income and earnings, likely impedes the pace of income convergence compared to consumption, which can adapt more readily to policy changes and spending patterns. Regional economic conditions, such as employment opportunities and diversification, can also contribute to income lagging behind consumption due to slower job market adjustments in treated districts (Hsieh (2009); Moretti (2010)). Our further analysis (Section 5.4.2) sheds light on the underlying mechanisms. The shift towards non-agricultural employment with its higher consumption proclivity in treated districts, facilitated by bank expansion, appears to be a key driver of the observed consumption convergence.

We extend the conditional convergence analysis to investigate how the bank branch expansion policy influenced consumption and income in districts categorized as above- and below-median income at baseline. Table 5 highlights that disaggregating the sample by income groups leads to increased standard errors for both consumption and income convergence estimates, due to the reduction in sample size from 371 districts (Table

4) to 185 and 186 districts. However, while the consumption convergence effects remain statistically significant, the income convergence effects lose significance. This is primarily because income convergence was already weaker in Table 4, with smaller coefficients compared to consumption convergence. Consequently, the added variability from data disaggregation renders the income effects statistically insignificant, although their magnitudes remain consistent with earlier results. For above-median income districts (columns 1 and 2), we find significant consumption convergence effects (-0.260, $p < 0.05$), while income convergence effects are not statistically significant. Similarly, for below-median income districts (columns 3 and 4), the interaction term for consumption is negative and significant (-0.317, $p < 0.01$), providing robust evidence for consumption convergence, while the income convergence effects remain insignificant. Although the point estimate of the interaction between lagged consumption and treatment is higher for the below-median income districts (column 3) compared to the above-median income districts (column 1), the difference in these coefficients is not statistically significant. Regardless of whether the district was richer or poorer at baseline, we observe consumption convergence of similar magnitudes, which consistently exceeds the levels of income convergence. Notably, the convergence coefficients for consumption are larger than those for income in both income groups, as was observed in Table 4, reinforcing the notion that financial inclusion policies facilitate faster adjustments in consumption patterns compared to the slower structural changes required for income convergence.

Overall, these results underscore the differential impact of the RBI bank branch expansion policy on consumption and income convergence across income groups. The policy was notably effective in reducing consumption disparities, aligning with previous studies that suggest consumption can converge more rapidly than income due to its sensitivity to changes in financial access (Kraay, 2006; Demirgüç-Kunt and Klapper, 2012). However, the observed weaker convergence in income highlights the continued importance of targeted financial inclusion initiatives to address deeper structural challenges and foster more inclusive growth across districts. Further policy efforts should prioritize expanding access to quality employment opportunities and financial services to enhance income convergence alongside the observed reductions in consumption inequality.

In conclusion, while improvements in living standards are evident through faster consumption convergence, tackling pre-existing structural disadvantages and income rigidities remains crucial for long-term, balanced growth. Also, while the empirical analysis does not directly test for spatial spillovers, the observed convergence in consumption and income across districts implies their potential presence. Increased financial access in treated districts may have induced positive externalities in neighboring areas, contributing to broader regional development and reduced inequality. Further research exploring spatial dynamics would be fruitful in this context.

5.4 Mechanisms through which Financial Access affects Inequality

In this section, we examine the mechanisms underlying the observed effects of bank presence on district-level inequality. We first examine how district-level output increases with bank presence, which provides the necessary platform for examining the distributional impact of the policy. Secondly, we examine the labor market effect of bank presence in terms of structural change in employment from agriculture to non-agricultural labor and earnings from employment. Third, we examine the impact of the policy on confidence in local institutions. Lastly, we examine which income groups benefit from the policy and show that the rise of middle-income household's consumption and wealth underlines the reduction in consumption and wealth inequality at the district level.

5.4.1 Impact of Financial Access on District GDP, Night-lights and Income

Within the broader context of examining the relationship between bank presence and inequality, the outcomes presented in Table 6 illustrate a pivotal role that banks assume in addressing economic growth locally. Notably, during the post-treatment time frame spanning 2007 to 2013, districts receiving treatment, initially characterized by relatively lower GDP, demonstrated substantial economic growth.[9] As evidenced in all columns of Table 6, treated districts experienced a gradual increase in district GDP from 2007-2013, with significant impacts observed from 2010-2013[10].

To corroborate our findings of the positive impact of bank expansion on district GDP, in Figure A8, we examine the impact of bank presence on total night-lights[11], with 2005 being the base year (total night-lights in a district in 2005 subtracted from each year). Pre policy, we do not see any impact of treatment on change in nightlights between the preceding years (2000–2004) and the base year 2005. After the policy, we see a significant increase in total night-lights in treatment districts. The increase in night-lights is significant at a 95% confidence interval from 2007-2009. Estimated coefficients for the difference in night-lights are shown in Table A8.

With an increase in the treated district's GDP, it becomes imperative to examine if the increased output at the district level is realized through higher income at the household level. To answer this question, in Table

[9]Due to data limitations, we do not observe the pre-policy district GDP in the pre-policy period.

[10]Though the number of districts in the ICRISAT data are sub-sample of the total districts in India, our findings are robust as the number of underbanked districts in the ICRISAT dataset (196 out of 305) are proportional to the overall tally of underbanked districts listed by the RBI (374 out of 581).

[11]Night-light luminosity has been extensively used as an alternate measure and proxy for economic growth (Asher et al., 2021).

7, we examine the impact of the bank expansion on household income at the district level, generated by using an adaptive LASSO variable selection model to the baseline socio-economic characteristics of the IHDS survey.[12]. In column 1, we show pre-policy smoothness; the policy did not affect income in 2005. In column 2, we show that post-policy, there is a significant increase of Rs. 13,397 in household income averaged at the district level (this corresponds to a $330 at 2012 exchange rate). In column 3, we estimate the impact of the policy on the difference in income before and after the policy. Here, we find that the difference in income increased by Rs. 8,479 ($207). Details on the constituent variables are shown below in Table 7. Increase in district's GDP and household income in treated districts underlines the reduction in inter-district inequality and convergence as shown in Table 4.

5.4.2 Impact of Financial Access on Structural Change

A potential channel through which financial access could reduce spatial inequality is transforming the underbanked district's labor market outcomes. In this section, as measures of structural change, first, we examine the impact of bank presence on the district-level switching of employment from agricultural to non-agricultural activity, and migration into treatment districts. Second, following Gupta and Sedai (2023) who analyzed the impact of the policy on household earnings, we examine if the inequality in earnings declined in the district following the policy.

In Table 8, we show the effect of bank presence on the average agricultural and non-agricultural employment at the district level and average district-level migration. In columns 1, 2 and 3, we show pre-policy smoothness. Column 4 shows that the RBI policy reduced the share of agricultural employment in the district by 6.1 percentage points, a 50 percent decline compared to the average of the control mean. In column 5, we see an equivalent increase of 5.5 percentage points (25 percent increase over the control mean) in the share of non-agricultural employment in treatment districts. In column 6, we see that the average district-level migration into treatment districts increased by 62,419, (approximately a 74 percent increase over the control mean). In columns 7 and 8, we find that the first switch to agricultural employment reduced while the first switch to non-agricultural employment increased significantly.

In Table 9, we examine the effect of the RBI policy on earnings inequality and average earnings from employment at the district level. In column 1, we find that earnings inequality was reduced by 0.032 units in treated districts, though not statistically significant at conventional levels. In column 2, we find a similar decrease in log of inequality in earnings by 11.5 percent in treated districts. Column 3 shows a 0.030 unit

[12]Variables used in the adaptive LASSO model are shown in the notes for Table 7.

reduction in the difference in Gini across the two survey waves. This is likely given the increased employment in the non-agricultural sector, which generally pays more than the agricultural sector. In column 4, we show that the average earnings at the district level increased by Rs. 6,416 ($160) in treated districts compared to control districts, with a 16 percent increase in earnings compared to the control mean of Rs. 36,041. From the analysis of employment and earnings, we observed movement from low productivity to higher productivity sectors and increased earnings at the district level. These structural changes in employment and earnings could be the underlying reasons for decreased consumption inequality in treatment districts.

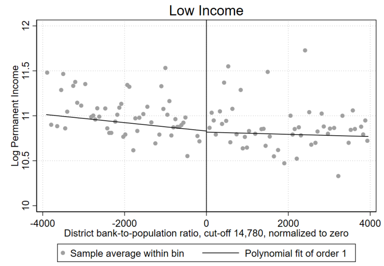
5.4.3 Middle Income Households Benefit from Large Scale Bank Expansion

Figure 3 using RD plots provides evidence of the bank expansion policy's impact on household income and consumption across income terciles.[13] Middle-income households experienced a discontinuous increase in consumption and income, but the same is not true for low and high-income households. Figure A9 shows insignificance in RD robust estimates of income and consumption for both low-income and high-income households, while the point estimates for the middle-class households are significant—11.2% increase in income and 16.5% increase in consumption.[14]. These findings highlight the significance of formal financial inclusion in fostering a growing middle-class demographic, which, in turn, played a pivotal role in reducing income inequality within treated districts. Our results provide new evidence that financial inclusion policies disproportionately benefit middle-income households, a key driver of economic mobility in both rural and urban contexts. This reinforces the need for targeted interventions to address the unique challenges and opportunities faced by this demographic. A similar rise of the middle-class consumption and income with bank branch expansion was found by Ji et al. (2023) in Thailand.

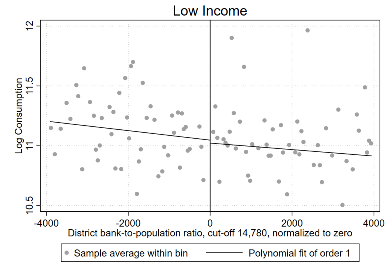
While bank expansion benefited middle-income households, null effects for poorer households underscore the complexities of large-scale financial inclusion policies. Existing research suggests barriers like pre-existing exclusion, limited financial literacy, market failures, and skill mismatches can impede their effectiveness in addressing economic disparities (Banerjee and Duflo (2007)). A plausible explanation for insignificant effects for high-income households stems from access to financial services prior to branch expansion policy, as has been found by Beck and Brown (2010) in transition economies.

Figure 4 provides additional evidence of the bank expansion policy's differential impacts on household outcomes across income terciles. The results show that middle-income households experienced significant increases in log per capita annual consumption, savings rates, and credit access, while also benefiting from

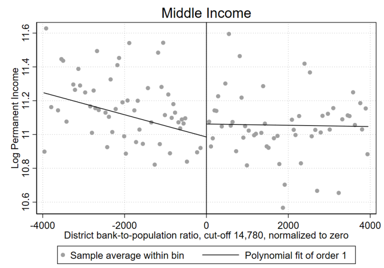
[13]The income terciles are calculated from the self-reported income variable in IHDS.
[14]The RD robust point estimates within the optimal bandwidths used in Figure A9 are shown in Table A9.



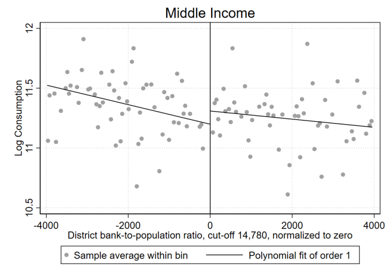
(A): Income



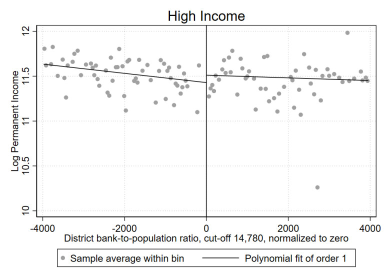
(B): Consumption



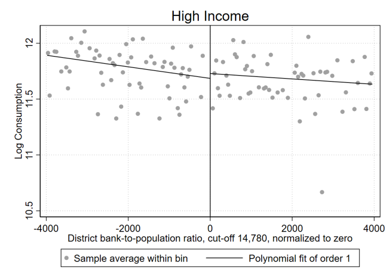
(C) Income



(D) Consumption



(E): Income



(F): Consumption

Figure 3: RD plot on Bank Presence, Income and Consumption by Income Tercile

Source: Authors' calculation, Data IHDS, 2012 and RBI MOF. Control variables: log of district population in 2001 and commercial bank branches in 1997.

greater engagement in regular wage employment. Specifically, middle-income households demonstrated an increase of approximately 16.5% in annual consumption and a notable improvement in access to bank savings and credit. These results reinforce the policy's role in fostering financial inclusion and enabling economic mobility for this demographic. In contrast, low-income households showed no significant changes across any of the outcomes, reflecting barriers such as pre-existing exclusion and limited financial literacy. Similarly, high-income households remained unaffected, likely due to their pre-existing access to financial services prior to the policy's implementation. By highlighting the significant role of middle-income households in driving consumption growth, formal savings, and participation in regular wage employment, Figure 4 illustrates the critical function of financial inclusion in consolidating a growing middle class. To rule out the possibility that the impact of the policy on middle income could be driven by the rural-urban heterogeneity, we examined whether the middle-income households are concentrated in urban areas. However, we find that the distribu-

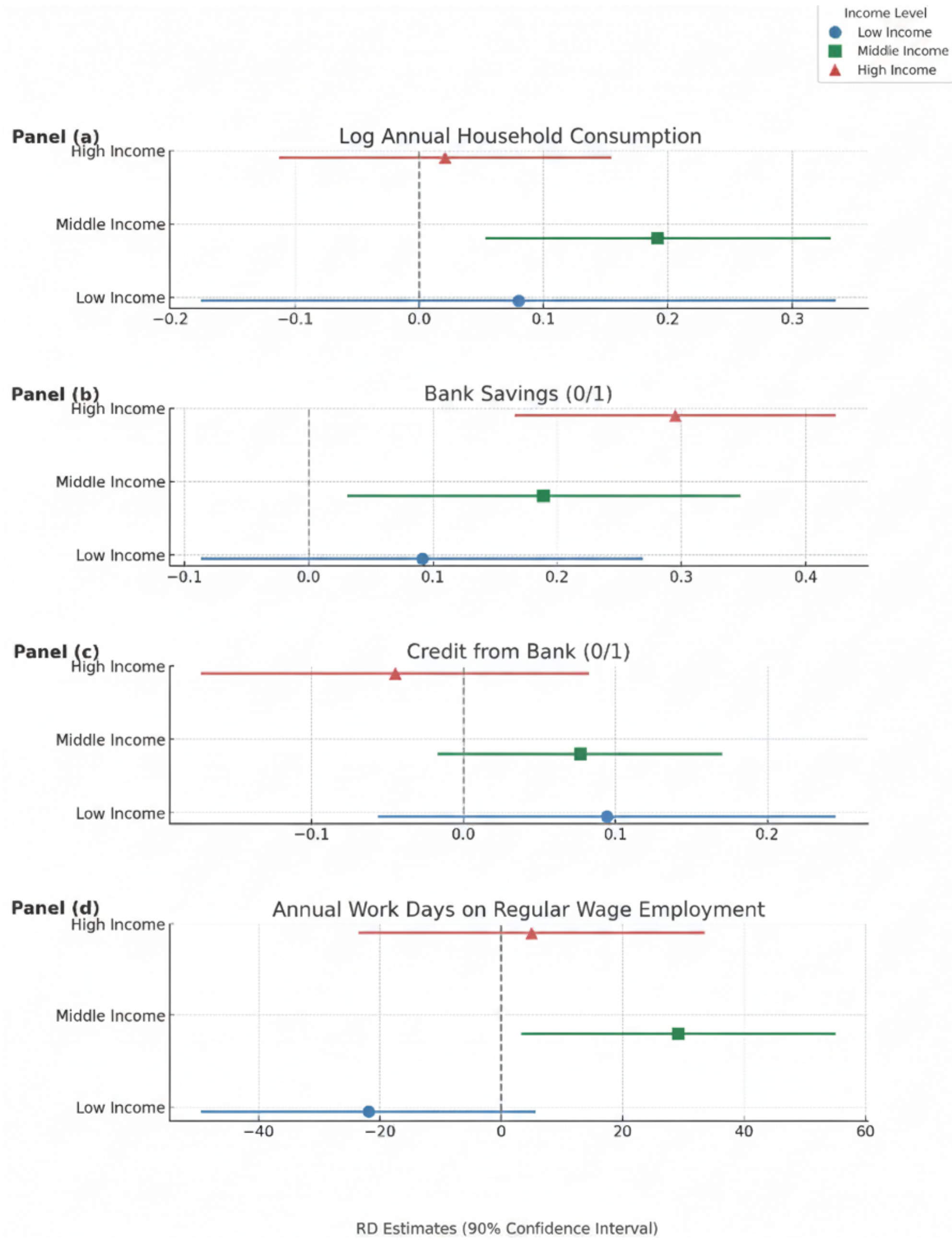


Figure 4: RD Estimates by Income Level and Outcome Variable

Notes: This figure displays RD estimates for Log Per Capita Annual Consumption, Bank Savings (0/1), Credit from Bank (0/1), and Annual Work Days on Regular Wage Employment, across income groups (Low, Middle, High). Confidence intervals at 95% are shown as horizontal lines, with different markers representing each income group. The vertical dashed line at zero indicates no effect.

tion of middle-income households is fairly similar in rural and urban areas, as shown in Table A11. Overall, our findings align with Ji et al. (2023), which documents the transformative role of financial inclusion in expanding economic opportunities for middle-income groups in emerging economies.

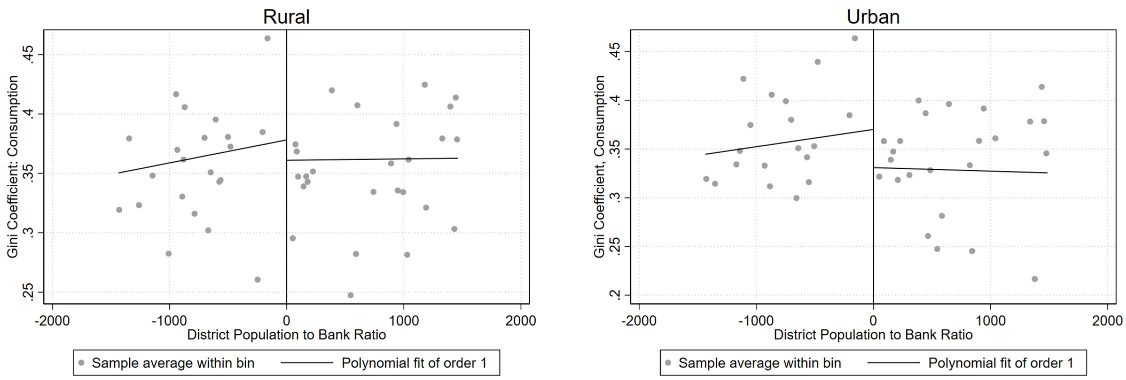
Consistent with these distributional patterns, we also find that the bank expansion policy improved institutional trust. Appendix A0.1 describes the construction of confidence indices, with results reported in Table A7 and visualized in Figure A9. Treated districts experienced substantial increases in trust: confidence in state government rose by 14.4 percentage points, confidence in public projects by 11.5 percentage points, and confidence in local leadership by 6.2 percentage points relative to the control mean. These institutional effects complement the economic gains, highlighting that financial inclusion reinforced both upward mobility and broader societal legitimacy.

5.5 Rural and Urban Heterogeneity

The impacts of the nationwide bank expansion policy reveal significant differences between rural and urban areas, challenging the uniform application of financial inclusion strategies. While Gupta and Sedai (2023) focus on the "business finance channel" driving urban gains, this study highlights important impacts for middle-income households in rural areas that have been overlooked in previous work. These findings underscore the varied ways financial inclusion policies reshape economic outcomes across regions and income groups.

Urban areas demonstrate a clear advantage from the bank expansion policy, with treated districts experiencing a 5.2 percentage-point reduction in the Gini coefficient for consumption inequality (Table A4, Figure 5). These gains are linked to expanded access to formal financial savings and insurance and increased participation in the formal labor market (Gupta and Sedai, 2023), resulting in higher wage income and improved financial resilience. Middle-income urban households, in particular, leveraged these changes to finance durable goods and smooth consumption.

In rural areas, while the overall reduction in inequality is modest, with a marginal decline in the Gini coefficient of 1 percentage point (Table A4, Figure 5), the policy demonstrates significant benefits for middle-income households. The treated middle-income households in rural districts exhibit a 6.8% increase in consumption levels (Table A10), which, though smaller compared to urban areas, contributes meaningfully to the observed decline in rural inequality. These effects, as argued by Burgess and Pande (2005) and Bruhn and Love (2014), are driven by improved access to financial resources and reduced dependence on informal credit. Unlike poor or wealthy rural households, which show either no changes in consumption, the middle-income group stands out as the key beneficiary of the bank expansion policy in rural regions, which is consistent with our findings in Figure 3 and 4. This increase in consumption aligns with their relatively



(A) Gini, Consumption, Rural

(B) Gini, Consumption, Urban

Source: Authors' calculations. Data: IHDS 2012, RBI, MOF. Panel (A) and (B) reflect rural population shares per 2001 census.

Figure 5: Banks and Consumption Inequality for Rural and Urban Households

higher ability to utilize formal financial services effectively, fostering modest but important improvements in their economic well-being. These findings highlight the role of rural middle-income households in driving the observed policy impacts, even within the constraints of a largely informal rural economy.

These results suggest that the "household demand channel" operates meaningfully in rural areas, particularly for middle-income households. This finding contrasts with Gupta and Sedai (2023) conclusions, which emphasize the exclusion of rural households from the benefits of financial inclusion policies. By focusing on aggregate outcomes, their analysis overlooks the significant gains achieved by middle-income rural households, who are better positioned to absorb the benefits of financial participation.

The differences between rural and urban impacts are rooted in the structural features of these regions. Urban areas, characterized by greater economic diversification and formal labor markets, amplify the redistributive effects of financial inclusion. Rural areas, on the other hand, face structural constraints, including limited access to non-agricultural employment and a reliance on informal networks. These challenges dampen the overall effects of bank expansion. However, for middle-income rural households, financial inclusion reduces dependency on informal credit and fosters asset accumulation, which helps to bridge the gap between the poorest and wealthiest rural households.

Our findings highlight the need for region-specific approaches to financial inclusion. Urban gains can be bolstered by policies that support formal-sector employment and encourage firm borrowing. In rural areas, targeted interventions are required to unlock the potential of middle-income households. Expanding access to non-agricultural enterprises, improving rural financial literacy, and designing credit programs tailored to poorer households can amplify the observed benefits and address structural barriers. Our study calls for a balanced approach that ensures rural poor are not left behind.

6 Robustness Tests

To show the robustness of our empirical design, we conduct a battery of generic RD tests, including pre-policy smoothness, quadratic estimates, donut hole tests, placebo cut-offs, bandwidth multipliers, and bandwidth selectors. In addition, we use an alternate measure of consumption inequality (Theil's index) to examine any bias in outcomes and rely on existing studies using the RBI branch expansion policy to nullify threats to the identification strategy.

6.1 Generic RD Tests

We follow Cramer (2025) in showing the validity of the estimates derived from RD regressions. First, we analyze data from pre and post-policy periods, showcasing smooth trends before the policy shift to validate our subsequent findings. Second, we introduce quadratic estimates in Table A12, which reveals a comparable 0.035 reduction in consumption Gini (column 3), while maintaining pre-policy smoothness in column 1. Third, we perform a Donut hole test in our RD design (specifically, we cut 1 percent of the running variable out from the left and right side of the cut-off), confirming that our results aren't overly dependent on values near the cut-off (Cattaneo et al. (2023)). The results, reported in Table A13, affirm that our main results in Table 2 aren't reliant on values close to the cut-off. Fourth, we conduct the classical placebo cut-off test for the RD design by examining smoothness around placebo cut-offs. Specifically, we analyze two cut-off points on each side of the true cut-off (normalized to zero), i.e., -3000, -1000, 1000, and 3000. Results for the same are reported in Table A14. We find no evidence of significance in p-values for the RD estimates in any of the placebo cut-offs considered. It is valid for all the outcomes analyzed in this study. Fifth, we check whether the coefficients remain statistically significant for different bandwidth choices. Specifically, we multiply the RD robust bandwidth to the left and right by 0.50x, 0.75x, 1.25x, and 1.50x, respectively, and examine if we lose the statistical significance of the RD estimates. As shown in Table A15, over 85% of the estimates are significant with the bandwidth selectors. Sixth, we examine the statistical significance of RD estimates to different bandwidth selectors. Specifically, we use the (i) mean square error optimal bandwidth, (ii) two-way mean square error optimal bandwidth, (iii) coverage error ratio optimal bandwidth and (iv) two-way coverage error ratio optimal bandwidth selector. As shown in Table A16, over 80% of the RD estimates from various bandwidth selectors are significant. The optimal bandwidth selector we use for our analysis of consumption Gini, 'mserd' yields the same estimate as the bandwidth selector 'cerrd', i.e., a 9 percent decline in inequality.

6.2 Alternate Measure of Inequality and Household Data

The other set of robustness tests we show relates to alternate measures of inequality and a more granular level of consumption inequality. First, as an alternate measure of consumption inequality, we show the treatment effects on Theil's index.[15] As shown in Table A17 Theil's index of consumption inequality at the district level reduces by 0.018 units (a 13 percent decrease over the control mean). In relative terms, the decline in inequality is higher in Theil's index, which suggests that the reduced inequality shown in Theil's index is a conservative estimate. Using household-level data instead of district data provides us with more observations and, consequently, more binned means around the cut-off from which to infer the impact of the policy on consumption inequality. Here again, in Panel (A), we show pre-policy smoothness,[16] and in Panel (B) we show the discontinuous decrease in consumption inequality. Overall, we find an 8-13 percent decline in inequality in all our estimations of district inequality in treatment districts.

Drawing from recent studies by Gupta and Sedai (2023) and Cramer (2025) that employed the BAP, 2005, we rely on their thorough identification and robustness tests, which we briefly outline. One potential concern is whether political parties manipulated the population-to-bank ratio around the cut-off to affect district categorization as underbanked before policy implementation. However, this is implausible given the RD design's timeline: district populations in 2001 couldn't have been manipulated four years prior to policy introduction, and bank branches are under the jurisdiction of RBI. Another issue is the possibility of wealth-based household migration influencing inequality in treatment districts. Cramer (2025) didn't find evidence of pre-treatment household migration to underbanked districts, mitigating this concern. Additionally, in our structural change analysis, we find no significant migration into treatment districts in 2001. Gupta and Sedai (2023) investigated if using a subset of districts from IHDS biased the treatment design and found no such bias when comparing 371 IHDS districts to the 581 in RBI MOF. Lastly, since the policy excluded regional rural banks, Cramer (2025) demonstrated that it had no discernible impact on the number of these banks in treatment districts.

[15] We do not use Theil's index as the main outcome of interest due to the study design. The Theil's index is based upon a Lorenz derivation; therefore, it suffers from the problem of intersecting Lorenz curves when comparing different geographic areas (Braun (1988)).

[16] The pre-policy smoothness is more clearly shown with household-level data compared to the district-level data as the number of observations are higher on both sides of the cut-off.

7 Conclusion

This paper investigates the impact of increased banking activity on economic inequality in developing economies, focusing on India's nationwide district-level bank branch expansion policy initiated by the Reserve Bank of India in 2005. We employ robust analytical methods, including Regression Discontinuity Design (RDD) and a β-convergence model, to assess the causal effects of commercial bank expansion on intra- and inter-district economic inequality in consumption and wealth.

Our findings indicate that the policy significantly reduced consumption and wealth inequality in the treated districts and facilitated convergence in consumption and income across treated (underbanked) and control (banked) districts. These results are supported by increases in district Gross Domestic Product (GDP), night-light luminosity, and household income in the treated districts. Additionally, the policy induced structural changes in employment and increased migration to treated districts. We observe a notable decrease in earnings inequality and an increase in both earnings and household confidence in political institutions in treated districts. The benefits were most pronounced for middle-income households, highlighting the policy's limited effect on reducing inequality between the rich and the poor.

Despite its contributions, our study has certain limitations. The reliance on district-level data may not fully capture local variations, suggesting the need for more granular bank and household-level data to explore intra-district disparities in greater detail. Future research should also consider the long-term sustainability of the observed effects to provide deeper insights into the enduring impact of financial inclusion policies. Moreover, further investigation into the role of other financial inclusion initiatives and their interactions with bank expansion policies is warranted.

Our study uniquely contributes to the literature by examining the impact of banking expansion on confidence and trust in institutions, thereby highlighting the broader societal benefits of financial inclusion. These insights are critical for policymakers aiming to enhance living standards in developing economies. The policy implications of our findings are multifaceted. Policymakers should adopt both place-based and people-based approaches to ensure that the benefits of financial inclusion are equitably distributed across different income groups. Specifically, the evidence on regional convergence highlights the necessity of place-based policies tailored to the unique socio-economic conditions of underdeveloped districts. By addressing spatial inequalities, financial inclusion policies can drive inclusive growth and reduce disparities across regions. Targeted interventions to support non-agricultural sectors could further amplify the positive effects on labor income and overall economic growth. Continuous monitoring and adaptive policy frameworks are essential to sustain the gains from financial inclusion initiatives and effectively address local disparities.

As developing economies continue their drive toward financial inclusion, our findings underscore the importance of micro-structuring and expanding financial access to address local disparities in both absolute and relative terms. By incorporating district-level analyses, a β-convergence framework, and wealth-based inequality metrics, this study provides a comprehensive framework for evaluating the structural and long-term impacts of financial inclusion policies. These contributions offer critical insights for policymakers and researchers aiming to design more effective interventions for fostering regional equity and sustainable economic development. In the broader context of global economic inequality, our research provides robust evidence on the role of financial inclusion in mitigating relative inequality in developing economies.

8 Tables and Figures

Table 1: Descriptive Statistics, IHDS, 2005 and 2012

	2005					2012				
	Banked		Underbanked			Banked		Underbanked		t-test
	Mean	SD	Mean	SD	t-test	Mean	SD	Mean	SD	
Gini Coeff. Cons.	0.236	0.056	0.266	0.054	***	0.281	0.039	0.266	0.058	**
Theil's Index Cons.	0.096	0.039	0.122	0.043	***	0.132	0.033	0.130	0.043	
Income	109358.7	25818.8	78808.6	23746.0	***	98730.6	23214.0	73528.1	20329.4	***
Ag. Wage Emp. (0/1)	0.151	0.158	0.241	0.200	***	0.120	0.137	0.184	0.161	***
Non Ag. Wage Emp.	0.192	0.113	0.216	0.142	**	0.216	0.109	0.264	0.143	***
Gini Coeff. Earnings	0.405	0.114	0.439	0.114	***	0.440	0.106	0.461	0.112	*
Earnings Emp.	54335.6	21647.5	39922.0	22244.8	***	36041.5	16390.5	25067.1	14911.3	***
Growth of Cons.						-0.448	0.241	-0.464	0.295	
Growth of Perm. Inc.						-0.099	0.146	-0.062	0.194	***
Pre Policy Covariates (District Level)										
Wealth	14.276	3.339	10.173	3.531	***					
Poverty	0.149	0.126	0.313	0.213	***					
Years Education	8.371	1.926	6.932	2.145	***					
Observations	150		221			150		221		

Notes: Table 1 reports the mean and standard deviations of our main outcome variables from IHDS, for banked and underbanked districts, both in pre-policy (2005) and post-policy (2012) periods. Significant mean difference between district-level averages of households in banked and underbanked districts in a given year based on t-tests. $*p < 0.10, **p < 0.05, ***p < 0.01$. Variables in monetary terms are deflated using the survey deflator. Consumption, earnings and income are winsorized at 10 and 90%. Gini and Theil's value are population weighted. *t*-test assesses if the observed mean difference between treatment and control groups is statistically significant. The variable Deflator adjusts for temporal price variations across states. It represents the ratio of 2011-12 CPI-AL (Consumer Price Index for Agricultural Laborers) and CPI-IW ((Consumer Price Index for Industrial Workers) to their 2004-05 values. The pre-policy covariates are computed by aggregating household data at the district level, and are used as control variables in analyzing inter-district inequality.

Table 2: Bank Presence and Consumption Inequality in India

	(1)	(2)	(3)	(4)	(5)
	Pre		Post		
	Gini Coeff	Log Gini	Gini Coeff	Log Gini	Diff Gini
Treatment	0.004	-0.034	-0.025**	-0.102**	-0.037**
	(0.017)	(0.070)	(0.011)	(0.052)	(0.015)
Untreated Mean	0.236	-1.109	0.280	-1.071	0.044
Bandwidth	6,329	5,746	6,459	6,717	5,831
Observations	371	371	371	371	371

Notes: Table 2 reports the results from the RD robust regression of the impact of RBI bank branch expansion policy (2005) on intra-district consumption inequalities in India. District-level Gini coefficients and the log of Gini coefficients are used as indicators of consumption inequality. Standard errors in parentheses are clustered at the district level. Significance levels are $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Data sources: India Human Development Survey (2005 and 2012), Master Office File (MOF), Reserve Bank of India (RBI), and district-level data. Covariates: (i) number of non-regional rural bank branches in the district in 1997, (ii) district population based on the 2001 census, (iii) pre-policy Gini coefficient, (iv) pre-policy period district wealth (average number of household assets at the district level). Untreated Mean denotes the district-level average of the outcome in the post-policy period for control districts. The first stage gauges the probability of treatment conditional on the population-to-bank ratio exceeding 14,780 (Cramer, 2025). Bandwidth refers to the district population-to-banks ratio on both sides of the cut-off.

Table 3: Bank Presence and Wealth Inequality. NFHS, 2015

	(1)	(2)	(3)
	Gini Coeff	Log Gini	Wealth Index
Treatment	-0.030*	-0.146**	0.311***
	(0.021)	(0.107)	(0.163)
Untreated Mean	0.217	-1.394	2.985
Bandwidth	4,625	4,933	5,219
Observations	580	580	580

Notes: Table 3 reports the results from the RD robust regression of the impact of RBI bank branch expansion policy (2005) on intra-district wealth inequalities in India. District-level Gini coefficients calculated from the wealth index and the log of Gini coefficients are used as indicators of wealth inequality. Standard errors in parentheses are clustered at the district level. Significance levels of the bias corrected p value are $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Data: National Family Health Survey, 2014/2015, and MOF, RBI, district-level data. Wealth index range 1-5.

Table 4: Bank Presence and Inter-District β-convergence in Consumption and Income

	(1)	(2)	(3)	(4)
	DID β-Convergence		Differences-in-Discontinuity β-Convergence	
Variables	Growth Consumption	Growth Income	Growth Consumption	Growth Income
Test for β convergence				
Treatment	1.984**	1.144**	2.711***	1.222**
	(0.854)	(0.536)	(0.984)	(0.621)
L. Log Consumption	-0.833***		-0.788***	
	(0.0858)		(0.0945)	
L. Log Income		-0.717***		-0.778***
		(0.0603)		(0.0630)
L. Log Consumption*Treatment	-0.173**		-0.237***	
	(0.0759)		(0.0873)	
L. Log Income*Treatment		-0.100**		-0.107**
		(0.0467)		(0.0543)
RD Robust Bandwidth			6,459	6,459
Observations	371	371	262	262
R-squared	0.540	0.634	0.563	0.682

Notes: Table 4 reports the results from β convergence DID model, the impact of RBI bank branch expansion policy (2005) on convergence in consumption and income in India. $*p < 0.1$, $**p < 0.05$,$***p < 0.01$. Standard errors in parentheses are clustered at the district level. Data: IHDS panel, 2005 and 2012, and MOF, RBI, district-level data. Both variables are winsorized at 10% and 90%. Here, β-convergence implies convergence in mean values of consumption and across districts. The baseline control variables aggregated at the district level include (i) household poverty (ii) consumption gini, (iii) household wealth, and (iv) household head's education. Additional regional fixed effects are included for the seven major regions in India. In columns (3) and (4), following Khanna and Mukherjee (2023), we use the difference-in-discontinuity design within the β-convergence framework. The optimal bandwidth for these models is derived from our main result on the Gini coefficient,$\pm 6,459$, as shown in column (3) of Table 2. We conducted the analysis without winsorizing the outcome variables and the results remain consistent with stronger and significant convergence in consumption, and weaker and insignificant convergence in income.

Table 5: β-convergence in Consumption and Income for Districts Above and Below Median Income level

	(1)	(2)	(3)	(4)
	Above Median Income		Below Median Income	
Variables	Growth Consumption	Growth Income	Growth Consumption	Growth Income
Treatment	2.999**	1.462	3.548***	1.453
	(1.392)	(1.201)	(1.333)	(1.720)
L.Log Consumption	-0.717***		-0.831***	
	(0.109)		(0.116)	
L.Log Income		-0.610***		-0.735***
		(0.105)		(0.145)
L.Log Consumption*Treatment	-0.260**		-0.317***	
	(0.122)		(0.119)	
L.Log Income*Treatment		-0.128		-0.129
		(0.103)		(0.156)
Observations	185	185	186	186
R-squared	0.514	0.378	0.631	0.711

Notes: Table 5 reports the results from β convergence DID model, the impact of RBI bank branch expansion policy (2005) on convergence in consumption and income in India for districts above and below median income level at baseline (2005). $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors in parentheses are clustered at the district level. Data: IHDS panel, 2005 and 2012, and MOF, RBI, district-level data. Both the outcome variables are winsorized at 10% and 90%. Here, β-convergence implies conditional convergence in mean values of consumption and income across districts. The baseline control variables aggregated at the district level include (i) household poverty (ii) consumption gini, (iii) household wealth, and (iv) household head's education. Additional regional fixed effects are included for the seven major regions in India. The z-statistic (0.334, column 1 and 3) for consumption and (0.005, column 2 and 4) for income indicates that the difference between the coefficients is not statistically significant across above and below median districts.

Table 6: Bank Presence and District GDP, Current in Million (Rs.) Base year, 2004

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	2007	2008	2009	2010	2011	2012	2013
Treatment	29,448	34,472	40,070	59,595*	73,533**	81,942**	87,735**
	(20,890)	(24,086)	(27,795)	(32,945)	(34,793)	(35,107)	(37,582)
Untreated Mean	128,568.9	148,060.5	170,172.7	200,247.7	225,233.4	249,182.8	276,927.3
Bandwidth	4,076	3,971	4,576	4,863	5,008	4,807	4,917
Observations	305	305	305	305	305	305	305

Notes: Table 6 reports the results from the RD robust regression of the impact of RBI bank branch expansion policy (2005) on current district-level GDP (millions in Rs.) in India, for the years 2007-2013. $*p < 0.1$, $**p < 0.05$,$***p < 0.01$. Standard errors in parentheses are clustered at the district level. Data: ICRISAT-Data on district-level GDP in current prices, base year is 2004. The data is available for 305 districts of the 20 major states in India. 109 districts are banked and 196 districts are underbanked in this data set. States in the ICRISAT data: Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Telangana, Uttar Pradesh, Uttarakhand, West Bengal. Control variables: number of functioning commercial bank branches in 2005 and natural log of district population.

Table 7: Bank Presence andIncome, LASSO Selection Variable.

	(1)	(2)	(3)
Variables	Pre	Post	Post Difference
LASSO Selection			
Income			
Treatment	6,024	13,397**	8479.1*
	(8,263)	(7,175)	(4721)
Untreated Mean	109,482	98,289	-11,193
Bandwidth	5,888	5,404	5,442
Lag of Outcome	N	N	Y
Observations	371	371	371

Notes: Table 7 reports the results from the RD robust regression of the impact of RBI bank branch expansion policy (2005) on the district average of household incomes in India. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors in parentheses are clustered at the district level. Data sources: India Human Development Survey (2005 and 2012), and MOF, RBI. Household incomes are calculated using the adaptive LASSO model and then it was averaged at the district level. Income at the district is winsorized at 10 and 90%. Pre-policy variables utilized for predicting income encompass income, religion, caste, house floor, access to water and electricity, household head's education, literacy, ownership of cultivated land, business, house, motor vehicles, fridge, air conditioner, livestock, and household assets including bicycle, motorcycle, sewing machine, generator set, mixer grinder, cooler, air conditioner, black and white and color television, clock, chair/table, cot, telephone, cell phone, refrigerator, pressure cooker, car, washing machine, computer, credit card, footwear, and livestock.

Table 8: Bank Presence, Migration, Agriculture and Non-Agricultural Wage Labor

	(1)	(2)		(3)	(4)		(5)	(6)
	Pre			**Post**			**First Diff.**	
	Agri.	Non Agri.	Migration	Agri.	Non Agri.	Migration	Agri.	Non Agri.
Employment and Migration								
Treatment	-0.059	-0.049	16,867	-0.061**	0.055*	62,419**	-0.046	0.082**
	(0.065)	(0.038)	(24,104)	(0.029)	(0.033)	(33,944)	(0.036)	(0.036)
Untreated Mean	0.151	0.192	53,280	0.120	0.216	83,441	-0.030	0.023
Bandwidth	5710	6967	4,052	5409	5374	4,448	5287	5795
Lag Y	N	N	N	Y	Y	N	N	N
Observations	371	371	581	371	371	581	371	371

Notes: Table 8 reports the results from the RD robust regression of the impact of RBI bank branch expansion policy (2005) on the agricultural and non-agricultural wage labor and migration in India. $*p < 0.1$, $**p < 0.05$,$***p < 0.01$. Standard errors in parentheses are clustered at the district level. Data: India Human Development Survey, 2005 and 2012, and MOF, RBI, district level data for Agri and Non-Agri employment. For migration data, we merge the RBI MOF with the population Census of 2001 and 2011, using 2001 census boundaries. Agricultural and Non-agricultural wage employments are household-level dummy variables, which are averaged at district-level to get fraction of households in the district employed in agricultural and non-agricultural labor. Migration is the average district level in-migration into the district.

Table 9: Bank Presence, Inequality, and Total Household Earnings at the District Level

	(1)	(2)	(3)	(4)
	Gini Coeff.	Log Gini Coeff.	Diff Gini	Earnings
Inequality in Earnings				
Treatment	-0.032	-0.115*	-0.030	6,415.9*
	(0.028)	(0.074)	(0.027)	(4,211.5)
Untreated Mean	0.440	-0.850	0.035	36,041.47
Bandwidth	5446	4484	5616	4672
Observations	370	370	370	371

Notes: Table 9 reports the results from the RD robust regression of the impact of RBI bank branch expansion policy (2005) on the intra-district inequalities in total household earnings in India. $*p < 0.1$, $**p < 0.05$,$***p < 0.01$. Standard errors in parentheses are clustered at the district level. Data: India Human Development Survey, 2005 and 2012, and MOF, RBI, district level data.

References

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. (2023). When should you adjust standard errors for clustering? The Quaterly Journal of Economics, 138(1):1–35.

Abbott, B. and Gallipoli, G. (2022). Permanent-income inequality. Quantitative Economics, 13(3):1023–1060.

Aguiar, M. and Bils, M. (2015). Has consumption inequality mirrored income inequality? American Economic Review, 105(9):2725–2756.

Ait Lahcen, M. and Gomis-Porqueras, P. (2021). A model of endogenous financial inclusion: Implications for inequality and monetary policy. Journal of Money, Credit and Banking, 53(5):1175–1209.

Arunachalam, R. and Shenoy, A. (2017). Poverty traps, convergence, and the dynamics of household income. Journal of Development Economics, 126:215–230.

Asher, S., Lunt, T., Matsuura, R., and Novosad, P. (2021). Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in india using the shrug open data platform. The World Bank Economic Review, 35(4):845–871.

Ashraf, Q., Gershman, B., and Howitt, P. (2017). Banks, market organization, and macroeconomic performance: An agent-based computational analysis. Journal of Economic Behavior Organization, 135:143–180.

Badarinza, C., Balasubramaniam, V., and Ramadorai, T. (2019). The household finance landscape in emerging economies. Annual Review of Financial Economics, 11:109–129.

Bai, J., Jayachandran, S., Malesky, E. J., and Olken, B. A. (2019). Firm growth and corruption: empirical evidence from Vietnam. The Economic Journal, 129(618):651–677.

Banerjee, A., Duflo, E., Glennerster, R., and Kinnan, C. (2015). The miracle of microfinance? Evidence from a randomized evaluation. American Economic Journal: Applied Economics, 7(1):22–53.

Banerjee, A. V. and Duflo, E. (2007). The economic lives of the poor. Journal of economic perspectives, 21(1):141–167.

Barboni, G., Field, E., and Pande, R. (2022). Rural banks can reduce poverty: Experimental evidence from 870 indian villages. Technical report, Working Paper, Yale Economic Growth Center.

Barro, R. J., Sala-i Martin, X., Blanchard, O. J., and Hall, R. E. (1991). Convergence across states and regions. Brookings papers on economic activity, pages 107–182.

Bazillier, R., Héricourt, J., and Ligonnière, S. (2021). Structure of income inequality and household leverage: Cross-country causal evidence. European Economic Review, 132:103629.

Beck, T. and Brown, M. (2010). Which households use banks? evidence from the transition economies (replaced by ebc dp 2011-024).

Beck, T., Demirguc-Kunt, A., and Levine, R. (2004). Finance, inequality, and poverty: Cross-country evidence.

Beck, T., Demirguc-Kunt, A., and Peria, M. S. M. (2007). Reaching out: Access to and use of banking services across countries. Journal of Financial Economics, 85(1):234–266.

Beck, T., Levine, R., and Levkov, A. (2010). Big bad banks? the winners and losers from bank deregulation in the united states. Journal of Finance, 65(5):1637–1667.

Blinder, A. S. (2007). What explains the rising trend in us income inequality? Economic Journal, 117(519):1–27.

Braun, D. (1988). Multiple measurements of US income inequality. Review of Economics and Statistics, pages 398–405.

Bruhn, M. and Love, I. (2014). The real impact of improved access to finance: Evidence from Mexico. Journal of Finance, 69(3):1347–1376.

Burgess, R. and Pande, R. (2005). Do rural banks matter? evidence from the Indian social banking experiment. American Economic Review, 95(3):780–795.

Calonico, S., Cattaneo, M. D., and Farrell, M. H. (2020). Optimal bandwidth choice for robust bias-corrected inference in regression discontinuity designs. The Econometrics Journal, 23(2):192–210.

Calonico, S., Cattaneo, M. D., Farrell, M. H., and Titiunik, R. (2019). Regression discontinuity designs using covariates. Review of Economics and Statistics, 101(3):442–451.

Cattaneo, M. D., Keele, L., and Titiunik, R. (2023). A guide to regression discontinuity designs in medical applications. arXiv preprint arXiv:2302.07413.

Cattaneo, M. D. and Titiunik, R. (2022). Regression discontinuity designs. Annual Review of Economics, 14:821–851.

Célerier, C. and Matray, A. (2019). Bank-branch supply, financial inclusion, and wealth accumulation. Review of Financial Studies, 32(12):4767–4809.

Chancel, L., Piketty, T., Saez, E., and Zucman, G. (2022). World inequality report 2022. Harvard University Press.

Cramer, K. F. (2025). Bank presence and health. Review of Finance, 29(5):1497–1535.

Crawford, G. S., Pavanini, N., and Schivardi, F. (2018). Asymmetric information and imperfect competition in lending markets. American Economic Review, 108(7):1659–1701.

Dang, D. A. and La, H. A. (2019). Does electricity reliability matter? evidence from rural Vietnam. Energy Policy, 131:399–409.

Demirgüç-Kunt, A. and Klapper, L. (2012). Financial inclusion in africa: An overview. Journal of African Economies, 21(3):34–68.

Demirgüç-Kunt, A. and Levine, R. (2009). Finance and inequality: Theory and evidence. Annu. Rev. Financ. Econ., 1(1):287–318.

Desai, S. and Vanneman, R. (2018). National Council of Applied Economic Research, New Delhi. India Human Development Survey (IHDS), 2012. Ann Arbor, MI: Inter-university Consortium for Political and Social Research, University of Michigan.

Emran, S. (2023). Personal communication. Email.

Evans, P. and Karras, G. (1996a). Convergence revisited. Journal of monetary economics, 37(2):249–265.

Evans, P. and Karras, G. (1996b). Do economies converge? evidence from a panel of us states. The review of Economics and Statistics, pages 384–388.

Fischer, R. and Huerta, D. (2021). Wealth inequality and the political economy of financial and labour regulations. Journal of Public Economics, 204:104553.

Fonseca, J. and Matray, A. (2022). The real effects of banking the poor: Evidence from brazil. Technical report, National Bureau of Economic Research.

Gibson, J., Olivia, S., Boe-Gibson, G., and Li, C. (2021). Which night lights data should we use in economics, and where? Journal of Development Economics, 149:102602.

Gupta, N. and Sedai, A. (2023). Disentangling the effects of financial inclusion on household well-being. Available at SSRN 4393250.

Heblich, S. and Trew, A. (2019). Banking and industrialization. Journal of the European Economic Association, 17(6):1753–1796.

Hsieh, C.-T. (2009). The allocation of talent and us economic growth. Quarterly Journal of Economics, 124(2):717–768.

Imbens, G. and Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. Review of Economic Studies, 79(3):933–959.

Islam, N. (1995). Growth empirics: a panel data approach. Quarterly Journal of Economics, 110(4):1127–1170.

Jack, W. and Suri, T. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. American Economic Review, 104(1):183–223.

Ji, Y., Teng, S., and Townsend, R. M. (2023). Dynamic bank expansion: spatial growth, financial access, and inequality. Journal of Political Economy, 131(8):2209–2275.

Jiao, D. and Mo, M. (2023). Bank expansion, firm dynamics, and structural transformation: Evidence from india's policy experiment. Firm Dynamics, and Structural Transformation: Evidence from India's Policy Experiment (May 1, 2023).

Karlan, D. and Zinman, J. (2011). Microcredit in theory and practice: Using randomized credit scoring for impact evaluation. Science, 332(6035):1278–1284.

Khanna, G. and Mukherjee, P. (2023). Political accountability for populist policies: Lessons from the world's largest democracy. Journal of Public Economics, 219:104819.

Kraay, A. (2006). When is growth pro-poor? evidence from a panel of countries. Journal of Development Economics, 80(1):198–227.

Lamba, R. and Subramanian, A. (2020). Dynamism with incommensurate development: The distinctive indian model. Journal of Economic Perspectives, 34(1):3–30.

Lamichhane, D. K. and Mangyo, E. (2011). Water accessibility and child health: Use of the leave-out strategy of instruments. Journal of Health Economics, 30(5):1000–1010.

Levitt, S. D. and Snyder Jr, J. M. (1997). The impact of federal spending on house election outcomes. Journal of political Economy, 105(1):30–53.

Madsen, J. B., Islam, M. R., and Doucouliagos, H. (2018). Inequality, financial development and economic growth in the oecd, 1870–2011. European Economic Review, 101:605–624.

Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A contribution to the empirics of economic growth. Quarterly Journal of Economics, 107(2):407–437.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. Journal of Econometrics, 142(2):698–714.

Merfeld, J. and Morduch, J. (2023). Poverty at higher frequency.

Mian, A., Sufi, A., and Verner, E. (2019). How do credit supply shocks affect the real economy? the productive capacity and household demand channels. The Journal of Finance.

Moretti, E. (2010). Local labor markets. Handbook of Labor Economics, 4:1237–1313.

Mumtaz, H. and Theophilopoulou, A. (2017). The impact of monetary policy on inequality in the UK. an empirical analysis. European Economic Review, 98:410–423.

Ohlan, R. (2013). Pattern of regional disparities in socio-economic development in india: District level analysis. Social indicators research, 114:841–873.

Philippon, T. and Reshef, A. (2012). Wages and human capital in the us finance industry: 1909–2006. The Quarterly Journal of Economics, 127(4):1551–1609.

Prakash, N., Rockmore, M., and Uppal, Y. (2019). Do criminally accused politicians affect economic outcomes? evidence from india. Journal of Development Economics, 141:102370.

Rajan, R. G. (2015). A hundred small steps: Report of the committee on financial sector reforms.

Rajan, R. G. and Ramcharan, R. (2011). Land and credit: A study of the political economy of banking in the united states in the early 20th century. Journal of Finance, 66(6):1895–1931.

Rajan, R. G. and Zingales, L. (1998). Financial dependence and growth. The American Economic Review, 88(3):559.

Sala-i Martin, X. X. (1996). The classical approach to convergence analysis. The economic journal, 106(437):1019–1036.

Sedai, A. K., Vasudevan, R., Pena, A. A., and Miller, R. (2021). Does reliable electrification reduce gender differences? evidence from india. Journal of Economic Behavior & Organization, 185:580–601.

Young, A. T., Higgins, M. J., and Levy, D. (2008). Sigma convergence versus beta convergence: Evidence from us county-level data. Journal of Money, Credit and Banking, 40(5):1083–1093.

Young, N. (2017). Banking and growth: Evidence from a regression discontinuity analysis.

Data Availability Statement

The administrative and household survey data used in this study are publicly available. The RBI–MOF administrative data were obtained under agreement from Kim Fe Cramer and cannot be publicly shared. For replication purposes, these data have been shared with the journal staff. Interested researchers may request access to the RBI–MOF data from the original source.