**Ashish K. Sedai**
Assistant Professor, Department of Economics, University of Texas at Arlington
Arlington, Texas, United States
Email: ashish.sedai@uta.edu · Phone: 970.690.3511
Web: sites.google.com/view/ashishsedai

August 14, 2026

Selection Committee
Workshop on Development Economics and Networks for Early-Career Researchers
National Bureau of Economic Research
Cambridge, Massachusetts

Dear Professors Breza, Viviano, and Chandrasekhar,

I am writing to apply to the Workshop on Development Economics and Networks for Early-Career Researchers, to be held at the NBER in Cambridge on December 5, 2026. I am an Assistant Professor in the Department of Economics at the University of Texas at Arlington. I received my PhD in Economics from Colorado State University in 2022 and so fall within the workshop's window for researchers within five years of the doctorate. My work sits at the intersection of development economics, finance, and the economics of networks.

I would like to present my working paper, "Financial Inclusion and the Reshaping of Ethno-Linguistic Divisions," written with Saumitra Jha (Stanford Graduate School of Business) and Pratyush Kumar Panda (Indian Institute of Management, Ahmedabad). Using a fuzzy regression discontinuity design built on India's 2005 Bank Branch Authorization Policy, we find that financial inclusion lowered measured ethnic fractionalization while raising incomes and reducing conflict, but that it did so by relocating groups and sorting them anew through caste and kin networks rather than by integrating them. Networks are the mechanism at the center of the paper. They carry the jobs, credit, and insurance that draw migrants, they govern how those migrants settle, and they hold the interethnic complementarity whose erosion we measure. The paper fits the workshop's focus on the frontier of empirical network research in development, and I would value the chance to discuss it there.

Should my application be shortlisted, Dr. Ray Miller (Associate Professor of Economics, Colorado State University; ray.miller@colostate.edu) can provide a letter of recommendation.

My complete contact information appears above, and I am happy to supply anything further the committee needs. Thank you for considering the application.

Sincerely,

Ashish K. Sedai

# Statement of Purpose

Ashish K. Sedai · Workshop on Development Economics and Networks for Early-Career Researchers

My research asks how the spread of markets and formal institutions reshapes the social structure of developing economies, not only how much people earn but who they live beside, transact with, and depend on. I work at the intersection of development economics, finance, and the economics of networks, using research designs built on natural policy experiments and nationally representative microdata from India to recover effects that headline aggregates hide.

The paper I would present, "Financial Inclusion and the Reshaping of Ethno-Linguistic Divisions" (with Saumitra Jha and Pratyush Kumar Panda), is the current center of this agenda. We study India's 2005 Branch Authorization Policy, which mandated bank branch expansion into districts where the ratio of population to branches exceeded the national average, and we exploit the resulting discontinuity in a fuzzy regression discontinuity design. Branch expansion lowered measured fractionalization by roughly seventeen percent, raised consumption, reduced poverty, and cut local crime and conflict. Read the usual way, this looks like modernization confirmed: prosperity arriving alongside integration. We show the opposite. Diversity fell not because groups blended but because they separated across space. Minority and landless households left initially homogeneous districts for expanding, diverse labor markets, and at their destinations they sorted into existing caste and kin networks rather than dissolving into the population.

Networks are not incidental to this story. They are the mechanism. The caste and kin ties that migrants travel along are the channels through which jobs, credit, and insurance actually flow, so financial access redraws the map of who lives beside whom by working through them. What erodes as the two groups converge on the same work is the interethnic economic complementarity, the interdependence that a large literature treats as a foundation of tolerance. Measuring these ties directly, and the cohesion within groups that a polarization index captures where a fractionalization count cannot, is where I most want to strengthen the paper.

This is my reason for wanting to attend. The workshop covers the questions my work now runs into: how to measure social networks, how to identify diffusion and complementarity through them, and how to conduct inference when units are connected and treatment spills from one to another. These are problems my design raises but does not fully settle, and the workshop's format, in which work in progress is discussed with more established researchers, suits that stage well. I would also welcome the exchange with other economists early in their careers who work on related questions.

More broadly, my interests span financial inclusion and its effects on household welfare and gender, access to energy, water, and infrastructure in developing economies, the care economy and health, and the political economy of division and conflict, most of it built on field experiments and large survey and administrative data from India. Across these projects I keep returning to one view: that the social consequences of economic policy are often large, frequently unintended, and visible only when we look past headline aggregates to the networks and relationships beneath them. That is the perspective I would bring to the workshop, and the work I would hope to sharpen there.

# CURRICULUM VITAE

**Ashish K. Sedai**

*Assistant Professor, Economics*
Department of Economics
University of Texas at Arlington
*Arlington, Texas, United States*

Email: ashish.sedai@uta.edu
Website: sites.google.com/view/ashishsedai
Phone: 970-690-3511

## 1 Academic Positions

| | |
|---|---|
| Sep 2025 – Dec 2025 | *Visiting Scholar*, SIEPR, Stanford University |
| Aug 2022 – Present | *Assistant Professor*, Department of Economics, University of Texas at Arlington |
| Aug 2019 – Present | *Research Associate*, CAMA, Australian National University |
| 2012 – 2017 | *Assistant Professor*, Department of Economics, University of Delhi |

## 2 Education & Training

| | | |
|---|---|---|
| Colorado State University | Fort Collins, CO | Ph.D. Economics, May 2022 |
| Jawaharlal Nehru University | New Delhi, India | M.Phil. Economics, July 2015 |
| Jamia Millia Islamia | New Delhi, India | M.A. Economics, July 2012 |
| University of Delhi | New Delhi, India | B.A. (Hons.) Economics, July 2010 |

## 3 Working Papers

- Does Financial Inclusion Mitigate Social Exclusion? Revise and Resubmit: *Oxford Bulletin of Economics and Statistics*.
- Signing for Safety: Can Mandatory Marriage Registration Reduce Domestic Violence? Revise and Resubmit: *Economic Development and Cultural Change*.
- Digital Payments and Gendered Labor Reallocation.
- The Triple Engine Effect: Does Full Vertical Alignment Unlock the State?.
- Spousal Relationship and Adolescent Psychosocial Health: Evidence from a Randomized Control Trial. Funded RCT, Under Review: *Experimental Economics*.
- Can Financial Inclusion Increase Household Resilience to Natural Disasters? Selected for Special Issue Conference: *Journal of the Association of Environmental and Resource Economists*.
- Natural Disasters and Electoral Consequences: Evidence for Voter Participation and Choice in U.S. Presidential Elections.
- Disentangling the Impact of Financial Inclusion on Households: The Business Finance Channel. Working paper.
- Financialization and Fractionalization. Manuscript in preparation.
- Daughters Rise, Norms Fall. Manuscript in preparation.
- When Knowing is Not Enough: WASH Habits and Human Development. Funded RCT, Manuscript in preparation.
- Unemployment Counseling and Labor Market Aspirations. Funded RCT, Manuscript in preparation.
- Heat Trap: Can Climate Shrink Intergenerational Mobility? Under Review: *Journal of Environmental Economics and Management*.

## 4 Publications

### 4.1 Household Finance and Gender

- Pakrashi, D., Rahut, D., Sedai, A.K., Sinha, A., Sonobe, T. (2026). Reshaping gender norms and building trust: Evidence from a community-based couple counseling RCT. *European Economic Review*.
- Sedai, A.K., Yasar, M., Crowder, W., & Bhukta, R. (2025). Banks and Inequality: Evidence from a Nationwide Branch Expansion Policy. *Journal of Money, Credit and Banking*.
- Bhukta, R., Jha, C.K., Joshi, S., & Sedai, A.K. (2025). Does bank expansion reduce domestic violence? Causal evidence from India. *Journal of Economic Behavior & Organization*.
- Maitra, P., Miller, R., & Sedai, A.K. (2023). Household welfare effects of ROSCAs. *World Development*.
- Sedai, A.K., Vasudevan, R., & Peña, A.A. (2021). Friends and benefits? Endogenous rotating savings and credit associations as an alternative for women's empowerment in India. *World Development*.

### 4.2 Household Infrastructure and Gender

- Miller, R., Mudenda, L.D., Sedai, A.K., & Vilims, L. (2025). Private sanitation and psychosocial health in adolescent girls. *World Bank Economic Review*.
- Sedai, A.K. (2026). Pipe Water, Employment and Health: A Gendered Analysis in India. *Review of Development Economics*.
- Bhukta, R., Pakrashi, D., Saha, S., & Sedai, A. (2024). Community electrification and women's autonomy. *Energy Economics*.
- Sedai, A.K., Jamasb, T., & Nepal, R. (2022). Electrification and socio-economic empowerment of women in India. *The Energy Journal*, 43(2).
- Sedai, A.K., Nepal, R., Jamasb, T., & Miller, R. (2021). Electrification and welfare for the marginalized: Evidence from India. *Energy Economics*, 102.
- Sedai, A.K., Jamasb, T., & Nepal, R. (2021). Flickering lifelines: Electrification and household welfare in India. *Energy Economics*, 94.
- Sedai, A.K., Vasudevan, R., Peña, A.A., & Miller, R. (2021). Does reliable electrification reduce gender differences? Evidence from India. *Journal of Economic Behavior & Organization*, 185.

### 4.3 Care Economy and Health

- Sonobe, T., Sedai, A.K., Sinha, A., & Rahut, D.B. (2025). Elderly Caregiving: A Gendered Analysis on Caregivers' Labor, Time-use, and Well-being. *Asian Economic Papers*, MIT Press, 24(1), 159–177.
- Sinha, A., Sedai, A.K., Rahut, D.B., & Sonobe, T. (2024). Well-being costs of unpaid care: Gendered evidence from a contextualized time-use survey in India. *World Development*, 173, 106419.
- Miller, R., Mudenda, L.D., & Sedai, A.K. (2024). Persistent agricultural shocks and child poverty. *Journal of Development Studies*, 1–16.
- Sinha, A., & Sedai, A.K. (2024). Why care for the care economy: Empirical evidence from Nepal. *Eastern Economic Journal*.
- Miller, R., Chin, S., & Sedai, A.K. (2022). The welfare cost of late-life depression. *Journal of Economic Behavior & Organization*, 204, 15–36.
- Miller, R., & Sedai, A.K. (2022). Opportunity costs of unpaid caregiving: Evidence from panel

time diaries. *The Journal of the Economics of Ageing*, 100386.

### 4.4 Environment, Human and Physical Capital

- Cruz, M.D., Jha, C.K., Kirşanlı, F., & Sedai, A.K. (2023). Corruption and FDI in natural resources: The role of economic downturn and crises. *Economic Modelling*, 106122.
- Sedai, A.K., Sinha, A., Nepal, R., & Kumar, A. (2023). Are autocracies bad for the environment? Global evidence from two centuries of data. *The Energy Journal*, 44(2).
- Azhgaliyeva, D., Rahut, D., & Sedai, A. (2026). Gender and energy–unveiling the nexus of equality and sustainability. *Energy Economics*, 109266.
- Sedai, A.K. (2019). Wages in imperfect markets: A post-reforms study of Indian manufacturing. *Journal of South Asian Development*, 14(3), 257–280.
- Sedai, A.K. (2017). Market concentration and labour employment in Indian organized manufacturing, post-reforms. *Journal of Social & Economic Development*, 19(1), 94–110.

### 4.5 Industrial Organization, Finance and Political Economy

- Sinha, A., & Sedai, A.K. (2025). National river conservation plan and water pollutants in India. *Economic Analysis and Policy*, 85, 2192–2206.
- Sedai, A.K. (2019). Why so serious about foreign capital? *International Journal of Financial Studies*, 7(3), 47.
- Sedai, A.K. (2019). History of anxiety and possibility: Revisiting Keynes' technological unemployment. *Economic & Political Weekly*, 54(44).
- Sedai, A.K., & Kulkarni, K. (2018). Competition to catch the capital flight. *Journal of Applied Business & Economics*, 20(5).
- Sedai, A.K. (2017). Wage determination under imperfect competition. *Economic & Political Weekly*, 52(49), 77.

### 4.6 Policy Papers

- Bhukta, R., Pakrashi, D., Saha, S., & Sedai, A. (2025). Powering progress: How reliable community electrification boosts women's autonomy. *Ideas for India*.
- Azhgaliyeva, D., Dirksen, J., Korwatanasakul, U., Lima de Miranda, K., Okitasari, M., Rahut, D., Sedai, A.K., Sonobe, T., & Takemoto, A. (2024). Towards an evidence base for the just transition (G-7 meeting Italy). *Istituto Affari Internazionali*.
- Sedai, A.K. (2022). Who benefits from an indoor piped drinking water supply? A gendered analysis. *Ideas for India*.
- Bernasek, A., Bhattarai, N., Brundage, B., Miller, R., Mudenda, L., Nguyen, A., Nguroho, W., Pena, A., Sedai, A., Shakya, P., & Thongam, A. Exploring Economic Empowerment and Marginalization using Data from Developing Countries. REDI Report.

## 5 Teaching Experience

| | |
|---|---|
| 2025 | Macroeconomics; Applied Econometrics |
| 2024 | Advanced Business Data Analytics |
| 2023 | Applied Econometrics; Economic Growth and Development |
| 2022 | Principles of Microeconomics; Principles of Macroeconomics |
| 2021 | Principles of Microeconomics; Economics of International Finance |
| 2020 | Gender in the Economy; Principles of Macroeconomics |
| 2017 | Intermediate Macroeconomics; Statistical Methods for Economics |
| 2016 | Economic Development; Money and Banking; Environmental Economics |
| 2012 – 2015 | Intermediate Microeconomics; Econometrics; Statistics; Macroeconomics |

## 6 Grants & Professional Experience

| | |
|---|---|
| Sep 2024 | Principal Investigator, Field Experiment<br>Informal Arbitration in India<br>Sponsor: Asian Development Bank Institute; USD 52,000 |
| Sep 2024 | Principal Investigator, Randomized Control Trial<br>Youth Unemployment in India<br>Sponsor: Asian Development Bank Institute; USD 75,000 |
| Sep 2023 | Principal Investigator, Randomized Control Trial<br>WASHing up the Futures<br>Sponsor: Asian Development Bank Institute; USD 65,000 |
| May 2022 | Principal Investigator, Randomized Control Trial<br>Unpaid Care and Time-use in India<br>Sponsor: Asian Development Bank Institute; USD 65,000 |
| 2018 – 2021 | Research Associate, Poverty Action Center, Colorado State University |
| 2020 | Consultant, United Nations, Economic and Social Commission for Asia Pacific |
| 2019 | Consultant, World Bank, Global Trade Analysis Project, Washington, D.C. |
| 2018 | Consultant, United Nations, Economic and Social Commission for West Asia |
| 2018 | Summer Research Assistant, 2M Research, Washington, D.C. |
| 2016 | Research Assistant, J-PAL India |

## 7 Media Mentions

- UTA economist earns global prize for mental health study (2025).
- Channel 5, NBC & Union of Auto Workers Strike's Economic Implications (September 2023).
- Underrated Guests, Mercatus Center (Ideas for India, Review), George Mason University (2023).
- Economic expert says not to panic over announced tariffs' effect on the stock market yet.

## 8 Department, University, Editorial & Referee Service

**University Service**

Search Committee Chair: Synergies for Sustainable Development Cluster Hire (2026).
Assurance of Learning (AOL) Committee Member Professional Development (2026).

Search Committee Member: Synergies for Sustainable Development Cluster Hire (2025).
Member, Department of Economics Scholarship Committee (2023–Present).

**Editorial Service**
Associate Editor, *Economic Analysis and Policy* (2025–present).
Guest Editor (Special Issue), *Energy Economics*: Gender and Energy (2024).

**Referee Service**
Journal of Development Economics, Journal of Banking and Finance, World Bank Economic Review, Journal of Economic Behavior and Organization, World Development, Energy Policy, Energy Economics, Review of Social Economy, Journal of Policy Analysis and Management, The Electricity Journal, Economic Modeling, Economic Inquiry, Southern Economic Journal

**Professional Memberships**
American Economic Association (AEA), Indian Economic Association, Association for Social Economics (ASE), Eastern Economic Association (EEA).

## 9 Invited Talks & Papers Selected for Conferences

2026 Stanford Behavioral Economics Workshop (Daughters Rise, Norms Fall)
2026 Invited Talk on Climate Change in Coasts, Asian Development Bank
2025 Stanford Eddie Lunch (Financialization and Fractionalization)
2025 Economics of Mental Health Workshop, University of Virginia
2025 Eastern Economic Association Conference
2025 Invited Speaker, Department of Economics, Indian Institute of Technology, Kanpur
2025 Amitava Bose Memorial Workshop, Indian Institute of Management, Kolkata
2025 Invited Speaker, 21st Century India Center Virtual Seminar Series, UC San Diego
2024 NTxEC Inaugural Conference, University of North Texas
2024 KDI & World Bank Conference on Development Economics, Seoul, South Korea
2024 Inaugural TEXHEN Conference on Health, University of Texas at San Antonio
2024 6th World Bank Public Finance Conference, Washington, D.C.
2023 NBER Conference, Capital Markets, Technology, Financial Inclusion, and Economic Growth
2023 Firms, Trade, and Development Conference (co-hosted by Yale University, EGC and IGC)
2023 Chair, Developmental Issues and Policies in South Asia, Southern Economic Association
2023 Invited Speaker, International Water Management Institute, CGIAR, New Delhi, India
2023 American Economic Association, ASSA, New Orleans, Louisiana
2022 North American Meetings of the Regional Science Association, Montreal, Canada
2022 Southern Economic Association Conference, Florida
2022 Allied Social Science Associations (ASSA) Conference, Boston (Online)
2021 Korea Development Institute Annual Conference, Seoul (Online)
2021 Sustainable Energy Transformation Initiative, Duke University, North Carolina
2021 ASSA, American Economic Association Meeting (Online)

## 10 Honors, Scholarships and Fellowships

| | |
|---|---|
| 2025 | Standard Error Best Paper Award<br>Economics of Mental Health Conference, University of Virginia |
| 2025 | Visiting Scholarship, Stanford University |
| 2022 | Warren Samuel's Prize for Best Paper, Association for Social Economics |
| 2021 | Invited Presentation, Korea Development Institute Conference |
| 2021 | Outstanding Graduate Researcher Award, Dept. of Economics, Colorado State University |
| 2021 | Graduate Dissertation Fellowship, Department of Economics, Colorado State University |
| 2019 | Best Paper Award, Association for Institutional Thought, WSSA |
| 2017 – 2022 | Graduate Student Fellowship, Colorado State University |
| 2016 | Best Graduate Thesis Award, Jawaharlal Nehru University |

## 11 References

| **Name** | **Relationship** | **Affiliation** |
|---|---|---|
| Ramaa Vasudevan | Professor | Colorado State University; ramaa.vasudevan@colostate.edu |
| Dil Bahadur Rahut | Vice Chair of Research | Asian Development Bank Institute; drahut@adbi.org |
| Ray Miller | Assistant Professor | Colorado State University; ray.miller@colostate.edu |
| Anita Alves Pena | Professor | Colorado State University; anita.pena@colostate.edu |

## 12 PhD Coursework

*Colorado State University, Fort Collins, CO. PhD in Economics, 2017 to 2022*

**Core Courses**

- ECON 501 Quantitative Methods for Economists
- ECON 505 History of Economic Thought
- ECON 606 Microeconomic Analysis I
- ECON 706 Microeconomic Analysis II
- ECON 604 Macroeconomic Analysis I
- ECON 704 Macroeconomic Analysis II
- ECON 635 Econometric Theory I
- ECON 737 Advanced Econometrics
- ECON 705 Heterodox Approaches to Economics

**Field and Advanced Electives**

- ECON 735 Econometric Theory II
- ECON 760 Theories of Economic Development
- ECON 765 Natural Resources and Economic Development
- ECON 741 Advanced Environmental Economics
- ECON 740 Advanced Natural Resource Economics
- ECON 698 Research (Technical Paper)

# Financial Inclusion and the Reshaping of Ethno-Linguistic Divisions*

Saumitra Jha† Pratyush Kumar Panda‡ Ashish K Sedai§

August 14, 2026

**Abstract**

Does financial development dissolve ethnic divisions or reorganize them? We study India's 2005 Branch Authorization Policy, which mandated bank branch expansion into districts whose ratio of population to branches exceeded the national average, and we exploit the resulting discontinuity in a fuzzy regression discontinuity design. Branch expansion lowered ethno-religious fractionalization by roughly seventeen percent, raised household consumption, reduced poverty, and produced large declines in local crime and conflict. Yet the fall in measured diversity was not integration. The economic gains concentrated in initially diverse districts, where credit constraints bound most tightly, and drew minority and landless workers out of initially homogeneous districts toward expanding labor markets. Their departure, together with faster majority household formation in the places they left, raised the majority share at the origin, so that fractionalization fell where diversity had been low rather than where it had been high. At their destinations, migrants sorted into existing caste and kin networks rather than dissolving into the population, and the occupational complementarity between the two groups eroded as their work converged, so that the economic interdependence binding them thinned even as fractionalization fell. What kept this reorganization peaceful was the size of the economic dividend: lower poverty suppressed the grievances on which collective violence feeds. Financial inclusion, we conclude, can reduce measured fractionalization and secure social peace while deepening, rather than dissolving, the divisions it appears to erase.

*We thank Marcella Alsan, Matthew Gentzkow, Ilya Segal, Modibo Camara, Debraj Ray, Maitreesh Ghatak, and other participants at the Eddie Lunch, Stanford University, 2025 and Amitava Bose Memorial Workshop, IIM-C, 2025.

†Stanford Graduate School of Business, Stanford University. Email: saumitra@stanford.edu

‡Indian Institute of Management, Ahmedabad. Email: phd23pratyushk@iima.ac.in

§Department of Economics, University of Texas at Arlington and SIEPR, Stanford University. Email: ashish.sedai@uta.edu

# 1 Introduction

Economic development is widely expected to dissolve the divisions of caste, language, and creed. As markets thicken and incomes rise, the argument runs from Montesquieu to modern modernization theory, ascriptive identities lose their grip and diverse societies grow more integrated. This paper studies a large and cleanly identified episode of financial development in India and reaches a conclusion at odds with that expectation. The expansion of formal banking did reduce measured ethnic diversity, and it did so while raising incomes and cutting violence, the very picture of development succeeding. But it lowered diversity by driving groups apart, not by drawing them together.

The distinction between these two routes to a lower number is not a nicety. Ethnic fractionalization is among the most durable correlates of weak public goods provision, fragile institutions, and civil conflict, and a large empirical literature reads a decline in it as unambiguous good news (Easterly and Levine, 1997; Alesina et al., 2003; Miguel, Satyanath, and Sergenti, 2004; Montalvo and Reynal-Querol, 2005). We show that the same decline can be produced by a reorganization that leaves groups more separated, and more sharply opposed, than before. What falls is a statistic; what it is taken to stand for, the easing of relations between groups, need not move at all, and here it moved the other way. Recovering this requires opening up the mechanism behind the number, and it is the mechanism, more than the number, that is our subject.

We reach it by studying finance, a force at once among the most powerful and the least examined of those acting on social composition. Credit and insurance are among the most unequally held of economic resources, and in fragmented societies their distribution has long traced the lines of division, with lower castes and religious minorities furthest from the formal system (Burgess and Pande, 2005; Hnatkovska, Lahiri, and Paul, 2012; Deshpande, 2000). When a bank arrives, it can redraw the local map of opportunity within a few years. Yet finance is almost always studied for what it does to income and almost never for what it does to who lives where. India after 2005 lets us ask the second question with unusual clarity.

The logic is visible in miniature in two districts of coastal Gujarat. In 2004, Bhavnagar, on the Saurashtra peninsula, and Bharuch, at the mouth of the Narmada, were nearly indistinguishable: mid sized industrial and port districts within one state, sharing a language, an administrative history, and a comparable economic base. Household consumption in the two differed by two percent, and their social composition by less, with ethno-religious fractionalization at 0.697 in Bhavnagar and 0.698 in Bharuch. They differed in one respect that neither chose. Under the Reserve Bank of India's 2005 Bank Branch Authorization Policy, a district counted as underbanked if its ratio of population to bank branches exceeded the national average of 14,820. Bhavnagar, at 15,635 people per branch, sat just above that line; Bharuch, at 11,130, sat well below it. The rule steered the mandated wave of new branches toward Bhavnagar and left Bharuch, already counted as adequately served, untouched. Nothing about the two places explains which side of the line each fell on; the line was drawn in Mumbai, from a national ratio, and it happened to

run between them.

Over the seven years that followed, formal finance reached one district and not the other, and the two came apart. The share of households holding a bank loan rose from two percent to twenty in Bhavnagar while barely moving in Bharuch, and poverty in Bhavnagar fell by ten percentage points, roughly three times the decline next door. So far this is a familiar story of credit and welfare. What is not familiar is the third divergence. The two districts, identical in social composition at the outset, pulled apart in it: fractionalization in Bhavnagar fell to 0.57 while Bharuch's held at 0.65. The eight point gap opened in exactly the years their banking networks diverged, and it cannot be charged to one district having had further to fall, since the two began within a thousandth of one another. Finance moved not only incomes but the measured composition of a place.

Two districts, of course, settle nothing. Bhavnagar and Bharuch differ in ways beyond the branch rule, and a single comparison can neither rule out coincidence nor recover a causal effect. What gives the comparison force is that the 2005 policy drew the same line through every district in India, by a predetermined national metric that no local actor could manipulate: districts just above the threshold received a surge of branches, those just below did not. We exploit this discontinuity in a fuzzy regression discontinuity design over the full national sample, instrumenting a district's realized underbanked status with whether its population to branch ratio crossed the national average. What is visible in Gujarat recurs across the country.

Branch expansion reduced ethno-religious fractionalization by about seventeen percent relative to the sample mean, an effect that holds across measures built from a nationally representative household panel, from repeated employment surveys, and from the population census, and along the caste, religious, and linguistic margins alike. Diversity fell as consumption rose, poverty fell, formal credit spread, and local crime and conflict declined sharply, property and violent crime by a quarter to a half and recorded conflict and casualties by more still. Off the headline numbers, this is modernization vindicated: prosperity arriving hand in hand with integration.

It is not, and the way it is not is the argument of the paper. The gains from branch expansion did not fall evenly across space. They concentrated in the districts where financial exclusion had bitten hardest, the initially diverse ones, where credit had been scarcest and coordination weakest, and there they were largest: consumption rose, casual labor gave way to salaried work, and workers moved out of agriculture into manufacturing and services. Within these districts the gains accrued disproportionately to minority households, those who had begun furthest from the formal system and who stood to gain most when a branch opened nearby. And it was these households who moved. Drawn toward the expanding districts, minorities left the initially homogeneous ones in disproportionate numbers.

The mechanism now turns on an arithmetic that a story of integration cannot accommodate. Fractionalization is the chance that two people drawn at random belong to different groups, and it falls whenever a population tilts toward a dominant group. When minority households leave a homogeneous district, the share of the majority they leave behind rises, and measured

fractionalization falls, not in the district that received them but in the one they left. Diversity declined, in other words, where it had been low rather than where it had been high, in the places that sent their minorities away rather than in the places that took them in, and the decline was deepened by faster household formation among the majority that remained. Finance lowered measured fractionalization by separating groups across space, not by blending them within any place. This is the paper's signature fact, and it inverts the usual reading of the index: the decline is located at the origins of migration and is a symptom of separation, not of its reverse.

What unfolded at the destinations was further still from integration. Arriving in the diverse, dynamic districts, migrants did not dissolve into them but sorted into their own caste and kin networks, the channels through which jobs, credit, and insurance actually flowed. What became of the economic relationship between the groups is the concrete mark of deepening division. As migrants took up work alongside the majority, the occupational distributions of the two converged; doing more of the same work rather than filling distinct and interdependent roles, they became more substitutable and less complementary. The interethnic economic complementarity that a large literature identifies as a foundation of tolerance, the interdependence that gives each group a stake in the other's prosperity and safety (Jha, 2013b,a), did not deepen as prosperity spread. It eroded. Alongside this, the ties within groups tightened: inter-caste marriage rose within the majority bloc while marriage across religion did not move, and the majority grew in demographic weight where minorities had thinned. We treat this marriage and household-formation evidence as suggestive and report it in the appendix; it is the erosion of complementarity, which we measure directly, that carries the argument.

This is the question the paper is built to answer: if groups turned inward and the ties between them thinned, why did violence fall? The answer is the size of the shared dividend. Lower poverty and higher, more secure incomes suppressed the material grievances on which collective violence feeds, and forcefully enough to override the pressures pushing the other way, the sharper boundaries, the growing dominance of the majority, and the very erosion of complementarity that ordinarily breeds friction. Prosperity, in this setting, did the work that integration is usually assumed to do; it substituted for the interethnic ties it was dissolving. The tension is genuine. Financial inclusion delivered large and broadly shared material gains and a real reduction in violence, achievements that should not be understated. But it secured social peace by making groups prosperous, not by bringing them together, and it deepened rather than dissolved the divisions its headline measure appears to erase.

These findings speak to four strands of literature. To the large body of work that treats ethnic fractionalization as a deep and largely fixed feature of a place, impeding public goods, growth, and cooperation (Easterly and Levine, 1997; Alesina et al., 2003; Miguel, Satyanath, and Sergenti, 2004; Putnam, 2007), we show that measured diversity responds to economic policy over a few years and, more consequentially, that it can fall without any improvement in the relations the index is meant to proxy, a caution that applies wherever the index serves as an outcome. To the study of finance and real outcomes in developing economies, and in India from the social

banking experiment onward (Burgess and Pande, 2005; Young, 2017; Cramer, 2025; Dehejia and Gupta, 2022; Gupta and Sedai, 2023), which has shown that branch expansion raises consumption and relaxes credit constraints, we add its effects on the composition of the population and the structure of relations between groups, outcomes finance has not previously been shown to move.

To the literature on inter-ethnic complementarity and tolerance, which holds that economic interdependence restrains conflict by giving groups a stake in one another's security (Jha, 2013b,a), we bring a case in which the tie eroded and yet peace held, identifying prosperity as a pacifying force that can substitute for complementarity rather than presuppose it; whether a peace resting on the dividend is as durable as one resting on complementarity is a question our setting, in which prosperity does not reverse, cannot settle, and we say so. To work on migration and the spatial sorting of populations (Bau et al., 2025), we show that directed migration, not assimilation in place, is the channel through which financial access redraws the map of who lives beside whom. A measure that weights the internal cohesion of groups rather than merely counting their diversity registers the same reorganization directly; we report this polarization-based corroboration in Appendix B.

The paper proceeds as follows. Section 2 develops the conceptual framework, isolating the arithmetic by which measured diversity can fall as groups separate and setting out the predictions we test. Section 3 describes the data and Section 4 the design and its validity. Section 5 presents the effect on fractionalization and works through the mechanisms, the concentration of gains, the reorganization of the labor market, directed migration, and social consolidation, before turning to crime and conflict. Section 6 examines heterogeneity, Section 7 reports robustness, and Section 8 concludes.

## 2 Conceptual Framework

The argument has a simple structure. Measured diversity is a property of the shares of a population, not of the relations among them, so a policy that rearranges those shares in space can lower measured diversity while pulling groups apart. Financial access is such a policy, because the returns it creates are largest where fragmentation was greatest, and the workers it moves are drawn from the places fragmentation was least. And the reorganization it sets off can be peaceful, not because it softens the boundaries between groups but because the prosperity it delivers outweighs them. This section develops each step through the relevant theory.

### 2.1 What fractionalization measures, and what it does not

For a district $d$ with ethno-religious groups $i \in \{1, \ldots, G\}$ and population shares $p_{id}$, fractionalization is the probability that two individuals drawn at random belong to different groups (Easterly

and Levine, 1997; Alesina et al., 2003),

$$\text{ERF}_d \;=\; 1 - \sum_{i=1}^{G} p_{id}^2. \tag{1}$$

The index rises with the number and evenness of groups and falls as a population tilts toward a dominant one. Two features of (1) do the work that follows. First, $\text{ERF}_d$ is silent on how groups relate: it is equally low for a district whose communities live in harmony and for one whose single group has driven the others out. It records the composition of a place, not its cohesion, a limitation long recognized in the measurement literature and the motivation for indices of polarization that weight within group identification (Montalvo and Reynal-Querol, 2005; Esteban, Mayoral, and Ray, 2012). Second, and as a consequence, $\text{ERF}_d$ moves with the spatial redistribution of groups. Take a district with a dominant majority of share $p$ and a minority of share $1-p$; as the minority departs, $p \to 1$ and $\text{ERF}_d \to 0$. Measured diversity falls at the place the minority leaves, and it falls not because anyone integrated but because groups separated. The same movement raises the majority's share at the origin while adding, at the destination, migrants who cluster within their own group, so the receiving district, already diverse, is left comparatively unchanged. A policy that draws the minorities of homogeneous places toward diverse ones therefore lowers aggregate fractionalization even as it pushes groups apart. Appendix Table D1 fixes the magnitude: shifting a district of four equal groups toward a dominant one lowers ERF from 0.750 to 0.715. The essential point to carry forward is that a fall in this number is consistent with integration and equally consistent with its opposite, and the two are distinguished not by the number but by where the fall occurs and by what becomes of the ties between groups. A measure that weights within group cohesion resolves the ambiguity in the same direction; we defer this polarization-based check to Appendix B.

### 2.2 Why finance separates groups

Districts enter the policy differing in initial diversity and in the tightness of the credit constraints their households face, and the two are linked. Where formal finance was thinnest and collateralizable relationships scarcest, in the fragmented districts, exclusion had bitten hardest, so this is where bank entry does the most to lower the cost of credit, underwrite non agricultural enterprise, and raise the returns to locating in the district. These become the dynamic destinations. The workers most responsive to the shift are those with the least holding them in place and the most to gain from entering the formal economy: minority households, historically furthest from formal credit, and landless households, without land to anchor them. Improved returns pull them toward the diverse districts.

How they settle is governed by network complementarity. Migrants reach jobs, credit, and insurance through their own caste and kin networks, so they cluster within their own group at the destination rather than dispersing across it, which raises within group density and the incidence

of marriage within the group. Consolidation of a place's dominant community need not fragment it: as the majority's internal subgroups draw together, the majority coheres as a bloc even while its component castes blur, so that the boundary fractionalization is most apt to register, the one between the majority and the minorities, grows sharper rather than softer. This is why a decline in the index and a hardening of the principal social cleavage can occur together, and it is the first half of the reorganization the data reveal.

### 2.3 Consolidation and the erosion of complementarity

The second half concerns the economic relationship between groups. A long tradition in political economy holds that interdependence sustains tolerance: where groups occupy distinct and complementary roles in production, each has a material stake in the other's prosperity and security, and this stake restrains conflict (Jha, 2013b,a). Complementarity is the tie; its opposite, substitutability, is rivalry, as groups competing for the same work have reason to see one another's gain as their own loss. The reorganization set off by financial access works against complementarity. As migrants enter the local labor market alongside the majority, they take up similar work, and the occupational distributions of the two groups converge; the groups become more substitutable and less complementary, and the economic interdependence that had bound them thins. Consolidation within and disengagement between are thus two faces of one process, and both are the reverse of integration. The prediction that follows is sharp and, on the complementarity account, ominous: as the tie between groups weakens, the standard restraint on conflict should weaken with it.

### 2.4 Conflict: grievance against rank

That prediction is one of two the reorganization generates, and they point in opposite directions. On one side, the growth of a dominant, cohesive bloc and the thinning of ties between groups raise friction: shifts in relative group size are associated with heightened victimization of the group whose standing is changing (Cikara, Fouka, and Tabellini, 2022), and the erosion of complementarity removes a restraint that would otherwise temper it (Jha, 2013b). On the other, the material dividend of branch expansion, lower poverty and higher, more secure incomes, suppresses the grievances on which collective violence feeds (Miguel, Satyanath, and Sergenti, 2004). The net effect is an empirical question of magnitudes, and it is the central one the crime and conflict results adjudicate. Our reading, borne out below, is that where the dividend is large it dominates: prosperity secures peace even as the ties that ordinarily secure it dissolve, and in this sense prosperity substitutes for complementarity rather than requiring it.

### 2.5 Testable implications

These considerations yield four implications that structure the empirical analysis.

**Proposition 1 (Directed migration and fractionalization)** *Bank branch expansion induces directed in migration of minority and landless workers toward initially diverse districts and out migration from initially homogeneous districts. Measured fractionalization falls, and the decline concentrates at the homogeneous origins rather than at the diverse destinations.*

**Proposition 2 (Concentration of gains)** *The gains from branch expansion, higher consumption, lower poverty, wider credit access, and structural change out of agriculture, concentrate in initially diverse districts and accrue disproportionately to minority households.*

**Proposition 3 (Consolidation without integration)** *The economic complementarity between groups weakens as their occupational distributions converge. Consistent with this, and more suggestively, ties within groups tighten, through marriage within the majority bloc and faster majority household formation in homogeneous districts.*

**Proposition 4 (Peace through prosperity)** *Crime and conflict fall, as the material dividend dominates the countervailing rank and complementarity pressures generated by consolidation.*

## 3 Data

We obtain annual district-level data on the number of commercial bank branches (excluding Regional Rural Banks, which were not covered under the BAP) from the Quarterly Statistics on Deposits and Credits of Scheduled Commercial Banks maintained by the Reserve Bank of India in its Basic Statistical Returns (BSR) database. Using information on district population from the Population Census 2001, we constructed the required running variable for the RD design. Compared with Young's (2017) national average of 14,915 and Cramer's (2025) estimate of 14,780, our computed national average of 14,820 is qualitatively consistent with previous studies.[1] The principal database for our study is the India Human Development Survey (IHDS), a nationally representative panel data survey of over 40,000 households, conducted in the form of two rounds between 2004-2005 (IHDS-1) and 2011-2012 (IHDS-2). This panel data allows us to examine pre-policy smoothness as well as evaluate the post-policy impact on our outcome variables. We merge this panel household survey data with the RBI BSR data and observe a total of 371 districts for our analysis. We create indices of fractionalization on ethnic and religious dimensions from the panel data; a companion index of polarization, which we use only for corroboration in the appendix, is constructed from the same information.[2]

Following Easterly and Levine (1997) and Alesina et al. (2003), we define ERF for a district to quantify the probability that two randomly selected individuals in a community belong to

[1] Appendix Figure C2 presents the histogram of population to bank branch ratio at the district level. The vertical line indicates the national average of the ratio: 14,820.

[2] See Appendix Table D15 for details on the definition and construction of the indices and data sources.

different ethno-religious groups.

$$\text{ERF}_d = 1 - \sum_{i=1}^{G} {p_{id}}^2$$

where $p_{id}$ is the population share of an ethno-religious group $i \in \{1, 2, ... G\}$ in a district $d$, with $G$ being the total number of groups in the district. This index captures the degree of heterogeneity along two distinct dimensions: the social group affiliation and the religion of the household. We complement this above metric with ERF index from the NSS $61^{st}$ (July 2004 - June 2005) and $68^{th}$ (July 2011 - June 2012) Employment and Unemployment Surveys and Ethno-Linguistic Fractionalization (ELF) from the 2001 and 2011 Population Census of India. We use measures of household consumption and poverty from IHDS: *Per Capita Consumption*, defined as annual per capita real consumption expenditures in rupees (winsorized and log transformed); and *Poverty*, a binary indicator that takes a value of one if the household's consumption expenditures are below the state poverty line, and zero otherwise. To capture financial inclusion, we use: *Loan from Bank*, a binary indicator that is equal to one if the household has taken a loan from bank, and zero otherwise; *Monthly Interest on Loan*, which is the average monthly interest rate paid on loans; and *Life Insurance Ownership*, a binary indicator that is equal to one if the household has owns a Life Insurance, and zero otherwise. The key mechanism for our analysis is migration. To provide evidence for compositional shifts across the pre-policy high and low fractionalized areas over the two years, we construct a binary indicator variable to capture whether a household belonged to an ethno-religious majority group in the pre-policy period, or not. We use this indicator to examine the inflow of in-migrants into a district by the level of fractionalization over the years. To document evidence on out-migration, we rely on the Tracking File from IHDS Round 2 (2011-12) and use our pre-policy indicator for the highly fractionalized areas to study out-migrants from initially High-ELF vs Low-ELF districts, along with their reasons. In addition, as suggestive evidence on the consolidation of the majority as a bloc, we examine the post-policy number of inter-caste marriages and births for the majority and minority groups across initially High-ERF and Low-ERF districts, which we report in the appendix. This is consistent with our argument that compositional changes in the population rationalize the observed decline in fractionalization. We supplement our household-level outcomes on migration with district-level administrative data using the Population Census Migration Tables. This database provides us information on the universe of migrants for all the districts of the Indian economy. We use the 2001 census to show pre-policy smoothness and the 2011 census to study in-migration for for the high and less fractionalized districts from our IHDS-RBI(BSR) matched sample. We provide some suggestive evidence on the impact of bank expansion on crime and conflict, which are a functional correlate of ethno-religious fractionalization. We use district-wise annually available administrative data from the National Crime Records Bureau (NCRB, 2004 and 2010) and the South Asia Terrorism Portal (SATP, 2004 and 2013). We draw information on various crimes from the NCRB database and total number of conflicts and casualties from the SATP corpus.

# 4 Empirical Strategy

## 4.1 Regression Discontinuity

We estimate the causal impact of bank branch expansion on ERF using a fuzzy regression discontinuity (RD) design (Young, 2017; Cramer, 2025; Gupta and Sedai, 2023). This design employs a two-stage estimation framework. In the first stage, we use the actual assignment of underbanked status by the RBI as the outcome variable. The first-stage discontinuity plot, as shown in Figure 1, tests the effectiveness of the computed district-level population to bank branch ratio to predict the assignment of underbanked status by the RBI. There is an evident discontinuous jump at the cutoff point in the likelihood of a district being underbanked[3]. In the second stage, we use the predicted value of the underbanked status, and estimate the Local Average Treatment Effect of bank expansion on our outcome variables with a triangular kernel function (Imbens and Lemieux, 2008; Cattaneo and Titiunik, 2022):

$$Y_{h,d} = \alpha + \beta_1 Treated_d + f(Population\ per\ Branch\ - Cutoff)_d + \varepsilon_d \tag{2}$$

where $Y_{h,d}$ is a household level outcome in district $d$, $Treated_d$ is an indicator variable equal to 1 if a district's $Population\ per\ Branch_d\ -\ Cutoff\ >\ 0$, qualifies the assignment rule to underbanked-status; $f(\cdot)$ is a flexible functional form to implement the fuzzy design; and $\varepsilon_d$ is an idiosyncratic error at the treatment level.

## 4.2 Sample Balancedness

Table **??** provides evidence on the validity of the RD design by examining pre-policy balance in observable district and household characteristics around the population-to-branch cutoff that determined under-banked status. The table reports mean values and corresponding standard errors for baseline covariates—including demographic characteristics, household consumption, access to credit, poverty incidence, and measures of social participation, across treated and control districts. Columns (1) and (2) show unconditional mean differences for all treated and control observations in the sample. Columns (3) and (4) restrict the comparison to observations lying within the optimal bandwidth on either side of the population-per-branch cutoff, estimated using the MSE-optimal bandwidth selector of Calonico et al. (2017). Standard errors, clustered at the district level, are reported in parentheses beneath each mean to account for intra-district correlation. Column (5) reports the local fuzzy RD estimates of the difference in means between treated and control districts within the same optimal bandwidth. These are bias-corrected using the procedure proposed by Calonico, Cattaneo, and Titiunik (2014), with standard errors adjusted for small-sample bias and clustering. The reported coefficients thus capture the discontinuous jump,

[3]We use the McCrary (2008) density test and fail to reject smoothness around the cutoff, as illustrated in Panel B of Figure 1. This test provides evidence that there is no selective sorting of districts into the treatment status around the national average cutoff of the policy

if any, in pre-policy characteristics at the national threshold that defined under-banked status. Across all specifications, none of the estimated coefficients in Column (5) are statistically significant at conventional levels. This absence of discontinuities in observable pre-policy characteristics confirms that districts just above and below the cutoff were ex ante similar in demographic structure, economic activity, and financial inclusion outcomes. In other words, the assignment rule generated by the 2005 Branch Authorization Policy produced a locally randomized environment around the threshold. This balance supports the identifying assumption that any post-policy differences in outcomes between treated and control districts can be causally attributed to the expansion of bank branches rather than to pre-existing differences in characteristics or trends. In addition, Appendix Table **??** extends these tests to supplementary outcomes including household in-migration and employment composition, showing similar smoothness and reinforcing the robustness of our design.

# 5 Impact of bank expansion on Fractionalization

## 5.1 Ethno-Religious Fractionalization

**Household Panel based Evidence.** We first examine the impact on fractionalization using the ERF index constructed from the IHDS panel survey, reported in Table 1. We rule out pre-policy discontinuity for the index in Panel (A) - Column (1). Compared to the control group, we find a 17% decrease in the post-policy index (Column (2)), relative to the sample mean. Estimates control for log population of the district from the 2001 Population Census, and log number of open functioning bank branches in the district in 2001. Panels B and C report comparable declines of 18% in ELF and Ethnic fractionalization among Hindus respectively, while satisfying pre-policy smoothness. Panels (A) and (B) of Figure 5 show the pre-policy smoothness and post-policy discontinuity in this household-based ELF index. We complement our results on IHDS-based ERF with the NSS and Census based measures, shown in Appendix Table D5. Panel A demonstrates the impact on ERF, constructed using information on the social group and religion affiliation of households from the NSS 2004-05 and 2011-12 Employment and Unemployment Surveys. Column (1) confirms pre-policy smoothness at the cutoff: the estimate is small and statistically insignificant, indicating that treated and control districts did not differ in ethno-religious fragmentation before the policy. Column (2) reports a 22.3% decline in ethno-religious fractionalization in treated districts, relative to the control mean of 0.623. Panel B shows the impact on ethnic fractionalization, restricting the analysis to Hindus, which isolates the caste dimension of fragmentation. Column (1) shows pre-policy smoothness, while Column (2) reports a post-policy estimate of -0.180, representing a 33.9% decline relative to the control mean of 0.530. Panel C reports the results from using the population-based fractionalization measure.[4] Column (1) reports the pre-policy coefficient, which shows smoothness in the outcome

[4]We draw on district-level population data on language groups and broad categories of Scheduled Castes and Scheduled Tribes from Population Censuses 2001 and 2011. Since different forms of ethnic division strengthen each

from the 2001 Population Census. Column (2) reports the post-policy RD estimate. Compared to the control group, the outcome from the 2011 Population Census exhibits around 30% decline, relative to the sample mean, after controlling for log district population from the 2001 Population Census and accounting for the male and female inter-district in-migration within a state, with residence in current district for above 20 years (Ashraf and Galor, 2013; Michalopoulos, 2012). This result provides evidence that the policy's effect on fractionalization is not confined to the caste-and-religion dimensions, but extends to language composition of households. Taken together, Panels (A) through (C) establish that formal bank branch expansion reduced fractionalization consistently across ethnic, religious, and linguistic margins, underscoring a broad-based change in social structure rather than an artifact of any single dimension. Figure 4 shows why the RD-induced decline in ethno-religious fractionalization matters for welfare and governance. Districts with higher household-based ELF display higher conflict and local crime and systematically lower social cohesion, network participation, and confidence in institutions, consistent with the view that fragmentation undermines cooperation and institutional performance. These patterns echo established findings that ethnic heterogeneity weakens collective action and public-goods provision (Alesina et al., 2003; Miguel, Satyanath, and Sergenti, 2004) and that polarization predicts weaker governance and greater conflict risk (Montalvo and Reynal-Querol, 2005; Putnam, 2007). Complementing this local evidence, cross-country regressions for 166 countries indicate a robust negative association between financial development and both fractionalization and polarization (Appendix D.3). As reported in Table D3, the coefficients remain stable across alternative specifications and with year fixed effects; Figure C4 visualizes the global pattern. Taken together, the micro- and macro-evidence are consistent with a common mechanism: financial deepening, whether through local bank branch expansion or broader financial development, is associated with lower social fragmentation and stronger institutional foundations. We identify districts that were initially highly and less fractionalized using the median of the pre-policy ERF index and re-estimate our RD impacts on fractionalization within each subsample. Table 2 shows that the decline in fractionalization is concentrated entirely among initially Low-ERF districts. Column (4) suggests about 49% decline in ERF in these districts post bank expansion relative to the control mean of 0.523, while Column (3) establishes pre-policy smoothness in ERF for these districts. Columns (1) and (2) indicate no discernible movement in ERF among initially High-ERF districts.

## 5.2 Mechanisms

### 5.2.1 Economic Development and Heterogeneity

We provide evidence for concentration of economic development and benefits in initially highly fractionalized areas by exploiting heterogeneity in the policy's effects on the basis of level of

other (Vanhanen, 1999), we combine these two dimensions of ethnic and linguistic heterogeneity and construct our district level population-based ELF index for each year.

fractionalization in the pre-policy survey: Initially High-ERF and Low-ERF areas. We study the impact of this policy on households' economic welfare and financial inclusion in Table 3, using log real per capita consumption of households, binary indicator for poverty, binary indicator for bank loan availed, average Monthly Interest Rate paid on outstanding loans (in %) and binary indicator for Life Insurance ownership. Columns 1 and 3 establish pre-policy smoothness between the treated and control group for the outcomes. Following bank branch expansion, we find that real per capita consumption expenditures are 23% higher for the treated households in initially highly fractionalized districts, relative to the sample mean. We also document a 10.7 percentage point decline in the poverty in initially highly fractionalized districts which got treated over the control mean. These post-policy coefficients are statistically insignificant for initially Low-ELF districts. With greater bank presence, we observe that treated households in initially High-ERF districts have a 53% higher likelihood of taking a loan from bank, relative to the sample mean. For a median Indian household, taking loans from institutional sources can lead to gains equivalent to 2-4% of annual income (Ramadorai, 2017). Further, treated households in initially High-ERF districts pay about 0.62% lower interest on loans than the control group having a sample mean of 2.05%, qualitatively reiterating Gupta and Sedai (2023) who find that bank expansion reduces household reliance on high-interest loans. However, we find that these effects are concentrated in initially High-ERF districts and not in Low-ERF districts. Additionally, compared to the control group, treated households in initially High-ERF areas are about 36% more likely to own Life Insurance, relative to the sample mean. We find no effects among households in initially Low-ERF districts. We now graphically establish these causal findings. Figure 6 demonstrates pre-policy smoothness for real per capita consumption (Panels A1 and A3) and poverty (Panels B1 and B3) in initially High-ERF and Low-ERF districts. For initially High-ERF districts, we observe post-policy increase in real per capita consumption in Panel A2 and decrease in poverty in Panel B2. Panels A4 and B4 rule out effects for these outcomes in initially Low-ERF districts. Figure 7 graphically establishes pre-policy smoothness for loan from bank (Panels A1 and A3), monthly interest paid on loan (Panels B1 and B3), and life insurance ownership (Panels C1 and C3) for initially High-ERF and Low-ERF districts. For initially High-ERF districts, the policy had a significantly positive impact on loan from bank (Panel A2) and life insurance ownership (Panel C2), while reducing average monthly interest on loan (Panel B2). We find no effects on these outcomes among households in initially Low-ERF districts (Panels A4, B4 and C4). These results indicate that the economic and financial gains from bank branch expansion were not evenly distributed but were concentrated precisely where social divisions were deeper. In initially High-ERF districts, financial access catalyzed welfare improvements. The absence of comparable effects in Low-ERF districts underscores that inclusive financial infrastructure yields the largest marginal returns where coordination failures and market exclusion are most severe. These findings suggest that financial inclusion reshapes social composition by transforming the economic geography of opportunity, concentrating development gains in communities that were historically fragmented. We provide supplementary evidence for concentration in economic benefits in initially High-ERF

districts by studying different components of household consumption in Appendix Table D9. With greater bank presence, food consumption expenditures are 17% higher for the treated households in initially High-ERF districts, relative to the sample mean, without any significant effect in in initially Low-ERF districts (Panel A). Expenditure on tuition fee and books are higher for treated households, regardless of the level of fractionalization (Panel B). We also document that in initially High-ERF districts, treated households have roughly 30% higher likelihood of owning a motor vehicle (Panel C) and 8% higher likelihood of owning a cell phone (Panel D), relative to the sample mean. Effects are insignificant for initially Low-ERF districts.

### 5.2.2 Economic Opportunity and Structural Change

Having established that bank branch expansion reduced fractionalization through directed in-migration toward initially diverse districts, we now identify the economic forces that made those districts attractive destinations. If financial access reshaped the spatial distribution of population by drawing workers toward expanding regions, it should be evident in the local labor market. Table 4 reports the effect of bank branch expansion on labor force participation and the composition of employment, across districts with initially higher and lower levels of ethno-religious fractionalization (ERF).[5] Across all panels, the pre-policy estimates (Columns 1 and 3) are statistically indistinguishable from zero, confirming that treated and control districts were on smooth, comparable trajectories at the cutoff before the policy and that the post-policy estimates are not driven by pre-existing differences in labor market structure.

The post-policy results reveal that the labor market gains from branch expansion are concentrated in initially High-ERF districts. Panel A shows that bank presence raises labor force participation by 4.3 percentage points in High-ERF areas, against a control mean of 0.505 (Column 2), while the effect in Low-ERF areas is negative and statistically insignificant (Column 4). Given a control-group participation rate of roughly 50%, this represents an economically meaningful expansion of the active workforce, to the tune of 8.5%, in districts that were initially highly fragmented. The more striking pattern emerges in the composition of employment. In High-ERF districts, bank branch expansion increases the likelihood of working in a regular salaried job by 7.4 percentage points (Panel B, Column 2), a gain of roughly 27% relative to the control mean of 0.270. This formalization of work is mirrored by a corresponding decline in precarious employment: casual wage labor falls by 5.7 percentage points in the same districts (Panel C, Column 2), indicating a 26% decline, against a control mean of 0.215. Taken together, Panels B and C indicate that financial access did not merely add jobs at the margin but shifted the structure of employment away from informal daily-wage work and toward stable, formal-sector employment.

[5]The National Sample Surveys (NSS) do not collect any information pertaining to the language affiliation of the households. However, the NSS Employment and Unemployment Surveys (EUS) are the only nationally representative data providing information on individual-level labor-market status. Thus, we examine the impacts on employment and structural transformation across the pre-policy highly and less fractionalized districts on ethnic and religious dimensions. This is not a substantive departure from our main analysis, since we show that the bank branch expansion reduced fractionalization along ethnic, religious, and linguistic margins.

None of these compositional effects are present in Low-ERF districts, where the RD estimates are small and insignificant. The unpaid household work results in Panel D are consistent with this interpretation. The statistically significant 7.5 percentage point reduction in unpaid family work in Low-ERF districts (Column 4), likely reflects out-migration of marginal workers rather than local job creation. In High-ERF districts, by contrast, the absence of any decline in unpaid work alongside rising salaried employment indicates that new formal jobs were filled without simply reclassifying existing unpaid labor. These labor market patterns provide the economic rationale for our migration mechanism. The directed-migration model predicts that improved financial access generates new economic opportunities that pull marginalized and minority workers toward initially diverse districts. Table 4 documents the labor demand counterpart of that pull: the labor market becomes the channel through which financial inclusion translates into the agglomeration and re-sorting that drives the observed decline in fractionalization. Appendix Table D10 sharpens our results by examining sectoral reallocation out of agriculture, across pre-policy High-ERF and Low-ERF districts. We the impact on movement across the structural transformation ladder, using binary outcomes indicating employment in manufacturing (Panel A) and services (Panel B) sectors relative to agriculture. As earlier, the pre-policy estimates are uniformly insignificant, establishing smoothness at the cutoff prior to the policy. The post-policy estimates show that bank branch expansion accelerated structural transformation, and that this acceleration was confined to initially High-ERF districts. In these districts, branch expansion raised the likelihood of an individual working in manufacturing rather than agriculture by 12.9 percentage points (Panel A, Column 2), suggesting a 25% increase against a control mean of 0.516; and raised the likelihood of working in services rather than agriculture by 12.0 percentage points (Panel B, Column 2), indicating a 20% against a control mean of 0.609. Both effects are economically substantial relative to their control means. In Low-ERF districts, the corresponding estimates (Columns 4) are small and statistically insignificant, indicating no detectable structural shifts in relatively homogeneous areas, prior to the policy. This heterogeneity demonstrates that financial access did not produce uniform industrialization; it produced a concentrated reallocation of labor out of agriculture and into manufacturing and services in the very districts that were initially the most fragmented on ethno-religious grounds. New bank branches relaxed credit constraints and supported the formation of non-agricultural enterprises in highly fractionalized districts, which raised the returns to locating there and drew in workers, especially from minority and landless backgrounds, consistent with our migration patterns. This result is a self-reinforcing dynamic: financial inclusion seeds economic opportunity, that attracts directed migration, and the resulting agglomeration both transforms the local employment structure and mechanically consolidates group shares, lowering measured fractionalization. Read together, Tables 4 and D10 establish that the welfare and demographic effects emphasized in the paper are grounded in a beneficial reorganization of the local economy. Branch expansion in initially diverse districts pulled workers into the labor force, formalized their employment into salaried jobs, displaced casual wage labor, and moved labor out of agriculture into manufacturing and services. These economically dy-

namic, opportunity-rich conditions substantiate the directed in-migration of marginalized groups, and explain the decline in fractionalization, along with the concentration of the welfare gains and the reduction in material grievance in highly fractionalized areas rather than spread evenly across treated districts.

### 5.2.3 Migration

Migration is the critical mechanism to facilitate significant changes in the ethno-religious composition of districts, and consequently affect fractionalization. We begin by providing evidence for post-policy increase in short-term migration, driven by migration for job-related reasons. Table 5 reports these results using data from the Employment and Unemployment Surveys conducted by the NSSO during July 1999 - June 2000 (Round 55) and July 2007 - June 2008 (Round 64), the only nationally representative surveys around the bank policy roll-out which provide individual-level information on migration status. We construct binary outcomes to analyze whether an individual migrated out, and the reasons for migration. Outcomes demonstrate pre-policy smoothness at the cutoff. We observe that, compared to the control group, bank presence immediately increases the likelihood of migration among treated banked individuals by about 60% relative to the sample mean (Column 2). Panels A and B of Appendix Figure C10 graphically depicts the corresponding pre-policy smoothness and post-policy increase in migration. Furthermore, treated individuals having formal access to banks are 58% more likely to migrate for job-related reasons (3 years after the policy roll-out) compared to the control group individuals, relative to the sample mean (Column 4). We also note that treated individuals are 27% less likely to migrate for non-job-related reasons, relative to the sample mean, although this estimate is marginally significant (Column 6). This points towards an increase in migration towards economic opportunities[6]. To corroborate the movement towards initially highly fractionalized areas, we examine longer-term out-migration patterns disaggregated by a district's initial High-ERF or Low-ERF status. We utilize the Tracking File of the IHDS Round 2011-12, which collected information on individuals who migrated out after 2005 (IHDS Round 1). We construct binary indicators to study out-migration, permanent out-migration, and out-migration for work and non-work reasons. Table 6 reports these results, where we observe statistically significant increase in these outcomes from initially Low-ELF districts. Compared to the control group, treated individuals from initially Low-ERF districts are 42% more likely to migrate out (Panel A, Column 2), 47% more likely to move out permanently (Panel A, Column 4), and 70% more likely to migrate for work (Panel B, Column 2). We do not see any statistically significant impacts on migration for non-work reasons, including marriage, education, family, and other purposes, relative to their (respective) sample means. No effects are observed for out-migration from initially High-ERF districts (Columns 1

[6]Appendix Figure C10 shows pre-policy smoothness in migration for Job-related and Non-Job-related reasons in Panels C and E respectively. With greater bank presence, we observe post-policy increase in migration for Job-related reasons in Panel D and decline in migration for Non-Job-related reasons in Panel F

and 3).[7] Importantly, we identify that the out-migration from initially Low-ERF areas is driven by households belonging to ethno-religious minority groups.[8] We provide evidence for this in Table 7, where we use the decompose the impact on out-migration (from the IHDS Tracking File) across pre-policy ethno-religious majority and minority groups. We document a 66% increase in out-migration by the minority groups from the less fractionalized areas (Column 4), while observing no change in out-migration among the majority groups. We graphically establish these results in Figure 8. While Table 3 shows that the economic dividend of bank branch expansion materialized in highly fractionalized districts, Table 8 examines the distribution of the economic dividend among the majority and minority households, independent of the district composition. Column 4 shows that treated minority households experienced an 18.8% increase in real per capita consumption relative to the sample mean (Panel A), a 10.8 percentage point decline in poverty (Panel B), and a significant improvement in self-perceived economic condition (Panel C), while majority households show no significant change on any of these margins (Column 2). Columns 1 and 3 rule out pre-policy discontinuities in the outcomes for both groups. That minority status predicts the gain establishes the individual-level incentive underlying the migration mechanism set out in Section 2.2: independent of the geographic effects, it is minority households, whose returns to formal credit improved most sharply, consistent with their disproportionate out-migration from homogeneous origins documented in Table 7. Appendix Figure C8 graphically substantiates our estimated post-policy impacts on economic dividend for the treated minority households, while establishing pre-policy smoothness. Now, we provide evidence on in-migration into the current district of residence for a duration of one to four years of stay since they migrated, disaggregated across initially High-ERF districts and Low-ERF districts. We obtain this district-level information from the Population Census Migration Tables for 2001 and 2011. We analyze the total number of in-migrants (log transformed) into their current district of residence from all States of India (Panel A) and within the State of current residence (Panel B) in Table 9. For both categories of origin, Columns (1) and (3) establish pre-policy smoothness in in-migration, irrespective of the extent of fractionalization. We observe about $45-48\%$ increase in migration into initially High-ERF districts (Column 2), while documenting statistically insignificant effects for migration into initially Low-ERF districts (Column 4). We supplement our argument by providing evidence on post-policy in-migration by classifying households on the basis of land-based dominance from pooled cross-section household-level data on migration and the land-holding status of the households from the National Sample Survey (NSS) on housing conditions conducted by the Indian Ministry of Statistics and Program Implementation (MOSPI) during July 2002 - December 2002 (Round 58) and July 2012 - December 2012 (Round 69). Based on the extensive literature

[7] Appendix Figure **??** maps the intensity of out-migration from initially High-ERF and Low-ERF districts in India using retrospective information on out-migration from IHDS 2011-12. We observe a spatial pattern of relatively higher out-migration from initially less fractionalized areas.

[8] We segregate households into ethno-religious majority and minority groups based on their pre-policy district of residence. For each district, we compute the population shares of the ethno-religious groups, and designate as the majority group the category with the largest population share in that district (with ties assigned joint majority status).

on dominance rooted in socio-economic dimensions and landownership established by Anderson (2011); Dumont (1980); Iversen et al. (2014), we classify households into land-owning (dominant) and landless (non-dominant) households. In Appendix Table D11, we examine whether the household moved into their current residence of enumeration in the previous one year before the date of survey, for these two groups. With greater bank presence, we find a statistically significant increase of 3.7 percentage points in migration (seven years after the policy roll-out) among the landless households into the treated districts, relative to the control group having a sample mean of 0.049 (Column 4). No effects are observed among the land-owning households (Column 2). Columns 1 and 3 rule out pre-policy changes in migration among these groups. These results are consistent with our theoretical proposition (1) and reveal that bank expansion triggered a systematic re-sorting of India's population along ethno-religious lines. Treated districts that were initially homogeneous experienced significant out-migration, while highly fractionalized districts became destinations for new in-migrants—especially minorities and landless households seeking economic opportunity. This selective and directional mobility amplified demographic convergence across space: diverse districts became economically dynamic yet more internally cohesive, while homogeneous districts lost out-migrants to High-ERF areas. These migration flows are consistent with the model's prediction that financial inclusion reduces local fractionalization by attracting marginalized groups toward expanding regions, thereby altering the composition and spatial distribution of ethno-religious groups.

#### 5.2.4 Social Consolidation and the Erosion of Complementarity

Two developments complete the picture of what happened where migrants settled and where they left: the consolidation of the majority as a bloc, for which the evidence is suggestive, and the erosion of economic complementarity between groups, which we can measure directly and which accordingly carries the argument. We report the suggestive evidence first. Using the Eligible Women module of the IHDS, we examine inter-caste marriage and the number of births to majority and minority households across initially High-ERF and Low-ERF districts. Inter-caste marriage rose within the ethno-religious majority in initially diverse districts, blurring the majority's internal caste lines even as its boundary with minorities held, while marriage across religion did not move; and the number of births to majority households rose in initially homogeneous districts, where the departure of minorities left the majority a larger and demographically faster-growing share. Neither margin is estimated as precisely as our other results, and we report both in Appendix Table D12. Taken together, they are consistent with the consolidation of the majority as a bloc, both in the districts that received migrants and in those they left. The direct evidence concerns the economic relationship between the two groups. We assess whether the majority and minority groups held interdependent or substitutable occupational roles. Drawing motivation from the notion of inter-ethnic economic interdependence developed by Jha (2013c), we examine the impact on ethno-religious complementarity in the labor market, thereby comple-

menting our primary metrics of fractionalization.[9] First, we construct the Duncan Dissimilarity Index, $D = \frac{1}{2}\sum_{f=1}^{13} |s_f^{majority} - s_f^{minority}|$, to capture the degree of occupational segregation between majority and minority workers, where $D = 0$ indicates identical occupational distributions and $D = 1$ indicates completely distinct distributions. Second, we construct a Complementarity index, $K = \sum_{a=1}^{13}\sum_{b=1}^{13} s_a^{majority} s_b^{minority} C_{ab}$, to quantify the probability that a randomly paired majority and minority worker hold functionally interdependent roles, where $C_{ab} \in \{0, 0.5, 1\}$ is a symmetric matrix encoding the strength of economic complementarity between functions $a$ and $b$ in the traditional division of labor. For instance, cultivators and traders, or artisans and transport workers, receive high complementarity weights, while functionally substitutable roles receive a weight of zero. Table 10 reports the RD estimates for the occupational segregation and complementarity indices. Panel A shows the Duncan Index falling by 0.273 (Column 3), a large decline relative to the control mean of 0.340, indicating convergence in their occupational distributions, i.e., branch expansion sharply reduced occupational segregation between majority and minority workers. Panel B shows the Complementarity Index falling by 0.180 (Column 3) relative to the control mean of 0.564, indicating that the functional interdependence between majority and minority occupations weakened over the same period. These results suggest that majority and minority workers increasingly crowded into the same expanding functions, plausibly the salaried and manufacturing/services roles documented in Table 4. This lends support to the erosion of inter-ethnic economic interdependence anticipated in Section 2.3, and it provides the mechanism through which social ties can thin even as occupational boundaries blur. Appendix Figure C11 shows the corresponding RD plots. These results reconcile the headline decline in fractionalization and our claim of deepening, and not dissolving, divisions.

### 5.3 Crime and Conflict

The cumulative implication of reduced fractionalization is a tangible improvement in social stability. As financial inclusion reorganized communities into more cohesive local networks, it lowered coordination failures, mistrust, and resource-based rivalries that often underlie violence in fragmented societies. This mechanism echoes the cross-country evidence linking ethnic diversity to weaker governance and higher conflict risk (Montalvo and Reynal-Querol, 2005; Rohner and Zhuravskaya, 2024), but demonstrates that inclusive economic policy can reverse this channel. We first discuss results for impact on different crimes, as presented in Table 11. We observe that, with bank expansion, treated districts exhibited a 36.3% decline in theft over the control group having a sample mean of 5.508, 63.1% decline in robbery over the control group having a sample mean of 2.784, 26.0% decline in burglary over the control group having a sample mean of 4.588.

[9] We use the vocational caste-occupation schedule provided in the 1931 Census of India, which enumerates thirteen traditional functional roles, spanning forest-based livelihoods, pastoralism, cultivation, artisanal production, transport, trade, and professional/religious service. We use this as a coarse taxonomic anchor and construct a comparable thirteen-function classification for the NCO occupation codes reported in the IHDS. For each district-year-majority group cell, we compute the within-group share of workers in each of the thirteen functions and use them to build the two metrics.

Bank expansion led to significant decline in social and other violent crimes: 30.1% decline in kidnapping over the control group having a sample mean of 3.266, 29.3% decline in rape cases over the control group having a sample mean of 2.962, and 27.1% decline in murders over the control group having a sample mean of 3.354. We also note a 38.3% decline in deceit and frauds. Other IPC crimes also declined by 26.4% over the control group having a sample mean of 6.641. The aggregate measure also shows a significant 17.5% decline in all IPC crimes over the control group having a sample mean of 7.622. Next, we provide evidence on decline in conflict intensity (measured using log number of total conflict events) and casualties (measured using log number of total people killed and injured) in Appendix Table D13. Following bank expansion, treated districts experienced a 44.4% decline in the conflict intensity over the control group having a sample mean of 0.318, and 72.8% decline in casualties over the control group having a sample mean of 0.129. In Figure C9, Panels A and C graphically illustrate pre-policy smoothness in Total Conflicts and Casualties, while Panels C and D depict the post-policy significant decline in conflicts and casualties respectively. By reducing fractionalization through network consolidation and shared economic participation, bank expansion fostered social peace, translating economic integration into measurable declines in crime, conflict, and casualties. While relative group size increases are typically linked to higher victimization (Cikara, Fouka, and Tabellini, 2022), our results suggest the material gains from financial inclusion can override these rank-based tensions.

## 6 Heterogeneity

**Ethno-Religious Fractionalization** Following Gupta and Sedai (2023), we examine the impact on fractionalization in the urban and rural areas. Column 1 of Appendix Table D6 shows pre-policy smoothness for the index in the urban (Panel A) and rural (Panel B) samples respectively. With greater bank presence, we observe statistically similar decline in fractionalization in the urban sample vis-à-vis the rural sample (Column 2): compared to the control group, we document a 17% decline in fractionalization in treated urban areas (Panel A) and 18% decline in fractionalization in treated rural areas (Panel B), relative to the sample mean, with the same set of controls. Graphically, Panels A and B of Appendix Figure C7 establish pre-policy smoothness and the post-policy discontinuities in the ERF Index for the urban and rural samples respectively. Appendix Table D7 provides qualitatively identical evidence with the help of an extensive margin analysis of the level of fractionalization in districts for the full sample, and urban and rural sub-samples. A potential concern is that the observed decline in fractionalization could simply reflect rural–urban migration into large cities. Panel C of Appendix Table D6 demonstrates the pre-policy smoothness in ERF and shows that the post-policy decline persists even within non-metropolitan districts[10], confirming that the effect is not driven by urban re-sorting but by genuine local demographic change. Panel C of Appendix Figure C7 graphically confirms

[10]We exclude Mumbai, Delhi, Kolkata, Chennai, Bangalore, and Hyderabad from the full sample to construct our Non-METRO Sample.

the pre-policy smoothness and post-policy discontinuity in ERF for the Non-METRO areas. We also exploit heterogeneity in the geographic characteristics of sub-samples of states in Appendix Table D8. We follow Topalova and Khandelwal (2011) to form samples of Coastal states and Land-locked states. We observe a significant decline in fractionalization in Coastal states (Panel A, −0.106) and in non-Land-locked states (Panel B, −0.129), suggesting the interacting effects of geographic economic history with the social impact of financial inclusion.

# 7 Robustness

## 7.1 Generic RD Tests

We assess the sensitivity and validity of the fractionalization results through a battery of standard checks for the regression discontinuity design, collected in Appendix E. The estimated post-policy decline is stable across bandwidth choices: re-estimating the effect on ethno-religious fractionalization at a range of MSE- and CER-optimal bandwidth selectors, and at fractions and multiples of the baseline bandwidth, leaves its sign, magnitude, and significance essentially unchanged. Placebo cutoffs set away from the national population-to-branch threshold produce no comparable discontinuity, so that the effect is specific to the actual policy cutoff rather than an artifact of the functional form. The McCrary (2008) density test in Figure 1 rules out manipulation of the running variable, and the pre-policy smoothness documented throughout—for every fractionalization index and for the baseline covariates in Table **??**—confirms that treated and control districts were comparable before the policy. The decline also survives aggregation from households to the district level (Appendix Table D4) and correction for panel attrition (Appendix Table D14), and, as shown in Section 6, is not driven by re-sorting into the six largest metropolitan areas.

## 7.2 Fixed Effects Validation: Evidence from the 1990s

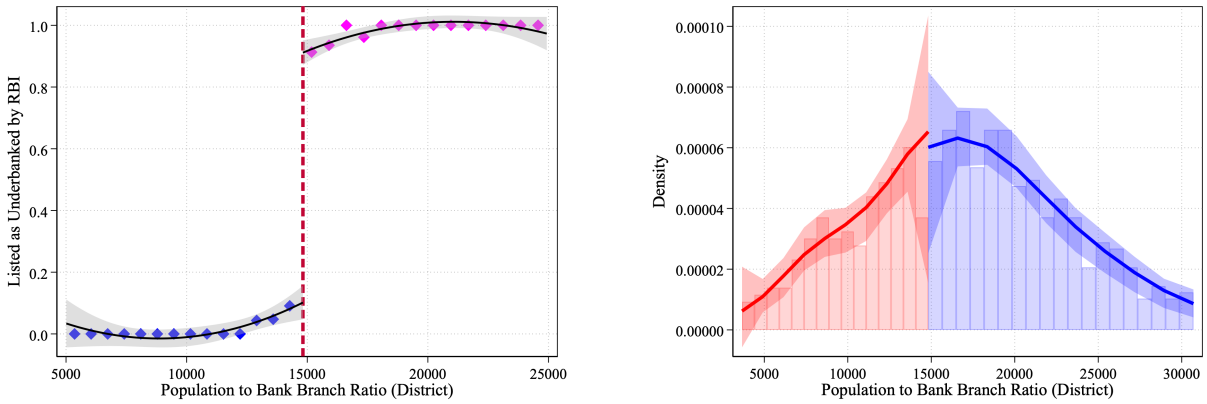
We corroborate our causal findings using a set of robust decadal fixed-effects analyses. We construct ethno-religious fractionalization indices using district-level population data on ethnic and religious groups from Population Censuses 1991 and 2001, and establish significant negative association with greater bank presence using district-level bank branch information from the RBI's Basic Statistical Returns (BSR) for the years 1991 and 2001 in Appendix Table D.2, by leveraging policy-induced exogenous variation in banking infrastructure using the location of government-owned bank branches in 1991 (Dehejia and Gupta, 2022). There could be concerns regarding other concurrent national or sub-national programs, such as district-level policies related to health (National Rural Health Mission 2005), child development (Integrated Child Development Services program), employment (National Rural Employment Guarantee Scheme 2005), and others, potentially confounding the identification around the RBI 2005 BAP cutoff. We acknowledge Cramer (2025), who carefully examined and ruled out these potential threats to the identification strategy.

# 8 Conclusion

India's 2005 Branch Authorization Policy offers a rare opportunity to watch formal finance reach into a fragmented society along a line no local actor drew, and to trace what it did to the composition of places rather than only to their incomes. Across a national fuzzy regression discontinuity, mandated branch expansion lowered ethno-religious fractionalization by about seventeen percent, raised household consumption, cut poverty, widened access to formal credit, and produced large declines in local crime and in recorded conflict and casualties. Read off these headline numbers alone, the episode looks like modernization working as advertised, with prosperity and social integration advancing together. That reading is mistaken, and correcting it has been the purpose of this paper. The gains did not fall evenly. They concentrated in the districts where financial exclusion had bitten hardest, the initially diverse ones, and there they drew minority and landless workers out of the homogeneous districts around them. Because fractionalization is a property of population shares rather than of the relations among groups, the departure of those workers raised the majority's share in the places they left and lowered measured diversity there, at the origins of migration rather than at its destinations. What the index recorded as a fall in diversity was, on the ground, a separation of groups across space, deepened by faster majority household formation where minorities had thinned. Finance lowered the number by moving groups apart, not by blending them together. Nor did the groups that came together in the expanding districts integrate once there. Migrants reached work, credit, and insurance through their own caste and kin networks and settled within them, and as they took up the same expanding occupations as the majority, the occupational distributions of the two groups converged. The economic complementarity between them, the interdependence that a long tradition treats as a foundation of inter-ethnic tolerance, eroded rather than deepened as prosperity spread. A polarization measure that weights within-group cohesion, and more suggestive evidence on marriage within the majority bloc and on majority household formation, points the same way; we report both in the appendix. The consistent picture is one of divisions hardening beneath a falling index, not dissolving with it. The puzzle this leaves is why, with boundaries sharpening and the ties between groups thinning, violence fell rather than rose. Our answer is the size of the shared dividend. Lower poverty and higher, more secure incomes suppressed the material grievances on which collective violence feeds, and did so forcefully enough to override the countervailing pressures that consolidation generated. Prosperity, in this setting, did the work that integration is usually assumed to do: it substituted for the inter-ethnic interdependence it was dissolving. Whether a peace resting on the dividend rather than on complementarity is as durable, whether it would survive a reversal of the prosperity that underwrites it, is a question our setting, in which incomes do not fall back, cannot answer, and we do not claim otherwise. Three implications follow. First, a decline in ethno-religious fractionalization cannot be read, on its own, as an easing of relations between groups; the same fall in the index is produced by integration and by its opposite, and the two are distinguished only by where the decline occurs and by what becomes of the ties the index is taken to proxy.

Wherever fractionalization serves as an outcome, this caution applies. Second, formal finance is not neutral with respect to social composition: by concentrating opportunity where exclusion was deepest, it redraws the map of who lives beside whom, an effect that sits alongside the consumption and credit effects for which finance is usually studied. Third, prosperity can secure social peace even as it deepens social separation, which should temper both the hope that development dissolves ascriptive divisions and the fear that sharpening divisions must bring violence. Financial inclusion in India delivered large, broadly shared material gains and a real reduction in conflict, achievements we do not understate. But it secured peace by making groups prosperous, not by bringing them together, and it deepened rather than dissolved the divisions its headline measure appears to erase.

# 9 Figures




**A:** *Likelihood of being underbanked*

**B:** *McCrary Manipulation Test*

**Figure 1: Likelihood of being under-banked and the McCrary manipulation test.** Panel A shows the likelihood that a district is classified as under-banked if the population-to-bank-branch ratio exceeds the national average. Panel B demonstrates the McCrary test for manipulation of the original running variable, population-to-bank-branch ratio at the district level, around the threshold (McCrary, 2008). This graph plots a density of districts along the original running variable. The solid line(s) shows the local polynomial estimate, while the darkened shaded areas show the 95% confidence bands. Based on the Robust Discontinuity estimate ($-0.1580$) with corresponding p-value (0.8745) obtained from the test, we fail to reject the null hypothesis of smoothness at the cutoff: 14,820 persons per bank branch, thus, establishing a lack of manipulation.

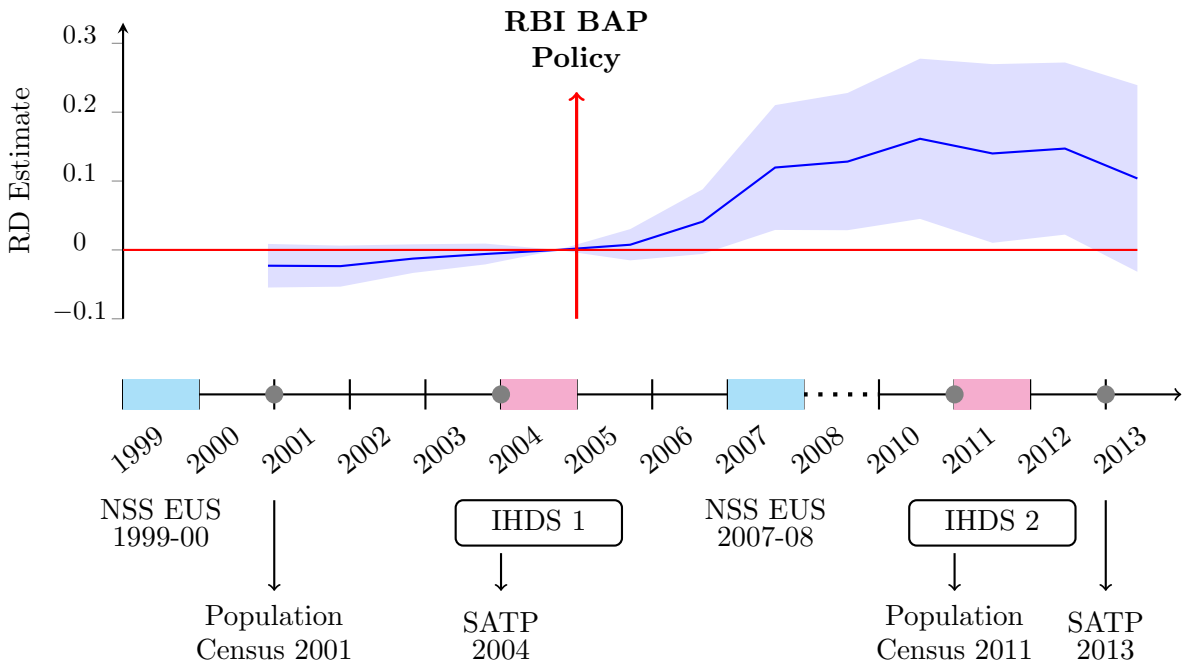
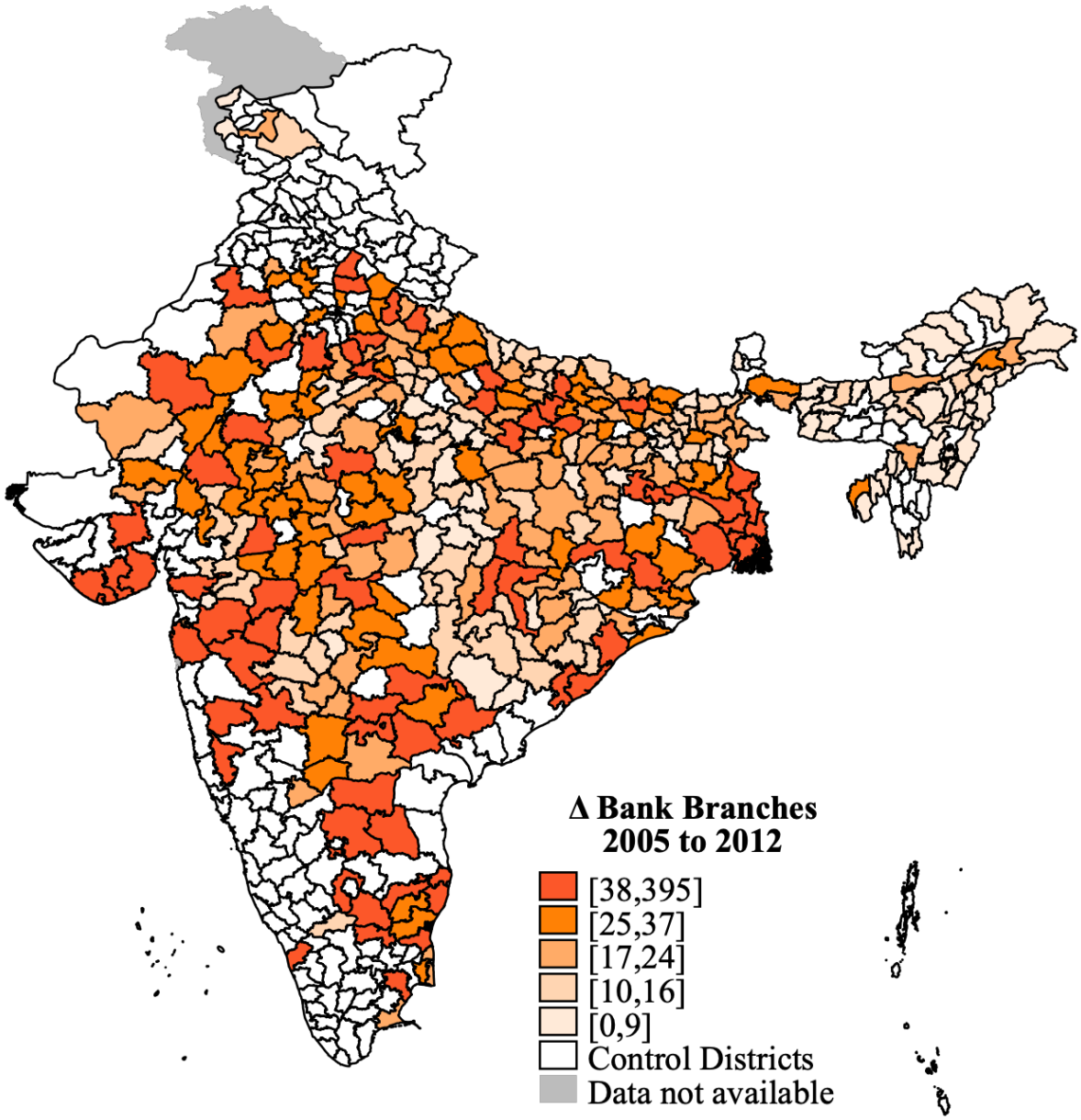



**Figure 2: Timeline: Bank Branch Expansion in India**

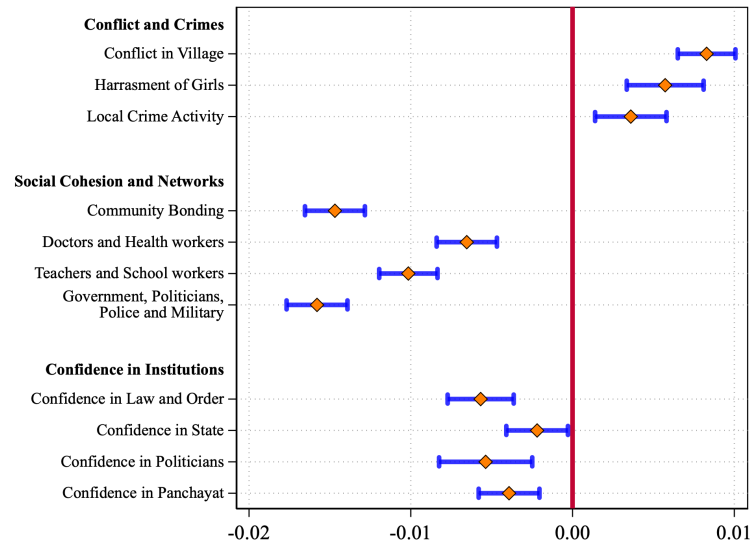
Figure shows the timeline from 1999 till 2013, marking the RBI 2005 Bank Branch Authorization Policy (BAP) along with the important data sources utilized in the analysis.

The graph above the timeline plots the year-wise causal regression discontinuity (RD) estimates evaluating the impact of the policy on the Log Total Number of Bank Branches excluding Regional Rural Banks (RRBs). We obtained annual district-level information for this outcome variable from the Basic Statistical Returns (BSR) database of Reserve Bank of India. The specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all the regressions control for the log district population from the 2001 Population Census and the log number of open functioning bank branches (excluding RRBs) in the district in 2005. The solid blue line reports the bias-corrected point estimates. The shaded area highlights the 95% confidence bands for the respective estimates, with standard errors clustered at the district level.

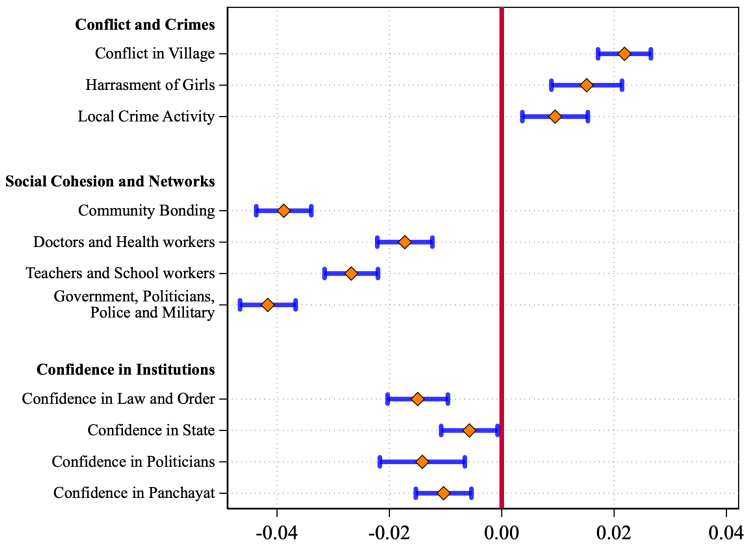



Source: RBI (BSR)

**Figure 3: Growth in Bank Branches in Underbanked Districts between 2005 and 2012 (RBI)**




**A:** *Socio-institutional correlates of ERF: OLS regressions*

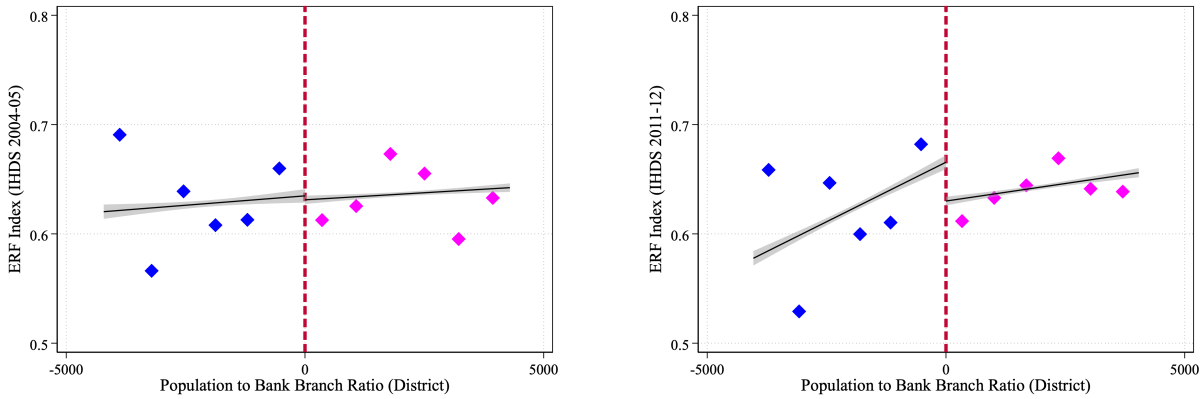



**B:** *Socio-institutional correlates of ERF: Fractional probit regressions*



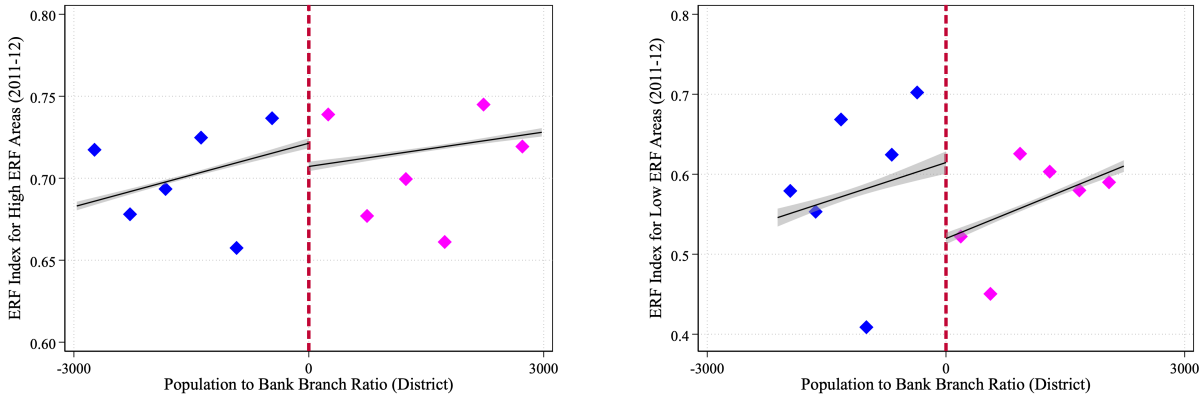
**Figure 4: Correlations of Ethno-Religious Fractionalization with socio-institutional outcomes**

Panel (A) presents estimated coefficients from a series of univariate robust OLS regressions of the Ethno-Religious Fractionalization (ERF) index on various household-reported binary indicator variables, constructed from the India Human Development Survey 2004-05 and 2011-12 (panel data), controlling for year fixed effects. These include conflict in village, harassment of girls, local crime activity, community bonding, networks with doctors and health workers, networks with teachers and school workers, networks with government, politicians, police and military, confidence in law, confidence in the State, confidence in politicians, and confidence in village panchayat. Positive estimates reflect a positive correlation of ERF with the corresponding indicator, while negative estimates indicate a negative correlation. Panel (B) presents estimates using univariate robust fractional response regressions using a probit model for the conditional mean since the outcome (ERF index) lies in the $[0, 1]$ range, while controlling for year fixed effects. Robust standard errors have been estimate to compute the confidence bands.




*ERF (2004-05)* *ERF (2011-12)*

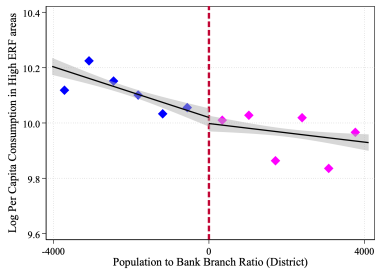
**A: Impact on ERF (Full Sample)**



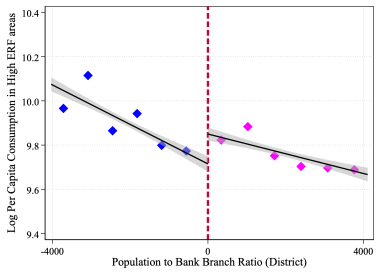

*Initially High ERF Areas* *Initially Low ERF Areas*

**B: Impact on ERF in 2011-12**

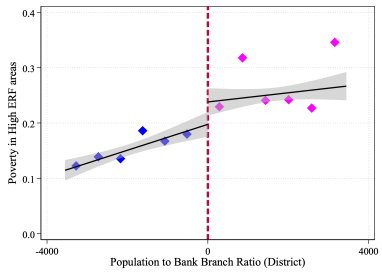
**Figure 5: Pre-policy smoothness and post-policy discontinuity in Ethno-Religious Fractionalization Index: Full Sample and across pre-policy fractionalized areas**
Figure shows local RD estimates for the Ethno-Religious Fractionalization Index, constructed using household level information on ethnic and religious affiliations from the IHDS panel survey (Rounds 2004-05 and 2011-12). Panel A shows the results for the full sample. Panel B shows post-policy impact on ERF in initially highly fractionalized areas and less fractionalized areas, identified based on the median of the pre-policy ERF index. Each graph plots binned means around the district population per bank branch cutoff (normalized to zero) within optimal bandwidths, along with 95 percent confidence intervals.



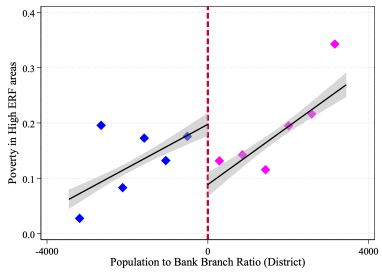

**A1:** *Pre Policy: Per Capita Consumption in High ERF areas*



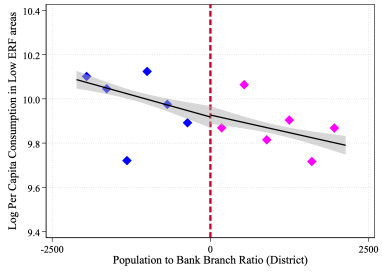

**A2:** *Post Policy: Per Capita Consumption in High ERF areas*



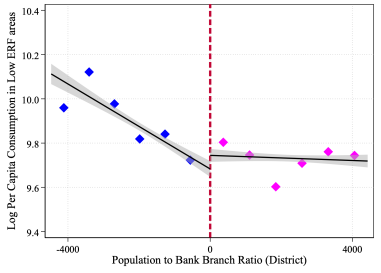

**B1:** *Pre Policy: Poverty in High ERF areas*



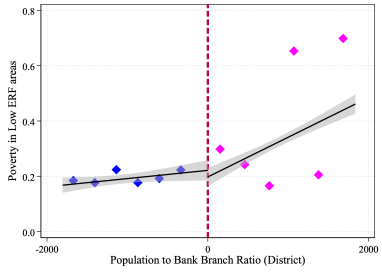

**B2:** *Post Policy: Poverty in High ERF areas*



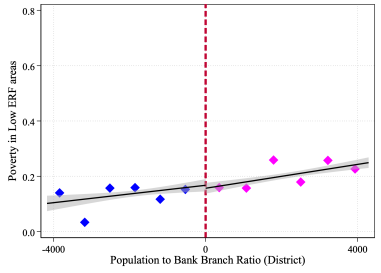

**A3:** *Pre Policy: Per Capita Consumption in Low ERF areas*




**A4:** *Post Policy: Per Capita Consumption in Low ERF areas*




**B3:** *Pre Policy: Poverty in Low ERF areas*

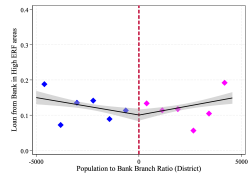



**B4:** *Post Policy: Poverty in Low ERF areas*

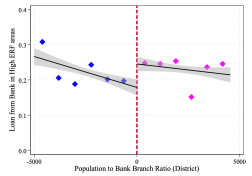
**A: Per Capita Consumption** **B: Poverty Incidence**

**Figure 6: Pre-policy smoothness and post-policy discontinuity in outcomes indicating Economic Welfare of Households**

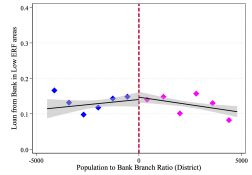
Figure shows local RD estimates for log per capita consumption expenditure of households in Panel (A) and their poverty status/incidence in Panel (B). The sub-figures within each panel present the estimates stratified by the level of pre-policy ethno-religious fractionalization (High ERF and Low ERF areas) and timing of the policy (pre versus post). Each graph plots binned means around the district population per bank branch cutoff (normalized to zero) within optimal bandwidths, along with 95 percent confidence intervals.



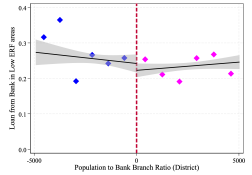

**A1:** *Pre Policy: Loan from Bank in High ERF areas*




**A2:** *Post Policy: Loan from Bank in High ERF areas*

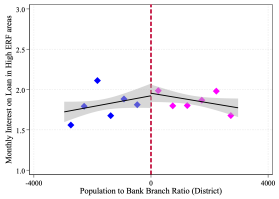



**A3:** *Pre Policy: Loan from Bank in Low ERF areas*

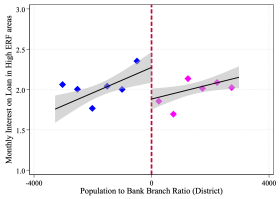



**A4:** *Post Policy: Loan from Bank in Low ERF areas*

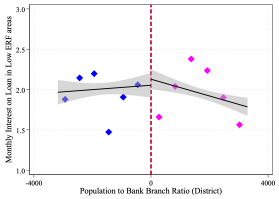
**A: Loan from Bank**



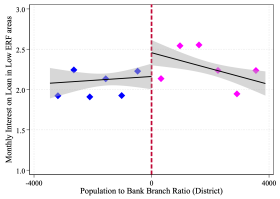

**B1:** *Pre Policy: Monthly Interest on Loan in High ERF areas*




**B2:** *Post Policy: Monthly Interest on Loan in High ERF areas*

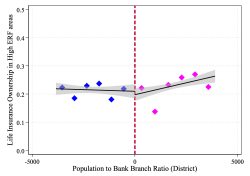



**B3:** *Pre Policy: Monthly Interest on Loan in Low ERF areas*

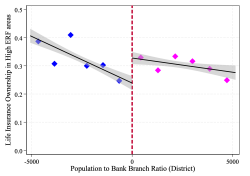



**B4:** *Post Policy: Monthly Interest on Loan in Low ERF areas*

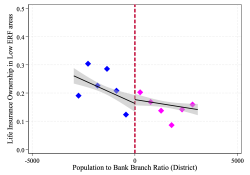
**B: Monthly Interest on Loan**



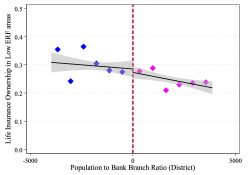

**C1:** *Pre Policy: Life Insurance Ownership in High ERF areas*




**C2:** *Post Policy: Life Insurance Ownership in High ERF areas*



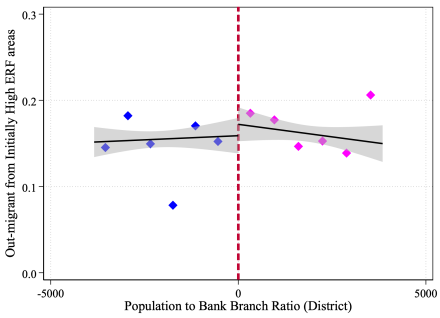

**C3:** *Pre Policy: Life Insurance Ownership in Low ERF areas*

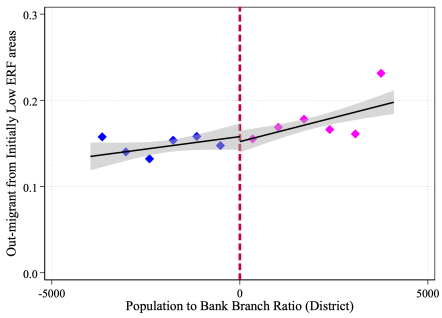



**C4:** *Post Policy: Life Insurance Ownership in Low ERF areas*

**C: Life Insurance Ownership**

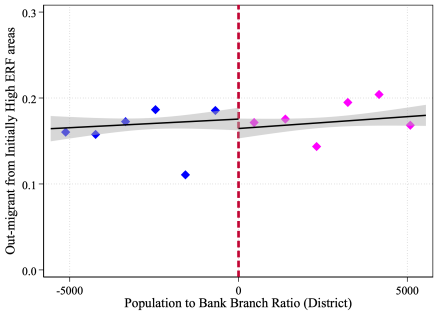
**Figure 7: Pre-policy smoothness and post-policy discontinuity in outcomes indicating Financial Inclusion**
Panel (A) shows RD estimates for loan from bank availed by the households, Panel (B) shows RD estimates for monthly interest rate paid on loans by the households and Panel (C) shows RD estimates for whether a household has a life insurance (either government or private). The sub-figures within each panel present the estimates stratified by the level of pre-policy ethno-religious fractionalization (High ERF and Low ERF areas) and timing of the policy (pre versus post). Each graph plots binned means around the district population per bank branch cutoff (normalized to zero) within optimal bandwidths, along with 95 percent confidence intervals.

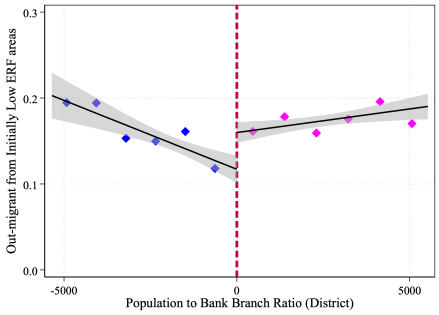



*Out-Migration from Initially High ERF areas* *Out-Migration from Initially Low ERF areas*

**A: Ethno-Religious Majority Groups**




*Out-Migration from Initially High ERF areas* *Out-Migration from Initially Low ERF areas*

**B: Ethno-Religious Minority Groups**

**Figure 8: Post-policy impact on Out-Migration by Ethno-Religious Majority and Minority groups from initially High and Low ERF areas**

Figure presents local RD estimates evaluating post-policy impact on out-migration by Ethno-Religious Majority and Minority groups, constructed using retrospective migration histories of individuals from initially High ELF and Low ERF areas. We construct the binary outcome for out-migration using individual-level information from the Tracking File of IHDS 2: Round 2011-12, which asks the household respondents if any member of the household migrated after 2005 (IHDS 1: Round 2004-2005). Following Bau et al. (2025), we link the migration information to IHDS 1 to identify the household demographics of the out-migrants and classify them into ethno-religious majority and minority groups. Each graph plots binned means around the district population per bank branch cutoff (normalized to zero) within optimal bandwidths, along with 95 percent confidence intervals.

# 10 Tables

**Table 1:** Impact of Bank Branch Expansion on Ethno-Religious Fractionalization

| | Pre Policy | Post Policy |
|---|---|---|
| | (1) | (2) |
| **A: Ethno-Religious Fractionalization (ERF)** | | |
| RD Estimate | -0.057 | -0.105** |
| | (0.049) | (0.052) |
| | [0.241] | [0.045] |
| Control Mean | 0.620 | 0.620 |
| Observations | 40,018 | 40,018 |
| Banked Districts | 133 | 131 |
| Unbanked Districts | 170 | 167 |
| Covariates | ✓ | ✓ |
| Bandwidth | 4,883.857 | 4,406.899 |
| **B: Ethno-Linguistic Fractionalization (ELF)** | | |
| RD Estimate | -0.038 | -0.114** |
| | (0.037) | (0.051) |
| | [0.308] | [0.024] |
| Control Mean | 0.654 | 0.639 |
| Observations | 40,018 | 40,018 |
| Banked Districts | 135 | 131 |
| Unbanked Districts | 174 | 168 |
| Covariates | ✓ | ✓ |
| Bandwidth | 4,996.890 | 4,402.902 |
| **C: Ethnic Fractionalization among Hindus** | | |
| RD Estimate | -0.039 | -0.102* |
| | (0.049) | (0.053) |
| | [0.432] | [0.055] |
| Control Mean | 0.553 | 0.557 |
| Observations | 39,669 | 39,724 |
| Banked Districts | 127 | 121 |
| Unbanked Districts | 164 | 158 |
| Covariates | ✓ | ✓ |
| Bandwidth | 5,024.800 | 4,369.034 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on Fractionalization, constructed using household level information from the IHDS panel survey (Rounds 2004-05 and 2011-12). Panel A shows Ethno-Religious Fractionalization (ERF) index constructed based on ethnic and religious affiliations of households. Panel B shows Ethno-Linguistic Fractionalization (ELF) index constructed based on ethnic, religious and linguistic affiliations of households. Panel C shows Ethnic Fractionalization among Hindus. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population of the district from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 2:** Impact of Bank Branch Expansion on Ethno-Religious Fractionalization conditional on initial level of Fractionalization

| | **High ERF areas** | | **Low ERF areas** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
| RD Estimate | -0.008 | -0.028 | -0.081 | -0.258** |
| | (0.017) | (0.024) | (0.067) | (0.127) |
| | [0.629] | [0.230] | [0.227] | [0.042] |
| Control Mean | 0.712 | 0.703 | 0.513 | 0.523 |
| Observations | 19,763 | 19,763 | 20,255 | 20,255 |
| Banked Districts | 61 | 62 | 55 | 50 |
| Unbanked Districts | 66 | 69 | 80 | 77 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 3,206.976 | 3,263.704 | 3,180.280 | 2,364.425 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on Ethno-Religious Fractionalization (ERF) in initially highly fractionalized areas and less fractionalized areas, identified based on the median of the pre-policy ERF index. The index has been constructed using household level information on ethnic and religious affiliations from the IHDS panel survey (Rounds 2004-05 and 2011-12). All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population, log density and number of towns and villages in the district from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 3:** Impact of Bank Branch Expansion on Economic Welfare of Households

| | High ERF areas | | Low ERF areas | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
| **A: Log Per Capita Consumption** | | | | |
| RD Estimate | 0.060 | 0.228** | -0.103 | 0.129 |
| | (0.123) | (0.103) | (0.084) | (0.088) |
| | [0.627] | [0.027] | [0.221] | [0.143] |
| Control Mean | 10.150 | 9.945 | 10.123 | 9.927 |
| Observations | 15,929 | 16,014 | 16,258 | 15,775 |
| Bandwidth | 3,295.807 | 3,306.937 | 7,233.455 | 6,498.144 |
| **B: Poverty Status** | | | | |
| RD Estimate | 0.059 | -0.107** | 0.110 | -0.019 |
| | (0.075) | (0.054) | (0.085) | (0.055) |
| | [0.428] | [0.048] | [0.196] | [0.736] |
| Control Mean | 0.136 | 0.109 | 0.131 | 0.109 |
| Observations | 19,733 | 19,751 | 20,240 | 20,243 |
| Bandwidth | 3,806.466 | 2,858.006 | 5,731.549 | 6,719.676 |
| **C: Loan from Bank** | | | | |
| RD Estimate | 0.056 | 0.125* | -0.070 | -0.082 |
| | (0.047) | (0.075) | (0.057) | (0.078) |
| | [0.237] | [0.095] | [0.220] | [0.292] |
| Control Mean | 0.134 | 0.238 | 0.122 | 0.246 |
| Observations | 19,742 | 19,723 | 20,241 | 20,233 |
| Bandwidth | 4,045.101 | 4,193.648 | 4,060.405 | 4,355.293 |
| **D: Monthly Interest on Loan** | | | | |
| RD Estimate | -0.002 | -0.623*** | -0.102 | 0.465 |
| | (0.261) | (0.241) | (0.397) | (0.479) |
| | [0.994] | [0.010] | [0.797] | [0.332] |
| Control Mean | 1.542 | 2.049 | 1.832 | 2.055 |
| Observations | 8,146 | 6,238 | 9,226 | 6,802 |
| Bandwidth | 3,136.494 | 2,282.158 | 5,201.461 | 4,994.213 |
| **E: Life Insurance Ownership** | | | | |
| RD Estimate | -0.006 | 0.127** | -0.047 | -0.067 |
| | (0.046) | (0.057) | (0.045) | (0.052) |
| | [0.899] | [0.028] | [0.304] | [0.202] |
| Control Mean | 0.254 | 0.351 | 0.239 | 0.365 |
| Observations | 19,730 | 19,694 | 20,179 | 20,174 |
| Bandwidth | 3,580.330 | 3,599.690 | 6,803.143 | 6,193.872 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on economic welfare and financial inclusion of households in districts with high and low levels of ethno-religious fractionalization, where the split is based on the median value of the pre-policy ERF Index. Panel A shows Log Per Capita Consumption, defined as the log of annual per capita real consumption expenditures in rupees. The level form is deflated using the panel survey estimator and trimmed at the $10^{th}$ and $90^{th}$ percentiles. Panel B shows Poverty Status, a binary indicator variable which takes a value of one if the household's consumption expenditures are below the state poverty line, and zero otherwise. Panel C shows Loan from Bank, a binary indicator variable equal to one if the household has taken a debt from bank, and zero otherwise. Panel D shows Monthly Interest on Loan, which measures the monthly interest rate paid on outstanding loans by households in percentage (%). Panel E shows Life Insurance Ownership, a binary indicator that is equal to one if the household has a life insurance (either government or private), and zero otherwise. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log district population from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. For bank loan, we control for log district population, a binary variable equal to one indicating the presence of a literate adult or head of the household in the pre-policy survey and a binary variable equal to one if the household was in an urban location in the pre-policy survey. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 4:** Impact of Bank Branch Expansion on Labor Force Participation and Employment

| | High ERF Areas | | Low ERF Areas | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
| **A: Labor Force Participation** | | | | |
| RD Estimate | -0.050 | 0.043* | -0.069 | -0.048 |
| | (0.033) | (0.024) | (0.062) | (0.033) |
| | [0.126] | [0.072] | [0.266] | [0.151] |
| Control Mean | 0.564 | 0.505 | 0.583 | 0.522 |
| Observations | 184,387 | 145,146 | 185,746 | 149,205 |
| Bandwidth | 5,614.171 | 4,305.484 | 4,781.610 | 2,498.170 |
| **B: Formal Employment (Salaried)** | | | | |
| RD Estimate | 0.069 | 0.074** | -0.006 | 0.008 |
| | (0.045) | (0.037) | (0.040) | (0.047) |
| | [0.121] | [0.043] | [0.878] | [0.870] |
| Control Mean | 0.210 | 0.270 | 0.190 | 0.250 |
| Observations | 104,098 | 73,523 | 106,296 | 75,663 |
| Bandwidth | 5,307.376 | 5,425.381 | 4,303.483 | 4,255.723 |
| **C: Casual Wage Labor** | | | | |
| RD Estimate | -0.037 | -0.057** | -0.003 | 0.023 |
| | (0.040) | (0.026) | (0.047) | (0.044) |
| | [0.353] | [0.029] | [0.940] | [0.595] |
| Control Mean | 0.240 | 0.215 | 0.172 | 0.197 |
| Observations | 104,098 | 73,523 | 106,296 | 75,663 |
| Bandwidth | 5,485.659 | 3,087.425 | 5,264.043 | 3,226.998 |
| **D: Unpaid Household Work** | | | | |
| RD Estimate | -0.041 | 0.022 | -0.058 | -0.075** |
| | (0.043) | (0.025) | (0.052) | (0.033) |
| | [0.346] | [0.374] | [0.265] | [0.023] |
| Control Mean | 0.163 | 0.120 | 0.215 | 0.150 |
| Observations | 104,098 | 73,523 | 106,296 | 75,663 |
| Bandwidth | 4,294.737 | 3,543.200 | 4,775.841 | 4,929.808 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on Labor Force Participation and Employment, for individuals aged 15-65 years, in districts with high and low levels of ethno-religious fractionalization, where the split is based on the median value of the pre-policy ERF Index. Panel A shows Labor Force Participation using a binary indicator equal to one if an individual is either working or unemployed, and zero if attending educational institution, engaged in domestic duties, unable to work due to disability, receiving pensions, rents, and remittances, and begging (Dehejia and Gupta, 2022). Panel B shows Formal Employment using a binary indicator equal to one if an individual is working in a regular salaried job, and zero otherwise. Panel C shows Casual Wage Labor using a binary indicator equal to one if an individual is engaged in casual wage labor (public works and/or daily wage work), and zero otherwise. Panel D shows Unpaid Household Work using a binary indicator equal to one if an individual is an unpaid family worker, and zero otherwise. Panels B, C and D are for individuals in the labor force only. We construct these outcomes using individual-level information from the NSS $61^{st}$ (July 2004 - June 2005) and $68^{th}$ (July 2011 - June 2012) Employment and Unemployment Surveys. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population of the district from the 2001 Population Census. Post-policy regressions, additionally, control for density of the district, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We also account for region fixed effects to examine labor-force participation; number of villages for casual wage labor and unpaid household work; and years of education completed by individual engaged in casual wage labor. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 5:** Impact of Bank Branch Expansion on Migration

| | **Migrant** | | **Migrated for Job-related reasons** | | **Migrated for Non-Job-related reasons** | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
| RD Estimate | 0.009 | 0.052*** | 0.004 | 0.030** | 0.001 | -0.008* |
| | (0.009) | (0.016) | (0.006) | (0.013) | (0.004) | (0.004) |
| | [0.327] | [0.001] | [0.525] | [0.016] | [0.756] | [0.065] |
| Control Mean | 0.066 | 0.087 | 0.031 | 0.052 | 0.029 | 0.030 |
| Observations | 507,427 | 498,241 | 507,427 | 498,241 | 507,427 | 498,241 |
| Banked Districts | 122 | 112 | 124 | 147 | 113 | 156 |
| Unbanked Districts | 184 | 165 | 187 | 211 | 178 | 233 |
| Covariates | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 4,552.771 | 2,911.868 | 4,600.853 | 3,783.464 | 4,333.291 | 4,471.431 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on migration. The first outcome Migrant is a binary indicator variable capturing the extensive margin of migration. The second and third outcomes Migrated for Job-related reasons and Migrated for Non-Job-related reasons, disaggregate overall migration based on the reported reason for migrating. To construct these outcomes, we gather individual-level pooled cross-sectional data on migration from the National Sample Survey (NSS) on employment and unemployment conducted by the Indian Ministry of Statistics and Program Implementation (MOSPI). We draw on data from Employment and Unemployment Survey, July 1999 - June 2000 (Round 55) to test for pre-policy smoothness, and Employment, Unemployment and Migration Survey, July 2007 - June 2008 (Round 64) to examine post-policy impact on migration. The surveys include information on each individual's migration status and reason for migrating. A migrant is defined as a person whose current district is different from their last district of residence. We limit this definition to an individual who reported having left their last usual place of residence within the past three years as of the time of the surveys. This restriction aligns with the three-year window following the policy's implementation in 2005 and isolates migrants who plausibly migrated due to the policy as opposed to other points in time. For each migrant, the surveys also collect information about the main reason for migrating. The options include Job-related reasons (migrating to find a job or a better job, to take up a job offer, because of a job transfer, or because the primary income-earning member of the household migrated) and Non-Job-related reasons (migrating for studies, for housing-related issues, due to social or political problems, for health reasons, or for marriage). All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population of the district from the 2001 Population Census. Additionally, post-policy regressions control for density of the district from the 2001 Census to examine migration; and area of the district from the 2001 Census and log number of open functioning bank branches (excluding RRBs) in the district in 2001 to examine reasons for migration. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.

Significance Levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 6:** Impact of Bank Branch Expansion on Out-Migration conditional on the Initial level of Fractionalization

| | *High ERF areas* | *Low ERF areas* | *High ERF areas* | *Low ERF areas* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **A:** | **Migrated out** | | **Migrated Permanently** | |
| RD Estimate | 0.030 | 0.066** | -0.054* | 0.062* |
| | (0.027) | (0.032) | (0.032) | (0.035) |
| | [0.258] | [0.038] | [0.093] | [0.080] |
| Control Mean | 0.156 | 0.156 | 0.108 | 0.132 |
| Observations | 74,099 | 73,193 | 12,321 | 12,769 |
| Banked Districts | 47 | 66 | 50 | 60 |
| Unbanked Districts | 57 | 104 | 57 | 89 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 2,926.402 | 6,144.013 | 3,530.141 | 4,718.830 |
| **B:** | **Migrated for Work** | | **Migrated for Non-Work Reasons** | |
| RD Estimate | -0.011 | 0.133*** | -0.077 | 0.011 |
| | (0.030) | (0.046) | (0.062) | (0.058) |
| | [0.710] | [0.004] | [0.216] | [0.852] |
| Control Mean | 0.186 | 0.187 | 0.408 | 0.440 |
| Observations | 12,321 | 12,769 | 12,321 | 12,769 |
| Banked Districts | 52 | 57 | 43 | 63 |
| Unbanked Districts | 60 | 79 | 54 | 97 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 3,374.997 | 4,193.435 | 3,316.579 | 5,566.191 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on out-migration from districts with initially high and low levels of ethno-religious fractionalization, where the split is based on the median value of the pre-policy ERF index. We use individual-level information from the Tracking File of the Indian Human Development Survey (IHDS) Round 2011-12 to construct the outcomes. The survey asks the household respondents if any member of the household migrated after 2005 (IHDS 1). Panel A shows binary indicators for whether individual migrated out; and migrated out permanently: equal to one if the migrant left their residence permanently, and zero otherwise. Panel B shows whether individual migrated for work and non-work reasons, using binary indicators, equal to one if the migrant migrated for work and purposes other than work (including marriage, study, family, and others) respectively, and zero otherwise. Permanent migration, migration for work and non-work reasons are analyzed only for the migrants. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population and number of towns and villages in the district from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 7:** Impact of Bank Branch Expansion on Out-Migration by Ethno-Religious Majority and Minority Groups conditional on the Initial level of Fractionalization

| | **Ethno-Religious Majority Groups** | | **Ethno-Religious Minority Groups** | |
|---|---|---|---|---|
| | (1) *Initially High ERF areas* | (2) *Initially Low ERF areas* | (3) *Initially High ERF areas* | (4) *Initially Low ERF areas* |
| RD Estimate | 0.032 | 0.032 | 0.009 | 0.106** |
| | (0.026) | (0.030) | (0.031) | (0.045) |
| | [0.216] | [0.289] | [0.764] | [0.017] |
| Control Mean | 0.152 | 0.153 | 0.158 | 0.160 |
| Observations | 26,707 | 40,313 | 47,392 | 32,880 |
| Banked Districts | 59 | 67 | 46 | 64 |
| Unbanked Districts | 62 | 105 | 57 | 97 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 4,526.279 | 6,466.140 | 3,194.398 | 5,696.052 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on Out-migration by Ethno-Religious Majority and Minority Groups from districts with initially high and low levels of ethno-religious fractionalization (ERF), where the split is based on the median value of the pre-policy ERF index. We use individual-level information from the Tracking File of the Indian Human Development Survey (IHDS) Round 2011-12, which asks the household respondents if any member of the household migrated after 2005 (IHDS Round 1). We use these responses to construct the binary outcome, whether migrated out. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population of the district from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 8:** Impact of Bank Branch Expansion on Economic Welfare of Initially Ethno-Religious Majority and Minority Households

| | ER-Majority Households | | ER-Minority Households | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
| **A: Log Per Capita Consumption** | | | | |
| RD Estimate | -0.011 | 0.124 | -0.003 | 0.188*** |
| | (0.107) | (0.095) | (0.071) | (0.060) |
| | [0.920] | [0.194] | [0.967] | [0.002] |
| Control Mean | 10.147 | 9.952 | 10.128 | 9.922 |
| Observations | 16,028 | 15,740 | 16,159 | 16,049 |
| Banked Districts | 129 | 131 | 148 | 151 |
| Unbanked Districts | 162 | 166 | 189 | 201 |
| Bandwidth | 4,449.964 | 4,540.632 | 5,962.052 | 6,551.136 |
| **B: Poverty Status** | | | | |
| RD Estimate | 0.106 | -0.012 | 0.043 | -0.108*** |
| | (0.075) | (0.070) | (0.050) | (0.032) |
| | [0.159] | [0.865] | [0.396] | [0.001] |
| Control Mean | 0.124 | 0.098 | 0.144 | 0.119 |
| Observations | 19,924 | 19,931 | 20,049 | 20,063 |
| Banked Districts | 144 | 142 | 150 | 146 |
| Unbanked Districts | 183 | 182 | 190 | 184 |
| Bandwidth | 4,952.573 | 4,710.431 | 5,634.112 | 5,659.798 |
| **C: Economic Condition** | | | | |
| RD Estimate | -0.089 | -0.083 | -0.038 | 0.165** |
| | (0.094) | (0.081) | (0.099) | (0.073) |
| | [0.342] | [0.305] | [0.699] | [0.025] |
| Control Mean | 0.459 | 0.352 | 0.454 | 0.324 |
| Observations | 19,930 | 19,606 | 20,061 | 19,732 |
| Banked Districts | 133 | 131 | 141 | 150 |
| Unbanked Districts | 173 | 168 | 179 | 191 |
| Bandwidth | 4,837.441 | 4,568.685 | 4,629.514 | 5,521.526 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on economic welfare of households belonging to Ethno-Religious Majority and Minority groups, identified using the pre-policy ERF index. Panel A shows Log Per Capita Consumption, defined as the log of annual per capita real consumption expenditures in rupees. Panel B shows Poverty Status, a binary indicator variable which takes a value of one if the household's consumption expenditures are below the state poverty line, and zero otherwise. Panel C shows Economic Condition, an ordinal variable measuring perceived change of household in well-being over the past 6–7 years, coded as -1 (worse off), 0 (same), and 1 (better off). All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.

Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 9:** Impact of Bank Branch Expansion on In-migration (for one to four years of residence) conditional on the Initial level of Fractionalization

| | **Into Initially High ERF areas** | | **Into Initially Low ERF areas** | |
|---|---|---|---|---|
| | (1) *Pre Policy* | (2) *Post Policy* | (3) *Pre Policy* | (4) *Post Policy* |
| **A: From all States of India** | | | | |
| RD Estimate | -0.280 | 0.457** | 0.537 | -0.051 |
| | (0.304) | (0.205) | (0.430) | (0.264) |
| | [0.357] | [0.026] | [0.211] | [0.846] |
| Control Mean | 11.525 | 11.851 | 10.888 | 11.241 |
| Observations | 185 | 185 | 186 | 186 |
| Banked Districts | 66 | 66 | 63 | 44 |
| Unbanked Districts | 81 | 81 | 86 | 64 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 4,312.890 | 4,223.353 | 5,119.717 | 3,646.147 |
| **B: From within current State of Residence** | | | | |
| RD Estimate | -0.148 | 0.488** | 0.481 | 0.107 |
| | (0.306) | (0.214) | (0.442) | (0.217) |
| | [0.630] | [0.022] | [0.277] | [0.623] |
| Control Mean | 11.192 | 11.550 | 10.506 | 10.928 |
| Observations | 185 | 185 | 186 | 186 |
| Banked Districts | 64 | 63 | 63 | 67 |
| Unbanked Districts | 81 | 80 | 86 | 89 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 4,203.443 | 4,101.704 | 5,155.606 | 5,471.280 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on in-migration, disaggregated by the extent of fractionalization of the district of current residence of the migrant in the pre-policy survey. Using district-level information from the Population Census Migration Tables for the years 2001 and 2011, we examine the total stock of migration into a district from two categories of origin: all States of India, and within the State of current residence. We draw on data on the total number of people who have migrated into their current district of residence, for one to four years of stay since they migrated, and log transform them. We use our pre-policy indicator for highly fractionalized districts (based on pre-policy ERF index), constructed using household-level data from the IHDS panel survey, and identify whether the current district of residence was initially a High ERF district or a Low ERF district. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), regressions control for the area of the current district of residence from the 2001 Population Census. Post-policy regressions, additionally, account for the density of the district, and the log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 10:** Impact of Bank Branch Expansion on Ethno-Religious Complementarity in Labor

| | **Pre-policy** | **Post-policy** | **Change in Index** |
|---|---|---|---|
| | (1) | (2) | (3) |
| **A: Duncan Index** | | | |
| RD Estimate | 0.029 | -0.207*** | -0.273*** |
| | (0.063) | (0.065) | (0.079) |
| | [0.645] | [0.001] | [0.001] |
| Control Mean | 0.346 | 0.340 | -0.006 |
| Observations | 371 | 370 | 370 |
| Banked Districts | 151 | 115 | 137 |
| Unbanked Districts | 195 | 149 | 178 |
| Covariates | ✓ | ✓ | ✓ |
| Bandwidth | 5,742.154 | 3,695.773 | 4,921.737 |
| **B: Complementarity Index** | | | |
| RD Estimate | -0.048 | -0.177*** | -0.180** |
| | (0.060) | (0.057) | (0.078) |
| | [0.425] | [0.002] | [0.021] |
| Control Mean | 0.566 | 0.564 | -0.002 |
| Observations | 371 | 370 | 370 |
| Banked Districts | 142 | 144 | 147 |
| Unbanked Districts | 181 | 183 | 187 |
| Covariates | ✓ | ✓ | ✓ |
| Bandwidth | 4,675.287 | 5,122.490 | 4,179.772 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on Duncan Index, measuring between-group occupational dissimilarity (Panel A) and Inter-ethno-religious Complementarity Index (Panel B). Change in Index (Column 3) measures the difference between the 2011-12 index and the 2004-05 index. These outcomes have been constructed from the IHDS panel survey (Rounds 2004-05 and 2011-12). All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for density and area of district from the 2001 Population Census, log number of open functioning bank branches (excluding RRBs) in the district in 2001, and state fixed effects. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 11:** Impact of Bank Branch Expansion on Administrative reported Crimes

| | *Pre* | *Post* | *Pre* | *Post* | *Pre* | *Post* |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Theft** | | **Robbery** | | **Burglary** | |
| RD Estimate | -0.283 | -0.363* | -0.250 | -0.631** | -0.031 | -0.260** |
| | (0.187) | (0.211) | (0.286) | (0.270) | (0.192) | (0.113) |
| | [0.131] | [0.085] | [0.383] | [0.020] | [0.872] | [0.022] |
| Control Mean | 5.291 | 5.508 | 2.512 | 2.784 | 4.617 | 4.588 |
| Banked Districts | 190 | 170 | 170 | 159 | 186 | 188 |
| Unbanked Districts | 289 | 245 | 246 | 227 | 282 | 283 |
| Bandwidth | 5,929.492 | 4,538.113 | 4,728.450 | 4,354.890 | 5,610.260 | 5,606.950 |
| | **Kidnapping** | | **Rape** | | **Murder** | |
| RD Estimate | 0.195 | -0.301* | 0.167 | -0.293* | -0.228 | -0.271* |
| | (0.208) | (0.170) | (0.200) | (0.163) | (0.155) | (0.154) |
| | [0.349] | [0.076] | [0.405] | [0.072] | [0.142] | [0.079] |
| Control Mean | 2.920 | 3.266 | 2.665 | 2.962 | 3.381 | 3.354 |
| Banked Districts | 195 | 161 | 184 | 186 | 174 | 181 |
| Unbanked Districts | 298 | 233 | 280 | 282 | 254 | 272 |
| Bandwidth | 6,367.402 | 4,176.210 | 5,497.143 | 4,764.642 | 4,883.974 | 5,096.032 |
| | **Deceit** | | **Other IPC Crimes** | | **Total IPC Crimes** | |
| RD Estimate | 0.057 | -0.383** | -0.005 | -0.264** | -0.122 | -0.175** |
| | (0.206) | (0.195) | (0.178) | (0.119) | (0.117) | (0.078) |
| | [0.782] | [0.050] | [0.977] | [0.026] | [0.300] | [0.024] |
| Control Mean | 3.737 | 4.083 | 6.467 | 6.641 | 7.468 | 7.622 |
| Banked Districts | 196 | 192 | 188 | 191 | 198 | 178 |
| Unbanked Districts | 302 | 291 | 283 | 289 | 309 | 262 |
| Bandwidth | 6,542.204 | 5,933.699 | 5,729.325 | 4,934.540 | 6,720.524 | 4,810.270 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on administrative reported crime-related outcomes at the district-year level using data from the National Records Crime Bureau (NCRB). The sample includes **577 districts**. We use 2004 as the pre-policy period and 2010 as the post-policy period. The outcomes measure the number of respective cases or events reported in a district in a year. For each year, all outcome variables have been winsorized at the $98^{th}$ percentiles of their respective distributions and have been log transformed. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population, density and number of towns and district in 2001 from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in district in 2001. Post-policy regressions additionally account for the log number of total IPC crimes in 2004. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.

Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## References


Alesina, Alberto, Reza Baqir, and William Easterly. 1999. "Public goods and ethnic divisions." Quarterly Journal of Economics 114 (4):1243–1284.

Alesina, Alberto, Arnaud Devleeschauwer, William Easterly, Sergio Kurlat, and Romain Wacziarg. 2003. "Fractionalization." Journal of Economic Growth 8 (2):155–194.

Anderson, Siwan. 2011. "Caste as an Impediment to Trade." American Economic Journal: Applied Economics 3 (1):239 – 63.

Ashraf, Quamrul and Oded Galor. 2013. "Genetic Diversity and the Origins of Cultural Fragmentation." American Economic Review 103 (3):528 — 533.

Bau, Natalie, Gaurav Khanna, Corinne Low, and Alessandra Voena. 2025. "Traditional institutions in modern times: Dowries as pensions when sons migrate." The Quarterly Journal of Economics :qjaf041.

Bhukta, Rikhia, Debayan Pakrashi, Sarani Saha, and Ashish Sedai. 2023. "Does Financial Inclusion Mitigate Social Exclusion?" Available at SSRN 4686788 .

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

Calonico, Sebastian, Matias D Cattaneo, Max H Farrell, and Rocio Titiunik. 2017. "rdrobust: Software for regression-discontinuity designs." The Stata Journal 17 (2):372–404.

———. 2019. "Regression discontinuity designs using covariates." Review of Economics and Statistics 101 (3):442–451.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik. 2014. "Robust nonparametric confidence intervals for regression-discontinuity designs." Econometrica 82 (6):2295–2326.

Cattaneo, Matias D and Rocio Titiunik. 2022. "Regression discontinuity designs." Annual Review of Economics 14:821–851.

Cikara, Mina, Vasiliki Fouka, and Marco Tabellini. 2022. "Hate crime towards minoritized groups increases as they increase in sized-based rank." Nature human behaviour 6 (11):1537–1544.

Cramer, Kim Fe. 2025. "Bank presence and health." Review of Finance :1–29.

Dehejia, Rajeev and Nandini Gupta. 2022. "Financial Development and Micro-Entrepreneurship." Journal of Financial and Quantitative Analysis 57 (5):1834–1861.

Deshpande, Ashwini. 2000. "Does caste still define disparity? A look at inequality in Kerala, India." American Economic Review 90 (2):322–325.

Desmet, Klaus, Ignacio Ortuño-Ortín, and Shlomo Weber. 2009. "Linguistic Diversity and Redistribution." Journal of the European Economic Association 7 (6):1291–1318.

Dumont, Louis. 1980. Homo hierarchicus: The caste system and its implications. University of Chicago Press.

Dutta, Arnab, Sahil Gandhi, and Richard K Green. 2025. "Do housing regulations affect rural–urban migration? Evidence from rent control in India." Journal of Economic Geography :1 – 26.

Easterly, William and Ross Levine. 1997. "Africa's Growth Tragedy: Policies and Ethnic Divisions." The Quarterly Journal of Economics 112 (4):1203–1250.

Esteban, Joan, Laura Mayoral, and Debraj Ray. 2012. "Ethnicity and Conflict: An Empirical Study." American Economic Review 102 (4):1310—-1342.

Esteban, Joan and Debraj Ray. 2011. "A model of ethnic conflict." Journal of the European Economic Association 9 (3):496–521.

Esteban, Joan-Maria and Debraj Ray. 1994. "On the measurement of polarization." Econometrica 62 (4):819–851.

Fang, Fei and Razvan Vlaicu. 2024. "Local banking supply and private firm activity: Evidence from branch closures in Brazil." Tech. rep., Inter-American Development Bank, Washington, DC. URL https://publications.iadb.org/publications/english/document/Local-Banking-Supply-and-Private-Firm-Activity-Evidence-from-Branch-Closures.pdf.

Fearon, James D. 2003. "Ethnic and Cultural Diversity by Country." Journal of Economic Growth 8 (2):195–222.

Gupta, Apoorv, Jacopo Ponticelli, and Andrea Tesei. 2024. "Language Barriers, Technology Adoption and Productivity: Evidence from Agriculture in India." The Review of Economics and Statistics :1–28.

Gupta, Nandini and Ashish Sedai. 2023. "Disentangling the Effects of Financial Inclusion on Household Well-Being." Available at SSRN 4393250 .

Hnatkovska, Viktoria, Amartya Lahiri, and Sourabh B. Paul. 2012. "Castes and labor mobility." American Economic Journal: Applied Economics 4 (2):274–307.

Ho, Ching Sheng and Björn Berggren. 2020. "The effect of bank branch closures on new firm formation: The Swedish case." Annals of Regional Science 65 (2):319–350.

Imbens, Guido W and Thomas Lemieux. 2008. "Regression discontinuity designs: A guide to practice." Journal of Econometrics 142 (2):615–635.

International Monetary Fund. 2024. "Financial Access Survey 2024 Highlights: Marking 15 years of supporting financial inclusion." URL https://data.imf.org/FAS. Annex II.

Iversen, Vegard, Adriaan Kalwij, Arjan Verschoor, and Amaresh Dubey. 2014. "Caste Dominance and Economic Performance in Rural India." Economic Development and Cultural Change 62 (3):423–457.

Jha, Saumitra. 2013a. "Can Financial Innovations Mitigate Ethnic and Civil Conflict?" World Financial Review :3–6.

———. 2013b. "Trade, Institutions, and Ethnic Tolerance: Evidence from South Asia." American Political Science Review 107 (4):806–832.

———. 2013c. "Trade, Institutions, and Ethnic Tolerance: Evidence from South Asia." American Political Science Review 107 (4):806–832.

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

Michalopoulos, Stelios. 2012. "The Origins of Ethnolinguistic Diversity." American Economic Review 102 (4):1508 —- 1539.

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti. 2004. "Economic shocks and civil conflict: An instrumental variables approach." Journal of Political Economy 112 (4):725–753.

Montalvo, Jose G. and Marta Reynal-Querol. 2005. "Ethnic polarization, potential conflict, and civil wars." American Economic Review 95 (3):796–816.

Putnam, Robert D. 2007. "E Pluribus Unum: Diversity and community in the twenty-first century. The 2006 Johan Skytte Prize Lecture." Scandinavian Political Studies 30 (2):137–174.

Ramadorai, Tarun. 2017. "Indian Household Finance: Report of the Household Finance Committee." Retrieved from .

RBI. 2007. "Master Circular on Branch Authorisation." https://rbidocs.rbi.org.in/rdocs/notification/PDFs/78431.pdf. Accessed: 2025-14-06.

———. 2011. "Master Circular on Branch Authorisation." https://www.rbi.org.in/commonman/Upload/English/Notification/PDFs/100BA010711F.pdf. Accessed: 2025-14-06.

Reserve Bank of India. 2005. "Basic Statistical Returns of Scheduled Commercial Banks in India." http://www.rbi.org.in/scripts/AnnualPublications.aspx?head=Basic%20Statistical%20Returns. Accessed: 2025-01-04.

Rohner, Dominic and Ekaterina Zhuravskaya. 2024. "The Economics of Nation-Building: Methodological Tool Kit and Policy Lessons." Annual Review of Economics 17.

Steele, Liza G. and Lamis Abdelaaty. 2019. "Ethnic diversity and attitudes towards refugees." Journal of Ethnic and Migration Studies 45 (11):1833–1856.

Steele, Liza G., Amie Bostic, Scott M. Lynch, and Lamis Abdelaaty. 2022. "Measuring Ethnic Diversity." Annual Review of Sociology 48:43–63.

Sutton, Catherine N. 2007. "The role of the financial services sector in expanding economic opportunity." Tech. rep., Harvard Kennedy School, Corporate Social Responsibility Initiative, Cambridge, MA. URL https://www.hks.harvard.edu/sites/default/files/centers/mrcbg/programs/cri/files/report_19_EO%2BFinance%2BFinal.pdf.

The Global Economy. 2025. "Bank branches per 100,000 people – Country rankings." https://www.theglobaleconomy.com/rankings/bank_branches/.

Topalova, Petia and Amit Khandelwal. 2011. "Trade Liberalization and Firm Productivity: The Case of India." The Review of Economics and Statistics 93 (3):995–1009.

Vanhanen, Tatu. 1999. "Domestic Ethnic Conflict and Ethnic Nepotism: A Comparative Analysis." Journal of Peace Research 36 (1):55–73.

Young, Nathaniel. 2017. "Banking and growth: Evidence from a regression discontinuity analysis."

# A Institutional Background

## A.1 Banking Policy and Financial Inclusion in India

India has a long history of directed bank expansion policies aimed at improving financial access for underserved populations. From 1969 through the 1980s, India pursued a "social banking" initiative that mandated commercial banks to open rural branches and allocate credit to priority sectors. This earlier wave of branch expansion was found to significantly reduce rural poverty and increase output (Burgess and Pande, 2005). However, the banking sector reforms of the 1990s and early 2000s shifted focus towards profitability, leading to concerns that poorer and remote areas were being left behind in access to banking services. By the early 2000s, large swathes of India's rural and semi-urban districts remained under-banked, with few bank branches (8.9 branches for 100,000 people as of 2004) relative to their population. In 2005, the RBI introduced the Branch Authorization Policy (BAP) to renew progress on financial inclusion. The BAP included a specific guideline: any bank seeking to open a new branch in a well-banked ("bank-saturated") district must open at least four new branches in under-banked districts. The RBI categorized a district as under-banked if its population-to-bank-branch ratio exceeded the national average (Cramer, 2025; Young, 2017; Gupta and Sedai, 2023). Districts with a population-per-branch ratio above the national average were classified as under-banked. This policy effectively created a discontinuous incentive at the threshold of the national average branch ratio. Banks that wanted to expand in lucrative urban markets could only do so if they also expanded in less-developed markets where branch penetration was low.[11] The result was a surge of branch openings in previously neglected districts after 2005. From 2005 to 2010, scheduled commercial banks opened thousands of new branches across India, with a disproportionately large share going to districts classified as under-banked. In contrast, districts just below the cutoff (slightly better off in terms of branch coverage) did not experience such a mandated inflow of new branches. The designation of under-banked status is based on an exogenous national metric and was not manipulable by individual districts, making it a suitable instrument for branch expansion. The institutional setting thus provides a rare opportunity to assess the causal effects of expanding formal finance, using a credible identification strategy. The expansion of formal physical bank branches is a critical element of financial inclusion, particularly for underserved districts. These institutions serve as essential points for access to credit, financial literacy, and economic participation. As evident in Figure 2, there has been an exponential increase in the total number of commercial bank branches per capita from 2005 until 2013, potentially signaling improved access to banking in underserved areas.[12] However, the growth rate plateaued after that and the expansion has stagnated, raising concerns on maintaining growth and extending access to the most remote populations in the face of shifting market dynamics, digital banking, and sector consolidation. Bank expansion matters because banking institutions, by their very presence, anchor local economic organization, creating jobs, entrepreneurship, and trust networks that extend beyond credit intermediation (Ho and Berggren, 2020; Fang and Vlaicu, 2024; Sutton, 2007), and thereby remain foundational to inclusive growth amid evolving financial technologies and market structures.[13]

## A.2 Ethno-Religious Diversity in India

India's social fabric is extraordinarily diverse, encompassing multiple dimensions of ethnicity, language, religion, and caste. The concept of *ethno-religious fractionalization* (ERF) captures the probability that two randomly selected individuals from a given area belong to different groups,

[11] According to the RBI (2007) Master Circular, new commercial banks were required to ensure at least 25% of their total branches were in semi-urban and rural areas on an ongoing basis. Later in 2011, the policy changed the requirement from 25% to 33% (RBI, 2011).

[12] A dynamic expansion of banks post BAP (19%) growth in commercial banks in treated districts compared to the control group in 2011 is noted in Cramer (2025) and Gupta and Sedai (2023).

[13] According to the IMF's Financial Access Survey, India had only about 14.47 commercial bank branches per 100,000 adults in 2023, compared with a global sample average of roughly 60 branches per 100,000 adults in 2021 (International Monetary Fund, 2024; The Global Economy, 2025). This large gap suggests that India's physical banking outreach remains markedly below both regional and advanced-economy norms.

based on a defined set of ethnic categories (Fearon, 2003). In the Indian context, social group (or caste) and religion are two salient markers of ethnic identity. Our measure of ERF combines household-level information on social group and religion affiliation of households to quantify fractionalization at the district level. The index ranges from 0 (complete homogeneity) to 1 (maximum heterogeneity). As of the early 2000s, household-based district-level ERF index ranged from below 0.3 in homogeneous regions to around 0.8 in highly diverse areas; diversity is particularly high in historically poorer BIMARU states[14]. Ethno-religious diversity in India has been linked to variations in local public good provision and social outcomes. Studies have shown that areas with greater caste and religious fragmentation have poorer delivery of public services and weaker local governance (Alesina et al., 2003; Alesina, Baqir, and Easterly, 1999). There is also evidence that social capital (such as trust and participation in collective activities) is lower in more fragmented villages and districts (Miguel, Satyanath, and Sergenti, 2004). Communal conflicts and caste-based violence tend to flare up in areas where multiple groups contend for resources and political power, especially when institutional mechanisms for conflict resolution are weak (Montalvo and Reynal-Querol, 2005; Esteban and Ray, 2011). At the same time, India's diversity can be a source of economic dynamism and complementary skills, but only if different groups are equally included in development processes. Prior to our study period, financial inclusion in India was unevenly distributed, and it often mirrored these ethnic and linguistic divides (Burgess and Pande, 2005; Bhukta et al., 2023; Gupta, Ponticelli, and Tesei, 2024). Marginalized communities, such as lower castes and linguistic/religious minorities, have historically had lower access to bank credit and formal financial services (Hnatkovska, Lahiri, and Paul, 2012). This can be attributed to discrimination, lower financial literacy, or residence in remote areas that lack banking facilities. Social exclusion in finance reinforces economic disparities: for example, if lower caste households are denied credit or face higher borrowing costs due to prejudice or lack of collateral, they remain trapped in informal debt cycles and cannot invest in education or businesses, perpetuating income gaps (Deshpande, 2000). One central question is whether expanding formal banking infrastructure in a community can break these patterns by offering underserved groups greater opportunities. Our empirical setting, India around the mid-2000s, thus features the confluence of an ambitious financial inclusion policy and deeply entrenched social diversity. This provides a platform to examine how the two interact.

[14]Panel A of Appendix Figure C6 illustrates the variation in the ELF index from IHDS 2011-12 at the district level. Further, Panel B portrays the spatial distribution of IPC Crime Intensity from National Crime Records Bureau (NCRB) 2013 over Panel A.

# B Ethno-Religious Polarization

Fractionalization counts the diversity of a place but is silent on how cohesive its groups are and how sharply they stand apart. If, as the migration and consolidation evidence indicates, financial access drew many small groups into fewer, larger, and more internally cohesive blocs, a measure that weights within group cohesion should register that movement even where fractionalization records only a fall in diversity. We examine this using the Esteban and Ray index of ethno-religious polarization, $P_d(\alpha) = C \sum_i \sum_j p_{id}^{1+\alpha} p_{jd} \, \delta_{ijd}$ with $\delta_{ijd} = \mathbb{1}(i \neq j)$, where the affinity parameter $\alpha$ governs the weight on within group identification and, as it rises, increasingly rewards the few large cohesive blocs that fractionalization penalizes. We treat these polarization results as corroboration rather than as a primary finding, since $\alpha$ must be calibrated rather than observed; the direction of the divergence we report is robust to the calibration.

## B.1 Estimating Group Affinity ($\alpha$) for the Indian Economy

The Esteban-Ray framework developed by Esteban and Ray (1994) to construct the ethno-linguistic polarization index hinges critically on the group affinity parameter reflecting effective antagonism between groups (Desmet, Ortuño-Ortín, and Weber, 2009; Steele and Abdelaaty, 2019; Steele et al., 2022). In the absence of reliable granular district-level data on social cohesion for the Indian economy, we follow Esteban, Mayoral, and Ray (2012, pp. 1333–1334) and draw data on indicators related to group commitment, belongingness, adhesion to social norms, and others, from the **World Values Survey** Wave 5 (2005 - 2009) to construct a theoretically grounded proxy for group cohesion. In particular, we use the answers to the following questions asked in the survey.

**Table B1:** Survey Questions from World Values Survey Wave 5 to estimate Group Affinity ($\alpha$)

| Variable | Question asked in Survey |
|---|---|
| V84 | It is important to this person to help the people nearby; to care for their well-being |
| V87 | It is important to this person to always behave properly; to avoid doing anything people would say is wrong |
| V89 | Tradition is important to this person; to follow the customs handed down by one's religion or family |
| V7 | For each of the following, indicate how important it is in your life. Would you say it is: Politics |
| V9 | For each of the following, indicate how important it is in your life: Religion |
| V211 | People have different views about themselves and how they relate to the world. Using this card, would you tell me how strongly you agree or disagree with each of the following statements about how you see yourself?: I see myself as part of my local community |

*Note:* All variables are normalized to a 1 – 4 scale.

## B.2 The Effect of Bank Branch Expansion on Polarization

We calibrate $\alpha$ in two ways, backing out $\alpha = 1.60$ from Esteban, Mayoral, and Ray (2012) and estimating $\alpha = 1.7623$ from the indicators of group commitment and adhesion to norms for India in the World Values Survey described above. Table B3 reports the effect of bank branch expansion on polarization for three values of $\alpha$. At low affinity ($\alpha = 0.10$), where the index behaves much like fractionalization, polarization falls by 0.108 after the policy, about twenty percent of

the control mean, tracking the decline in diversity. At the high affinity values the Indian data support, polarization instead rises, by 0.020 and 0.023, roughly a quarter of the control mean. Appendix Table D1 shows the logic: redistributing population toward a dominant group lowers fractionalization from 0.750 to 0.715 while raising high affinity polarization from 0.065 to 0.077. Through a distinct measure, then, the same reorganization that lowered the probability that two individuals differ raised the antagonistic bloc structure of the district, corroborating the finding that the fall in measured diversity coincided with a deepening, not a dissolution, of the divisions between groups.

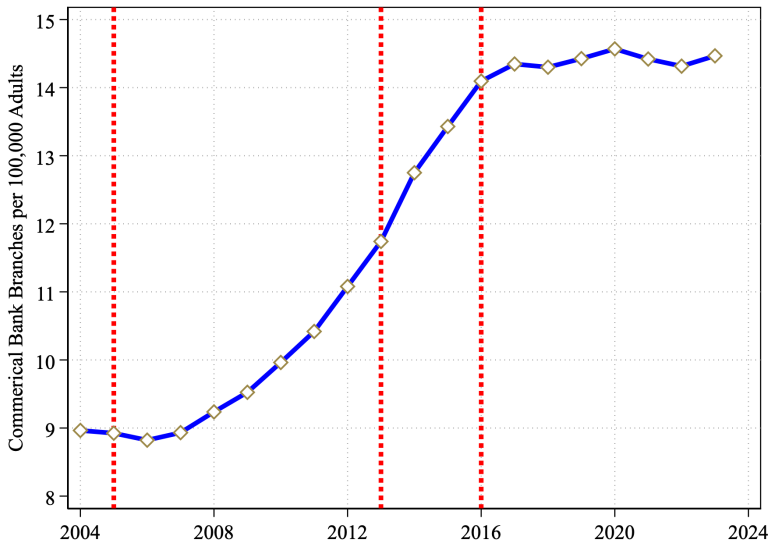
**Table B3:** Impact of Bank Branch Expansion on Ethno-Religious Polarization

| | **Pre Policy** | **Post Policy** |
|---|---|---|
| | (1) | (2) |
| **A: Low Group Affinity** ($\alpha = 0.10$) | | |
| RD Estimate | -0.065 | -0.108** |
| | (0.043) | (0.044) |
| | [0.125] | [0.015] |
| Control Mean | 0.540 | 0.540 |
| Observations | 40,018 | 40,018 |
| Banked Districts | 120 | 115 |
| Unbanked Districts | 158 | 149 |
| Covariates | ✓ | ✓ |
| Bandwidth | 4,256.775 | 3,770.753 |
| **B: High Group Affinity** ($\alpha = 1.60$) | | |
| RD Estimate | 0.001 | 0.020* |
| | (0.008) | (0.010) |
| | [0.949] | [0.057] |
| Control Mean | 0.108 | 0.107 |
| Observations | 40,018 | 40,018 |
| Banked Districts | 135 | 112 |
| Unbanked Districts | 175 | 142 |
| Covariates | ✓ | ✓ |
| Bandwidth | 4,990.124 | 3,900.904 |
| **C: High Group Affinity** ($\alpha = 1.7623$) | | |
| RD Estimate | 0.003 | 0.023** |
| | (0.009) | (0.010) |
| | [0.738] | [0.028] |
| Control Mean | 0.093 | 0.093 |
| Observations | 40,018 | 40,018 |
| Banked Districts | 133 | 112 |
| Unbanked Districts | 171 | 142 |
| Covariates | ✓ | ✓ |
| Bandwidth | 4,855.003 | 3,878.798 |

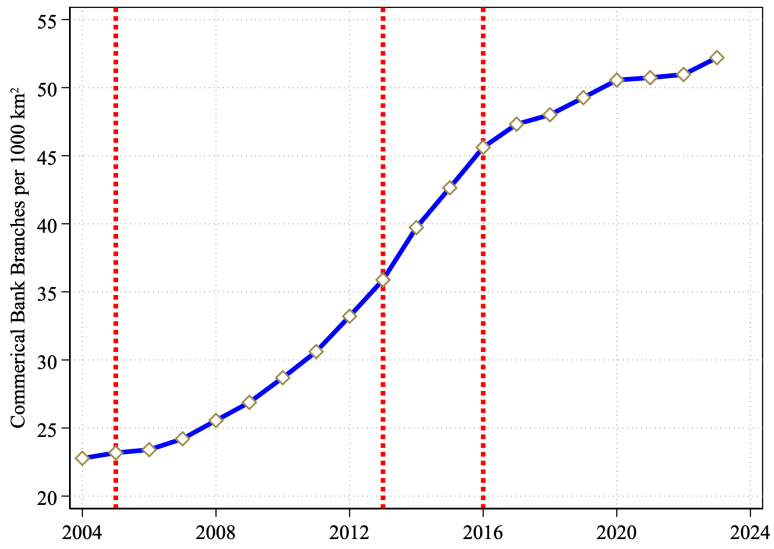
*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on the Esteban Ray Index of Ethno-Religious Polarization, constructed using household-level information on social group and religious affiliation from the IHDS panel survey (Rounds 2004-05 and 2011-12). Panel A shows the estimates for low within-group social cohesion: $\alpha = 0.10$, fixed by considering the maximum value of ELF index (Montalvo and Reynal-Querol, 2005), and Panels B and C show the estimates for high within-group social cohesion: $\alpha = 1.60$ (obtained by back-tracking the ethno-linguistic polarization index constructed by Esteban, Mayoral, and Ray (2012)) and $\alpha = 1.7623$ (estimated using country-level data on India from World Values Survey Wave 5 (2005 - 2009) as elaborated in Appendix B.1) respectively. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population and log density of the district from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.

Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# C Appendix Figures




**A:** *Commercial Bank Branches per 100,000 Adults*




**B:** *Commercial Bank Branches per 1000 km$^2$*

**Figure C1: Growth in Commercial Bank Branches with respect to Number of Adults and Distance in India**
Figure presents the expansion in the number of commercial bank branches per 100,000 adults (Panel A) and per 1000 km$^2$ (Panel B) for India from 2004 till 2023. These annual indicators have been taken from the Federal Reserve Economic Data (FRED), maintained by the Federal Reserve Bank of St. Louis.

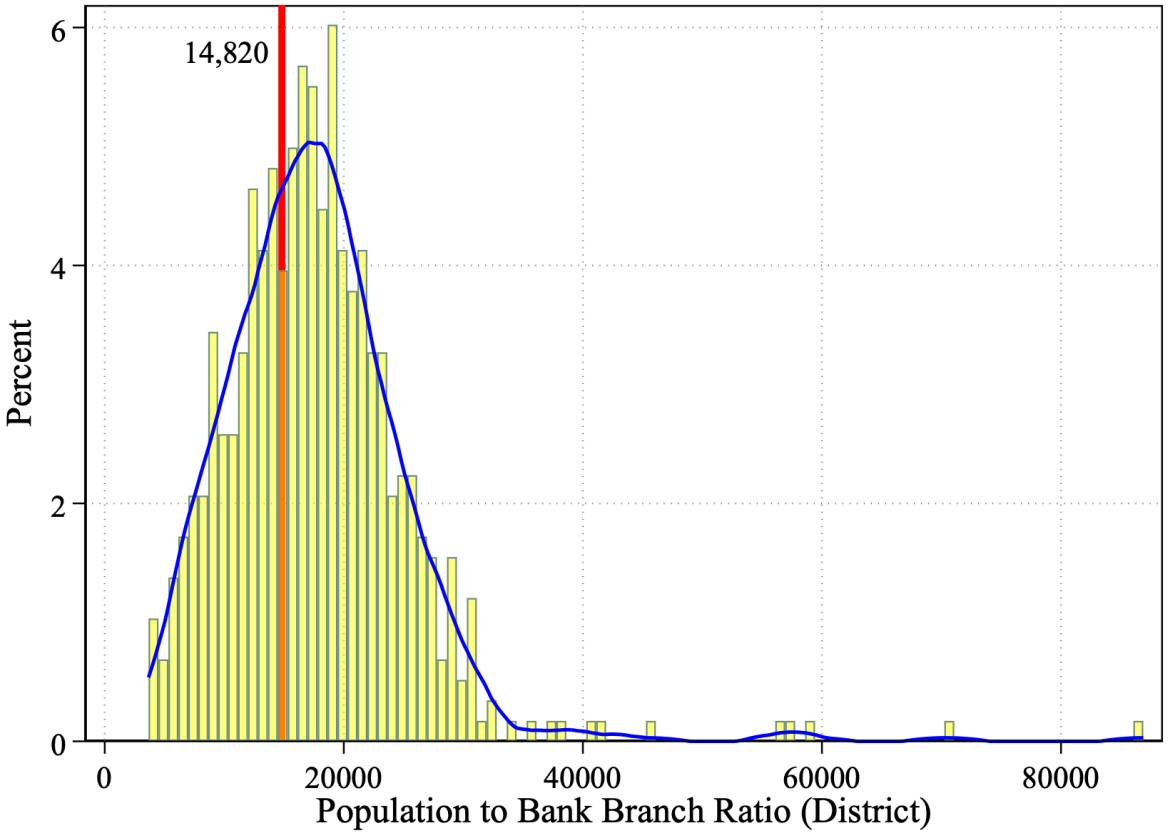
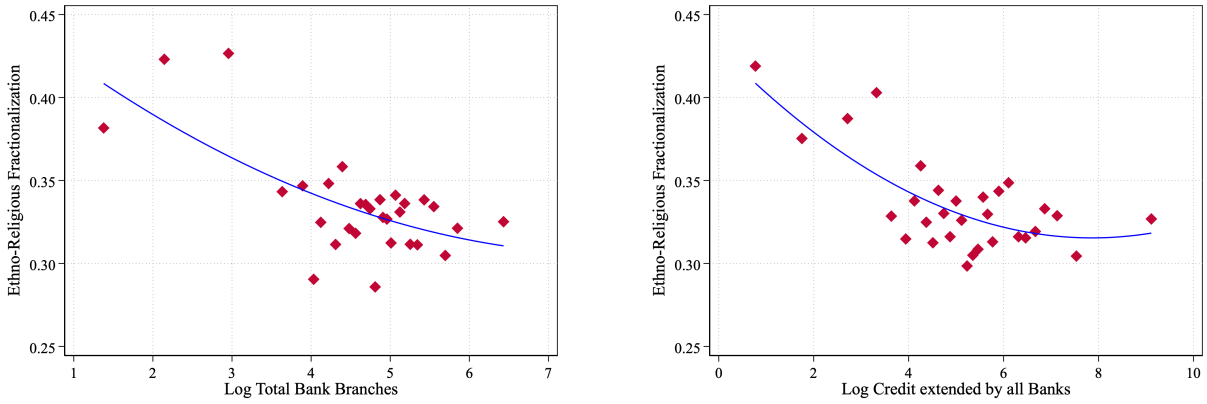



**Figure C2: Distribution of Population to Bank Branch Ratios at the district level.** Figure shows the distribution of the running variable, Population to Bank Branch Ratio, defined at the district level. The vertical red line marks the cutoff, indicating the national average of population to bank branch ratio (14,820) in 2005.




**A:** *ERF and Total Bank Branches* **B:** *ERF and Credit extended by Banks*

**Figure C3: Relationship between Ethno-Religious Fractionalization (ERF) and Financial Development in India: 1991 – 2001**

Figure presents bivariate relationship, using binned scatter plots with quadratic fits, between Ethno-Religious Fractionalization Index and Financial Development in India using a district-year panel for the years 1991 and 2001. We obtain district level population data for different religions and categories of Scheduled Caste and Scheduled Tribes from the Population Census of India for 1991 and 2001. We use these information to construct fractionalization measures based on religion and social group. Since different forms of ethnic division strengthen each other (Vanhanen, 1999), we combine these two dimensions of ethnic and religious heterogeneity and construct our district level index of ethno-religious fractionalization for each year. Panel A shows the relationship of ERF with total number of bank branches (log transformed), and Panel B shows the relationship of ERF with total credit extended by all banks (log transformed). The data for these financial development indicators has been drawn from the Reserve Bank of India's Basic Statistical Returns (1991–2001).

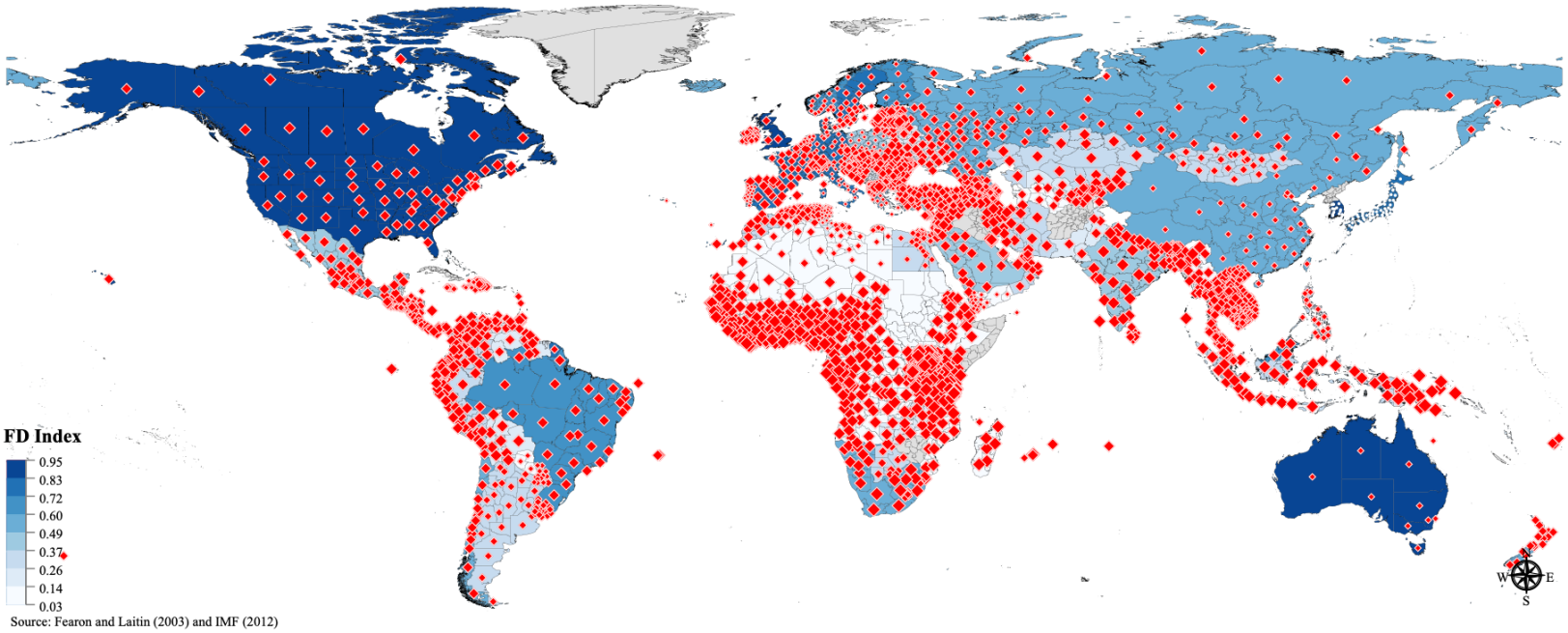
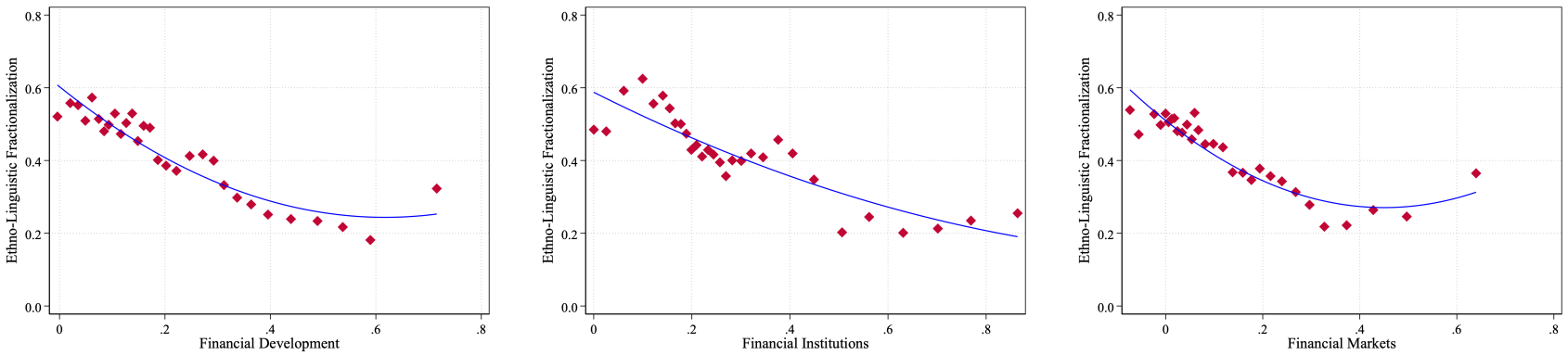



**Figure C4: Spatial Distribution of Financial Development and Ethnic Fractionalization**

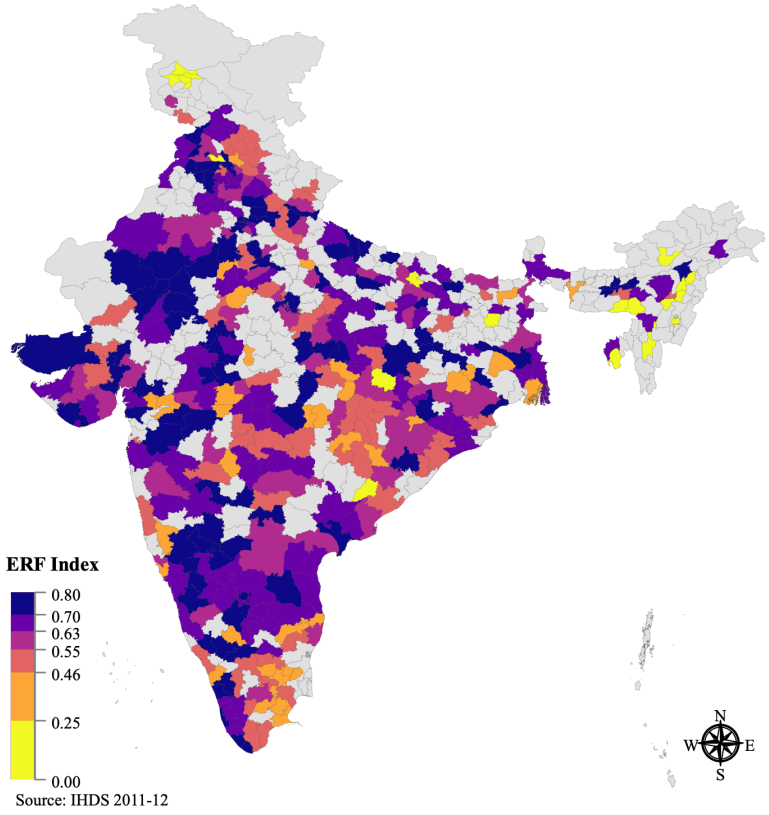
Figure presents a heat map of the level of financial development of different countries for the financial year 2012-13, with the index values ranging from 0.03 (low financial development) to 0.95 (high financial development). Data for this index has been obtained from the IMF's Financial Development database. Onto this map is overlaid Fearon's Ethnic Fractionalization Index, represented by circles plotted on the country centroids, with size proportional to the value of the index. Data on this index has been taken from Fearon (2003).



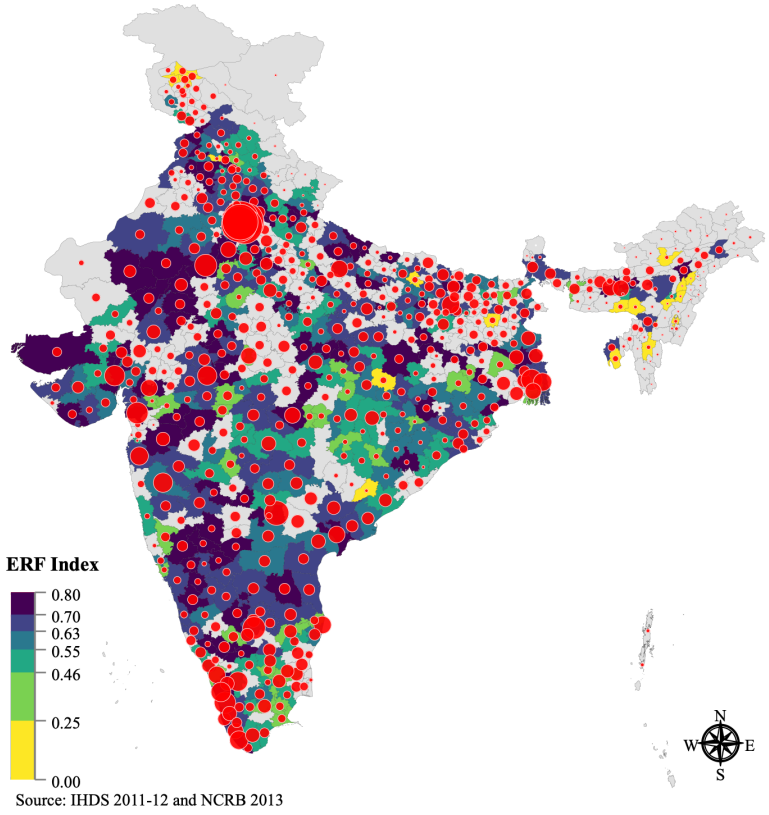

**A:** *ELF and Financial Development* **B:** *ELF and Financial Institutions* **C:** *ELF and Financial Markets*

**Figure C5: Cross-country relationship between Ethno-Linguistic Fractionalization (ELF) and Financial Development and its components: 1980 – 1999**

Figure presents bivariate relationship, using binned scatter plots with quadratic fits, between Ethno-Linguistic Fractionalization (ELF) Index and Financial Development using a country-year panel for 166 countries for the period 1980 – 1999. We obtain data on Fearon's ELF Index from Fearon (2003) and the indices for Financial Development, and its components: Financial Institutions and Financial Markets, from IMF's database. All the scatter plots account for year fixed effects, while binning the data.



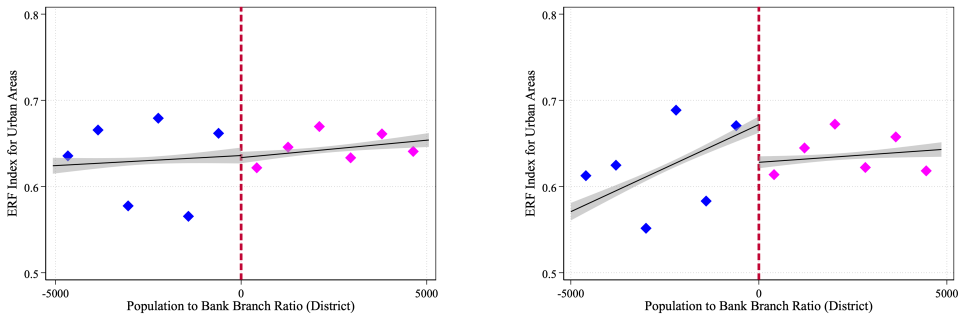

**A:** *Ethno-Religious Fractionalization in India (2011-12)*




**B:** *Ethno-Religious Fractionalization (2011-12) and Total IPC Crimes (2013) in India*

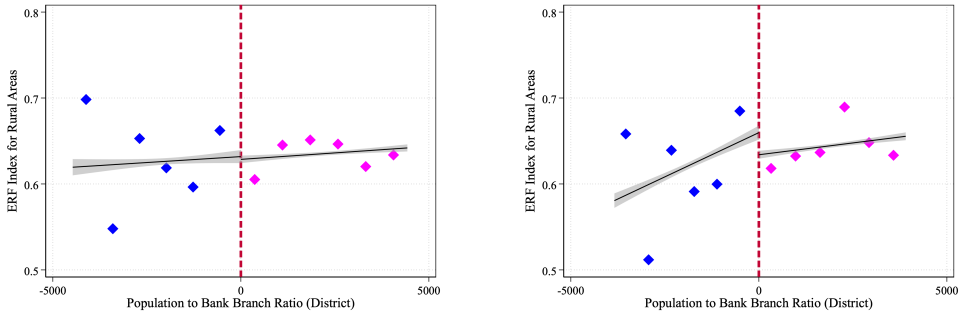
**Figure C6: Ethno-Religious Fractionalization (ERF) and IPC crime intensity in India**

Panel A presents a heat map of Ethno-Religious Fractionalization across the districts of the Indian economy, with the index values ranging from 0 (complete homogeneity) to about 0.83 (maximum diversity). The index is constructed using household-level social group and religion affiliation data from the Indian Human Development Survey II (IHDS 2011-12), capturing the probability that two randomly selected individuals from a district belong to different ethno-religious groups. Onto this heat map, Panel B overlays the total number of reported IPC (Indian Penal Code) crimes for the year 2013, using administrative data from the National Crime Records Bureau (NCRB). Crime intensity is visualized using circles centered on district centroids, with circle size proportional to the absolute number of total IPC crimes in each district.



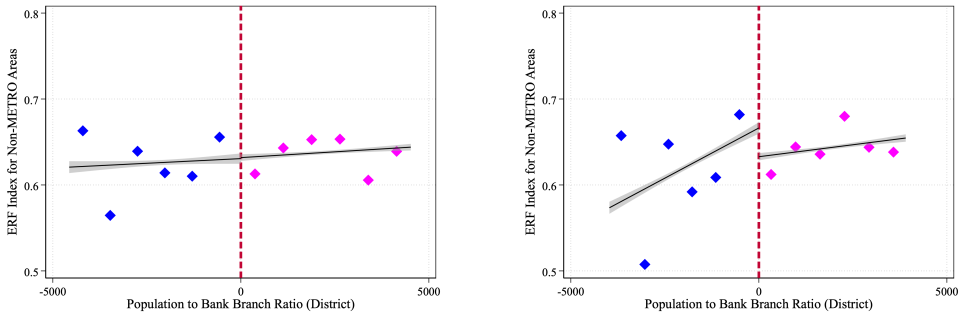

*Pre Policy: ERF Index* *Post Policy: ERF Index*

**A: Urban Areas**




*Pre Policy: ELF Index* *Post Policy: ERF Index*

**B: Rural Areas**

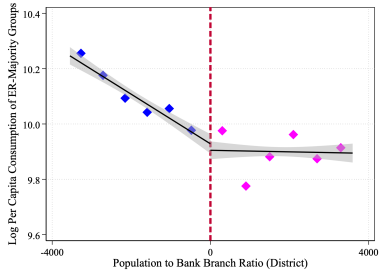



*Pre Policy: ERF Index* *Post Policy: ERF Index*

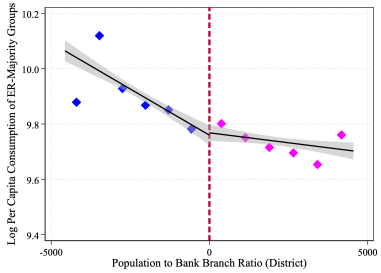
**C: Non-METRO Areas**

**Figure C7: Pre-policy smoothness and post-policy discontinuity in Ethno-Religious Fractionalization Index for different sub-samples**

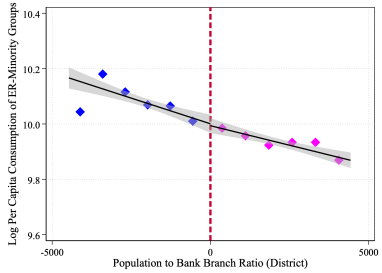
Figure shows local RD estimates for the Ethno-Religious Fractionalization (ERF) Index constructed using household-level data on social affiliation and religion from the IHDS panel survey (Rounds 2004-05 and 2011-12) for different sub-samples. Panel A shows the estimates for Urban areas, Panel B shows the estimates for Rural areas, and Panel C shows the estimates for Non-METRO areas. We exclude Mumbai, Delhi, Kolkata, Chennai, Bangalore, and Hyderabad from the full sample to identify the Non-METRO areas. Each graph plots binned means around the district population per bank branch cutoff (normalized to zero) within optimal bandwidths, along with 95 percent confidence intervals.



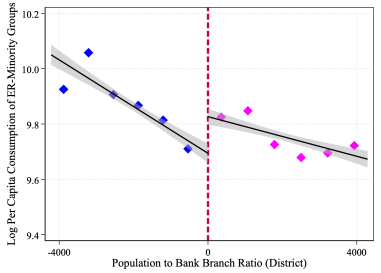

**A1:** *Pre Policy: Per Capita Consumption of ER-Majority Groups*




**A2:** *Post Policy: Per Capita Consumption of ER-Majority Groups*

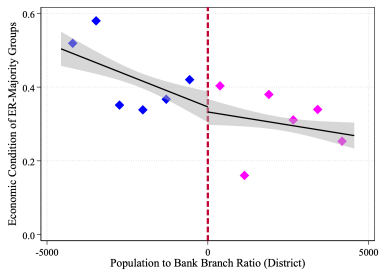



**A3:** *Pre Policy: Per Capita Consumption of ER-Minority Groups*

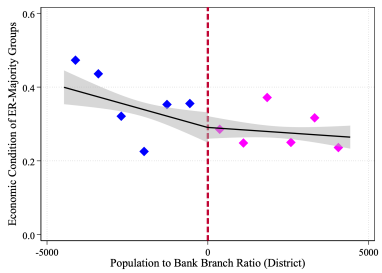



**A4:** *Post Policy: Per Capita Consumption of ER-Minority Groups*

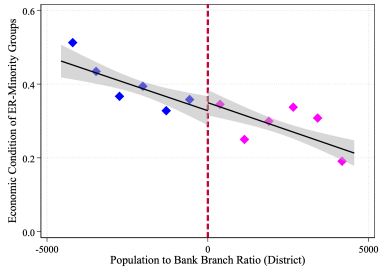
**A: Per Capita Consumption**



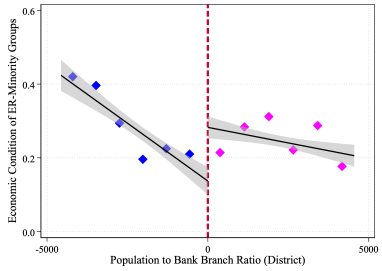

**B1:** *Pre Policy: Economic Condition of ER-Majority Groups*




**B2:** *Post Policy: Economic Condition of ER-Majority Groups*




**B3:** *Pre Policy: Economic Condition of ER-Minority Groups*

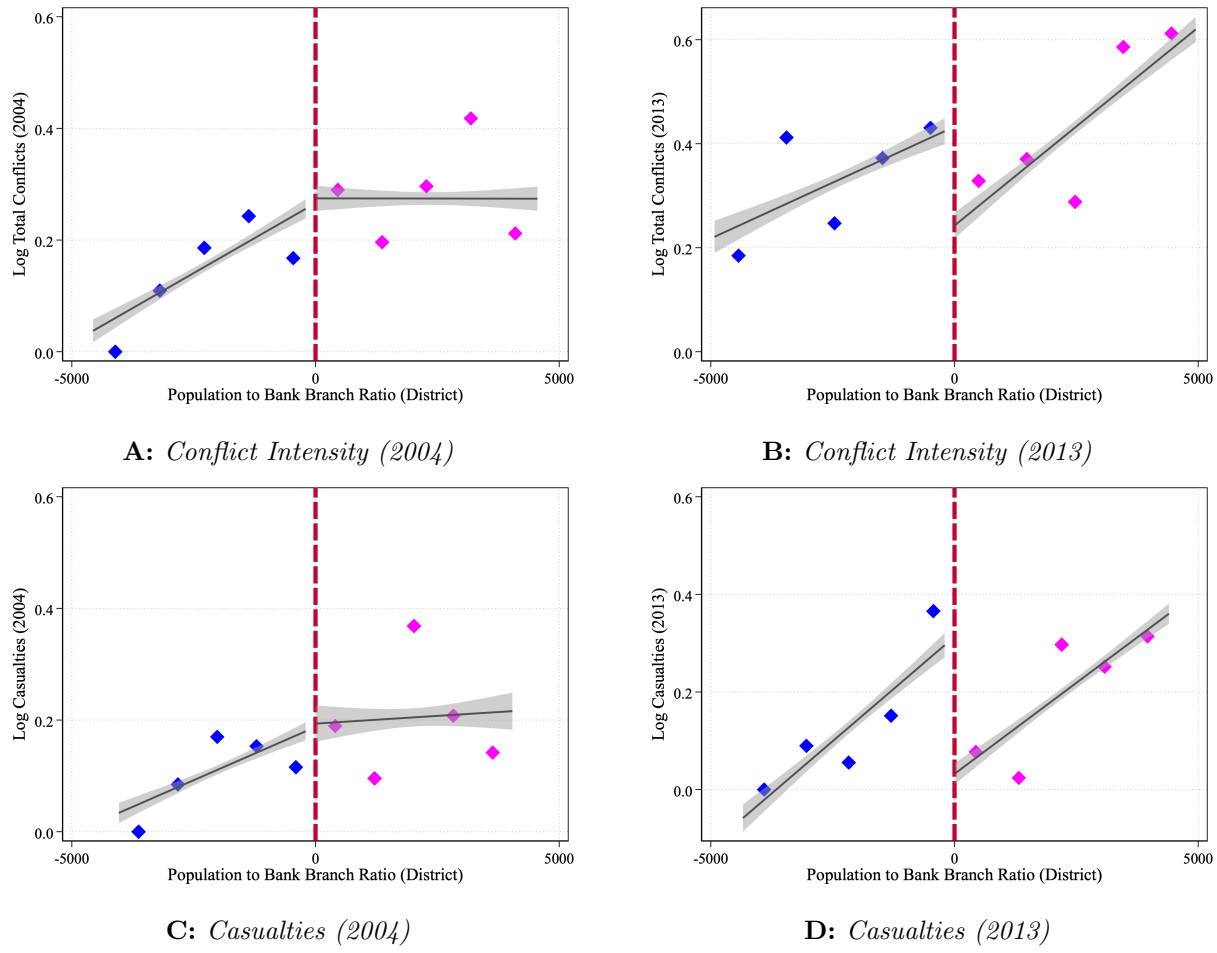



**B4:** *Post Policy: Economic Condition of ER-Minority Groups*

**B: Economic Condition**

**Figure C8: Pre-policy smoothness and post-policy discontinuity in outcomes indicating Economic Welfare of Ethno-Religious Majority and Minority Households**

Figure shows local RD estimates for log per capita consumption expenditure of households in Panel (A) and their economic condition (using a categorical variable equal to one for households relatively better off in the 6-7 years preceding the date of survey, equal to zero if they were in the same condition, and equal to -1 if they were in worse condition) in Panel (B). The sub-figures within each panel present the estimates for households belonging to Ethno-Religious Majority and Minority Groups for pre- and post-policy periods respectively. Each graph plots binned means around the district population per bank branch cutoff (normalized to zero) within optimal bandwidths, along with 95 percent confidence intervals.




**A:** *Conflict Intensity (2004)*

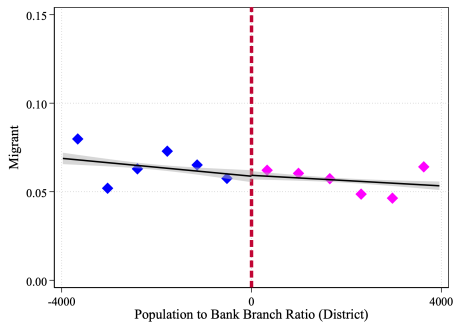
**B:** *Conflict Intensity (2013)*

**C:** *Casualties (2004)*

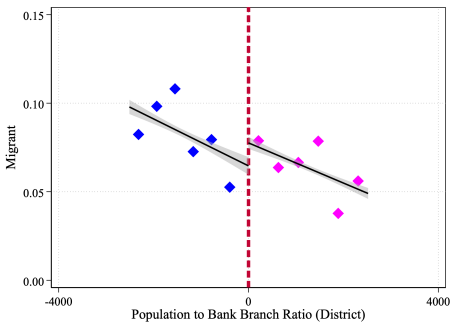
**D:** *Casualties (2013)*

**Figure C9: Pre-policy smoothness and post-policy discontinuity in administrative reported Conflicts and Casualties**

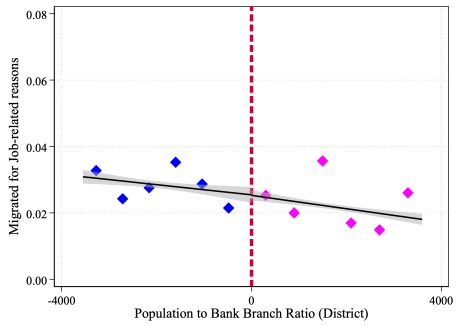
Figure shows local RD estimates for total conflicts and casualties using district-level information from the South Asia Terrorism Portal (SATP) corpus. We use data for 2004 to show pre-policy smoothness and 2013 to examine the post-policy impact. Outcomes have been winsorized at the tails of their respective distributions for each year and have been log transformed. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), post-policy RD specifications control for log district population from the 2001 Population Census, log number of open functioning bank branches (excluding RRBs) in the district for the years 2001 and 2003, and pre-policy values of the respective outcomes. Each graph plots binned means around the district population per bank branch cutoff (normalized to zero) within optimal bandwidths, along with 95 percent confidence intervals.



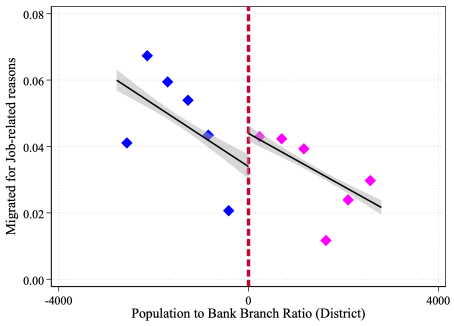

**A:** *Pre Policy: Migration*



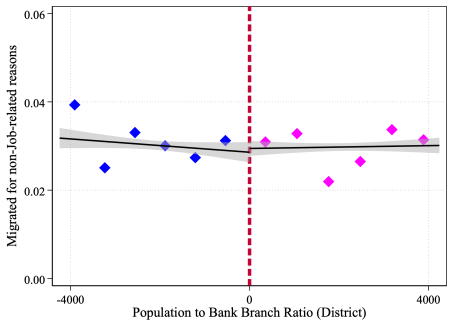

**B:** *Post Policy: Migration*



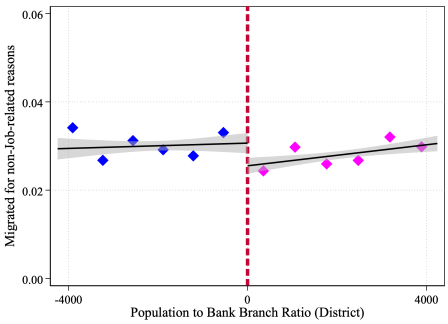

**C:** *Pre Policy: Migration for Job-related reasons*




**D:** *Post Policy: Migration for Job-related reasons*




**E:** *Pre Policy: Migration for Non-Job-related reasons*




**F:** *Post Policy: Migration for Non-Job-related reasons*

**Figure C10: Pre-policy smoothness and post-policy discontinuity in outcomes indicating Migration in the Indian economy**

Panels (A) and (B) show local RD estimates for whether an individual migrated out. Panels (C) and (D) show local RD estimates for whether migration happened for Job-related-reasons. Panels (E) and (F) show local RD estimates for whether migration happened for Non-Job-related reasons. Pre-policy outcomes are from the the $55^{th}$ round of the National Sample Survey's (NSS) Employment and Unemployment Survey (EUS) (1999-2000), and post-policy outcomes are from the $64^{th}$ round of the NSS EUS (2007-2008). These outcomes show the immediate (very short-term) impacts of the bank branch expansion on overall migration in the economy and the reasons for migration. Each graph plots binned means around the district population per bank branch cutoff (normalized to zero) within optimal bandwidths, along with 95 percent confidence intervals.

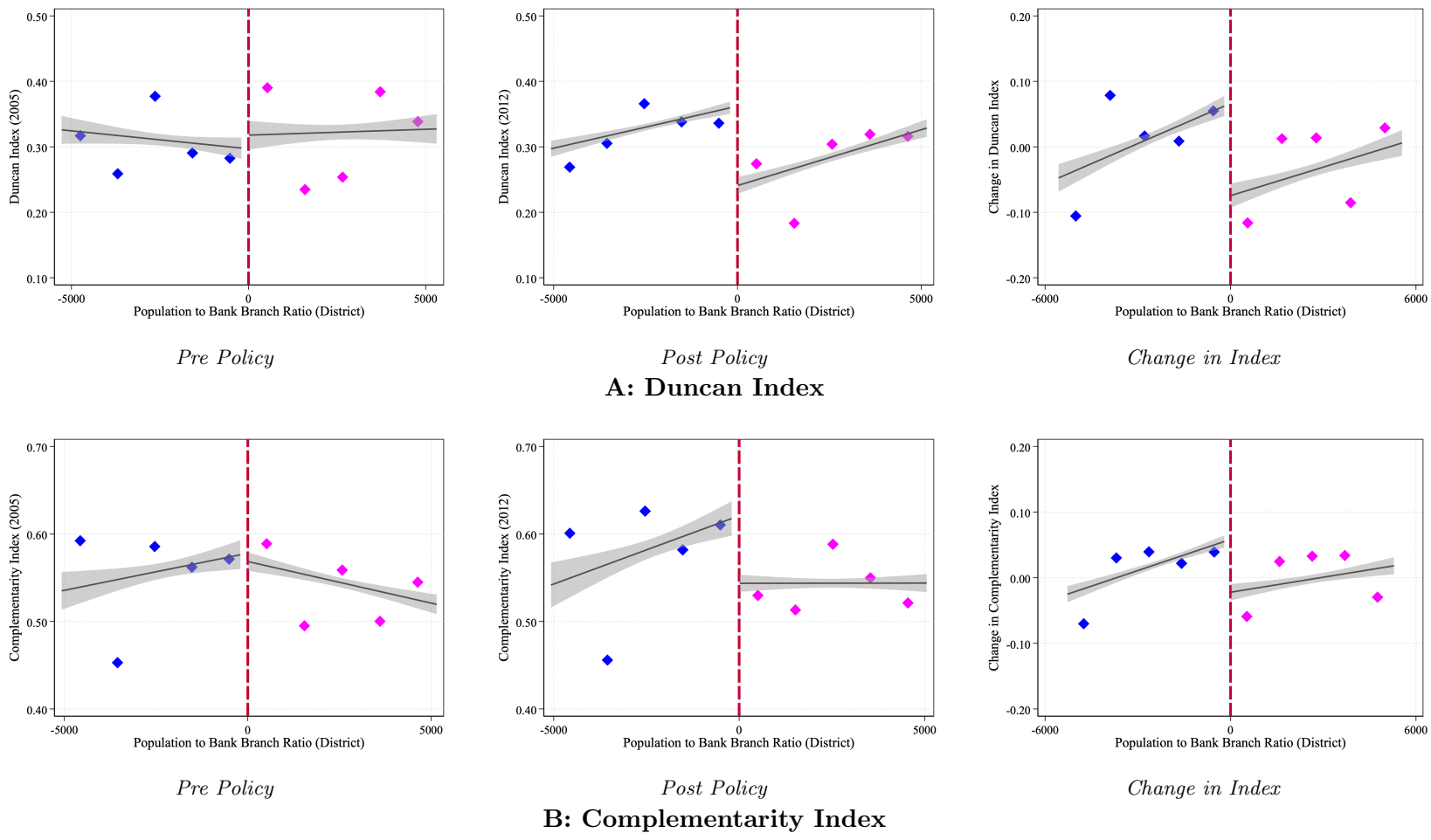



**Figure C11: Pre-policy smoothness and post-policy discontinuity in Ethno-Religious Complementarity in Labor**
Figure shows local RD estimates for Duncan Index, measuring between-group occupational dissimilarity (Panel A) and Inter-ethno-religious Complementarity Index (Panel B). Change in Index measures the difference between the 2011-12 index and the 2004-05 index. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for state fixed effects. Each graph plots binned means around the district population per bank branch cutoff (normalized to zero) within optimal bandwidths, along with 95 percent confidence intervals.

# D Appendix Tables

## D.1 Numerical Illustration: Fractionalization and Polarization

**Table D1:** Population Shares and Fractionalization

| | **Pre-policy** | **Post-policy** |
|---|---|---|
| **Population shares** | A = 0.25<br>B = 0.25<br>C = 0.25<br>D = 0.25 | A = 0.40<br>B = 0.25<br>C = 0.20<br>D = 0.15 |
| **Fractionalization** | | |
| ERF $= 1 - \sum p_i^2$ | $= 0.750$ | $= 0.715$ |
| **Polarization** | | |
| ER Index $\mid (\hat{\alpha} = 0.10) = \sum_{i \neq j} p_i^{1+0.10} p_j$ | $\approx 0.6529$ | $\approx 0.6237$ |
| ER Index $\mid (\hat{\alpha} = 1.7623) = \sum_{i \neq j} p_i^{1+1.7623} p_j$ | $\approx 0.0651$ | $\approx 0.0769$ |

*Note:* Table illustrates the computation of fractionalization and polarization indices for a community having four distinct ethno-religious groups A, B, C, and D, along with the impact of changes in the shares on the two metrics. Prior to the policy change, each group constitutes 25% of the population, whereas, post-policy, the shares get redistributed.

## D.2 Panel Fixed Effects (Decadal) analysis using Population Census

We move beyond the RBI 2005 BAP experiment and study the relationship between bank-based formal financial inclusion and fractionalization using district-level administrative data from the Population Census and Basic Statistical Returns maintained by the Reserve Bank of India, spanning two decades. We measure Ethno-Religious Fractionalization (ERF) using district-level population data on social groups and religions from Population Census 1991 and 2001. To capture bank-based financialization, we draw on information on the number of bank branches and credit extended by banks for the years 1991 and 2001. Appendix Figure C3 presents binned scatter plots of the ERF index against total number of bank branches and total credit extended by all the banks (both measures log transformed), demonstrating a negative relationship between bank-based financial development and ethno-religious fractionalization. We leverage both cross-sectional and temporal variation in financial infrastructure and adopt a two-pronged approach to study their static and dynamic effects on fractionalization in the Indian economy. Following Dehejia and Gupta (2022), we delve into the expansion of total bank branches in 1991, and government-owned bank branches to mitigate the potential endogeneity of bank branch location driven by post-reform economic growth factors, and show a significant negative association between bank branch presence and ethno-religious fractionalization. Appendix Table D2 reports these results using a robust fixed effects framework by controlling for a vector of fixed effects and/or state-specific time trends to account for heterogeneity in the temporal trajectories of economic and social changes across states. Columns 1 and 2 show the static relationship using bank branch density for 1991, while columns 3 and 4 capture the dynamic relationship using bank branch density for both 1991 and 2001. Furthermore, we follow Dehejia and Gupta (2022) and re-run these specifications with credit provided by banks at the district level as an alternative measure of access to finance and provide strong corroborating evidence for the stabilizing effect of bank-based financial development on fractionalization, irrespective of the time and source dimensions.

**Table D2:** Financial Development and Ethno-Religious Fractionalization

| | Bank Branches | | | | Access to Credit | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Log Total Bank Branches | -0.021*** | | -0.037*** | | | | | |
| | (0.007) | | (0.011) | | | | | |
| Log Government-owned Bank Branches | | -0.016*** | | -0.025*** | | | | |
| | | (0.006) | | (0.008) | | | | |
| Log Credit extended by all Banks | | | | | -0.008** | | -0.012** | |
| | | | | | (0.004) | | (0.006) | |
| Log Credit extended by Government-owned Banks | | | | | | -0.007** | | -0.014** |
| | | | | | | (0.004) | | (0.006) |
| Observations | 855 | 845 | 861 | 851 | 855 | 855 | 861 | 861 |
| Clusters (District × Year) | 843 | 833 | 854 | 844 | 843 | 843 | 854 | 854 |
| State Fixed Effects | ✓ | ✓ | | | ✓ | ✓ | | |
| District Fixed Effects | | | ✓ | ✓ | | | ✓ | ✓ |
| Year Fixed Effects | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State × Year Fixed Effects | ✓ | ✓ | | | ✓ | ✓ | | |
| State Time Trends | | | ✓ | ✓ | | | ✓ | ✓ |
| Adjusted-$R^2$ | 0.406 | 0.423 | 0.968 | 0.971 | 0.401 | 0.400 | 0.968 | 0.968 |

*Note:* Table reports the estimated coefficients from district-year panel regressions of ethno-religious fractionalization (ERF) on the log of total number of bank branches from 1991 and 2001. Column (1) uses the total bank branches in 1991 and Column (2) uses the government-owned bank branches in 1991, following Dehejia and Gupta (2022), to address concerns regarding the potential endogeneity of bank branch location. Specifically, contemporaneous bank branch locations are likely to be influenced by unobserved district-level characteristics that are also correlated with individual and firm-level choices, which could bias the estimates. By using 1991 government-owned bank branch district locations, we exploit a period when the location of branches was primarily determined by the 1:4 licensing policy introduced by the RBI in 1977, which targeted rural and unbanked areas based on population size and pre-existing financial infrastructure, rather than being driven by profit-seeking motives (Burgess and Pande, 2005). As such, the location of government-owned bank branches in 1991 reflects a more exogenous distribution of financial services, less likely to be influenced by post-reform economic growth factors. This specification assumes that the number of government bank branches in 1991 is correlated with subsequent branch locations, while avoiding the bias that would arise from using contemporaneous or privately-owned branch locations. In these models, we introduce state fixed effects to account for unobserved time-invariant characteristics that are specific to each state, year fixed effects to capture nationwide trends, and their interaction to account for state-specific shocks over time, acknowledging that different states may experience different trajectories in terms of economic development, banking expansion, or ethno-religious dynamics. Columns (3) and (4) augment the analyses by incorporating data on bank branches from both 1991 and 2001, allowing us to capture the dynamic relationship between bank branch density and ethno-religious fractionalization over time. Although these two specifications may be subject to some of the endogeneity concerns elaborated above, they help to observe a more comprehensive picture of bank branch distribution. In these specifications, we account for district fixed effects, year fixed effects, and State time trends. Columns (5) to (8) present present alternate specifications, using credit provided by banks at the district level as an alternative measure of access to finance. Robust standard errors clustered at district × year level are reported in parentheses.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

### D.3 Cross-country Evidence on Financialization and Fractionalization

We present an additional piece of evidence in a cross-country context, which expands our understanding of the relationship between financial development and social fragmentation. We obtain data on country-level fractionalization and polarization indices from Montalvo and Reynal-Querol (2005), and Fearon (2003), along with explanatory variables, including Log real GDP per capita ($LGDPC$), percent of mountainous terrains ($MOUNTAINS$), binary indicator for country having noncontiguous states ($NONCONT$), binary indicator for democracy of country ($DEMOCRACY$), and a lagged indicator of armed conflict in a country generating more than 25 deaths yearly ($PRIO25lag$). We match this data with country-level data on Financial Development Index from the IMF Financial Development database. The final matched sample includes 166 countries for the period $1980-1999$. Appendix Figure C5 presents binned scatter plots of Fearon's ELF index against the Financial Development Index and its components: Financial Institutions Index and Financial Markets Index, demonstrating a negative relationship between financial development and ethno-linguistic fractionalization. Appendix Table D3 establishes significant negative association between the fractionalization and polarization indices and financial development in different specifications. The results remain robust to accounting for year fixed effects.

**Table D3:** Relationship between Fractionalization and Polarization Indices and Financial Development

| | **Fearon's Ethno-Linguistic Fractionalization Index** | | | | **Esteban Ray Index of Ethno-Linguistic Polarization** | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Financial Development | -0.548*** | -0.135*** | -0.142*** | -0.098** | 0.002 | -0.053*** | -0.056*** | -0.042*** |
| | (0.028) | (0.038) | (0.039) | (0.044) | (0.005) | (0.008) | (0.008) | (0.010) |
| LGDPC | | -0.095*** | -0.094*** | -0.088*** | | 0.012*** | 0.012*** | 0.016*** |
| | | (0.006) | (0.006) | (0.006) | | (0.001) | (0.001) | (0.001) |
| MOUNTAINS | | | | -0.001*** | | | | 0.000*** |
| | | | | (0.000) | | | | (0.000) |
| NONCONT | | | | -0.093*** | | | | -0.018*** |
| | | | | (0.013) | | | | (0.004) |
| DEMOCRACY | | | | 0.046*** | | | | -0.004 |
| | | | | (0.010) | | | | (0.003) |
| PRIO25lag | | | | 0.084*** | | | | 0.024*** |
| | | | | (0.011) | | | | (0.004) |
| Constant | 0.542*** | 1.198*** | 1.194*** | 1.130*** | 0.047*** | -0.034*** | -0.036*** | -0.073*** |
| | (0.008) | (0.040) | (0.041) | (0.041) | (0.002) | (0.009) | (0.009) | (0.010) |
| Year FE | | | ✓ | ✓ | | | ✓ | ✓ |
| Observations | 2,406 | 2,344 | 2,344 | 2,284 | 2,406 | 2,344 | 2,344 | 2,284 |
| Adjusted$-R^2$ | 0.168 | 0.255 | 0.249 | 0.267 | -0.000 | 0.025 | 0.018 | 0.059 |

*Note:* Table reports the results of OLS regressions estimating the relationship between the fractionalization and polarization indices and the IMF's financial development index. The outcome variables, Fearon's Ethno-Linguistic Fractionalization Index and the Esteban Ray Index of Polarization, have been obtained from Montalvo and Reynal-Querol (2005) and Fearon (2003). The sample includes 166 countries for the period $1980 - 1999$. We also add explanatory variables from these sources, including LGDPC (Log real GDP per capita), MOUNTAINS (percent of mountainous terrains), NONCONT (Noncontiguous states indicator), DEMOCRACY (indicator for Democracy of country) and PRIO25lag (Lag: Armed conflict generating more than 25 deaths yearly). Robust standard errors are reported in parentheses.

Significance Levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table D4:** Impact of Bank Branch Expansion on Fractionalization: District Panel Analysis (IHDS)

| | Pre Policy | Post Policy |
|---|---|---|
| | (1) | (2) |
| **A: Ethno-Religious Fractionalization (ERF)** | | |
| RD Estimate | -0.046 | -0.105** |
| | (0.045) | (0.049) |
| | [0.314] | [0.031] |
| Control Mean | 0.594 | 0.595 |
| Observations | 371 | 371 |
| Banked Districts | 133 | 131 |
| Unbanked Districts | 170 | 167 |
| Covariates | ✓ | ✓ |
| Bandwidth | 5,315.317 | 4,662.311 |
| **B: Ethno-Linguistic Fractionalization (ELF)** | | |
| RD Estimate | -0.033 | -0.121** |
| | (0.037) | (0.050) |
| | [0.368] | [0.015] |
| Control Mean | 0.626 | 0.614 |
| Observations | 371 | 371 |
| Banked Districts | 135 | 131 |
| Unbanked Districts | 174 | 168 |
| Covariates | ✓ | ✓ |
| Bandwidth | 5,385.576 | 4,301.645 |
| **C: Ethnic Fractionalization among Hindus** | | |
| RD Estimate | -0.085 | -0.131** |
| | (0.054) | (0.057) |
| | [0.117] | [0.022] |
| Control Mean | 0.523 | 0.530 |
| Observations | 364 | 365 |
| Banked Districts | 127 | 121 |
| Unbanked Districts | 164 | 158 |
| Covariates | ✓ | ✓ |
| Bandwidth | 4,588.657 | 4,487.187 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on Fractionalization in a district panel, constructed using household level information from the IHDS panel survey (Rounds 2004-05 and 2011-12). Panel A shows Ethno-Religious Fractionalization (ERF) index constructed based on ethnic and religious affiliations of households. Panel B shows Ethno-Linguistic Fractionalization (ELF) index constructed based on ethnic, religious and linguistic affiliations of households. Panel C shows Ethnic Fractionalization among Hindus. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population and density of the district from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table D5:** Impact of Bank Branch Expansion on Ethno-Linguistic and Ethno-Religious Fractionalization

| | Pre Policy | Post Policy |
|---|---|---|
| | (1) | (2) |
| **A: Ethno-Religious Fractionalization (NSS)** | | |
| RD Estimate | -0.056 | -0.139** |
| | (0.047) | (0.068) |
| | [0.226] | [0.039] |
| Control Mean | 0.632 | 0.623 |
| Observations | 583,402 | 444,984 |
| Banked Districts | 100 | 107 |
| Unbanked Districts | 131 | 140 |
| Covariates | ✓ | ✓ |
| Bandwidth | 2,218.581 | 1,845.722 |
| **B: Ethnic Fractionalization among Hindus (NSS)** | | |
| RD Estimate | -0.057 | -0.180*** |
| | (0.049) | (0.066) |
| | [0.242] | [0.007] |
| Control Mean | 0.539 | 0.530 |
| Observations | 574,146 | 438,580 |
| Banked Districts | 114 | 100 |
| Unbanked Districts | 167 | 124 |
| Covariates | ✓ | ✓ |
| Bandwidth | 2,926.896 | 1,831.152 |
| **C: Ethno-Linguistic Fractionalization (Census)** | | |
| RD Estimate | -0.041 | -0.098** |
| | (0.049) | (0.045) |
| | [0.397] | [0.031] |
| Control Mean | 0.319 | 0.328 |
| Observations | 581 | 581 |
| Banked Districts | 164 | 183 |
| Unbanked Districts | 238 | 267 |
| Covariates | ✓ | ✓ |
| Bandwidth | 3,962.084 | 4,587.157 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on fractionalization indices constructed using nationally representative household survey data and administrative population data. Panel A shows Ethno-Religious Fractionalization (ERF) Index constructed using social group and religion affiliation of households from the NSS $61^{st}$ (July 2004 - June 2005) and $68^{th}$ (July 2011 - June 2012) Employment and Unemployment Surveys. Panel B shows Ethnic Fractionalization among different social groups, but restricting the sample to Hindus. Panel C shows Ethno-Linguistic Fractionalization (ELF) Index constructed using district level population data on social group (including Scheduled Caste and Scheduled Tribe) and languages from the 2001 and 2011 Population Censuses. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log number of open functioning bank branches (excluding RRBs) in the district in 2001. Regressions in Panels A and B control for log population and density of the district from the 2001 Population Census, and region fixed effects. Post-policy regression in Panel C accounts for the number of male and female inter-district in-migrants within a state, who have stayed in their current district of residence for above 20 years (Ashraf and Galor, 2013; Michalopoulos, 2012). We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table D6:** Impact of Bank Branch Expansion on Ethno-Religious Fractionalization: Urban vs Rural Heterogeneity

| | Pre Policy | Post Policy |
|---|---|---|
| | (1) | (2) |
| **A: Urban Areas** | | |
| RD Estimate | -0.062 | -0.108** |
| | (0.050) | (0.052) |
| | [0.213] | [0.039] |
| Control Mean | 0.622 | 0.620 |
| Observations | 11,813 | 11,813 |
| Banked Districts | 101 | 101 |
| Unbanked Districts | 91 | 91 |
| Covariates | ✓ | ✓ |
| Bandwidth | 5,756.899 | 5,778.365 |
| **B: Rural Areas** | | |
| RD Estimate | -0.073 | -0.125* |
| | (0.065) | (0.066) |
| | [0.263] | [0.061] |
| Control Mean | 0.619 | 0.621 |
| Observations | 28,205 | 28,205 |
| Banked Districts | 91 | 90 |
| Unbanked Districts | 125 | 124 |
| Covariates | ✓ | ✓ |
| Bandwidth | 3,820.621 | 3,517.583 |
| **C: Non-Metro Areas** | | |
| RD Estimate | -0.057 | -0.103* |
| | (0.053) | (0.055) |
| | [0.284] | [0.062] |
| Control Mean | 0.612 | 0.615 |
| Observations | 36,981 | 36,981 |
| Banked Districts | 124 | 122 |
| Unbanked Districts | 155 | 154 |
| Covariates | ✓ | ✓ |
| Bandwidth | 4,148.626 | 3,803.271 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on Ethno-Religious Fractionalization (ERF) in Urban areas (Panel A), Rural Areas (Panel B), and Non-Metro Areas (Panel C). The ERF index has been constructed using household level information on ethnic and religious affiliations from the IHDS panel survey (Rounds 2004-05 and 2011-12). We exclude Mumbai, Delhi, Kolkata, Chennai, Bangalore, and Hyderabad from the full sample to identify the Non-Metro areas. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population of the district from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We additionally account for the log density of the district in Panel C. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table D7:** Impact of Bank Branch Expansion on Ethno-Religious Fractionalization: Extensive Margin Analysis

| | Pre Policy | Post Policy |
|---|---|---|
| | (1) | (2) |
| **A: Full Sample** | | |
| RD Estimate | 0.090 | -0.783*** |
| | (0.224) | (0.258) |
| | [0.688] | [0.002] |
| Control Mean | 0.540 | 0.514 |
| Observations | 40,018 | 40,018 |
| Banked Districts | 133 | 113 |
| Unbanked Districts | 169 | 142 |
| Covariates | ✓ | ✓ |
| Bandwidth | 4,957.585 | 3,376.828 |
| **B: Urban Sample** | | |
| RD Estimate | 0.062 | -0.439* |
| | (0.240) | (0.245) |
| | [0.797] | [0.073] |
| Control Mean | 0.535 | 0.494 |
| Observations | 11,813 | 11,813 |
| Banked Districts | 98 | 96 |
| Unbanked Districts | 90 | 85 |
| Covariates | ✓ | ✓ |
| Bandwidth | 4,850.628 | 4,686.655 |
| **C: Rural Sample** | | |
| RD Estimate | 0.008 | -0.909*** |
| | (0.303) | (0.295) |
| | [0.978] | [0.002] |
| Control Mean | 0.542 | 0.526 |
| Observations | 28,205 | 28,205 |
| Banked Districts | 82 | 82 |
| Unbanked Districts | 115 | 114 |
| Covariates | ✓ | ✓ |
| Bandwidth | 3,925.761 | 3,113.946 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on the extensive margin of Ethno-Religious Fractionalization (ERF) using a binary indicator for highly fractionalized areas, equal to one for districts with an ERF index greater than the median value within the survey round and zero otherwise. Panel A shows the estimates for the full sample, and Panels B and C show the estimates for Urban and Rural areas respectively. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population and log density of the district from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.

Significance Levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table D8:** Impact of Bank Branch Expansion on Ethno-Religious Fractionalization: Heterogeneity Analysis (across States)

| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **A:** | **Coastal States** | | **Non-Coastal States** | |
| RD Estimate | -0.030 | -0.106** | -0.086 | -0.007 |
| | (0.045) | (0.051) | (0.128) | (0.114) |
| | [0.503] | [0.037] | [0.504] | [0.951] |
| Control Mean | 0.635 | 0.638 | 0.603 | 0.600 |
| Observations | 18,749 | 18,749 | 21,269 | 21,269 |
| Banked Districts | 70 | 70 | 63 | 94 |
| Unbanked Districts | 77 | 77 | 91 | 92 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 4,930.098 | 4,801.002 | 3,522.984 | 3,597.336 |
| **B:** | **Land-locked States** | | **Non-Land-locked States** | |
| RD Estimate | -0.030 | 0.035 | -0.061 | -0.129** |
| | (0.124) | (0.112) | (0.049) | (0.056) |
| | [0.812] | [0.752] | [0.218] | [0.020] |
| Control Mean | 0.620 | 0.621 | 0.620 | 0.620 |
| Observations | 20,106 | 20,106 | 19,912 | 19,912 |
| Banked Districts | 52 | 52 | 88 | 89 |
| Unbanked Districts | 89 | 90 | 81 | 82 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 3,525.578 | 3,666.496 | 5,006.873 | 4,931.298 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on the Ethno-Religious Fractionalization Index constructed from the IHDS panel survey across states. Following the literature on migration patterns and state contiguity (Montalvo and Reynal-Querol, 2005; Fearon, 2003), we identify Coastal and Land-locked states to exploit spatial heterogeneity in state-level economic and sociopolitical dynamics (Topalova and Khandelwal, 2011). Panels A and B show the results for Coastal and Land-locked states, along with their respective counterparts. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population of the district from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table D9:** Impact of Bank Branch Expansion on Components of Household Consumption

| | High ERF areas | | Low ERF areas | |
|---|---|---|---|---|
| | (1) *Pre Policy* | (2) *Post Policy* | (3) *Pre Policy* | (4) *Post Policy* |
| **A: Log Food Consumption** | | | | |
| RD Estimate | -0.022 | 0.168*** | 0.053 | 0.091 |
| | (0.072) | (0.046) | (0.075) | (0.088) |
| | [0.764] | [0.000] | [0.484] | [0.303] |
| Control Mean | 7.868 | 7.510 | 7.836 | 7.514 |
| Observations | 15,750 | 14,472 | 16,141 | 14,156 |
| Bandwidth | 3,460.669 | 3,701.862 | 6,441.402 | 5,528.738 |
| **B: Log School Expenditure** | | | | |
| RD Estimate | 0.119 | 0.511** | 0.217 | 0.515** |
| | (0.201) | (0.256) | (0.244) | (0.229) |
| | [0.552] | [0.046] | [0.374] | [0.024] |
| Control Mean | 7.370 | 7.050 | 7.355 | 7.099 |
| Observations | 7,988 | 9,052 | 8,625 | 9,468 |
| Bandwidth | 3,388.703 | 3,410.399 | 6,514.411 | 5,356.678 |
| **C: Motor Vehicle Ownership** | | | | |
| RD Estimate | -0.005 | 0.117* | 0.009 | 0.034 |
| | (0.051) | (0.062) | (0.054) | (0.068) |
| | [0.915] | [0.062] | [0.869] | [0.616] |
| Control Mean | 0.259 | 0.393 | 0.216 | 0.336 |
| Observations | 19,719 | 19,754 | 20,214 | 20,244 |
| Bandwidth | 3,515.563 | 3,213.383 | 6,151.821 | 6,113.182 |
| **D: Cell Phone Ownership** | | | | |
| RD Estimate | 0.028 | 0.068** | 0.037 | 0.030 |
| | (0.022) | (0.031) | (0.034) | (0.060) |
| | [0.205] | [0.026] | [0.278] | [0.611] |
| Control Mean | 0.117 | 0.871 | 0.103 | 0.874 |
| Observations | 19,692 | 19,753 | 20,197 | 20,242 |
| Bandwidth | 3,734.849 | 3,534.499 | 5,918.555 | 6,068.681 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on consumption of non-durable and durable goods and services of households for districts with high and low levels of ethno-religious fractionalization, where the split is based on the median value of the pre-policy ERF Index. Panel A shows Log Food Consumption, defined as the log of annual real expenditures on food consumption in rupees. Panel B shows Log School Expenditure, defined as the log of annual real expenditures on tuition fee and books in rupees. The level form of both variables is deflated using the panel survey estimator and trimmed at the $10^{th}$ and $90^{th}$ percentiles. Panel C shows Motor Vehicle Ownership, a binary indicator variable equal to one if the household owns a motor vehicle, and zero otherwise. Panel D shows Cell Phone Ownership, a binary indicator variable equal to one if the household owns a cell phone, and zero otherwise. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log district population from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table D10:** Impact of Bank Branch Expansion on Sectoral Shifts in Employment

| | High ERF Areas | | Low ERF Areas | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
| **A: Agriculture to Manufacturing** | | | | |
| RD Estimate | 0.032 | 0.129*** | 0.087 | 0.040 |
| | (0.046) | (0.044) | (0.094) | (0.070) |
| | [0.488] | [0.004] | [0.357] | [0.563] |
| Control Mean | 0.392 | 0.516 | 0.317 | 0.456 |
| Observations | 66,602 | 43,451 | 71,661 | 45,615 |
| Banked Districts | 104 | 106 | 73 | 66 |
| Unbanked Districts | 150 | 154 | 117 | 108 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 4,856.226 | 5,717.333 | 3,527.230 | 3,848.569 |
| **B: Agriculture to Services** | | | | |
| RD Estimate | 0.033 | 0.120*** | 0.110 | 0.032 |
| | (0.050) | (0.035) | (0.071) | (0.075) |
| | [0.516] | [0.001] | [0.122] | [0.673] |
| Control Mean | 0.493 | 0.609 | 0.403 | 0.541 |
| Observations | 78,092 | 50,908 | 81,419 | 53,172 |
| Banked Districts | 102 | 107 | 72 | 52 |
| Unbanked Districts | 145 | 156 | 115 | 80 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 4,568.091 | 5,162.950 | 3,714.747 | 2,869.188 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on sectoral shifts in employment, for individuals aged 15-65 years, in districts with high and low levels of ethno-religious fractionalization, where the split is based on the median value of the pre-policy ERF Index. Panel A shows shift from Agriculture to Manufacturing sector in employment using a binary indicator equal to one if an individual is working in Manufacturing industry, and zero for Agricultural industry. Panel B shows shift from Agriculture to Services sector in employment using a binary indicator equal to one if an individual is working in Services industry, and zero for Agricultural industry. We construct these outcomes using individual-level information from the NSS $61^{st}$ (July 2004 - June 2005) and $68^{th}$ (July 2011 - June 2012) Employment and Unemployment Surveys. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log population of the district from the 2001 Population Census. Post-policy regressions, additionally, control for density of the district, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table D11:** Impact of Bank Branch Expansion on In-Migration by Land-owning status of Households

| | **Land-owning Households** | | **Landless Households** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
| RD Estimate | -0.006 | 0.005 | 0.005 | 0.037** |
| | (0.006) | (0.005) | (0.023) | (0.017) |
| | [0.318] | [0.351] | [0.843] | [0.024] |
| Control Mean | 0.025 | 0.018 | 0.045 | 0.049 |
| Observations | 74,354 | 69,312 | 17,709 | 24,841 |
| Banked Districts | 86 | 131 | 125 | 151 |
| Unbanked Districts | 121 | 189 | 184 | 212 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 2,908.876 | 3,763.018 | 3,846.518 | 3,523.507 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on in-migration, disaggregated by land-holding status of households. The outcome variable captures the extensive margin of in-migration: whether a household moved into the current district of residence during the last one year. To construct this variable, we gather pooled cross-section household-level data on migration and the land-holding status of the households from the National Sample Survey (NSS) on housing conditions conducted by the Ministry of Statistics and Program Implementation (MOSPI), Government of India. We draw on data from the Housing Condition Survey conducted during July - December 2002 (Round 58) to test for pre-policy smoothness, and the Drinking Water, Sanitation, Hygiene and Housing Condition Survey conducted during July 2012 - December 2012 (Round 69) to examine post-policy impact on in-migration. Both survey rounds ask the households whether they moved into their current residence of enumeration during the last 365 days before the date of survey. We use the response to this question and construct a binary indicator variable to observe in-migration to the current district of residence (Dutta, Gandhi, and Green, 2025). The pre-policy survey does not record the religion of the household. Furthermore, both surveys lack language-related information on the households. So, fractionalization cannot be captured either on ethno-lingusitic dimensions or on ethno-religious dimensions. However, the surveys record details on the land possessed by the households as on the date of survey. We use this information to construct a binary indicator variable that takes a value of one if the household owns land and zero otherwise. Based on the extensive literature on dominance rooted in socio-economic dimensions and landownership by Anderson (2011), Dumont (1980) and Iversen et al. (2014), we use this binary indicator to capture in-migration among households belonging to dominant (land-owning) and non-dominant (landless) socio-economic groups. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). All regressions control for log population and density of the district from the 2001 Population Census, log number of open functioning bank branches (excluding RRBs) in the district in 2001, and household size. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table D12:** Impact of Bank Branch Expansion on Social Consolidation

| | Ethno-Religious Majority Groups | | Ethno-Religious Minority Groups | |
|---|---|---|---|---|
| | (1) *Initially High ERF areas* | (2) *Initially Low ERF areas* | (3) *Initially High ERF areas* | (4) *Initially Low ERF areas* |
| **A: Inter-Caste Marriage** | | | | |
| RD Estimate | 0.060* | -0.059 | 0.008 | -0.030 |
| | (0.036) | (0.101) | (0.036) | (0.040) |
| | [0.093] | [0.561] | [0.826] | [0.455] |
| Control Mean | 0.066 | 0.076 | 0.069 | 0.036 |
| Observations | 6,051 | 9,564 | 9,230 | 6,899 |
| Bandwidth | 4,977.019 | 4,198.165 | 3,549.254 | 4,104.877 |
| **B: Number of Births since January 2005** | | | | |
| RD Estimate | 0.068 | 0.218** | 0.118 | -0.020 |
| | (0.156) | (0.096) | (0.124) | (0.100) |
| | [0.663] | [0.023] | [0.342] | [0.844] |
| Control Mean | 0.485 | 0.443 | 0.518 | 0.549 |
| Observations | 6,078 | 9,624 | 9,274 | 6,937 |
| Banked Districts | 53 | 73 | 52 | 71 |
| Unbanked Districts | 68 | 97 | 63 | 93 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 5,233.115 | 5,433.291 | 3,217.689 | 5,245.322 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on social consolidation, disaggregated by households belonging to Ethno-Religious Majority groups (Columns 1-2) and Minority groups (Columns 3-4). Columns (1) and (3) are for initially High ERF areas, and Columns (2) and (4) are for initially Low ERF areas, respectively. Panel A shows estimates for Inter-Caste Marriage, a binary indicator equal to one if the responding woman has married to a man of different caste, and zero otherwise. Panel B shows Number of Births since January 2005. These outcomes have been obtained from the Eligible Women Module of IHDS 2011-12 survey. We treat these results as suggestive evidence on the consolidation of the majority as a bloc. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), regressions control for log population of the district from the 2001 Population Census, log number of open functioning bank branches (excluding RRBs) in the district in 2001, and a binary indicator equal to one if the household was in an urban location in the pre-policy survey. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table D13:** Impact of Bank Branch Expansion on Conflicts and Casualties

| | **Conflict Intensity** | | **Casualties** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
| RD Estimate | 0.029 | -0.444** | 0.033 | -0.728*** |
| | (0.185) | (0.192) | (0.164) | (0.215) |
| | [0.877] | [0.021] | [0.839] | [0.001] |
| Control Mean | 0.126 | 0.318 | 0.079 | 0.129 |
| Observations | 532 | 524 | 531 | 522 |
| Banked Districts | 165 | 163 | 172 | 159 |
| Unbanked Districts | 250 | 241 | 273 | 239 |
| Covariates | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 5,046.227 | 4,958.668 | 5,732.937 | 4,718.069 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on administrative reported conflicts and casualties at the district-year level using data from the South Asia Terrorism Portal (SATP). We use 2004 as the pre-policy period and 2013 as the post-policy period. The first outcome Conflict Intensity captures the total number of conflict events reported in a district in a year. The second outcome Casualties measures the total number of persons either killed or injured. For each year, both outcome variables have been winsorized at the $2^{nd}$ and $98^{th}$ percentiles of their respective distributions and have been log transformed. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log district population from the 2001 Population Census, log number of open functioning bank branches (excluding RRBs) in the district for the years 2001 and 2003. Post-policy regressions, additionally, account for the pre-policy values (2004) of the respective outcomes. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table D14:** Impact of Bank Branch Expansion on Economic Welfare of Households: Robustness to accounting for Attrition

| | ER-Majority Households | | ER-Minority Households | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Pre Policy* | *Post Policy* | *Pre Policy* | *Post Policy* |
| **A: Log Per Capita Consumption** | | | | |
| RD Estimate | 0.153 | 0.373** | -0.064 | 0.225* |
| | (0.132) | (0.145) | (0.103) | (0.124) |
| | [0.245] | [0.010] | [0.535] | [0.071] |
| Control Mean | 10.158 | 9.950 | 10.144 | 9.948 |
| Observations | 14,034 | 12,101 | 13,647 | 11,774 |
| Banked Districts | 58 | 62 | 41 | 39 |
| Unbanked Districts | 66 | 67 | 66 | 51 |
| Bandwidth | 4,465.111 | 4,462.946 | 3,654.258 | 2,788.891 |
| **B: Poverty Status** | | | | |
| RD Estimate | -0.001 | -0.193** | 0.060 | -0.049 |
| | (0.093) | (0.085) | (0.082) | (0.077) |
| | [0.993] | [0.023] | [0.468] | [0.522] |
| Control Mean | 0.138 | 0.111 | 0.122 | 0.105 |
| Observations | 17,138 | 15,030 | 17,163 | 15,113 |
| Banked Districts | 57 | 57 | 40 | 37 |
| Unbanked Districts | 60 | 65 | 62 | 47 |
| Bandwidth | 3,882.724 | 3,019.909 | 3,389.580 | 2,840.796 |
| **C: Monthly Interest on Loan** | | | | |
| RD Estimate | -0.529 | -0.899** | 0.326 | 0.103 |
| | (0.422) | (0.438) | (0.341) | (0.423) |
| | [0.210] | [0.040] | [0.339] | [0.808] |
| Control Mean | 1.546 | 2.090 | 1.850 | 2.077 |
| Observations | 7,096 | 4,575 | 7,589 | 5,141 |
| Banked Districts | 50 | 39 | 41 | 53 |
| Unbanked Districts | 51 | 40 | 67 | 77 |
| Bandwidth | 3,800.821 | 1,811.140 | 3,676.515 | 4,376.204 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on economic welfare and financial inclusion of households in districts with high and low levels of ethno-religious fractionalization, where the split is based on the median value of the pre-policy ERF Index. Panel A shows Log Per Capita Consumption, defined as the log of annual per capita real consumption expenditures in rupees. The level form is deflated using the panel survey estimator and trimmed at the $10^{th}$ and $90^{th}$ percentiles. Panel B shows Poverty Status, a binary indicator variable which takes a value of one if the household's consumption expenditures are below the state poverty line, and zero otherwise. Panel C shows Monthly Interest on Loan, which measures the monthly interest rate paid on outstanding loans by households in percentage (%). All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Optimal bandwidth is calculated using MSE-optimal bandwidth selector for the RD treatment effect (Calonico et al., 2017). Using the covariate-adjustment approach developed by Calonico et al. (2019), all regressions control for log district population from the 2001 Population Census, and log number of open functioning bank branches (excluding RRBs) in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table D15:** Data Appendix

| Variable | Description |
|---|---|
| **IHDS Panel Survey (Rounds 2004-05 and 2011-12)** | |
| **Fractionalization and Polarization Indices** | |
| *Ethno-Religious Fractionalization* | ELF Index$_d = 1 - \sum_{i=1}^{G} {p_{id}}^2$ Index of ethno-religious fractionalization reflects the probability that two randomly selected individuals belong to different ethno-religious groups. It is computed using the shares of different ethno-religious groups in a district. $G$ represents the total number of ethno-religious groups in a district. $p_{id}$ denotes the proportion of the population in a particular group $i$ in a district $d$. |
| *Ethno-Religious Polarization* | ER Index of Polarization $= C \sum_{i=1}^{G} \sum_{j=1}^{G} {p_{id}}^{1+\alpha} p_{jd} \delta_{ijd}$ Esteban-Ray Index of ethno-religious polarization captures the idea that polarization is maximized when a society is split into a few large, equally sized groups that are very different from one another (Esteban and Ray, 1994). This measure incorporates a parameter to capture effective antagonism between groups. $C$ is a general scaling parameter. $\alpha$ is an affinity parameter, emphasizing within-group cohesion if $\alpha > 0$. $i$ and $j$ are indices for groups. $\delta_{ijd}$ is a distance measure. We substitute the Euclidean income distance $\delta_{ijd} = \lvert y_i - y_j \rvert$, by a discrete metric (belong or do not belong) to get a discrete polarization index (Montalvo and Reynal-Querol, 2005). $$\delta_{ij} = \mathbb{I}(i \neq j) = \begin{cases} 0, & \text{if } i = j \\ 1, & \text{if } i \neq j \end{cases}$$ |
| **Economic Welfare and Financial Inclusion** | |
| *Real Per Capita Consumption* | Per capita real consumption expenditure of households (in rupees), deflated using panel survey deflator, and trimmed at 10%. |
| *Poverty Status* | Binary indicator equal to one if household's consumption expenditures are below the state poverty line; and zero otherwise. |

| | |
|---|---|
| *Loan from Bank* | Binary indicator equal to one if household has taken a debt from bank; and zero otherwise. |
| *Monthly Interest Rate on Loan* | Monthly interest rate paid on outstanding loans by households in percentage (%). |
| *Life Insurance Ownership* | Binary indicator equal to one if household has a life insurance (either government or private); and zero otherwise. |
| **Components of Household Consumption Expenditure** | |
| *Food Consumption* | Real food consumption expenditure of households (in rupees), deflated using panel survey deflator, and trimmed at 10%. |
| *School Expenditure* | Real expenditure of households on tuition fee and books (in rupees), deflated using panel survey deflator, and trimmed at 10%. |
| *Motor Vehicle Ownership* | Binary indicator equal to one if household owns a motor vehicle; and zero otherwise. |
| *Cell Phone Ownership* | Binary indicator equal to one if household owns a cell phone; and zero otherwise. |
| **IHDS Tracking File (Round 2011-12)** | |
| *Migrated out* | Binary indicator equal to one if an individual migrated after 2005 (IHDS 1); and zero otherwise. |
| *Migrated out permanently* | Binary indicator equal to one if a migrant left their residence permanently; and zero otherwise. |
| *Migrated for Work* | Binary indicator equal to one if a migrant migrated for work; and zero otherwise. |
| *Migrated for Non-Work Reasons* | Binary indicator equal to one if a migrant migrated for purposes other than work (including marriage, study, family, and others); and zero otherwise. |
| **NSS Employment and Unemployment Surveys (2004-05 and 2011-12)** | |
| *Labor Force Participation* | Binary indicator equal to one if an individual is either working or unemployed, and zero if attending educational institution, engaged in domestic duties, unable to work due to disability, receiving pensions, rents, and remittances, and begging (Dehejia and Gupta, 2022). |
| *Formal Employment (Salaried)* | Binary indicator equal to one if an individual is working in a regular salaried job; and zero otherwise. |

| | |
|---|---|
| *Casual Wage Labor* | Binary indicator equal to one if an individual is engaged in casual wage labor (public works and/or daily wage work); and zero otherwise. |
| *Unpaid Household Work* | Binary indicator equal to one if an individual is an unpaid family worker, and zero otherwise. |
| **National Crime Records Bureau (2004 and 2010)** | |
| *Number of cases* | Number of administrative-reported cases of theft, robbery, burglary, kidnapping, rape, murder, deceit, and other IPC crimes and total IPC crimes. |
| **South Asia Terrorism Portal (2004 and 2013)** | |
| *Number of cases* | Number of conflict events and casualties (killed or injured). |
| **Montalvo and Reynal-Querol (2005) and Fearon (2003)** | |
| *Fractionalization and Polarization Indices* | Fearon's Ethno-Linguistic Fractionalization Index and Esteban Ray Index of Ethno-Linguistic Polarization, measured at the country level. |
| *Covariates* | Real GDP per capita, Percent of Mountainous Terrain, indicators for Noncontiguous states and Democracy in country. |
| **Population Census of India 2001** | |
| *District characteristics* | Population, Density, Area, Number of Towns and Villages |
| **RBI Basic Statistical Returns (BSR)** | |
| *Bank Branches* | Annual district-level data on the number of commercial bank branches (non - Regional Rural Banks, which were excluded from the BAP) from the Quarterly Statistics on Deposits and Credits of Scheduled Commercial Banks maintained by the Reserve Bank of India. |
| *Underbanked status of district in 2005* | Binary indicator for district defined as underbanked by the RBI in 2005 in its Bank Branch Authorization Policy. |

# E Robustness

This appendix collects the robustness checks summarized in Section 7. The first table re-estimates the effect of bank branch expansion on ethno-religious fractionalization across a range of bandwidth selectors and bandwidth multiples; the second reports placebo-cutoff tests, in which the treatment threshold is shifted to values away from the national population-to-branch average.

**Table E1:** Impact of Bank Branch Expansion on Ethno-Religious Fractionalization: Sensitivity to alternative Bandwidth Selection Methods

| | **MSERD** | **MSETWO** | **MSESUM** | **CERRD** | **CERTWO** | **CERSUM** |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RD Estimate | -0.105** | -0.173*** | -0.089* | -0.123** | -0.286* | -0.114** |
| | (0.052) | (0.061) | (0.046) | (0.062) | (0.150) | (0.055) |
| | [0.045] | [0.004] | [0.054] | [0.046] | [0.057] | [0.040] |
| Control Mean | 0.620 | 0.620 | 0.620 | 0.620 | 0.620 | 0.620 |
| Observations | 40,018 | 40,018 | 40,018 | 40,018 | 40,018 | 40,018 |
| Banked Districts | 131 | 85 | 131 | 131 | 85 | 131 |
| Unbanked Districts | 167 | 207 | 166 | 167 | 207 | 166 |
| Covariates | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 4,406.899 | 1,956.602 | 5,429.964 | 3,278.419 | 1,455.573 | 4,039.506 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on Ethno-Religious Fractionalization Index, constructed using household-level information from the IHDS 2011-12 survey, using different optimal Bandwidth Selection Methods. In Column 1, we use MSERD: the (default) one common MSE-optimal bandwidth selector for the RD treatment effect estimator. In Column 2, we use MSETWO: two different MSE-optimal bandwidth selectors (below and above the cutoff) for the RD treatment effect estimator. In Column 3, we use MSESUM: one common MSE-optimal bandwidth selector for the sum of regression estimates. In Column 4, we use CERRD: one common CER-optimal bandwidth selector for the RD treatment effect estimator. In Column 5, we use CERTWO: two different CER-optimal bandwidth selectors (below and above the cutoff) for the RD treatment effect estimator. In Column 6, we use CERSUM: one common CER-optimal bandwidth selector for the sum of regression estimates. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Using the covariate-adjustment approach developed by Calonico et al. (2019), regressions control for the log population of district from the 2001 Population Census, and log number of open functioning bank branches in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets.
Significance Levels: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table E2:** Impact of Bank Branch Expansion on Ethno-Religious Fractionalization: Sensitivity to Placebo Cut-offs

| | **-2,100** | **-1,400** | **-700** | **0** | **700** | **1,400** | **2,100** |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| RD Estimate | 0.054 | -0.045 | 0.587 | -0.105** | 0.075 | -0.153 | 0.112 |
| | (0.293) | (0.263) | (0.441) | (0.052) | (0.177) | (0.208) | (0.174) |
| | [0.853] | [0.864] | [0.183] | [0.045] | [0.674] | [0.461] | [0.519] |
| Control Mean | 0.620 | 0.620 | 0.620 | 0.620 | 0.620 | 0.620 | 0.620 |
| Observations | 40,018 | 40,018 | 40,018 | 40,018 | 40,018 | 40,018 | 40,018 |
| Banked Districts | 85 | 89 | 89 | 131 | 161 | 150 | 150 |
| Unbanked Districts | 133 | 128 | 128 | 167 | 173 | 143 | 135 |
| Covariates | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bandwidth | 3,317.515 | 2,303.526 | 3,339.587 | 4,406.899 | 5,344.248 | 4,183.217 | 5,038.812 |

*Note:* Table reports results from the regression discontinuity (RD) estimations evaluating the impact of the RBI's 2005 Bank Branch Authorization Policy (BAP) on Ethno-Religious Fractionalization Index, constructed using household-level information from the IHDS 2011-12 survey, across different placebo cut-offs. The values in the columns {-2100, -1400, -700, 0, 700, 1400, 2100} correspond to different cut-offs. All specifications implement a fuzzy RD estimation with a local linear polynomial in the running variable and instrument the treatment using the likelihood of a district's under-banked status. We use a triangular kernel function to weight observations near the cutoff. Using the covariate-adjustment approach developed by Calonico et al. (2019), regressions control for the log population of district from the 2001 Population Census, and log number of open functioning bank branches in the district in 2001. We report bias-corrected point estimates in the results, bias-corrected standard errors clustered at the district level in parentheses, and bias-corrected p-values in square brackets. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$