Can Financial Inclusion Increase Household Resilience to Natural Disasters? *

Nandini Gupta[†] Ashish K. Sedai[‡]

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Abstract

Using a regression discontinuity design based on a nationwide bank expansion policy in India, we study the causal impact of bank expansion on households affected by natural disasters. Bank branch expansion reduces consumption volatility, and increases food consumption, and child schooling of disaster-affected households in treated districts compared to disaster-affected households in control districts. Investigating the financial mechanisms, we find that disaster-affected households in treated districts increase borrowing, savings, purchase of crop insurance, and loans for land purchase, and make lower interest payments compared to disaster-affected households in control group districts. Studying the labor market effects, we observe that bank expansion increases non-farm employment, and permanent and seasonal migration among disaster-affected households. Lastly, we find that financial inclusion reduces consumption volatility of households living in areas that experience extreme rises in temperature or excessively high or low rainfall. These results show that financial inclusion can play an important role in insuring households against the negative effects of natural disasters and climate change.

Keywords: Natural Disasters, Financial Inclusion, Bank Branch Deregulation, Regression Discontinuity, Household well-being, Migration, Structural Transformation, Financial Development

JEL Codes: G21, G38, G51, Q54, Q58

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[†]Department of Finance, Kelley School of Business, Indiana University Email: nagupta@indiana.edu

[‡]Department of Economics, College of Business, University of Texas at Arlington. ashish.sedai@uta.edu

1 Introduction

Between 2000 and 2019, natural disasters caused 1.2 million deaths, inflicted over $3 trillion in damages, and disrupted the lives of more than 4 billion people globally (United Nations, 2019). The burden of these catastrophes falls disproportionately on poorer nations, which experience seven times more fatalities, and ten times higher disaster costs relative to GDP compared to wealthier countries. Developed economies, such as the United States, offset the economic and social impacts of disasters through institutional safety nets like insurance markets and government aid (Gallagher and Hartley, 2017; Deryugina, 2017). For instance, while the U.S. allocated $120 billion for Hurricane Katrina in 2005, India spent just $200 million on Cyclone Amphan in 2020, one of the region's costliest hurricanes. This stark disparity underscores the limitations of public disaster relief in developing nations and raises critical questions about alternative mechanisms, such as financial inclusion, to bolster resilience among vulnerable populations.

Access to finance can mitigate the devastating impacts of natural disasters by enabling households to smooth consumption, stabilize income, and recover more effectively. Financial mechanisms such as borrowing, savings, and insurance provide households with the tools to absorb immediate shocks and invest in adaptive strategies, such as migration to less-affected regions (Meghir et al., 2021; Bazzi, 2017; Imbert and Papp, 2020). In the absence of robust institutional safety nets, financial inclusion offers a pathway to reduce vulnerability and foster recovery. However, the role of financial access remains underexplored in contexts like India, which experiences the third highest number of natural disasters globally (United Nations, 2019) and where 85% of the population faces climate-related risks (Mohanty and Wadhawan, 2021). With a per capita income just one-tenth that of the U.S., India presents a critical case for understanding how financial inclusion can bridge the gap between institutional constraints and household resilience.

In this paper, we examine whether financial inclusion, through bank expansions, increases household resilience to natural disasters and climate change in developing economies. Using a regression discontinuity design, we isolate the causal impact of financial constraints on consumption, employment, and migration outcomes of disaster-affected households in India. By leveraging the unique context of India's vulnerability and a nationwide policy to expand financial access, our study provides novel insights into the mechanisms through which financial inclusion mitigates

the unequal impacts of natural disasters. Our findings contribute to ongoing debates on the role of financial systems in addressing climate risks, offering evidence-based strategies to enhance resilience in regions most exposed to such challenges.

To causally identify the impact of bank branch expansion we use a regression discontinuity (RD) design built upon a major policy intervention that oversaw the nationwide expansion of bank branches in India (Young (2017); Khanna and Mukherjee (2020); Cramer (2021)). In 2005, India's central bank, the Reserve Bank of India, incentivized commercial banks to open new branches in under-banked districts with a population-to-branch ratio above the national average. This cutoff lends itself to an RD design where we compare economic outcomes in districts just above the cutoff to those just below. To address the identification challenge that the impact of natural disasters on household resilience is likely to vary based on initial characteristics such as household wealth, we study the impact of financial inclusion only on households affected by natural disasters. Specifically, we compare disaster-affected households in treated districts with a population-to-branch ratio just above the national average to disaster-affected households in control districts with a population-to-branch ratio just below the national average. Disasters include floods, fires, crop failures, extreme temperature changes, excessive rainfall, and drought.

Comparing households affected by natural disasters in treated versus control group districts, we find the following: First, consumption volatility decreases, total consumption expenditures rise, and consumption growth increases; Second, food consumption, meals per day, and child schooling hours rise; Third, we observe an increase in the use of financial services including loans, amount borrowed, savings, crop insurance, and loans for land purchase, and a decrease in monthly interest rates; Fourth, we show that financial inclusion increases both permanent and seasonal migration and the transition to non-agricultural jobs by treated disaster-affected households. Lastly, using meteorological data, we study households that experience climate change as measured by rainfall and temperature. We find that bank expansion significantly reduces consumption volatility and increases consumption growth for households living in districts with excessive rainfall or drought. Our results show that access to banks can reduce the negative impact of natural disasters and climate change on households by increasing access to financial services and facilitating migration and occupational change.

We make the following contributions to the literature: First, we provide novel evidence on the impact of bank access on the economic outcomes of households affected by natural disasters and climate change. Second, we also provide novel evidence on the financial and labor market mechanisms through which bank presence affects the well-being of households experiencing disasters and climate change. Our results also inform the literature on the effects of climate change, which has shown that climate change slows down structural transformation and migration ((Liu, Shamdasani, and Taraz, 2023)). We find that financial inclusion increases migration and shifts disaster-affected households from agriculture to non-farm work. Our findings have policy implications for developing countries with limited institutional capacity to provide public goods such as disaster relief.[1]

Our paper is related to a growing literature that studies the impact of natural disasters on households. For example, Gallagher and Hartley (2017) study the impact of flooding on household finances, and Billings, Gallagher, and Ricketts (2022) show that credit-constrained households experience more bankruptcies following a flood. Studying the macroeconomic impact of the 1950s US drought, Rajan and Ramcharan (2023) find that bank lending, net immigration, and population growth fall in affected areas with initial low access to bank finance. Ho et al. (2023) find that natural disasters often exacerbate financial distress among affected households, leading to increased defaults and financial strain. Their study on the effects of a fire disaster in Canada revealed significant spikes in financial distress indicators, such as higher default rates and reduced access to credit, which underscores the vulnerability of households in disaster-stricken areas. From the supply side, Xu and Xu (2023) find that even minor, non-damaging seismic activities can significantly alter the risk perception of mortgage lenders, leading to changes in lending behavior and tighter credit conditions in affected areas. Their finding underscores the sensitivity of financial markets to natural events. While these papers study the impact of natural disasters on economic outcomes, we study the impact of financial inclusion on households and firms affected by natural disasters. We also identify the financial and labor market mechanisms by which banks affect household resilience in a natural disaster.

Our paper is also related to two recent studies, which study the impact of climate change and

[1]For example, per capita spending on disaster relief in India is 1/10 of that in the United States.

disasters on labor markets. Liu, Shamdasani, and Taraz (2023) show that rising temperatures inhibit structural transformation in Indian labor markets, and Albert, Bustos, and Ponticelli (2021) find that droughts increase the outflow of capital and population in affected regions in Brazil. Our paper complements this literature by showing that financial inclusion can mitigate the negative effects of climate change on labor markets. We find that bank access increases both migration and transition out of agricultural work into non-farm work among households affected by natural disasters.

We also contribute to the large literature that studies the impact of banks on households and firms (Petersen and Rajan, 1995; Jayaratne and Strahan, 1996; Cetorelli and Gambera, 2001; Black and Strahan, 2002; Beck, Demirgüç-Kunt, and Maksimovic, 2004; Burgess and Pande, 2005; Beck, Demirgüç-Kunt, and Levine, 2007; Bruhn and Love, 2014; Célerier and Matray, 2019; Brown, Cookson, and Heimer, 2019; Cramer, 2021; Breza and Kinnan, 2021; Suri, Bharadwaj, and Jack, 2021; Dehejia and Gupta, 2022; Fonseca and Matray, 2022; Gupta and Sedai, 2023; Barboni, Field, and Pande, 2022; Dubey and Purnanandam, 2023). We contribute to this literature by studying whether bank access can mitigate the negative impact of natural disasters on households.

2 Bank Expansion Policy and Regression Discontinuity Design

In 2005, the Reserve Bank of India (RBI) introduced the Branch Authorization Policy (BAP) that incentivized scheduled commercial banks (government-owned and private banks) to open branches in "underbanked" districts if they sought branch-opening licenses for favored locations, under the 4:1 rule (4 banks in underbanked locations for one license in favored location). The condition for 'underbankedness' in the BAP can be exploited with a regression discontinuity design. Following Young (2017), Cramer (2021), Acharya et al. (2022), Khanna and Mukherjee (2023) and Gupta and Sedai (2023), we use the cross-sectional variation in the district level population-to-branch ratio in 2006 as the running variable in the regression discontinuity design to study the impact of bank branch expansion.

Out of the 581 districts in the RBI data, the national average correctly predicts the status of under-bankedness for 578 districts. We cannot perfectly predict the status of three districts.[2]

[2]For comparison, Young (2017) does not match five out of 572 districts used in their analysis.

Since the RBI could have used their discretion to classify these three districts, we estimate local average treatment effects with a triangular kernel using the following fuzzy RD design (Lee and Lemieux (2010)):

$$Y_{h,d} = \alpha + \gamma_1 Treated_d + f(Population\ per\ Branch - Cutoff)_d + \epsilon_d \tag{1}$$

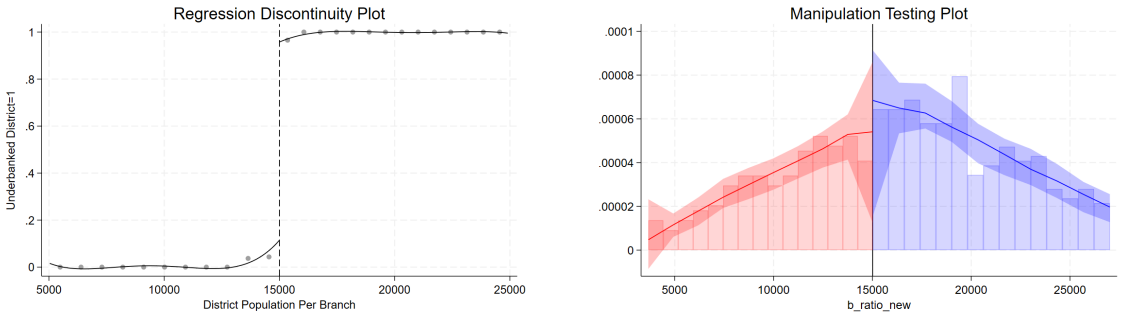
where $Y_{h,d}$ is a banking, household, or enterprise-level outcome in district d, $Treated_d$ is an indicator variable that is equal to 1 if a district's $Population\ per\ Branch_d - Cutoff > 0$, satisfying the rule for assignment to under-banked status, which incorporates a stringent threshold and an adaptable fuzzy element; $f(Population\ per\ Branch - Cutoff)$ is a flexible functional form estimating the fuzzy approach; and ϵ_d is an idiosyncratic error term at the treatment level (districts).

Equation (1) describes the fuzzy RD design estimated using two-stage least squares, with the probability of a district's under-banked status as an instrument for actual assignment. The coefficient of interest is γ_1, and the estimator shows the local average treatment effects (LATE) of being in a treated district. Under standard continuity assumptions, the 'unadjusted' local linear estimator is consistent for the continuity-based RD treatment effect and robust bias-corrected inferences (Cattaneo, Keele, and Titiunik (2021); Cattaneo and Titiunik (2022)).[3]

Panel (A) of Figure 1 shows a large jump in the probability that a district is listed as under-banked when the district's population to bank branch ratio crosses the national average.

To examine heterogeneous treatment effects for the sub-sample of households that experience natural disasters, we test the validity of the RD design by assigning a categorical value 1 to each drought/flood/fire, crop failure and the combination of both the variables, and 0 otherwise. The results in Table A1 show that the RD design is not affected by the heterogeneity analysis. In addition, we check if the proportion of compliers is large enough for each sub-sample, and if the sub-sample local average treatment effect estimator of the first stage is strong. The choice of optimal bandwidth follows the 'rdrobust' command in stata ((Calonico et al., 2017)).

[3]The bias-corrected p-value mitigates potential biases arising from the discontinuity threshold by accounting for local polynomial estimation biases around the threshold. This enhancement contributes to the robustness and internal validity of the RD robust estimates ((Cattaneo and Titiunik, 2022)).



Panel (A) Panel (B)

Figure 1: Likelihood of being under-banked and McCrary manipulation test. The left panel shows likelihood that a district is classified as under-banked if the population to branch ratio exceeds the national average, and the right panel shows the McCrary manipulation test, where the t-stat for McCrary discontinuity estimate is 0.1483 with a p-value of 0.8821.

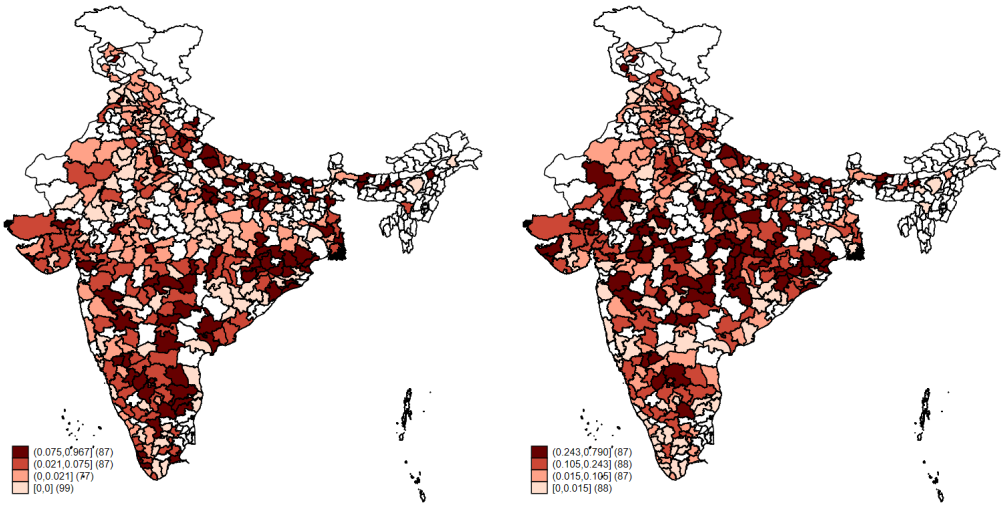
3 Data

3.1 Reserve Bank of India Quarterly Branch Statistics

We collect the RBI Quarterly Branch Statistics data on the number of bank branches in a given district from 2000-2015. The RBI policy in 2005 was to incentivize commercial banks constituting of (a) State Bank of India (SBI) and its associates, (b) Nationalized Banks, (c) Private Sector Banks, (d) Foreign Banks, and (e) Regional Rural Banks (RRBs). The policy excluded Rural Regional Banks ((Cramer, 2020; Young, 2017)). The RBI data show a significant expansion of bank branches in treatment districts following the branch expansion policy. We merge these data with population data from the 2001 Census to derive the district population to bank branch ratio, which is used as the running variable for the RD estimation.

3.2 India Human Development Survey

The India Human Development Survey (IHDS) is the largest, nationally representative panel of households in India. The first wave was conducted in 2005 and the second wave in 2012 ((Desai and Vanneman, 2018)). The survey collects information on natural disasters at the household level. Specifically, the survey asks respondents "*Is there any incidence of large amount of expenditure/loss in your household during last six or seven years since we visited you, such as (i) drought/flood/fire (ii) crop failure?*" Figure 2 shows the distribution of occurrence of natural dis-



Panel (A): Flood/Drought/Fire Panel (B): Crop Failure

Figure 2: District level average natural disasters in India. Figure 2 shows the occurrence of flood/drought/fire in Panel (A) and crop failure in Panel (B) at the district level as reported by households.

asters reported by households averaged at the district level. Data on natural disasters is only available for 2012, and we are not able to test for pre-policy smoothness. However, since we observe panel data, this allows us to control for pre-policy outcomes and to calculate growth effects.

After balancing the panel survey, we have 40,018 observations in both waves of the survey. We merge these household data with the RBI district-level data to carry out the analysis. A total of 371 districts from 581 districts in the RBI data are merged with the IHDS panel. However, this does not threaten our study because the IHDS dataset is nationally representative and is consistent in terms of social composition, literacy and education with other pan-India surveys (National Family Health Survey, 2014 and National Sample Survey, 2011) and the Census (Economic Census, 2013). Additionally, the first stage of the RD design remains unbiased when restricting the RBI data to the 371 districts in the IHDS.

We report the summary statistics of the main variables used in our analysis for households affected by natural disasters and those not affected by disasters in Table A2. *Natural Disasters* is a dummy variable that is equal to one if a household has experienced any of the following: flood,

drought, fire and crop failures in the years since they were interviewed in IHDS 1, 2005. The descriptive statistics show that households that experience natural disasters have lower consumption expenditures, higher short term morbidity, lower borrowing, and lower business revenues. Households affected by natural disasters are more dependent on farm employment and wage labor, more likely to take-up bank loans, and more likely to migrate.

3.3 Drought Affected Districts

We obtain district level data on drought occurrence from the National Disaster Management Authority (NDMA) database and create a categorical variable for drought affected districts, coded as 1 for drought and 0 otherwise, for the years 2010 and 2011, which is when the second wave of the IHDS was conducted in 2011/2012.The formal definition of drought by the NDMA is when the seasonal southwest monsoon rainfall is less than -50%. In Panel (A) of Figure A1, the darker districts indicate severe drought occurrence. We also find that household response to natural disasters in the IHDS survey is correlated with district-level drought data from NDMA as shown in Table A4, which provides external validity for the self-reported disaster data.

3.4 Rainfall and Temperature Data

We obtain rainfall and temperature data from the Climate Hazards Group Infrared Precipitation (CHIRPS) dataset. CHIRPS is a quasi-global rainfall dataset that incorporates high-resolution satellite imagery to create rainfall and temperature time series information. We extract daily precipitations for the monsoon season (June 1 - September 30) and aggregate these annually. We construct the rainfall z-score for 2011 as a deviation from the long-term average precipitation between 1996 and 2011, and scale it with the long-run standard deviation of rainfall. Panel (B) in figure A1 shows the rain z-score at the district level. We also acquire temperature data at the district level, and subtract the temperature in 1981 from 2010 to create the district level temperature change measure. Following (Sanjay et al., 2020), we condition on this temperature difference being greater than 0.40 degrees celsius as an indicator of high growth in temperature. Table A3 reports the summary statistics for rain z score and temperature change variables at the household level across treated and untreated districts.

4 Results

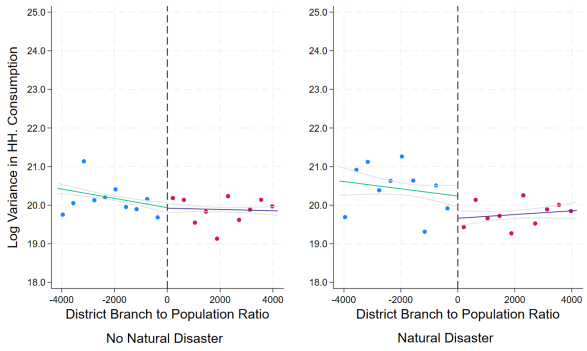
4.1 Impact of Bank Expansion on Households Affected by Natural Disasters

We start by studying the impact of bank branch expansion on consumption volatility, consumption growth, and total consumption expenditures of households affected by natural disasters. Specifically, we estimate the regression discontinuity model described in specification (1), where we compare households that experience natural disasters in treated districts that are just above the cutoff to disaster-affected households in control group districts that are just below the cutoff.

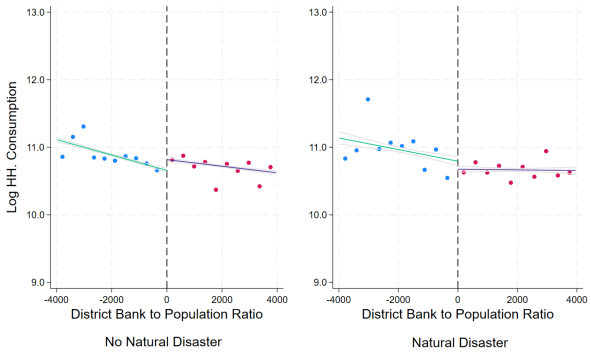
In Table 1 we report the results from estimating specification (1) with *Consumption Volatility* measured as the log of the variance of annual consumption expenditures; *Total Consumption* measured as the log of annual consumption expenditures; and *Consumption Growth* measured as change in consumption expenditures between 2005 and 2012, as the dependent variables. Columns (1) and (2) report the linear and quadratic estimates respectively, for the subset of households that have experienced a natural disaster such as a flood, fire, or drought. Columns (3) and (4) report the linear and quadratic estimates respectively, for the subset of households that have not experienced a natural disaster.

The results show that households that experience a natural disaster have significantly lower consumption volatility and higher consumption growth in treated districts compared to control group districts. The results reported in columns (3) and (4) for households that did not experience a natural disaster provide a benchmark showing that bank branch expansion increases total consumption and consumption growth, but does not have a significant impact on consumption volatility. These findings are similar to Suri, Bharadwaj, and Jack (2021), who find similar resilience to economic shocks for households having access to digital finance (M-Shwari in Kenya). In their study, poor and vulnerable households with M-Shwari were 6.3 percentage points less likely to forego any expenses in response to a negative shock.

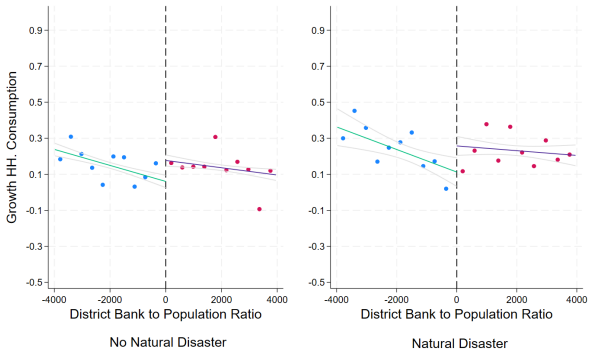
Figure 3 shows the RD plots for consumption volatility, total consumption, and consumption growth for the two sub-samples of households affected by natural disasters, and households not affected by natural disasters. The results show a clear discontinuity and larger jump for treated households facing natural disasters when compared to treated households not affected by natural



Panel A: Consumption Volatility



Panel B: Total Consumption



Panel C: Consumption Growth

Figure 3: Bank Presence and Household Consumption

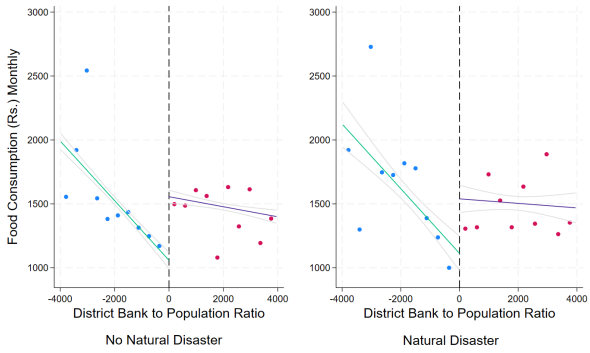
disasters.

In Table 2 we report results with *Food Consumption* expenditures, *Meals per day*, and *Child Schooling Hours* as the dependent variables. Columns (1) and (2) show the results for the subset of households that have experienced a natural disaster such as a flood, fire, or drought. Columns (3) and (4) show the results for the subset of households that have not experienced a natural disaster.

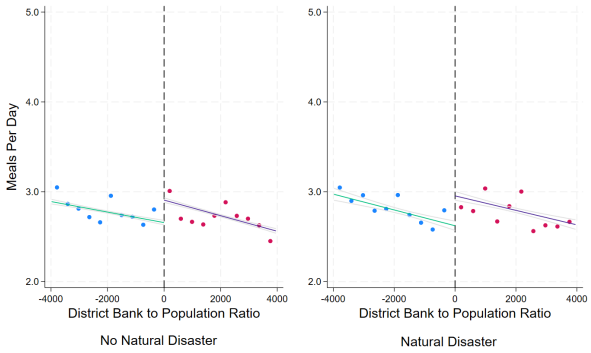
The results reported in Panel (A) of Table 2 show that households that experience natural disasters in treated districts have significantly higher food consumption expenditures than control group disaster-affected households.In Panel A, columns (3) and (4) of Table 2 we also observe an increase for households not affected by natural disasters, but the economic magnitude is lower for this sub-sample compared to households affected by disasters.

Using *Meals per Day* as the dependent variable in Panel C, we find that food security, measured

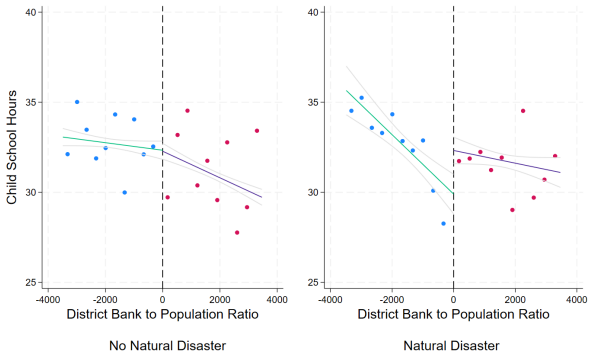
by the number of meals per day, increases significantly for treated households that experienced natural disasters compared to control group households that experience natural disasters. Lastly, from the results reported in Panel D, where the dependent variable is *Child schooling hours*, we note that bank expansion has a significant and positive impact on child schooling for disaster-affected households. In contrast, bank presence does not have a significant impact on the child schooling hours of households not affected by a natural disaster. These results suggest that bank branch expansion can reduce the negative impact of natural disasters on households.



Panel A: Food Consumption (Rupees) Monthly



Panel B: Meals Per Day



Panel C: Child Schooling Hours, Weekly

Figure 4: Bank Presence and Household Food Security and Schooling

Figure 4 shows the RD graphs for food consumption, meals per day, and schooling hours for the two sub-samples of households affected by natural disasters, and households not affected by natural disasters. The graphs show an increase in food consumption and meals per day for both sub-samples, and a discontinuous jump in child schooling hours for disaster-affected households in treated districts.

5 Financial and Labor Market Mechanisms

Banks can mitigate the adverse impact of natural disasters on households and firms by providing access to financial services including loans, savings, and insurance. In the labor market, loans can help households migrate to other areas for jobs. Banks can also ease financial constraints for firms, increasing employment opportunities for households. Below we investigate these two mechanisms.

5.1 Impact of Bank Presence on Household Use of Financial Services

We investigate whether bank branch expansion improves the well-being of disaster-affected households by providing them access to financial products. Specifically, we estimate specification (1) and study the impact of bank presence on the likelihood that a household has a bank loan (*Bank Loan*), a binary variable that is equal to one if the household has a loan from a bank; *Log Loan Amount*, which is the total loan amount in rupees, *Monthly Interest on Loan*, which is the average monthly interest rate paid on loans, *Bank Savings*, a binary variable that is equal to one if the household has a bank savings account, *Crop Insurance*, a binary variable equal to one if the household purchased crop insurance, and *Loans for land purchase*, a binary variable equal to one if the household takes out a loan to purchase land. The results are reported in Table 3.

The results in Panel A of Table 3 show that disaster-affected households in treated districts have a 15 percentage point higher likelihood of taking a bank loan compared to disaster-affected households in untreated districts. In contrast, treated households not affected by disasters are not more likely to borrow from banks.

In Panel B, we report results with *Log Loan Amount* as the dependent variable. The results show that disaster-affected households in treatment districts borrow significantly more than disaster-affected households in control districts. For example, we observe a 7% increase relative to the mean in the loan amounts for treated households affected by natural disasters compared to non-treated households. In Panel C, we observe a 68% decline in the monthly interest paid on loans by disaster-affected households in treatment districts compared to disaster-affected households in control districts. For households not affected by natural disasters, we find that bank branch expansion does not have a significant impact on bank loans or loan amounts, although

monthly interest rates also decline significantly.

In Panel D of Table 3, we observe that bank branch expansion increases the use of savings accounts by treated disaster-affected households by 66% relative to the mean, compared to the control group (column (1)). Savings also increase for households not affected by disasters, although by a lower amount (columns (3) and (4)).

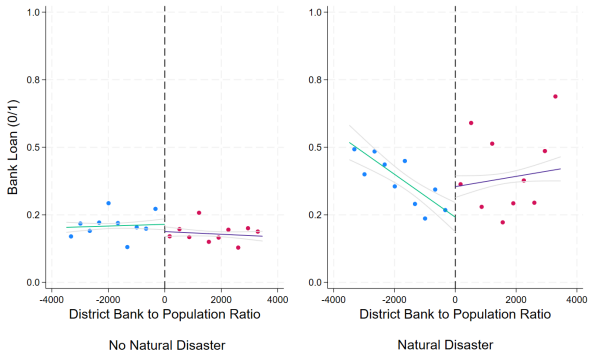
Studying the impact on the purchase of crop insurance, the results in Panel E of Table 3 show that bank presence increases the purchase of crop insurance by 14% by treated disaster-affected households compared to the control group (column (1)). Access to crop insurance is particularly critical among farming households as it can help hedge the risk of crop failures (Boucher et al., 2024; Bertram-Huemmer and Kraehnert, 2018; Cai et al., 2016). Columns (3) and (4) show that bank presence does not significantly affect the likelihood of purchasing crop insurance for treated households not affected by disasters.

Lastly, we investigate whether bank presence facilitates the purchase of land by disaster-affected households. For example, farming households may seek to expand their small farm sizes to manage the risks of a natural disaster. In Panel F of Table 3 we observe that bank branch expansion increases the likelihood of taking out a loan for land purchase by 4% among disaster-affected households in treated districts compared to the control group. There is no impact on households not affected by natural disasters.

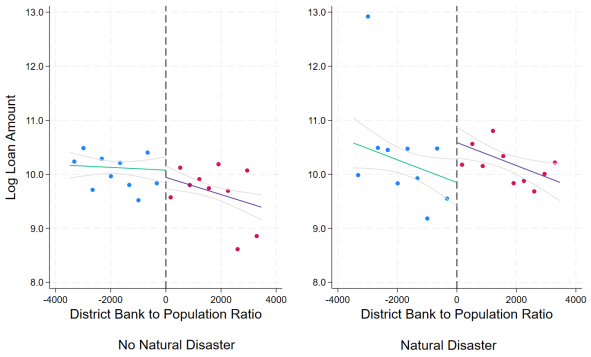
In Figure 5, we graphically show the discontinuity in the bank borrowing and savings variables for households affected by natural disasters and households that are not. The results show a clear discontinuity and a larger jump for treated households facing natural disasters when compared to treated households not affected by natural disasters. Bank presence can improve the well-being of households experiencing natural disasters by providing access to financial services including loans, savings, and insurance.

5.2 Impact of Bank Presence on Occupations and Migration

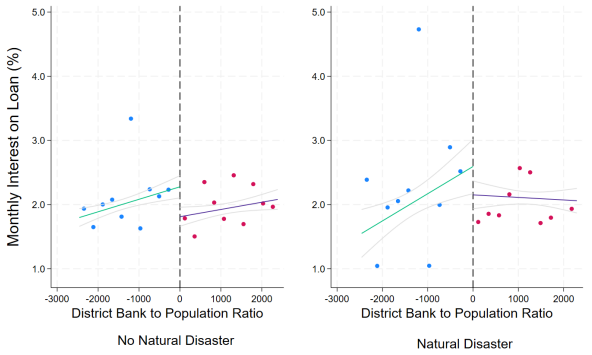
Natural disasters and extreme weather events may reduce agricultural output productivity and agricultural labor demand. Climate change-induced extreme temperature rises also inhibit structural transformation, where workers move out of low-productivity agricultural work into more



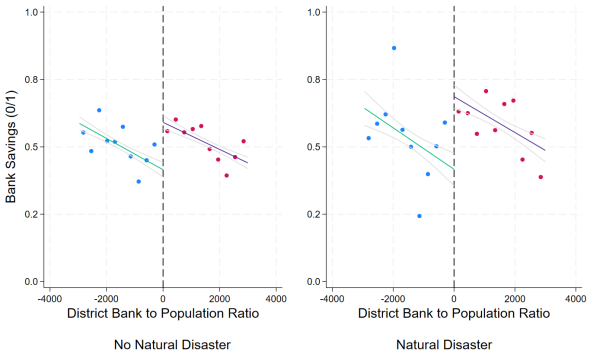
Panel A: Bank Loan



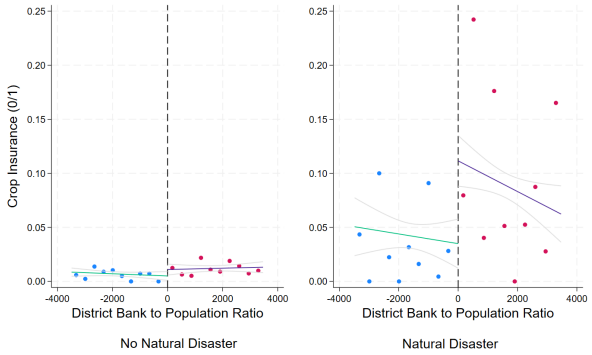
Panel B: Log Loan Amount



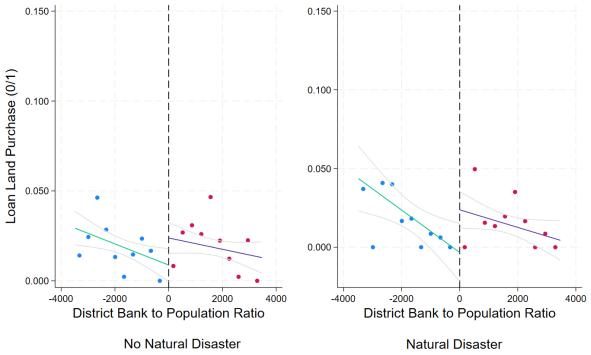
Panel C: Monthly Interest on Loan



Panel D: Bank Savings (0/1)



Panel E: Crop Insurance (0/1)



Panel F: Loan for Land Purchase (0/1)

Figure 5: Bank Presence and Household Borrowing

productive non-farm employment because a declining surplus from agricultural work reduces demand for non-agricultural workers (Liu, Shamdasani, and Taraz, 2023). Bank access may provide workers with short-term loans that facilitate migration and the move to non-farm work.

To study the labor market impact of bank access on households, we start by considering the impact of bank presence on the employment outcomes of households and whether they are more likely to work in agriculture or if they move into industry or services. We estimate specification

(1) using the following employment outcomes as the dependent variable: *Non-Farm Wage Labor*, a dummy variable that is equal to one if a member of the household works in the non-agricultural sector, and zero otherwise and *Farm Wage Labor*, a dummy variable that is equal to one if a member of the household works in the agricultural sector, and zero otherwise.

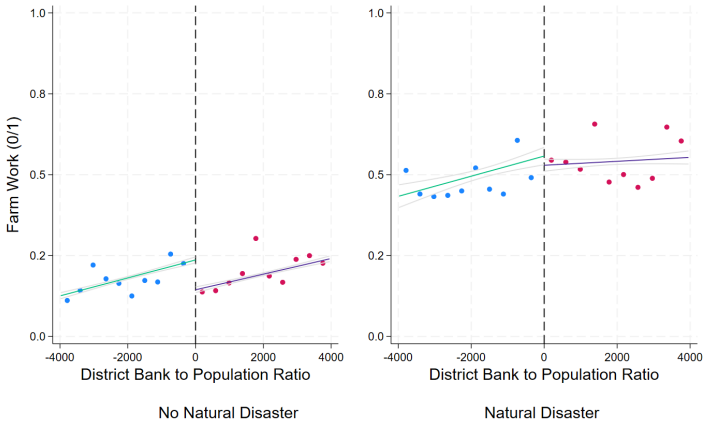
From the results reported in column (1) of Panel A, Table 4, we observe that bank presence has a positive impact on the likelihood that households affected by natural disasters obtain non-agricultural work. Specifically, in column (1), we find that the likelihood that a member of the household shifts to non-farm work for wages increases by 77% relative to the sample mean for treated disaster-affected households, compared to the control group. Households not affected by disasters are also more likely to take non-farm employment, but the magnitude is lower (column (3)).

Studying the impact on *Farm Wage Labor*, we find a negative impact on treated households that experience a natural disaster, although the coefficient is not statistically significant. Bank presence appears to significantly reduce the likelihood of agricultural work among households not affected by natural disasters (columns (3) and (4)).

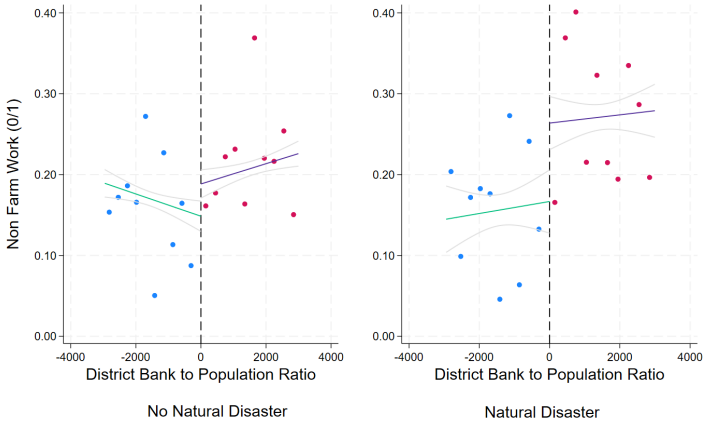
In Figure 6 we graphically show the impact of bank branch expansion on household occupational choice between agricultural and non-agricultural employment. Panel A shows a discontinuous decrease in agricultural employment among non-disaster-affected households but no impact on disaster-affected households. Panel B shows a larger discontinuous increase in non-farm wage employment among disaster-affected households compared to households that are not affected by natural disasters during this period.

We study the impact of bank presence on migration using the following measures: *Permanent Migration*, a binary variable that is equal to one if any member of the household permanently migration after 2005; *Seasonal Migration*, a binary variable that is equal to one if any member of the household left to find seasonal work and returned; and *In Migration*, which is a continuous variable at the district level that captures inward migration into a district. The results are reported in Panels C-E of Table 4.

From Panel C, we observe that bank presence increases the likelihood of permanent migration by 71% relative to the sample mean among treated disaster-affected households compared to the



Panel A: Farm Wage Labor (0/1)



Panel B: Non-Farm Wage Labor (0/1)

Figure 6: Bank Presence and Occupational Choice

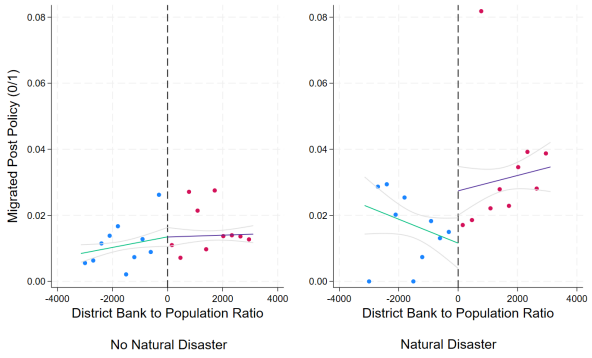
control group. There is no impact on permanent migration among households not affected by natural disasters.

In Panel D, we find that treated households affected by a natural disaster are 67% more likely to migrate seasonally for temporary employment compared to control group households affected by natural disasters (column (1)). In contrast, seasonal migration does not increase for households not affected by natural disasters. Our analysis aligns with findings from the U.S., where hurricanes and floods have been shown to significantly influence domestic migration patterns. Households in disaster-affected areas often relocate to less affected regions in search of better opportunities, as seen in migration trends following major hurricanes (Sheldon and Zhan, 2022). In this context, increased presence of banks could allow households the necessary credit to finance their migration.

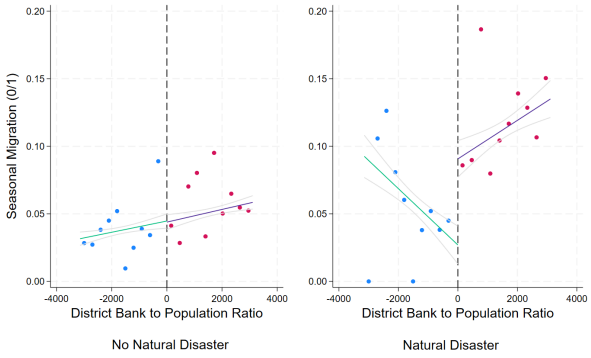
Lastly, using population data from the 2011 Census we construct *Inward Migration*, which

captures the number of people who migrated into a given district from a different district. The results reported in Panel E show that bank presence increases inward migration by 82% relative to the sample mean in treated disaster-affected districts compared to the control group (column (1)). Inward migration also increases in treated districts not affected by disasters, and by a greater amount (columns (3) and (4)). This result suggests that bank presence increases economic opportunities in the district.

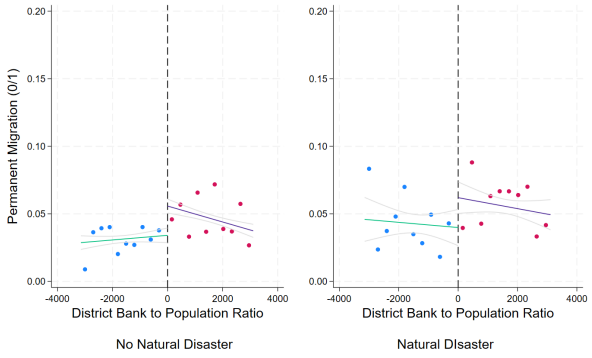
Figure 7 graphically shows the impact of bank presence on migration. Specifically, Panels A-C shows a significant increase in migration in the post-policy period among treated households affected by natural disasters. Among non-disaster-affected households, permanent migration increases slightly, but none of the other migration measures change significantly. Comparing inward migration, we observe that inward migration discontinuously increases into all treated districts in Panel D.



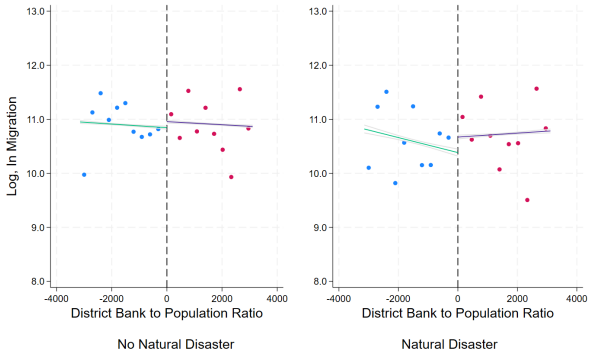
Panel A: Migrated Post Policy (0/1)



Panel B: Seasonal Migration (0/1)



Panel C: Permanent Migration (0/1)



Panel D: Log Inward Migration

Figure 7: Bank Presence and Migration

Overall, our results show that bank presence has a significant impact on households through

the labor market. From a policy perspective, an important finding is that bank presence facilitates structural transformation by moving workers out of farm occupations into non-farm employment, especially for disaster-affected households, and increases migration for all households.

6 Impact of bank presence on households affected by climate change

We use meteorological data to study the impact of bank presence on households living in districts affected by floods, droughts, and extreme temperature rises. In Table 6 we use precipitation data to capture the incidence of floods and droughts. In columns (1) and (2), we study districts that have drought-like conditions and in columns (3)-(5) we we study districts that have flood-like conditions, based on annual precipitation and the *Rainfall z score*.

The results reported in columns (1)-(3) of Table 6, Panel A show that in districts experiencing droughts (column (2)) or excessive rainfall (column (5)), bank presence significantly reduces consumption volatility for households. There is no impact on total consumption expenditures. The results in Panel C show that bank presence significantly increases consumption growth in districts experiencing excessive rainfall (columns (3)-(5)).

Climate change has led to record-high temperatures across the Indian subcontinent. We investigate the impact of bank presence on households located in districts that have experienced extreme temperature rises. We provide results for a range of temperature increases from 0.3 to 0.6 centigrade in a decade. According to standard definitions, an extreme temperature rise is defined as a decadal increase of 0.4 degrees centigrade.

In Table 7 we consider the impact of bank presence on treated households compared to control group households located in districts that have experienced extreme rise in temperatures. The results reported in Panel A show that bank presence significantly reduces consumption volatility for treated households living in districts that experience a 0.4 degree centigrade or higher decadal increase in temperature (columns (2)-(4)) show that bank presence leads to a significant increase in consumption expenditures and meals per day. The results in Panel B show that total consumption expenditures increase for households in treated districts with 0.3 and 0.4 degree

centigrade increases in temperature (columns (1) and (2)). Lastly, Panel C shows that consumption growth increases significantly for treated households living in districts that experience 0.3 degree centigrade and higher decadal increases in temperature.

7 Robustness Checks

7.1 Comparing household reported disaster measures to government reports of natural disasters

In Table A4, we show the results from a linear regression of household measures of disasters *Drought, Crop Failure, Drought/Crop Failure* on government-recorded droughts in that district. The results show that the variables are significantly and positively correlated. These results confirm that household reported disaster measures pick up actual disasters.

Further, we differentiate between analyses based on household-reported disaster experiences and those using district-level drought classifications from the National Disaster Management Authority (NDMA). While the primary analysis relies on household-level data to identify disaster-affected households, here we use NDMA data to classify districts as drought-affected (D) or non-drought-affected (ND). This approach enables us to validate whether the impacts of bank presence are consistent across different disaster classification methods. Table A5 reports the effects of bank presence on key outcomes—consumption volatility, consumption growth, food security (measured as meals per day), and non-farm labor participation—separately for drought-affected and non-drought-affected districts. The findings reveal a strong alignment between the two approaches: in drought-affected districts, bank presence significantly reduces consumption volatility, increases food security, and facilitates greater participation in non-farm labor. These effects mirror those observed using household-level disaster classifications. By demonstrating consistent results across independent measures of disaster exposure, these findings further substantiate the robustness of our main results.

7.2 Do banks channel government relief to households?

In Table A6 we investigate the alternative mechanism that the government channels relief through banks to households affected by natural disasters. The results show no significant difference in the relief received by treated households that experience a natural disaster compared to control group households. These results suggest that impact of banks on disaster-affected households occurs through the financial and labor market mechanisms described above.

7.3 Generic RD Tests

We conduct a series of robustness tests to ensure the reliability of our RD estimates, addressing concerns regarding the validity of the results under alternative specifications and assumptions. First, we employ placebo cut-off analysis (Table A7), which examines whether estimated treatment effects persist when the RD framework is applied to arbitrary, non-true cut-off points. The absence of significant effects at these placebo thresholds supports the validity of the RD design, as it indicates that observed treatment effects are not driven by chance or other unrelated discontinuities in the data.

Second, we perform a bandwidth multiplier analysis (Tables A8 and A9). This involves re-estimating the RD treatment effects using different multiples of the optimal bandwidth around the cut-off. By varying the bandwidth, we test the sensitivity of our results to the choice of data included in the estimation. Robust findings across different bandwidth specifications suggest that the estimates are not overly dependent on the specific bandwidth used and that the results are consistent across a range of plausible choices.

Finally, we conduct bandwidth selection tests (Tables A10 and A11) using various data-driven approaches, such as the Mean Squared Error (MSE) minimizing and Coverage Error Rate (CER) optimizing bandwidth selectors. These tests evaluate whether the chosen bandwidth balances bias and variance optimally, providing credible estimates of treatment effects. Robust results across these selection methods indicate that our estimates are well-calibrated and not sensitive to the exact bandwidth determination process.

Overall, the results of these robustness checks confirm that our RD estimates satisfy the necessary criteria for reliability and validity. The absence of significant effects in placebo analyses,

the stability of estimates under varying bandwidths, and the robustness to alternative bandwidth selection methods collectively affirm the strength of our findings.

8 Conclusion

Exploiting a regression discontinuity design of a bank branch deregulation policy and rich household data on Indian households we study whether banks can mitigate the negative impact of natural disasters. Using data on disaster-affected households and firms, we show that access to banks reduces the negative impact of disasters on household consumption volatility, total consumption, consumption growth, food consumption, and schooling. We show that bank expansion benefits households by increasing access to financial services, including loans, savings, and crop insurance. Studying the labor market mechanisms we find that bank access facilitates migration and moves households out of agricultural work into non-farm employment.

Given the increasing occurrence of natural disasters due to climate change, particularly in the poorest and most populous nations, our research findings has significant practical implications. They suggest that countries could potentially alleviate the negative effects of disasters on households and firms by expanding bank access.

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Table 1: Impact of Bank Expansion on Households Affected by Natural Disasters

	(1)	(2)	(3)	(4)
	Natural Disaster		No Natural Disaster	
	p (1)	p (2)	p (1)	p (2)
(A): Log Consumption Volatility				
Treatment	-0.59**	0.52*	-0.34	-0.35
	(0.23)	(0.318)	(0.26)	(0.26)
Control Mean	20.08		20.09	
Bandwidth	3,504	8,726	3,132	8,328
Observations	7,919	7,919	32,030	32,030
(B): Log Consumption				
Treatment	0.02	0.04	0.15*	0.13*
	(0.12)	(0.12)	(0.08)	(0.08)
Control Mean	11.12		10.96	
Bandwidth	4,067	9,598	3,673	9,197
Observations	7,919	7,919	32,030	32,030
(C): Consumption Growth				
Treatment	0.30**	0.30**	0.21***	0.21***
	(0.13)	(0.12)	(0.07)	(0.07)
Control Mean	0.20		0.15	
Bandwidth	5,109	9,151	4,926	15,160
Observations	7,760	7,760	31,359	31,359

Note: Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. p(1) stands for a linear estimate, and p(2) represents a quadratic estimate. The binary variable Natural Disaster takes the value 1 when households experience events like droughts, floods, fires or crop failures. The treatment variable focuses on expanding bank branches in underserved districts. The data is collected from RBI, quarterly branch statistics, and IHDS I and II (2005 and 2012) at the household and individual level. Covariates include the district population in 2001, pre-policy average PSU level poverty and pre-policy values of respective outcome variables. Continuous variables are adjusted within the 5th and 95th percentiles. We adjust nominal values using the survey deflator. Log Consumption Volatility capture the natural log of the variance of annual consumption expenditure in rupees.

Table 2: Bank presence and well-being of households affected by natural disasters.

	(1)	(2)	(3)	(4)
	Natural Disaster		No Natural Disaster	
	p (1)	p (2)	p (1)	p (2)
(A): Food Consumption (Rs.)				
Treatment	344.96*	534.74**	299.92	382.26**
	(206.40)	(216.23)	(191.08)	(188.71)
Control Mean	1,331		1,342	
Bandwidth	2,953	7,133	3,064	7,646
Observations	7,297	7,297	29,317	29,317
(B): Meals per day				
Treatment	0.69***	0.63***	0.26	0.28*
	(0.22)	(0.22)	(0.17)	(0.16)
Control Mean	2.815		2.831	
Bandwidth	4,036	8,798	4,717	11,188
Observations	7,869	7,869	31,584	31,584
(C): Child School Hours				
Treatment	4.984*	5.380*	-0.912	-1.626
	(2.573)	(3.069)	(1.740)	(1.776)
Control Mean	32.67		32.78	
Bandwidth	4,091	6,945	5,378	11,892
Observations	7,590	7,590	27,386	27,386

Note: Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. p(1) stands for a linear estimate, and p(2) represents a quadratic estimate. The binary variable Natural Disaster takes the value 1 when households experience events like droughts, floods, fires or crop failures. The treatment variable focuses on expanding bank branches in underserved districts. The data is collected from RBI, quarterly branch statistics, and IHDS I and II (2005 and 2012) at the household and individual level. Covariates include the district population in 2001, pre-policy average PSU level poverty and pre-policy values of respective outcome variables. Continuous variables are adjusted within the 5th and 95th percentiles. We adjust nominal values using the survey deflator. Food Consumption reflects the monthly household spending on essential food items like rice, wheat, sugar, pulses, oil, milk, cereals, vegetables, salt, spices, tea, coffee, and fruits. Child School Hours are reported on a weekly basis.

Table 3: Bank presence and use of financial products by households affected by natural disasters

	(1)	(2)	(3)	(4)
	Natural Disaster		No Natural Disaster	
	p (1)	p (2)	p (1)	p (2)
(A): Bank Loan				
Treatment	0.15*	0.14	-0.03	-0.06
	(0.08)	(0.09)	(0.04)	(0.04)
Control Mean	0.36		0.22	
Bandwidth	2,950	6,833	3,084	7,712
Observations	7,922	7,922	32,069	32,069
(B): Log Loan Amount				
Treatment	0.72*	0.57	-0.19	-0.21
	(0.39)	(0.38)	(0.22)	(0.23)
Control Mean	10.33		10.26	
Bandwidth	3,898	8,106	4,084	9,537
Observations	2,784	2,784	7,245	7,245
(C): Monthly Interest on Loan				
Treatment	-1.47**	-0.96	-0.82***	-0.61**
	(0.72)	(0.77)	(0.29)	(0.30)
Control Mean	2.15		2.18	
Bandwidth	2,896	6,562	3,179	7,572
Observations	3,135	3,135	9,746	9,746
(D): Bank Savings				
Treatment	0.37**	0.28**	0.22***	0.18**
	(0.16)	(0.14)	(0.08)	(0.08)
Control Mean	0.56		0.59	
Bandwidth	2,848	8,979	2,634	8,364
Observations	7,902	7,902	31,969	31,969
(E): Crop Insurance				
Treatment	0.14**	0.15*	0.01	0.01
	(0.07)	(0.08)	(0.01)	(0.01)
Control Mean	0.025		0.007	
Bandwidth	5,588	9,646	4,750	10,214
Observations	7,935	7,935	32,083	32,083
(F): Loan for Land Purchase				
Treatment	0.04***	0.04*	0.02	0.02
	(0.01)	(0.02)	(0.01)	(0.01)
Control Mean	0.013		0.019	
Bandwidth	3,167	5,506	3,221	5,715
Observations	5,406	5,406	16,301	16,301

Notes: Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Data RBI, MOF & IHDS II (2011/2012), household level. Covariates include district population, number of functioning bank branches except regional rural banks in 2005 and lag of the outcome variable. Bank Loan is a dummy variable which takes value 1 if the households have taken a loan from the bank, and 0 otherwise. Log Loan Amount is a natural log transformation of the highest amount borrowed by the household in the past 5 years. Monthly interest on loan is the interest paid in percentage on the household loan every month. Bank savings is a dummy variable that takes value 1 if the household owns a savings account in a bank, 0 otherwise. Crop insurance is a dummy variable that takes value 1 if the household has a crop insurance policy from a govt. or private source, 0 otherwise. Loan for purchase of land is dummy variable that takes value 1 if the household has taken any loan for purchase of land, 0 otherwise.

Table 4: Bank presence and labor market outcomes for households affected by natural disasters

	(1)	(2)	(3)	(4)
	Natural Disaster		No Natural Disaster	
	p (1)	p (2)	p (1)	p (2)
(A): Non-Farm Wage Labor (0/1)				
Treatment	0.10***	0.07**	0.06**	0.03
	(0.04)	(0.03)	(0.02)	(0.0266)
Control Mean	0.13		0.18	
Bandwidth	2,855	7,987	2,958	9,233
Observations	25,194	25,194	97,118	97,118
(B): Farm Wage Labor (0/1)				
Treatment	-0.07	-0.04	-0.07**	-0.08**
	(0.09)	(0.08)	(0.03)	(0.03)
Control Mean	0.50		0.13	
Bandwidth	2,979	7,725	3,211	9,452
Observations	25,194	25,194	97,118	97,118
C: Annual Work Days				
Treatment	62.75**	24.39	38.04	40.20
	(26.14)	(36.05)	(36.23)	(40.27)
Control Mean	263		224	
Bandwidth	2,356	6,175	3,371	6,165
Observations	21,904	21,903	75,267	75,256

Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. p(1) is a polynomial of order 1 (linear regression) and p(2) is a polynomial of order 2 (quadratic) estimates. Natural Disaster takes the value of 1 if the household experiences a drought, flood, fire etc or a crop failure. Treatment variable is the expansion of bank branches in underbanked districts. Data IHDS II (2011/2012), household level. Covariates include log of district variable and log of number of open and functioning bank branches except regional rural banks in 2005. Panel (A) shows the likelihood of joining non-farm wage employment, Panel (B) shows the likelihood of joining farm wage employment, and Panel (C) shows the total number of days worked by an individual annually.

Table 5: Bank presence and migration outcomes for households affected by natural disasters

	(1)	(2)	(3)	(4)
	Natural Disaster		No Natural Disaster	
	p(1)	p(2)	p(1)	p(2)
A: *Migrated for Work (0/1)*				
Treatment	0.03**	0.02	0.01	0.01
	(0.01)	(0.02)	(0.00)	(0.01)
Control Mean	0.03		0.02	
Bandwidth	2,081	5,783	1,749	5,116
Observations	25,206	25,206	91,175	91,175
(B): Short Term Migration (0/1)				
Treatment	0.08***	0.08***	-0.00	-0.02
	(0.03)	(0.03)	(0.02)	(0.02)
Control Mean	0.12		0.06	
Bandwidth	3,213	7,734	4,404	11,119
Observations	25,194	25,194	97,118	97,118
C: Permanently Migrated (0/1)				
Treatment	0.05***	0.05**	0.05***	0.02***
	(0.02)	(0.02)	(0.00)	(0.00)
Control Mean	0.02		0.02	
Bandwidth	2,366	6,660	1,958	7,284
Observations	25,206	25,206	91,175	91,175
D: Migration to Urban Areas (0/1)				
Treatment	0.05***	0.06*	0.02*	0.01
	(0.01)	(0.03)	(0.01)	(0.01)
Control Mean	0.06		0.06	
Bandwidth	1,431	4,388	2,315	7,157
Observations	25,206	25,206	91,175	91,175
E: In Migration				
Treatment	68,900***	89,693**	166,817**	261,523**
	(24,458)	(37,824)	(79,748)	(116,188)
Control Mean	82,366		137,211	
Bandwidth	3,424	7,004	3,604	7,520
Observations	25,194	25,194	97,118	97,118

Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. p(1) is a polynomial of order 1 (linear regression) and p(2) is a polynomial of order 2 (quadratic) estimates. Natural Disaster takes the value of 1 if the household experiences a drought, flood, fire etc or a crop failure. Treatment variable is the expansion of bank branches in underbanked districts. Data IHDS II (2011/2012), individual level. Covariates include individual's age, household size and status of poverty, district population and number on non-regional banks in the districts in 2005. *Migrated for Work* is derived from the tracking file of IHDS 2 which asks household respondents if any member of the household migrated after 2005 (IHDS 1). We code non-migrants and migration for purpose other than work as 0, and migration for work as 1. The questionnaire from which the variable is derived reads as "Why did the migrant migrate". *Short Term Migration* is a dummy variable which takes the value 1 if the seasonal migrant had gone to seek work 1 year ago, and 0 otherwise. *Permanently Migrated* is derived from the question that asks: "Has [NAME] gone permanently or do you think she/he will return to live here?". We create a dummy variable from the response which takes value 1 if the respondent says the migrated person will not return, and 0 if the migrant could return or if there is no migration from the household. *Migrated to Urban Areas* is a dummy variable which takes the value 1 if the migrant had gone to town, cities and abroad, or 0 if migrated to another village and if there was no migration from the household. *In migration* is a continous variable derived from the 2011 population census which asks individuals if they had migrated from another district.

Table 6: Bank presence and household well-being in drought or flood affected areas

	(1)	(2)	(3)	(4)	(5)
Variables	Rain Z<-0.5	Rain Z<-0.75	Rain Z>0.5	Rain Z>0.75	Rain Z>1
A: Consumption Volatility					
Treatment	-0.295	-0.696***	-0.413	-0.576	-0.907**
	(0.545)	(0.182)	(0.402)	(0.430)	(0.422)
Bandwidth	1,927	1,610	3,113	3,304	3,021
Observations	4,467	3,348	22,609	17,446	12,869
B: Log Total Consumption					
Treatment	0.051	0.058	0.076	0.012	0.070
	(0.101)	(0.075)	(0.066)	(0.072)	(0.094)
Bandwidth	2,278	1,782	4,542	3,321	2,274
Observations	4,467	3,348	22,609	17,446	12,869
C: Consumption Growth					
Treatment	0.086	0.179	0.215**	0.185*	0.277**
	(0.179)	(0.165)	(0.094)	(0.106)	(0.115)
Bandwidth	2,721	2,201	3,974	4,085	2,975
Observations	4,467	3,348	22,609	17,446	12,869
D: Non Farm Labor					
Treatment	0.107**	0.104**	0.072**	0.107***	0.146***
	(0.049)	(0.052)	(0.032)	(0.034)	(0.039)
Bandwidth	2,098	2,590	4,848	4,151	3,154
Observations	4,475	3,353	22,649	17,448	12,870
E: Short Term Migration					
Treatment	0.011	0.028***	0.007	0.017**	-0.001
	(0.011)	(0.004)	(0.006)	(0.006)	(0.005)
Bandwidth	2,023	1,651	4,453	3,239	2,021
Observations	4,474	3,352	22,649	17,448	12,870

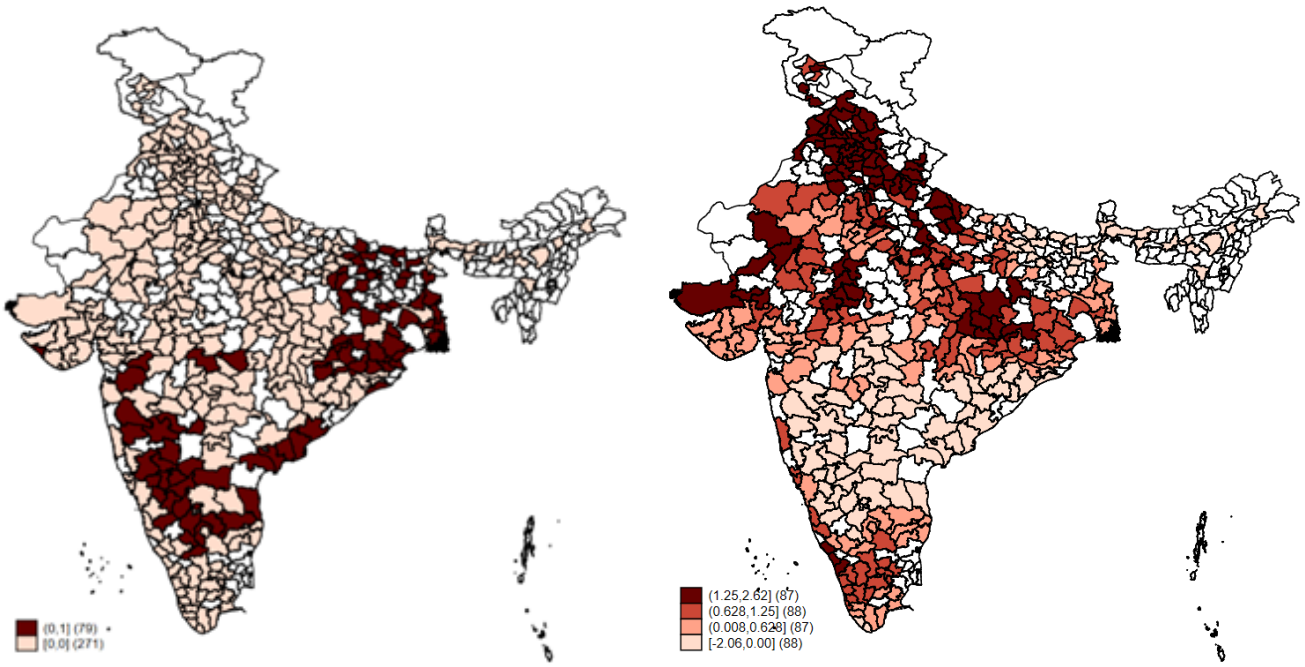
Note: Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Treatment variable is the expansion of bank branches in underbanked districts. Data IHDS II (2011/2012), household level. Covariates include lag of the outcome variable. Rainfall Natural Disasters measured as the z-score in a single season's rainfall is constructed from Climate Hazards Group Infrared Precipitation (CHIRPS). We extract daily precipitation for each day in a monsoon season that is 1st June to 30th September and sum it for a given year. We construct rainfall z-score for the year 2011 as a deviation from the long-term average precipitation (1996-2011) and scale it with long term standard deviation.

Table 7: Bank presence and household well-being with significant temperature increase

	(1)	(2)	(3)	(4)
Variables	Temp>0.30*	Temp>0.40*	Temp>0.50*	Temp>0.60*
A: Consumption Volatility				
Treatment	-0.403	-0.986**	-0.887**	-1.510***
	(0.303)	(0.444)	(0.417)	(0.461)
Bandwidth	4,820	4,447	3,489	2,873
Observations	25,900	18,526	13,166	10,817
B: Log Total Consumption				
Treatment	0.217**	0.252**	0.104	0.012
	(0.090)	(0.124)	(0.492)	(0.996)
Bandwidth	3,471	3,820	4,081	2,780
Observations	25,900	18,526	13,169	10,817
C: Consumption Growth				
Treatment	0.321***	0.261*	0.264**	0.232**
	(0.0996)	(0.141)	(0.117)	(0.113)
Bandwidth	3,508	3,977	3,598	3,098
Observations	25,900	18,526	13,166	10,817
D: Non Farm Labor				
Treatment	-0.003	0.018	0.021	0.048*
	(0.037)	(0.049)	(0.056)	(0.025)
Bandwidth	3,321	4,425	3,519	1,726
Observations	75,819	53,385	37,809	31,202
D: Short Term Migration				
Treatment	0.004	0.002	0.001	0.032
	(0.007)	(0.012)	(0.013)	(0.039)
Bandwidth	3,210	4,385	3,737	4,507
Observations	77,991	55,034	39,061	32,285

Note: Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Treatment variable is the expansion of bank branches in underbanked districts. Data IHDS II (2011/2012), household level. Covariates: district population, number of functioning bank branches in the district in 2005, excluding regional rural banks, lag of the outcome variable. We calculate district-level temperature change by subtracting 1981 average growing season temperature from those in 2010.

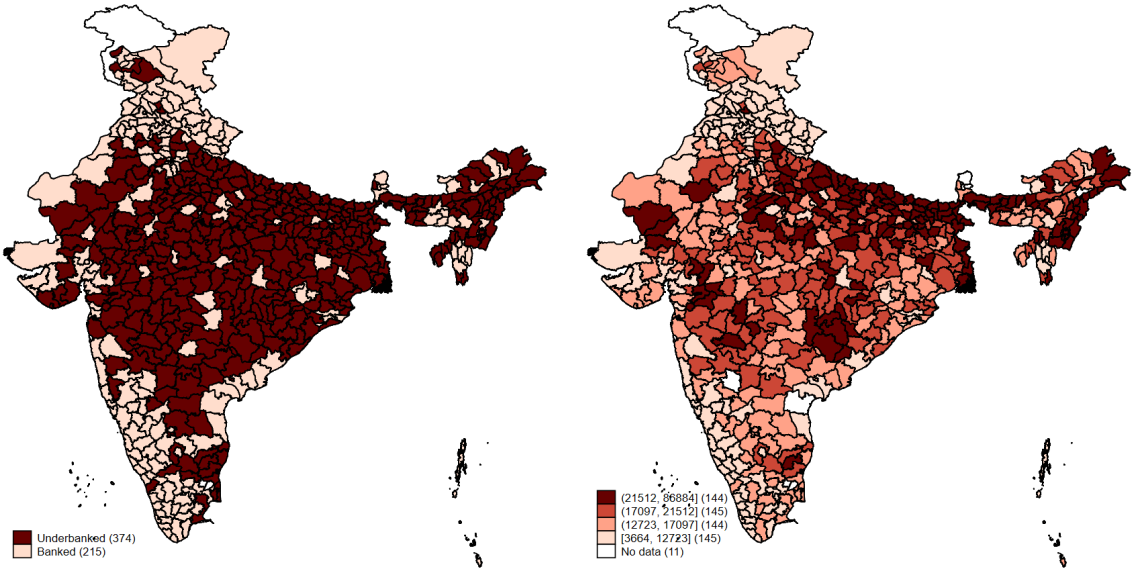
Appendix



Panel (A) Districts with drought Panel (B) Long Term Rain Z Score

Figure A1: District level rain z score and district affected by natural disasters in 2010 and 2011, Indian Meteorological Department.

Source: Indian Meteorological Department, 2010-2011, and Climate Hazards Infrared Precipitation Survey, 1996-2011.



Panel (A) Panel (B)

Figure A2: Banked and Under-banked Districts. Panel (A): RBI classification, 374 districts of 581 are defined as underbanked, shown in darker shades. Panel (B): Bank branch to population ration in the district. Source: RBI quarterly branch statistics.

Table A1: Bank branch expansion and occurrence of natural disaster at the household level

	(1)	(2)	(3)
	Drought	Crop Failure	Drought or Crop Failure
Treatment	0.03	0.06	0.08
	(0.06)	(0.06)	(0.07)
Control Mean	0.06	0.11	0.13
Bandwidth	4,828	3,313	3,472
Observations	39,969	39,964	40,018

Note: Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Treatment variable is the expansion of bank branches in underbanked districts. Data IHDS II (2011/2012), household level.

Table A2: Summary Statistics for households affected and not affected by natural disasters.

	Natural Disaster			No Natural Disaster			
Variables	Obs.	Mean	SD	Obs	Mean	SD	t-test
Underbankedness							
Household in Underbanked District	7935	0.724	0.446	32083	0.522	0.499	***
Population to Bank Ratio District	7935	17295.87	5745.48	32083	15188.46	5893.86	***
Household well-being outcomes							
Total Consumption (Rs.)	7925	58,927	57,066	32069	64,200	66982	***
Total Food Cons. (Rs.)	7302	1146	730	29350	1217	760	**
Growth Rate of Consumption	7919	-0.380	0.640	32030	-0.434	0.645	***
Meals Per Day	7869	2.755	0.594	31814	2.746	0.575	***
Log outcomes							
Log Consumption	7925	10.740	0.627	32069	10.803	0.646	***
Log Amount Borrowed	4630	9.896	1.236	13572	9.876	1.259	
Log Variance Consumption	7,925	20.00	2.74	32,069	19.96	2.73	
Individual Data IHDS							
Non-farm Wage Labor (0/1)	31393	0.163	0.370	118983	0.144	0.351	***
Migration Last Year (0/1)	31388	0.020	0.140	118965	0.009	0.093	***
Seasonal Migration (0/1)	30916	0.125	0.331	116625	0.057	0.231	***
Child School Hours	7590	32.396	8.732	27386	32.110	8.740	*
Farm Employment (0/1)	31393	0.534	0.499	118983	0.210	0.407	***
Migrated for Work	25,397	0.04	0.194	188,000	0.03	0.165	
Permanently Migrated	25,397	0.04	0.184	188,000	0.02	0.152	***
Migrated to Urban Areas	25,397	0.07	0.263	188,000	0.06	0.236	**
Natural Disasters							
Droughts Flood Fire etc. (0/1)	7887	0.408	0.492	32082			
Crop Failure (0/1)	7887	0.836	0.370	32077			
Mechanisms							
Bank Loan (0/1)	7922	0.331	0.471	32069	0.195	0.396	***
Interest Rate on Loan (Monthly)	3135	2.525	2.300	9746	2.262	2.260	***
Bank Savings (0/1)	7902	0.583	0.493	31969	0.567	0.495	**
Crop Failure (0/1)	7935	0.046	0.210	32083	0.008	0.087	***
Loan for Land Purchase	5406	0.015	0.120	16301	0.016	0.125	***

Note: t-test measures the mean difference between households and individuals affected or not affected by natural disasters, significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Data IHDS II 2012, and IHDS I (2005) and II (2012) for the growth rate variables, household and individual level.

Table A3: Summary Statistics: Rain Z score and Temperature Change by Bank Presence

	Not Underbanked			Underbanked		
Variable	Obs.	Mean	SD	Obs.	Mean	SD
(A): **Full Sample**						
Rain z score <-0.5	64578	0.098	0.297	85798	0.114	0.317
Rain z score <-0.75	64578	0.083	0.276	85798	0.075	0.263
Rain z score >0.5	64578	0.659	0.474	85798	0.535	0.499
Rain z score >0.75	64578	0.561	0.496	85798	0.368	0.482
Rain z score >1	64578	0.453	0.498	85798	0.245	0.430
Temperature >0.3*c	17448	0.502	0.500	22514	0.762	0.425
Temperature >0.4*c	17448	0.287	0.452	22514	0.600	0.489
Temperature >0.5*c	17448	0.121	0.327	22514	0.490	0.499
Temperature >0.6*c	17448	0.084	0.278	22514	0.414	0.492
(B): **Optimal Bandwidth (+,- 3,000)**						
Rain z score <-0.5	24541	0.194	0.395	34882	0.164	0.370
Rain z score <-0.75	24541	0.154	0.361	34882	0.132	0.303
Rain z score >0.5	24541	0.539	0.499	34882	0.588	0.492
Rain z score >0.75	24541	0.469	0.499	34882	0.433	0.496
Rain z score >1	24541	0.333	0.471	34882	0.272	0.445
Temperature >0.3*c	6661	0.583	0.493	9245	0.635	0.481
Temperature >0.4*c	6661	0.338	0.473	9245	0.427	0.494
Temperature >0.5*c	6661	0.206	0.404	9245	0.320	0.466
Temperature >0.6*c	6661	0.158	0.364	9245	0.206	0.404

Notes: Rainfall Natural Disasters measured as the z-score in a single season's rainfall is constructed from Climate Hazards Group Infrared Precipitation (CHIRPS). We extract daily precipitation for each day in a monsoon season that is 1st June to 30th September and sum it for a given year. We construct rainfall z-score for a given year as a deviation from the long-term average precipitation (1996-2011) and scale it with long term standard deviation. Temperature data is extracted for the growing season (June to September) within a year, Climate Research Unit (CRU) at the University of East Anglia. We derive the change in temperature from 1981 to 2011 to cover three decades. Data is matched to the IHDS wave 2012.

Table A4: Government declaration of drought/ and household response to drought/flood occurrence.

	(1)	(2)	(3)
Household affected by	Drought	Crop Failure	Drought/Crop Failure
Drought affected districts (2010/2011)	0.05***	0.04***	0.05***
	(0.00)	(0.01)	(0.01)
Control Mean	[0.05]	[0.15]	[0.18]
State Fixed Effects	Y	Y	Y
Observations	39,969	39,964	40,018
R-squared	0.123	0.064	0.074

Note: Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Impact of Bank Presence on Consumption, Food Security and Employment for Districts Affected by Drought (D) and not affected by Drought (ND)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ND	D	ND	D	ND	D	ND	D
	Log Consumption Variance		Consumption Growth		Meals Per Day		Non Farm Labor	
Treatment	-0.60*	-0.50*	0.29*	0.25***	0.61***	0.43***	0.07**	0.10
	(0.36)	(0.27)	(0.17)	(0.08)	(0.19)	(0.17)	(0.03)	(0.06)
Bandwidth	2,081	3,331	2,492	3,323	2,512	3,812	1,712	1,954
Observations	9,698	30,203	9,698	30,203	9,601	30,033	29,660	92,652

Note: Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimates are polynomial of order 1 (linear regression). ND means no drought in 2010/2011 and D means drought in 2010/11. Data IHDS II (2011/2012), household and individual level, RBI quarterly branch statistics and National Disaster Management Authority (NDMA) declaration of drought affected districts in 2010 and 2011. Covariates include log of number of open and functioning bank branches except regional rural banks in 2005 pre-policy education level of the household head.

Table A6: Bank presence and provision of government relief for natural disasters

	(1)	(2)	(3)	(4)
	Natural Disaster		No Natural Disaster	
	p (1)	p (2)	p (3)	p (4)
Drought/flood compensation from govt.				
Treatment	535.9*	43.45	940.1	872.4
	(293.2)	(569.4)	(739.7)	(750.2)
Control Mean	365		219	
Bandwidth	2,745	5,533	7,211	16,824
Observations	7,930	7,930	32,075	32,075

Note: Robust standard errors in parentheses clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Here, p(1) is a polynomial of order 1 (linear regression) and p(2) is a polynomial of order 2 (quadratic) estimates. Natural Disaster is a dummy which takes value 1 if the household experiences a drought, flood, fire etc or a crop failure. Treatment variable is the expansion of bank branches in underbanked districts. Data IHDS II (2011/2012), household level. Covariates include log of district variable and log of number of open and functioning bank branches except regional rural banks in 2005 and the pre-policy average community (IDPSU) level poverty. The outcome variable is measured in Rs. annually.

Table A7: Placebo Cutoffs for Well-being Outcomes and Mechanisms: RDD Test

Cutoff	Log Cons. Var.	Log Cons.	Cons. Growth Rate	Food Cons.	Meals/day	Child Schooling Hrs
-3000	0.407	0.506	0.754	0.546	0.923	0.456
-1500	0.781	0.974	0.685	0.612	0.297	0.384
0 (Main)	0.012	0.967	0.142	0.071	0.001	0.073
1500	0.343	0.978	0.235	0.399	0.869	0.325
3000	0.205	0.200	0.670	0.614	0.858	0.365
Cutoff	**Bank Loan**	**Log Loan Amt.**	**Loan Int. Rate**	**Bank Savings**	**Crop Insurance**	**Land Loan**
-3000	0.779	0.779	0.410	0.403	0.894	0.573
-1500	0.363	0.883	0.683	0.212	0.862	0.434
0 (Main)	0.080	0.089	0.088	0.074	0.085	0.006
1500	0.841	0.169	0.373	0.356	0.452	0.259
3000	0.779	0.473	0.427	0.377	0.932	0.773
Cutoff	**Non-Farm Wage**	**Farm Wage**	**Perm. Mig.**	**Short-term Mig.**	**In Mig.**	
-3000	0.554	0.458	0.684	0.588	0.377	
-1500	0.376	0.568	0.225	0.349	0.383	
0 (Main)	0.006	0.214	0.005	0.004	0.008	
1500	0.513	0.722	0.238	0.732	0.406	
3000	0.613	0.556	0.611	0.745	0.971	

Notes: p-values of respective RD regressions with different (placebo) cutoffs shown. Sample includes households affected by natural disasters.

Table A8: Robustness to Different Bandwidth Multipliers: Household Well-being

Bandwidth Multiplier	Log Cons. Var.	Log Cons.	Cons. Growth	Food Cons.	Meals/day	Child School Hrs
0.50x	-0.910***	-0.051	0.441***	312**	0.692**	5.041**
	(0.242)	(0.149)	(0.147)	(186)	(0.290)	(2.109)
0.75x	0.657***	-0.016	0.396***	350**	0.617***	4.872*
	(0.267)	(0.133)	(0.139)	(199)	(0.284)	(2.067)
1.00x	-0.586**	0.017	0.304**	344*	0.687***	4.984*
	(0.231)	(0.124)	(0.126)	(206)	(0.225)	(2.573)
1.25x	-0.671**	0.003	0.349***	412**	0.675***	4.620*
	(0.212)	(0.109)	(0.116)	(189)	(0.221)	(2.331)
1.50x	-0.644***	0.018	0.334***	404**	0.631***	4.175
	(244)	(0.104)	(0.111)	(198)	(0.226)	(2.152)

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Estimates and standard errors are displayed in parenthesis below the RD estimate. Sample includes households affected by natural disasters.

Table A9: Robustness to Different Bandwidth Multipliers: Mechanisms for Household Well-being

Bandwidth Multiplier	Bank Loan	Log Loan Amt.	Monthly Interest	Bank Savings	Crop Insurance	
0.50x	0.113*	0.628*	-1.132**	0.282*	0.117	
	(0.064)	(0.365)	(0.711)	(0.151)	(0.063)	
0.75x	0.127*	0.671*	-1.656**	0.320**	0.136*	
	(0.071)	(0.383)	(0.698)	(0.169)	(0.071)	
1.00x	0.153*	0.724*	-1.472**	0.371**	0.140*	
	(0.085)	(0.391)	(0.727)	(0.162)	(0.067)	
1.25x	0.169*	0.715*	-1.287*	0.358**	0.134*	
	(0.092)	(0.393)	(0.690)	(0.171)	(0.064)	
1.50x	0.138	0.639*	-1.390*	0.388**	0.154*	
	(0.087)	(0.381)	(0.699)	(0.175)	(0.068)	
Bandwidth Multiplier	**Land Loan**	**Non-Farm Wage**	**Farm Wage**	**Perm. Mig.**	**Short-Term Mig.**	**In Mig.**
0.50x	0.061***	0.089**	-0.089	0.042*	0.072**	65,133***
	(0.012)	(0.041)	(0.081)	(0.022)	(0.027)	(25,492)
0.75x	0.057***	0.106**	-0.077	0.044**	0.084**	64,581***
	(0.014)	(0.042)	(0.082)	(0.019)	(0.029)	(24,676)
1.00x	0.047***	0.101***	-0.073	0.051***	0.081***	68,900***
	(0.013)	(0.043)	(0.091)	(0.022)	(0.028)	(24,458)
1.25x	0.042**	0.093***	-0.068	0.047**	0.077**	69,919***
	(0.014)	(0.042)	(0.099)	(0.023)	(0.027)	(25,904)
1.50x	0.048**	0.079***	-0.083	0.041**	0.071**	67,416***
	(0.019)	(0.040)	(0.092)	(0.021)	(0.028)	(25,526)

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors in parentheses. Sample includes households affected by natural disasters.

Table A10: Robustness to Different Bandwidth Selectors: Main Results

Bandwidth Selector	Log Var. Cons.	Log Cons.	Cons. Growth	Food Cons.	Meals/Day	Child School Hrs
MSE Common	-0.586**	0.017	0.304**	344*	0.687***	4.984*
	(0.231)	(0.120)	(0.126)	(206)	(0.215)	(2.573)
MSE Two-Sided	-0.667***	-0.031	0.337***	344*	0.694***	4.775**
	(0.217)	(0.135)	(0.104)	(195)	(0.197)	(2.298)
CER Common	-0.647***	-0.007	0.334**	133	0.756***	4.561*
	(0.230)	(0.134)	(0.141)	(227)	(0.213)	(2.311)
CER Two-Sided	-0.582***	-0.073	0.322***	404*	0.733***	4.849**
	(0.207)	(0.145)	(0.107)	(218)	(0.197)	(2.211)

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Estimates and standard errors are shown in separate rows for each bandwidth selector. The MSE-optimal columns represent identical and two-sided bandwidths, while the CER-optimal columns represent similar configurations (Calonico, Cattaneo, and Farrell, 2020; Calonico, Cattaneo, and Titiunik, 2014).

Table A11: Robustness to Different Bandwidth Selectors: Mechanisms for Household Well-being

Bandwidth Selector	Bank Loan	Log Loan Amt.	Monthly Interest	Bank Savings	Crop Insurance	
MSE Common	0.153*	0.724*	-1.132**	0.371**	0.140*	
	(0.085)	(0.391)	(0.711)	(0.162)	(0.067)	
MSE Two-Sided	0.158**	0.743**	-1.656**	0.355**	0.153**	
	(0.074)	(0.330)	(0.698)	(0.163)	(0.064)	
CER Common	0.161**	0.701*	-1.472**	0.343**	0.142*	
	(0.085)	(0.376)	(0.727)	(0.152)	(0.070)	
CER Two-Sided	0.164*	0.684*	-1.287*	0.356**	0.145**	
	(0.076)	(0.370)	(0.690)	(0.156)	(0.064)	
Bandwidth Selector	**Land Loan**	**Non-Farm Wage**	**Farm Wage**	**Perm. Mig.**	**Seasonal Mig.**	**In Mig.**
MSE Common	0.047***	0.101***	-0.073	0.051***	0.081***	68,900***
	(0.013)	(0.043)	(0.091)	(0.022)	(0.028)	(24,458)
MSE Two-Sided	0.048***	0.098***	-0.074	0.048***	0.078***	65,455***
	(0.014)	(0.040)	(0.090)	(0.020)	(0.026)	(23,567)
CER Common	0.042***	0.105***	-0.069	0.054***	0.074***	67,711***
	(0.013)	(0.039)	(0.099)	(0.023)	(0.029)	(24,045)
CER Two-Sided	0.048***	0.106***	-0.076	0.055***	0.073***	68,255***
	(0.015)	(0.046)	(0.096)	(0.019)	(0.029)	(24,688)

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors are in parentheses. MSE-optimal columns represent identical and two-sided bandwidths, while CER-optimal columns represent similar configurations (Calonico, Cattaneo, and Farrell, 2020; Calonico, Cattaneo, and Titiunik, 2014).