ESSAYS ON FINANCIAL INCLUSION, EXTREME WEATHER EVENTS AND DEVELOPMENT

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

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August 2024

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ESSAYS ON FINANCIAL INCLUSION, EXTREME WEATHER EVENTS AND DEVELOPMENT

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Cornell University 2024

This dissertation examines how economic policy changes and extreme weather events influence gender and development outcomes. It focuses on the impacts on different population groups, especially women, and underscore the need for gender-specific outcomes in policy-making and fair resource distribution to support resilient communities. The essays combine publicly available datasets with quasi-experimental techniques for causal inference.

BIOGRAPHICAL SKETCH

Tarana Chauhan is an applied micro economist studying questions at the intersection of labor, gender and development, and climate change and development. Her research examines the distributional effects of economic policy changes and extreme weather events using quasi-experimental techniques on publicly available datasets. Before the Ph.D., she helped evaluate a program on maternal and child health and nutrition with the International Food Policy Research Institute in India. She completed her Master's in Development Studies at the Tata Institute of Social Sciences, Mumbai and received a Bachelor's degree in Economics from the University of Delhi (Lady Shri Ram College for Women).

This dissertation is dedicated to my parents, Amita Chauhan and M.C. Chauhan, and my sister, Aanchal Chauhan, who have continuously inspired me to grow professionally and personally.

ACKNOWLEDGEMENTS

I would like to thank my advisers Chris Barrett, Brian Dillon, Carolina Castilla and Francine Blau who have been incredibly supportive of my pursuit of research questions. I have benefited enormously from their wide and rich experience, their patience, and care for my best interest. I am grateful to the faculty at Dyson School of Applied Economics and Management and visiting faculty who critically engaged with my research and were generous with their feedback. Thanks also to professor Shanjun Li, graduate field coordinators Michelle Taber and Yiyi Grazul for their support in sharing my research outside Cornell and opportunities within the department.

I am thankful to Keith Jenkins, the GIS/Geospatial Applications Librarian at Cornell University who introduced me to the tools most amenable for geospatial analysis which played a defining role in the data and methods used in this dissertation. I owe a huge thanks to my peers at Dyson who have taught me theory, methods and life skills in the last six years.

This journey would not have been possible without the guidance of Kalyani Raghunathan and Tushaar Talwar as I applied to graduate school, the unconditional love and unlimited support of my family and friends in India; the warmth and home away from home created by my friends in the US; and the understanding and new experiences provided by my community in Ithaca.

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CHAPTER 1
INTRODUCTION

The literature in development economics has studied issues of poverty, lack of infrastructure in rural areas and household welfare in response to economic shocks, among many other topics. Government interventions such as legislations, transfer programs and provision of public goods serve as natural experiments for quasi-experimental analyses when they vary the timing of implementation, are unanticipated and implemented with little gap between enforcement and announcement. Such policy changes or projects allow testing of key hypotheses on how the population as a whole is affected by these changes without investment in field experiments studying the effects on a representative sample of the population. Although the research design of randomized controlled experiments controls more effectively for prospective confounding variation within the sample, intentional experiments may lack external validity and their large costs make it prohibitive for many researchers. The use of natural experiments combined with publicly available data offers a more accessible research method for development economists. This dissertation relies on natural experiments and publicly available data to make inferences about key development issues.

Another motivation to analyze natural experiments using quasi-experimental methods is to measure the effects on sub-groups within a population. The literature shows that economic shocks such as financial inclusion or climate change have consequences for households' economic well-being (Burgess and Pande, 2005; Brune et al., 2015; Schaner, 2017; Zhu and Troy, 2018; Jiang and Liu, 2022). Some groups (e.g. higher income households) can benefit from the positive shocks more or absorb the negative shocks better. There may be potential adverse consequences of natural or policy shocks on vulnerable groups, such as women, that policy makers should keep in mind when designing welfare policies or in their mitigation efforts.

This dissertation explores the distributional effects of economic policy changes and extreme weather events on gender and development outcomes. The three main chapters examine how these events impact different segments of the population, particularly women, and the intersection between gender dynamics and environmental changes. Together, these studies underscore the necessity of considering gender-specific outcomes in policy-making and the importance of equitable resource distribution in fostering resilient communities amidst growing environmental challenges.

Chapter 2 investigates the impact of a gender-blind financial inclusion policy on women's empowerment outcomes in India. This chapter is motivated by the global expansion in financial inclusion in the last decade, which coincided with a reduction in the gender gap in account ownership. It examines the impact of a 2014 policy that provided free bank accounts to unbanked individuals. Prior to the policy shock, one in three men and one in five women had an account they actively used (Financial Inclusion Insights survey 2014). The chapter examines three outcomes of empowerment: household resource allocation, women's self-reports of participation in purchase decisions and availability of money for autonomous use, and police reports of crimes against women by a spouse or his family members. When the wife of the household head opens an account, I find that households increased their use of formal savings and credit and reduced their monthly consumption expenditure. Expansion in account ownership within a district did not lead to significant changes in either women's self-reports of participation in purchase decisions nor in the availability of money for autonomous use. However, in districts with greater trust and engagement with banking institutions, faster expansion of accounts led to more women reporting participation in household purchases. Finally, there was a decline in police reports of harassment by the spouse and his family in districts with faster expansion of account ownership.

This chapter contributes to the literature on women's financial inclusion and empowerment that has been concentrated globally around micro-finance programs and in India, on the access to banking infrastructure. The results are relevant for policy makers to understand the distributional effects of policies that target the general population. In addition, the results suggest limited effects on women's decision-making ability in the short term in the absence of measures to address barriers to women's account use.

Chapter 3 focuses on the gender implications of extreme weather events in Sub-Saharan Africa, particularly examining the link between extreme cold or hot temperatures and intimate partner violence (IPV). It studies the behavioral impacts of extreme temperature such as heightened irritability and aggression and its correspondence with IPV. Staying indoors may not be sufficient to dissipate temperature-induced aggression in the absence of weather-resilient buildings. Extreme weather also negatively affects workers in outdoor occupations. Therefore, this problem is likely to be more acute in rural, agrarian societies and in lower-and-middle income countries.

In this chapter, I combine self-reported IPV in the past 12 months with Earth observation data of temperature during this period for 22 countries in Sub-

Saharan Africa between 2005 and 2018. Using ordinary least squares estimation, I find that in years with higher maximum temperatures than the historical average, there was a higher prevalence of physical acts of IPV and lower prevalence of acts of emotional or sexual violence. Reports of violence were systematically larger for women whose partners consumed alcohol than others. There was a positive correlation between the intensity of humidity-adjusted temperature (Discomfort Index) in the past year and the frequency of physical IPV. These results underscore the urgent need for public policy interventions and legal reforms to address climate-induced gender violence.

Chapter 4 analyzes the economic recovery from floods in five states of India between 2008 and 2013, investigating whether political affiliations influence the allocation of government resources in the months after a flood event. The literature identifies political gains from discriminating in relief provision (Ashworth, 2005; Garrett and Sobel, 2003; Bechtel and Hainmueller, 2011; Reeves, 2011; Cole et al., 2012; Lazarev et al., 2014; Bodet et al., 2016; Ashworth et al., 2018). The chapter uses the monthly aggregated night-time luminosity of a constituency to analyze changes in economic activity before and after a flood. It employs a two-way fixed effects ordinary least squares estimation and a regression discontinuity analysis to assess the recovery outcomes of constituencies based on their political links to the ruling party.

The findings suggest that there were no significant differences in recovery of post-flood economic activity by affiliation with the state ruling party. However, there was faster (slower) recovery by increasing margin of loss (victory) for the ruling party candidate in the first two months after a flood. The ruling parties in the sample were more likely to prioritize their staunch opposition in post-flood relief and restoration versus their loyal supporters. There was no evidence that the state governments prioritized voters at the margin. The incumbency of the state governments corresponded with faster post-flood recovery. After the first month post-flood, there were differential trends in recovery by proximity to the next election. The regression discontinuity analysis did not find significant differences in recovery between the constituencies that elected a member of the state ruling party versus those that did not. With increasing natural hazards and weather shocks from climate change, this chapter contributes to the critical examination of factors that can potentially affect a local community's preparedness and recovery.

CHAPTER 2

ACCOUNTING FOR EMPOWERMENT? EXAMINING WOMEN'S FINANCIAL INCLUSION IN INDIA

2.1 Introduction

The study of financial inclusion on women's outcomes in low-and-middle income countries is concentrated in the evaluation of microfinance programs. When provided access to formal savings and credit, women increase savings (Dupas and Robinson, 2013; Klapper and Hess, 2016) and their participation in household resource allocation for food, healthcare and education (Duflo, 2003; Prina, 2015; Karlan et al., 2016; Steinert et al., 2018). Often, these programs include training and social messaging, and enable peer groups that positively impact women's self-esteem and personal agency (Basargekar, 2009; Kato and Kratze, 2013; Morgan and Coombes, 2013), and reduce experience of intimate partner violence (Goetz and Gupta, 1996; Rahman, 1999; Ahmed, 2005). However, financial inclusion can also have negative gendered consequences. For instance, access to credit may shift the economic burden of loan repayment to women or increase risk of extractive violence from family members (Kofman and Payne, 2020). Women in many low-income settings lack control over economic resources, and social norms frequently limit their agency. The increased supply of Automatic Teller Machine (ATM) cards in this context can lower transaction costs for a male spouse to access a woman's savings in bank accounts, reducing her use of these accounts (Schaner, 2017). These differences by gender may significantly alter the benefits observed from bringing women into the formal banking sector making it implicitly difficult to predict the impacts of women's financial inclusion on their autonomy and decision making ability.

This chapter tests the effects of bank account ownership on women's empowerment by exploiting an exogenous shock to account ownership. In 2014, less than 50% of women in India owned an account, just over 10% reported saving in a formal institution and almost 5% borrowed from a formal lending institution (Demirguc-Kunt et al., 2015). The Government of India implemented a policy in August 2014 that required licensed commercial banks to provide zero-cost bank accounts for unbanked individuals *on demand*. By removing account opening and maintenance fees, the policy led to an unprecedented expansion of bank accounts. It was awarded a Guinness World Record for opening more than 18 million accounts within the first week. This chapter tests the effects of the policy on women's empowerment through her account ownership and aggregate-level expansion in accounts within the first year of implementation.

Using the sharp timing of the policy and a household longitudinal survey, I test the effect of women's account ownership on households' consumption patterns and uptake of banking services with an Inverse Probability Weighted Difference-in-Difference (IPW DiD). The analysis is restricted to households where the wife of the male household head did not have a bank account before policy change. A household is classified as "treated" if the wife opened a bank account in the survey wave immediately after the account expansion policy took effect and "comparison" if she remained unbanked after policy change. A propensity score of the ex-ante likelihood of a wife in the sample owning a bank account is estimated from observable household characteristics and used to re-weight observations in the Treatment and Comparison groups. A difference-in-difference (DiD) of outcomes across the 2 groups before and after policy change shows that when the wife opens a bank account, household's uptake of borrowing from formal sources such as banks, employer and registered credit organizations increases and persists over 8-12 months after account opening. There is no significant impact on borrowing from informal sources such as relatives and moneylender. The positive impact on uptake of savings in banks and government schemes and bonds increases over the course of a year. These results serve as a lower bound estimate of uptake of banking on the extensive margin by women. I also test for household consumption of goods associated with women's empowerment in the literature (Beegle et al., 2001; Quisumbing and Maluccio, 2003; Duflo and Udry, 2004; Doss, 2006). There is a decline or no change in household's monthly expenditure on clothing and footwear, accessories and jewelry, time saving appliances, cosmetics and toiletries, beauty goods and services, utensils, food and education. Household's total monthly expenditure declines in response to account ownership, driven by reduced expenditure on consumer durables such as kitchen, household and mobile appliances; communication and conveyance.

The policy led to different rates of expansion of account ownership between districts based on pre-policy banking infrastructure. I leverage this spatial and time variation in acceleration of *total* account ownership, not specifically women's, to test for changes in women's self-reported outcomes of decision making that are consistently observed at the district level. Self-reported survey data is widely used in the literature to estimate women's empowerment (Allendorf, 2007; Connelly et al., 2010; Swaminathan et al., 2012; Field et al., 2021; Annan et al., 2021; Kosec et al., 2022; Doss et al., 2022; Quisumbing et al., 2023a; Heckert et al., 2023; Quisumbing et al., 2023b). A DiD estimates the effects of policy-induced district-wise expansion of bank account ownership on women's empowerment. I find no significant changes in women's self-reported outcomes of empowerment in response to significantly faster growth in total accounts within a district. The results are consistent with Field et al. (2021) who test for effects of ownership and active use of women's accounts on their self-reported empowerment. Information of women's participation in decisions within the household on expenditure, saving, food, education, employment and healthcare are commonly used in the literature to infer her weight within the household (Patel et al., 2007; Reggio, 2011; Pitt et al., 2006; Doss, 2013; Strauss and D., 1995).

A test for the effect of expanded bank account ownership on police reports of harassment from spouse or his family members in a district shows that districts with faster expansion of account ownership corresponded with a significantly larger decline in complaints filed.

Altogether, these results help understand the short-term effect of bank account ownership on women's empowerment. This chapter uses heterogeneity tests to explore norms that affect women's access to their bank account and her empowerment. In districts with faster growth in account ownership, there is higher participation of women in household purchase decisions for households which had higher trust in banking institutions relative to households with lower trust within the district or districts where the policy had a lower impact. Limited uptake of services in response to low trust in institutions is seen in other sectors as well (Pelras and Renk, 2022). There are no heterogeneous effects of ex-ante gender parity within household and women's mobility outside home.

This chapter expands the literature on financial inclusion and women's empowerment, specifically, the effects of access to banking services in India on poverty and women's economic empowerment. Burgess and Pande (2005) find positive effects of bank branch expansion on rural poverty. Proximity to a bank branch directly improves women's uptake of credit for entrepreneurship (Garg and Gupta, 2022). Instead of estimating the effect of bank branch availability, this chapter holds banking infrastructure fixed and estimates the effect of account ownership on women's empowerment at home.

This chapter aligns closely with the field experiment on account ownership, training and use by Field et al. (2021) conducted in four districts in Central India. The experiment found that individual account ownership and use improved female labor supply but did not affect self-reported measures of empowerment. In this chapter, I expand this question to married women across rural and urban India, and to multiple empowerment outcomes such as household's consumption patterns and police reported crime data.

This chapter complements the work by Agarwal et al. (2017) who study the effect of the 2014 account expansion policy on demand for lending and defaults on new loans. Using the same household longitudinal survey analyzed in this chapter, the authors find evidence of reduced volatility in household food consumption and increased medical expenditure financed by banks.

This chapter also relates to the literature on income concealing among spouses as households' increased uptake of formal savings could potentially be the wife's attempt to improve privacy over money and reduce surveillance by other members of the household. Ashraf (2009) and Castilla (2019) find evidence of spouses allocating more money to themselves when they can keep their income private.

Lastly, the chapter contributes evidence to a global policy agenda. In the last decade, financial inclusion has been a key priority for governments and multilateral development banks to help households exit poverty ((Burgess and Pande, 2005; Jiang and Liu, 2022). Bank accounts linked with brick and mortar banks act as an entry point for financial inclusion in several low and middle income countries. Consistent with policy efforts, the percentage of global banked adult population increased from 50 to 76 between 2011 and 2021 (World Bank, 2022). Improved access to savings and credit help increase capital accumulation (Brune et al., 2015), investment in human capital formation, smooth long term consumption (Sherraden, 2000; Beverly et al., 2003) and insure against adverse economic shocks. However, the distributional effects may vary based on factors that systematically restrict uptake of banking services for socially vulnerable groups such as women. The results of this chapter show that women are more likely to use formal savings instruments in response to account ownership. District-wise expansion in account ownership did not affect women's participation in decisions around purchase and use of money but police-reported crimes against women reduced.

The next section describes the state of financial inclusion in India, account ownership policy and expected impact on women's empowerment. Section 3 summarizes the data and variables used for analysis. Section 4 tests the effect of wife's account ownership on household's resource allocation and uptake of banking services. Section 5 estimates the effect of the policy on district-wise growth in account ownership and women's empowerment. The last section summarizes the findings of this chapter and outlines the scope of future research on financial inclusion and women's empowerment.

2.2 Background and Hypotheses

2.2.1 Financial inclusion in India before policy shock

According to the 2011 Population Census, only 58.7% of households reported access to banking services (brick and mortar bank, service agent or microfinance institution) in India. The Financial Inclusion Insights (FII), a nationally representative survey of Indian population aged 15 and above, found that among 45,024 surveyed, 54% didn't have a bank account[1] at the end of 2013. Reasons for not owning an account included not having money (56%) and not making any transactions (27%). Some other reasons commonly reported in the World Bank's 2011 Findex survey in India included the costs of maintaining an account, using another family member's account, distance to bank, lacking documentation and trust in institutions. Almost 56% (40%) of adult men (women) owned a bank account. The average age of these account holders was 39 years and 80% of banked men and 34% of banked women were employed. The survey respondents reported using their account to store money safely (30% men, 27%

[1]The FII defines a bank account as a Savings, Current, Fixed Deposit, Recurring or Student Account.

women) and to save with a bank (26%, 23%, respectively). The primary source of credit was a private moneylender (43% of 3,884 adults) while almost 90% of the banked respondents (8,389) used their account to save money for future payments. There was a significant gender gap in the mobile phone ownership of account holders (79% men and 44% women).

2.2.2 Free account ownership policy

Given the low levels of account ownership in 2014, the Government of India implemented a policy in mid-August requiring all licensed commercial banks to provide a free savings account to an unbanked individual on demand. In India, a savings account is used for both transactions and saving. The account can accrue an interest of 2.5-7% quarterly/annually based on the size of deposit. Policy efforts before 2014 focused on increasing the supply of bank branches and did not boost account ownership as effectively as this one. Efforts by the government to switch welfare payments from cash to direct bank transfers in 2013 likely had a limited impact as they were implemented without adequate infrastructure or , in the case of the cooking gas subsidy, had to be rolled back (Jain et al., 2018).

Under the 2014 policy, banks could not charge account opening or maintenance fees to the account holder and beneficiaries were required to provide only one government validated identification. An account could be opened at a brank branch or with the help of bank's field agents (called Business Correspondents) that would travel to villages. The account was bundled with additional financial services such as a debit card free of charge, an accident insurance of USD 1,638 (in nominal terms, USD 5,439 in purchasing power parity terms[2]) and an overdraft facility of up to USD 82 (in nominal terms, 272 in purchasing power parity terms) after six months of satisfactory savings/credit performance. Anyone who opened the account in the first five months of the policy was eligible for life insurance. One of the goals of the policy was to provide basic financial literacy to help new account owners keep their accounts active.

The first phase of the policy was implemented nationwide from mid-August 2014 to mid-August 2015, except in states with infrastructure and connectivity constraints and districts affected by armed insurgency[3]. Figure 2.1 (left panel) highlights the districts not covered by the policy in its first phase in gray. Union Territories are excluded from the analysis as they are small in geographical size and divided into few districts. They are under the Central government's jurisdiction which further limits their comparability with districts of other states. The government reported the opening of 125 million accounts in the first five months after policy implementation, with an average account balance of INR 836.8 per account (USD 45.5, purchasing power parity). In the first phase, the policy aimed to ensure that every household owned a bank account. This concurrently resulted in an increase in the number of accounts per household. Members of the household who previously used a family member's account were more likely to open their own account. The World Bank Global Findex survey shows a closing of the gender gap in savings accounts after policy implementation (Figure 2.2).

[2]Estimated using OECD Data on Purchasing Power Parities available here.

[3]These include states in the North East - Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland and Tripura - as well as parts of Himachal Pradesh, Jammu & Kashmir and Uttarakhand. A list of 35 districts worst affected by "Left-Wing Extremism" is available here.

This chapter analyzes effects of the first year of policy implementation for two reasons. First, it aligns with the timing of the household survey that captures self-reported outcomes of women's empowerment after policy implementation. Second, it avoids confounding results with a monetary policy that increased deposits in bank accounts, reduced cash supply and boosted e-wallet transactions (Chodorow-Reich et al., 2019). Figure 2.4 shows that monthly trends in ATM and mobile banking transactions in 2014-16 remained stable until November 2016, when this policy was implemented. The interacting effects of digital banking services and account ownership on women's empowerment are excluded from this chapter as the use of mobile banking and Automatic Teller Machines (ATMs) for personal transactions was limited at the time of the account ownership policy. Figure 2.3 shows that the annual transaction values through mobile banking and ATMs were a fraction of the value of total bank deposits.

2.2.3 Defining women's empowerment and expected impact of account ownership

Empowerment is a nuanced and complex phenomenon, largely defined by context. This chapter draws from four strands of literature to study the impact of account ownership on multiple aspects of women's empowerment.

First, the literature on women's account ownership in lower-middle income countries finds an increase in their uptake of banking services such as savings (Dupas and Robinson, 2013) and credit (Chavan, 2020). Second, women's asset ownership leads to increased household expenditure on consumption of clothes, time-saving appliances, jewelry, food, health and education (Beegle et al., 2001; Quisumbing and Maluccio, 2003; Duflo and Udry, 2004; Mishra and Abdoul G., 2016). Evidence from Indonesia highlights a positive correspondence between high nutrient foods and women's share of liquid assets such as jewelry and savings while ownership of non-liquid assets did not significantly impact expenditures (Pangaribowo et al., 2019). Amir-ud Din et al. (2023) find a positive, significant association between women's asset ownership and participation in decisions on their healthcare, large household purchases and visiting friends or relatives in a multi-country analysis across South Asia, Sub-Saharan Africa and the Middle East. Third, recent literature on women's empowerment relies on survey-based measures where women report their participation in various decision making processes (Quisumbing et al., 2023a,b; Heckert et al., 2023; Doss et al., 2022; Kosec et al., 2022; Annan et al., 2021; Field et al., 2021; Swaminathan et al., 2012; Connelly et al., 2010; Allendorf, 2007). Fourth, Raj et al. (2018) find that women owning a bank account reduces their risk of intimate partner violence (IPV) in rural Maharashtra (India) while McDougal et al. (2019) show that in countries with high male controlling behaviors, there is a positive association between women's financial inclusion and experience of IPV. The effects of asset ownership on women's experience of violence also vary based by type of asset: Land and house ownership have inconclusive correspondence with reports of intimate partner violence (Pereira et al., 2017).

In this chapter, I analyze three categories of outcome variables: household resource allocation, women's (self-reported) decision-making power and police records of cruelty against women by spouse and family members. Table 2.1 includes descriptive statistics that suggest the absence of an account women corresponds with lower decision making ability and higher experience of violence. Married women (between ages 15 and 49) without an account had lower participation in decisions of large household purchases, lower decision-making ability to visit their friends or relatives and less control over use of cash than women with an account (India Human Development Survey (IHDS) 2011-12). Larger percentage of unbanked women reported acts of emotional, physical and sexual violence by their partner/ husband (Demographic Health Survey (DHS) 2015-16).

This chapter hypothesizes that account ownership can improve women's control over how money is spent (household resource allocation), and improve her participation in decisions and experience of violence. It is difficult to disaggregate effects by the type of account ownership. An individually owned bank account may improve a woman's privacy in saving and spending but could lower trust between her and her spouse and increase the risk of violence to extract her resources. Conversely, a joint account may reduce women's privacy in handling money but could increase trust between spouses and lower controlling behavior by her husband. The administrative data on account ownership and household survey data does not distinguish women's account by individual or joint ownership. Therefore, this chapter examines the aggregated effect of *any* account on empowerment. A potential negative consequence of account ownership is women having limited access to the money and less control over how it is spent if it is deposited in the bank account. Therefore, I explore the interaction of account ownership with factors that can potentially impact women's access to their account such as - household's ex-ante trust in banking institutions, gender norms at home, and women's mobility outside their home. Greater trust, more equitable gender norms and higher mobility are likely to correspond with improved access to the bank account and, therefore, higher empowerment.

2.3 Data description

i. Household resource allocation

The Consumer Pyramids Households Survey (CPdx) is the world's largest household panel dataset. Beginning in January 2014, this nationally representative longitudinal survey continuously interviews over 174,000 households three times a year. Employing a two-stage stratification method (described in the Appendix), it collects information on household demographics, consumption expenditure, assets, borrowing and investment, financial inclusion, employment, and income. Conducted by the Centre for Monitoring Indian Economy, it monitors demographics, consumption expenditure, borrowing, and saving behavior at the household level and financial inclusion of each household member. I use the first five survey waves, which interviewed 166,744 households (47,715 rural and 119,029 urban) in 438 districts in the first wave (January to April 2014) and 158,666 households (46,604 rural and 112,062 urban) in 425 districts in the fifth wave (May-August 2015). These waves allow for examining trends in financial inclusion and resource allocation eight months before and up to a year after the policy. Employment status of individual members is not reported for these survey waves.

Table 2.2 describes the summary statistics used in the analysis by survey wave. The surveyed households surveyed have an average of atleast 4 members and more than two-thirds of the households were located in urban areas. Over 90% of the households have a male head, and before the policy shock, almost half the sample had a bank account owned by the wife of the male household head. This percentage increased to nearly 60% in the wave after policy implementation (September to December 2014) and continued to rise. Despite an almost equal number of adult men and women in a household, the number of women with a bank account, credit card, and mobile phone has remained consistently lower than that of men, indicating a gender gap in financial inclusion. One-third of the households belong to the higher socioeconomic stratification (intermediate or upper caste). The sample used for analysis is a balanced panel of households where the wife of the male household head was unbanked until the second wave.

ii. Women's decision-making power within the household

The India Human Development Survey (IHDS), 2004-05 and 2011-12, and Demographic Health Survey (DHS) 2015-16 interview women between ages 15 and 49 on a variety of topics such as household demographics and asset ownership, employment, women's health and nutrition, gender issues and family planning.Covering a total of 34 states and union territories, the IHDS interviews over 42,000 households and 200,000 individuals and the DHS interviews close to 700,000 individuals. A household is selected based on the presence of a woman in the age group specified above. While the IHDS is a longitudinal survey of two rounds, the DHS is a repeated cross-section. Both are nationally representative surveys, and their sampling stratification is explained in the Appendix. Key outcome variables analyzed from these surveys include women's reports of , alone or jointly, in decisions on large household purchases, and having cash available for autonomous use. These indicators are chosen based on the availability of consistently measured variables across the two surveys (description provided in appendix). Table 2.3 (panel A) summarizes characteristics of interviewed women, their household and community. The surveys primarily cover households living in rural areas (around 70%). Approximately one in ten households has a female head. Over 80% of the household heads follow Hinduism. Half of the interviewed women were employed in the past year (2011-12), with most working in the agricultural sector. Over 35% of the women interviewed before the policy shock had a bank account, and more than half reported owning an account after the policy change. While individual-level information is available, the chapter aggregates the IHDS and DHS waves in a district-level balanced panel to analyze trends before and after the 2014 policy change. Observations are restricted to households where the woman is *currently married* and to districts enumerated by both IHDS and DHS (consistent with 2001 Population Census boundaries).

iii. Police records of cruelty against women

The National Crime Records Bureau (NCRB) within the Ministry of Home Affairs publishes annual reports of district-wise crimes against women in India. This chapter uses the number of cases recorded under ”Cruelty by husband or his relatives” (Section 498A of the Indian Penal Code) from 2013 to 2016. This category includes any conduct that drives the woman to harm herself or harasses the woman or her relatives to meet any unlawful demand for property or valuable security. It does not capture direct physical or sexual violence by the husband and serves as a proxy for emotional violence that a woman may experience from her spouse or his relatives for control over material resources. This variable provides a lower-bound estimate of such emotional violence against women, as it only includes reported cases.

iv. Administrative and population data

The chapter examines annual changes in district-wise bank accounts and bank branches between 2006 and 2017 using the time series data published in the "Database on the Indian Economy" by the Reserve Bank of India (RBI). This database includes branch and account information of all banks that meet RBI's requirements such as the cash reserve ratio and paid-up capital. The district-level data on accounts includes all savings and business accounts held within the district in a year. These accounts are not distinguished by individual or joint ownership. Bank branches can be disaggregated by the following types of ownership: public sector, foreign, regional rural, private sector and small finance. The variables are reported by financial year: April 1 of the preceding calendar year until March 31 of the current calendar year. The average number of bank branches in a district increased from over 725 in the years 2006-14 to 1100 in 2015-17 (Table 2.3). The total number of bank accounts more than doubled.

District-wise demographic and infrastructure variables such as rural/urban population, number of schools, access to paved road and electricity are included as time-varying covariates from the Population Censuses 2001 and 2011.

2.4 Women's account ownership and household resource allocation

2.4.1 Outcome and explanatory variables

Trends in household resource allocation are measured using two sets of outcome variables. First, binary variables of households' uptake of credit, savings and investment. Second, continuous variables of monthly household expenditures on goods associated with women, men and children. The binary variables capture whether the household has any outstanding debt, savings and investment in formal/ informal sources at the time of interview. Women-associated consumption include clothing and footwear, accessories and jewelry, time saving appliances, utensils, cosmetics and toiletries, beauty products and services, food and education. Consumption associated with children include school fees, private coaching, stationery; and for men, shaving articles, intoxicant and fuel other than for cooking. The monthly consumption variables are generated through recall of the past four months at the time of visit. Table A.1 describes each of the indicators of uptake of banking services and consumption in detail.

The key explanatory variable is whether the wife of the household head owns a bank account at the time of interview. Demographic characteristics of a household such as caste, religion, sex composition, education and asset ownership are included as covariates in the analysis. Time-varying covariates include the number of women/men in household owning a bank account, debit card, credit card, trading account, insurance as well as changes in account ownership of men and other women in the household.

2.4.2 Inverse Probability of Treatment Weighting

An inverse probability of treatment weighting (IPTW) helps estimate the causal effect of woman's account ownership on household consumption and uptake of formal financial services. The analysis exploits the exogenous shift in demand for banking in response to the policy and restricts the analysis to households where the woman did not own a bank account in August 2014. In order to capture effects for the woman with the highest potential to influence household spending, the sample is restricted to households where she is the oldest woman. The following households are excluded from the analysis - in the top 5% of monthly expenditure distribution at least once during the analysis period, relocated to another district, have no adult member, the head of the household changed in between survey waves.

The households where the wife was unbanked until policy implementation are split into two groups. The *treated* group (n=5,999) includes households where she opened a bank account in the survey wave immediately after policy implementation (September to December 2014). The *comparison* group (n=14,443) includes all households where she remained unbanked between August 2014 and August 2015, covering the first phase of the policy. Equation 2.1 estimates the likelihood of the woman opening a bank account in response to the policy ($Pr(Banked = 1|\boldsymbol{X})$). The estimation uses the following observed characteristics of the household in the survey wave before policy implementation: religion and caste of household head; sex ratio of adults within household; urban/ rural location; age and years of completed education of head of household and wife; number of women and men in the household who own a bank account, trading account, credit card and mobile phone. Changes in account ownership of men and other women in the household are also included.

$$Pr(Banked = 1|\boldsymbol{X_{hdsw}}) = \frac{1}{1 + e^{-}(\beta_0 + \beta_1 X_1 + ... + \beta_k X_k)} \tag{2.1}$$

Figure 2.5 plots the common support of banked and comparison group for the propensity score constructed using a logit model. Given the overall balance between the two groups, observations are not trimmed from the data. This allows estimation of the average treatment effect for the treated as well as average treatment effect. The propensity score is also balanced across the treatment and comparison arms for each covariate in $\boldsymbol{X_{hdsw}}$ (Table 2.4). The score is used to generate inverse probability weights where each treated household is assigned a weight equal to the inverse of the propensity score and each comparison group household is assigned a weight equal to the inverse of one minus the propensity score. This allows approximating household in the comparison arm as a counterfactual to households in the treatment arm. Table 2.4 reports the mean standardized differences between the covariates across treatment and comparison groups for the original, unweighted sample and the one re-weighted using inverse probability weights (IPW). The difference for each variable is close to 0.

Following this re-weighting, I estimate the effect of wife's bank account ownership on household's uptake of credit, savings and investment using the DiD specified in equation 2.2 for household h in district d and state s in survey wave w. The IPW DiD compares trends of households where wife of the household head opened a bank account after policy implementation with households who were similar to the wife-opening-account households in all observable characteristics except for post-policy account ownership. The model includes a binary dummy variable for banked and unbanked households before policy change ($SpouseBanked_{hds}$) and a time variable ($Post_w$) to measure effect between survey waves before and after policy shock. It includes district fixed effects and time-varying household covariates X_{hdw}. Standard errors are clustered at the district level. Coefficient δ estimates the causal effect of the wife opening a bank account on household's consumption, borrowing and saving decisions.

$$Y_{hdw} = \alpha + \beta SpouseBanked_{hd} + \gamma Post_w + \delta(SpouseBanked_{hd} \times Post_w) + \theta_d + \rho_{\mathbf{4}} \mathbf{X_{hdw}} + \epsilon_{hdw} \tag{2.2}$$

Table 2.5 tests for pre-treatment trends in household's borrowing and savings and finds no significant differences between households in the treatment and comparison groups. Tables 2.6, 2.8, 2.7 and 2.9 report tests for pre-trends in women, children and men associated consumption and total household consumption expenditure, respectively. I report the sharpened two-stage q values to control for the risk of false discovery rate (Type 1 errors) while testing multiple hypotheses (Benjamini et al., 2006). The following outcomes satisfy test for parallel trends - cosmetics and toiletries, time saving appliances and services, food, stationery, schooling and private coaching fees, intoxicants, shaving articles and fuel. The pre-treatment share of expenditures of women, children and men associated goods of household's total monthly expenditure also remains stable between treatment and comparison groups (Table 2.9). Two outcomes that do not satisfy the test for parallel trends are - expenditure on clothing, footwear and accessories, and beauty goods and services. Overall, households in the treatment and comparison groups do not vary in their preferences for consumption, borrowing and investment before policy change. Tables 2.10, 2.11, 2.12, 2.13, 2.14 and 2.15 report households' uptake of financial services in response to female spouse's account ownership. Tables 2.16- 2.26 estimate differential trends in consumption between treatment and comparison group households.

2.4.3 Results

Effects of wife's account ownership on household resource allocation

Households' uptake of credit from formal sources increased and they were more likely to save in banks, registered loan companies and through their employer in response to women's account ownership. This trend persists upto a year after the wife's account ownership (Table 2.10). Column 1 reports outcomes for the first survey wave after policy implementation, and columns 2 and 3 report aggregate effects for upto 2 and 3 survey waves after policy. Since the variable captures household decisions and not individual demand, the result is a lower bound estimate of women's preferences to save in formal institutions. There was no corresponding decline in treatment group's borrowing from informal sources relative to the comparison group during this time (Table 2.11). Although households did not switch away from borrowing from moneylenders, shops and relatives; the uptake of credit from banks and other formal, registered institutions increased. Households in the treatment group significantly increased their saving in banks, government schemes and bonds (Table 2.12). There were no significant changes in households' uptake of savings in microfinance institutions. I explore two kinds of investment by the household: one which involves larger participation by women in decision making such as jewelry and various gold assets, and those typically decided by men, such as investments in mutual funds, private equity, and real estate. Household's preferences for either type of investment did not change significantly in response to women's account ownership (Tables 2.15 and 2.14). The short-term effects on investment may be insignificant because households likely make these decisions infrequently.

Households where the female spouse opened an account in response to policy spent less on total monthly consumption after policy implementation (Table 2.16). There was a decline in consumption of cosmetics and toiletries (Table 2.17) and time saving appliances used in the kitchen and services such as domestic help (Table 2.18). Tables 2.20 and 2.25 report that monthly expenditure on education declined - this is largely driven by school/college fees. Household expenditure on private coaching remains unchanged (Table 2.26). Consumption of goods associated with men's demand such as shaving articles, intoxicants (tobacco products and liquor) and fuel remained unaffected by wife's account ownership. Tables 2.27 and 2.28 report other categories of household expenditure that explain the systematic decline in total expenditure of banked households. These include all household appliances (including mobile phones), communication (phone, TV and internet usage) and transport services. Recurring payments such as rent and utilities remain unchanged. Health expenditures increased in response to account ownership in wave of account opening but the effect dissipated over time. The results suggest that households, on average, spent more conservatively in response to women's bank account ownership. This indicates households reduced consumption to save and invest.

Account ownership and household resource allocation in an unconstrained setting

Analyzing household monthly consumption provides limited insights on women's preferences and contribution to household purchase decisions compared to individual consumption expenditures. Since the survey does not capture individual demand, I analyze households' trends in an "unconstrained" setting where the account-opening woman is the primary decision maker of the household. While it is reasonable to expect that empowerment outcomes of female heads of households are systematically different from the wives of male household heads, this analysis provides some expectations for how households may allocate resources when women participate in decision making. I restrict the analysis to households with a female head who was unbanked until the second wave and follow the steps of an IPW DiD in equations 2.1 and 2.2. Figure 2.6 shows a significant increase in households' uptake of formal and informal borrowing in the survey wave that the female head opens an account, compared to the comparison group. Savings in formal institutions remain similar across the treatment and comparison groups until the fifth survey wave where households with a banked female head are more likely to save in these institutions. Savings in gold and other investments are not statistically different in response to account ownership. Two consumption categories do not satisfy the test for parallel trends: clothing, footwear and accessories and time saving appliances. There are no significant differences in consumption of the other categories between the two groups (Figure 2.7).

2.5 District-wise account ownership and women's empowerment

The policy led to different expansion rates of account ownership across districts based on pre-policy banking infrastructure. The district-wise variable of account ownership includes all accounts held by men and women in a district. I examine whether faster expansion in account ownership within a district led to significantly higher levels of women's empowerment using a district-level balanced panel from April 2005 to March 2017. This panel merges variables from the IHDS, DHS, RBI's data on accounts and banking infrastructure, and the Population Censuses 2001 and 2011. The panel is restricted to the 329 districts (defined by 2001 Population Census boundaries) where the policy was implemented in phase 1.

Variables and estimation samples

The indicators of women's empowerment in this district-wise analysis include: self-reported participation in decision-making and police reports of women's harassment by spouse and his family members. These variables are observed consistently at the district level before and after policy implementation. Self-reported variables ask whether the interviewed woman has joint or individual participation in decisions around large household purchases, and if she has cash available for autonomous use. These are all the indicators measured consistently in both the IHDS and DHS. Table 2.3 summarizes the explanatory variables using household weights provided in the survey. Statistical difference of the mean estimates is not reported as the surveys were conducted in different times. The indicator of crimes against married women is a count of the total cases reported in a district in a year.

2.5.1 Empirical strategy

I use a DiD to examine changes in women's empowerment in response to the policy-induced expansion of account ownership. I first verify a difference in the expansion rates of account ownership driven by pre-policy levels of banking infrastructure (Eq. 2.3). Districts with limited infrastructure experienced a faster increase in account ownership after policy than others. I combine these two sources of variation to test for differences in women's empowerment outcomes in response to district-wise expansion in account ownership. Given that outcome variables are observed consistently before and after policy using cross-sectional household surveys, this analysis is at the district level. Testing the effect of exogenously driven, district level, changes in account ownership addresses the selection concern in section 2.4 that studies empowerment outcomes of women that open an account, and strengthens the chapter's analysis.

Defining treatment and comparison group

Before policy implementation, a bank account was usually opened on site, that is, at the bank's branch. Therefore, districts with higher pre-policy banking infrastructure also had higher levels of account ownership. Figure 2.8 shows the upward sloping relationship between bank branch and account density in March 2014. With the policy's push for every household to own at least one bank account in its first phase (2014-15), and increased coverage of households through Business Correspondents (bank representatives providing basic banking services[4]), there was a faster growth in account ownership in the districts with lower infrastructure. I classify districts as "high impact" if their bank branch density before policy implementation was at the state median level or below, and districts above the state median into the "low impact" group. A district's branch density is measured as the total number of bank branches in that district per 100,000 population. The indicator captures the pre-policy access to banking services for an individual. Sorting districts based on the state-wise median instead of national median accommodates the heterogeneity in economic growth and banking infrastructure levels across states. It prevents grouping highly banked districts from states with few bank branches with low banked districts from states with many bank branches. Figure 2.1 (left panel) maps the branch density for all districts included in the analysis and their corresponding classification into high and low impact (right panel). The districts not covered in the first phase of the policy or not covered consistently by the household surveys implemented before and after policy are excluded from the analysis.

Figure 2.9 plots the differences in growth of account ownership between low and high impact districts over time relative to 2006[5] These coefficients are adjusted for district-wise observable characteristics that may be correlated with both growth in account ownership and treatment assignment. These variables are collected from the cross-sectional household survey implemented before policy and the Population Census 2001 and 2011. They are selected using post double selection methodology by Belloni et al. (2013) which runs two Least Ab-

[4]These include opening of bank accounts, cash deposit, cash withdrawal, transfer of funds, balance enquiries and mini statement facility.

[5]In this graphical representation, a year is consistent with Government of India's financial year starting April 1 of preceding year and ending March 31 of that calendar year.

solute Shrinkage and Selection Operator (LASSO) regressions. The first regression tests for effects of all potential controls on the growth in account ownership and the second tests the effect of the same controls on the binary variable of banking infrastructure. Table 2.29 reports a balance test of the union of controls selected in both LASSO estimations and they account for the level differences in account ownership between high and low impact districts before the policy change. Descriptive statistics of these covariates for the two groups show that households in the high impact districts have lower income and asset ownership. The women surveyed in the high impact districts are typically younger and have lower education attainment. There are less number of schools and colleges in these districts. Respondent woman and her spouse are more likely to be employed in the agricultural sector. The districts have similar access to electricity which affects industrial and commercial activity.
I formally test if the two groups capture variation in the impact of the policy using equation 2.3. The dependent variable is the total number of bank accounts in a district in year y relative to the first year of analysis, 2006. In this estimation, y is defined starting April 1 in $y-1$ and ending on March 31 in y[6]. The binary variable $HighImpact_d$ assigns 1 to high impact districts and 0 otherwise. $Post$ time dummy marks years after 2014 as 1, and 0 otherwise.

The coefficient ρ_3 estimates the double difference between high and low impact districts and over time. The matrix $\boldsymbol{X}_{ds}$ includes characteristics of a district that predict its classification as high/low impact and are also correlated with the dependent variable. The model controls for potential state-wise differences in policy implementation using state fixed effects. The standard errors are clustered at the state level to allow for within state correlation in trends of account

[6]The administrative data on bank branches and accounts is available by financial year (April 1 – March31).

ownership.

$$
\begin{aligned}
(Accounts_y/Accounts_{2006})_{ds} =& \rho_0 + \rho_1 HighImpact_{ds} + \rho_2 \left(HighImpact \times Post\right)_{dsy} \\
& + \boldsymbol{\rho_3 X}_{dsy} + \phi_s + \theta Post_y + \epsilon_{dsy} \qquad (2.3)
\end{aligned}
$$

Table 2.30 reports the differential trends in growth of bank accounts and natural log of annual account ownership in high impact districts relative to low impact. I report trends for the years 2011 to 2017, which coincides with the pre and post analysis of women's outcomes, and also from 2006 to 2017 to correspond with the time frame for trends in women's outcomes. Since the policy's effect on aggregate account ownership is consistent across short and longer time windows and estimates of account ownership, I can use the growth rate in account ownership relative to 2006 as the dependent variable. Table 2.31 breaks down the year-by-year growth in account ownership and is an analog to Figure 2.9. Tables 2.32 and A.4 use other candidate measures of high and low impact districts to verify the robustness of predictions in account ownership. The scale and functionality of commercial banks in India varies by type of ownership: state, private sector, foreign owned, regional etc. As some banks may have better capacity to implement this policy, I test trends in account ownership for banks by the two predominant categories of ownership: Central Government and private sector. Table 2.32 reports changes in account ownership between districts classified as high and low impact by type of bank ownership.

Table A.4 tests trends in account ownership by continuous measures of treatment intensity instead of discrete classification by median. Higher bank branch density corresponds with lower relative increases in bank accounts after policy implementation. The trends in account ownership are consistent if instead of testing spatial variation based on banking infrastructure in 2014, I use the 2013 bank branch density as a measure of treatment intensity (results are available on request). Any efforts by policymakers to improve bank account ownership before 2014 did not impact account ownership in a different direction from the results in 2014. Since bank branch density and account density were correlated before policy shock, the median account density was also a candidate measure for treatment intensity of the policy. As expected, a test for trends in account ownership before and after policy implementation by pre-policy account density estimate shows a significantly larger growth in accounts in districts at or below median account density than districts above. These results are available on request.

Effect of account expansion on women's empowerment

Using the policy-induced variation in acceleration of bank account ownership, I estimate the average effect of increased total accounts in a district on women's self-reported participation in decision making and police reports of women's harassment by spouse or his family members. The model described below is similar to the specification in equation 2.3.

The construction of these indicators are provided in the Appendix. The dummy variables identifying high and low impact districts and before/ after policy are the same as in equation 2.3. The specification includes the district-specific covariates ($\boldsymbol{X}_{ds}$) from equation 2.3 as well as individual-specific time varying characteristics that are correlated with the dependent variables ($\boldsymbol{Z}_{idsy}$). Both sets of covariates are selected using post double selection method. The model controls for district-specific trends using fixed effects and standard errors are clustered at the state level to allow for within-state correlation in outcomes.

Equation 2.4 uses a linear regression model to estimate differences in women's aggregate decision making between high and low impact districts before and after policy change. Tables 2.33 and 2.34 report tests for parallel trends in women's empowerment outcomes before policy implementation. The results in empowerment outcomes in response to the exogenous account expansion are reported in Tables 2.35 and 2.36.

$$\begin{aligned} Y_{idsy} = \beta_0 + \beta_1 HighImpact_{ds} + \beta_2 \left(HighImpact \times Post\right)_{dsy} + \boldsymbol{\beta_3 X}_{ds} \\ + \boldsymbol{\beta_4 Z}_{idsy} + \phi_s + \theta_y + \epsilon_{idsy} \end{aligned} \tag{2.4}$$

2.5.2 Results

In the years prior to policy change, women's decision making outcomes across high and low impact districts were parallel. The coefficient of the interaction term is close to 0 and statistically insignificant in Table 2.33.

Table 2.35 estimates effects of the policy on women's average decision making through growth in account ownership at the district level. The results compare women's outcomes observed across survey rounds 2011-12 and 2015-16, capturing aggregate effects of the first phase of the policy. Estimates of the differences between districts based on their exposure to the policy and across time are reported in the first row. The coefficients are close to 0 and statistically insignificant suggesting that policy-induced expansion of account ownership did not yield gains in women's self-reported outcomes. There was a decline in harassment reports in high impact districts relative to the rest (Table 2.36).

Robustness Checks

Participation in household purchase decisions and autonomous use of money is correlated with women having access to an independent source of income. Table 2.38 reports heterogeneous treatment effects by respondent's employment in the agricultural and non-agricultural sector and finds no differential trends in outcomes for women in either sector in a district relative to unemployed women.

There are no systematic differences in changes in women's outcomes between banked and unbanked samples across high and low impact districts (Table 2.39). Lastly, Figure 2.10 plots the differential trends on bank branch density before and after policy. Despite an increase in account ownership, the gap in infrastructure widened after policy implementation. This suggests that opening bank accounts in the absence of corresponding infrastructure is unlikely to affect women's empowerment at home.

Implicit assumptions of the district-wise analysis

This analysis makes three assumptions: First, that women's account ownership increased in response to the policy which is evident from the World Bank Findex survey (Fig. 2.2). Second, that the number of accounts opened by women was significantly larger in the high impact districts than others. Estimating the proportion of women banked among the survey respondents in IHDS and DHS, shows no significant differences between the high and low impact districts in response to the policy (Table 2.37). Third, that regardless of the type of account ownership (individual or joint), banked women had access to their account. I examine district-wise variation in women's access to their account using three types of norms observed in the household survey data: trust in banking institutions, gender parity at home and women's mobility outside home. A household's trust in banking can influence the decision to store money as cash or in a bank account. Variables such as whether household has confidence in banks to keep money and borrowed from a bank in the last five years help estimate households' trust in the institution. Women's access to money is likely to be influenced by intrahousehold inequality. This is estimated as a score using variables on household's division of labor, spousal relations and norms around spousal violence (see Table A.3 for the definition of each variable). Access to money deposited in the bank is a function of her mobility outside the home. This is defined using variables on her ability to travel outside home alone and the need to take permission from other members of the household. Tables 2.40 and 2.41 explore the interaction of these norms with differential expansion of account ownership in high/ low impact districts.

Trust in bank institutions in districts with a high impact of the policy positively correspond with women's decision making on large household purchases. There are no differential trends for autonomous use of money. In the same high impact districts, low trust in banking institutions corresponds with lower participation of women in purchase decisions prior to policy change. This is consistent with the work by Pelras and Renk (2022) where they find lower uptake of vaccination services in response to lack of trust in institutions. Other factors such as gender parity and women's mobility do not show any differential trends in women's empowerment outcomes by type of district.

2.6 Summary of results and conclusion

The chapter provides evidence of the short-term effects of bank account ownership on women's empowerment power using three, distinct sets of outcomes: household's resource allocation, women's self reports of decision making and police reports of harassment by spouse/ his family members. It exploits a natural experiment from an exogenous policy shock that removed account opening and maintenance fees, increasing first time account holders. Before this policy, only three (two) out of five adult men (women) reported owning a bank account in the Financial Inclusion Insights survey of 2013. As intended, the policy significantly increased account ownership of previously unbanked groups and regions. More women opened a bank account and districts with lower bank branch penetration saw a faster growth of accounts.

When the wife of the male household head opened an account after policy implementation, households increased their uptake of formal savings and credit and reduce their monthly consumption expenditure. The uptake of formal savings and credit is consistent with bank account ownership of women in an unconstrained environment - where they are the head of the household.

The policy induced a district-wise variation in expansion of account ownership. Districts below state median banking infrastructure had a "higher policy impact", i.e., significantly faster expansion in account ownership after policy implementation than the rest. However, women's average participation in household purchase decisions and autonomous use of money did not improve in the high impact districts relative to others. There was a decline in crimes in districts with faster expansion of account ownership. The household and district level analyses use different quasi-experimental identification strategies owing to the structure of the data. The differences in sampling methods of the data used to estimate empowerment outcomes mean they capture effects for overlapping but different sub-groups of married, adult women in India. While one set of results cannot be extrapolated to the context of another set, together, they help piece together a clearer picture (than has been available before in observational studies) of the different expected outcomes of account ownership on women's empowerment at home.

The policy shock analyzed in this chapter was the largest bank account expansion policy around the world. Although it provided free of cost bank accounts to unbanked invdividuals, Agarwal et al. (2017) find that 81% of a sample of 15 million accounts opened during the first 10 months of the policy did not receive a deposit in the first six months and the average monthly balance was approximately USD 7 (nominal terms, USD 23 in purchasing power parity terms). This may help in interpreting the null result of district-wise expansion of account ownership on women's empowerment. However, two years after policy implementation, 77% of the accounts had a positive balance. The results of this chapter are relevant for policy makers to understand the distributional effects of policies that target the general population. The analysis coincides with the global expansion of account ownership in middle and low income countries, where the percentage of adults with a bank account increased from 33 to 65 between 2011 and 2021 and the gender gap in account ownership reduced from 10 to 6 percentage points (World Bank, 2022). The chapter also lays the groundwork for considering the role of norms and how they interact with account ownership to affect empowerment outcomes. Preliminary evidence in the form of heterogeneity tests is reported as motivation to test these links experimentally.

2.7 Figures and Tables

2.7.1 Figures

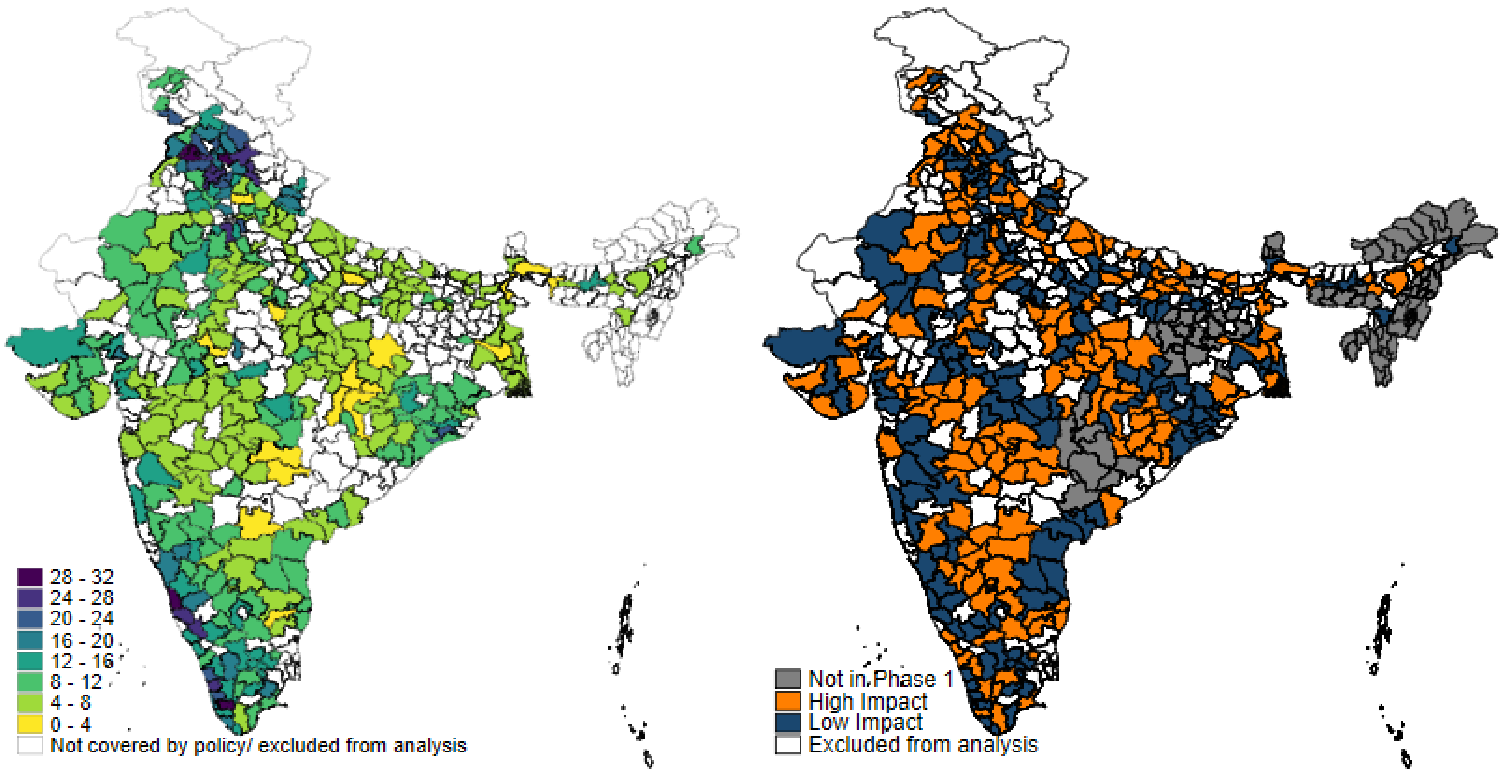

Figure 2.1: District-wise branch density before policy (left) and Classification of districts by policy exposure (right)

Notes: The left map depicts the total number of bank branches per 100,000 population in March 2014. The non-shaded (white) districts were not included in the first year of policy implementation or excluded from the analysis because of unbalanced observations before and after policy change. The right map characterizes districts by their expected exposure to the policy. 'High impact districts" are districts with less than/equal to state median bank branch density in March 2014 and "Low impact" are districts above state median branch density. Districts excluded from policy implementation in the first year and excluded from the analysis to create a balanced panel are highlighted separately. The map uses district boundaries of 2001 for consistency with the India Human Development Survey used to estimate women's empowerment.
Sources: Basic Statistical Returns, Reserve Bank of India and Population Census 2011. Author's calculations.

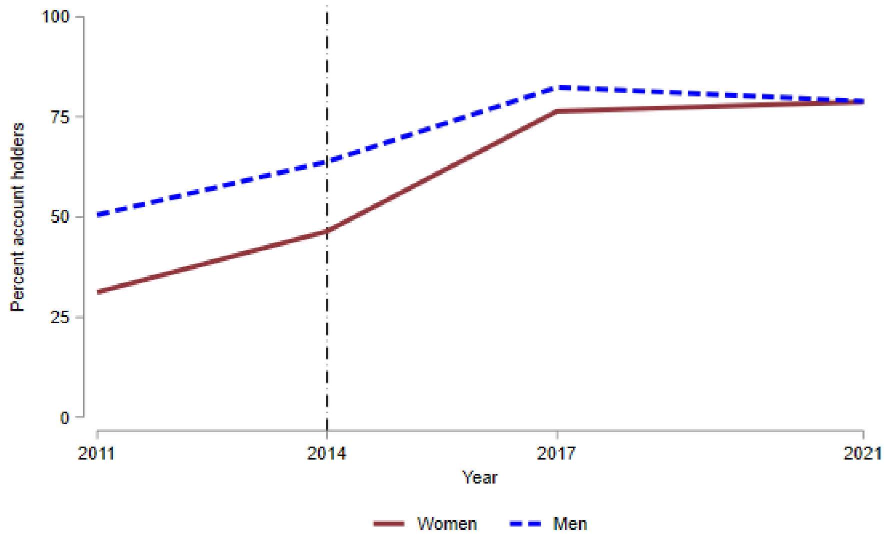

Figure 2.2: Gender gap in bank account ownership over time

Notes: The gender gap in account ownership started decreasing since 2014, the year of policy implementation.
Source: World Bank's Global Findex. Author's calculations.

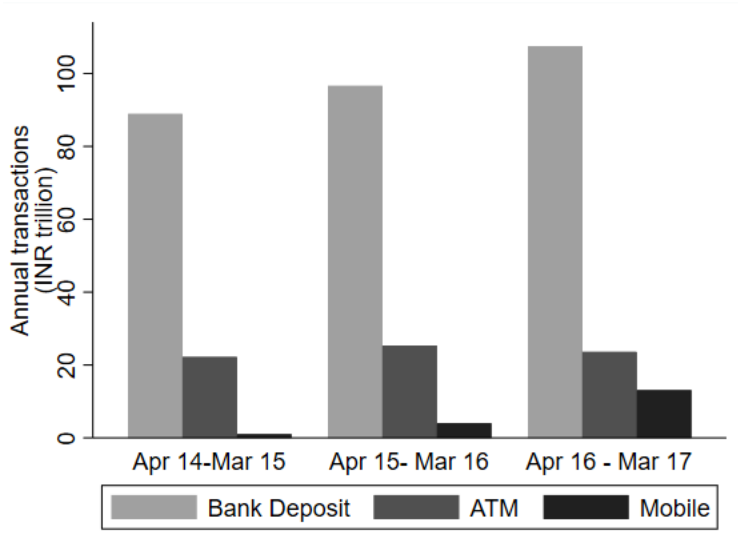

Figure 2.3: Annual volume of deposits versus digital transactions (2014-17)

Notes: Annual volume of deposits versus mobile and ATM transactions shows that a small fraction of the money held in savings accounts was transacted digitally between 2014 and 2017. The volume (in INR Trillion) is given in nominal terms.
Source: Basic Statistical Returns, Reserve Bank of India. Author's calculations.

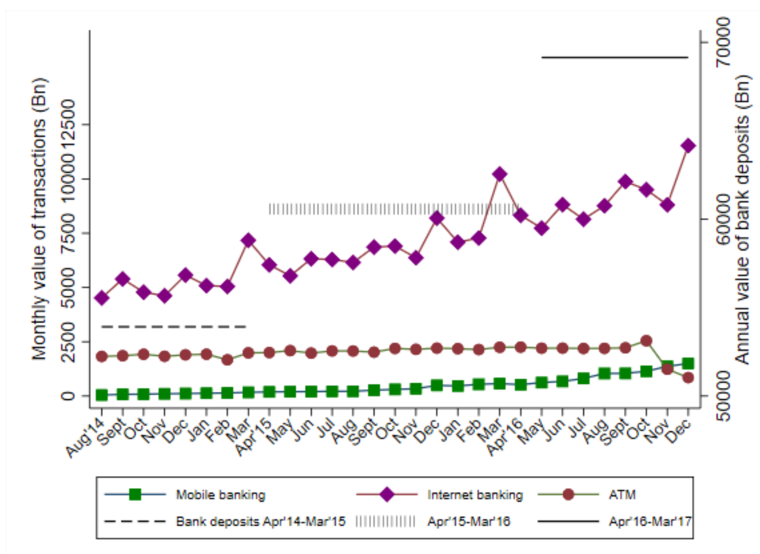

Figure 2.4: Monthly value of digital transactions in India (2014-16)

Notes: This figure shows the monthly volume of digital transactions (in INR Billion) in nominal terms by individuals using mobile phones, internet and ATMs. The horizontal lines in black (dash and solid) are the size of total bank deposits during that year. The figure identifies the effect of a nationwide change in monetary policy implemented in November 2016 (outside the analysis period).
Source: Basic Statistical Returns, Reserve Bank of India. Author's calculations.

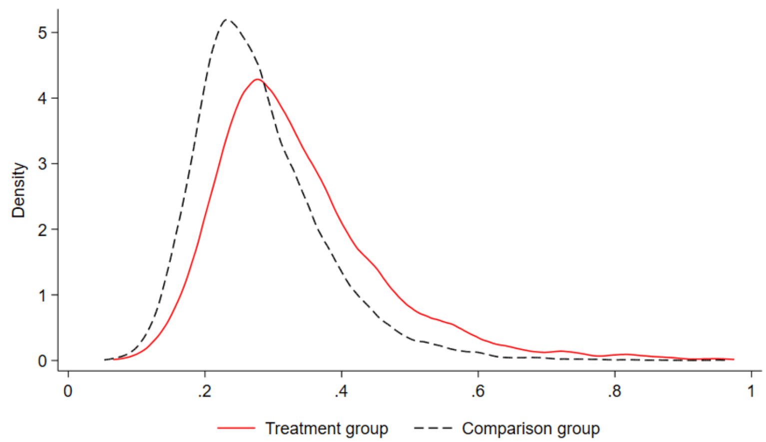

Figure 2.5: Distribution of Propensity Score across Treatment and Comparison Groups

Notes: The figure plots the predicted likelihood of wife of male household head opening a bank account in the survey wave after policy implementation (September to December 2014) for treatment and comparison groups. The treatment group consists of all households where the wife was unbanked before policy and opened a bank account in the survey wave after policy implementation. The comparison group includes households where the wife did not own a bank account before and through the first phase of the policy (until August 2015). Section 2.4 describes the covariates used to measure the propensity score and the logit regression (equation 2.1).

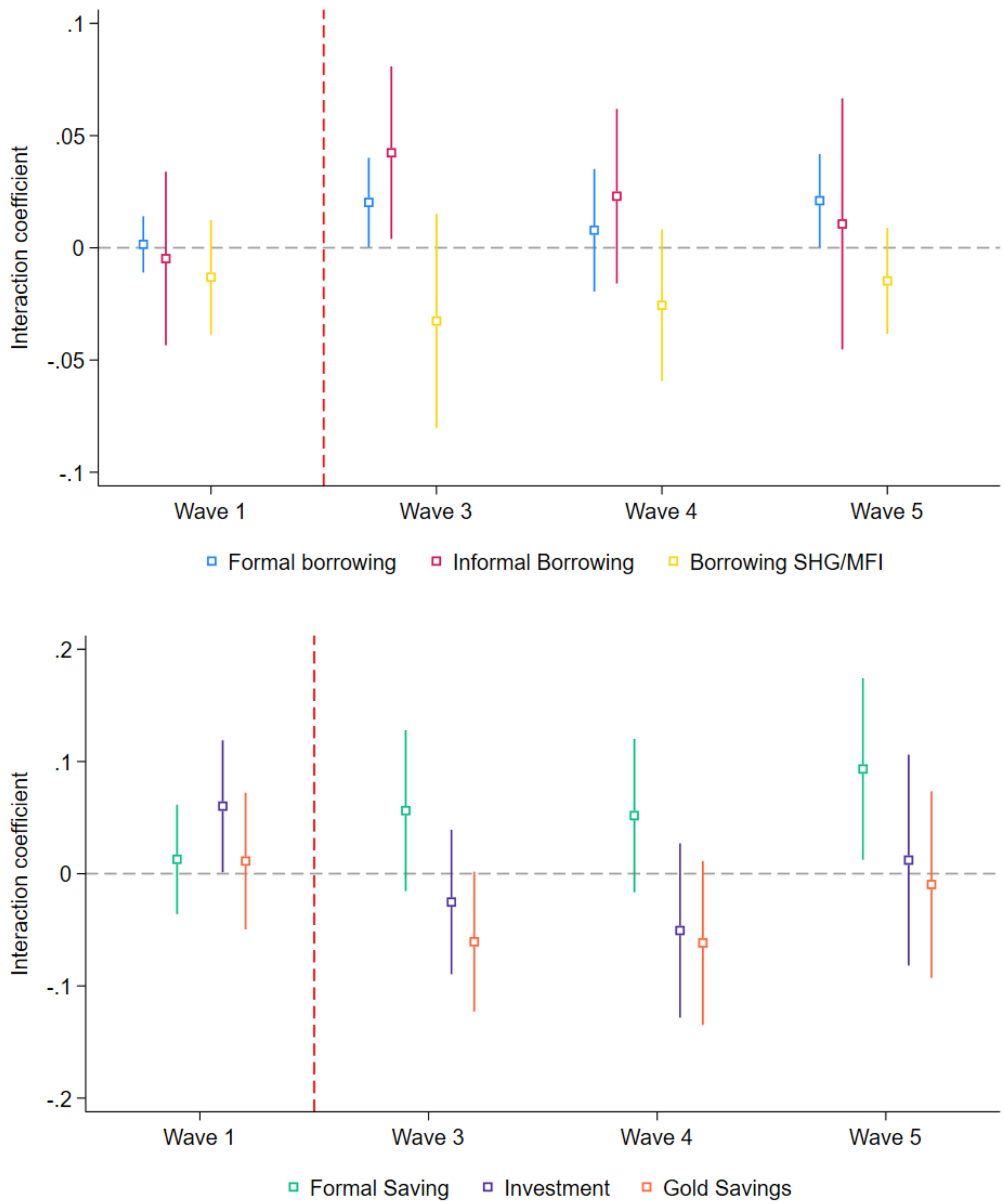

Figure 2.6: Effect of female head of household's account ownership on borrowing, savings and investment

Notes: The figure shows the differences in formal and informal borrowing and saving between households where the female head opened a bank account relative to households where she didn't. Estimates are reported by survey wave. The analysis is restricted to households where the female head of the household did not have a bank account before policy shock. Each point measures the difference in outcome variable between households in treatment and comparison group conditional on household controls and district fixed effects. The observations are re-weighted using weights generated in Eq. 2.1 for households in the comparison group to approximate households in the treatment group as a counterfactual. The vertical bars show 95% confidence intervals and the dashed red line indicates the timing of the policy. Standard errors are clustered at the district level.

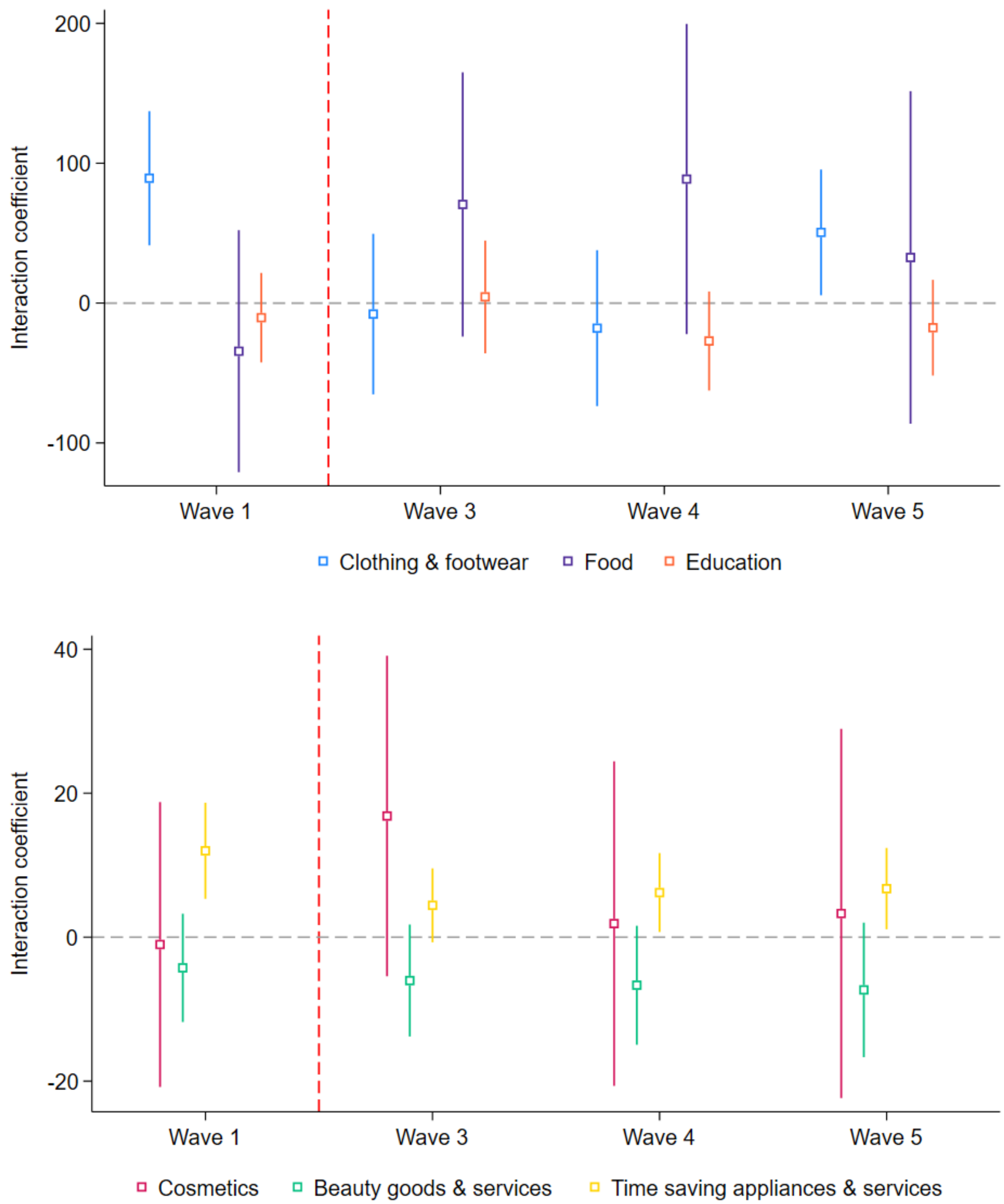

Figure 2.7: Effect of female head of household's account ownership on women-associated consumption expenditure

Notes: The figure shows the differences between households where the female head opened a bank account relative to households where she didn't on monthly consumption of goods associated with women. Estimates are reported by survey wave. The analysis is restricted to households where the female head of the household did not have a bank account before policy shock. Each point measures the difference in outcome variable between households in treatment and comparison group conditional on household controls and district fixed effects. The observations are re-weighted using weights generated in Eq. 2.1 for households in the comparison group to approximate households in the treatment group as a counterfactual. The vertical bars show 95% confidence intervals and the dashed red line indicates the timing of the policy. Standard errors are clustered at the district level.

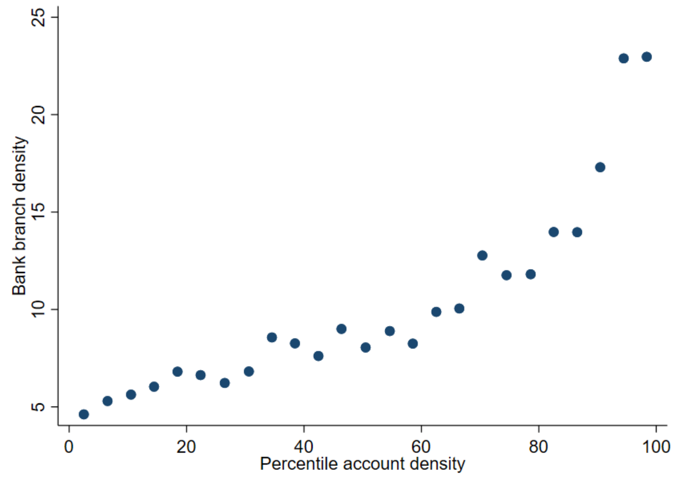

Figure 2.8: Relationship between bank branch and account density before policy

Notes: The figure plots the relationship between bank branch and account density before policy implementation. Districts are binned into percentile scores of account density. The average bank branch density in each bin plotted against the average percentile score in each bin shows that districts with higher account density had higher bank branch density. The density variables are measured per 100,000 population during April 2013- March 2014.
Source: Basic Statistical Returns, Reserve Bank of India and Population Census of India 2011. Author's calculations.

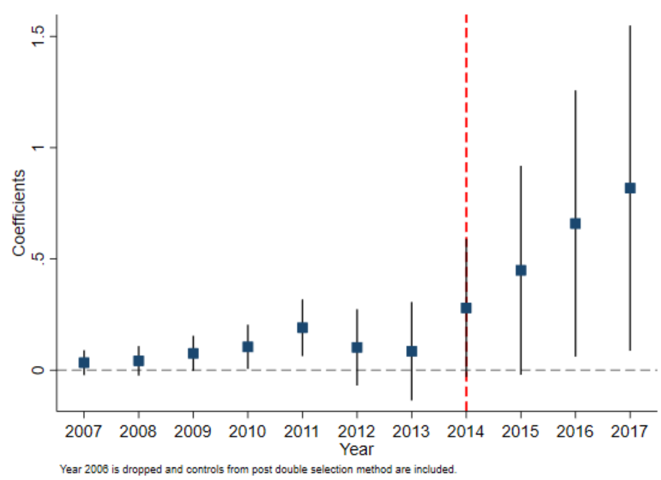

Figure 2.9: Year-wise differences in growth in account ownership

Notes: The figure plots treatment effect of the account expansion policy on growth in bank accounts by year. In this graphical representation, a year is consistent with Government of India's financial year starting April 1 of preceding year and ending March 31 of that calendar year. Each square is the coefficient of the interaction of the dummy variable identifying districts as high or low impact with a year dummy from the specification in equation 2.3. The vertical black lines are 95% confidence intervals and the red dashed line indicates the year of policy implementation. See Table 2.31 for standard errors of coefficients.

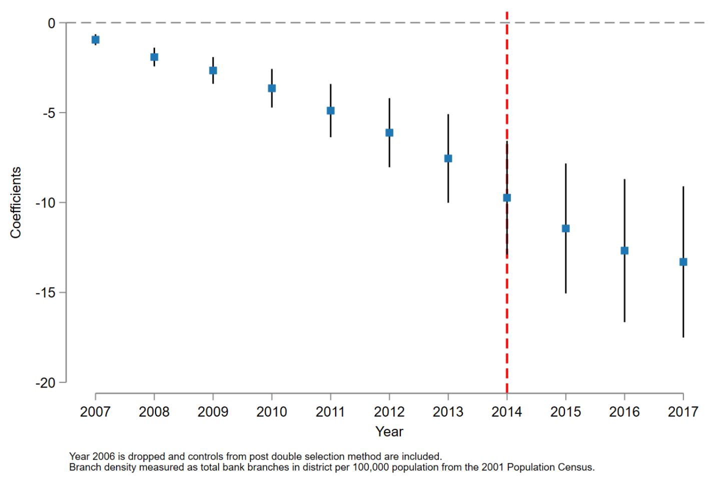

Figure 2.10: Year wise differences in bank branch density between high and low impact districts

Notes: The figure plots treatment effect of the account ownership policy on bank branch density by year. Each square is the coefficient of the interaction of the dummy variable identifying districts as high or low impact with a year dummy. The estimation includes the same covariates as equation 2.3. The vertical black lines are 95% confidence intervals and the red dash line indicates the year of policy implementation.

2.7.2 Tables

Table 2.1: Summary statistics: Women's empowerment by account ownership

Variable	No account Mean (SE)	No account N	Has account Mean (SE)	Has account N	Pairwise t-test Mean difference
Women's decision making by account ownership (IHDS)					
Alone/joint decision on large hh purchase	0.480	20316	0.547	12128	-0.067***
	(0.011)		(0.012)		
Individually decided large HH purchase	0.036	20316	0.068	12128	-0.032***
	(0.003)		(0.005)		
Individual decision to visit friends/ relatives	0.116	20228	0.147	12129	-0.031**
	(0.012)		(0.018)		
Partner decides if she can visit friends/ relatives	0.012	20230	0.010	12129	0.002
	(0.003)		(0.002)		
Cash she alone decides how to use	0.874	20475	0.956	12189	-0.082***
	(0.006)		(0.005)		
Women's experience of intimate partner violence by account ownership (DHS)					
Any emotional violence	0.145	29920	0.132	34122	0.013***
	(0.004)		(0.005)		
Any less severe violence	0.312	29920	0.281	34122	0.031***
	(0.007)		(0.008)		
Any severe violence	0.098	29920	0.088	34122	0.009***
	(0.003)		(0.004)		
Any sexual violence	0.079	29920	0.062	34122	0.018**
	(0.004)		(0.003)		

Notes: First two columns report mean (standard error in parentheses) and number of observations for women without a bank account and the next two columns report statistics for women with a bank account. The variables on women's decision making are extracted from the India Human Development Survey (IHDS) 2011-12 and variables on women's experience of violence are from the Demographic Health Survey (DHS) 2015-16. "Any emotional violence" includes acts of humiliation, threats and insults by partner/ husband. "Less severe violence" includes pushing, arm twisting, slapping, punching and kicking. "Severe violence" includes kick/dragging, choking, and threatening/attacking with weapon. "Sexual violence" includes forced to perform sexual intercourse/ acts and threatened to perform sexual acts. The estimates use individual weights provided in respective surveys. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.2: Summary statistics of household longitudinal survey

	Wave 1 (Jan-Apr'14)		Wave 2 (May-Aug'14)		Wave 3 (Sep-Dec'14)		Wave 4 (Jan-Apr'15)		Wave 5 (May-Aug'15)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Wife of household head owns... (%)										
Bank account	47.109	49.903	48.735	49.974	59.145	49.149	66.979	47.024	74.453	43.608
Credit card	0.377	6.126	0.400	6.316	1.230	11.021	0.853	9.195	0.632	7.928
Own mobile phone	39.135	48.794	40.156	49.010	46.757	49.888	50.535	49.992	53.449	49.876
Number of women in the household with...										
Bank account	0.714	0.797	0.742	0.802	0.896	0.833	1.008	0.844	1.100	0.835
Credit card	0.006	0.079	0.006	0.083	0.020	0.156	0.013	0.126	0.010	0.111
Own mobile phone	0.634	0.757	0.648	0.753	0.744	0.780	0.795	0.788	0.817	0.781
Number of men in the household with...										
Bank account	1.388	0.821	1.420	0.806	1.474	0.811	1.496	0.823	1.502	0.827
Credit card	0.055	0.254	0.055	0.253	0.093	0.346	0.073	0.297	0.061	0.269
Own mobile phone	1.459	0.822	1.479	0.804	1.498	0.807	1.504	0.806	1.477	0.799
Household demographics										
Household size	4.319	1.597	4.285	1.573	4.269	1.579	4.208	1.573	4.064	1.559
Number Adults	3.078	1.254	3.062	1.238	3.067	1.240	3.043	1.230	2.976	1.205
Adult sex ratio	1.040	0.548	1.035	0.541	1.040	0.552	1.038	0.549	1.033	0.541
Households with female head (%)	9.607	29.469	9.836	29.780	10.063	30.084	10.453	30.595	10.803	31.042
Real monthly total expenditure	8499.57	5249.39	8448.29	4902.09	8236.61	4588.89	8068.99	4457.61	8250.74	4416.89
Urban (%)	70.304	45.692	70.484	45.611	70.387	45.655	69.517	46.034	70.141	45.764
Hindu	0.830	0.376	0.839	0.368	0.836	0.370	0.839	0.367	0.842	0.365
Muslim	0.107	0.309	0.108	0.310	0.109	0.312	0.107	0.309	0.104	0.305
Christian	0.017	0.130	0.015	0.121	0.016	0.126	0.016	0.124	0.018	0.132

	Wave 1 (Jan-Apr'14)		Wave 2 (May-Aug'14)		Wave 3 (Sep-Dec'14)		Wave 4 (Jan-Apr'15)		Wave 5 (May-Aug'15)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Jain	0.002	0.042	0.002	0.042	0.002	0.044	0.002	0.044	0.002	0.045
Buddhist	0.005	0.068	0.005	0.068	0.005	0.068	0.005	0.068	0.004	0.066
Scheduled Caste	0.178	0.383	0.178	0.382	0.179	0.384	0.183	0.387	0.181	0.385
Scheduled Tribe	0.031	0.174	0.030	0.170	0.030	0.170	0.031	0.172	0.030	0.170
Other Backward Caste	0.376	0.484	0.379	0.485	0.381	0.486	0.384	0.486	0.387	0.487
Intermediate Caste	0.098	0.297	0.096	0.294	0.095	0.294	0.093	0.290	0.093	0.290
Upper caste	0.316	0.465	0.317	0.465	0.314	0.464	0.309	0.462	0.310	0.462
Male head: Age	49.036	12.541	49.055	12.544	49.337	12.463	49.559	12.408	49.507	12.388
Male head: Education	8.236	5.477	8.253	5.470	8.203	5.466	8.154	5.456	8.207	5.369
Wife: Age	42.804	11.552	42.886	11.528	43.142	11.503	43.341	11.461	43.272	11.478
Wife: Education	6.506	5.480	6.490	5.476	6.507	5.489	6.514	5.473	6.595	5.397
Female head: Age	54.005	12.087	54.242	12.055	54.353	11.870	54.383	11.872	54.383	11.837
Female head: Education	4.374	5.062	4.256	5.037	4.264	4.994	4.244	4.998	4.294	4.989
N	144,886		140,627		136,762		134,060		135,705	

Notes: The table uses household weight provided by the survey to reports statistics for five waves ending August 2015. Each wave includes four consecutive months.

Table 2.3: Summary statistics of district panel

	Panel A: Individual and household covariates					
	Before policy				After policy	
	IHDS 2005		IHDS 2011-12		DHS 2015-16	
	Mean	SD	Mean	SD	Mean	SD
Respondent has bank a/c	0.167	0.373	0.366	0.482	0.517	0.500
Household has bank a/c	0.356	0.479	0.670	0.470	0.908	0.289
Household size	5.595	2.487	5.439	2.423	5.511	2.605
Number Adults	2.972	2.459	2.980	2.495	3.489	1.751
Adult sex ratio	1.119	0.558	1.167	0.610	1.132	0.583
Households with female head	0.081	0.273	0.126	0.332	0.100	0.300
Urban	0.328	0.470	0.310	0.462	0.269	0.444
Hindu: Head	0.825	0.380	0.829	0.377	0.812	0.391
Muslim: Head	0.119	0.324	0.125	0.330	0.134	0.340
Christian: Head	0.021	0.144	0.016	0.127	0.022	0.147
Sikh: Head	0.014	0.119	0.013	0.111	0.017	0.128
Jain: Head	0.002	0.047	0.002	0.046	0.002	0.042
Buddhist: Head	0.007	0.086	0.008	0.089	0.008	0.091
Scheduled Caste: Head	0.226	0.418	0.046	0.210	0.215	0.411
Scheduled Tribe: Head	0.074	0.262	0.211	0.408	0.099	0.298
Other Backward Caste: Head	0.049	0.216	0.432	0.495	0.455	0.498
Intermediate Caste: Head	0.237	0.425	0.081	0.272	0.232	0.422
Upper Caste: Head	0.049	0.216	0.046	0.210		
Head: Education	5.230	4.778	5.454	4.831	6.048	5.076
Head: Age	32.817	8.079	47.028	12.542	46.737	13.061
Respondent: Education	3.985	4.574	5.011	4.862	5.914	5.153
Respondent: Age	33.475	7.946	34.171	8.413	32.787	8.530
Respondent employed	0.258	0.437	0.506	0.500	0.299	0.458
Employed in Agriculture	0.444	0.497	0.366	0.482	0.165	0.166
Employed in Non-agriculture	0.086	0.281	0.188	0.391	0.134	0.149
Number districts	350		350		575	

	Panel B: District-level banking			
	Mean	SD	Mean	SD
Total branches	725.466	619.604	1097.399	895.130
Total accounts	1,520,931.473	1,564,501.266	3,142,346.893	2,580,975.683
Number districts	329		325	

Notes: The individual and household covariates are population weighted aggregates from nationally representative household surveys (IHDS and DHS). The sample districts are defined by 2001 Population Census boundaries. The district level banking aggregates are generated using administrative census data (RBI's Basic Statistical Returns). "Before Policy" includes aggregates of annual observations between April 2006 and March 2014 from the banking data. Aggregates for the banking variables in the period "After Policy" are estimated between April 2014 to March 2017.

Table 2.4: Balance of covariates in original and inverse probability weighted (IPW) sample

	Original sample			Inverse Probability Weighted Sample		
	Mean Treatment	Mean Comparison	Standardized Mean Diff.	Mean Treatment	Mean Comparison	Standardized Mean Diff.
	(1)	(2)	(3)	(4)	(5)	(6)
Buddhist	0.006	0.001	0.021	0.002	0.002	-0.001
Christian	0.007	0.006	0.006	0.006	0.006	0.001
Hindu	0.845	0.831	0.024	0.833	0.831	0.002
Jain	0.001	0.000	0.003	0.000	0.000	0.000
Muslim	0.104	0.131	-0.047	0.127	0.128	-0.001
Intermediate Caste	0.114	0.072	0.078	0.081	0.081	0.000
Other Backward Caste	0.388	0.387	0.001	0.392	0.393	-0.001
Scheduled Caste	0.215	0.228	-0.020	0.231	0.229	0.004
Scheduled Tribe	0.048	0.060	-0.025	0.057	0.058	-0.001
Upper Caste	0.222	0.231	-0.014	0.218	0.219	0.000
Household head education level	4.004	3.653	0.160	3.719	3.704	0.007
Number women in household	2.028	2.020	0.008	2.049	2.050	-0.001
Number men in household	2.351	2.461	-0.107	2.416	2.415	0.001
Urban	0.694	0.607	0.126	0.628	0.625	0.004
Any woman in household: credit card	0.001	0.001	0.002	0.000	0.000	0.000
Any woman in household: retirement savings	0.010	0.009	0.001	0.007	0.007	0.000
Any man in household:bank account	0.926	0.944	-0.037	0.939	0.939	0.000
Any man in household:credit card	0.015	0.011	0.012	0.009	0.009	-0.001
Any man in household: Trading account	0.002	0.002	-0.001	0.001	0.001	0.001
Any man in household: Mobile	0.963	0.956	0.016	0.960	0.959	0.002

Notes: The table reports mean estimates of variables in wave 2 (pre-policy) for the (original) sample of households drawn from CPdx (columns 1-2), and the standardized difference (column 3). The sample includes households where the wife of the male household head did not have a bank account in wave 2. In these households, she is the only spouse, and there is no older female present. A household is treated if the wife opened a bank account in the survey wave after policy implementation. In the comparison group, the wife did not own a bank account throughout waves 1-5. Columns 3 and 4 report means of the sample transformed using inverse probability weighting, and column 6 estimates the standardized mean difference between them.

Table 2.5: Pre-trends test: Effect of women's bank account ownership on household borrowing, savings and investment

	Formal borrowing	Informal borrowing	Formal saving	Women associated saving	Investment	Gold savings
	(1)	(2)	(3)	(4)	(5)	(6)
Woman banked in wave 3	-0.000	-0.001	0.005	0.001	0.015	0.009
× Pre-treatment	[0.775]	[0.736]	[0.584]	[0.783]	[0.559]	[0.525]
Woman banked in wave 3	-0.002	-0.004	0.008	-0.000	-0.008	0.000
	[0.430]	[0.337]	[0.323]	[0.936]	[0.559]	[0.997]
Pre-treatment time dummy	-0.000	0.000	-0.022	-0.001	-0.073	-0.040
	[0.995]	[0.927]	[0.001]	[0.447]	[0.000]	[0.001]
Comparison group mean	0.007	0.03	0.069	0.004	0.082	0.058
Sharpened q-values	1	1	1	1	1	1
Observations	40123	40123	40123	40123	40123	40123
Non-zero observations	385	1455	3264	315	4578	3259
R^2	0.110	0.289	0.444	0.264	0.479	0.486
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls included	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing differential trends in household's uptake of financial services between treatment and comparison groups in the pre-policy time period. The dependent variables specified in column title are binary indicators of whether-household has outstanding borrowing from a formal source (Column 1), informal source (Column 2), saved in a formal source (Column 3), saved in a source more common for women eg. Self-Help group, Chit fund, microfinance institute (Column 4), outstanding investment (Column 5) and saved in gold (Column 6). The observations are at household level-survey wave level. The first row estimates differences in dependent variable between Treatment and Comparison groups over two survey waves before policy implementation. The pre-trend dummy variable is assigned 1 for CPdx's survey wave 2 (May to August 2014) and 0 for survey wave 1 (January to April 2014). The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion, changes in account ownership of men and other women in household and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that corrects the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses. Non-zero observations report the number of observations where households report positive uptake of financial service/product.

Table 2.6: Pre-trends test: Effect of women's bank account ownership on women-associated consumption

	Clothing, Footwear & Accessories	Cosmetics & Toiletries	Beauty goods & Services	Time saving appliances & services	Food
	(1)	(2)	(3)	(4)	(5)
Woman banked in wave 3 $\times$ Pre-treatment	-36.335	7.820	9.870	-1.933	47.779
	[0.006]	[0.175]	[0.001]	[0.028]	[0.059]
Woman banked in wave 3	11.803	-1.793	-4.331	0.933	6.609
	[0.151]	[0.680]	[0.029]	[0.078]	[0.694]
Pre-treatment time dummy	-11.301	-7.265	37.779	-0.360	26.549
	[0.421]	[0.225]	[0.000]	[0.624]	[0.307]
Comparison group mean	169.951	381.699	49.026	4.29	3468.913
Sharpened q-values	.058	0 .401	0.008	0.165	0.206
Observations	159639	159639	159639	159639	159639
R^2	0.473	0.633	0.362	0.243	0.816
State FE	Yes	Yes	Yes	Yes	Yes
Controls included	Yes	Yes	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing differential trends in household real monthly consumption patterns (base year 2012) in Indian National Rupees (INR) between treatment and comparison groups in the pre-policy time period. The dependent variables specified in column title are winsorized at 5th and 95th percentile and their description is provided in Table A.1. The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups over two survey waves before policy implementation. The pre-trend dummy variable is assigned 1 for CPdx's survey wave 2 (May to August 2014) and 0 for survey wave 1 (January to April 2014). The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5).The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that corrects the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses. Household consumption of 'clothing, footwear and accessories' and 'beauty products and services' exhibit differential trends in pre-policy time period.

Table 2.7: Pre-trends test: Effect of women's bank account ownership on men-associated consumption

	Intoxicants	Shaving articles	All fuel (except cooking)
	(1)	(2)	(3)
Woman banked in wave 3 × Pre-treatment	1.515	-0.076	-8.032
	[0.773]	[0.924]	[0.347]
Woman banked in wave 3	9.206	0.179	-6.498
	[0.202]	[0.809]	[0.514]
Pre-treatment time dummy	41.249	-0.011	-2.266
	[0.000]	[0.989]	[0.727]
Comparison group mean	221.185	18.289	284.677
Sharpened q-values	1	1	0.581
Observations	159639	159639	159639
R^2	0.471	0.379	0.627
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing differential trends in household real monthly consumption patterns (base year 2012) in INR between treatment and comparison groups in the pre-policy time period. The dependent variables specified in column title are winsorized at 5th and 95th percentile and their description is provided in Table A.1. The observations are at household-month level. TThe first row estimates differences in dependent variable between Treatment and Comparison groups over two survey waves before policy implementation. The pre-trend dummy variable is assigned 1 for CPdx's survey wave 2 (May to August 2014) and 0 for survey wave 1 (January to April 2014). The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that corrects the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.8: Pre-trends test: Effect of women's bank account ownership on children-associated consumption

	Total Education	Academic books	Stationery	School/ College fees	Private coaching fees
	(1)	(2)	(3)	(4)	(4)
Woman banked in	1.047	0.514	-0.143	-8.132	0.430
wave 3 × Pre-treatment	[0.865]	[0.098]	[0.894]	[0.077]	[0.618]
Woman banked in wave 3	0.761	0.000	-0.071	1.008	1.772
	[0.892]	[.]	[0.929]	[0.805]	[0.048]
Pre-treatment time dummy	16.639	0.000	-0.073	13.446	3.594
	[0.012]	[.]	[0.954]	[0.003]	[0.010]
Comparison group mean	169.537	2.84	14.7	116.064	12.63
Sharpened q-values	1	0.262	1	0.245	1
Observations	159639	80039	159639	159639	159639
R^2	0.359	0.127	0.260	0.329	0.354
Non-zero Obs.	71069	3687	35769	45697	10434
State FE	Yes	Yes	Yes	Yes	Yes
Controls included	Yes	Yes	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing differential trends in household real monthly consumption patterns (base year 2012) in INR between treatment and comparison groups in the pre-policy time period. The dependent variables specified in column title are winsorized at 5th and 95th percentile and their description is provided in Table A.1. The observations are at household-month level. There are few observations for a positive amount of monthly expenditure on academic books by households. The first row estimates differences in dependent variable between Treatment and Comparison groups over two survey waves before policy implementation. The pre-trend dummy variable is assigned 1 for CPdx's survey wave 2 (May to August 2014) and 0 for survey wave 1 (January to April 2014). The pre-trend dummy variable is assigned 1 for survey wave 2 (May to August 2014) and 0 for survey wave 1 (January to April 2014). The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5).The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that corrects the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.9: Pre-trends test: Effect of women's bank account ownership on total consumption and consumption shares

	Total expenditure	Share of total expenditure		
		Female	Male	Children
	(1)	(2)	(3)	(4)
Woman banked in wave 3 × Pre-treatment	-276.143	-0.001	-0.002	-0.002
	[0.024]	[0.638]	[0.070]	[0.047]
Woman banked in wave 3	354.597	0.002	0.003	0.001
	[0.000]	[0.128]	[0.019]	[0.297]
Pre-treatment time dummy	2.544	0.007	0.008	0.004
	[0.974]	[0.005]	[0.000]	[0.000]
Comparison group mean	6346.128	0.095	0.075	0.022
Sharpened q-values	0.165	1	0.581	0.51
Observations	159639	159639	159639	159639
R^2	0.610	0.375	0.443	0.250
State FE	Yes	Yes	Yes	Yes
Controls included	Yes	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing differential trends in household real monthly consumption patterns (base year 2012) in INR between treatment and comparison groups in the pre-policy time period. The dependent variables are specified in column title and observations are at household-month level. Column 1 tests for changes in household's real monthly expenditure winsorized at 5th and 95th percentile and Columns 2-4 are share of female, male and children-associated expenditures in the total. Female share includes clothing, footwear and accessories; cosmetics and toiletries; time saving appliances and services. Male share includes expenditure on intoxicants, shaving articles and fuel (except for cooking). Children's share includes academic books, stationery, school and college fees and fees for private coaching. Each consumption category is described in Table A.1.The first row estimates differences in dependent variable between Treatment and Comparison groups over two survey waves before policy implementation. The pre-trend dummy variable is assigned 1 for CPdx's survey wave 2 (May to August 2014) and 0 for survey wave 1 (January to April 2014). The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5).The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that corrects the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.10: Inverse Probability Weighted DiD: Effect of women's bank account ownership on formal borrowing

	Formal borrowing (1)	Formal borrowing (2)	Formal borrowing (3)
Woman banked in wave 3 × Post1	0.010		
	[0.000]		
Post1	-0.003		
	[0.098]		
Woman banked in wave 3 × Post2		0.008	
		[0.000]	
Post2		-0.003	
		[0.110]	
Woman banked in wave 3 × Post3			0.007
			[0.001]
Post3			-0.003
			[0.138]
Woman banked in wave 3	-0.003	-0.002	-0.002
	[0.231]	[0.286]	[0.263]
Comparison group mean	.007	.007	.007
Sharpened q-values	0.002	0.002	0.003
Observations	40141	80257	100323
R^2	0.087	0.074	0.067
Non-zero observations	1042	1042	1042
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is binary indicator of whether household borrowed from formal sources such as banks, employers, registered companies. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-survey wave level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses. Non-zero observations report the number of observations where households report positive uptake of formal borrowing.

Table 2.11: Inverse Probability Weighted DiD: Effect of women's bank account ownership on informal borrowing

	Informal borrowing (1)	Informal borrowing (2)	Informal borrowing (3)
Woman banked in wave 3 × Post1	-0.004		
	[0.662]		
Post1	-0.003		
	[0.401]		
Woman banked in wave 3 × Post2		-0.010	
		[0.216]	
Post2		-0.003	
		[0.294]	
Woman banked in wave 3 × Post3			-0.009
			[0.251]
Post3			-0.004
			[0.141]
Woman banked in wave 3	-0.007	-0.006	-0.006
	[0.287]	[0.276]	[0.299]
Comparison group mean	.031	.032	.03
Sharpened q-values	0.702	0.373	0.381
Observations	40141	80257	100323
R^2	0.247	0.257	0.245
Non-zero observations	3179	3179	3179
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is binary indicator of whether household borrowed from informal sources such as moneylenders, shops or relatives. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-survey wave level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses. Non-zero observations report the number of observations where households report positive uptake of informal borrowing.

Table 2.12: Inverse Probability Weighted DiD: Effect of women's bank account ownership on formal saving

	Formal saving (1)	Formal saving (2)	Formal saving (3)
Woman banked in wave 3 × Post1	0.087		
	[0.002]		
Post1	0.012		
	[0.117]		
Woman banked in wave 3 × Post2		0.095	
		[0.001]	
Post2		0.009	
		[0.307]	
Woman banked in wave 3 × Post3			0.103
			[0.000]
Post3			0.017
			[0.057]
Woman banked in wave 3	-0.027	-0.032	-0.047
	[0.069]	[0.029]	[0.007]
Comparison group mean	.053	.063	.069
Sharpened q-values	0.005	0.003	0.003
Observations	40141	80257	100323
R^2	0.420	0.378	0.387
Non-zero observations	11208	11208	11208
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is binary indicator of whether household saved in banks, government's savings schemes and bonds. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September-December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-survey wave level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5).The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses. Non-zero observations report the number of observations where households report positive uptake of formal saving.

Table 2.13: Inverse Probability Weighted DiD: Effect of women's bank account ownership on women-associated savings

	Women associated saving (1)	Women associated saving (2)	Women associated saving (3)
Woman banked in wave 3 × Post1	0.001		
	[0.705]		
Post1	-0.004		
	[0.080]		
Woman banked in wave 3 × Post2		0.001	
		[0.580]	
Post2		-0.006	
		[0.047]	
Woman banked in wave 3 × Post3			0.002
			[0.375]
Post3			-0.006
			[0.033]
Woman banked in wave 3	0.000	-0.000	-0.001
	[0.778]	[0.932]	[0.695]
Comparison group mean	.005	.005	.004
Sharpened q-values	0.702	0.702	0.525
Observations	40141	80257	100323
R^2	0.151	0.146	0.121
Non-zero observations	511	511	511
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is binary indicator of whether household saved in Self-Help groups, chit funds and other microfinance institutes. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-survey wave level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses. Non-zero observations report the number of observations where households report positive uptake of these women-associated saving platforms.

Table 2.14: Inverse Probability Weighted DiD: Effect of women's bank account ownership on investment

	Investment (1)	Investment (2)	Investment (3)
Woman banked in wave 3 × Post1	-0.004		
	[0.722]		
Post1	-0.021		
	[0.046]		
Woman banked in wave 3 × Post2		0.009	
		[0.597]	
Post2		-0.056	
		[0.000]	
Woman banked in wave 3 × Post3			0.012
			[0.463]
Post3			-0.061
			[0.000]
Woman banked in wave 3	-0.002	-0.005	-0.007
	[0.837]	[0.595]	[0.504]
Comparison group mean	.071	.09	.082
Sharpened q-values	0.702	0.702	0.642
Observations	40141	80257	100323
R^2	0.387	0.321	0.267
Non-zero observations	8271	8271	8271
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is binary indicator of whether household invested in mutual funds, shares, real estate and equity in an unlisted company. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-survey wave level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses. Non-zero observations report the number of observations where households report positive uptake of investment.

Table 2.15: Inverse Probability Weighted DiD: Effect of women's bank account ownership on saving in gold

	Gold savings (1)	Gold savings (2)	Gold savings (3)
Woman banked in wave 3 × Post1	0.010		
	[0.356]		
Post1	-0.020		
	[0.044]		
Woman banked in wave 3 × Post2		0.016	
		[0.183]	
Post2		-0.038	
		[0.001]	
Woman banked in wave 3 × Post3			0.019
			[0.106]
Post3			-0.041
			[0.001]
Woman banked in wave 3	0.009	0.002	-0.001
	[0.205]	[0.768]	[0.859]
Comparison group mean	.052	.063	.058
Sharpened q-values	0.525	0.373	0.221
Observations	40141	80257	100323
R^2	0.404	0.331	0.280
Non-zero observations	6096	6096	6096
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is binary indicator of whether household saved in gold or gold bonds. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-survey wave level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). Estimation controls for household composition, demographic characteristics and gender-wise financial inclusion prior to policy (list in Table 2.4), changes in account ownership of men and other women in household, and district fixed effects. Standard errors are clustered at the district level. The p-values of the coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses. Non-zero observations report the number of observations where households report positive uptake of saving in gold.

Table 2.16: Inverse Probability Weighted DiD: Effect of women's bank account ownership on total household expenditure

	Total expenditure (1)	Total expenditure (2)	Total expenditure (3)
Woman banked in wave 3 × Post1	-470.252		
	[0.000]		
Post1	-21.319		
	[0.809]		
Woman banked in wave 3 × Post2		-741.848	
		[0.000]	
Post2		123.072	
		[0.194]	
Woman banked in wave 3 × Post3			-745.938
			[0.000]
Post3			294.137
			[0.000]
Woman banked in wave 3	480.338	557.934	598.835
	[0.000]	[0.000]	[0.000]
Comparison group mean	6063.132	6097.616	6195.068
Observations	159989	318572	394188
R^2	0.596	0.569	0.556
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is total monthly household expenditure in real terms (base year 2012) winsorized at 5th and 95th percentile. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5).The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.17: Inverse Probability Weighted DiD: Effect of women's bank account ownership on cosmetics and toiletries

	Cosmetics & Toiletries (1)	Cosmetics & Toiletries (2)	Cosmetics & Toiletries (3)
Woman banked in wave 3 × Post1	-1.364		
	[0.835]		
Post1	-3.342		
	[0.628]		
Woman banked in wave 3 × Post2		1.236	
		[0.859]	
Post2		3.367	
		[0.638]	
Woman banked in wave 3 × Post3			-1.360
			[0.847]
Post3			9.798
			[0.154]
Woman banked in wave 3	0.725	-0.971	-0.122
	[0.911]	[0.846]	[0.982]
Comparison group mean	369.289	374.359	381.699
Sharpened q-values	0.98	0.98	0.98
Observations	159989	318572	394188
R^2	0.650	0.627	0.630
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on cosmetics and toiletries winsorized at 5th and 95th percentile. These include dental care products, bathing soap, face wash, hair oil, shampoo and hair conditioner, powder, creams, deodorants and perfumes, detergent bar/powder/liquids, scourer and housecleaning agents, henna, hair color, hair gel, etc., lipstick and other cosmetics and other housecare products. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5).The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.18: Inverse Probability Weighted DiD: Effect of women's bank account ownership on time saving appliances and services

	Time saving appliances & services (1)	Time saving appliances & services (2)	Time saving appliances & services (3)
Woman banked in wave 3 × Post1	-1.212		
	[0.023]		
Post1	0.744		
	[0.232]		
Woman banked in wave 3 × Post2		-1.864	
		[0.001]	
Post2		-0.410	
		[0.541]	
Woman banked in wave 3 × Post3			-1.850
			[0.002]
Post3			0.639
			[0.210]
Woman banked in wave 3	0.337	0.696	0.873
	[0.466]	[0.074]	[0.042]
Comparison group mean	3.835	3.965	4.29
Sharpened q-values	0.062	0.009	0.011
Observations	159989	318572	394188
R^2	0.173	0.180	0.174
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on time saving appliances and services winsorized at 5th and 95th percentile. It includes gadgets such as toasters, water filters, microwave oven, refrigerator, cooking range, stove, mixer/grinder, juicer, coffee machine, grill, induction, chimney, exhaust system and any other appliances that are used in kitchens to improve the efficiency of cooking as well as salary paid to maid servants, cooks, drivers, guards, gardeners, baby sitters and other staff, and laundry services. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5).The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.19: Inverse Probability Weighted DiD: Effect of women's bank account ownership on food

	Food (1)	Food (2)	Food (3)
Woman banked in wave 3 × Post1	16.762 [0.509]		
Post1	59.268 [0.071]		
Woman banked in wave 3 × Post2		27.250 [0.367]	
Post2		85.125 [0.010]	
Woman banked in wave 3 × Post3			20.068 [0.485]
Post3			57.14 [0.032]
Woman banked in wave 3	32.772 [0.097]	18.238 [0.316]	16.872 [0.391]
Comparison group mean	3415.239	3438.553	3468.913
Sharpened q-values	0.664	0.604	0.657
Observations	159989	318572	394188
R^2	0.821	0.808	0.803
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on food winsorized at 5th and 95th percentile. It includes expenses on cereals & pulses, edible oils, spices, vegetables & fruits, meat, fish & eggs, milk & milk products, ready-to-eat food, spices, bread, biscuits, salty snacks, noodles & pasta, flakes, muesli & oats, confectionery & ice-creams, health supplements, tea, coffee, sweeteners, and beverages, juices & bottled water. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September-December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct

Table 2.20: Inverse Probability Weighted DiD: Effect of women's bank account ownership on education

	Education (1)	Education (2)	Education (3)
Woman banked in wave 3 × Post1	-12.710		
	[0.074]		
Post1	27.595		
	[0.003]		
Woman banked in wave 3 × Post2		-16.492	
		[0.023]	
Post2		17.905	
		[0.017]	
Woman banked in wave 3 × Post3			-19.540
			[0.003]
Post3			16.986
			[0.003]
Woman banked in wave 3	11.114	13.425	18.314
	[0.074]	[0.013]	[0.001]
Comparison group mean	161.98	161.137	169.537
Sharpened q-values	0.155	0.06	0.015
Observations	159989	318572	394188
R^2	0.348	0.352	0.356
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on education winsorized at 5th and 95th percentile. It includes stationery, school/college fees, private tuition fees, additional professional education, overseas education, hobby classes and others education. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.21: Inverse Probability Weighted DiD: Effect of women's bank account ownership on intoxicants

	Intoxicants (1)	Intoxicants (2)	Intoxicants (3)
Woman banked in wave 3 × Post1	-6.907		
	[0.184]		
Post1	41.422		
	[0.000]		
Woman banked in wave 3 × Post2		-2.661	
		[0.671]	
Post2		57.505	
		[0.000]	
Woman banked in wave 3 × Post3			0.920
			[0.897]
Post3			45.240
			[0.000]
Woman banked in wave 3	14.699	10.329	7.405
	[0.076]	[0.184]	[0.365]
Comparison group mean	217.656	213.763	221.185
Sharpened q-values	0.337	0.838	1
Observations	159989	318572	394188
R^2	0.504	0.478	0.465
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on intoxicants winsorized at 5th and 95th percentile.It includes expenditure on cigarettes, bidis, other tobacco products and liquor. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.22: Inverse Probability Weighted DiD: Effect of women's bank account ownership on shaving articles

	Shaving articles (1)	Shaving articles (2)	Shaving articles (3)
Woman banked in wave 3 × Post1	0.424		
	[0.692]		
Post1	-0.256		
	[0.778]		
Woman banked in wave 3 × Post2		0.152	
		[0.891]	
Post2		-0.790	
		[0.400]	
Woman banked in wave 3 × Post3			0.194
			[0.866]
Post3			-0.722
			[0.435]
Woman banked in wave 3	-0.289	-0.291	-0.279
	[0.769]	[0.723]	[0.748]
Comparison group mean	18.082	18.224	18.289
Sharpened q-values	0.838	1	0.98
Observations	159989	318572	394188
R^2	0.367	0.348	0.353
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on shaving articles winsorized at 5th and 95th percentile. It includes shaving brush, razors (both traditional and electric), blades, shaving foams, shaving gels, shaving lather sticks, after shave lotions and shaving creams. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September-December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.23: Inverse Probability Weighted DiD: Effect of women's bank account ownership on fuel (except for cooking)

	Fuel (except cooking) (1)	Fuel (except cooking) (2)	Fuel (except cooking) (3)
Woman banked in wave 3 × Post1	9.077		
	[0.229]		
Post1	-62.226		
	[0.000]		
Woman banked in wave 3 × Post2		11.608	
		[0.134]	
Post2		-83.475	
		[0.000]	
Woman banked in wave 3 × Post3			12.001
			[0.130]
Post3			-90.077
			[0.000]
Woman banked in wave 3	-22.585	-18.133	-18.294
	[0.034]	[0.066]	[0.071]
Comparison group mean	283.082	281.884	284.677
Sharpened q-values	0.424	0.249	0.249
Observations	159989	318572	394188
R^2	0.614	0.608	0.603
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on fuel such as petrol and diesel (except for cooking) winsorized at 5th and 95th percentile. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy genderwise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.24: Inverse Probability Weighted DiD: Effect of women's bank account ownership on stationery

	Stationery (1)	Stationery (2)	Stationery (3)
Woman banked in wave 3 × Post1	-0.747		
	[0.575]		
Post1	4.315		
	[0.005]		
Woman banked in wave 3 × Post2		-1.113	
		[0.393]	
Post2		1.577	
		[0.244]	
Woman banked in wave 3 × Post3			-1.344
			[0.326]
Post3			2.242
			[0.108]
Woman banked in wave 3	1.768	1.615	2.251
	[0.060]	[0.049]	[0.016]
Comparison group mean	13.531	13.824	14.7
Sharpened q-values	0.754	0.604	0.546
Observations	159989	318572	394188
R^2	0.248	0.232	0.229
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on stationery winsorized at 5th and 95th percentile. It includes notebooks, writing pads, paper, pens and pencils, markers, erasers, rulers, compass set, pins, staplers, post-it and other similar articles. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.25: Inverse Probability Weighted DiD: Effect of women's bank account ownership on school/ college fees

	Schooling fees	Schooling fees	Schooling fees
Woman banked in wave 3 × Post1	-8.356		
	[0.145]		
Post1	20.255		
	[0.003]		
Woman banked in wave 3 × Post2		-13.559	
		[0.016]	
Post2		17.604	
		[0.002]	
Woman banked in wave 3 × Post3			-15.167
			[0.002]
Post3			17.930
			[0.000]
Woman banked in wave 3	1.583	5.458	8.887
	[0.718]	[0.171]	[0.031]
Comparison group mean	111.416	110.379	116.064
Sharpened q-values	0.249	0.047	0.011
Observations	159989	318572	394188
R^2	0.340	0.340	0.348
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on fees for school/ college winsorized at 5th and 95th percentile. It includes admission fees, donations or capitation fees, school/college tuition fees, laboratory fees, library fees, fees paid for extra classes, sports facilities, sports participation fees, compulsory donations or contribution for any purpose or cause, canteen charges, picnic charges, expedition charges, charges for badges, ties and uniform. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.26: Inverse Probability Weighted DiD: Effect of women's bank account ownership on private coaching fees

	Private coaching (1)	Private coaching (2)	Private coaching (3)
Woman banked in wave 3 × Post1	0.053		
	[0.932]		
Post1	2.199		
	[0.006]		
Woman banked in wave 3 × Post2		-0.007	
		[0.994]	
Post2		3.597	
		[0.017]	
Woman banked in wave 3 × Post3			-0.622
			[0.504]
Post3			2.915
			[0.008]
Woman banked in wave 3	1.963	2.154	2.589
	[0.019]	[0.005]	[0.001]
Comparison group mean	12.317	11.89	12.63
Sharpened q-values	1	1	0.664
Observations	159989	318572	394188
R^2	0.379	0.366	0.360
State FE	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on fees for private coaching winsorized at 5th and 95th percentile. This includes training for competitive examinations like government jobs, engineering colleges, medical colleges, management colleges, etc. Column 1 estimates differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Column 2 estimates trends between two survey waves before policy change (January to August 2014) and two survey waves after (September 2014 - April 2015). Column 3 estimates trends between two survey waves pre-policy and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5). The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.27: Inverse Probability Weighted DiD: Effect of women's bank account ownership on miscellaneous categories

	Appliances		Rent & Utilities		Communication	
	(1)	(2)	(3)	(4)	(5)	(6)
Woman banked in	-2.478		0.475		-9.471&	
wave 3 × Post1	[0.079]		[0.689]		[0.006]	
Post1	5.148		0.457		0.594	
	[0.004]		[0.754]		[0.871]	
Woman banked in		-4.164		0.787		-11.057***
wave 3 × Post3		[0.006]		[0.604]		[0.003]
Post3		4.987		-0.944		1.447
		[0.001]		[0.276]		[0.686]
Woman banked in wave 3	0.727	1.298	-0.993	-1.377	3.144	5.820
	[0.476]	[0.199]	[0.415]	[0.253]	[0.297]	[0.064]
Comparison group mean	9.584	10.994	16.389	15.488	255.475	259.917
Sharpened q-values	0.169	0.024	0.838	0.754	0.024	0.015
Observations	159989	394188	159989	394188	159989	394188
R^2	0.205	0.203	0.425	0.407	0.645	0.621
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls included	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on categories specified in column title and winsorized at 5th and 95th percentile. This includes kitchen, household and mobile appliances (Columns 1-2), house rent and utilities (Columns 3-4) and communication such as phone, cable TV, cell phone, internet usage (Columns 5-6). Columns 1, 3 and 5 estimate differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Columns 2, 4 and 6 estimate trends between two survey waves pre-policy (January - August 2014) and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5).The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.28: Inverse Probability Weighted DiD: Effect of women's bank account ownership on miscellaneous categories (continued)

	Health		Vehicle repairs		Transportation	
	(1)	(2)	(3)	(4)	(5)	(6)
Woman banked in wave 3 × Post1	8.516		-0.622		-29.721	
	[0.016]		[0.413]		[0.000]	
Post1	1.625		-3.026		35.522	
	[0.644]		[0.003]		[0.000]	
Woman banked in wave 3 × Post3		5.424		-0.321		-42.667
		[0.123]		[0.747]		[0.000]
Post3		4.012		-3.916		53.384
		[0.161]		[0.000]		[0.000]
Woman banked in wave 3	-5.075	-3.849	-2.609	-1.844	21.691	30.977
	[0.076]	[0.149]	[0.001]	[0.021]	[0.000]	[0.000]
Sharpened q-values	0.047	0.249	0.604	0.886	0.001	0.001
Observations	159989	394188	159989	394188	159989	394188
R^2	0.325	0.292	0.217	0.203	0.438	0.441
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls included	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column is an inverse probability weighted DiD (see eq.2.2) testing effect of women's account ownership on dependent variable for different lengths of post time period. The dependent variable is real monthly household expenditure (base year 2012) in INR on categories specified in column title and winsorized at 5th and 95th percentile. This includes expenditure on medicines, doctor's/physiotherapists and hospitalization fees, medical tests and health insurance (Columns 1-2); vehicle repairs (Columns 3-4) and different modes of transport (Columns 5-6). Columns 1, 3 and 5 estimate differences between the first survey wave before and after policy implementation (May - August and September- December 2014, respectively). Columns 2, 4 and 6 estimate trends between two survey waves pre-policy (January - August 2014) and three survey waves after (September 2014 to August 2015). The observations are at household-month level. The first row estimates differences in dependent variable between Treatment and Comparison groups before and after policy implementation. The treatment group includes households where female spouse of household head opened a bank account post-policy in survey wave 3 (September - December 2014) and comparison group includes households where the spouse didn't own a bank account before policy and at least 1 year after implementation (waves 1-5).The estimation controls for household composition, demographic characteristics and pre-policy gender-wise financial inclusion (list in Table 2.4), changes in account ownership of men and other women in household, total monthly consumption expenditure and district fixed effects. Standard errors are clustered at the district level. p values of coefficient terms are included in parentheses. The table reports sharpened two-stage q-values that correct the p-value of the interaction coefficient for the false discovery rate from testing multiple hypotheses.

Table 2.29: Balance test of covariates selected using LASSO

Variable	High impact Mean	SE	Low impact Mean	SE	Pairwise t-test Mean difference
	(1)	(2)	(3)	(4)	(5)
Household income quintile	2.923	0.051	3.235	0.050	-0.312***
Household asset quintile	2.658	0.069	3.109	0.071	-0.451***
Years of education: Head of household	5.108	0.140	6.096	0.147	-0.988***
Hindu head of household	0.820	0.016	0.830	0.015	-0.010
Muslim head of household	0.127	0.014	0.111	0.012	0.015
Christian head of household	0.011	0.003	0.026	0.006	-0.015***
Head of household Scheduled Caste	0.213	0.011	0.199	0.010	0.014
Head of household Other Backward Class	0.050	0.005	0.065	0.006	-0.015**
Age of respondent	32.495	0.130	33.326	0.136	-0.831***
Years of education: Respondent	3.755	0.165	4.895	0.179	-1.140***
Age gap between respondent and spouse	-5.172	0.115	-5.448	0.114	0.276***
Respondent employed in agricultural sector	0.199	0.016	0.161	0.015	0.039***
Spouse employed in agricultural sector	0.312	0.016	0.249	0.015	0.063***
Spouse employed in non-agricultural sector	0.431	0.014	0.451	0.013	-0.019
Number colleges	11.701	0.714	20.463	1.904	-8.762***
Number high schools	29.781	2.097	46.964	4.354	-17.182***
Power supply for all users	0.790	0.025	0.783	0.026	0.007
N	169		160		329

Notes: First two columns report statistics for high impact districts where the policy had a larger effect on account ownership (Eq. 2.3) and columns 3 and 4 report statistics for low impact districts. High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. Household characteristics are drawn from the nationally representative household characteristics (IHDS and DHS) and infrastructure variables are derived from Population Censuses 2001 and 2011. These variables are selected using post double (LASSO) selection method by Belloni et al. (2013) and predict assignment of district into High/Low impact as well as expansion in account ownership in response to policy. Column 5 reports t test of mean differences between high and low impact districts. High impact districts lag behind in almost all socio-economic characteristics. Social identity of household head in high and low impact districts is similar on religion and scheduled caste composition. Share of spouses in non agricultural sector are also similar.

Table 2.30: DiD estimation of policy on growth in account ownership

	2012-17		2006-17	
	Accounts/ Accounts 2011	Ln(accounts)	Accounts/ Accounts 2006	Ln(accounts)
	(1)	(2)	(3)	(4)
High impact × Post	0.180***	0.067***	0.226***	0.199***
	[0.061]	[0.020]	[0.078]	[0.042]
Post	0.759***	0.446***	0.753***	0.390***
	[0.056]	[0.021]	[0.060]	[0.031]
High impact district	-0.039	-0.137***	-0.075*	-0.175***
	[0.028]	[0.046]	[0.042]	[0.058]
Constant	1.610***	14.169***	1.080***	12.693***
	[0.437]	[0.664]	[0.271]	[0.601]
Observations	1950	1950	3904	3904
R^2	0.575	0.587	0.673	0.619
Adjusted R^2	0.573	0.583	0.671	0.617
State FE	Yes	Yes	Yes	Yes
LASSO controls included	Yes	Yes	Yes	Yes

Notes: The columns reports DiD estimation of policy implementation on expansion in bank account ownership between high and low impact districts ((Eq. 2.3) where the dependent variable estimating expansion is specified in column title. High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. Post is a binary variable that assigns 1 to all observations post policy implementation in 2014 and 0 otherwise. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. Columns 1 and 2 test equation 2.3 for years 2012-17 with the dependent variable defined as ratio of total bank accounts relative to 2011. Column 2 includes results for 2012-17 with dependent variable as natural log of total bank accounts for each year. Columns 3 and 4 expand the analysis to years 2006-17 for consistency with timing of the first household survey included in the analysis (IHDS 2005). The estimation includes controls (full list in Table 2.29) selected by post double (LASSO) selection method (Belloni et al., 2013) and state fixed effects. Standard errors reported in parentheses are clustered at state level. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.31: Year-wise effects of policy on growth in account ownership

	Accounts/Accounts 2006
High impact × Year= 2007	0.034
	[0.027]
High impact × Year= 2008	0.042
	[0.032]
High impact × Year= 2009	0.076*
	[0.038]
High impact × Year= 2010	0.105**
	[0.047]
High impact × Year= 2011	0.191***
	[0.061]
High impact × Year= 2012	0.103
	[0.082]
High impact × Year= 2013	0.085
	[0.106]
High impact × Year= 2015	0.449*
	[0.224]
High impact × Year= 2016	0.659**
	[0.286]
High impact × Year= 2017	0.818**
	[0.349]
High impact × Year= 2014	0.280*
	[0.148]
Constant	2.571***
	[0.477]
Observations	3894
R^2	0.720
Adjusted R^2	0.717
State FE	Yes
LASSO controls included	Yes

Notes: The table reports year-by-year differences in expansion in account ownership between high and low impact districts. The dependent variable given in column title is ratio of total bank accounts in a year relative to 2006. The interaction term for the year 2006 is dropped as reference category. High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. The estimation follows eq. 2.3 and includes controls (full list in Table 2.29) selected by post double (LASSO) selection method (Belloni et al., 2013) and state fixed effects. Standard errors reported in parentheses are clustered at state level. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.32: Robustness check of districts' classification into high and low impact

	Median number branches			Median branch density	
	All branches	Govt owned	Govt + Pvt	Govt owned	Govt + Pvt
	(1)	(2)	(3)	(4)	(5)
High impact × Post	0.205***	0.148**	0.185**	0.010	0.114
	[0.063]	[0.061]	[0.072]	[0.065]	[0.070]
Post	0.766***	0.793***	0.774***	0.864***	0.811***
	[0.043]	[0.051]	[0.045]	[0.069]	[0.070]
High impact	-0.002	-0.005	0.009	0.000	-0.070*
	[0.042]	[0.044]	[0.044]	[0.033]	[0.035]
Comparison group	2.108	2.134	2.122	2.224	2.196
Observations	3904	3904	3904	3904	3904
R^2	0.672	0.670	0.673	0.670	0.670
Adjusted R^2	0.670	0.668	0.671	0.668	0.669
State FE	Yes	Yes	Yes	Yes	Yes
LASSO controls included	Yes	Yes	Yes	Yes	Yes

Notes: The columns report effect of policy on expansion in bank account ownership (eq. 2.3) using different definitions of High and Low impact districts. The dependent variable is a ratio of total bank accounts in a year relative to 2006. Column 1 defines High impact as a binary variable that is assigned 1 when the district's total bank branches is equal to or less than state median and 0 otherwise. Column 2 specifies High/Low impact based on total branches of central government owned banks in a district. Column 3 includes government and private sector banks. Column 4 classifies districts based on branch density of central government owned banks and Column 5 for branch density of Central government and private sector banks. Bank branch density is measured as the total bank branches per 100,000 population in a district. Post is a binary variable that assigns 1 to all observations post policy implementation in 2014 and 0 otherwise. All specifications include controls (full list in Table 2.29) selected by post double selection method (Belloni et al., 2013) and state fixed effects. Standard errors are clustered at state level. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.33: Parallel trends test of account ownership on decision making

	Alone/ joint decision on big household purchases	Money available for autonomous use
	(1)	(2)
High impact × Pre-treatment	0.004	-0.006
	[0.020]	[0.033]
High impact district	-0.001	-0.009
	[0.014]	[0.023]
Pre-treatment time dummy	0.054**	0.063*
	[0.025]	[0.031]
Comparison group	0.495	0.867
Observations	42594	30123
R^2	0.194	0.074
Adjusted R^2	0.193	0.072
State FE	Yes	Yes
LASSO controls included	Yes	Yes

Notes: Columns 1 and 2 are DiD (see eq. 2.4) testing aggregate differences in dependent variables (specified in column title) between high and low impact districts in the pre-policy time period. The variables are binary indicators of whether a woman participates jointly or with spouse on decisions to purchase big household items (Column 1) and whether women have money available that they can use autonomously (Column 2). High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. Pre-treatment is a binary variable that assigns 1 to all observations from the IHDS survey in 2012 and 0 to observations from IHDS 2005. All specifications include controls (full list in Table 2.29) selected by post double selection method (Belloni et al., 2013) and state fixed effects. Standard errors are given in parentheses and clustered at state level. Empowerment outcomes and household/women-specific characteristics are extracted from nationally representative household surveys (IHDS, DHS), district-wise bank branch density and infrastructure are estimated using data from RBI and Population Census, respectively. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.34: Parallel trends test: expansion in account ownership and police-reported domestic violence

	Cruelty by husband or his relatives
	(1)
High impact × (Year = 2011)	26.428
	[15.691]
High impact × (Year = 2012)	22.038*
	[12.709]
High impact × (Year = 2013)	11.744
	[10.081]
High impact district	-2.327
	[17.368]
Year 2011	-22.303*
	[12.543]
Year 2012	-15.012
	[11.880]
Year 2013	-1.422
	[13.112]
Comparison group mean	188.511
Observations	1813
R^2	0.336
State FE	Yes
LASSO controls included	Yes

Notes: Column 1 tests aggregate differences in police-reported violence/ harassment by spouse/his relatives between high and low impact districts in pre-treatment years (2011-13). Observations are at the district level. The first row report coefficient of the interaction of High impact variable with binary variable for year 2011, and so on. High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. The specification includes demographic and infrastructure variables from the Population Census 2011 selected by post double selection method (Belloni et al., 2013) as covariates and state fixed effects. Standard errors are given in parentheses and clustered at state level. Crime data is extracted from the NCRB's publicly available data on Violence Against Women. District-wise bank branch density is estimated using data from RBI. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.35: DiD: Expansion in account ownership and women's (self-reported) empowerment outcomes

	Alone/ joint decision on big household purchases	Money available for autonomous use
	(1)	(2)
High impact × Post	-0.002	-0.009
	[0.020]	[0.015]
High impact	-0.004	-0.003
	[0.023]	[0.012]
Post	0.229***	-0.152***
	[0.016]	[0.019]
Comparison group	0.649	0.807
Observations	76306	76453
R^2	0.058	0.038
State FE	Yes	Yes
LASSO controls included	Yes	Yes

Notes: Columns 1 and 2 are DiD (see eq. 2.4) testing aggregate differences in dependent variables (specified in column title) between high and low impact districts in response to policy implementation. The variables are binary indicators of whether a woman participates jointly or with spouse on decisions to purchase big household items (Column 1) and whether women have money available that they can use autonomously (Column 2). High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. Post is a binary variable that assigns 1 to observations from household survey after policy implementation (DHS 2015-16) and 0 to observations from survey before policy implementation (IHDS 2012). All specifications include controls (full list in Table 2.29) selected by post double selection method (Belloni et al., 2013) and state fixed effects. Standard errors are given in parentheses and clustered at state level. Empowerment outcomes and household/women-specific characteristics are extracted from nationally representative household surveys (IHDS, DHS), district-wise bank branch density and infrastructure are estimated using data from RBI and Population Census, respectively. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.36: DiD: Expansion in account ownership and police-reported domestic violence

	Include 2014	Exclude 2014
	(1)	(2)
High impact × Post	-26.116	-26.901
	[0.100]	[0.102]
High impact district	16.357	18.335
	[0.478]	[0.435]
Post time dummy	13.584	13.195
	[0.335]	[0.371]
Comparison group mean	184.087	184.087
Observations	1813	1510
R^2	0.337	0.330
State FE	Yes	Yes
Year FE	Yes	Yes
LASSO controls included	Yes	Yes

Notes: Table reports aggregate differences in police-reported violence/ harassment by spouse/his relatives between high and low impact districts in response to post-policy expansion in account ownership. Observations are at the district level. Column 1 includes observations from year of policy implementation (2014) in analysis and column 2 excludes. High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. Post is a binary variable that assigns 1 to observations from district-wise crime data for years 2015 and 2016 and 0 to observations from 2011-14. The specification includes demographic and infrastructure variables from the Population Census 2011 selected by post double selection method (Belloni et al., 2013) as covariates and state fixed effects. p-values are reported in parentheses and standard errors are clustered at the state level. Crime data is extracted from the NCRB's publicly available data on Violence Against Women. District-wise bank branch density is estimated using data from RBI. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.37: DiD: Proportion of surveyed women with bank account

	Proportion of banked women in district
	(1)
High impact $\times$ Post	0.023
	[0.023]
Median and below	-0.031
	[0.023]
Year $>$ 2014	-0.280***
	[0.021]
Observations	309231
R^2	0.774
Comparison group mean	0.119

Notes: The table reports a DiD (see eq. 2.4) testing aggregate differences in dependent variable (specified in column title) between high and low impact districts in the pre-policy time period. The dependent variable is the proportion of women surveyed women that own a bank account. High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. Post is a binary variable that assigns 1 to responses in the DHS 2015-16 survey and 0 to the IHDS 2012 respondents. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. The specification includes state fixed effects. Standard errors are given in parentheses and clustered at state level. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.38: Aggregate effects of account ownership on women's empowerment by women's type of employment

	Alone/ joint decision on big household purchases (1)	Cash available for autonomous use (2)
Ag employment × High impact × Post	-0.0037	-0.0158
	[0.025]	[0.016]
Non-Ag employment × High impact × Post	-0.0020	0.0062
	[0.020]	[0.017]
Employed in Agricultural sector	0.0520***	0.0064
	[0.018]	[0.007]
Employed in Non-Agricultural sector	0.1329***	0.0639***
	[0.010]	[0.009]
High impact district	-0.0051	-0.0024
	[0.022]	[0.012]
Post	0.2137***	-0.1459***
	[0.017]	[0.018]
Comparison group	0.63	0.77
Observations	42950	43097
R^2	0.074	0.041
State FE	Yes	Yes
District covariates included	Yes	Yes
Individual covariates included	Yes	Yes

Notes: Columns 1 and 2 are DiD (see eq. 2.4) testing aggregate differences in dependent variables (specified in column title) between high and low impact districts in response to policy implementation by women's employment status. The dependent variables are binary indicators of whether a woman participates jointly or with spouse on decisions to purchase big household items (Column 1) and whether women have money available that they can use autonomously (Column 2).High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. Post is a binary variable that assigns 1 to observations from household survey after policy implementation (DHS 2015-16) and 0 to observations from survey before policy implementation (IHDS 2012). The triple interaction with binary variables for women's employment in agricultural and non-agricultural sector tests if there are heterogeneous effects of district-wise expansion in account ownership on women's empowerment by their sector of employment. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. All specifications include controls (full list in Table 2.29) selected by post double selection method (Belloni et al., 2013) and state fixed effects. Standard errors are given in parentheses and clustered at state level. Empowerment outcomes and household/women-specific characteristics are extracted from nationally representative household surveys (IHDS, DHS), district-wise bank branch density and infrastructure are estimated using data from RBI and Population Census, respectively. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.39: Aggregate effects of account ownership on women's empowerment by sample of banked households and women

	Banked households		Banked women	
	Alone/ joint decision on big household purchases	Cash available for autonomous use	Alone/ joint decision on big household purchases	Cash available for autonomous use
	(1)	(2)	(3)	(4)
Banked sample × High impact × Post	0.0343	-0.0075	-0.0191	-0.0051
	[0.024]	[0.029]	[0.021]	[0.016]
High impact × Post	-0.0287	-0.0030	0.0147	-0.0068
	[0.032]	[0.033]	[0.020]	[0.020]
Comparison group	0.566	0.81	0.583	0.774
Observations	76125	76300	64543	64617
R^2	0.060	0.042	0.080	0.057
State FE	Yes	Yes	Yes	Yes
District covariates included	Yes	Yes	Yes	Yes
Individual covariates included	Yes	Yes	Yes	Yes

Notes: Columns 1 and 2 are DiD (see eq. 2.4) testing aggregate differences in dependent variables (specified in column title) between high and low impact districts in response to policy implementation by banking status of households within the sample. Columns 3 and 4 test this relationship for women's banking status. The dependent variables are binary indicators of whether a woman participates jointly or with spouse on decisions to purchase big household items (Column 1) and whether women have money available that they can use autonomously (Column 2). High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. Post is a binary variable that assigns 1 to observations from household survey after policy implementation (DHS 2015-16) and 0 to observations from survey before policy implementation (IHDS 2012). The triple interaction with binary variables for household's (women's) account ownership tests if there are heterogeneous effects of district-wise expansion in account ownership on women's empowerment by account ownership of surveyed households (women). The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. All specifications include controls (full list in Table 2.29) selected by post double selection method (Belloni et al., 2013) and state fixed effects. Standard errors are given in parentheses and clustered at state level. Empowerment outcomes and household/women-specific characteristics are extracted from nationally representative household surveys (IHDS, DHS), district-wise bank branch density and infrastructure are estimated using data from RBI and Population Census, respectively. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.40: Effect of trust in banking institutions and gender parity on women's empowerment

	Trust in Banks		Gender parity at home	
	Alone/ joint decision on big household purchases	Cash available for autonomous use	Alone/ joint decision on big household purchases	Cash available for autonomous use
	(1)	(2)	(3)	(4)
Norms × High impact × Post	0.1022*	0.0225	0.0068	-0.0080
	[0.051]	[0.096]	[0.048]	[0.087]
High impact × Post	-0.1239*	-0.0364	-0.0109	0.0004
	[0.060]	[0.123]	[0.053]	[0.112]
Constant	0.6629***	0.9314***	0.5291***	0.8546***
	[0.067]	[0.042]	[0.041]	[0.040]
Marginal effect	-0.033	-0.021	0.001	0.007
	[0.046]	[0.081]	[0.013]	[0.009]
Observations	76255	76402	76255	76402
R^2	0.058	0.038	0.058	0.038
State FE	Yes	Yes	Yes	Yes
Covariates included	Yes	Yes	Yes	Yes

Notes: Columns 1 and 2 are DiD (see eq. 2.4) testing aggregate differences in dependent variables (specified in column title) between high and low impact districts in response to policy implementation by ex-ante trust in banking institutions within a district. Columns 3 and 4 test this relationship for ex-ante gender parity at home. See Table A.3 for construction of these scores. The dependent variables are binary indicators of whether a woman participates jointly or with spouse on decisions to purchase big household items (Column 1) and whether women have money available that they can use autonomously (Column 2). High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. Post is a binary variable that assigns 1 to observations from household survey after policy implementation (DHS 2015-16) and 0 to observations from survey before policy implementation (IHDS 2012). The triple interaction tests if there are heterogeneous effects of district-wise expansion in account ownership on women's empowerment by ext-ante trust in banking and gender parity within a sample district. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. All specifications include controls (full list in Table 2.29) selected by post double selection method (Belloni et al., 2013) and state fixed effects. Standard errors are given in parentheses and clustered at state level. Empowerment outcomes and household/women-specific characteristics are extracted from nationally representative household surveys (IHDS, DHS), district-wise bank branch density and infrastructure are estimated using data from RBI and Population Census, respectively. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

Table 2.41: Effect of women's mobility outside home on her empowerment

	Requires permission		Can visit alone	
	Alone/ joint decision on big household purchases	Cash available for autonomous use	Alone/ joint decision on big household purchases	Cash available for autonomous use
	(1)	(2)	(3)	(4)
Mobility × High impact × Post	0.0228	-0.0010	0.0064	-0.0080
	[0.054]	[0.089]	[0.047]	[0.088]
High impact × Post	-0.0299	-0.0085	-0.0096	0.0002
	[0.057]	[0.115]	[0.052]	[0.113]
Constant	0.4347***	0.8517***	0.4613***	0.8520***
	[0.056]	[0.037]	[0.038]	[0.029]
Marginal effect	-0.004	-0.017	0.053	0.021
	[0.021]	[0.018]	[0.015]	[0.02]
Observations	76255	76402	76255	76402
R^2	0.058	0.038	0.058	0.038
State FE	Yes	Yes	Yes	Yes
Covariates included	Yes	Yes	Yes	Yes

Notes: Columns 1-4 are DiD (see eq. 2.4) testing aggregate differences in dependent variables (specified in column title) between high and low impact districts in response to policy implementation by ex-ante estimate of women's mobility within a district. Columns 1 and 2 test this relationship using a score of places she needs permission to visit, and columns 3 and 4 test this for places she can visit on her own. See Table A.3 for construction of these scores. The dependent variables are binary indicators of whether a woman participates jointly or with spouse on decisions to purchase big household items (Column 1) and whether women have money available that they can use autonomously (Column 2). High impact includes districts at state median bank branch density and below. Low impact includes the districts above state median. Median bank branch density is measured as the state median bank branches per 100,000 population. Post is a binary variable that assigns 1 to observations from household survey after policy implementation (DHS 2015-16) and 0 to observations from survey before policy implementation (IHDS 2012). The triple interaction tests if there are heterogeneous effects of district-wise expansion in account ownership on women's empowerment by ex-ante mobility of women within a sample district. The sample districts are selected from all districts in the 2001 Population Census where the account expansion policy was implemented from mid-August 2014 to mid-August 2015. A district is excluded if it was surveyed in one of the household surveys observing women's empowerment outcomes but not both. All specifications include controls (full list in Table 2.29) selected by post double selection method (Belloni et al., 2013) and state fixed effects. Standard errors are given in parentheses and clustered at state level. Empowerment outcomes and household/women-specific characteristics are extracted from nationally representative household surveys (IHDS, DHS), district-wise bank branch density and infrastructure are estimated using data from RBI and Population Census, respectively. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

CHAPTER 3

EXTREME TEMPERATURE AND INTIMATE PARTNER VIOLENCE: EVIDENCE FROM SUB-SAHARAN AFRICA

3.1 Introduction

In recent years, increasing global temperatures and changing weather patterns have severely affected countries with poor infrastructure, where agriculture is the largest employer and there is limited technology adoption to combat these weather fluctuations. Miles-Novelo and Anderson (2019) predict two pathways of violence from global warming. The first is a direct effect of heat on the individual's mood, with increased heat likely to cause irritability and aggressive behaviors. The second is an indirect effect through the reduction of agricultural output, economic instability, natural disasters and displacement of populations that increase the likelihood of violence-prone adults and inter-group conflict. Both channels are likely to affect outcomes of intimate partner violence (IPV) (Rotton and Frey, 1985; Henke and Hsu, 2020; Stevens, 2022). Other indirect effects of temperature highlighted in the literature include alcohol consumption (Cohen and Gonzalez, 2018), income and worker productivity.

This chapter analyzes the relationship between extreme heat/ cold with IPV in Sub-Saharan Africa. It summarizes the relationship between annual average daily temperature and the prevalence of IPV. The analysis examines whether deviations from the expected maximum and minimum temperature in a year have a significant association with the incidence of IPV. Weather fluctuations serve as an exogenous shock, helping to understand the influence of temperature on

IPV. The analysis controls for the indirect economic channel of temperature and violence through variables such as household insulation, nature of partner's economic activity (outdoor versus indoor), and household's ownership of agricultural land. Further analysis using the discomfort index (DI) accounts for dry heat and humidity. The chapter explores changes on the intensive margin through a reduced form estimation of the number of days within the past year in ordered bins of the DI on reported frequency of violence. Throughout the chapter, I examine trends by type of violence (physical, emotional and sexual) separately. The chapter also discusses the marginal effect of annual precipitation on IPV. It tests the heterogeneity of outcomes by risk and protective factors of IPV such as partner's alcohol consumption and women's empowerment (age, education and employment), respectively.

This chapter analyzes outcomes for women aged 15-49 in 22 countries between 2005 and 2018. Using survey-based self reports of IPV from the Demographic Health Surveys (DHS) of women aged 15- 49 and remote sensing data on temperature and precipitation of survey locations, the analysis finds a positive correspondence between unexpected heat in the year prior to survey and prevalence of physical IPV. The prevalence of emotional and sexual acts of violence are lower when heat was higher than the historical average in the year prior to survey. The same pattern emerged when testing the correspondence between days of discomfort from humidity and heat and frequency of each category of IPV. Heterogeneity tests of partner's alcohol consumption shows a higher prevalence of physical, sexual and emotional IPV among women whose partners drink in years of unexpected heat or cold weather.

There exists a vast body of literature that documents the effect of temperature on crime (Anderson and Anderson, 1984; Anderson, 1987; Ranson, 2014; O'Loughlin et al., 2014; Michel et al., 2016; Blakeslee and Fishman, 2018; Prudkov and Rodina, 2019; Cruz et al., 2020; Heilmann et al., 2021; Mukherjee and Sanders, 2021), group-based conflicts (Burke et al., 2009; Hsiang et al., 2013; von Uexkull et al., 2016; Baysan et al., 2018), aggressive behaviors (Boyanowsky et al., 1981; Kenrick and MacFarlane, 1986; Anderson, 1987; Reifman et al., 1991; Yasayko, 2010), and family disturbances (Rotton and Frey, 1985; Stevens, 2022). In addition, there are several studies that demonstrate the impact of rising temperatures on economic outcomes such as agricultural output (Schlenker and Lobell, 2010; Zhu and Troy, 2018) and agricultural productivity (Colmer, 2021; Ortiz-Bobea et al., 2021), the cognitive activity of an individual (Hancock and Vasmatzidis, 2003; Seppänen et al., 2005; Melo and Suzuki, 2019; Graff Zivin et al., 2018; Schmit et al., 2017; Park, 2022), and worker productivity (Graff Zivin and Neidell, 2014; Adhvaryu et al., 2019; LoPalo, 2023).

This chapter adds to the literature that focuses exclusively on domestic violence outcomes (summarized in Table B.1) and aligns closely with multi-country studies such as Zhu et al. (2023) which uses the same datasets to find a positive effect of annual mean temperature on IPV in South Asia; and Cools et al. (2020) that find no significant effects of rainfall shocks on IPV in Sub-Saharan Africa. Building on these results, this chapter contributes in the following ways. First, it empirically tests whether both extreme heat and cold correspond to higher aggression and incidence of IPV. There is a disagreement in the literature on the relationship between temperature and aggression and this chapter examines it in the context of Sub-Saharan Africa. Second, it explores the effects on both prevalence and frequency of IPV.

Section 2 of the chapter theorizes how extreme heat/ cold causes physiological and psychological changes that can lead to IPV, reviews the current literature, and hypothesizes how different risk/ mitigating factors of IPV may interact with temperature. Section 3 describes the data and relationship between temperature and IPV as well as household characteristics by incidence of IPV. Section 4 outlines the empirical specifications, and Section 5 summarizes the results. Section 6 discusses the effect of precipitation and heterogeneity by risk and mitigating factors of IPV. Section 7 concludes with the findings of this chapter and policy recommendations.

3.2 Conceptual framework

Physiological and psychological effects of temperature

Several theories explain the physiological and psychological effects of temperature. The General Affective Aggression Model (Anderson et al., 2000) is a useful overarching framework that outlines how situational factors such as heat can potentially affect a person's internal state through three routes: cognitive state (aggressive thoughts), affective state (feelings of hostility and anger) and arousal state (increasing heart rate). A person may respond in an automatic appraisal (e.g. fight/ flight response) and/or controlled reappraisal (a slower and more thought-out response such as revenge). It is worth noting that temperature may have contradictory effects on arousal: increasing heart rate, blood circulation rate and sweating (physiological arousal) while increasing lethargy (psychological arousal). Therefore, the aggressive behavior emitted would be a function of an individual's aggressive personality and changes in internal state. It is unclear which of the two effects (psychological or physiological arousal) dominates during extreme high and low temperatures. This fosters a disagreement in the literature about the shape of the relationship between temperature and aggression.

Anderson et al. (2000) predict an inverted U shaped function to explain the relationship between temperature and aggression. The Negative Affect Model suggests that at comfortable temperatures, we can expect more crimes outdoors instigated by more outside activity and an increase in sexual desires. When the heat increases to uncomfortable levels, there is more lethargy and higher likelihood that an individual will stay indoors. This can be extended to an M-shaped curve by accounting for similar patterns during extreme cold. In the absence of insulation and air conditioning, however, the uncomfortable temperatures outside match the temperature inside, providing no escape from the situation. Cohn (1993) predicts this will bring victims in contact with offenders. Jacobs (1961) and Straus et al. (1980) discuss the decrease in guardians such as police and "natural surveillance" by the community that increases the likelihood of IPV. The Excitation Transfer/ Misattribution of Arousal theory predicts that temperature-induced aggression can be mis-attributed to another person if temperature is not salient as a cause of arousal and negative feelings dissipate slowly (Zillman, 2008). This implies a U-shaped relationship: aggression would be higher as temperature rises or falls. Berkowitz (1983) also describes a model (uncomfortable weather primes aggressive thoughts) with a similar functional relationship.

Literature review of weather shocks and IPV

The current body of empirical evidence on weather shocks and IPV supports the Misattribution theory as maximum temperatures and droughts are positively associated with prevalence of IPV, in particular physical acts of violence. This effect persists in low- and high-income countries (Table B.1). The literature is restricted to studying effects of either daily maximum temperature or precipitation. Rainfall shocks associated with floods have a positive effect on IPV in some countries in Sub-Saharan Africa and null effect in others. There is no consolidated analysis that examines the effects of both high and low temperatures as well as precipitation. The two sources of data used in the literature to test impacts on IPV are: administrative records of the police department (phone call or in person) and survey-based measures of women's self-reports of IPV (from the Demographic Health Surveys). The weather variables are extracted from a variety of projects processing data from remote-sensing satellites or ground-level monitoring stations.

Effects of precipitation, risk and mitigating factors on IPV

The literature finds a negative relationship between rainfall and crime outdoors (Horrocks and Menclova (2011), Michel et al. (2016)). While the Excitation theory predicts higher IPV in response to heavy rainfall, the chapters on floods and IPV find contrasting evidence. Alcohol consumption is more common on hot days, linked with "mood disturbances" and anger, and expected to compound the effects of extreme temperature on IPV (Cohen and Gonzalez, 2018; Munala et al., 2023). Women's empowerment estimated using relative wages, inheritance rights, age and education can mitigate the effects of temperature-based violence (Abiona and Koppensteiner (2018), Epstein et al. (2020), Henke and Hsu (2020)).

Economic effects of temperature on threshold for violence

Baysan et al. (2018) assume that violence increases with temperature and provide an analytical model to determine the threshold of temperature at which an agent chooses to exercise violence against another agent. This is determined by the present discounted value of an agent's consumption of their initial assets, the value of consumption of initial and captured assets, cost of violence, and labor productivity and the level of violence at every temperature. Using their model, if consumption is as a function of temperature, the estimated threshold of temperature for choosing violence would be different from the case where consumption is independent of temperature (see Appendix). This result implies that households which own agricultural land or earn income from agricultural harvest or farm labor would be affected by temperature differently from households which do not. I control for these expected differences in the analysis.

3.3 Data and Descriptive Statistics

3.3.1 Variables and sources

Prevalence and frequency of IPV

The outcome variables and controls are extracted from the Demographic Health Surveys (DHS) conducted in Sub-Saharan Africa between 2005 and 2019. The survey adopts a stratified two-stage cluster sampling design in which the enumeration areas are generally selected from the country's census and a sample of households is drawn from each enumeration area. The sample is representative at the national level, residence level (rural/ urban) and a regional level (state/ province).

These repeated cross-sectional surveys ask questions about violence from intimate partner to women ages 15-49. Respondents can define who is an intimate partner but it is typically the current/ most recent husband or a partner she is living with as if married or has intimate relations with. Only one woman in the selected household is interviewed about her experience of violence to safeguard the respondent's safety. All DHS rounds that included questions on domestic violence and geolocation data are included in the analysis. Table 3.1 lists the year of survey rounds and number of observations per round.

This chapter examines IPV outcomes for all surveyed women who are currently (ever) married or cohabiting, widowed, divorced or separated. The total number of women included in the sample is 209,123. I define the prevalence of IPV as binary indicators based on respondents' report of any type of physical, sexual or emotional violence from an intimate partner in the last 12 months. The acts of violence under "physical" include pushed, shook or had something thrown by intimate partner, slapped, punched with fist/ hit by something harmful, kicked/ dragged, strangled/ burnt, threatened with knife/gun or other weapon, or had arm twisted/ hair pulled. "Sexual" acts of violence include physically forced into unwanted sex, forced into other unwanted sexual acts or physically forced to perform sexual acts against the respondent's will. Lastly, threat or humiliation by partner, being threatened with harm or insulted and made to feel bad are types of "emotional" violence covered in the survey. Severity of violence is measured as categorical variables of the frequency of physical, sexual and emotional violence - "often", "sometimes" or "not in the last 12 months". Severity of violence is marked as "often in the last 12 months" if at least one activity under the category is reported as often.

Temperature and precipitation estimates

The weather variables are extracted from the European Centre for Medium-Range Weather Forecasts Reanalysis V5 (ERA5) that combines meteorological data with its models to forecast hourly estimates of weather variables for grids of size 30*30 kms at the equator since 1979. The variables include daily maximum, minimum and mean air temperature, dewpoint temperature and total daily precipitation at 2m height from surface. These weather variables are linked to respondents interviewed in the DHS by a unique coordinate for the cluster of households within an enumeration area. The DHS randomly displaces the latitude/longitude by upto 10 kms to preserve the anonymity of respondents. Therefore, I aggregate temperature and precipitation variables within a 10 km radius around the survey coordinates provided for each enumeration area. This can generate a classical measurement error in the estimates.

For each DHS respondent, I estimate the trends in temperature and precipitation upto a year before the date of interview using ERA5 variables. Figure 3.1 reports the "past year" annual and historical averages of maximum, minimum and mean daily temperatures by country-survey-year. The past year annual variable for each respondent is estimated over the 365 (/366) days prior to interview. The historical average is a long term average from 1979 until a year prior to DHS survey round. The past year average maximum and minimum temperature was higher than the historical average in several survey rounds and figure B.1 in Appendix A shows the distribution of normalized deviation of annual maximum and minimum temperatures from the historical average. The dry and dewpoint averages available in the dataset are used to estimate relative humidity and the discomfort index (calculation provided in Appendix B3). Figure B.2 plots the distribution of the index which is expressed in Fahrenheit by construction (Thom, 1959).

3.3.2 Environmental and demographic characteristics correlated with IPV

Relationship between temperature and IPV

I plot the average of mean daily temperature in the past year for every country included in the sample against the percentage of respondents that reported IPV in the country. Figure 3.2 includes a panel each for physical, sexual and emotional violence. These crude country-wise estimates show a downward sloping trend between physical and sexual IPV and mean temperature. There was lower prevalence of physical and sexual violence from intimate partner in countries where the mean temperature was between 25 to 30°C. The relationship between annual estimates of mean temperature and emotional violence is inverse U-shaped. Figure 3.3 plots the country-wise annual average of the DI against prevalence of IPV. There is a clear negative relationship between temperature-and-humidity-based-discomfort and prevalence of sexual IPV. The negative correspondence between DI and prevalence of physical IPV is subtle and there is no relationship between DI and emotional IPV.

Demographic characteristics by incidence of IPV

Violence against women can be understood through a combination of risk factors that increase the likelihood of violence, protective factors that lower the incidence, and situational triggers that precipitate violence (The Prevention Collective, 2020). The literature describes the following as "risk factors": the time of first marriage, age gap with spouse Angelucci (2008), difference in years of education with the spouse (Ackerson et al. (2008), Hornung et al. (1981)), woman and spouse's working status, women's perceived acceptability of spousal violence in the community, spouse's controlling behaviours and consumption of alcohol, her personal history (Heise, 1998) such as witnessing marital violence as a child (Pollak, 2004). While age at the time of survey, years of completed education (Eswaran and Malhotra (2011), Farmer and Tiefenthaler (1997)) and having a female head of household may constitute "protective factors" implying they correspond with lower incidence of IPV.

Table 3.2 reports summary statistics of key demographic characteristics and some risk and protective factors by respondent women's experience of IPV : yes but not in the past year, in the last twelve months, and never experienced IPV. I use the individual weights provided by DHS to generate population relevant estimates. There is no evidence of the relationship predicted in the literature between women and spouse's age gap and IPV, or women's education and employment. However, partner's outdoor employment corresponds with the incidence of violence. Among women that experienced IPV in the past year, 65% had partners working in agriculture, construction or other outdoor occupations. For women who experienced violence but not in the last year, 62% had partners working in outdoor jobs and 58% for women who never experienced IPV. Physical acts of IPV were the most prevalent amongst women having experienced IPV ever or in the past year.

3.4 Analysis

3.4.1 Temperature anomalies and IPV prevalence

I explore the unanticipated effects of extreme temperature using discrete and continuous measures of deviation of the annual average of maximum (minimum). The annual average is calculated as the mean over 365 or 366 days before the interview of each respondent i. These are estimates for the 10 km circular region around the coordinates of each DHS enumeration area e. In the discrete variables estimation, I examine the linear correspondence between unanticipated temperature trends and prevalence of IPV by comparing respondents who experienced 1 standard deviation greater than historical average of annual maximum temperature with the other respondents, and or an annual minimum temperature less than 1 standard deviation of the historical average. The binary indicator $NormDevMax_{ect}$ ($NormDevMin_{ect}$) is equal to 1 when the normalized score of maximum (minimum) temperature is greater (lesser) than 1 (-1), and 0 otherwise. The binary variable $PositiveDev_{ect}$ identifies all observations where $NormDevMax_{ect} > 0$ and $NegativeDev_{ect}$ identifies the observations of $NormDevMin_{ect} < 0$). The outcome variables are the respondent woman i's experience of IPV in category k (physical, emotional and sexual). The model controls for the average $RelativeHumidity_{iect}$ in the past year (calculation in Appendix) as well as various individual-and-household-specific characteristics (X_{iect}) such as rural/urban location, religion, perceptions on the acceptability of spousal violence, partner's controlling behaviors, partner's education, her witnessing violence between mother and father as a child, sex of the head of the household and sex ratio of all household members. The equation controls for differences between countries and survey years through fixed effects, γ_c and τ_t, respectively. Standard errors are clustered at the enumeration area level.

$$\begin{aligned} IPV_{k,iect} = & \alpha_0 + \alpha_1 \mathbb{1}\{NormDevMax_{ect} > 1\} + \alpha_2 PositiveDev_{ect} \\ & + \alpha_3 \mathbb{1}\{NormDevMax_{ect} > 1\} \times PositiveDev_{ect} \\ & + \alpha_4 \mathbb{1}\{NormDevMin_{ect} < -1\} + \alpha_5 NegativeDev_{ect} \\ & + \alpha_6 \mathbb{1}\{NormDevMin_{ect} < -1\} \times NegativeDev_{ect} \\ & + \alpha_7 \overline{RelativeHumidity}_{iect} + \alpha_8' \mathbf{X}_{iect} + \gamma_c + \tau_t + \epsilon_{k,iect} \end{aligned} \tag{3.1}$$

where

$$NormDevMax_{ect} = \frac{AnnualMax_{ect} - \overline{HistMax}_{ec}}{SD_{ec}}$$

and $NormDevMin$ is defined similarly. The following equation uses a continuous indicator to measure the linear correspondence between gap in annual and historical averages and the prevalence of IPV in category k (physical, emotional and sexual) for respondent woman i during that year. Panels A and B of Tables 3.3, 3.4 and 3.5 report results of equations 3.1 and 3.2, respectively.

$$\begin{aligned} IPV_{k,iect} =& \alpha_0' + \alpha_1'(\frac{AnnualMaxTemp}{HistMaxTemp})_{ect} + \alpha_2'(\frac{AnnualMinTemp}{HistMinTemp})_{ect} \\ &+ \alpha_3'\overline{RelativeHumidity}_{iect} + \alpha_4''\mathbf{X}_{iect} + \gamma_c' + \tau_t' + \epsilon_{k,iect}' \end{aligned} \tag{3.2}$$

While column 1 reports estimates of models described above, columns 2-6 include additional controls which may affect how temperature corresponds with IPV. Column 2 tests the hypothesis that households where the male partner's economic activity is outdoors (such as agriculture and construction) would have a significantly different correspondence between temperature and IPV than households where the partner's economic activity is indoors. Column 3 controls for agriculture as a source of income using a binary variable of whether household owns agricultural land. Following the extension of Baysan et al. (2018) in Section 3.2 where the threshold of temperature at which an agent chooses to exercise violence varies when temperature affects consumption, households dependent on agriculture are expected to have a different effect of extreme heat/cold on IPV than others. Their income and consumption are more directly affected by temperature shocks in the past year. Column 4 controls for differences between households by insulation for well-insulated households are likely to be less affected by extreme heat or cold than others. It includes binary variables for insulated roof (eg. thatch, bamboo, wood, sod) and floor (earth, mud, dung, wood, palm/bamboo, ceramic tiles, carpet). Column 5 controls for woman's empowerment which can help mitigate the effect of temperature on IPV. This includes her age, years of completed education, employment status and age at the time of first marriage. Lastly, column 6 controls for survey month to partial out effects from seasons experienced by respondent in past year recall.

3.4.2 Linear correspondence between discomfort index and IPV

The Discomfort Index defined in Thom (1959) helps account for discomfort from both temperature and humidity. An index value greater than 75 is uncomfortable while above 80 is discomfort. Equation 3.3 tests the correspondence between the annual average DI and prevalence of IPV in category k. It includes the same fixed effects and controls as equation 3.1. I use the equation to explore the difference between respondents that experienced "uncomfortable" weather in the past year and the rest.

$$IPV_{k,iect} = \beta_0 + \beta_1 DI_{ect} + \beta_3' \mathbf{X}_{iect} + \gamma_c + \tau_t + \epsilon_{k,iect} \tag{3.3}$$

I next explore the severity of discomfort and frequency of IPV in Table 3.8 by examining a non-linear estimation between the number of days in the following DI bins and frequency of IPV in each category k: 60 or below, 61-65, 66-70, 71-75, 76-80, 81-85, 86-90, above 90. Equation 3.4 below describes an ordered logistic regression where for each category k, the dependent variable is 0 in case of "no incidence of violence in last 12 months", 1 in case of experience "sometimes" and 2 for ”often in the last 12 months”.

$$FreqIPV_{k,iect} = \sum_{b=1}^{B} \delta_{kb} DIbin_{b,ect} + \theta_k' \mathbf{X}_{iect} + \gamma_c + \tau_t + \epsilon_{k,iect} \tag{3.4}$$

The coefficient δ_{kb} for each equation k (physical/ sexual/ emotional) would estimate the expected increase in the log odds of the severity of violence k in past year from an additional day in DI bin b in the past year t for respondent i. The model includes fixed effects for country and survey round, and the standard errors are clustered at the enumeration area level.

3.5 Results

3.5.1 Deviations in extreme temperatures and IPV

Panel A of Table 3.3 shows that women who experienced higher than the expected maximum temperatures were more likely to report experiencing some form of physical violence from their intimate partner. There is no significant difference in (physical) IPV prevalence between observations where the annual minimum was below the expected average. Panel B reports estimates of the continuous measure of the ratio of annual to historical averages. The ratio of annual to historical maximum temperature has a statistically insignificant relationship with the prevalence of physical acts of IPV. However, an increasing ratio of annual to historical minimum temperatures, suggesting more ambient temperatures in the last year, corresponded with lower prevalence of physical IPV. This pattern is reversed for emotional acts of violence where deviations from the historical maximum (discrete and continuous measures) correspond with lower prevalence of emotional acts of IPV.

In case of sexual IPV, while observations where the maximum temperature in the last year was at least 1 standard deviation higher than the expected average correspond with lower prevalence of IPV, there is a positive correspondence between the continuous measure of gap between annual and historical average and the outcome variable. higher maximum temperatures recorded relative to the historical maximum.

3.5.2 Robustness checks for extreme weather and IPV prevalence

While these estimations control for relative humidity in the past year, it is difficult to interpret how uncomfortable the rising ratio of annual maximum (minimum) to historical maximum (minimum) are for the surveyed households. Therefore, I estimate the correspondence between IPV prevalence and discomfort from both rising temperature and humidity (Table 3.6). The continuous indicator of weather based discomfort has a negative correspondence with the prevalence of emotional and sexual acts of IPV. This is consistent with the negative correspondence between IPV and deviation from historical maximum temperatures suggesting that as discomfort from rising heat and humidity increases, women are less likely to report having experienced humiliation, threats, forced to have sex/ perform unwanted sexual acts. While there is no significant correspondence between the continuous indicator DI and physical IPV, there is higher prevalence among respondents that experienced DI of uncomfortable levels (≥ 75) in the last year than the rest.

Table 3.7 controls for mean temperature and the estimated discomfort index on the day of survey to account for reporting bias from the weather conditions on when respondents were interviewed. The estimation includes the full set of controls tested earlier such as demographic characteristics, results for physical and sexual violence are consistent with the linear correspondence between unanticipated weather extremities/ DI and prevalence of physical IPV. The prevalence of emotional IPV is significantly lower for both discrete and continuous measures of deviations from the expected historical averages as well as DI.

3.5.3 Days of discomfort and frequency of violence

Examining the intensity of temperature based discomfort on the frequency of reported IPV using the ordered logit in equation 3.4 shows that as the number of days in the higher intervals of the DI increase for a respondent, she reports a higher frequency of physical IPV while the frequency of reported sexual and emotional violence reduces with increased days of uncomfortable weather (DI above 75). Further decomposing the frequency of IPV as binary variables of extreme severity (often versus sometimes or not in the last 12 months) and moderate severity (sometimes versus not in the last 12 months) reveals that these patterns are largely driven by moderate severity of violence. While there is higher likelihood of severe acts of physical and sexual violence with more days of weather-based discomfort in the past year, the correspondence between severe emotional violence and days of discomfort is insignificant. The coefficients in the following tables are reported as odds ratio.

3.5.4 Rainfall shocks and IPV

The literature examining rainfall shocks and IPV finds contrasting evidence on the correspondence between excessive rainfall (or floods) on self-reported IPV. Díaz and Saldarriaga (2023) and Cools et al. (2020) find null effect of floods while Munala et al. (2023) finds a positive correspondence with IPV. Estimating the marginal effect of annual mean precipitation on IPV in the past year for each country-survey wave using an ordinary least squares regression suggests that as the average annual precipitation increases, the marginal effect of rainfall on physical and emotional IPV declines (Figure 3.4). For emotional acts of violence, at higher levels of annual rainfall, there is a decline in emotional violence with a unit increase in rain in mm. For physical acts of violence, the effect of rainfall on violence is smaller at higher levels of annual rainfall but positive. In case of sexual IPV, higher levels of annual rainfall correspond with an increase in the marginal effect of rain on IPV (negative to positive).

3.5.5 Risk and mitigating factors of IPV

It is well established in the literature that partner's alcohol consumption exacerbates the likelihood of IPV (Kwagala et al. 2013; Devries et al. 2014; Kaufman et al. 2014; Adjah and Agbemafle 2016; Curtis et al. 2019). A heterogeneity test of IPV prevalence by partner's alcohol consumption is consistent with the hypothesis that alcohol consumption would exacerbate temperature-induced violence. Table 3.11 shows that for respondents experiencing minimum temperatures lower than the historical average by at least 1 standard deviation were more likely to report experience of physical, sexual and emotional violence from their intimate partner than the comparison group which either did not experience this weather extremity or whose partner does not drink. For temperatures higher than the historical average by 1 standard deviation, partner's alcohol consumption corresponded with higher likelihood of emotional violence. Increasing discomfort from head and humidity interacted with partner's alcohol consumption corresponds with lower sexual violence.

Heterogeneity tests of variables documented in the literature as significantly correlated with women's empowerment show there is lower prevalence of physical and sexual IPV for older women. Increasing age corresponds with more reports of physical and emotional violence for women who experienced maximum temperatures larger than the historical average by 1 standard deviation. Years of education correspond with higher prevalence of emotional and sexual violence in years of extreme heat. There exists conflicting evidence on the relationship between women's employment and experience of IPV in the literature. Evidence from developed countries finds that an increase in employment and access to resources reduces the likelihood of IPV for women (Bowlus and Seitz, 2006; Aizer, 2010; Anderberg et al., 2016). Studies in low-income countries find the opposite effect (Bloch and Rao, 2002; Eswaran and Malhotra, 2011; Bobonis et al., 2013; Heath, 2014), implying that this relationship may be context specific (Bhalotra et al., 2020). Respondent's employment has neither exacerbating or mitigating correspondence with outcomes of violence in extreme heat. However, in years of extreme cold weather, women's age and employment correspond with lower prevalence of physical and sexual violence.

3.6 Conclusion

With increasing weather extremes caused by global warming and climate change, there has been a concerted push towards studying outcomes on the economy and society as well as public policy measures to help mitigate these effects. What is overlooked are the distributional effects of these weather changes on women. The negative spillover effects of extreme hot or cold days on women include the displacement of weather-induced aggression of the partner on her. Extreme weather is also likely to force individuals to retreat indoors and increase exposure to their intimate partner. The reduced mobility and limited social interactions can result in perverse outcomes of domestic violence. Evidence from the pandemic shows an increased severity of violence such as physical assault during lockdown (Gibbens et al. 2021; Nesset et al. 2021; Olufunmilayo et al. 2021; Glowacz et al. 2022). Therefore, it is critical to examine the effects of such weather shocks on women's experience of IPV.

In this chapter, I use self-reported data on the incidence and frequency of IPV in the last year and combine it with weather information during the recall period to test if there is any correspondence between unexpected weather fluctuations and the prevalence of IPV. While extreme heat is correlated with more women reporting physical acts of violence from their intimate partner, there is a decline in the prevalence of emotional and sexual acts of violence. This result is consistent when I examine the severity of weather-based discomfort and frequency of IPV. Interaction with risk and mitigating factors of IPV shows that women whose partners consume alcohol are more likely to report physical, sexual and emotional IPV when faced with extreme weather. Women's age and years of completed education interacted with unanticipated heat correspond with higher reports of physical, emotional and sexual violence. On the other hand, the interaction of age and employment with uncharacteristic lower temperatures in a year correspond with lower prevalence of physical violence. Sexual violence increases with age and falls with respondent's employment during these cold years.

Given the data constraints of an annual recall of violence and absence of longitudinal data, this chapter is unable to test for causal effects of extreme temperature on violence. Partialling out the indirect effect of temperature on IPV through economic channels is also an important analysis outside the scope of this chapter. This manuscript provides useful descriptive evidence of how temperature and precipitation correlate with IPV and is a useful starting point to motivate the study of gender dynamics in the context of climate change.

3.7 Figures and Tables

3.7.1 Figures

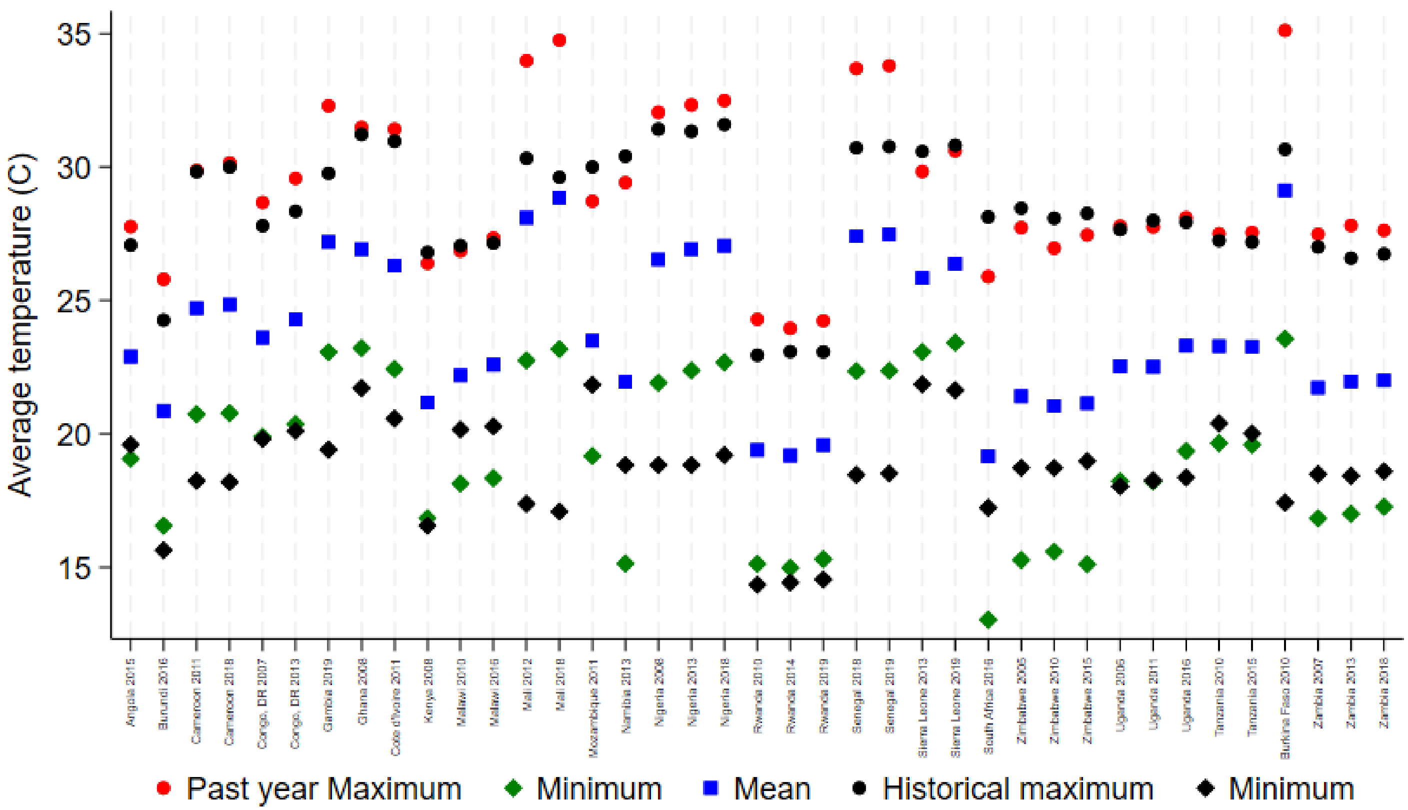

Figure 3.1: Annual and historical averages of maximum, mean and minimum temperature (°C) of DHS countries included in analysis

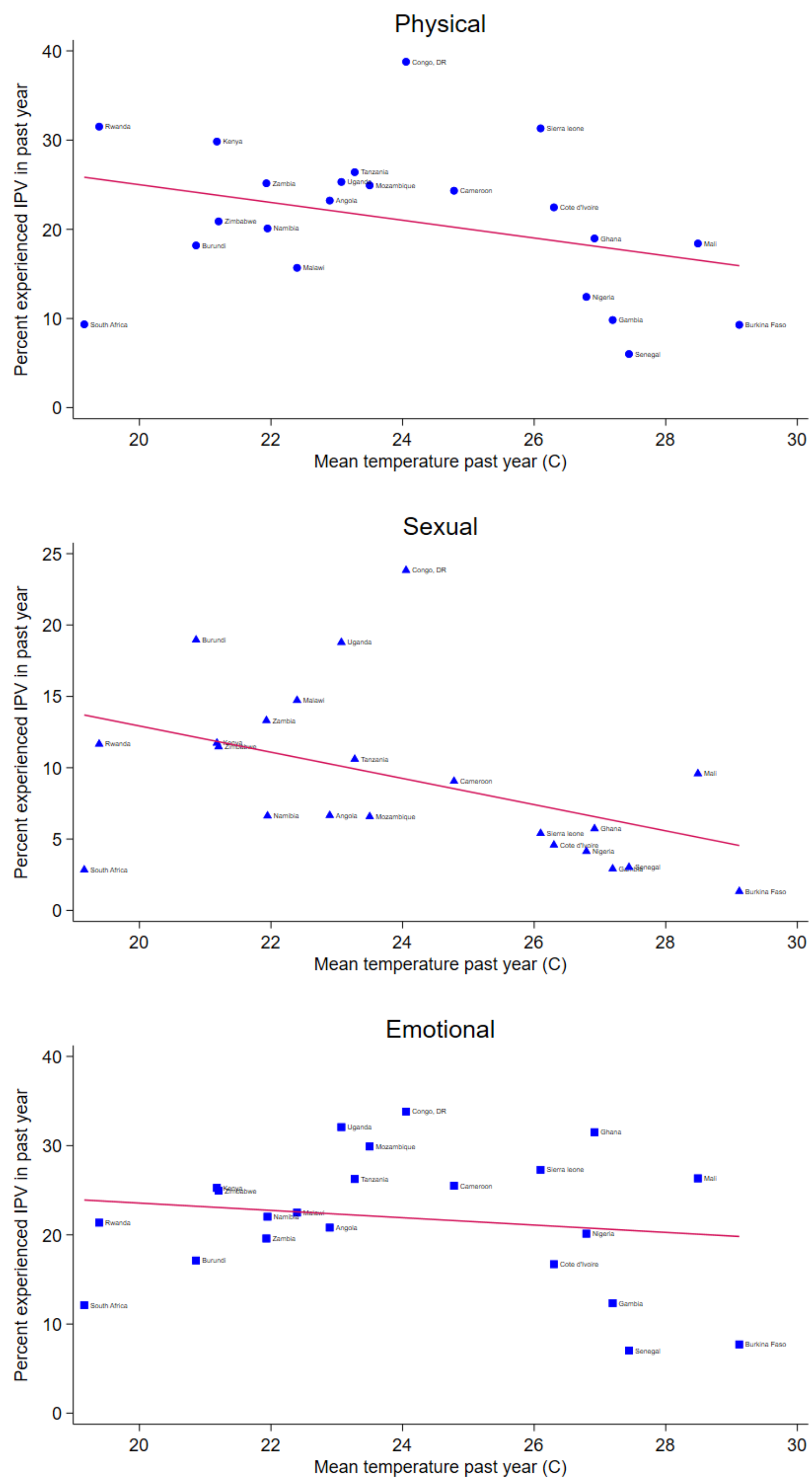

Figure 3.2: Country-wise relationship between annual mean temperature and IPV prevalence

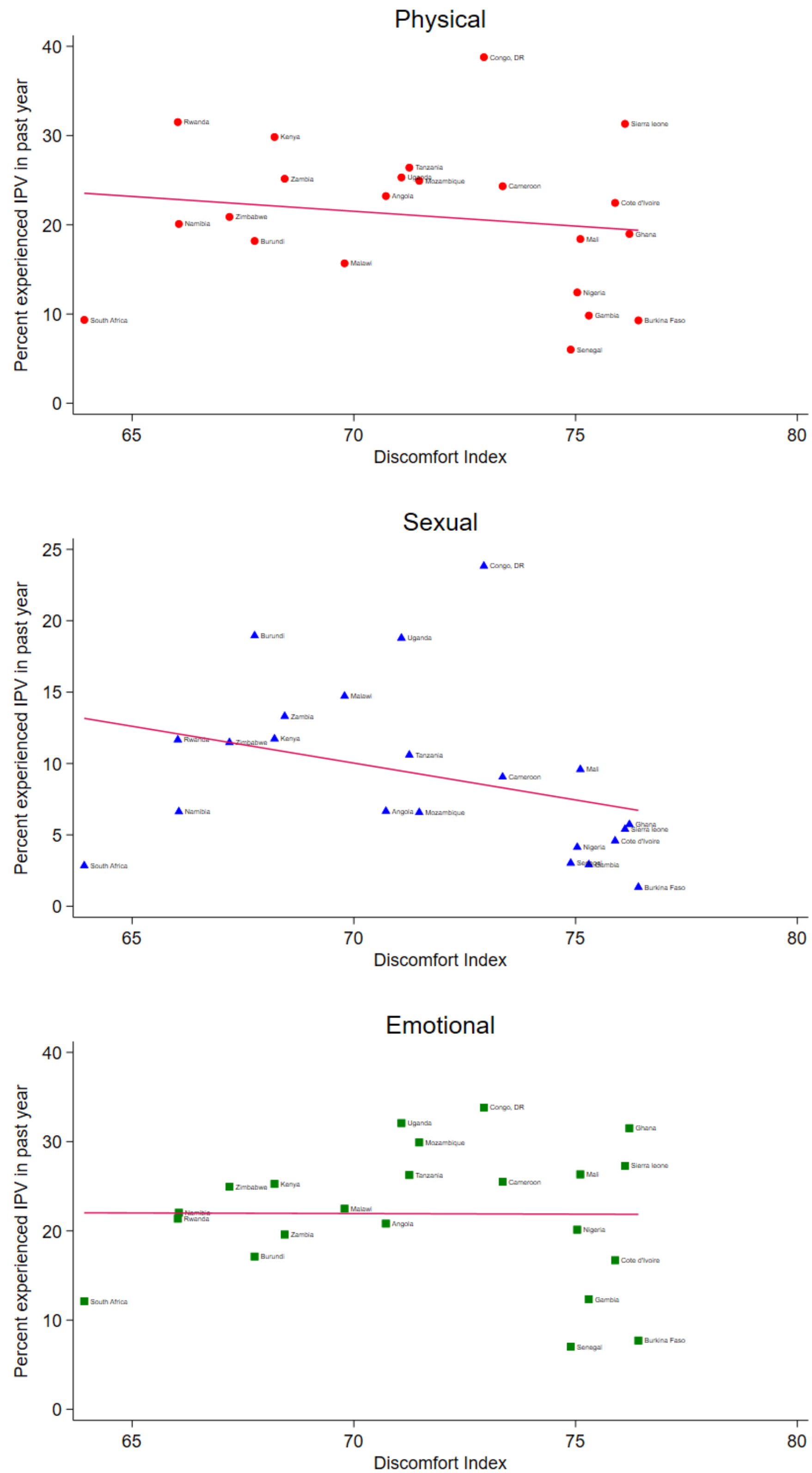

Figure 3.3: Country-wise relationship between Discomfort Index and annual IPV prevalence

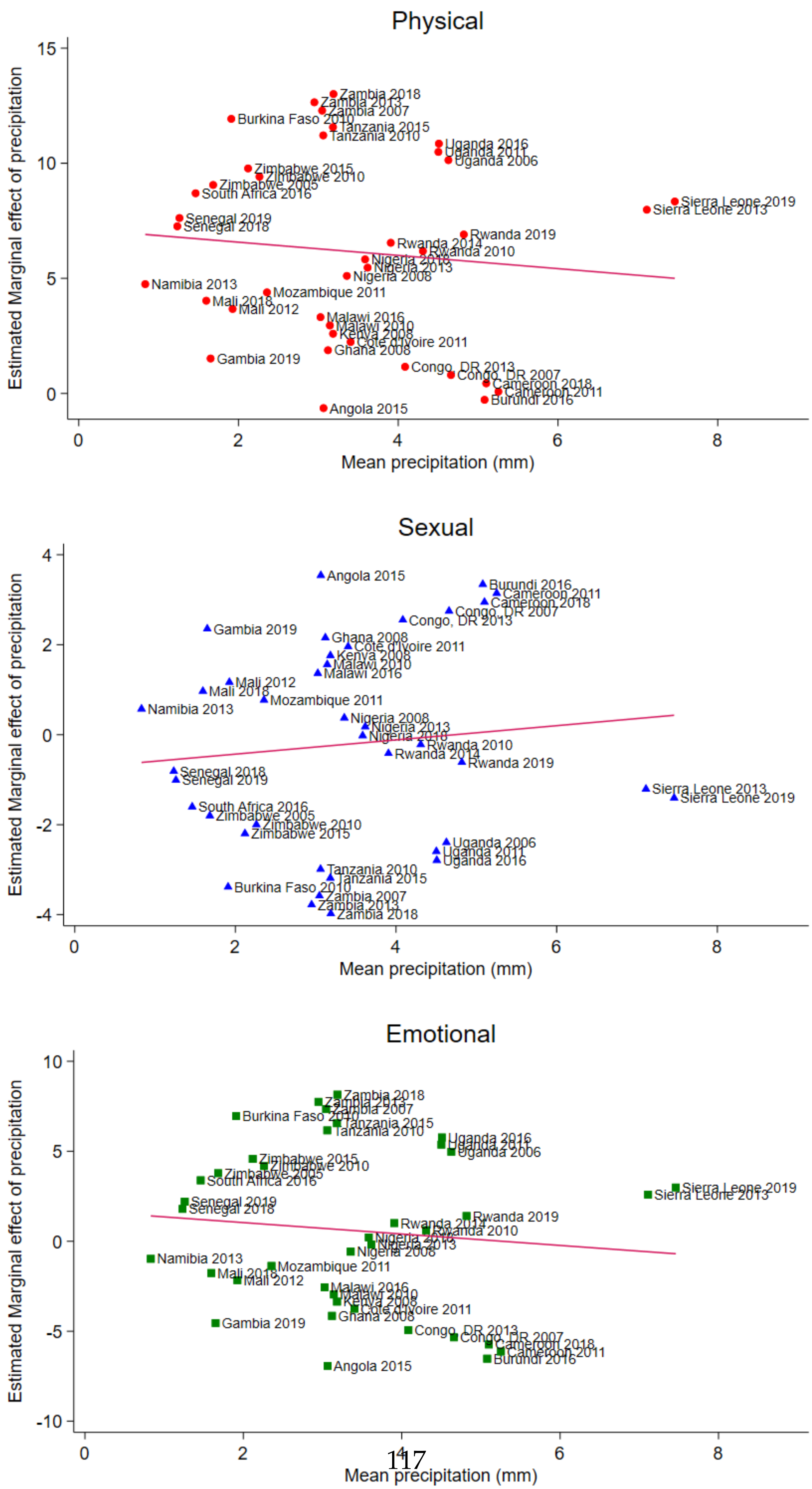

Figure 3.4: Marginal effect of precipitation on IPV by annual mean precipitation

3.7.2 Tables

Table 3.1: DHS survey rounds included in analysis

Country	Survey Years	Sample
Angola	2015	7,669
Burkina Faso	2010	9,340
Burundi	2016	7,338
Cameroon	2011 // 2018	4,003 // 4,690
Côte d'Ivoire	2011	4,874
Congo, Dem. Rep.	2007 // 2013	2,795 // 5,211
Gambia	2019	1,953
Ghana	2008	1,798
Kenya	2008 // 2014	4,888 //4,519
Malawi	2010 // 2016	5,254 // 5,406
Mali	2012 // 2018	3,120 // 3,356
Mozambique	2011	5,824
Namibia	2013	1,449
Nigeria	2008 // 2013 // 2018	19,389 // 22,101 // 8,835
Rwanda	2010 // 2014 // 2019	3,476 // 1,908 // 1,852
Senegal	2018 // 2019	1,506 // 1,468
Sierra Leone	2013 // 2019	4,315 // 3,917
South Africa	2016	2,354
Tanzania	2010 // 2015	5,490 // 7,597
Uganda	2006 // 2011 // 2016	1,600 // 1,686 // 7,416
Zambia	2007 // 2013 // 2018	4,246 // 9,383 // 7,224
Zimbabwe	2005 // 2010 // 2015	4,963 // 5,096 // 4,333

Notes: The sample includes women aged 15 to 49 who have been married, cohabiting (currently or ever), divorced, separated or widowed at least once and were interviewed about experience of IPV in the DHS survey.

Table 3.2: Pooled statistics of households by experience of IPV

	Last 12 months		Yes but not last year		Never	
	Mean	SD	Mean	SD	Mean	SD
Household size	7.280	4.467	8.335	5.634	8.269	5.655
Household sex ratio	1.446	1.129	1.439	1.081	1.449	1.110
Household head female	0.212	0.409	0.300	0.458	0.246	0.431
Religion: Christian	0.384	0.486	0.349	0.477	0.310	0.463
Religion: Muslim	0.609	0.488	0.646	0.478	0.684	0.465
Religion: Other	0.005	0.074	0.007	0.081	0.007	0.083
Respondent: Age	31.515	7.981	34.828	8.239	32.359	8.692
Respondent: Education	3.959	4.405	3.700	4.374	3.831	4.749
Respondent: Employed	0.805	0.396	0.840	0.366	0.741	0.438
Spouse: Age	40.364	11.437	43.922	11.437	42.031	12.308
Spouse: Education	4.939	5.291	4.537	5.296	4.574	5.462
Spouse: Indoor employment	0.274	0.446	0.300	0.458	0.334	0.471
Spouse: Outdoor employment	0.651	0.477	0.622	0.485	0.580	0.494
Rural	0.608	0.488	0.609	0.488	0.581	0.493
Physical violence	0.218	0.413	0.356	0.479	0.644	0.479
Sexual violence	0.057	0.233	0.083	0.275	0.917	0.275
Emotional violence	0.210	0.407	0.083	0.275	0.720	0.449
N	66,895		18,277		122,143	

Notes: First two columns report summary statistics for households where interviewed woman report having experienced IPV but not in the past year. The next two columns summarize households where the respondent woman experienced IPV in past year and the last two columns are for households where the woman never experienced IPV. The sample includes women between ages 15 and 49 that have been married or in a union at least once. These are pooled estimates of all DHS survey waves included in the analysis (see Table 3.1). They use survey weights provided by the DHS for representativeness of the interviewed woman to the country population.

Table 3.3: Unanticipated temperature trends in past year and physical IPV prevalence

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Normalized deviation from historical average						
Normalized deviation of max temperature > 1 SD	0.015**	0.015**	0.015**	0.015**	0.015**	0.016**
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Normalized deviation of min temperature < -1 SD	-0.001	-0.003	-0.001	0.000	-0.002	-0.002
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Constant	0.029*	0.019	0.034**	0.018	0.085***	0.084***
	[0.015]	[0.015]	[0.015]	[0.015]	[0.016]	[0.016]
Panel B: Ratio of annual temperature to historical average						
Max temp past year/Historical max	-0.051	-0.031	-0.051	-0.055	-0.030	-0.030
	[0.040]	[0.041]	[0.041]	[0.040]	[0.042]	[0.042]
Min temp past year/Historical min	-0.192***	-0.198***	-0.204***	-0.195***	-0.222***	-0.222***
	[0.021]	[0.022]	[0.021]	[0.021]	[0.022]	[0.022]
Constant	0.422***	0.398***	0.449***	0.419***	0.501***	0.500***
	[0.038]	[0.039]	[0.040]	[0.038]	[0.040]	[0.040]
Observations	161693	153714	159937	161693	151300	151300

Notes: The dependent variable is a binary variable for whether respondent experienced physical violence in the last 12 months at least once. Panel A reports estimates from equation 3.1 and Panel B from 3.2. Standard errors clustered at the survey enumeration area level are reported in brackets. Columns 2-6 include controls such as partner's economic activity is indoors (2), household owns agricultural land (3), household has insulated roof (eg. thatch, bamboo, wood, sod) or floor (earth, mud, dung, wood, palm/bamboo, ceramic tiles, carpet) (4), women's age, years of completed education, employment status and age at the time of first marriage (5), and survey month (6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: Unanticipated temperature trends in past year and emotional IPV prevalence

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Normalized deviation from historical average						
Normalized deviation of max temperature > 1 SD	-0.028***	-0.029***	-0.029***	-0.028***	-0.031***	-0.030***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Normalized deviation of min temperature < -1 SD	-0.009	-0.011*	-0.009	-0.009	-0.014**	-0.014**
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Constant	0.111***	0.114***	0.111***	0.106***	0.126***	0.115***
	[0.017]	[0.018]	[0.018]	[0.017]	[0.018]	[0.019]
Panel B: Ratio of annual temperature to historical average						
Max temp past year/Historical max	-0.259***	-0.252***	-0.263***	-0.263***	-0.244***	-0.243***
	[0.050]	[0.051]	[0.050]	[0.050]	[0.051]	[0.051]
Min temp past year/Historical min	-0.033	-0.040	-0.045	-0.035	-0.053*	-0.056**
	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]
Constant	0.495***	0.496***	0.520***	0.497***	0.517***	0.509***
	[0.048]	[0.050]	[0.050]	[0.048]	[0.051]	[0.051]
Observations	161692	153712	159936	161692	151298	151298

Notes: The dependent variable is a binary variable for whether respondent experienced emotional violence in the last 12 months at least once. Panel A reports estimates from equation 3.1 and Panel B from 3.2. Standard errors clustered at the survey enumeration area level are reported in brackets. Columns 2-6 include controls such as partner's economic activity is indoors (2), household owns agricultural land (3), household has insulated roof (eg. thatch, bamboo, wood, sod) or floor (earth, mud, dung, wood, palm/bamboo, ceramic tiles, carpet) (4), women's age, years of completed education, employment status and age at the time of first marriage (5), and survey month (6).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: Unanticipated temperature trends in past year and sexual IPV prevalence

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Normalized deviation from historical average						
Normalized deviation of max temperature >1 SD	-0.010**	-0.012***	-0.011**	-0.010**	-0.012***	-0.012**
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Normalized deviation of min temperature <-1 SD	0.007	0.007	0.007	0.007	0.005	0.005
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Constant	-0.008	-0.009	-0.011	-0.014	0.013	0.009
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.012]
Panel B: Ratio of annual temperature to historical average						
Max temp past year/Historical max	0.065**	0.081***	0.070**	0.060**	0.095***	0.095***
	[0.030]	[0.030]	[0.030]	[0.030]	[0.030]	[0.030]
Min temp past year/Historical min	0.004	0.002	0.005	0.002	-0.010	-0.011
	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]
Constant	-0.081***	-0.100***	-0.093***	-0.079***	-0.079***	-0.082***
	[0.028]	[0.029]	[0.029]	[0.028]	[0.029]	[0.029]
Observations	161666	153689	159910	161666	151276	151276

Notes: The dependent variable is a binary variable for whether respondent experienced sexual violence in the last 12 months at least once. Panel A reports estimates from equation 3.1 and Panel B from 3.2. Standard errors are clustered at the survey enumeration area level are reported in brackets. Columns 2-6 include controls such as partner's economic activity is indoors (2), household owns agricultural land (3), household has insulated roof (eg. thatch, bamboo, wood, sod) or floor (earth, mud, dung, wood, palm/bamboo, ceramic tiles, carpet) (4), women's age, years of completed education, employment status and age at the time of first marriage (5), and survey month (6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Uncomfortable weather and prevalence of IPV

	Physical		Emotional		Sexual	
	(1)	(2)	(3)	(4)	(5)	(6)
Discomfort Index	0.001		-0.003***		-0.002***	
	[0.001]		[0.001]		[0.000]	
Uncomfortable (DI>=75)		0.009**		-0.011**		-0.009***
		[0.004]		[0.005]		[0.002]
Constant	0.098**	0.149***	0.328***	0.081***	0.162***	0.028***
	[0.040]	[0.011]	[0.046]	[0.011]	[0.029]	[0.008]
Sharpened q values	0.03	0.009	0.001	0.01	0.001	0.001
Observations	150099	150099	150097	150097	150075	150075

Notes: The dependent variable is a binary variable of experiencing violence in the past 12 months at least once. Controls include - household size, sex ratio of household members, household head is female, household is christian, household located in rural area, household owns agricultural land for rent/ cultivation, household has insulated floor and walls, years of completed education of partner, partner has controlling behaviors, partner's employment activity is outdoors, respondent witnessed father beating mother as a child, respondent's views of the acceptability of IPV, her current age, age at the time of first marriage, years of completed education and whether she works. Standard errors are clustered at survey enumeration area level are reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Temperature on survey date and prevalence of IPV

	Physical			Emotional			Sexual		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Normalized deviation of max >1 SD	0.019***			-0.026***			-0.016***		
	[0.006]			[0.008]			[0.005]		
	(0.003)			(0.003)			(0.003)		
Normalized deviation of min <-1 SD	-0.007			-0.021***			0.009*		
	[0.006]			[0.007]			[0.005]		
	(0.108)			(0.004)			(0.046)		
Max temp past year/Historical max		-0.035			-0.246***			0.095***	
		[0.042]			[0.052]			[0.030]	
		(0.143)			(0.001)			(0.003)	
Min temp past year/Historical min		-0.219***			-0.056*			-0.009	
		[0.022]			[0.029]			[0.015]	
		(0.001)			(0.001)			(0.196)	
Discomfort Index			0.000			-0.001*			-0.002***
			[0.001]			[0.001]			[0.000]
			(0.32)			(0.046)			(0.001)
Constant	0.107***	0.509***	0.163***	0.179***	0.584***	0.179***	-0.036**	-0.084***	0.141***
	[0.022]	[0.043]	[0.034]	[0.027]	[0.053]	[0.040]	[0.016]	[0.030]	[0.025]
Observations	150099	150099	150099	150097	150097	150097	150075	150075	150075

Notes: The dependent variable is a binary variable of experiencing violence in the past 12 months at least once. Columns 1-9 replicate results in Tables 3.3, 3.4, 3.5 and 3.6 with the addition of a control for mean temperature or DI on the day of interview. Other controls include - household size, sex ratio of household members, household head is female, household is christian, household located in rural area, household owns agricultural land for rent/ cultivation, household has insulated floor and walls, years of completed education of partner, partner has controlling behaviors, partner's employment activity is outdoors, respondent witnessed father beating mother as a child, respondent's views of the acceptability of IPV, her current age, age at the time of first marriage, years of completed education and whether she works. Standard errors are clustered at survey enumeration area level and reported in square brackets. Sharpened q values in round brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3.8: Days of discomfort and frequency of IPV

	Physical	Emotional	Sexual
	(1)	(2)	(3)
Num of days DI=60 and below	1.000	1.000	0.999
	[0.001]	[0.001]	[0.001]
Num of days DI between 66 & 70	1.001***	1.001***	1.000*
	[0.000]	[0.000]	[0.000]
Num of days DI between 71 & 75	1.001***	1.000	1.000
	[0.000]	[0.000]	[0.000]
Num of days DI between 76 & 80	1.001**	0.999***	0.999***
	[0.000]	[0.000]	[0.000]
Num of days DI above 80	0.998***	1.001	0.998*
	[0.001]	[0.001]	[0.001]
Observations	150214	150078	150120

Notes: The dependent variable is a categorical variable of frequency of violence (not in past 12 months, sometimes or often). Controls include - household size, sex ratio of household members, household head is female, household is christian, household located in rural area, household owns agricultural land for rent/ cultivation, household has insulated floor and walls, years of completed education of partner, partner has controlling behaviors, partner's employment activity is outdoors, respondent witnessed father beating mother as a child, respondent's views of the acceptability of IPV, her current age, age at the time of first marriage, years of completed education and whether she works. Exponentiated coefficients; Standard errors are clustered at survey enumeration area level are reported in brackets; Reference category omitted: Days between 61 and 65. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: Days of discomfort and IPV often in past 12 months

	Physical (1)	Emotional (2)	Sexual (3)
Num of days DI=60 and below	1.002*	1.001	1.002*
	[0.001]	[0.001]	[0.001]
Num of days DI between 66 & 70	1.000	1.001*	1.002***
	[0.001]	[0.000]	[0.000]
Num of days DI between 71 & 75	1.001	1.000	1.001***
	[0.001]	[0.000]	[0.000]
Num of days DI between 76 & 80	1.000	1.000	1.000
	[0.001]	[0.000]	[0.001]
Num of days DI above 80	0.999	0.999	1.000
	[0.002]	[0.001]	[0.002]
Observations	150214	150078	150120

Notes: The dependent variable is a binary variable of experiencing violence often in the last 12 months relative to sometimes or not at all. Controls include - household size, sex ratio of household members, household head is female, household is christian, household located in rural area, household owns agricultural land for rent/ cultivation, household has insulated floor and walls, years of completed education of partner, partner has controlling behaviors, partner's employment activity is outdoors, respondent witnessed father beating mother as a child, respondent's views of the acceptability of IPV, her current age, age at the time of first marriage, years of completed education and whether she works. Exponentiated coefficients; Standard errors are clustered at survey enumeration area level are reported in brackets; Reference category omitted: Days between 61 and 65. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: Days of discomfort and IPV sometimes in past 12 months

	Physical	Emotional	Sexual
	(1)	(2)	(3)
Num of days DI=60 and below	1.000	1.000	0.998**
	[0.001]	[0.001]	[0.001]
Num of days DI between 66 & 70	1.001***	1.001***	1.000
	[0.000]	[0.000]	[0.000]
Num of days DI between 71 & 75	1.001***	1.000	1.000*
	[0.000]	[0.000]	[0.000]
Num of days DI between 76 & 80	1.001***	0.999***	0.999***
	[0.000]	[0.000]	[0.000]
Num of days DI above 80	0.998***	1.001	0.997**
	[0.001]	[0.001]	[0.001]
Observations	147248	144837	147142

Notes: The dependent variable is a binary variable of experiencing violence sometimes in last 12 months relative to not at all. Controls include - household size, sex ratio of household members, household head is female, household is christian, household located in rural area, household owns agricultural land for rent/ cultivation, household has insulated floor and walls, years of completed education of partner, partner has controlling behaviors, partner's employment activity is outdoors, respondent witnessed father beating mother as a child, respondent's views of the acceptability of IPV, her current age, age at the time of first marriage, years of completed education and whether she works. Exponentiated coefficients; Standard errors are clustered at survey enumeration area level are reported in brackets; Reference category omitted: Days between 61 and 65. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.11: Spouse's alcohol consumption and discomfort on prevalence of IPV

	Physical		Emotional		Sexual	
	(1)	(2)	(3)	(4)	(5)	(6)
Normalized deviation of max > 1 SD * partner drinks	-0.006		0.010**		-0.006	
	[0.005]		[0.004]		[0.005]	
	(0.161)		(0.075)		(0.161)	
Normalized deviation of min < -1 SD * partner drinks	0.010**		0.010*		0.010**	
	[0.005]		[0.006]		[0.005]	
	(0.075)		(0.098)		(0.075)	
DI*partner drinks		0.000		0.001		-0.002***
		[0.000]		[0.001]		[0.000]
	(0.307)		(0.123)		(0.001)	
Partner drinks	0.043***	0.114***	0.004	0.054	0.043***	0.167***
	[0.003]	[0.035]	[0.003]	[0.037]	[0.003]	[0.027]
Constant	-0.012	0.137***	-0.020	0.168***	-0.012	0.020
	[0.012]	[0.029]	[0.024]	[0.035]	[0.012]	[0.021]
Observations	147722	147745	147812	147742	147722	147722

Notes: The dependent variable is a binary variable of experiencing violence in the past 12 months at least once. The table reports heterogeneity in outcome variables by whether the spouse drinks. Only interaction terms and partner's drinking habit are reported in the table but estimation includes binary variable of each normalized deviation. Controls include - household size, sex ratio of household members, household head is female, household is christian, household located in rural area, household owns agricultural land for rent/ cultivation, household has insulated floor and walls, years of completed education of partner, partner has controlling behaviors, partner's employment activity is outdoors, respondent witnessed father beating mother as a child, respondent's views of the acceptability of IPV, her current age, age at the time of first marriage, years of completed education and whether she works. Standard errors are clustered at survey enumeration area level and reported in square brackets. Sharpened q values in round brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.12: Women's empowerment and discomfort on prevalence of IPV

	Physical		Emotional		Sexual	
	(1)	(2)	(3)	(4)	(5)	(6)
Normalized deviation	0.00119***		0.00060**		-0.00012	
of max > 1 SD *	[0.000]		[0.000]		[0.000]	
Respondent's age	(0.001)		(0.041)		(0.461)	
Normalized deviation	0.00041		0.00198***		0.00083**	
of max > 1 SD *	[0.001]		[0.001]		[0.000]	
Respondent's education	(0.397)		(0.003)		(0.048)	
Normalized deviation	-0.00159		-0.00109		0.00136	
of max > 1 SD *	[0.005]		[0.006]		[0.004]	
Respondent works	(0.643)		(0.7)		(0.641)	
Normalized deviation	-0.00073**		-0.00022		-0.00058**	
of min < -1 SD *	[0.000]		[0.000]		[0.000]	
Respondent's age	(0.036)		(0.461)		(0.029)	
Normalized deviation	-0.00038		0.00073		-0.00052	
of min < -1 SD *	[0.001]		[0.001]		[0.001]	
Respondent's education	(0.478)		(0.349)		(0.353)	
Normalized deviation	-0.02149***		-0.00173		0.00819*	
of min < -1 SD *	[0.006]		[0.006]		[0.004]	
Respondent works	(0.001)		(0.643)		(0.078)	
DI * Respondent's age		0.00012***		0.00000		0.00001
		[0.000]		[0.000]		[0.000]
		(0.001)		(0.39)7		(0.478)
DI * Respondent's education		0.00028***		-0.00002***		0.00008**
		[0.000]		[0.000]		[0.000]
		(0.001)		(0.001)		(0.03)
DI * Respondent works		0.00048		0.00049***		-0.00184***
		[0.000]		[0.000]		[0.000]
		(0.301)		(0.001)		(0.001)
Respondent: Age	-0.00198***	-0.01038***	0.00001		-0.00065***	-0.00154
	[0.000]	[0.002]	[0.000]		[0.000]	[0.001]
Respondent: Education	-0.00211***	-0.02298***	-0.00197***		-0.00074***	-0.00653***
	[0.000]	[0.003]	[0.000]		[0.000]	[0.002]
Respondent: Employed	0.02704***	-0.01471	0.03699***		0.01386***	0.15062***
	[0.004]	[0.032]	[0.004]		[0.003]	[0.024]
Constant	0.12899***	0.60655***	0.05692***	0.22380***	0.01570**	0.04932
	[0.011]	[0.063]	[0.012]	[0.033]	[0.008]	[0.049]
Observations	150099	150099	150097	150097	150075	150075

Notes: The dependent variable is a binary variable of experiencing violence in the past 12 months at least once. The table reports heterogeneity in outcome variables by whether the woman is empowered. Only interaction terms and the continuous indicators of empowerment are reported in the table but estimation includes binary variable of each normalized deviation. Controls include - household size, sex ratio of household members, household head is female, household is christian, household located in rural area, household owns agricultural land for rent/ cultivation, household has insulated floor and walls, years of completed education of partner, partner has controlling behaviors, partner's employment activity is outdoors, respondent witnessed father beating mother as a child, respondent's views of the acceptability of IPV, her current age, age at the time of first marriage, years of completed education and whether she works. Standard errors are clustered at survey enumeration area level and reported in square brackets. Sharpened q values in round brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

CHAPTER 4

POLITICAL INCENTIVES AND FLOOD RECOVERY IN INDIA

4.1 Introduction

Discrimination in resource allocation by political ideologies and social identities is widespread in both high- and low-income countries with weak or strong political institutions (Bardhan and Mookherjee, 2012; Stokes et al., 2013; Roland and Raschky, 2014; Himanshu et al., 2015; Ejdemyr et al., 2018; Hessami, 2018). This exchange of public goods, jobs, and other services for votes has been extensively criticized for its negative impact on long-term growth. It incentivizes investment in excludable goods and results in an underprovision of public-goods infrastructure (Persson and Tabellini, 1999; Lizzeri and Persico, 2001; Keefer and Vlaicu, 2008). In lower and middle income countries, these distributive strategies are more difficult to observe given the large gap in demand and supply of public services. However, private transfers become visible in events of extreme calamities such as natural disasters and conflicts.

In the event of a natural disaster, citizens expect governments to respond and provide relief to the public (Schneider, 2011). Leaders are motivated to use this as an opportunity to signal their quality to voters (Ashworth, 2005; Besley, 2006; Ashworth et al., 2018). Garrett and Sobel (2003); Bechtel and Hainmueller (2011); Cole et al. (2012); Lazarev et al. (2014); Bodet et al. (2016); Ashworth et al. (2018) find that voters respond to these signals of competency. The gains are higher if voters are more informed and responsive (Besley and Burgess, 2002; Lazarev et al., 2014). There is evidence of both voters punishing the incumbent because of natural disasters and rewarding them for relief packages. It helps frame this chapter's hypothesis that state governments have the incentive to use relief provision to maximize electoral gains. The literature describes two contrasting model of distributive politics. Political parties have backward-looking incentives to reward their core supporters by targeting investments and relief to the constituencies that elected them (Cox and McCubbins, 1986); and forward-looking incentives to spend resources on voters at the margin (Lindbeck and Weibull, 1987; Dixit and Londregan, 1996; Persson and Tabellini, 1999).

In this chapter, I investigate if post-flood economic recovery corresponds with a constituency's affiliation to the ruling party, whether there is evidence of rewarding voters or vote buying using an ordinary least squares regression that estimates mean difference between flooded and non-flooded constituencies and heterogeneity by election outcomes. Using Earth Observation data from MODIS satellites, I estimate whether a constituency experienced a flood shock: floods larger than 1 standard deviation (SD) of the historical average for that month, and compare it with other constituencies either flooded less than 1 SD or not at all. Instead of using government reports of compensating and rebuilding activities which are inaccurately reported, the analysis examines economic recovery through monthly changes in night time lights. I supplement this with a regression discontinuity analysis testing the causal effect of affiliation on recovery by the discontinuity around the vote margin of the ruling party candidate. Since electricity is critical to public and private infrastructure, it is reasonable to expect it to be restored quickly after any damage. Therefore, I analyze instances of extreme floods and recovery over a short time interval (upto three months) in this chapter. I test these distributive politics for assembly constituencies which elect the state government.

For the floods reported in the Dartmouth Flood Observatory's Global Archive for five states of India during 2008-13, I find that there are no significant differences in economic activity in the aftermath of a flood between flooded and non-flooded constituencies. However, there is variation by electoral outcomes for constituencies affected by a "flood shock": they recover faster (slower) with an increasing margin of loss (victory) for the state ruling party candidate. Swing constituencies do not recover faster, and there is a positive correspondence between the state ruling party's incumbency and proximity to elections with the recovery of a constituency after floods. A causal analysis of post-flood economic activity between constituencies by affiliation with state ruling party yields no significant differences. These findings are subject to some caveats. I use monthly night light estimates as a measure of economic activity. Since night lights only capture economic activity that is correlated with luminosity, I cannot rule out that political connections could lead to differences in post-flood outcomes in non-electrified areas. An analysis of month-by-month trends in nightlights makes it difficult to detect severe but short-lived negative effects. Nonetheless, while state governments may be responding to floods differently in different regions, we cannot conclude that flooded areas experience medium-term economic damages.

The number of people affected by natural hazards and related economic losses has steadily increased in the last decade. According to the Emergency Events Database, 194 million people were affected every year between 2000 and 2022, and the estimated annual losses were USD 140.8 billion (Delforge et al., 2023). Floods occur repeatedly in several parts of India, predominantly from heavy rainfall (NDMA, 2008). Widespread poverty impairs communities to respond effectively in regions affected by floods annually. The state governments of India have autonomy to mitigate and respond to natural hazards. This decentralization gives them the opportunity to adopt strategies customized to local needs and be recognized for them. It is not uncommon in Indian politics to use material benefits to win votes (Chandra, 2004; Bardhan and Mookherjee, 2012). The independent election processes of each state can motivate state governments to discriminate in relief provision.

This chapter advances the literature in four ways. First, it adds to the debate in the political economy literature on distributing politics with evidence from the most populous democracy in the world. Second, it adds to the literature on adaptation to natural hazards in a low-income country. Adaptation in such settings is typically neglected to prioritize poverty reduction and economic development. It tests whether political motives impact how local regions recover from floods while controlling for the underlying scarcity of public services. Third, this chapter speaks to the literature that uses night lights to measure the effect of an event or shock on economic activity (Beyer et al. (2018), Prakash et al. (2019), Chodorow-Reich et al. (2020)). The correlation between night light intensity and GDP levels of a country is well established in the literature (Chen and Nordhaus (2011), Ghosh et al. (2013), Henderson et al. (2012), Storeygard (2016)). Night lights measure the allocation of resources by the government as well as potentially indirect capital provided through private networks. The existing literature on voter appeasement studies government transfers and public works expenditure. This chapter uses night lights as a more holistic measure of the government's influence on recovery from a natural hazard. Fourth, it adds to the literature on the impact of democracy on economic growth and development (Arora et al., 2017; Acemoglu et al., 2019). The chapter examines whether political incentives in democracies lead to unequal disruption in public services that can negatively affect long-term development.

The remainder of the chapter is structured as follows. Section 2.2 describes the conceptual framework that summarizes the literature on voter appeasement using disaster relief, and the background of decentralized governance and flood management in India. Section 2.3 describes the data. Sections 2.4 and 2.5 explain empirical models and results. I conclude in section 2.6. Appendix B.1 describes the raw data and B.2 includes supplementary figures and tables.

4.2 Conceptual framework and Background

4.2.1 Distributive politics in relief provision

Discrimination in resource allocation is largely determined by the ability to segregate populations by an identity shared with the elected leader. Ejdemyr et al. (2018) find that public goods provision increases with spatial segregation of ethnic groups in Malawi. A multi-country analysis across almost two decades by Roland and Raschky (2014) shows that (administrative) sub-national regions that are birthplaces of the current head of the state have more intense nighttime luminosity than other regions.

The political ideology of a boundary based on their past voting behavior is another easier way to segregate resources. A political party or elected government may choose a strategy based on its overall performance in the previous election. Curto-Grau et al. (2018) find that allocations to local governments are generous when the regional government (grantor) in Spain expects to face undisputed elections. They target constituencies with swing voters in the likelihood of close elections. Similarly, Frederico (2004) finds evidence of public works expenditure as an increasing function of vote share in Brazil. Municipalities which support the state government are allocated less excludable public goods.

The literature examining voter response to events outside the leaders' control aims to understand voter rationality. Although this chapter focuses on outcomes of flood impact and not election, this literature is useful to frame hypotheses on how state governments in India would respond to floods. Ashworth et al. (2018) theorize a model showing that a disaster can amplify (mute) the effect of the type of incumbent (or competence) on governance outcomes and affect voter's threshold for reelection. More intense disasters increase (decrease) informativeness on the incumbent's competitiveness. A combination of incumbent's competitiveness versus the opposition, effect of the disaster on both informativeness and incumbent's type on government outcomes determine the likelihood of reelection. Huber et al. (2012) reveal biases in retrospective voting through three experiments. They find that voters weigh recent events more than overall performance of the incumbent, are affected by events outside the incumbent's control and can be manipulated through framing to weigh recent events more than overall performance. There is empirical evidence on both voters rewarding incumbents (Cole et al., 2012; Lazarev et al., 2014; Bodet et al., 2016) and punishing them (Achen and Bartels, 2017).

The timing of natural disaster and elections is pertinent. Cole et al. (2012) find that Indian voters reward government's relief provision only for rainfall shocks a year prior to election. In Germany, vote share of incumbent in the year of flooding increased by 7 percentage points: this reward declined by 75% in the election three years later and disappeared in the election seven years after the flood (Bechtel and Hainmueller, 2011).

The literature motivates the expectation that Indian state governments would use floods as an opportunity to maximize their electoral gains. However, with limited budget, it is unclear if aid is prioritized to areas of critical need or, as literature predicts, supporters or voters at the margin. Or, do state governments appease staunch supporters of the opposition instead?

4.2.2 Floods worldwide and in India

Floods are widely prevalent, constituting almost half the natural hazards recorded by EM-DAT in 2019. They caused 43.5% of total deaths from natural disasters worldwide in 2019, impacted the lives of 31 million people and led to losses of almost 37 billion USD. India was the worst affected in terms of number of deaths and total population injured, homeless or otherwise affected (UCLouvain et al., 2019). Floods most commonly occur in the months of June to September in India, when the country receives approximately 80% of its rainfall (NDMA, 2008).

4.2.3 Disaster management authority and funds in India

The state governments have autonomy in management of natural hazards and operate under broad guidelines of the central government. The State Disaster Management Authority (SDMA) is responsible for risk mitigation and recovery.

In the aftermath of a flood, the local leaders and administrative departments implement the flood management program. The immediate response includes identifying areas submerged, deploying rescue teams to evacuate people and providing shelter and amenities to those displaced. While disruption of essential services is resolved quickly, large damages to physical infrastructure and private property may take longer to restore depending on the availability of funds.

The national level government provides financial assistance to the state's management of hazards. All state governments are required to set up State Disaster Response Fund (SDRF), the size of which varies determined by past expenditure on disaster relief. The central government contributes a large share of this corpus (90% in the North-East and Himalayan states and 75% in all others). The SDRF is typically used for immediate relief provision and states rely on national-level funds for larger compensation and restoration (National Disaster Response Fund (NDRF) or the Prime Minister's relief fund). Money from these national funds takes a year or more to be disbursed, and this chapter restricts itself to measuring effects of recovery financed by the SDRF and other local resources.

4.2.4 State elections in India

Elections to form the state government are conducted every five years by the Election Commission of India where the state population is divided into electoral boundaries called assembly constituencies. Each constituency elects a leader (candidate securing the largest number of votes polled) that represents them in the state legislature. The political party with the largest number of seats in the state legislature is invited to form a government and is called the "ruling party".

The theory of swing voters assumes political competition as effectively between two political parties or alliances. Even in constituencies with more than two candidates (political parties), the competition is typically demanded by two. Although India is a multi-party system, the bulk of the electoral competition at the Central and State-level are usually between two political parties or alliances. Regional political parties play a prominent role in state-level elections.

4.3 Data

4.3.1 Flood event

The MODIS Near Real-Time Global Flood Product measures daily flood prevalence globally at 250 metres resolution from 2000 to 2018.[1] It maps floods from the Dartmouth Flood Observatory (DFO): a global archive managed by the University of Colorado. Floods and surface water are estimated from the optical images provided by the two MODIS satellites (Aqua and Terra) that survey the Earth twice daily. I estimate the area of a constituency flooded in each flood event and the mean area flooded in that month since 2000. The latter captures

[1] An earlier manuscript analyzed flood prevalence in 2008-13 using data from the National Remote Sensing Centre (NRSC), a centre of the Indian Space Research Organisation (ISRO). The National and State Disaster Management Authorities of India use the same data source to monitor floods. However, due to the limited years of data publicly available, the current version of this chapter uses the MODIS flood product.

the expected seasonal trend of floods in the constituency. The database includes variables for quality of flood data such as the percentage of cloud-free observations of a unique flood event. It is used control for differences in data quality between flood events. The optical satellite data cannot estimate the height of flood water.

4.3.2 Economic recovery of constituency

I use monthly night light estimates as proxy for infrastructure and economic activity, both of which are impacted in the aftermath of a flood. Klomp (2016) finds that hydrological disasters have a large negative impact on luminosity in developing countries. Night light estimates are a high frequency and spatially compact indicator which are ideal in settings such as this where no high frequency data of a constituency's income is available. The indicator is also free from reporting bias unlike state reports of flood damage that may over-report damages to maximize the receipt of financial assistance.

The data on nighttime luminosity is acquired from the US government's Defense Meteorological Satellite Program's Operation Linescan System (DMSP-OLS). The DMSP-OLS collects the number of lights detected in a region and the light intensity of each location from raw satellite images of approximately 0.86 kms spatial resolution at the equator. The DMSP data is top coded (there is an upper bound for the maximum value of light intensity reported). It captures private sources of lighting, industrial and commercial centers and public amenities. The monthly time series of the average luminosity for each pixel between 2008 and 2013 is produced by the Earth Observation Group, hosted by the Colorado School of Mines. The estimates average all the highest quality observations to correct for cloud cover, solar glare and moonlight. The accuracy of night light estimates may reduce over time with degradation of the satellites' sensors and is controlled for in the analysis.

4.3.3 Political affiliation and other characteristics

I analyze a constituency's election outcomes for the most recent election conducted before a flood event (election years are given in Appendix Table 4.3). The number of votes polled by every contesting candidate and their party affiliation is extracted from the Trivedi Centre for Political Data at the Ashoka University (Bhogale et al., 2013). I use newspaper articles and data published by IndiaVotes to verify the seat share of each political party and alliance in the state legislature. I included alliances announced before elections in "ruling party" if more than one political party formed the government in a state. I do not include post-election alliances (coalitions) in defining ruling party as the latter are indeterminate at the time of voting and can over-estimate the effect of affiliation. I also exclude parties that moved out of the government-forming alliance after the election. The electoral outcomes are merged with information on total population, employment and public infrastructure from the SHRUG dataset (Asher et al., 2020), which collects these indicators from the Population and Economic Census, and the Village Directory of India.

Additional information on the four datasets is given in Appendix B1.

4.4 Voter appeasement in post-flood recovery

This chapter examines the effect of floods and affiliation with the state ruling party on night lights in a constituency. Both flood and electoral outcomes recur during the years of analysis and can "switch" on and off over time. A constituency can be flooded in calendar year t and not flooded in year $t + 1$. Similarly, it may be linked to the state ruling party in year t and elect a member of the opposition party in the next election (year $t + 1$). In this section, I describe a linear regression model to test for correspondence between flood shocks and night lights. I discuss the limitations of the model to estimate a causal effect and other candidate estimators for causal inference. Finally, I explore the heterogeneity in recovery of night lights from flood shocks by electoral outcomes.

4.4.1 Empirical model

In this section, I describe the empirical models used to test: (1) the trends in night time lights before and after floods, (2) the difference in recovery of luminosity between constituencies by their affiliation to the state ruling party, (3) differences by vote share and (4) incumbency. This chapter analyzes 1,271 constituencies over 6 years (2008-13). As per the DFO repository, floods occur repeatedly in the analysis data between 2008 and 2013. Table 4.2 shows that an overwhelming majority of constituencies in the sample recorded more than one flood between 2008 and 2013. Figure 2 maps the mean area of flood for every constituency in the sample by year. On average, most constituencies report less than 20% area flooded every year. I define "flood shock", a binary variable identifying flood events larger than the expected flood in that calendar month, to address the concern of limited variation in the area flooded in a constituency over time. The distribution of the monthly average of nightlights is positively skewed (Fig. 4.1). Therefore, I define the outcome variable as logarithm of average night time luminosity plus 0.01, a specification consistent with the literature (Michalopoulos and Papaioannou, 2013, 2014; Roland and Raschky, 2014).

Flood shocks and recovery of night lights

Equation 4.1 estimates the difference in recovery of the outcome variable between constituencies flooded more than the long-term average and constituencies flooded less than 1 SD difference from this average *or* not at all in month m and year t. A "flood" or "flood event" is the unique flood event identified using the DFO's archive. $FloodShock_{cmt}$ is a binary variable that assigns 1 to constituencies where the difference between area flooded of a constituency c in flood month m and year t and the long-term average for the same constituency c in month m is greater than or equal to one standard deviation, and 0 otherwise. The long-term average is a mean estimate from the start year of the flood data product, 2000, until year $t-1$. A "flood month" includes all the months a unique flood event lasted. The time dummy $Post$ estimates differences in the outcome variable before and after a flood. The equation controls for type of elected leader in the constituency (incumbent or new), information on the constituency's population and infrastructure (roads, electricity, schools) and for differences over time (calendar month-year) and between units (constituency-state). I account for redrawing of electoral boundaries in 2008 by treating constituencies within a state before and after this process (called delimitation) as distinct from one another. The standard errors are clustered at the district level.

$$
\begin{aligned}
Y_{cmt} = &\alpha_1 + \alpha_2 FloodShock_{cmt} + \alpha_3 (FloodShock_{cmt} \times Post_{mt}) \\
&+ \alpha_4 Incumbent_{cmt} + \rho \mathbf{X}_{ct} + \theta_c + \tau_{mt} + \epsilon_{cmt}
\end{aligned} \tag{4.1}
$$

where

$$
FloodShock_{cmt} = \mathbb{1}\{(FloodArea_{cmy} - \overline{FloodArea_{cm,\{2000,t-1\}}}) \geq \sigma_{cm}\}
$$

Note on causal estimation using Difference-in-Difference estimators

The two-way fixed effects (TWFE) model can estimate the causal effect of a flood on night time light in a constituency if the flood event is unanticipated, occurs once, the evolution of night lights between flooded and non-flooded constituencies before the flood is parallel, the effect of flood on night light is homogeneous for all flooded constituencies, and that there are no spillover effects of the incidence of flood in one constituency on night lights of another. The TWFE is an inappropriate model for causal inference in this setting due to the recurrence of floods for most constituencies included in the analysis and limited observations in the sample satisfying the test for parallel trends (results available on request).

It would be useful to to examine the effect of differences in the area of flooding over time if in a constituency is flooded in consecutive years. Callaway, Goodman-Bacon and Sant'Anna (2024) define the difference in the unit's potential outcome with a marginal change in the dose of floods as a causal response while the difference in potential outcome between a positive flood dose d and not-flooded as a level treatment effect (Callaway, Goodman-Bacon and Sant'Anna 2024). A level treatment effect parameter summarizes the overall effect of floods on economic activity and infrastructure. Causal responses help identify which flood dose had a larger effect. A TWFE specification treats the lower-dose units as the comparison group for the higher-dose units (or treatment group). However, it requires the strong assumption of no heterogenous treatment effect across doses. Callaway, Goodman-Bacon and Sant'Anna (2024) propose causal response and levels decompositions using dose as weights for a two-period setting where *units do not anticipate floods in the future*. For multiple time periods and variation in treatment timing, the authors draw on an assumption from Callaway and Sant'Anna (2021) that when a unit is flooded with dose d it remains flooded with d in subsequent years. However, in this chapter's context, a constituency could be flooded in year 1 and not flooded in the next, violating this assumption. Given non-zero doses of floods in consecutive years, flood events may be anticipated and this can bias the effect on the outcome variable. Therefore, in this chapter, I do not use either of the DiD estimator proposed in Callaway and Sant'Anna (2021) and Callaway, Goodman-Bacon and Sant'Anna (2024) to estimate the effect of flooding and different flood doses on nighttime lights.

Variation in post-flood recovery by electoral outcomes

Building on the linear fixed effects estimation in equation 4.1, I explore heterogeneity in post-flood recovery of the outcome variable by constituency's affiliation to the state ruling party. The election outcomes of the most recent election before the flood are included in this analysis. The equation below includes a binary variable $RulingParty_{cmt}$ that is 1 when the constituency elected a leader from the ruling party and 0 otherwise.

$$
\begin{aligned}
Y_{cmt} = \beta_1 + \beta_2 RulingParty_{cmt} + \beta_3 FloodShock_{cmt} + \\
&+ \beta_4 (RulingParty_{cmt} \times FloodShock_{cmt}) \\
&+ \beta_5 (FloodShock_{cmt} \times Post_{mt}) + \beta_6 (RulingParty_{cmt} \times Post_{mt}) \\
&+ \beta_7 (RulingParty_{cmt} \times FloodShock_{cmt} \times Post_{mt}) + \beta_7 Incumbent_{cmt} \\
&+ \rho \mathbf{X}_{ct} + \theta_c + \tau_{mt} + \epsilon_{cmt}
\end{aligned} \tag{4.2}
$$

The regression model above is replicated to explore differences in recovery of nightlights by the vote margin of elected leader and whether it's a swing constituency. These estimates help examine whether the incentive to reward voters or expand voter base corresponds with a faster recovery from floods. The vote margin variable ($margin_{ct}$) is defined as the vote share by which the ruling party candidate won or lost the most recent election before flood in year t in constituency c.

$$
Margin_{ct} = \frac{RC_{ct} - NC_{ct}}{Tot_{ct}} \tag{4.3}
$$

RC_{ct} are the number of votes earned by the ruling party candidate in constituency c in the election prior to flood year t. NC_{ct} are the number of votes earned by the highest scoring candidate not affiliated with the ruling party, and Tot_{ct} are the total number of votes polled in that constituency. When the margin variable is greater than 0, the candidate elected by constituency c is member of the ruling party and when it is less than 0, the elected candidate is not affiliated with the ruling party.

The restoration of infrastructure might be largely explained by the candidate's knowledge of their constituency and prior experience in managing natural disasters. The heterogeneity by candidate and state ruling party's incumbency is reported in Table 4.9.

Since a large portion of the relief is provided from a national-level disaster management corpus or at the Central Government's discretion, I test for differential trends in post-flood recovery by constituency's (or state's) affiliation to the Central Government. Panel A (B) in Table 4.10 estimates equation 4.2 after replacing $RulingParty_{cmt}$ with $Affiliation_{cmt}$, a binary variable identifying constituency's (state's) links with the central government.

All tables report results with varying pre and post-flood time intervals to check for robustness of results.

4.4.2 Results

Coefficient α_3 in equation 4.1 estimates the changes in the outcome variable before and after a flood event between constituencies with floods larger than the expected mean and the rest. Table 4.4 reports these differences upto 3 months before and after the flood by interacting α_3 with a time dummy for each month. Column 2 controls for cloud-free observations of floods and the dependent variable. Using the interaction term for month $t-1$ as a reference category, I find that trends in the outcome variable are similar between flooded and non flooded constituencies over time except for three months prior to the flood event. These results are consistent with Table 4.5 where months are aggregated using a $Post_{mt}$ time dummy that estimates mean changes upto 1, 2 and 3 months after the flood. Columns 1-3 use 1 month before flood in the pre and post comparison while columns 4-6 use 2 months. Across both specifications, constituencies with floods larger than the historical average (by 1 SD) do not exhibit any statistically significant differences in the dependent variable in response to the flood.

Testing for heterogeneity in these aggregate changes shows that one month after a flood, the change in the outcome variable in response to flood is statistically insignificant between constituencies affiliated with the state ruling party and others (Table 4.5). In columns 1-3, the coefficient β_1 estimates the outcome variable in the one month before a flood event for non-flooded constituencies with a candidate not linked with the state ruling party or an incumbent. In columns 4-6, it is the average of two months before the flood event. The $RulingParty_{cmt}$ indicator if correlated with the constant term in columns 1-3. There is a negative correspondence between ruling party affiliation and recovery from an extreme flood shock in the first month after flood event when the pre-flood average of the dependent variable is defined as two months before flood. The mean dependent variable of flooded constituencies affiliated with state ruling party after a flood shock is significantly lower than constituencies that are not linked with the ruling party or assigned 0 for "flood shock". While the trends in the night lights are not significantly different between constituencies flooded greater than expected average and the rest, there is a slower recovery for ruling party constituencies in the first month after the flood. The differences are statistically insignificant when the post-flood analysis is expanded to second and third months after the flood. Table 4.7 explores this different by ruling party affiliation further using the margin variable defined in equation 4.3. A unit increase in the vote margin for the ruling party corresponds with a decline in the outcome variable of flooded constituencies by 75% in the first month post-flood relative to other constituencies affiliated with the state ruling party or experienced a flood greater than the expected average by 1 SD. The decline persists upto two months after flood event for both 1 and 2 months pre-flood reference periods.

Using a local linear regression around the margin variable, I estimate an optimal interval for constituencies that had a close electoral outcomes and define them as "Swing". This included constituencies where the ruling party narrowly won or lost the most recent election to test theories of favoring voters at the margin. Table 4.8 compares differences in the outcome variable between Swing constituencies and others. There are no statistically significant in the months following the flood. Therefore, the ruling party is not likely prioritizing recovery of voters at the margin.

I test for differential trends between constituencies by elected leader's incumbency as the literature suggests that voters punish the incumbent in response to economic and weather shocks but reward relief efforts. An incumbent may have more experience in emergency response and raising funds for disaster mitigation, increasing the likelihood of a faster recovery of their constituency from a flood larger than the expected average by atleast 1 SD. The results in Panel A of Table 4.9 show no systematic differences between constituencies by their elected candidate's incumbency. However, constituencies that witnessed a "flood shock" and where the state ruling party is incumbent witness a faster improvement in the outcome variable than the rest (Panel B). The trend persists with variation in the post-flood time interval.

Next, I explore a constituency and state's affiliation with the Central Government on post-flood recovery of the outcome variable. I find no significant differences by a constituency's affiliation with the Central government (Panel A, Table 4.10). However, there is a lower recovery of the outcome variable in the first month after the flood if the state is affiliated with the Central government. The difference becomes statistically insignificant in the second month after the flood. Given the short-term analysis period, it is reasonable to expect there aren't persistent effects of affiliation with the Central government. As discussed in Section 2.2.3, the Central government is the largest contributor to disaster management funds. However, these are resources for rebuilding and restoration activities of large-scale damages within a state and can take a year or more for disbursal the the states. Meanwhile, essential services (that also influence the outcome variable) may be restored more immediately through funds available with the State.

The timing of election is a significant factor in post-flood recovery. I define the time interval as the year of the most recent election minus the year of flood. The larger this interval, the closer the state is to the next election. This variable is correlated with the year fixed effects included in the analysis. While there are no significant differences in post-flood recovery in the first month by time past between previous election and the flood shock, there is a positive correspondence in aggregate differences in the outcome variable and gap between the election and flood years upto 2 or 3 months after the flood. This suggests that an upcoming election correspond positively with post-flood recovery.

4.5 Causal effect of ruling party affiliation on post-flood recovery

4.5.1 Empirical model

In addition to the effect of floods and interacting politics on the outcome variable varying by amount of flooding, there are additional endogneity concernes in the OLS estimations in section 4.4. First, voters' decision may be correlated with the region's resilience or vulnerability to floods and, therefore, an adaptive strategy. Voters in flood-prone regions might choose a candidate they assume as "more capable" of dealing with the crisis in anticipation of the flood event. Alternatively, they may elect the candidate affiliated to the ruling party, anticipating guaranteed receipt of partisan aid in exchange. Second, the slow recovery of a region can be the result of the elected leader's limitations. Third, distribution of resources to constituencies solely based on how severely they were affected may lead to flooded constituencies having higher median light intensity than not-flooded constituencies in the aftermath of a flood.

I use a regression discontinuity (RD) analysis to address potential reverse causality. If election results within a close margin of votes imply that the victory or loss of the ruling party is random, this method measures the causal effect of political affiliation on the outcome variable for all constituencies which were flooded. I identify constituencies with close election outcomes using the vote margin variable $margin_{ct}$. I assume that constituencies with victory margin scores close to 0 are similar in all characteristics impacting their night light estimates other than their affiliation status. This implies that the outcome variable conditional on election results within a finite interval (or bandwidth, as consistent with the regression discontinuity literature (Kolesár and Rothe (2018), Armstrong and Kolesár (2018), Cattaneo et al. (2020) and Pei et al. (2020)) of the margin variable is continuous. I verify this assumption by running the regression discontinuity analysis on indicators that can affect the outcome variable such as population, employment and access to public infrastructure. I estimate the effect of affiliation to the ruling party on these variables and find no significant effect for all variables. Table 9 reports the regression discontinuity estimates of these variables. I compare the outcome variable, on either side of the critical point ($margin_{ct} = 0$) to estimate the local average treatment effect of a constituency's alignment with the ruling party.

$$Y_{c,t} = \delta_0 + \delta_1 \mathbb{1}\left(margin_{ct} > 0\right) + \delta_2 margin_{ct} + \delta_3 margin_{ct} \times \mathbb{1}\left(margin_{ct} > 0\right) + \\ + \theta_c + \gamma_t + \epsilon_{ct} \quad (4.4)$$

Equation 4.4 estimates the effect of affiliation on log mean night light estimates of all flooded constituencies within an optimal bandwidth of election outcomes. This bandwidth is calculated by minimizing squared errors in a local linear regression estimation around $margin_{ct} = 0$. The regression estimation uses a triangular kernel to place more weight on observations with values closer to the cutoff. The model includes constituency (θ_c) and year fixed effects (γ_t) that control for correlations within constituency and flood year. I use robust standard errors clustered at the level of district, an administrative unit larger than the primary sampling unit (constituency). If recovery in terms of night lights is faster in constituencies affiliated to the ruling party, the coefficient δ_3 will be positive and statistically significant.

4.5.2 Results

In the regression discontinuity analysis, the point estimate of the effect of affiliation on the outcome variable of flooded constituencies is positive but statistically insignificant. Therefore, the post-flood economic activity as measured by night time luminosity is not better for a constituency affiliated to the state ruling party than others. Figure 4.2 plots this estimation for the mean square error minimizing bandwidth. The result is robust to small changes bandwidth size to include constituencies in the analysis (Figure 4.3 and Table 4.12).

4.5.3 Robustness checks

I check for discontinuities in the running variable ($margin_{ct}$) using the McCrary test (Fig. 4.4). The running variable identifies constituencies affiliated with the state ruling party when $margin_{ct} > 0$. By definition, the ruling party has a simple majority in the state legislature. Therefore, as expected, Figure 4.4 shows a larger proportion of constituencies on the right side of the threshold.

Using population and employment characteristics and infrastructure variables that are correlated with night time luminosity such as total households, schools and colleges, power supply and paved roads, Table 4.13 verifies the assumption that constituencies on either side of the threshold are statistically similar in observed characteristics correlated with the dependent variable except the election outcome.

4.6 Conclusion

The evidence in the literature is overwhelmingly in favor of democratic institutions' positive impact on the local economy. Acemoglu et al. (2019) find a positive impact of democracy on economic growth in their multi-country study. Well-functioning and fair institutions that improve equity and reduce patronage are critical for regions prone to natural hazards. Arora et al. (2017) show that elected leaders are more likely to allocate resources in line with citizens' preferences than appointed administrators. However, given limited budgets and the time sensitivity of a natural hazard, local leaders may be forced to discriminate in aid provision. The literature on voter rationality and appeasement by political parties suggests that local leaders have incentives to respond to crises based on which strategy would maximize their electoral gains.

Motivated by this concern, this chapter examines if relief provision is guided by either of the two theories of distributive politics: rewarding supporters or prioritizing voters at the margin. It uses optical satellite images to measure the extent of floods in a state assembly constituency each year between 2008-13 for five states of India. The economic activity and infrastructure restoration is estimated using log of monthly night time luminosity of a constituency. I test the effect of affiliation to the state ruling party on recovery from floods in India using two quasi-experimental methods.

The two-way fixed effects estimation does meet the assumptions for a causal estimation of impact of floods on the outcome variable. Therefore, I explore a linear correspondence between flood shocks (greater than the long-term average by at least 1 SD) and the dependent variable. Using heterogeneity tests, I explore the interaction of election outcomes and flood shocks. I find that affiliation with the state ruling party does not merit faster recovery of economic activity after a flood. There is a negative correspondence between recovery and vote margin. Severely affected constituencies that were staunch opposition (supporter) of the ruling party are likely to recover faster (slower). Therefore, in the short run, state governments are not prioritizing relief to their supporters as one strand of the literature predicts. There are no significant differences in post-flood recovery between swing constituencies and others as suggested by additional heterogeneity tests. While the ruling party's incumbency corresponds positively with faster recovery from a flood, incumbency of the elected candidate does not correspond with differential trends. The proximity of the flood to upcoming election does not reflect in recovery in the first month. However, constituencies severely affected and closer to the election experience larger increases in the outcome variable in the second and third months.

The regression discontinuity analysis tests a causal effect between affiliation with the state ruling party and recovery in economic activity from floods. I find no significant difference by affiliation. The null effects of political affiliation may be driven by the states included in the sample. While this chapter does not disaggregate its analysis by state, there is evidence of state-specific partisanship in the literature. For instance, the analysis of a major public works program in India showed evidence of preferential resource allocation in the state of Rajasthan where more work was allocated to villages where the local elected head resided (Himanshu et al., 2015). Meanwhile, Sheahan et al. (2016) found no political effects of the same program in Andhra Pradesh.

While this chapter opens the door for further examination of ex-post measures by the government in low-income settings, the literature on allocation of federal aid for electoral gains in the US (Garrett and Sobel, 2003; Reeves, 2011) highlights this as a relevant question for both high and low income countries. Discrimination in risk management activities and relief provision by the state is likely to exacerbate inequality and slow down adaptation to recurring natural hazards. As adaptation to climate change and natural hazards becomes increasingly necessary in different parts of the world, it is important to understand the factors that affect the community's and state's preparedness and recovery.

4.7 Figures and Tables

Figures

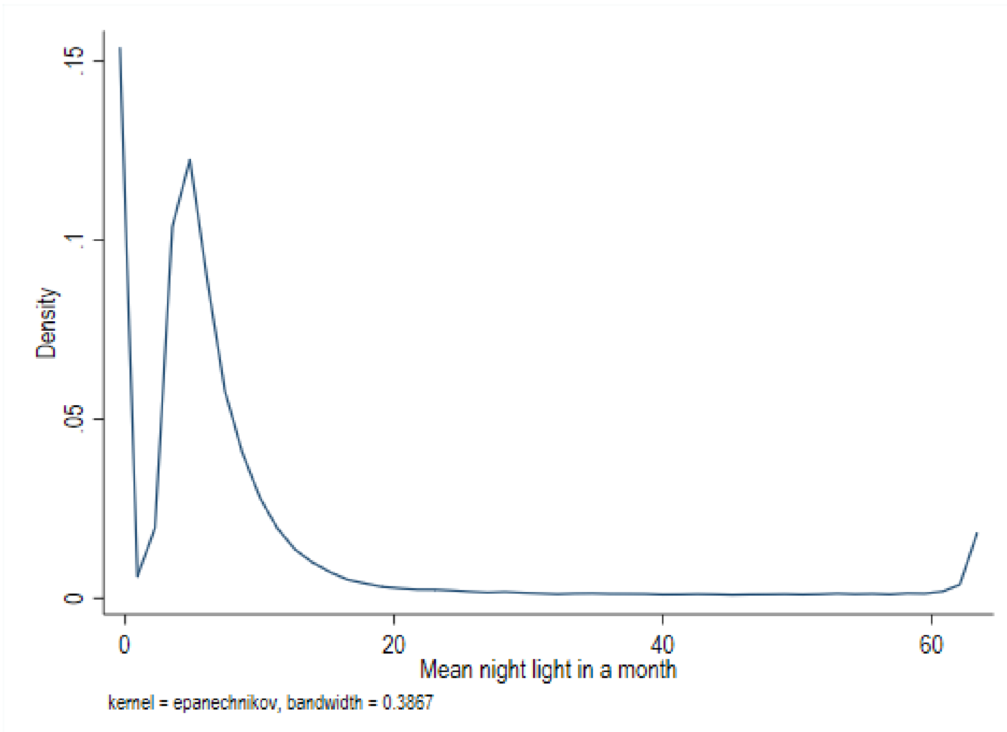

Figure 4.1: Distribution on the monthly average night light variable

Notes: The night light is a score of 0 to 63. This figure plots the distribution of monthly average value for constituencies in the sample between years 2008-13.

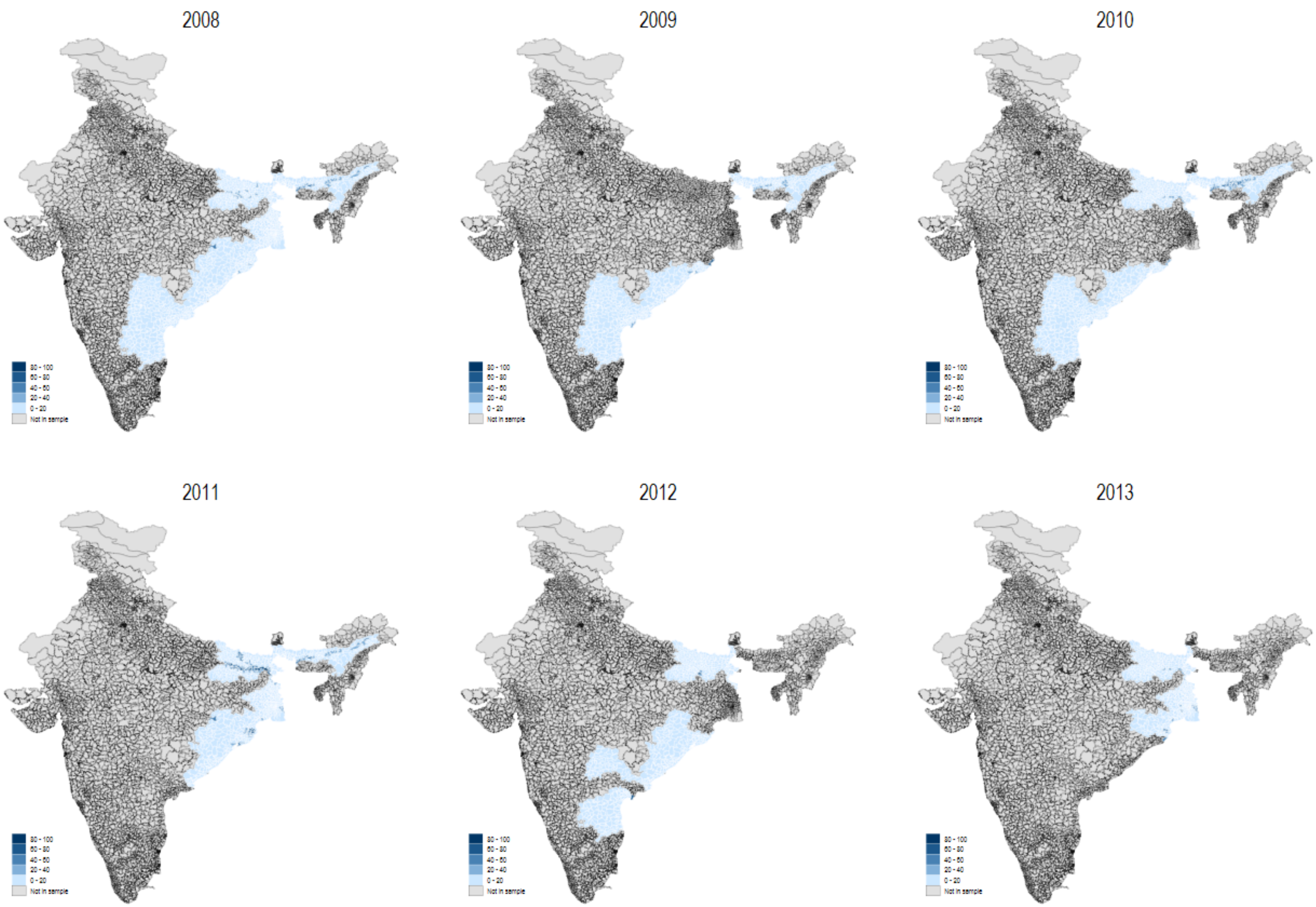

Figure 2: Mean flood area (%) by Constituency-Year

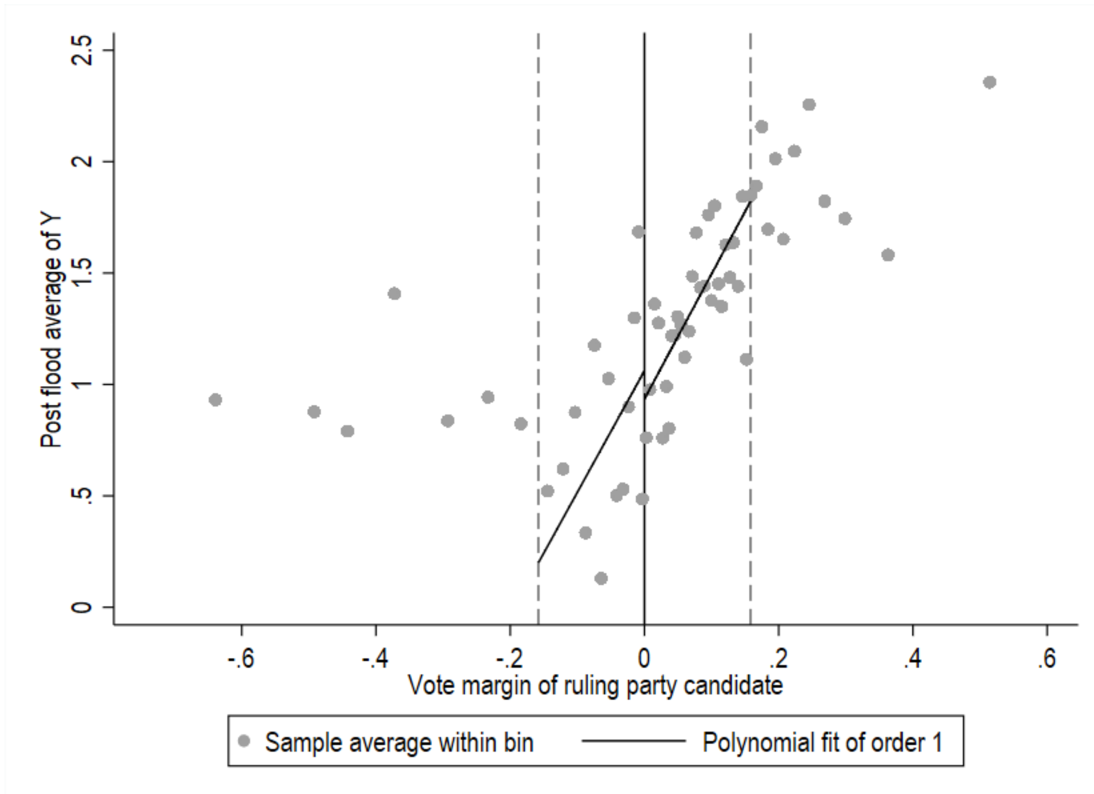

Figure 4.2: Local polynomial regression discontinuity effect of affiliation on outcome variable

Notes: The running variable is the margin of victory/loss of candidate affiliated to ruling party. Negative values represent the margin by which candidates affiliated to state ruling party lost, and positive values represent the margin by which they won the election. The outcome variable is the log of average night light intensity of a constituency c in a month m. Each dot represents the average of the outcome variable for the bins created by choosing non-overlapping intervals with approximately the same number of observations. The lines on either side of the cut off represent the local linear regression fit of the outcome variable on the running variable. The estimation uses constituency-state and month-year fixed effects, and clusters standard errors at the district level. The MSE optimal bandwidth is 0.158.

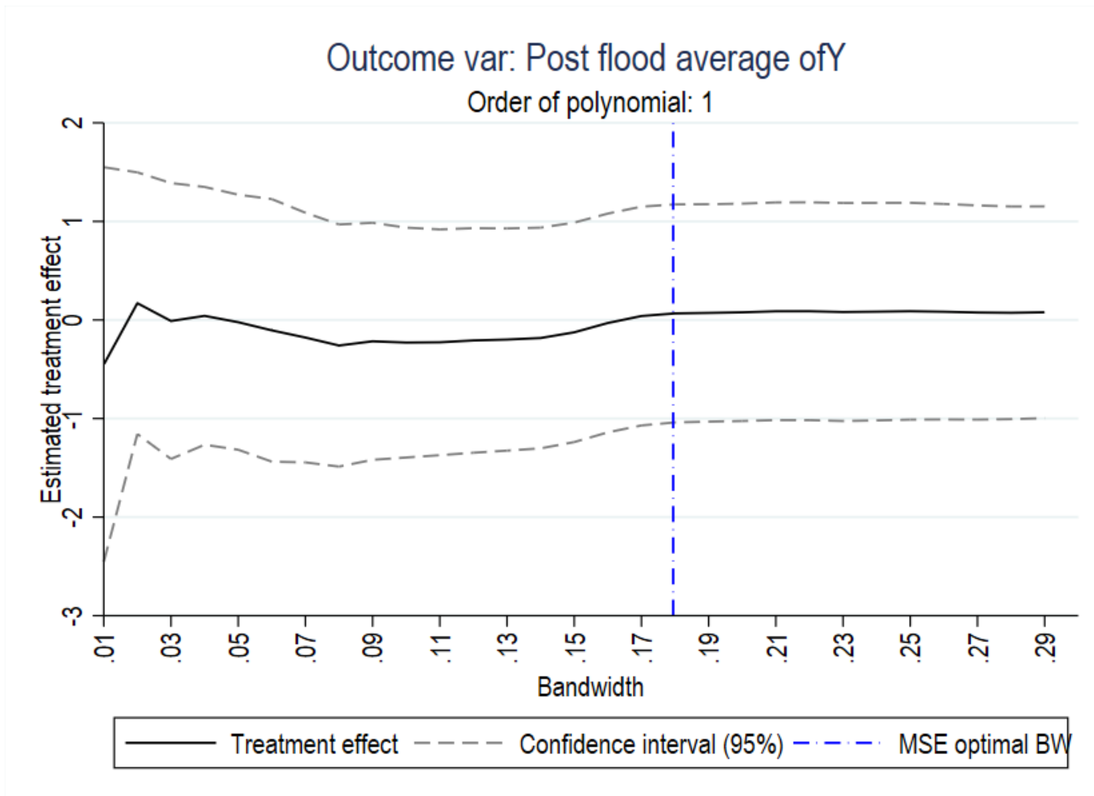

Figure 4.3: Effect of vote margin on outcome variable for different intervals

Notes: The outcome variable is the log of average night light intensity of a constituency c in a month m. The black solid line plots the effect of vote margin, $margin_{ct}$, on the outcome variable for varying bandwidths (or intervals). The dash grey lines on either side are the 95% confidence intervals of the point estimation. The vertical blue line indicates the MSE optimal interval/bandwidth 0.158. The estimation fits a local linear regression on either side of the cutoff using kernel density. The estimation uses constituency-state and month-year fixed effects, and clusters standard errors at the district level.

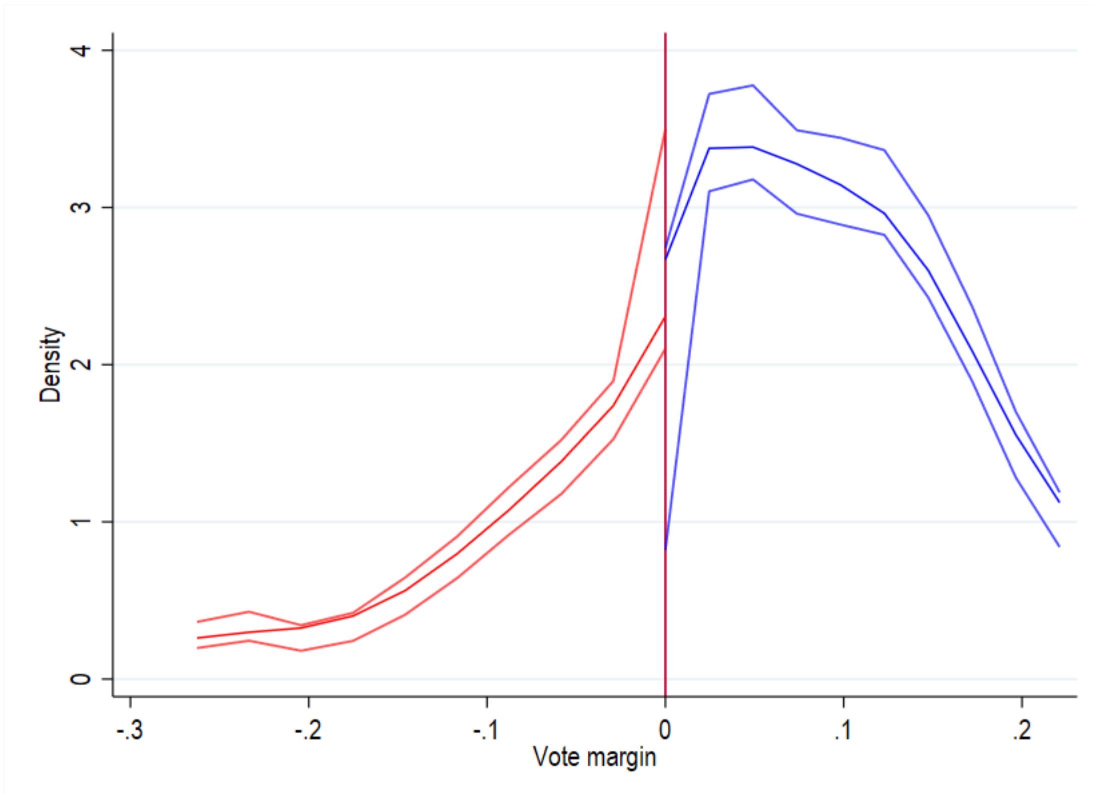

Figure 4.4: McCrary test

Notes: The running variable is the margin of victory/loss of candidate affiliated to ruling party. Negative values represent the margin by which candidates affiliated to state ruling party lost, and positive values represent the margin by which they won the election.

Tables

Table 4.1: Description of area flooded by State-Year

State	Year	Constituencies	Area flooded (%)		
			Mean	Minimum	Maximum
Bihar	2008	243	4.3	0	77.3
Bihar	2010	243	2.0	0	58.1
Bihar	2011	243	11.1	0	78.2
Bihar	2012	243	1.3	0	49.0
Bihar	2013	243	2.1	0	25.9
Assam	2008	126	8.0	0	93.1
Assam	2010	126	15.4	0	91.4
Assam	2011	126	8.1	0	58.5
West Bengal	2008	294	1.1	0	28.8
West Bengal	2010	294	2.1	0	41.6
West Bengal	2011	294	3.3	0	53.2
West Bengal	2012	294	1.0	0	23.0
West Bengal	2013	294	4.1	0	39.6
Odisha	2008	147	1.9	0	41.1
Odisha	2009	147	4.5	0	100.0
Odisha	2010	147	1.8	0	90.1
Odisha	2011	147	6.6	0	70.3
Odisha	2012	147	0.5	0	27.4
Odisha	2013	147	5.4	0	39.7
Andhra Pradesh	2008	294	0.6	0	20.6
Andhra Pradesh	2009	294	1.3	0	35.1
Andhra Pradesh	2010	294	0.3	0	14.8
Andhra Pradesh	2011	294	0.9	0	10.1
Andhra Pradesh	2012	294	0.9	0	89.0

Notes: The table describe the distribution of area flooded for a constituency in each state (column 1) and year (column 2) included in the sample. Column 3 gives the total number of constituencies in each state. The DFO does not record a flood event in every consecutive year between 2008-13 for some of the sample states.

Table 4.2: Recurrence of floods in sample

State	Constituencies	(%) Multiple floods	Mean floods in constituency
Bihar	243	99.6	3.7
Assam	126	97.6	2.4
West Bengal	294	92.9	2.3
Odisha	147	97.3	2.5
Andhra Pradesh	294	88.4	1.8

Notes: The table describe the percentage of constituencies for each state which had more than one flood between 2008 and 2013. The last column reports the mean number of floods for a constituency in each state.

Table 4.3: Electoral outcomes of Ruling Party

State	Election year	Seats	Ruling party	
			Vote share (%)	Incumbent
Bihar	2005	243	59.1	No
Bihar	2010	243	84.6	No
Assam	2006	126	45.1	Yes
Assam	2011	126	62.0	Yes
West Bengal	2006	294	60.1	Yes
West Bengal	2011	294	77.2	No
Odisha	2004	147	63.0	Yes
Odisha	2009	147	70.3	Yes
Andhra Pradesh	2004	294	63.5	No
Andhra Pradesh	2009	294	53.1	Yes

Notes: The table summarizes electoral outcomes for the ruling party in each state and election year included in the analysis. The total number of seats (or constituencies) in the state legislature are given in the third column. Vote share is the percent seats won by the state ruling party.

Table 4.4: Month-wise differences in Y by flood shock

Dependent variable: Log(Monthly average night light + 0.01)		
	(1)	(2)
FloodShock * t-3	-0.273	-1.235***
	[0.345]	[0.340]
FloodShock * t-2	0.506	0.062
	[0.406]	[0.338]
FloodShock * t0	0.229	-0.209
	[0.253]	[0.212]
FloodShock * t+1	0.098	-0.532
	[0.360]	[0.366]
FloodShock * t+2	1.263***	0.181
	[0.258]	[0.242]
FloodShock * t+3	-0.069	0.120
	[0.341]	[0.319]
Comparison group mean	0.562	0.562
Observations	1825	1825
R^2	0.779	0.853
Unit FE	Yes	Yes
Time FE	Yes	Yes
Time-varying controls	Yes	Yes
Cloud cover	No	Yes

Notes: The dependent variable is the log of average night light intensity of a constituency in a month. This table reports differences in the outcome variable between constituencies that experienced a flood shock greater than 1 SD of past years' average and all others by months relative to the flood. The interaction term for month t-1 is used as reference category. The model in column 2 includes controls for the number (percent) of cloud-free observations of night lights (flood) in a month. Comparison group includes constituencies where $FloodShock_{cmt} = 0$. Both models include unit fixed effects for constituency and time fixed effects for month-year. Time-varying characteristics such as population, school and road infrastructure, employment and rural/urban are included as well. Standard errors are clustered at district level and in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.5: TWFE estimation: Recovery of night lights after flood shock

Dependent variable: Log(Monthly average night light + 0.01)

	Last 1 month as reference			Last 2 months as reference		
	(1)	(2)	(3)	(4)	(5)	(6)
FloodShock * Post 1 month	0.235			0.129		
	[0.156]			[0.154]		
FloodShock * Post 2 months		-0.031			-0.065	
		[0.072]			[0.072]	
FloodShock * Post 3 months			-0.005			-0.035
			[0.058]			[0.058]
Flood Shock	0.113	0.028	0.013	0.180***	0.119**	0.093*
	[0.089]	[0.060]	[0.049]	[0.068]	[0.054]	[0.047]
Constant	5.779	5.573	1.581	0.416	0.882	0.081
	[5.972]	[4.869]	[2.108]	[4.363]	[3.733]	[2.007]
Comparison group mean	0.562	0.562	0.562	0.562	0.562	0.562
Observations	386	537	853	687	838	1154
R^2	0.983	0.980	0.982	0.985	0.984	0.985
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Cloud cover	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the log of average night light intensity of a constituency in a month. This table reports differences in the recovery of the outcome variable upto 1, 2 and 3 months (rows 1-3) after a flood shock. The flood shock is a binary variable that assigns 1 to constituencies that experienced a flood shock greater than 1 SD of past years' average and 0 otherwise. Comparison group includes constituencies where $FloodShock_{cmt} = 0$. Columns 1-3 compare changes in the outcome variable with reference to the mean Y in the month before the flood shock. Columns 4-6 use an average of the last two months as a reference. All models include controls for the number (percent) of cloud-free observations of night lights (flood) in a month, unit fixed effects for constituency and time fixed effects for month-year. Time-varying characteristics such as population, school and road infrastructure, employment and rural/urban are included as well. Standard errors are clustered at district level and in brackets. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 4.6: Heterogeneity analysis: Recovery of night lights by ruling party affiliation

Dependent variable: Log(Monthly average night light + 0.01)

	Last 1 month as reference			Last 2 months as reference		
	(1)	(2)	(3)	(4)	(5)	(6)
Ruling Party * FloodShock	-0.260			-0.434**		
* Post 1 month	[0.245]			[0.211]		
Ruling Party * FloodShock		-0.288			-0.282	
* Post 2 months		[0.178]			[0.210]	
Ruling Party * FloodShock			-0.083			-0.068
* Post 3 months			[0.171]			[0.145]
FloodShock * Post 1 month	0.656**			0.461*		
	[0.318]			[0.238]		
FloodShock * Post 2 months		0.293			0.152	
		[0.177]			[0.178]	
FloodShock * Post 3 months			0.109			0.001
			[0.149]			[0.112]
Ruling Party * FloodShock	0.242	0.208	0.184	0.076	0.109	0.103
	[0.195]	[0.172]	[0.145]	[0.118]	[0.108]	[0.090]
Ruling Party * Post	0.235	0.186	0.129	0.213	0.237*	0.201*
	[0.168]	[0.124]	[0.104]	[0.194]	[0.136]	[0.103]
Ruling Party	0.000	0.000	0.000	-0.100	-0.097	-0.093
	[.]	[.]	[.]	[0.089]	[0.087]	[0.086]
Flood Shock	-0.229	-0.203	-0.152	0.131	0.046	0.027
	[0.198]	[0.162]	[0.132]	[0.110]	[0.090]	[0.072]
Comparison group mean	0.548	0.548	0.548	0.548	0.548	0.548
Observations	686	992	1538	687	838	1154
R^2	0.984	0.982	0.981	0.985	0.984	0.985
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Cloud cover	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the log of average night light intensity of a constituency in a month. This table reports heterogeneity in recovery of outcome variable from Flood Shock by affiliation with the ruling party. Ruling Party is a binary indicator for constituencies affiliated with the state ruling party. Flood Shock assigns 1 to constituencies where the flood area is at least 1 standard deviation greater than the long-term mean, and 0 otherwise. Comparison group includes constituencies where $FloodShock_{cmt} = 0$ or constituency not affiliated with the state ruling party. Columns 1-3 compare changes in the outcome variable with reference to the mean Y in the month before the flood shock. Columns 4-6 use an average of the last two months as a reference. All models include controls for the number (percent) of cloud-free observations of night lights (flood) in a month, unit fixed effects for constituency and time fixed effects for month-year. Time-varying characteristics such as population, school and road infrastructure, employment and rural/urban are included as well. Standard errors are clustered at district level and in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7: Heterogeneity: Recovery of night lights by vote margin

Dependent variable: Log(Monthly average night light + 0.01)

	Last 1 month as reference			Last 2 months as reference		
	(1)	(2)	(3)	(4)	(5)	(6)
Vote margin * FloodShock	-0.812**			-0.900***		
* Post 1 month	[0.339]			[0.320]		
Vote margin * FloodShock		-1.141*			-1.114*	
* Post 2 months		[0.626]			[0.570]	
Vote margin * FloodShock			-0.392			-0.282
* Post 3 months			[0.374]			[0.339]
FloodShock * Post 1 month	0.255			0.157		
	[0.162]			[0.154]		
FloodShock * Post 2 months		0.051			0.012	
		[0.093]			[0.090]	
FloodShock * Post 3 months			0.023			-0.016
			[0.067]			[0.063]
Vote margin * FloodShock	0.477	0.579	0.391	0.373	0.393	0.276
	[0.390]	[0.387]	[0.289]	[0.306]	[0.317]	[0.263]
Vote margin * Post	0.305	0.444	0.353	0.265	0.357	0.309
	[0.291]	[0.354]	[0.292]	[0.287]	[0.325]	[0.263]
Vote margin	8.282***	3.127***	3.133***	-0.042	-0.055	-0.037
	[1.240]	[0.733]	[0.650]	[0.279]	[0.268]	[0.258]
Flood Shock	0.100	-0.006	-0.009	0.169**	0.102*	0.081*
	[0.097]	[0.071]	[0.055]	[0.068]	[0.055]	[0.048]
Comparison group mean	0.548	0.548	0.548	0.548	0.548	0.548
Observations	386	537	853	687	838	1154
R^2	0.983	0.981	0.982	0.985	0.984	0.985
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Cloud cover	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the log of average night light intensity of a constituency in a month. This table reports heterogeneity in recovery of outcome variable from Flood Shock by ruling party candidate's vote margin. Vote Margin is a continuous variable of votes polled by the ruling party candidate relative to the highest polled voter affiliated with the non-ruling party candidate. Flood Shock assigns 1 to constituencies where the flood area is at least 1 standard deviation greater than the long-term mean, and 0 otherwise. Comparison group includes constituencies where $FloodShock_{cmt} = 0$ or constituency not affiliated with the state ruling party. Columns 1-3 compare changes in the outcome variable with reference to the mean Y in the month before the flood shock. Columns 4-6 use an average of the last two months as a reference. All models include controls for the number (percent) of cloud-free observations of night lights (flood) in a month, unit fixed effects for constituency and time fixed effects for month-year. Time-varying characteristics such as population, school and road infrastructure, employment and rural/urban are included as well. Standard errors are clustered at district level and in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8: Heterogeneity: Recovery of night lights by Swing constituency

Dependent variable: Log(Monthly average night light + 0.01)

	Last 1 month as reference			Last 2 months as reference		
	(1)	(2)	(3)	(4)	(5)	(6)
Swing * FloodShock * Post 1 month	0.682			0.474		
	[0.411]			[0.370]		
Swing * FloodShock * Post 2 months		0.031			0.000	
		[0.252]			[0.245]	
Swing * FloodShock * Post 3 months			0.032			-0.008
			[0.130]			[0.131]
FloodShock * Post 1 month	-0.015			-0.059		
	[0.162]			[0.183]		
FloodShock * Post 2 months		-0.055			-0.073	
		[0.192]			[0.186]	
FloodShock * Post 3 months			-0.038			-0.048
			[0.084]			[0.087]
Post * Swing	-0.770*	-0.057	0.004	-0.542	0.004	0.046
	[0.439]	[0.178]	[0.121]	[0.412]	[0.174]	[0.116]
Swing * FloodShock	-0.028	0.132	0.080	0.168**	0.227***	0.185***
	[0.136]	[0.085]	[0.056]	[0.083]	[0.065]	[0.049]
Flood Shock	0.154*	0.016	0.011	0.161**	0.079	0.065
	[0.090]	[0.065]	[0.049]	[0.065]	[0.053]	[0.044]
Swing constituency	-0.866***	-0.338***	-0.342***	-0.103	-0.138	-0.104
	[0.134]	[0.105]	[0.086]	[0.100]	[0.089]	[0.081]
Comparison group mean	0.504	0.504	0.504	0.504	0.504	0.504
Observations	386	537	853	687	838	1154
R^2	0.984	0.981	0.982	0.985	0.984	0.985
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Cloud cover	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the log of average night light intensity of a constituency in a month. This table reports heterogeneity in recovery of the outcome variable from Flood Shock by whether it is a swing constituency. Swing is a binary indicator for constituencies where the vote margin of winning candidate from the second highest candidate is smaller than the bandwidth estimated using a local linear regression around the vote margin variable. Flood Shock assigns 1 to constituencies where the flood area is at least 1 standard deviation greater than the long-term mean, and 0 otherwise. Comparison group includes constituencies where $FloodShock_{cmt} = 0$ or $Swing_{cmt} = 0$. Columns 1-3 compare changes in the outcome variable with reference to the mean Y in the month before the flood shock. Columns 4-6 use an average of the last two months as a reference. All models include controls for the number (percent) of cloud-free observations of night lights (flood) in a month, unit fixed effects for constituency and time fixed effects for month-year. Time-varying characteristics such as population, school and road infrastructure, employment and rural/urban are included as well. Standard errors are clustered at district level and in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.9: Heterogeneity: Recovery of night lights by Incumbency

Dependent variable: Log(Monthly average night light + 0.01)

	Last 1 month as reference			Last 2 months as reference		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Elected candidate is incumbent					
Incumbent * FloodShock * Post 1 month	0.341 [0.489]			0.393 [0.437]		
Incumbent * FloodShock * Post 2 months		0.316 [0.245]			0.336 [0.213]	
Incumbent * FloodShock * Post 3 months			0.183 [0.173]			0.228 [0.142]
Comparison group mean	0.609	0.609	0.609	0.609	0.609	0.609
Observations	386	537	853	687	838	1154
R^2	0.983	0.981	0.982	0.985	0.984	0.985
	Panel B: Ruling party is incumbent					
Incumbent * FloodShock * Post 1 month	0.382* [0.210]			0.240 [0.190]		
Incumbent * FloodShock * Post 2 months		0.664** [0.277]			0.534** [0.241]	
Incumbent * FloodShock * Post 3 months			0.380** [0.154]			0.339** [0.142]
Comparison group mean	0.485	0.485	0.485	0.485	0.485	0.485
Observations	390	542	864	691	843	1165
R^2	0.984	0.981	0.983	0.985	0.984	0.985
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Cloud cover	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the log of average night light intensity of a constituency in a month. This table reports heterogeneity in recovery of outcome variable by incumbency. Panel A defines Incumbent as a binary variable for a constituency's elected leader. Panel B is a binary variable for whether the state ruling party is incumbent. Flood Shock assigns 1 to constituencies where the flood area is at least 1 standard deviation greater than the long-term mean, and 0 otherwise. Comparison group includes constituencies where $FloodShock_{cmt} = 0$ or constituency (state ruling party) is not incumbent. Columns 1-3 compare changes in the outcome variable with reference to the mean Y in the month before the flood shock. Columns 4-6 use an average of the last two months as a reference. All models include controls for the number (percent) of cloud-free observations of night lights (flood) in a month, unit fixed effects for constituency and time fixed effects for month-year. Time-varying characteristics such as population, school and road infrastructure, employment and rural/urban are included as well. Standard errors are clustered at district level and in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.10: Heterogeneity: Recovery of night lights by Central government affiliation

Dependent variable: Log(Monthly average night light + 0.01)

	Last 1 month as reference			Last 2 months as reference		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Elected candidate is affiliated with Central government						
Affiliation * FloodShock * Post 1 month	-0.230			-0.087		
	[0.369]			[0.328]		
Affiliation * FloodShock * Post 2 months		-0.068			-0.039	
		[0.234]			[0.204]	
Affiliation * FloodShock * Post 3 months			-0.133			-0.059
			[0.152]			[0.137]
Comparison group mean	0.453	0.453	0.453	0.453	0.453	0.453
Observations	386	537	853	687	838	1154
R^2	0.983	0.981	0.982	0.985	0.984	0.985
Panel B: State Ruling party is affiliated with Central government						
Affiliation * FloodShock * Post 1 month	-0.303*			-0.205		
	[0.179]			[0.222]		
Affiliation * FloodShock * Post 2 months		-0.074			-0.096	
		[0.187]			[0.189]	
Affiliation * FloodShock * Post 3 months			-0.051			-0.038
			[0.132]			[0.123]
Comparison group mean	0.339	0.339	0.339	0.339	0.339	0.339
Observations	386	537	853	687	838	1154
R^2	0.983	0.981	0.982	0.985	0.984	0.985
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Cloud cover	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the log of average night light intensity of a constituency in a month. This table reports heterogeneity in recovery of outcome variable from Flood Shock by constituency's affiliation with the Central government. Affiliation is a binary indicator for constituencies (states) affiliated with the Central government in Panel A (B). Flood Shock assigns 1 to constituencies where the flood area is at least 1 standard deviation greater than the long-term mean, and 0 otherwise. Columns 1-3 compare changes in the outcome variable with reference to the mean Y in the month before the flood shock. Comparison group includes constituencies where $FloodShock_{cmt} = 0$ or constituency (state) not affiliated with the Central government. Columns 4-6 use an average of the last two months as a reference. All models include controls for the number (percent) of cloud-free observations of night lights (flood) in a month, unit fixed effects for constituency and time fixed effects for month-year. Time-varying characteristics such as population, school and road infrastructure, employment and rural/urban are included as well. Standard errors are clustered at district level and in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.11: Heterogeneity: Recovery of night lights by years between election and flood

Dependent variable: Log(Monthly average night light + 0.01)

	Last 1 month as reference			Last 2 months as reference		
	(1)	(2)	(3)	(4)	(5)	(6)
Time interval * FloodShock * Post 1 month	-0.301			-0.185		
	[0.202]			[0.224]		
Time interval * FloodShock * Post 2 month		0.382^{*}			0.286^{*}	
		[0.201]			[0.157]	
Time interval * FloodShock * Post 3 month			0.087^{**}			0.039
			[0.040]			[0.036]
FloodShock * Post 1 month	1.203			0.715		
	[0.809]			[0.838]		
FloodShock * Post 2 months		-0.868^{**}			-0.716^{**}	
		[0.435]			[0.352]	
FloodShock * Post 3 months			-0.162^{**}			-0.103
			[0.074]			[0.083]
Time interval * FloodShock	-0.035	-0.069^{*}	-0.051^{**}	0.003	-0.015	0.002
	[0.062]	[0.037]	[0.024]	[0.035]	[0.024]	[0.022]
Flood Shock	0.183	0.163^{*}	0.120^{*}	0.169	0.158^{*}	0.091
	[0.155]	[0.093]	[0.066]	[0.136]	[0.084]	[0.070]
Time interval	0.000	0.000	0.000	0.000	0.000	0.000
	[.]	[.]	[.]	[.]	[.]	[.]
Comparison group mean	0.562	0.562	0.562	0.562	0.562	0.562
Observations	386	537	853	687	838	1154
R^2	0.983	0.980	0.982	0.985	0.984	0.985
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Cloud cover	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the log of average night light intensity of a constituency in a month. This table reports heterogeneity in recovery of outcome variable by years since last election. Time interval is a continuous variable of the number of years between most recent election and the year of flood event in a constituency. Flood Shock assigns 1 to constituencies where the flood area is at least 1 standard deviation greater than the long-term mean, and 0 otherwise. Comparison group includes constituencies where $FloodShock_{cmt} = 0$. Columns 1-3 compare changes in the outcome variable with reference to the mean Y in the month before the flood shock. Columns 4-6 use an average of the last two months as a reference. All models include controls for the number (percent) of cloud-free observations of night lights (flood) in a month, unit fixed effects for constituency and time fixed effects for month-year. Time-varying characteristics such as population, school and road infrastructure, employment and rural/urban are included as well. Standard errors are clustered at district level and in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.12: Regression discontinuity: Post-flood outcome variable

Dependent variable: Log(Monthly average night light + 0.01)

				Confidence intervals		Observations	
Bandwidth	RD estimate	Standard error	p-value	CI left	CI right	Left	Right
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0.158	-0.047	0.566	0.934	-1.157	1.063	119	174
0.079	-0.262	0.628	0.677	-1.493	0.969	71	114
0.316	0.089	0.542	0.870	-0.974	1.151	144	219

Notes: The dependent variable is the log of average night light intensity of a constituency in a month. The table includes estimates of the regression discontinuity analysis (4.4). The first row reports estimates of the mean square error minimising bandwidth, $h = 0.158$. The second row presents results of $h/2$ and third of $2h$. I report the conventional point estimates (Column 2), standard error (Column 3) and p-values (Column 4). Columns 5-6 provide the confidence intervals at 95% level and Columns 7-8 include the effective number of observations within the mean-squared error minimizing interval. The estimations use constituency-state and month-year fixed effects and clusters standard errors at the district level.

Table 4.13: Regression discontinuity: Test of placebo outcomes

	MSE BW	RD estimate	SE	p-value	Confidence intervals Left	Confidence intervals Right	Observations Left	Observations Right
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total population	0.106	167.245	525.726	0.750	-863.158	-863.158	77	110
Scheduled Caste population	0.100	55.510	186.342	0.766	-309.713	-309.713	75	108
Number of households	0.112	57.048	129.974	0.661	-197.697	-197.697	81	112
Scheduled Tribe population	0.098	-32.930	35.171	0.349	-101.864	-101.864	73	104
Literate population	0.102	121.684	319.022	0.703	-503.587	-503.587	75	109
Primary schools (village)	0.129	0.469	0.380	0.217	-0.275	-0.275	89	127
Middle schools (village)	0.155	0.009	0.137	0.950	-0.259	-0.259	99	148
Secondary schools (village)	0.109	0.097	0.066	0.142	-0.032	-0.032	80	112
Senior secondary school (village)	0.138	0.022	0.016	0.180	-0.010	-0.010	93	133
Colleges (village)	0.131	0.016	0.015	0.289	-0.013	-0.013	90	129
Accessibility by paved road (village)	0.115	0.037	0.077	0.630	-0.115	-0.115	83	117
Power supply	0.112	0.041	0.059	0.486	-0.075	-0.075	82	112
Primary schools (town)	0.110	-6.251	3.905	0.109	-13.905	-13.905	50	72
Middle schools (town)	0.116	-6.534	2.896	0.024	-12.209	-12.209	50	76
Secondary schools (town)	0.110	-2.391	2.034	0.240	-6.378	-6.378	49	71
Colleges (town)	0.146	-1.419	1.058	0.180	-3.494	-3.494	59	90
Senior secondary school (town)	0.096	-0.930	0.638	0.145	-2.181	-2.181	46	64
Non-farm employment	0.090	54.101	50.869	0.288	-45.600	-45.600	69	100
Rural population (%)	0.102	3.775	3.248	0.245	-2.592	-2.592	75	109

Notes: Each row presents results of the regression discontinuity analysis of a placebo outcome reported in the first column. I report the conventional point estimates (Column 3), standard error (Column 4) and p-values (Column 5). Columns 7-9 provide the confidence intervals at 95% level and Columns 8-9 include the effective number of observations within the mean-squared error minimizing interval. The estimations use constituency-state and month-year fixed effects and clusters standard errors at the district level.

APPENDIX A

CHAPTER 1 OF APPENDIX

A.1 Outcomes of women's empowerment

A.1.1 Sampling methodology of household surveys estimating women's empowerment

This section describes the sampling methodology of the three nationally representative household surveys used in the analysis.

India Human Development Survey (IHDS)

The survey was conducted in all states and union territories (except 2 - Andaman & Nicobar Islands and Lakshwadeep). It includes 382 of the 612 districts in India in 2001. The 2005 round interviewed 26,734 rural and 14,820 urban households. Both samples were selected by stratified sampling. The second round in 2011-12 re-interviewed 83% of households in the first survey round. counting split households as separate, the second round interviewed 27,579 rural and 14,573 urban households. They survey adopted 13,900 rural households from an older survey by the National Council of Applied Economics Research India and added an urban sample using enumeration areas from Census 2001. It selected towns using the probability proportional to population.

Demographic Health Surveys

The survey uses 2011 Census information to draw a stratified two-stage sample. The primary sampling unit (PSU) is the village in rural areas and the census enumeration block (CEB) in urban areas. Villages are selected with probability proportional to size from the sampling frame. Within each stratum (rural/urban), six substrata are created based on number of households in village and percentage share of scheduled casts and scheduled tribes in a village. The PSUs were sorted by literacy rate of women aged 6 and more, and final selection used probability proportional to size. Each selected urban and rural primary sampling unit was divided into segments of 100-150 households each and from each randomly selected segment, 22 households were randomly selected with systematic sampling.

Consumer Pyramids Household Survey (CPdx)

The CPdx stratifies 640 districts of the 2011 Population Census into 110 homogeneous regions (HRs) which groups districts with similar agro-climatic conditions, urbanization and female literacy levels as well as number of households. The North-Eastern states and Union Territories are each treated as a single HR. Each HR is further stratified based on population into a Rural stratum, a Very Large Towns stratum, a Large Towns stratum, a Medium-sized Towns stratum and a Small Towns stratum based on distinct classification by number of households and not the percentile households within the HR. Therefore, there are unequal number of strata observed across HRs. The following regions were not fully surveyed and having missing strata: Andaman & Nicobar Islands, Arunachal Pradesh, Dadra & Nagar Haveli, Diu & Daman, Lakshadweep, Manipur, Meghalaya, Mizoram, Nagaland and Sikkim. The sampling strategy across the stratum is different: 25-30 villages were selected from each rural stratum using simple random sampling and at least 1 town from each town-size stratum (if available). Households within each village are selected using Systematic Random Sampling where every n^{th} household was selected (n ranging from 5 to 15) to survey a total of 16 households per village. For each selected town, 21 CEBs were randomly selected and 16 households were selected from each CEB using systematic random sampling. The survey, therefore, has a larger sample of urban households. There were 166,744 households (47,715 rural and 119,029 urban) in 438 districts surveyed in the first wave (January to April 2014) and 158,666 households (46,604 rural and 112,062 urban) in 425 districts in the fifth wave (May-August 2015). Every sample household within a strata is meant to represent the same number of households from the population using the survey weight. These weights are calculated using population projections by the survey implementers. This weight is generated for each round of survey (wave).

A.1.2 Construction of indicators for household resource allocation

Table A.1: Description of raw indicators: household resource allocation

Category	Variable	Description
Women-oriented consumption expenditure	Monthly household expenditure on Clothing and Footwear	Garments, Footwear and accessories such as accessories such like socks, tie, scarves, handkerchiefs, fabric and tailoring
	Monthly household expenditure on accessories	Accessories like artificial jewelry, bags, wallets, watches, goggles, glasses and gems and jewelry
	Monthly household expenditure on cosmetics and toiletries	Includes 'dental care products', 'bathing soap', 'face wash', 'shaving articles', 'hair oil', 'shampoo and hair conditioner', 'powder', 'creams', 'deodorants and perfumes', 'detergent bar/powder/liquids', 'scourer and housecleaning agents', 'henna, hair color, hair gel, etc.', 'lipstick and other cosmetics' and 'other housecare products'
	Monthly household expenditure on beauty products and services	Beauty enhancement services like beauty parlors, hair stylists, barber services, salons and spas, masseur services, etc.
		Lipsticks, nail polishes, lip gloss, kajal pencils, foundation, eye-liners and other such products
	Monthly household expenditure on time saving appliances and services	Gadgets such as toasters, water filters, microwave oven, refrigerator, cooking range, stove, mixer/grinder, juicer, coffee machine, grill, induction, chimney, exhaust system and any other appliances that are used in kitchens to improve the efficiency of cooking
		Salary paid to maid servants, cooks, drivers, guards, gardeners, baby sitters and other staff, and laundry services
	Monthly household expenditure on utensils	Cookware including cups, saucers, plates, spoons, containers, frying pans etc. and kitchen accessories including kitchen knives, cutting plates, sieves (chalni), can openers, coffee filters, etc.
Child-associated consumption	School and college fees	Admission and exam fees, uniform, lab and library fees, extra classes, use of sport facilities etc.
	Private coaching	Private tutors or classes
	Stationery	Notebooks, writing pads, paper, pens and pencils, markers, erasers, rulers, compass set, pins, staplers, post-it and related articles

Men-associated consumption	Shaving articles	Shaving brush, razors, blades, shaving foams, shaving gels, shaving lather sticks, after shave lotions and shaving creams
	Intoxicant	Cigarettes, 'bidis', other tobacco products and liquor
	Fuel other than cooking	Petrol and diesel or any other petroleum fuel product for its own consumption
Borrowing	Household has outstanding debt in formal sources	- Banks - Employer - Registered companies engaged in the business of loans and advances, insurance business or chit business - Microfinance Institution - Credit card
	Women-oriented sources (formal/ informal)	- Self-Help Groups - Chit funds - Microfinance Institution
	Informal sources	- Moneylender - Relatives or friends - Shops - Other sources such as non-professional money-lender, religious institutions and missionaries etc.
Savings	Household has outstanding savings in formal sources	- Bank fixed deposits - Schemes offered by India Post (eg. Post Office Savings Account, Post Office Time Deposit Account, Senior Citizen Savings Scheme etc.) - Government bonds and Public Provident Funds - Kisan Vikas Patra - Employee Provident Fund
	Women-oriented source	- Gold assets or funds including gold bars, ornaments, jewelry and Gold Exchange Traded Funds
Investment	Household has outstanding investment	- Mutual funds - Listed shares - Private business enterprise including equity capital of an unlisted company, limited liability partnership or a contribution to a partnership or a proprietorship concern - Real investment including house, plot of land, apartment, bungalow, office space, shop or farmhouse

A.1.3 Construction of district-level empowerment outcomes

The indicators used to measure women's empowerment in the district-wise estimation include self-reported participation in household's big purchase decisions, autonomous use of money and violence from spouse or his relatives. The two indicators are available in the repeated cross-section household surveys IHDS and DHS described in Section 2.5. The third indicator is published in NCRB's reports on Crime against Women. Table A.2 describes the survey questions used to create the indicators. The first indicator, women's self reported participation in household's decisions on purchase of big/ expensive items is constructed as binary indicator which is assigned the value 1 when women respond if they make the decision independently or jointly with their spouse and 0 if the spouse and/or other members of the household make this decision. The indicator constructed for analysis is essentially a measure of joint decision making because the DHS asks respondents if she or other members "usually" make this decision, failing to capture whether the woman makes this decision independently always. The second indicator asks respondents if they have access to any money that they can decide how to spend. The variables in IHDS and DHS allow for a lower bound estimate of women's autonomous use of money as they differ in the source of money and type of expenditure they capture. The DHS asks if the money available to the woman is her own while the responses captured in IHDS could potentially include cash from another member's earnings. The IHDS specifically asks about household expenditures while the DHS does not limit the use of money by type of expenditure. The binary indicator constructed from these two variables is assigned 1 when they respond yes to a question and 0 if they respond no. Both indicators generate estimates for married women between the ages 15 and 49.

The third indicator,“cruelty” by spouse or his family members, includes any conduct that drives the woman to harm herself or harassment of the woman or her relatives “to meet any unlawful demand for any property or valuable security”.

Table A.2: Description of raw indicators: women’s self-reported decision-making and police-reported crimes

	Participation in purchase decisions (1)	Autonomous use of money (2)	Cruelty from spouse or family members (3)
IHDS (2005, 2012)	Who in your family decides the following: Whether to buy an expensive item such as a TV or fridge?	Do you yourself have any cash in hand to spend on household expenditures?	
DHS (2015-16)	Who usually makes decisions about making major household purchases: mainly you, mainly your husband, you and your husband jointly, or someone else?	Do you have any money of your own that you alone can decide how to use?	
NCRB (2013-2016)			Cruelty by Husband or his relatives (Sec. 498A Indian Penal Code)

Table A.3: Description of indicators used in heterogeneity analysis

Indicator	Type	Description
WomanAc	Binary	Takes the value 1 when woman holds an account (joint or individual) and 0 otherwise
HHMemberAc	Binary	Takes the value 1 when any member other than respondent woman holds an account and 0 otherwise
SocialNorms	Normalized score	1. Whether household took loan from bank in last 5 years 2. Whether household has confidence in bank to keep money safe
GenderParity	Normalized score	1. Family eats together or woman eats first 2. Woman does not practice purdah (scree, curtain/ veil) 3. Both men and women shop for food and vegetables 4. Both men and women supervise children's homework 5. Respondent and spouse discuss things that happen at work or farm 6. Respondent and spouse discuss what to spend money on 7. Respondent and spouse discuss things about the community such as elections or politics
GenderNorms	Normalized score	1. Is it usual for husband to beat wife if she goes out without telling him 2. Is it usual for husband to beat wife if her natal family does not give gifts (money/ jewelry) 3. Is it usual for husband to beat wife if she neglects house or child 4. Is it usual for husband to beat wife if she doesn't cook food properly 5. Is it usual for husband to beat wife if he suspects her of having relations with other men

A.2 Tables

Table A.4: DiD estimation of policy on growth in account ownership with continuous indicators of banking infrastructure

	Number of branches			Branch density		
	All branches (1)	Govt owned (2)	Govt + Pvt (3)	All branches (4)	Govt owned (5)	Govt + Pvt (6)
Continuous variable × Year> 2014	-0.00024***	-0.00101***	-0.00052***	-0.03361***	-0.10512***	-0.06646***
	[0.00005]	[0.00027]	[0.00011]	[0.00693]	[0.02539]	[0.01773]
Year>2014	1.09697***	1.04289***	1.03051***	1.20517***	1.06348***	1.09200***
	[0.09254]	[0.09788]	[0.08506]	[0.11710]	[0.10414]	[0.10736]
Continuous variable	-0.00002	0.00000	0.00007	0.00492	0.02172	0.01847***
	[0.00007]	[.]	[0.00013]	[0.00335]	[0.01704]	[0.00537]
Constant	1.01794***	1.05850***	1.20411***	1.36477***	0.74533**	0.65413*
	[0.27021]	[0.20401]	[0.37964]	[0.41195]	[0.29250]	[0.32608]
Observations	3904	3904	3904	3898	3898	3898
R^2	0.681	0.675	0.677	0.686	0.677	0.683
Adjusted R^2	0.679	0.674	0.675	0.684	0.674	0.681
State FE	Yes	Yes	Yes	Yes	Yes	Yes
LASSO controls included	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The above table reports effect of account expansion policy on bank account ownership using different continuous indicators measuring pre-policy banking infrastructure. Column 1 is the total number of bank branches in a district, Column 2 is total branches of central government owned banks, Column 3 branches of government and private sector banks. Column 4 is the branch density in district , Column 5 is branch density of central government owned banks and Column 6 is the branch density of Central government and private sector banks. All specifications include controls selected by post double selection method and state fixed effects. Standard errors are clustered at state level. $*$ p<0.1, $**$ p$<.05$, $***$ p$<.01$

APPENDIX B

CHAPTER 2 OF APPENDIX

B.1 Figures and Table

B.1.1 Figure

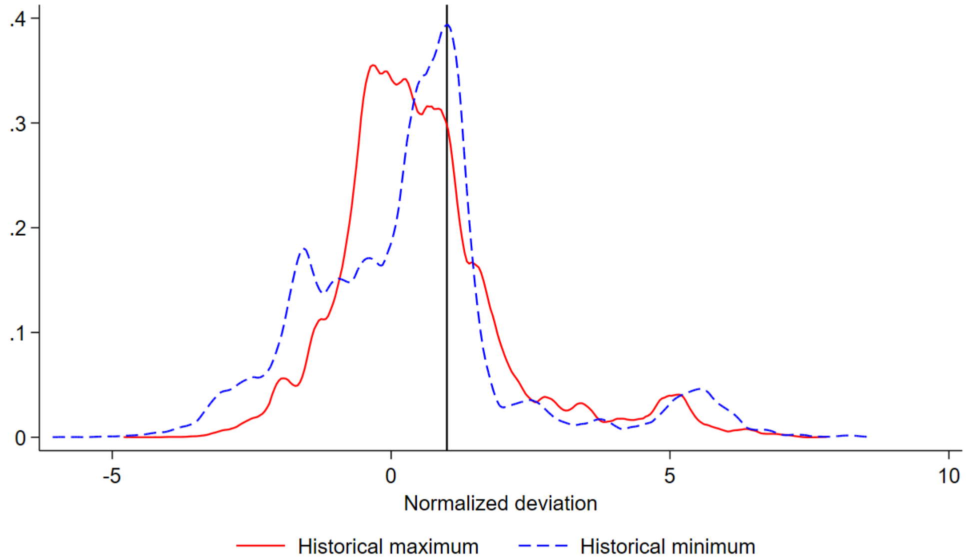

Figure B.1: Distribution of normalized deviation of annual maximum and minimum temperature of country-survey from historical mean

Notes: The normalized deviation is measured against the historical average of maximum (minimum) temperature up until a calendar year prior to recall months for a DHS interview. The vertical black line identifies the share of country-survey rounds where the deviation is greater than 1 standard deviation.

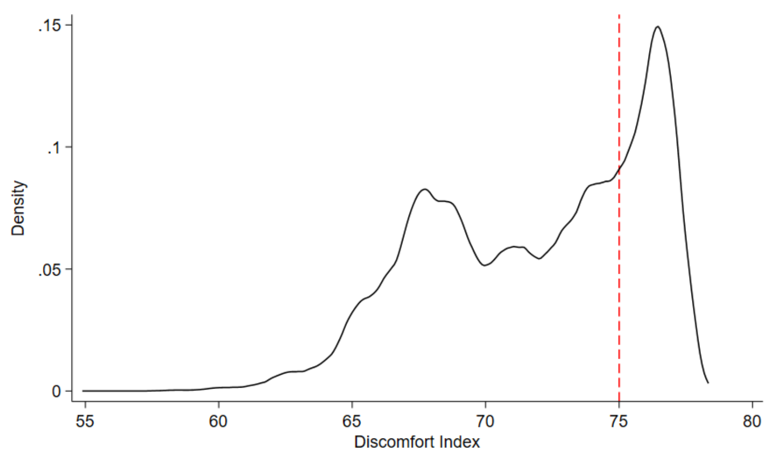

Figure B.2: Distribution of the Discomfort Index

Notes: The vertical red dashed line identifies the threshold beyond which values of the discomfort index are assigned as "uncomfortable" (Thom, 1959).

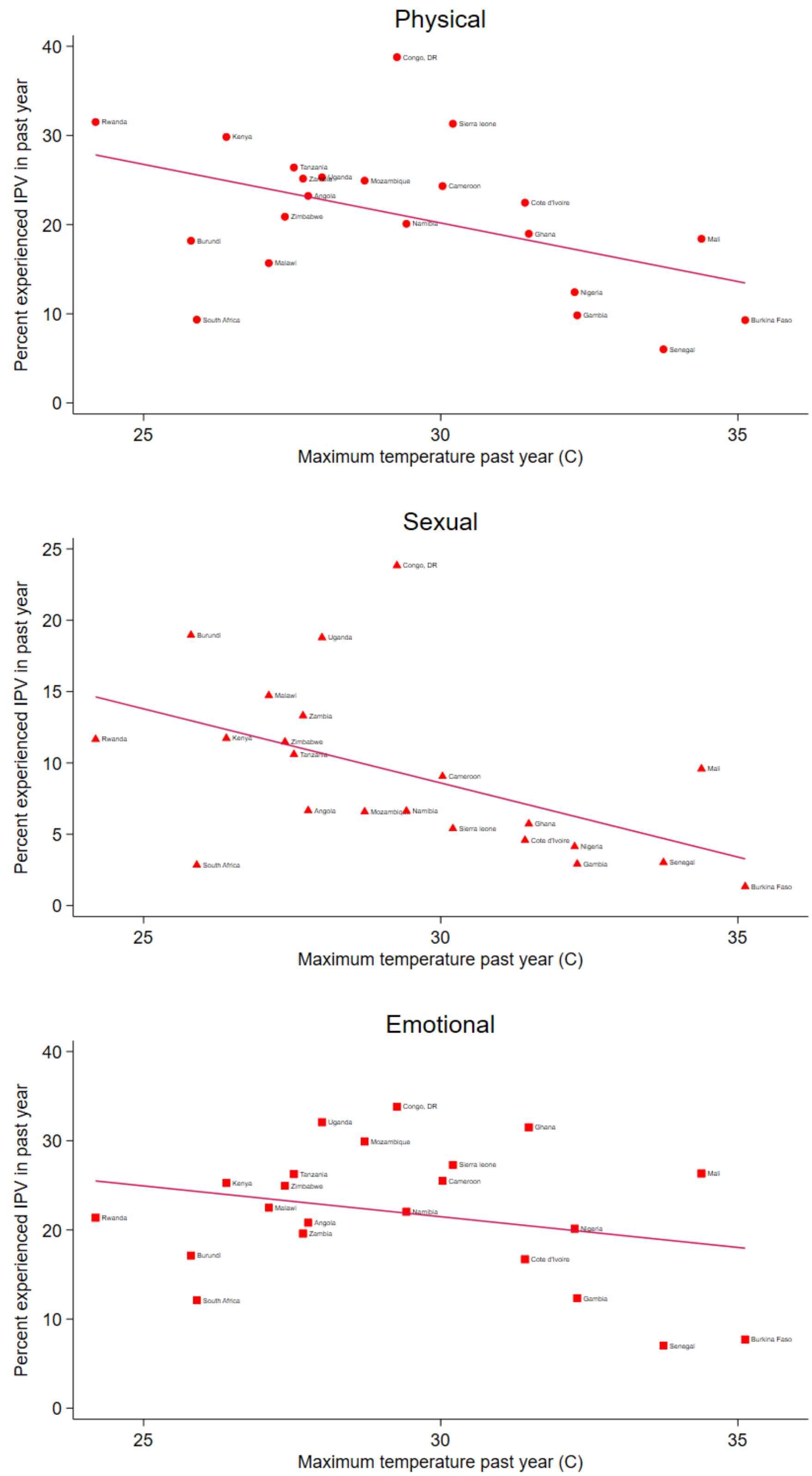

Figure B.3: Country-wise relationship between annual maximum temperature and IPV prevalence

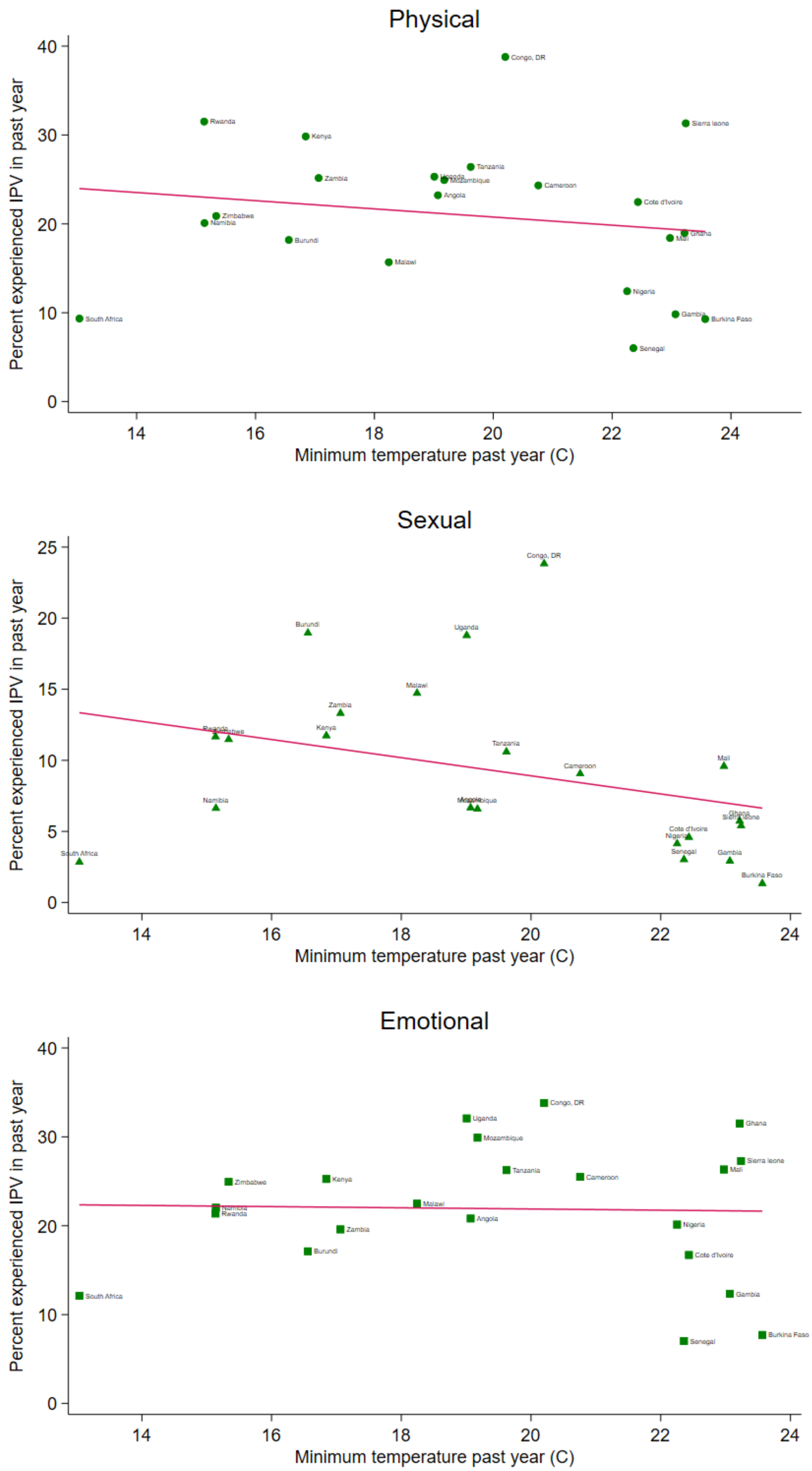

Figure B.4: Country-wise relationship between annual minimum temperature and IPV prevalence

B.1.2 Table

Table B.1: Literature examining weather effects on IPV

Paper	Setting	Dataset/ Source	Method	Explanatory (Weather) variables	Outcome variables	Sign of effect
Rotton and Frey (1985)	Dayton, USA 1976-76	Calls to police department, monthly estimates by National Oceanic and Atmospheric Administration	Distributed lag analysis	Daily temperature, wind speed, humidity levels	Family and household disturbances	+ (hot and dry weather)
Cohn (1993)	Minneapolis, Minnesota	Calls to Minneapolis Police Department (1985, 87-88), National Weather Service	linear regression	Temperature, wind speed, precipitation	Domestic violence, rape	-
Sekhri and Storey-gard (2014)	India (2002-07)	National Crime Records Bureau, Xie et al. (2002) data, Climate Research Unit University of East Anglia	Quasi-Maximum Likelihood	Negative rainfall shocks from long term annual district mean	Annual dowry deaths, domestic violence	+
Sanz-Barbero et al. (2018)	Madrid (2009-16)	Integral Monitoring System for Cases of Gender Violence (VioGen), State Meteorological Agency	Negative binomial and Poisson regressions	Daily max. temperature > 34C	Helpline calls, police reports on IP feminicide	+

Paper	Setting	Dataset/ Source	Method	Explanatory (Weather) variables	Outcome variables	Sign of effect
Abiona and Foureaux-Koppensteiner (2018)	Tanzania	Living Standards Measurement Study-Integrated Surveys on Agriculture	linear regression	Annual and seasonal Droughts; Floods	Self-reported IPV	+ (Droughts); Null (floods, mitigated by inheritance rights)
Diaz and Saldarriaga (2020)	Peruvian Andes (2005-14)	DHS, University of Delaware's Terrestrial Precipitation Gridded Monthly Time Series V 5.01, National Center for Atmospheric Research's Representative Concentration Pathways	Linear and conditional logistic regression	Floods (>95th pct), Drought (<5th pct)	Self-reported physical IPV	Null (Floods), + (Droughts)
Cools et al. (2020)	Sub-Saharan Africa (2003-13)	DHS, ERA-Interim Project	Linear regressions	Flood/drought last season and next-to-last season	Self-reported IPV	Null
Epstein et al. (2020)	Sub-Saharan Africa (2011-18)	DHS, Climate Hazards Group InfraRed Precipitation with Station	Logistic regression	Drought (in rainfall <10th percentile)	Self-reported IPV	+ (Heterogeneity by age, employment)

Paper	Setting	Dataset/ Source	Method	Explanatory (Weather) variables	Outcome variables	Sign of effect
Henke and Hsu (2020)	USA	National Incident-Based Reporting System (FBI), Global Summary of the Day (NOAA), North America Land Data Assimilation System	Negative binomial	Daily maximum temperature by county	Daily count of physical assaults by county	+ (Women's bargaining has mitigating effect)
Stevens (2022)	New South Wales, Australia	Violent crime reports to police (Bureau of Crime Statistics and Research), Australian Water Availability Project	Negative binomial model	Daily mean maximum ambient temperature and humidity	Daily count of domestic violence	+ Heterogeneity (indoors vs outdoors, day of week, month)
Munala et al. (2023)	Uganda 2006, Zimbabwe 2010, Mozambique 2011	Integrated Public Use Microdata Series Demographic and Health Survey, Emergency Events Database	Logistic regression, multivariate model	Flood> five days, 10,000 people and droughts >= 1month	Self-reported IPV	+ Spouse controls (inc alcohol)
Zhu et al. (2023)	India, Nepal, Pakistan (2010-18)	DHS, ERA5	Multi-variable mixed-effects logistics regression	Annual mean temperature	Self-reported IPV	+ Annual cumulative precipitation (control)

Notes: The last column summarizes the sign of effect of the explanatory variables on outcome. - implies negative and + implies positive.

B.2 Economic effects of temperature

Baysan et al. (2018) assume there are two agents $i \in I = 1, 2$ where each i can choose a violent or peaceful action $a \in A = V, P$. Labor input l is a numeraire and productivity is defined by θ. The cost of attacking for either agent is $c \in (o, 1]$ and the probability of i acquiring the other agent's resources when he/she attacks first is $p > 0.5$. The probability of acquiring resources when both agents attack simultaneously is $p = 0.5$. While the Baysan et al. (2018) model assumes that violence in time t is increasing with increasing temperature (τ), in my analysis, I hypothesize a U-shaped relationship between temperature and violence.

$$\gamma_t = (\tau - \underline{\tau})^2 \tag{B.1}$$

Agents are indifferent between acting violent or peaceful when the returns from both actions (including the present discounted value of resources) are equal.

$$\theta_t + \delta V^P = p(2\theta_t(1 - c) + \delta V^V) + \gamma_t \tag{B.2}$$

where δ is the discount factor, V^P is per-capita utility of consumption from the player's initial assets and V^V is per-capita expected utility from consumption of both their initial assets and the assets that they capture from their opponent.

The literature shows that temperature affects economic activity in the form of agricultural productivity and crop prices (Colmer, 2021), agricultural yield (Schlenker and Lobell (2010), Zhu and Troy (2018)) and manufacturing output (Adhvaryu et al., 2019). Following these findings, I assume that consumption is a function of temperature.

$$V^P = g(\tau) \quad \text{where} \quad g'(\tau) > 0 \text{ if } \tau < \underline{\tau} \tag{B.3}$$
$$g'(\tau) < 0 \text{ if } \tau > \underline{\tau}$$
$$V^V = f(\tau) \quad \text{where} \quad f'(\tau) > 0 \text{ if } \tau < \underline{\tau} \tag{B.4}$$
$$f'(\tau) < 0 \text{ if } \tau > \underline{\tau}$$

Substituting (1), (3) and (4) in (2):

$$\theta_t + \delta g(\tau) = p(2\theta_t(1-c) + \delta f(\tau)) + (\tau - \underline{\tau})^2$$

Differentiate with respect to τ:

$$\delta g'(\tau) = p\delta f'(\tau) + 2\tau - 2\underline{\tau}$$
$$\tau^* = \frac{\delta}{2}[pf'(\tau) - g'(\tau)] - \underline{\tau}$$

The optimal temperature threshold may differ based on whether there are economic effects of temperature. If consumption is not affected by temperature: $f'(\tau) = g'(\tau) = 0$ and $\tau^* = \underline{\tau}$. When consumption is affected by temperature: $\tau^* \lesseqgtr \underline{\tau}$. Therefore, at a given temperature the effect size on IPV may vary.

B.3 Discomfort Index

The ERA5 reports daily dry bulb temperature and dewpoint temperature (in K). I estimate the discomfort index proposed by Thom (1959) using the following steps:

1. Convert dry bulb and dew point temperature in Celsius

2. Estimate Relative Humidity (%) using Bolton (1980)

$$RH = 100 * (e/e_s) \tag{A.1}$$

where

$$e_s = 6.11 * exp((17.67T_{dry})/(T_{dry} + 243.5))$$
$$e = 6.11 * exp((17.67T_{dew})/(T_{dew} + 243.5))$$

3. Estimate wet bulb temperature (T_w) using equation 1 in Stull (2011)

$$\begin{aligned} T_{wet} =& T_{dry} * \arctan[0.151977(RH\% + 8.313659)^{1/2}] + \arctan(T + RH\%) \\ & - \arctan(RH\% - 1.676331) \\ & + 0.00391838(RH\%)^{3/2} \arctan(0.023101 RH\%) - 4.686035 \end{aligned} \tag{A.2}$$

4. Discomfort Index (expressed in Fahrenheit):

$$DI = 0.4(t_d + t_w) + 15 \quad \text{where } t_d, t_w \text{ are expressed in F} \tag{A.3}$$

APPENDIX C

CHAPTER 3 OF APPENDIX

C.1 Data preparation

The analysis includes the following four datasets:

1. Flood

   (a) Raw data

   The Global Flood Database is a repository of 913 flood events identified by the Dartmouth Flood Observatory between 2000 and 2018. The database extracts optical satellite images from two MODIS sensors at 250 metres resolution to produce unique flood maps for each event. The data extracted from MODIS is combined with the information on permanent water given in the JRC Global Surface Water dataset. The data also includes variables on the quality of data such as percent of clear day observations of the total number of days of a flood event.

   (b) Data processing

   The area of a constituency flooded is estimated on Google Earth Engine. First, I extract flood events in India between 2008-13 from the Global Flood Database. Second, I upload two shapefiles of India's (state) electoral constituency boundaries - one each for before and after delimitation. Third, I generate mean area flooded within each boundary and percent clear sky observations for each event. Fourth, these statistics are exported as a CSV file for analysis.

2. Night lights

   (a) Raw data

   Data from the US government's Defense Meteorological Satellite Program's Operation Linescan System (DMSP-OLS) collects the number of lights detected in a region and the light intensity of each location from raw satellite images of approximately 0.86 kms spatial resolution at the equator. The DMSP satellites captured images of the Earth every night between 8:30 and 10:30 pm for nearly twenty years (1992-2013) across $-180°$ to $180°$ longitude and $-65°$ to $75°$ latitude. The light intensity is measured by the DMSP satellites at a spatial resolution of approximately 0.86 kms at the equator (30 arc second grid) and is reported as a Digital Number (DN) which is a unit-less, six-bit variable that assigns values between 0 and 63 to each pixel in the raster image. The DMSP data is top coded (there is an upper bound for the maximum value of light intensity reported). The Earth Observation Group, hosted by the Colorado School of Mines. specializes in producing time series of night light estimates using raw satellite images. They calculated the mean light intensity of each pixel for every month in the years 2008-13. They drop observations with cloud cover and solar glare, and images affected by moonlight.

   (b) Data processing

   The following variables were provided as GeoTIFF files by the Earth Observation Group: monthly aggregated night light estimates and the number of cloud free observations per month. I layered each month's TIFF file over the (state) constituency boundary file using QGIS 3.12.0, and calculated the median night light estimate of each constituency for every month in 2008-13. I dropped constituencies with annual average light estimates above the 99th percentile (approximately 5% of the sample) to overcome the saturation of night light estimates in urban centres.

3. Election outcomes

   (a) Raw data

   The repository called Lok Daba is maintained by the Trivedi Centre for Political Data at the Ashoka University. It collates data from the Statistical reports of elections to state legislative assemblies published by the Election Commission of India since 1951. I use newspaper reports and the IndiaVotes databse (https://www.indiavotes.com/) to determine composition of pre-election alliances and coalition governments.

   (b) Defining ruling party

   Where more than one political party formed the government in a state, alliances announced before elections are assigned as "ruling party". I do not include post-election alliances (coalitions) in defining ruling party as the latter are indeterminate at the time of voting and can over-estimate the effect of affiliation. I also exclude parties that moved out of the government-forming alliance after the election.

4. Socioeconomic indicators

   Variables on population, employment and infrastructure are extracted from the Socioeconomic High-Resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2020) which maps village-level data to constituencies from the Population and Economic Censuses, and the

Village Directory of India.

C.2 Sample

This section discusses how the full sample was achieved, and the decisions taken to create a "sample for analysis". I explain the decisions in the sequence they were made.

1. Delimitation

   The most recent redrawing of state assembly constituencies came into effect in 2008. All state assembly elections conducted since 2008 adhere to this delimitation. I include only floods from 2008 in the sample.

2. Timing of flood and election

   Except for Bihar in 2010, elections were conducted prior to the flood in observations of flood events where the election and flood coincided in the same year, Thus, the ruling party and political affiliation were determined ex-ante. In 2010, the assembly elections in Bihar were conducted in the months of October and November 2010, which is after the flood event.

3. Night light data availability

   (a) The DMSP data is available until 2013, and so I restrict the analysis until 2013

   (b) Nightlight estimates for several months in calendar year 2009 are unavailable, and so flood observations from 2009 are omitted.

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