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Do Biometric Smartcards Help the Neediest Most? Evidence From a Large Scale Field Study in Andhra Pradesh

Do Biometric Smartcards Help the Neediest Most?
Evidence From a Large Scale Field Study in Andhra Pradesh

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Abstract

The largest challenge welfare programs in developing countries face is "leakage" due to corrupt officials pocketing funds before they reach beneficiaries. This paper evaluates the impact of a biometrically authenticated "smartcards" system on leakage from employment (NREGS) and pension (SSP) programs in Andhra Pradesh, India. Analyzing panel data from 97,073 individuals, I confirm at the individual level, prior findings at the household level, that smartcards significantly reduce leakage in both programs. Moreover, I find evidence that smartcards help reduce discrimination based on caste and religion, actively benefitting members of scheduled castes more than other castes. However, my evidence suggests more geographically isolated tribes are hurt by the program, possibly because incomplete implementation displaces corruption onto minorities with less access to smartcards. This indicates smartcards can improve welfare program efficacy in developing countries but will only properly address discrimination when governments ensure universal access to smartcards.

1 Introduction

Welfare programs in developing countries are plagued by failure to target payments to the intended beneficiaries [Pritchett, 2009]. This is largely due to corrupt officials involved in the distribution of welfare funds stealing subsidies intended for program beneficiaries in a process called leakage. A number of developing countries[1] attempt to correct this issue through the implementation of unique identity smartcards linked to individual beneficiaries' biometric information. Many studies work to quantify the success of these smartcards in correcting for leakage [Muralidharan et al., 2016, Barnwal, 2015, National Institute of Public Finance and Policy, 2013, Dutta et al., 2010, Eimicke and Buffett, 2018], however, most studies fail to study smartcards' success on an individual level. Moreover, there is significant debate surrounding how smartcards effect different groups in society, particularly disenfranchised minorities

[1] Such as India, Indonesia, the Philippines, Kenya, Uganda, Niger, and Malawi [Jack and Suri, 2014, Aker et al., 2016, Banerjee et al., 2014, Giné et al., 2011, Olken, 2007, Reinikka and Svensson, 2004, Zimmerman and Bohling, 2013a, Zimmerman and Bohling, 2013b]

[Aldrich, 2011,Bhatia and Bhabha, 2017,Dixon, 2017,Dutta et al., 2012], but the debate to this point has not been informed by significant quantitative evidence. I intend to address these gaps in the existing literature.

In this study I measure the heterogeneity of impact of smartcard implementation across beneficiary's caste, tribe, religion,[2] and annual consumption, and provide a theoretical model as to why smartcard rollout should effect each of these groups differently. I will be running several panel regressions designed to answer these questions on the 97,073 beneficiaries, across both NREGS and SSP programs, for whom complete panel data necessary to conduct the individual level heterogeneity analyses I run in this paper, was collected in the Indian state of Andhra Pradesh between 2010 and 2012. I will be running each of my regressions across three measures of efficacy in welfare program subsidy targeting: changes in official amounts the government reports paying beneficiaries,[3] changes in amounts beneficiaries report receiving in individual surveys,[4] and changes in leakage.[5] My regressions build off a base model used by Muralidharan et al., [Muralidharan et al., 2016]. Their model tests for changes in the three dependent variables at a household level due to smartcard implmentation. I depart from their analysis in two ways. First I run my regressions at the individual level as opposed to aggregating total leakage at the household level. Second, I expand their model to quantify heterogeneity of impact of smartcard rollout across caste, tribe, religion, and annual consumption. This stage of regressions includes two models. The first model adds caste, tribe, religion, and annual consumption as control variables, designed to measure the effect each of

[2] India has a long history of violence and discrimination against scheduled castes, otherwise known as Dalit or Untouchables, scheduled tribes, who make up a large number of disenfranchised minorities living on remote tribal land, and religious violence against both Christians and Muslims [Ministry of Social Justice and Empowerment, 1950b,Grim and Finke, 2010,Lobo, 2002].

[3] How much beneficiaries received according to official reports.

[4] How much beneficiaries actually received.

[5] The difference between official amounts reported and survey amounts received

these metrics has on welfare program efficacy. The second model is designed to measure how being in a subdistrict with smartcard access alters the effect that caste, tribe, religion, and annual consumption have on changes in official amounts reported, survey amounts paid, and leakage compared to the same effects in subdistricts without smartcards.

My results offer support for both propositions. My regressions show that smartcard implementation significantly improves welfare program efficacy for individual beneficiaries across both welfare programs (NREGS and SSP). Moreover, my results show decreases in leakage for scheduled castes[6] but increases in leakage for scheduled tribes.[7] This indicates that smartcard implementation helps correct for issues of discrimination in leakage targeting when individuals have access to smartcards, but incomplete program implementation shifts some of the leakage from certain marginalized groups onto others with less access to smartcards. My results on religion show that being in a smartcard enabled subdistrict generally helped reduce disparity in leakage experienced by marginalized religious groups but shows sufficient ambiguity in which religions were benefited most to warrant further study before serious conclusions can be drawn. My results on annual consumption show that, consistent with the predictions of the model I introduce in section 4, increased annual consumption is correlated with increased leakage, indicating that corrupt officials tend to steal more from wealthier beneficiaries.

The remainder of this paper is divided into eleven sections. Institutional background provides some context for the study and information to clarify what leakage is and how it originates. The literature review summarizes the current

[6]Members of the Dalit caste, characterized by social ostracization [Oommen, 2001,Ministry of Social Justice and Empowerment, 1950a].

[7]Scheduled tribes are characterized as both socially and geographically removed [Ministry of Social Justice and Empowerment, 1950b].

literature surrounding the question of biometric smartcard efficacy in correcting for leakage. The economic model section describes my economic theory behind why heterogeneity may be present in the system pre-smartcard implementation and why smartcards might have a greater effect on certain socioeconomic groups than others. The econometric model section describes the regression techniques I use in greater depth. The dataset section includes a more thorough discussion of the dataset used for my study. My results section provides a specific numerical report of my regression results. The robustness and other model variants section compares my individual level results to Muralidharan et al.'s [Muralidharan et al., 2016] household aggregated results and discusses other variations of my regression model that included language and sex as variables of interest. The discussion section summarizes my important results, analyzes their implications, and discusses the limitations of this study. The conclusion serves as a summary of this paper, the bibliography provides a list of references I use in this study, and the appendix holds tables, results, and analyses that are not included in the body of this report.

2 Institutional Background

The purpose of this section is to help readers understand my study in the context of the current literature. This section is broken down into three subsections. The first provides some brief background information on the two welfare programs my study tracks. The second covers what leakage is and the different types of leakage. The third covers the institutional setup for delivering payments to beneficiaries in Andhra Pradesh, why this setup allows for leakage pre-smartcard implementation, and how biometrics should address the issues of the old institutional framework.

2.1 Welfare Programs Under Study: Guaranteed Employment and Supplementary Pensions Programs

The two welfare programs my study examines are the National Rural Employment Guarantee Scheme (NREGS) and Social Security Pensions (SSP) programs. NREGS is the largest working welfare program in the world, covering 11% of the world's population [Muralidharan et al., 2016]. It guarantees every enrolled rural household with 100 days paid work every year. If an individual enrolls in NREGS, local governments must provide them with either paid labor or unemployment benefits.[8] NREGS relies heavily on the discretion of individual government officials to report who beneficiaries are, how much they should be paid, and to disperse funds to individual beneficiaries. This setup leaves substantial room for corrupt officials to steal funds from beneficiaries in their network [Dutta et al., 2012]. Though the presence of leakage in NREGS is evident, calculating a precise number on country wide leakage is very difficult [Sukhtankar, 2016]. However, Imbert and Papp [Imbert and Papp, 2011], find that household reports can only account for 42-56% of days officials report beneficiaries working in 2009-2010.[9] SSP programs provides rural poor who are unable to do work with subsidized income [Dutta et al., 2010]. To enroll in SSP individuals must be classified as below the poverty line and fall into one of four categories: 65 years or older, widowed, disabled, or practice certain displaced traditional occupations. SSP is better implemented than NREGS and relies significantly less on individual officials for reporting and delivering funds, therefore generally shows less room for leakage[10] [Muralidharan et al., 2016]. This is likely because SSP is a straightforward process, which involves a largely

[8]Though it is rare for individuals to receive unemployment benefits instead of paid labor [Muralidharan et al., 2016].

[9]This number underestimates the true leakage of funds as they are in terms of days, not rupees [Sukhtankar, 2016].

[10]Leakage in SSP is calculated as about 17 percent in Karnataka, less than half the rate found in other comparable welfare programs [Dutta et al., 2010].

fixed list of beneficiaries, each of whom receive a fixed amount in payments at a fixed time every month, each month of the year. By contrast, in NREGS, government officials need to determine who to pay within the 65 percent of the rural population with jobcards, and how much these beneficiaries should be paid[11] [Muralidharan et al., 2016]. However, SSP shows a much higher incidence of bribery playing a role in who gets placed on the beneficiary roll. This suggests that placement on the rolls of eligible recipients is likely to be more difficult for poorer disenfranchised minorities.

2.2 What is leakage?

Government leakage in welfare programs is the process by which funds dedicated to providing welfare subsidies to program beneficiaries are siphoned off by corrupt government officials, causing immense amounts of waste in social welfare programs. There are three main methods by which corrupt officials draw funds from these programs: the first can be thought of as underpaying while the latter two fall under the category of overreporting. Underpaying occurs when officials pay beneficiaries less than they are due with the knowledge that in a poor, corrupt, and disconnected system, the beneficiaries either will not notice or will not be able to do anything about the insufficient payments. Overreporting is responsible for a much larger portion of leakage and can be broken up into another two subcategories, simple overreporting and creation of ghost beneficiaries [Muralidharan et al., 2016].

Simple overreporting occurs when government officials inflate the amounts beneficiaries are due when submitting subsidy requests to the state [Niehaus and Sukhtankar, 2013]. Then, when subsidy funds are transferred to local governments to distribute to program beneficiaries, the officials keep the difference

[11] Both of these metrics can change from week to week.

between the amount they declared and the amount the beneficiary was actually due. Local officials often combine underpayment with simple overreporting.[12] Ghost beneficiaries are a more extreme form of overreporting, and responsible for even larger amounts of leakage [Barnwal, 2015]. Ghost beneficiaries can be separated into two main types, full ghosts and quasi-ghosts. Full ghosts are beneficiaries that do not exist. Government officials create fake beneficiaries and register them for welfare programs, reporting extensively on their subsidies deserved and hours worked, thereby receiving funds for individuals who are nonexistent and keeping all the money themselves [Barnwal, 2015]. While quasi-ghost beneficiaries work in much the same way, they differ from full ghosts because the reported beneficiaries are individuals who do exist but have never registered for any programs themselves [Barnwal, 2015]. This allows corrupt officials to enroll these individuals in welfare programs without their knowledge and pocket all the subsidies intended for the unaware enrollees. Together, these four methods of siphoning funds from welfare programs make up the estimated $16 billion (USD) of leakage a year in India, or around 1.6% of India's $1 trillion GDP in 2010 [Sathe, 2011]. For reference this leakage composes 70-85% of total funds spent on welfare programs in India [Programme Evaluation Organisation, 2005, Sathe, 2011].

[12] Local government officials often use underpaying and simple overreporting in tandem to siphon off tremendous amounts of money from these welfare programs. As an example, if a beneficiary of the National Rural Employment Guarantee Scheeme (NREGS), is due 100 rupees (Rs) for work done, the field assistant responsible for reporting payment due might report that the beneficiary is owed 150 Rs. When the field assistant receives the money to disperse amongst the workers he might pay the beneficiary in question 90 Rs, thereby extracting 60 Rs for himself, 50 Rs through overreporting and 10 Rs through underpaying [Muralidharan et al., 2016].

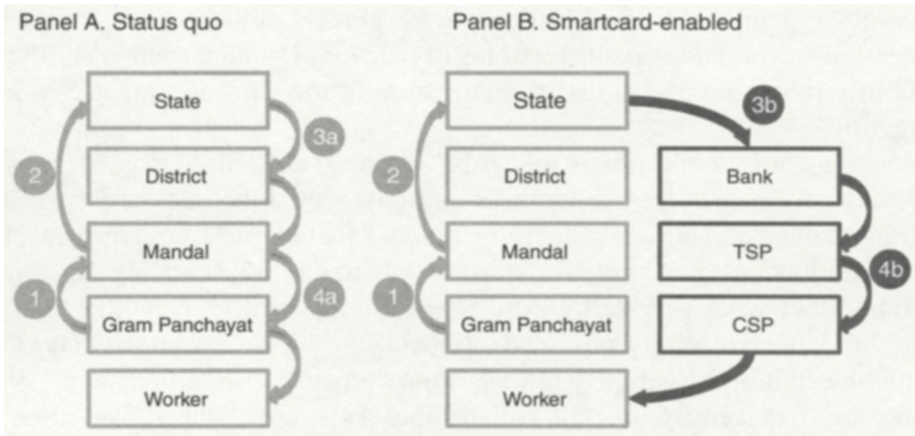

Figure 1: Comparison of pre-Smartcard and post-Smartcard payment methods. (from [Muralidharan et al., 2016])

2.3 How the old system left room for leakage and how can smartcards address these issues?

Before the Andhra Pradesh (AP) smartcard system took over (Figure 1; Panel A), all subsidy requests were reported through the local gram panchayat (GP)(local government) to the mandal (subdistrict government) computer centers in the form of paper muster rolls (Figure 1; 1). The mandals then send the digital muster roll data to the state financial system (Figure 1; 2). Next, the state government electronically passes down the funds requested to the district government, and to the mandal (Figure 1; 4a). Paper money is then sent via mail to the gram panchayat, who distribute the funds out to the program beneficiaries (Figure 1; 5a). This system leaves an enormous amount of room for corrupt officials to pocket funds as they are passed from the GPs to the intended recipients through overreporting and underpaying [Muralidharan et al., 2016].

The concept behind the smartcard system is that subsidy requests will be sent from local governments up through the previous chain of command all the way to the state (Figure 1; 1,2). The state government then passes down funds electronically through privately contracted banks to private technology service providers (TSPs) contracted by the banks to handle the details of electronic transfers. The TSPs then transfer down cash amounts to various customer service providers (CSPs) they hire and train themselves, from whom beneficiaries can receive cash payments after providing biometric authentication via fingerprint and retinal scans (Figure 1; 5b). In order to minimize the chances for corruption within the new system, privately contracted banks, TSPs, and CSPs are paid on commission for every payment verified upon receipt by the beneficiaries [Muralidharan et al., 2016].

This new model successfully cuts out most of the government intervention in the dispersal of funds to beneficiaries. Because the GPs do not handle cash disbursement under the new system, officials cannot engage in the most common forms of leakage—underpaying and simple overreporting. In both cases, the full amount reported is disbursed directly to the recipient, and GP officials have no opportunity to underpay and no incentive to overreport. Overreporting through ghost beneficiaries is controlled because it is extremely difficult to register multiple UIDs or register a UID already linked to another person's biometric information. [Muralidharan et al., 2016]. Gelb and Clark [Gelb and Clark, 2013] find that the probability of a duplicate ID not being caught to equal 0.035%. This shows that biometrics make it near impossible to register for multiple UIDs or register for a UID that is already linked to a person's biometric information. This indicates that the biometric Ids should attack overreporting by inhibiting government official's ability to create ghost beneficiaries [Gelb and Clark, 2013]. Therefore, the new system is designed to address all the central mechanisms of leakage.

3 Literature Review

The question of how to use a biometrics-based solution to increase state capacity and appropriately target subsidies has been a focus of many developing countries for the past decade or so [Gelb and Clark, 2013]. Implementation of biometric smartcard systems is on the rise globally. Gelb and Clark [Gelb and Clark, 2013] estimate that at least 230 programs have been attempted in over 80 countries. Most papers on the subject agree that these programs are largely organized to improve the performance of public welfare programs and increase financial inclusion for the poor Muralidharan et. al. [Muralidharan et al., 2016]. However, there are many concerns with the efficacy of implementation of such programs. The existing literature focuses around these two questions; how do smartcards increase state capacity for providing effective welfare programs, and how will smartcard implementation effect marginalized groups in society?

3.1 Smartcards' Role in Increasing Overall Welfare Program Efficacy

The majority of recent studies show biometric smartcards effectively improve the targeting of welfare subsidies to beneficiaries in developing countries. Muralidharan et. al. [Muralidharan et al., 2016] show biometric smartcards in the Indian state of Andhara Pradesh significantly decrease leakage of funds by 47% overall across two welfare programs, the Social Security Pensions program and the National Rural Employment Guarantee Scheme. Moreover, they show an overall increase in amount of money received by households with job cards [Muralidharan et al., 2016]. A similar study by Barnwal [Barnwal, 2015] finds a significant decrease in leakage in India's fuel subsidies market during periods of smartcard enforcement. Specifically, Barnwal linked the decrease in leakage to a noticeable decrease in the number of ghost beneficiaries selling subsidized fuel on the black market. Though India has the most advanced and documented implementations of smartcards for welfare program improvement, several other countries, particularly in Southeast Asia, have implemented more modest programs with similar results [Gelb and Clark, 2013].

Most studies agree on the method by which biometric IDs address leakage of funds from welfare programs. The mechanisms for leakage associated with the NREGS and SSP program study in Andhra Pradesh are found consistently throughout studies of leakage from welfare programs, and the literature about the mechanisms by which biometrics reduce leakage identifies similar disruptions to the leakage systems. Centrally, studies show linking smartcards to beneficiary's biometric information allows for very secure verification of payments received [Sathe, 2011]. This verification allows programs to be certain appropriate transfers had successfully reached the targeted beneficiaries, helping correct for the problem of underpaying [Sathe, 2011]. In many models correcting for issues with financial transfers, where transfer systems are directly linked to bank accounts with individual's UIDs, smartcard programs decrease the need for funds to be transferred through government institutions [Nilekani, 2010]. Removing dispersal of funds from the hands of the local governments curbs the ability of corrupt officials to skim funds from the system and disincentives simple overreporting. Moreover, tying verification processes to biometrics minimizes the ability of corrupt officials to create ghost beneficiaries, thereby cutting out major sources of overreporting [Gelb and Clark, 2013].

3.2 Concerns Regarding Heterogeneity

Though most papers agree that biometric smartcards effectively decrease leakage there are arguments on both sides concerning whether or not they effectively target all beneficiaries equally. Several papers express concern that corrupt officials with vested interests may subvert smartcard intervention and limit its effectiveness by implementing legal barriers to access for certain individuals [Parente and Prescott, 2000, Krusell and Ríos-Rull, 1996]. Other papers raise concerns that issues with governmental corruption may cause discrimination in program access and smartcard benefits between economic classes, social castes, religious groups, and geographically removed tribes, [Gelb and Clark, 2013, Bhatia and Bhabha, 2017, Oommen, 2001, Vaid, 2018]. Moreover, irrespective of intentions, a biometrics system could generate exclusion errors if genuine beneficiaries are not paid due to technical problems stemming from issues correlated with historically vulnerable minorities and beneficiaries [Khera, 2011]. For instance, Dixon [Dixon, 2017] find a failure to match rate of 49% in Jharkhand and a 37% failure to match rate in Rajasthan, which occurs when individuals are unable to verify their biometric information due to alterations in their fingerprints or retinal scans. This is particularly troubling as many rural residents of India might not be able to provide high quality fingerprints, due to scarring associated with manual labor, or retinal scans, associated with eye infections or common injuries [Gelb and Clark, 2013]. This indicates that issues with quality of biometric readers can cause genuine errors without discriminatory intent, that will disproportionately effect certain minorities and social classes. Finally, several studies raise concerns that reducing corruption in certain areas could displace it onto others [Yang, 2008], especially if this dampened incentives for corrupt officials to properly implement welfare programs to begin with [Leff, 1964].

These general concerns are consistent with Muralidharan et. al.'s [Muralidharan et al., 2016] survey of general opinion, which suggests barriers to access smartcard systems and welfare benefits are present in Andhra Pradesh. While the debate is active, it has largely remained in the realm of hypothetical potential problems and concerns, with some anecdotal evidence. There has been little empirical evidence to either support or refute the concern that the efficacy of smartcard programs is likely to differ meaningfully between different classes and types of beneficiaries.

3.3 Limitations

There exist several key limitations to the existing literature surrounding smartcard efficacy in mitigating leakage from public welfare programs. First, there is a significant lack of information on smartcard programs outside of sub-Saharan Africa, Southeast Asia, and Latin America. This is because of political issues with the uses of biometrics in non-developing countries. In non-developing countries, with already well established identity systems, majority literate populations, and high accountability, the implementation of biometrics is seen as surveillance motivated. In developing countries, with non-existent or non-functioning identity systems, high illiteracy, and weak accountability, the implementation of biometric identity cards is motivated by authentication or verification [Gelb and Clark, 2013]. Second, the majority of cases of using biometrics to promote financial access and facilitate social transfers outside Southeast Asia have been very small [Gelb and Clark, 2013]. Therefore, much of the data on using biometrics based UIDs to improve welfare programs comes from Southeast Asia, and from India, more than anywhere else. Finally, due to privacy concerns and issues with corrupt local governments, it is very difficult to acquire reliable individual level data. Therefore, many studies are unable to provide either individual level analyses on biometrics programs or empirical tests on heterogeneity of impact of smartcard implementation.

3.4 Contribution

Overall, the current literature surrounding biometrics-based smartcard programs agree that biometrically linked UIDs contribute positively to overall reduction of leakage and improvement of welfare subsidy programs. However, there is a significant debate surrounding whether there is heterogeneity of impact in how well these smartcard programs address welfare program targeting. Due to the difficulty in acquiring reliable personal level data many studies have been unable to run tests on the individual level effects of biometric smartcards and on whether smartcards help or hurt marginalized classes or races. Moreover, while many papers present concerns regarding heterogeneity of impact, few present formal models for where this heterogeneity might arise. I intend to correct this gap by running several regressions at the individual level, and using two models designed to test for heterogeneity of impact across four measures of socioeconomic status that I believe to be possible sources of heterogeneity.

4 Theoretical Underpinnings (Economic Model): Cost/Benefit Analysis of Leakage and Reporting Leakage

The biometrics based smartcard system is designed to cut out as much governmental input into welfare program's subsidy delivery as possible. Therefore, to understand why smartcards might effect certain groups in society more significantly than others requires an understanding of why different socioeconomic classes might be systematically targeted by corrupt officials before the introduction of smartcards. Comprehending this systematic targeting requires an understanding of the relation between the costs and benefits to beneficiaries of applying for benefits or reporting leakage, and the costs/benefits to corrupt officials of particular leaking tactics or choosing particular subpopulations as targets of their corruption.

4.1 Total Cost/Total Benefit of Obtaining Full Benefits

For each individual there exists some cost/benefit of requesting welfare program benefits and some cost/benefit of reporting underpayment. Each decision–first applying for benefits, and then enforcing against each instance of underpayment–follows a similar cost benefit analysis. A beneficiary's cost benefit analysis may justify applying for welfare program benefits in the first place, but not reporting underpayment later, or it may justify reporting some underpayments but not other, smaller amounts, or when subjective costs may be higher–say, a period during high tensions where risk of retaliation for reporting underpayment may be perceived as higher. For the purpose of concision discussion of the costs/benefits of reporting underpayment of funds due and costs/benefits of requesting welfare program benefits will be referred to as the costs/benefits of "obtaining full benefits" or "seeking full benefits," unless there is a specific difference in any given analysis between underpayment/non-challenging vs. overreporting/nonapplication. Let us begin discussion with total cost of obtaining full benefits.

Individuals' total costs (TC) can be envisioned as the work hours lost (W), plus some monetary cost (in rupees) of obtaining full benefits (MO),[13] plus any other, more subjective, costs of reporting leakage or applying for program benefits (OC).[14] This can be envisioned as $TC = W + MO + OC$. For each

[13] These represent costs of either applying for welfare benefits to begin with, or going through the arbitration process to determine whether the beneficiary was improperly paid. For instance, certain corrupt officials might require bribes in order to place the beneficiary applying for welfare program benefits on their muster roll.

[14] Other costs encompass elements like fear of retaliation from government officials, likelihood of request being ignored, and other subjective concerns that commonly apply to marginalized

individual this total cost is fixed regardless of levels of leakage.

As with total cost, there exists some benefit of obtaining full benefits for each individual in a gram panchayat.[15] This benefit (TB) is the amount of funds gained by the beneficiary either from being enrolled in a program or from correcting for underpayment (FG) times the marginal benefit a beneficiary gains from one more rupee in their pocket. This equation can be written as $TB = \beta FG$, where β represents the marginal benefit of a one rupee increase in payment obtained from seeking full benefits. A beneficiary's total benefit changes in direct proportion to the amount of funds received from the program or recovered from underpayments. Poorer beneficiaries will generally have a higher marginal benefit from obtaining full benefits, where one extra rupee stolen or gained could cause significantly more harm or good for that beneficiary compared to a wealthier individual. This increased marginal benefit makes them more likely to seek full benefits.

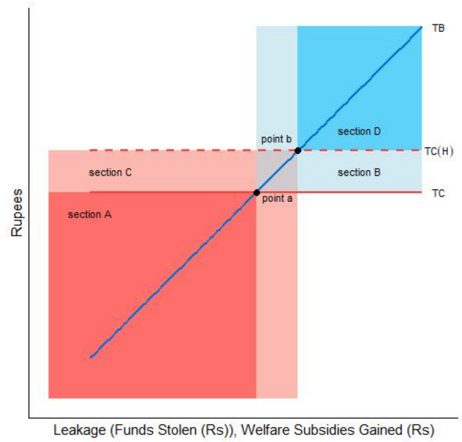

Figure 2: Plot of Total cost/Total Benefit to Beneficiary of Obtaining Full Benefits

castes and persecuted religions, each of whom are frequent targets of discrimination.

[15] Unlike total cost of reporting leakage, which is the same regardless of the form of leakage being committed, total benefit of reporting leakage does not apply to overreporting, because beneficiaries, as individuals, are not directly harmed by overreporting, even if overreporting does hurt beneficiaries indirectly by decreasing welfare programs' total budget.

These two equations can be visualized as a Total Cost/Total Benefit plot (Figure 2). For every individual, the area where the TB curve is below the TC curve, obtaining full benefits will result in a total loss of funds and is therefore not worth it. However, once the TB curve meets and passes the TC curve it becomes more beneficial for individuals to seek full benefits. The issue of heterogeneity arises from different individuals having different total cost curves and different marginal benefits of obtaining full benefits.

Let's begin by analyzing changes in total cost of seeking full benefits. Take an individual right on the median of a theoretical socioeconomic scale. He or she might have a total cost curve equal to TC in Figure 2. For this individual, seeking full benefits below point a (Figure 2; section A) would be pointless and cost more than they would receive in compensation/subsidies so individuals have no incentive to seek full benefits. If the amount that an individual is underpaid or the amount an individual would gain in program benefits increases past point a (Figure 2; section B), that individual would have incentive to seek full benefits. However, if we take an individual with a higher total cost curve (Figure 2; TC(H)), we see how it will only be worth it for them to seek full benefits once the amounts stolen or subsidies provided pass point b (Figure 2). Therefore, they have a smaller area in which they will be willing to seek

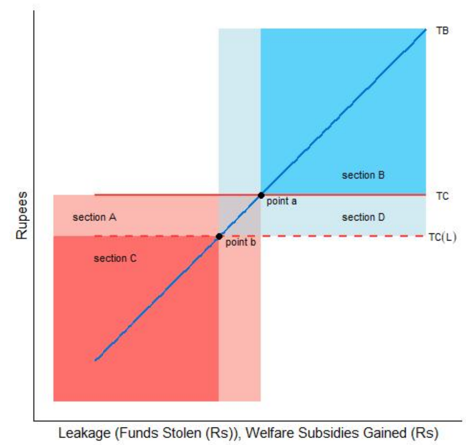

Figure 3: Plot of Total cost/Total Benefit to Beneficiary of Obtaining Full Benefits

full benefits (Figure 2; section D) and a larger area in which they will not seek full benefits (Figure 2; section C). Conversely, an individual with a lower total cost curve (Figure 3; TC(L)) would have a smaller area in which they would not seek full benefits (Figure 3; section C) and a larger area in which they would seek full benefits (Figure 3; section D).

Changes in marginal benefit of obtaining full benefits acts in a similar way. Take someone poorer than our median beneficiary (Figure 4; TB(H)). This beneficiary will have a higher marginal benefit from obtaining full benefits. As marginal benefit increases, the slope of the total benefit curve becomes steeper and more minor increases in stolen funds/welfare subsidies provided lead to higher incentive for the beneficiary to seek full benefits. This is because the extra rupee leaked or granted to them is more valuable to them than to our median beneficiary. Where a median income individual would not seek full benefits below point a (Figure 4; section A), an individual with a higher marginal benefit from obtaining full benefits (Figure 4; TB(H)) would seek full benefits above point b (Figure 4; section D), and therefore has a smaller area in which they would not seek full benefits (Figure 4; section C). The opposite is true of an individual with a lower marginal benefit of obtaining full benefits(Figure 4; TB(L)).

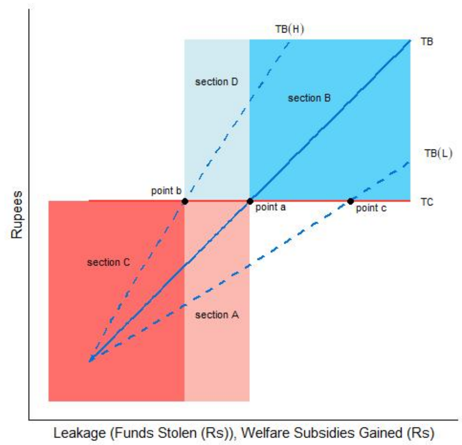

Figure 4: Plot of Total cost/Total Benefit to Beneficiary of Obtaining Full Benefits

Systemic heterogeneity comes into play when certain factors of beneficiaries' socioeconomic class create systemic patterns in individuals' total cost curves and marginal benefits from obtaining full benefits. If a beneficiary lives in more rural areas, further away from the GP's, as is characteristic of members of scheduled tribes, traveling to the GP to seek full benefits might cost many more work hours than for a more urban centered beneficiary. For scheduled castes, marginalized groups with a long history of being subjected to violence and persecution [Oommen, 2001], the serious risk of retaliation from government officials or request for program access being denied due to their caste could cause them to have higher other costs (OC), contributing to higher total cost curves. The same is true of historically persecuted religions, like Muslims or Christians [Grim and Finke, 2007, Grim and Finke, 2010, Lobo, 2002]. Moreover, wealth could have a systemic impact on total benefit from obtaining full benefits, with poorer individuals gaining higher marginal benefit from obtaining full benefits, increasing the slope of their TB curve, and vice versa for wealthier beneficiaries. Any number of socioeconomic characteristics could have systemic effects on where these two curves meet. Heterogeneity in leakage targeting occurs when corrupt officials use these socioeconomic characteristics to determine how much to leak, and from whom.

4.2 Marginal Cost/Marginal Benefit of Siphoning Funds

The costs and benefits to GP officials of leaking funds are affected by the probability of detection, which in turn is a function of the beneficiaries' likelihood of seeking full benefits. It is therefore important to visualize the cost/benefit curves of committing leakage for officials as marginal cost and marginal benefit of leaking one extra rupee from an individual beneficiary. MC responds proportionally with risk of leakage being discovered and MB responds inversely to risk of discovery. The marginal benefit/marginal cost of leaking funds (Figure 5) fluctuates directly with targeted beneficiaries' total cost/total benefit curves of seeking full benefits (Figures 2 - 4). For underpaying, as officials steal more funds from a beneficiary, the risk of crossing over a beneficiary's reporting point (Figures 2; point a) increases and the marginal cost outweighs the marginal benefit (Figure 5; point a). Therefore, officials want to steal funds in such a way to minimize risk of leakage being discovered, thereby shifting their marginal cost curves down (5: MC(a)).

For both underpaying and overreporting,[16] when a corrupt official leaks more money from an individual with a higher total cost of seeking full benefits (Figure 2; TC(H)), or a lower marginal benefit of obtaining full benefits (Figure 4; TB(L)), their risk of being caught is lower and therefore have a lower marginal cost of leaking one extra rupee (Figure 5; MC(a)). Conversely, if a corrupt official leaks from an individual with a lower total cost of seeking full benefits (Figure 3; TC(L)) or a higher marginal benefit from obtaining full benefits (Figure 4; TB(H)), they run a higher risk of being caught, either because the target of overreporting applied for program benefits[17] or because they cross over a beneficiary's reporting point (Figure 3; point b — Figure 4; point b) and are caught

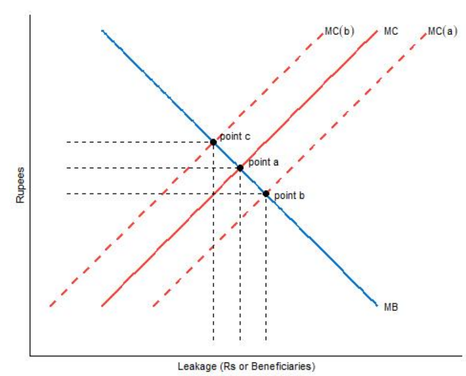

Figure 5: Plot of Marginal cost/Marginal Benefit to Government Official of Committing Leakage

[16]Particularly in the form of quasi-ghost beneficiaries.

[17]Or applied for increased program benefits, only to uncover they had been supposedly receiving significantly more than they were.

in the act of theft. In this case, they have a higher marginal cost of leaking one extra rupee (Figure 5; MC(b)). Moreover, if a corrupt official steals funds exclusively from one individual they become more and more likely to cross over that individual's reporting point (Figures 2-4; points a and b). On the other hand, if a corrupt official creates too many quasi-ghost beneficiaries the likelihood one of them will apply for program access increases, thereby increasing the chances they get caught. In this way the two cost/benefit curves are intertwined. As beneficiaries' total cost of seeking full benefits increases (Figure 2; TC(H)), or their marginal benefit from obtaining full benefits decreases (Figure 4; TB(L)), officials' marginal cost of committing leakage decreases (Figure 5; MC(a)). The opposite is true (Figure 5; MC(b)) for beneficiaries with lower total costs of seeking full benefits (Figure 2; TC(L)) and higher marginal benefits of obtaining full benefits (Figure 4; TB(L)).

4.3 Heterogeneity and Smartcard Solution

Due to the connection between beneficiaries' total cost/total benefit of seeking or obtaining full benefits and corrupt officials' marginal costs of committing leakage, it is in the interest of corrupt officials to target a large number of beneficiaries all of whom can be reasonably assumed to have high total costs of seeking full benefits (Figure 2; TC(H)) and/or lower marginal benefits from obtaining full benefits (Figure 4; TB(L)). Given that individuals' total cost/total benefit curves are not publicly known, corrupt officials must use certain indicators to gauge from which individuals to siphon funds. Therefore, by targeting a broad base consisting of both wealthier beneficiaries with lower marginal benefits from obtaining full benefits and disenfranchised minorities with less access to their local GP's and a higher costs of seeking full benefits, officials can leak funds with less risk, at lower marginal costs (Figure 5; MC(a)). The model gives us a some-what counterintuitive prediction: that smartcards will reduce leakage both for wealthier recipients and for disenfranchised minorities. However, if improperly implemented, smartcards could simply shift leakage from targeted groups with access to smartcards onto those with more difficulty obtaining biometric IDs, as corrupt officials concentrate their corruption onto programs serving those remaining populations that have not yet received smartcards.

5 Econometric Model

In this study I run three district level fixed effects models on survey[18] panel data at the individual beneficiary level. Model 1 is my base model, and the model Muralidharan et al. [Muralidharan et al., 2016] use to analyze the household level effects of smartcard implementation. Models 2 and 3 are based off of model 1, but with the purpose of measuring heterogeneity in the dependent variables. The models are run on panel data for both NREGS and SSP programs.

5.1 Base model

Model 1:

$$Y_{ipmd} = \beta_0 + \beta_1 Treated_{md} + \beta_2 \bar{Y}^0_{pmd} + \beta_3 District_d + \beta_4 PC_{md} + \epsilon_{ipmd}$$

Where i := household or individual, p := gram panchayat (GP), m := mandal, and d := district

All three models map Y_{ipmd} (the dependent variable) as the outcome Y for household or individual i in mandal m, panchayat p, and district d, where the dependent variables will measure aspects welfare program efficacy relating to leakage of funds. The independent variable $Treated_{md}$ signifies whether the

[18]Every model is run using survey weights to increase robustness of the coefficients and standard errors

mandal m in district d was Treatment or Control. $\bar{Y}^0_{ipmd}$[19] maps to the baseline gram panchayat level mean of the dependent variable, in order to increase precision and assess sensitivity to any randomization imbalances. $District_d$[20] is the fixed effects variable corresponding to each district measured. The model uses district level fixed effects because treatment groups were assigned at the mandal level. This means that using mandals or gram panchayats (which are local governments within mandals) as the fixed effects factor would lead to issues with perfect collinearity. Finally, PC_{md}[21] represents the principal component of a vector of mandal characteristics Muralidharan et al. use to stratify randomization, and ϵ_{ipmd} represents the error term for my regression.[22]

5.2 Heterogeneity—Models 2 and 3

Model 2:

$$Y_{ipmd} = \beta_0 + \beta_1 Treated_{md} + \beta_2 \bar{Y}^0_{pmd} + \beta_3 SC_{ipmd} + \beta_4 ST_{ipmd} + \beta_5 RA_{ipmd} + \beta_6 AC_{ipmd} + \beta_7 District_d + \beta_8 PC_{md} + \epsilon_{ipmd}$$

All of the elements described in model 1 remain consistent for model 2. Model 2 adds several control variables to model 1, each relating to different measures of socioeconomic class. Model 2 provides information on how each measure of socioeconomic class influences overall changes dependent variable. SC_{ipmd} and ST_{ipmd} are dummy variables that classify individual i in mandal m, panchayat p, and district d as belonging to a historically disenfranchised caste (scheduled

[19] The baseline mean of the dependent variable increases model robustness by increasing precision and assessing sensitivity to any randomization imbalances.

[20] District level fixed effects are used to account for any bias district could play in interaction between the dependent and independent variables

[21] Including stratification in the model allows for increased model robustness by accounting for how the vector of socioeconomic characteristics could bias interaction between the dependent and independent variables

[22] All regressions also include clustered standard errors at the mandal level

caste),[23] or historically disenfranchised tribe (scheduled tribe)[24] respectively.[25] The base group for both of these categories were non-members of scheduled tribes and castes because I specifically want to map how belonging to a historically disenfranchised group in society effected leakage. RA_{ipmd}, is a factor variable with 4 levels[26] that represents the religious affiliation of household or individual i in mandal m, panchayat p, and district d. I use Hindu as the base group for religion given it was the most common religion. AC_{ipmd}, is a continuous, quantitative variable that maps the annual consumption of household or individual i in mandal m, panchayat p, and district d.[27]

Model 3:

$$Y_{ipmd} = \beta_0 + \beta_1 Treated_{md} + \beta_2 \bar{Y}^0_{pmd} + \beta_3 Treated_{md} * I_{x_{ipmd}} + \beta_4 District_d + \beta_5 PC_{md} + \epsilon_{ipmd}$$

Where the x in $I_{x_{ipmd}}$ represents each one of the variables mapping to socioeconomic class listed in the description of model 2 (scheduled caste, scheduled tribe, religion, annual consumption). All of the elements described in model 1 remain consistent for model 3. Model 3 departs from model 1 by adding an interaction variable ($Treated_{md} * I_{x_{ipmd}}$) to map heterogeneity in the effect of smartcard implementation across each measure of socioeconomic class. $Treated_{md} * I_{x_{ipmd}}$ measures the interaction between the variable $Treated_{md}$ and each one of the variables ($I_{x_{ipmd}}$) that describe socioeconomic status, for

[23] Scheduled castes correspond to members of the Dalit caste, sometimes known as untouchables, who have a long history of discrimination and violence against them in India.

[24] Scheduled Tribes are communities of individuals who live in tribal areas, which are often more rural and more removed from government centers.

[25] To put it succinctly, scheduled castes are socially marginalized peoples, scheduled tribes are geographically and socially marginalized peoples.

[26] Corresponding to Hindu, Christian, Muslim, and Sikh

[27] I intend to use annual consumption as a measure of heterogeneity due to individuals' wealth. I chose to use annual consumption as a measure wealth over other measures, such as income, because of the permanent income hypothesis [Friedman, 1957], which states that individuals will spend money at a level consistent with their expected long-term income. This means that annual consumption will be a better measure of individuals' perceived long term wealth than current, short term, income.

individual i in mandal m, panchayat p, and district d.

I update Muralidharan et al.'s [Muralidharan et al., 2016] model to look at caste, tribe, religion, and annual consumption[28] because I am interested in seeing how each of these measures are correlated with changes in welfare program subsidy targeting (using model 2) and how smartcard implementation alters their effect on welfare program subsidy targeting (using model 3).

5.3 Dependent variables

I run my regressions over three dependent variables. All dependent variables are measured as change in value between baseline and endline surveys. I look at changes in officially reported payments,[29] changes in survey reported payments,[30] and changes in the difference between those two values (or leakage), all measured in rupees. All the dependent variables listed above are examined by Muralidharan et al. using model 1 at the household level. I regress models 2 and 3 on all three dependent variables to test heterogeneity of impact of smartcards on all three measures of welfare program efficacy across different measures of beneficiary's socioeconomic class. I run all regressions across both NREGS and SSP panels.

6 Dataset

6.1 Collection Process

[28] I also included language spoken and sex, in my original heterogeneity regressions, however they were only loosely connected to my theory behind heterogeneity in smartcard efficacy so current models only include caste, tribe, religion, and annual consumption. All expanded regressions and results can be found in the appendix in section 12.2

[29] Amounts officials reported paying beneficiaries.

[30] Amounts actually received by beneficiaries.

I use a dataset collected between 2010 and 2012 in the state of Andhara Pradesh [Muralidharan et al., 2016]. The dataset consists of panel data on official records of beneficiary lists and benefits paid from the Indian government, census data from the Indian government, and survey data the original researchers collected themselves. Their survey sample consists of 97,073 beneficiaries (58,493 from NREGS, and 38,580 from SSP) selected through a sampling design constructed to minimize sampling bias,[31] within 880 gram panchayat's (local governments), in 296 mandals (villages), sampled from the 8 districts in Andhra Pradesh that were forced to restart their smartcard programs in 2010, due to program failures earlier in the decade.

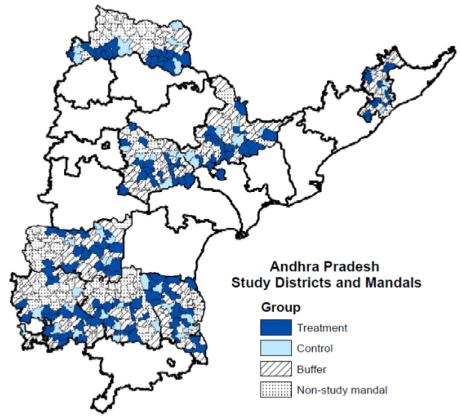

Figure 6: Map of Study Districts with Treatment and Control Mandals from Muralidharan et. al., 2016

The mandals are broken up into 3 groups for study: a treatment group consisting of 112 mandals (Figure 6;), a control group consisting of 45 mandals (Figure 6;), and a buffer group consisting of the remaining 139 mandals (Figure 6;). The smartcard program was restarted in 2010 in the treatment group. In the control group, the smartcard program was not implemented until 2012. The buffer group was created to ensure the researchers had time to conduct endline surveys after the smartcards program had been deployed in the treatment mandals but before it was implemented in the control mandals.

[31] Muralidharan et al. stratify randomization over district and the principal component of a vector of socioeconomic characteristics in order to minimize sampling bias in their final dataset. [Muralidharan et al., 2016].

During this time the smartcard program could be allowed to take place in the buffer mandals without affecting the control mandals. Muralidharan et. al. makes all this data publicly available.

6.2 Data Summary

Table 1: Summary statistics for change in official amounts reported paid, change in survey amounts reported paid, and change in leakage between Baseline and Endline surveys across Treatment and Control Groups, with corresponding T-tests for difference in means.

	Control		Treatment		T-test(Difference in Means)	
	NREGS	SSP	NREGS	SSP	NREGS	SSP
	(1)	(2)	(3)	(4)	(5)	(6)
Official Amounts Reported	61.528	259.005	61.884	262.625	0.29272	2.2167**
	(1.023)	(1.364)	(0.654)	(0.897)	(Not Diff)	(Diff)
Survey Amounts Paid	73.150	255.228	85.319	263.477	7.3***	4.8315***
	(1.323)	(1.456)	(0.989)	(0.934)	(Diff)	(Diff)
Leakage	−11.621	3.777	−23.435	−0.852	−8.0695***	−6.2298***
	(1.183)	(0.734)	(0.918)	(0.4866)	(Diff)	(Diff)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,549	11,247	41,944	27,333	58,493	38,580

Notes: *p<0.1; **p<0.05; ***p<0.01

**Columns 1-4 include mean values and (standard errors), measured in change in rupees, for each metric between baseline and endline surveys in the program by which their column is marked. Columns 5 & 6 list the t-value and (result of the t-test) for a difference in meanstest between the Control Group and the Treatment Group in each program (NREGS & SSP), where Diff = means are significantly different and Not Diff = means are not significantly different. All survey means reported are taken from a survey design that accounts for the principal component of a vector of socioeconomic characteristics used to stratify randomization, district level fixed effects, and clustered standard errors at the mandal level.*

Table 1 shows treatment and control groups' means values, standard errors,[32] and t-test results for difference in means between treatment and control groups, for changes in official amounts reported, survey amounts paid, and leakage for individuals between baseline and endline studies across both NREGS and SSP. The t-test results showed the mean values for changes in survey amounts paid and leakage in treatment mandals ares significantly different from the same mean

[32] Which are displayed in parenthesis underneath the means.

values in control mandals across both panels. The t-test results also show that mean values for official amounts reported are significantly different in treatment and control groups in SSP, but not in NREGS.

Table 2: Distribution of Population by Annual Consumption, Religion, Scheduled Caste, and Scheduled Tribe

	Control		Treatment	
	NREGS	SSP	NREGS	SSP
	(1)	(2)	(3)	(4)
SC	0.200	0.206	0.235	0.193
	(0.005)	(0.004)	(0.003)	(0.003)
ST	0.142	0.114	0.128	0.101
	(0.004)	(0.003)	(0.002)	(0.002)
Religion: Hindu	0.927	0.885	0.904	0.909
	(0.003)	(0.003)	(0.002)	(0.002)
Religion: Christian	0.030	0.038	0.042	0.031
	(0.002)	(0.002)	(0.001)	(0.001)
Religion: Muslim	0.040	0.077	0.053	0.056
	(0.003)	(0.003)	(0.002)	(0.002)
Religion: Sikh	0.001	0.00001	0.001	0.004
	(0.0004)	(0.00001)	(0.0001)	(0.0004)
Annual Consumption (1,000 Rs)	101.525	82.518	107.668	73.635
	(0.721)	(0.531)	(0.769)	(0.237)
District FE	Yes	Yes	Yes	Yes
Observations	16,549	11,247	41,944	27,333

Note: *p<0.1; **p<0.05; ***p<0.01

**Quantities for Annual Consumption, shown in row 7, represent mean and (se) values of annual consumption in each group. Quantities for all other metrics represent proportion and (se) of the total population each group makes up. All survey means and proportions reported are taken from a survey design that accounts for the principal component of a vector of socioeconomic characteristics used to stratify randomization, district level fixed effects, and clustered standard errors at the mandal level.*

Table 2 reports a breakdown of the treatment and control mandals by scheduled caste, scheduled tribe, religion, and annual consumption. Table 2 indicates that scheduled castes make up between 19 to 24% of the population across all groups and programs and scheduled tribes make up between 10 to 14% of the population across all groups and programs, whereas historically marginalized religions make up at most, 11.5%, of the population in any specific group and program[33]. This indicates that correcting for issues of leakage targeting for scheduled castes and tribes will have a much larger impact on general wellbeing of AP residents. I have included several figures regarding distribution of dependent variables across scheduled caste, scheduled tribe, religion, and annual consumption in the appendix (section 12.1; Figures 7-10).

7 Results

This section relays my results from regressing models 2 and 3 against changes in official amounts paid, survey amounts reported, and leakage between baseline and endline studies.[34] All results reported in the text are significant with a p-value < 0.01 unless otherwise noted. Section 7.1 (Model 2) relates my results exploring heterogeneity in the dependent variables due to caste, tribe, religion, and annual consumption. Section 7.2 (Model 3) relates my results testing for heterogeneity of impact of smartcard implementation across caste, tribe, religion, and annual consumption. Section 7.3 provides a summary of my most important results.[35]

7.1 Model 2

[33] SSP: 3.8% Christian + 7.7% Muslim

[34] Results at household aggregated and individual levels from regressing model 1 against all dependent variables can be found in the appendix in section 12.2, table 5

[35] All tables reported in the results section only display the correlations between the dependent variables and the variables of interest (treatment, caste, tribe, religion, annual consumption). However, in order to increase robustness of results, all regressions whose results are reported include: a) The Gram Panchayat-level mean of the dependent variable taken during the baseline study period, to increase precision of the regressions and assess sensitivity to randomization imbalances, b) The principal component of a vector of mandal characteristics used to stratify randomization of treatment assignment, c) Clustered standard errors at the mandal level, d) District level fixed effects, and e) an error term to measure the margin of error within each statistical model.

Table 3: Results of regressing model 2 on change in official amounts reported paid, change in survey amounts reported paid, and change in leakage between Baseline and Endline surveys.

	Dependent variable:					
	Official Amounts		Survey Amounts		Leakage	
	NREGS	SSP	NREGS	SSP	NREGS	SSP
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	2.013^{*}	3.449^{**}	13.918^{***}	7.858^{***}	-11.921^{***}	-4.900^{***}
	(1.192)	(1.638)	(1.646)	(1.730)	(1.513)	(0.879)
Scheduled Caste	4.478^{***}	2.227	15.657^{***}	-0.826	-10.995^{***}	3.224^{**}
	(1.363)	(1.947)	(2.155)	(2.120)	(2.086)	(1.443)
Scheduled Tribe	15.378^{***}	-17.502^{***}	12.713^{***}	-21.924^{***}	2.647	4.368^{***}
	(1.811)	(2.509)	(2.168)	(2.448)	(1.919)	(0.987)
Religion:Christian	7.051^{***}	13.821^{***}	1.985	29.520^{***}	4.542	-13.768^{***}
	(2.507)	(4.399)	(3.572)	(4.494)	(3.032)	(2.652)
Religion:Muslim	-16.185^{***}	30.267^{***}	-16.035^{***}	31.098^{***}	-0.526	-1.193
	(1.969)	(3.563)	(3.196)	(4.634)	(2.872)	(2.615)
Religion:Sikh	-21.746^{**}	55.664^{***}	-38.158^{***}	57.885^{***}	17.646^{*}	-1.095
	(9.218)	(15.654)	(9.209)	(15.157)	(9.971)	(3.126)
Annual Consumption (Rs)	-0.00001^{***}	-0.00003^{**}	-0.00001^{***}	-0.00001	0.00001^{**}	0.00001
	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00000)	(0.00001)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,493	38,580	58,493	38,580	58,493	38,580

Note: *p<0.1; **p<0.05; ***p<0.01

**All quantities reported reflect change in rupees (Rs) between baseline (2010) and endline (2012) studies. Though not displayed in the table, this regression included the Gram Panchayat-level mean of the dependent variables taken during the baseline study period, to increase precision of the regressions and assess sensitivity to randomization imbalances, the principal component of a vector of mandal characteristics used to stratify randomization of treatment assignment, clustered standard errors at the mandal level, and District level fixed effects*

My results from regressing model 2 on changes in official amounts reported paid to beneficiaries, survey amounts beneficiaries reported received, and leakage (Table 3) indicate two things: treatment continues to improve all measures of welfare program efficacy in the presence of added controls, and heterogeneity of impact from caste, tribe, religion, and annual consumption is present across all three of my dependent variables, but not in any sufficiently systemic way to indicate trends in leakage targeting without looking at the interaction terms from model 3 (Table 4). Table 3 shows that, treatment is correlated to increases in official amounts paid, with minor ($p < 0.1$) to moderate ($0.1 < p \leq 0.05$) significance, significant increases in survey amounts received, and significant decreases in leakage across both panels. Table 3 shows that belonging to a scheduled caste significantly increases official amounts paid and survey amounts reported, and significantly decreases leakage in the NREGS panel, but in the SSP panel belonging to a scheduled caste increases leakage with moderate significance. Table 3 shows that belonging to a scheduled tribe also significantly increases official amounts reported paid and survey amounts in the NREGS panel, the opposite is true for scheduled tribes in the SSP panel. Moreover, belonging to a scheduled tribe increases leakage in the SSP panel. Table 3 shows being Christian corresponds to increased official amounts reported in the NREGS panel compared to Hindus and increased official amounts paid and survey amounts received, and decreased in leakage in the SSP panel compared to Hindus. Table 3 showed being Muslim significantly decreases official amounts reported paid and survey amounts received compared to Hindus in the NREGS panel. In the SSP panel, the opposite is true. Sikhs show the same direction of changes as Muslims in both panels but with greater magnitudes with the sole exception of leakage, which increased for Sikhs compared to Hindus in the

NREGS panel. Finally, Table 3 shows increased annual consumption corresponds to a moderately significant decrease in official amounts reported across both panels, and in the NREGS panel also corresponds to a significant decrease in survey amounts reported and a moderately significant increase in leakage. These results indicate treatment still significantly improves every metric of welfare program efficacy across both panels under the conditions of added controls. Moreover, they show evidence of heterogeneity of impact across each measure of socioeconomic status, but display sufficient contradictions in effect between both programs within each of the control variables to warrant examining the results from the interaction terms implemented in model 3 (Table 4) before any conclusions can be drawn.

7.2 Model 3

My results from interacting caste, tribe, religion, and annual consumption with treatment (model 3) (Table 4) display two exceptionally important outcomes of smartcard implementation on scheduled castes and scheduled tribes, one moderately important outcome concerning annual consumption, and a important, but no less significant, result concerning religion. The first noteworthy result is treatment benefited scheduled castes significantly more than it benefited non-scheduled castes. The second, is that scheduled tribes in treatment mandals are left significantly worse off after treatment compared to scheduled tribes in control mandals. My moderatly important result, is that in treatment mandals, increased annual consumption is correlated with lower survey amounts paid and higher levels of leakage in NREGS, but higher survey amounts paid and lower levels of leakage in SSP. Finally, my slightly less conclusive result was that treatment helped reduce disparities in leakage across religious groups, but with sufficient ambiguity between programs, within religious groups, to make it

Table 4: Results for interaction of treatment on A) Caste, B) Tribe, C) Annual Consumption, and D) Religion for both panels.

	Dependent variable:					
	Official Amounts		Survey Amounts		Leakage	
	NREGS	SSP	NREGS	SSP	NREGS	SSP
	(1)	(2)	(3)	(4)	(5)	(6)
A) Scheduled Caste:						
Treatment	6.458***	8.501***	17.625***	9.850***	−11.219***	−1.797**
	(1.344)	(1.816)	(1.868)	(1.851)	(1.719)	(0.748)
Scheduled Caste	20.620***	22.400***	28.993***	12.300***	−8.457***	11.368***
	(2.526)	(3.482)	(3.346)	(4.200)	(2.989)	(2.951)
Treatment*SC	−22.010***	−25.445***	−18.721***	−11.579**	−3.023	−15.081***
	(2.840)	(4.067)	(4.015)	(4.762)	(3.696)	(3.347)
B) Scheduled Tribe:						
Treatment	3.178**	3.624**	14.957***	9.798***	−11.827***	−6.993***
	(1.283)	(1.758)	(1.830)	(1.870)	(1.660)	(0.978)
Scheduled Tribe	21.338***	−16.427***	14.323***	−7.444*	6.689**	−9.614***
	(2.993)	(3.798)	(3.352)	(3.965)	(3.251)	(1.394)
Treatment*ST	−8.955**	−4.967	−6.711*	−24.039***	−1.847	19.768***
	(3.576)	(4.684)	(4.045)	(4.761)	(3.802)	(1.882)
C) Annual Consumption:						
Treatment	3.108	0.643	10.857***	2.017	−7.919***	−0.941
	(2.011)	(2.923)	(3.118)	(3.211)	(2.843)	(1.762)
Annual Consumption	0.00000	−0.00005**	−0.00005*	−0.0001*	0.00005**	0.00004**
	(0.00002)	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00002)
Treatment*AC	−0.00001	0.00003	0.00003	0.0001*	−0.00004**	−0.00005***
	(0.00002)	(0.00003)	(0.00002)	(0.00003)	(0.00002)	(0.00002)
D) Religion:						
Treatment	2.860**	2.805	12.932***	6.319***	−10.098***	−4.291***
	(1.275)	(1.731)	(1.757)	(1.819)	(1.615)	(0.918)
Christian	21.856***	15.975**	−4.475	38.010***	25.727***	−20.637***
	(4.249)	(7.490)	(5.349)	(7.430)	(5.233)	(5.074)
Muslim	−14.782***	21.404***	−29.484***	11.103**	14.173***	9.301***
	(3.103)	(5.241)	(4.454)	(5.574)	(2.710)	(2.587)
Sikh	−41.752***	−41.546***	−36.787***	−50.261***	−5.558	0.648
	(11.281)	(2.512)	(4.337)	(2.639)	(12.907)	(1.353)
Treatment*Christian	−17.065***	1.162	20.212***	−11.227	−36.924***	13.021**
	(4.983)	(8.997)	(6.447)	(8.941)	(5.886)	(5.592)
Treatment*Muslim	−5.135	15.111**	11.683**	33.877***	−16.578***	−17.667***
	(3.903)	(6.899)	(5.791)	(8.625)	(4.441)	(4.792)
Treatment*Sikh	26.989*	98.575***	−1.688	108.175***	31.013*	0.584
	(16.337)	(15.741)	(13.378)	(15.260)	(17.399)	(3.068)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,493	38,580	58,493	38,580	58,493	38,580

Note: *p<0.1; **p<0.05; ***p<0.01

**All quantities reported reflect change in rupees (Rs) between baseline (2010) and endline (2012) studies. Though not displayed in the table, this regression included the Gram Panchayat-level mean of the dependent variables taken during the baseline study period, to increase precision of the regressions and assess sensitivity to randomization imbalances, the principal component of a vector of mandal characteristics used to stratify randomization of treatment assignment, clustered standard errors at the mandal level, and District level fixed effects*

difficult to draw broader conclusions from my results without further study.

7.2.1 Caste

Table 4, section A, shows the results of interacting treatment with caste (model 3). Interacting caste with treatment shows that for non-scheduled caste members in treatment mandals, average leakage significantly decreases by 11.219 rupees in the NREGS panel and 1.797 rupees in the SSP panel. The magnitude of this decrease increases by 8.457 Rs in NREGS and 3.713 Rs in SSP for scheduled caste members in treatment mandals. For non-scheduled caste members in treatment mandals, average official amounts reported significantly increase by 6.458 Rs in the NREGS panel and 8.501 Rs in the SSP panel. The magnitude of this increase decreases by 1.390 Rs in NREGS and 3.045 Rs in SSP for scheduled caste members in treatment mandals. For non-scheduled caste members in treatment mandals, average survey amounts received significantly increase by 17.625 Rs in the NREGS panel and 9.850 Rs in the SSP panel. The magnitude of this increase increases by 10.272 Rs in NREGS and 0.721 Rs in SSP for scheduled caste members in treatment mandals. To summarize, my results show that scheduled castes in treatment mandals show significantly smaller increases in official amounts reported, larger increases in survey amounts paid, and larger decreases in leakage compared to non-scheduled castes.

7.2.2 Tribe

Table 4, section B, shows the results of interacting treatment with tribe (model 3). Interacting tribe with treatment shows that for non-scheduled tribe members in treatment mandals, average leakage significantly decreases by 11.827 rupees in the NREGS panel and 6.993 rupees in the SSP panel. The magnitude of this decrease decreases by 6.689 Rs in NREGS. In SSP, the direction of this decrease changes, indicating in treatment mandals leakage increases for members of scheduled tribes by a total of 3.161 Rs. For non-scheduled tribe members in treatment mandals, average official amounts reported significantly increase by 3.178 Rs in the NREGS panel and 3.624 Rs in the SSP panel. The magnitude of this increase increases by 12.383 Rs in NREGS. In SSP, the direction of this increase changes, indicating in treatment mandals official amounts reported paid decrease for members of scheduled tribes by a total of 12.803 Rs. For non-scheduled tribe members in treatment mandals, survey official amounts recieved significantly increase by 14.957 Rs in the NREGS panel and 9.798 Rs in the SSP panel. The magnitude of this increase increases by 7.621 Rs in NREGS, but with only minor significance. In SSP, the direction of this increase changes, indicating in treatment mandals survey amounts received decreases for members of scheduled tribes by a total of at least 14.291 Rs with high significance and up to 21.685 Rs with minor significance. To summarize, my results show that in NREGS, scheduled tribes in treatment mandals show significantly larger increases in official amounts reported than survey amounts received, compared to all others, who see larger increases in survey amounts received then official amounts reported, and in SSP show significantly larger decreases in survey amounts received than official amounts reported. Moreover, being in a scheduled tribe in treatment mandal corresponds to a significantly smaller decrease in leakage in NREGS and an active increase in leakage in SSP. These results indicate that treatment did not help scheduled tribes as much as all others and in the case of SSP, actively harmed them.

7.2.3 Annual Consumption

Table 4 Section C) shows the results of interacting treatment with annual consumption (model 3). Interacting annual consumption with treatment significantly alters the effect of annual consumption on the leakage. In control mandals, a 1,000 Rs increase in annual consumption corresponds to a 0.05 Rs increase in leakage in NREGS with moderate significance and a 0.04 Rs increase in leakage in SSP with moderate significance. In treatment mandals, the magnitude of this correlation decreases by 0.04 Rs in NREGS, with moderate significance, but the direction of correlation significantly changes in SSP, indicating that in treatment mandals, a 1,000 Rs increase in annual consumption corresponds to a 0.01 Rs decrease in leakage in SSP. While treatment has no effect on the effect of annual consumption on survey amounts paid in NREGS, in SSP, treatment increases the effect of a 1,000 Rs increase in annual consumption on survey amounts paid by 0.01 Rs with minor significance, the exact opposite correlation as seen between annual consumption and survey amounts paid in control mandals. This indicates that, while treatment helps lessen the magnitude of heterogeneity in leakage due to annual consumption in NREGS, treatment switches the direction of the correlation between annual consumption and leakage in SSP, and significantly negates the correlation between annual consumption and survey amounts paid from negative to around 0. However, the low levels of significance in these results indicate they might not be as reliable as my other findings.

7.2.4 Religion

Table 4, Section D, shows the results of interacting treatment with religion (model 3). Analyzing the interactions of the various religions suggests that treatment decreases the differences in leakage across different religions, particularly Christians and Muslims. However, because the changes are not uniform across both programs or across historically persecuted religions there's enough ambiguity to be cautious about drawing larger conclusions from these results. The interactions suggest that treatment mostly decreases the degree to which Muslims and Christians suffered disparate leakage. As a baseline, interacting religion with treatment shows that for Hindus in treatment mandals, average leakage significantly decreases by 10.098 rupees in treatment mandals in the NREGS panel and 4.277 rupees in the SSP panel relative to control mandals. Table 4 shows that Christians in control mandals experience increased leakage in NREGS and decreased leakage in SSP. Treatment corrects for the increased leakage in NREGS, corresponding to a greater decrease in leakage for Christians in treatment mandals compared to Hindus in treatment mandals. However, in SSP, treatment decreases the magnitude of leakage decrease for Christians in treatment mandals compared to Christians in control mandals. Being Muslim in control mandals corresponds to increased leakage across both panels. Residing in a treatment mandal corrects for this issue and shows being Muslim in a treatment mandal corresponds to larger decreases in leakage than being Hindu in a treatment mandal. In treatment mandals, leakage decreases more for Christians than Muslims in the NREGS panel but decreases more for Muslims than Christians in the SSP panel. Being Sikh in a treatment mandal corresponds to a minorly significant increase in leakage in SSP, but with a standard error over half the size of the coefficient, which indicates questionable validity of this finding, especially considering the small proportion of Sikhs in NREGS treatment groups (Table 2, Column (3), Religion: Sikh). My results for official amounts reported paid and survey amounts received show significant heterogeneity between programs within religions, and between Muslims and Christians. These effects only introduce more ambiguity into my results and don't show any particularly systemic patterns that can be applied to heterogeneity of smartcard impact on marginalized religions.

7.3 Results Summary

My two most powerful results come from interacting treatment with caste and with tribe (Table 4: Section A and B). Interacting treatment with caste

(Table 4: Section A) shows that members of scheduled castes (SCs) benefit more highly from smartcard implementation than members of non-scheduled castes. The comparative decrease in leakage for SCs in treatment mandals, compared to non-SCs in treatment mandals across both panels indicates that biometric smartcards benefit SCs more than non-SCs, and help correct for previous issues of targeting of SCs pre-smartcard implementation. Moreover, the comparatively high increase in the amounts survey recipients reported they were actually paid and the comparatively low increase in official amounts paid to SCs in treatment mandals, compared to non-SCs in treatment mandals, indicates a decrease in overreporting and underpaying.[36] My results from interacting treatment with tribe (Table 4: Section B) indicate treatment had the exact opposite effect on members of scheduled tribes (STs) as it had on members of SCs. The comparative increase in leakage for STs in treatment mandals, compared to non-STs in treatment mandals across both panels indicates that members of STs were either not helped or affirmatively hurt by smartcard implementation. Moreover, in NREGS the official amounts reported paid to STs in treatment mandals increase by significantly more than the survey amounts reported received by STs in treatment mandals, indicating increased overreporting. Similarly, in SSP the survey amounts reported received by STs in treatment mandals decrease significantly more than official amounts reported received by STs in treatment mandals, indicating increased underpaying of STs in SSP programs. These results indicate increased targeting of STs in treatment mandals by corrupt officials through both overreporting and underpaying.

[36]Survey amounts increasing more than official amounts, indicates that both overreporting and underpayment were working in tandem here. Without underpaying we would see a more or less steady survey amount paid while official amounts reported decreased. Without overreporting, we would see a steady level of official amounts paid but increases in survey amounts paid. Therefore, increase of both metrics indicates a decrease in both mechanisms of leakage.

Beyond these primary results of importance, my remaining results identify two other areas where treatment had impact on outcomes of interest. First, my results interacting annual consumption with treatment (Table 4: Section C) show significant heterogeneity of impact of treatment on annual consumption between NREGS and SSP programs. In NREGS increased annual consumption is significantly correlated to decreased survey amounts received and increased leakage. In SSP, treatment significantly increases the correlation between survey amounts reported for individuals and higher levels of annual consumption and changes the direction of leakage, indicating increased annual consumption corresponds to a significant decrease in leakage. Second, my results interacting religion with treatment (Table 4: Section D) show significant evidence that treatment helped reduce disparities in leakage of payments to Christians and Muslims but given inconsistencies in direction and quality of impact between the two historically persecuted religions and within each religion between different programs, drawing meaningful conclusions about general impact of smartcards on historically persecuted religions is challenging.

8 Robustness and Expanded Heterogeneity Models

8.1 Household Replicated vs. Individual Level

In order to test my model construction I replicate Muralidharan et. al.'s [Muralidharan et al., 2016] results at the household level and regress my base model (model 1) on individual level data to test if Muralidharan et. al's findings aggregated at the household level, were consistent at the individual level.[37] I

[37]Tables comparing household aggregated and individual level results can be found in the appendix, in section 12.1 in table 5

find that across both programs (NREGS and SSP) being in a treatment mandal significantly increases amounts individual beneficiaries reported actually receiving and significantly decreases leakage of funds. These results corroborate Muralidharan et al.'s findings at the household aggregated level, that biometric smartcards significantly improve subsidy targeting by welfare programs for individual beneficiaries, at the individual level.

8.2 Expanded Models (adding Language and Sex)

In my original construction of models 2 and 3 I included two other variables measuring socioeconomic class, to see whether they had any correlation with the effect of smartcard implementation.[38] These variables were Language and Sex. I included these variables to explore whether either of these historical dimensions of marginalization would play a role in introducing heterogeneity of smartcard impact similar to the most obvious dimensions predicted by my model of caste, tribe, religion, and annual consumption. My results show that sex and language were largely insignificant. Sex only plays a minorly significant role in determining official amounts paid, and only in the NREGS panel, and language spoken shows some indication of heterogeneity of effect of smartcard rollout, but none that indicates any systemic patterns of targeting linguistic minorities.[39]

9 Discussion

My regression results indicate significant evidence of heterogeneity of impact of smartcard rollout on official amounts reported, survey amounts paid, and

[38] More detailed explanations of the expanded models can be found in the appendix in section 12.2.1

[39] Regression results adding language and sex as controls to model 2 can in table 6. Regression results interacting language and sex with treatment can be found in the appendix in 7. Both of these tables are in the appendix in section 12.2.2

leakage across caste, tribe, religion, and annual consumption. My two clearest and most important results relate to caste and tribe. Biometric smartcards significantly reduce the effects of discriminatory underpayment and overreporting targeted at scheduled castes in welfare subsidy programs. However, the data also shows a significant increase of leakage in payments due to members of scheduled tribes (STs). In combination, these results suggest that corrupt officials may displace their exploitation from one disenfranchised minority onto another, for whom access to smartcards may be more limited. Because the data did not include records of actual smartcard distribution at the individual level, this implication cannot be conclusively shown from the data. The significantly greater benefits that scheduled castes (SCs) experience in treatment mandals as compared to non-SCs in treatment mandals offer evidence that contradicts widely expressed concerns that smartcards might create barriers to access for historically disenfranchised castes and supports the idea that smartcards help correct for discrimination issues in welfare programs susceptible to corruption and leakage. Moreover, my results imply that treatment decreases both overreporting and underpaying for scheduled castes and corroborates my theory that poorer classes, like SCs, will be greater targets for underpaying and overreporting, possibly due to their relatively high total costs of reporting leakage. The significant displacement of leakage from non-STs onto STs in treatment groups supports the concerns that incompletely implemented programs could displace corruption onto others with less access to smartcards [Yang, 2008]. Finally, in the NREGS program, the significant evidence of increased underpaying for wealthier beneficiaries reinforces my theory that being wealthier, and thereby having a lower marginal benefit of reporting underpaying, is correlated with being the subject of higher levels of underpaying. Moreover, the positive correlation between annual consumption and leakage in NREGS, but negative correlation between annual consumption and leakage in SSP, both marginally significant, offer some support for the theory that the SSP programs leave less room for underpaying than NREGS [Dutta et al., 2010].

My study indicates that the implementation of smartcards generally improves welfare programs' ability to provide subsidies to individual beneficiaries and successfully decreases leakage. Moreover, it indicates that smartcards can correct for some discrimination in leakage targeting by providing greater leakage correction to historically disenfranchised socioeconomic groups. However, it also indicates that without complete implementation and universal access, implementation of biometric smartcards can shift the efforts of corrupt officials to exploit historically disenfranchised groups with less access to smartcards or welfare programs more generally. This implies that proper implementation of biometric smartcards is an important step for developing countries attempting to correct for issues of leakage in financial inclusion programs. In particular, it is important for developing countries to prioritize rollout of biometric smartcards to the most historically disenfranchised so as to preempt the intensification of corrupt officials' efforts on exploiting marginalized communities with delayed access to smartcard systems.

Despite the strong implications of my results, it is important to acknowledge the scope of my findings. The deeply ingrained caste system in India could mean that the results of this study are not applicable to other countries with different possible sources and levels of discrimination. For instance, my results might not be particularly applicable to countries without such a serious history of class discrimination (in the form of castes) and religious violence and persecution (like the Philippines [Zimmerman and Bohling, 2013b]). In countries where geographically remote tribes make up a much larger portion of the population (like in sub-Saharan Africa [Zimmerman and Bohling, 2013a, Jack and Suri, 2014, Reinikka and Svensson, 2004]) the negative impact on remote tribes might outweigh any positive impact on more geographically proximate, historically disenfranchised classes. The primary implication is that in countries where this is true, emphasizing rollout to remote tribes is even more important because of the potential of delayed rollout causing negative effects on them. Moreover, both programs I study deal with direct cash transfer subsidy programs. Therefore, it is possible the results of this study will not apply as significantly to other financial inclusion programs such as goods based subsidy programs like the fuel subsidies studied by Barnwal [Barnwal, 2015]. Despite these limitations, Andhra Pradesh's smartcard rollout was the largest scale implementation of a transfer payments program to incorporate experimental design, and given that the results are consistent with what theory predicts, the lessons seem meaningful to the future design of similar subsidy programs in countries where corruption and leakage are endemic.

Further research on this subject should focus on three things, determining the cause of heterogeneity of impact between different programs within religious groups and between different historically marginalized religions, distribution of smartcard access, and specific distribution of mechanisms of leakage. First my results for Christians and Muslims suggest that further study is warranted into why we observe heterogeneity of impact across different religious groups and within marginalized religions across different programs. My results indicate there might be some factor that interacts with, or is correlated with religious affiliation that my model failed to account for. Second, my interpretation of my results for STs, that they reflect displacement of leakage from marginalized groups with access to smartcards onto marginalized groups with less access to smartcards, cannot be conclusively tested on this data because the data does not include individual level data on the true distribution of smartcards across each socioeconomic class. Future studies would benefit from collecting data to determine actual distribution of biometric smartcards across individuals in different socioeconomic groups. This would help determine if my results truly correspond to lack of access to smartcards or if the correlation between isolated geographical location and decreased benefits from smartcard implementation are caused by some other factor I did not account for.[40] Third, future analyses should seek to test for changes in specific mechanisms of leakage. This would help clarify the extent of overreporting (including ghosts and quasi-ghosts) and underpaying, which groups are more heavily targeted by each mechanism of leakage, and which mechanisms of leakage are more effectively targeted by biometric smartcards.

10 Conclusion

The largest challenge facing welfare programs in developing countries is securely delivering payments to the correct beneficiaries. This problem is largely due to corrupt officials stealing money from the systems through a process called leakage. While the precise magnitude is unknown, several studies suggest that corrupt officials may siphon off 70-85% of public expenditures on subsidy programs in India [Sathe, 2011, Programme Evaluation Organisation, 2005]. In this paper I evaluated the impact of using biometrically authenticated smartcard payments on beneficiaries of two welfare programs in the Indian state of Andhra Pradesh, the National Rural Employment Guarantee Scheme and Social Security Pensions programs. Moreover, I measured to what extent smartcards show heterogeneity of impact across individuals caste, tribe, religion, and annual

[40] As well as lending insight into whether the increase of leakage for scheduled tribes was related lack of access to smartcards, this data might be able to clarify the ambiguity of my results regarding religion (if, for instance, certain religions had less access to smartcards than others).

consumption. I ran several regressions aimed at addressing these questions on a panel-level survey sample of 97,073 individuals for whom data was collected between 2010 and 2012 from a large scale experiment where smartcard rollout was randomized across 157 subdistricts and 19 million individuals. I found that smartcard rollout significantly reduces leakage of funds between the government and beneficiaries in both NREGS and SSP programs. Moreover, I found evidence that in the case of castes, smartcards benefit disenfranchised minorities more than their non-marginalized peers, but in the case of scheduled tribes, the program actually worsens leakage, likely due to displacement of the efforts of corrupt officials toward those more remote minorities where implementation was likely delayed or imperfect. Overall, my results suggest that investing in biometric smartcards can significantly improve welfare program efficacy in developing countries, but only properly address issues of discrimination when programs are fully and carefully implemented.

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12 Appendix

12.1 Robustness Tables and Distribution Figures

12.1.1 Model 1: Household Aggregated vs. Individual Level Results

Table 5 displays side by side comparisons of my household level replication of Muralidharan et al.'s [Muralidharan et al., 2016] results and my original, individual level, results across both NREGS and SSP programs. Figures 7 through 10 reflect the distributions of my dependent variables across sc, st, religion, and annual consumption across treatment and control models for both NREGS and SSP.

Table 5: Results for household level replicated and individual level original regressions for both NREGS and SSP programs.

	Dependent variable:					
	Official Amounts		Survey Amounts		Leakage	
	HHD replicated	Individual	HHD replicated	Individual	HHD replicated	Individual
	(1)	(2)	(3)	(4)	(5)	(6)
A) NREGS:						
Treatment	8.031	1.966^{*}	33.320^{**}	14.036^{***}	-24.175^{**}	-12.066^{***}
	(8.168)	(1.195)	(13.432)	(1.654)	(12.281)	(1.514)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,107	58,493	5,107	58,493	5,107	58,493
B) SSP:						
Treatment	4.859	2.360	11.976^{*}	7.446^{***}	-7.406^{*}	-4.889^{***}
	(6.045)	(1.646)	(6.683)	(1.735)	(4.015)	(0.882)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,139	38,580	3,139	38,580	3,139	38,580
Note:						*p<0.1; **p<0.05; ***p<0.01

12.2 Expanded Heterogeneity Models

12.2.1 Description of Expanded Models

Model 2 [expanded]:

$$Y_{ipmd} = \beta_0 + \beta_1 Treated_{md} + \beta_2 \bar{Y}^0_{pmd} + \beta_3 RA_{ipmd} + \beta_4 AC_{ipmd} + \beta_5 L_{ipmd} +$$
$$\beta_6 Sex_{ipmd} + \beta_7 SC_{ipmd} + \beta_8 ST_{ipmd} + \beta_9 District_d + \beta_1 0 PC_{md} + \epsilon_{ipmd}$$

All of the elements described in my econometric model section (section 5) remain consistent for this expanded version of model 2. This version of model 2 includes control variables for language and sex. L_{ipmd} is a factor variable with 8 levels that corresponds to the language spoken by household or individual i in mandal m, panchayat p, and district d. I used Telugu as the base group for language because it is the official language of the state of Andhra Pradesh, and the language in which all official processes are conducted [Office of the Registrar General Census Commissioner, 2011]. Sex_{ipmd} is a factor variable with 2 levels

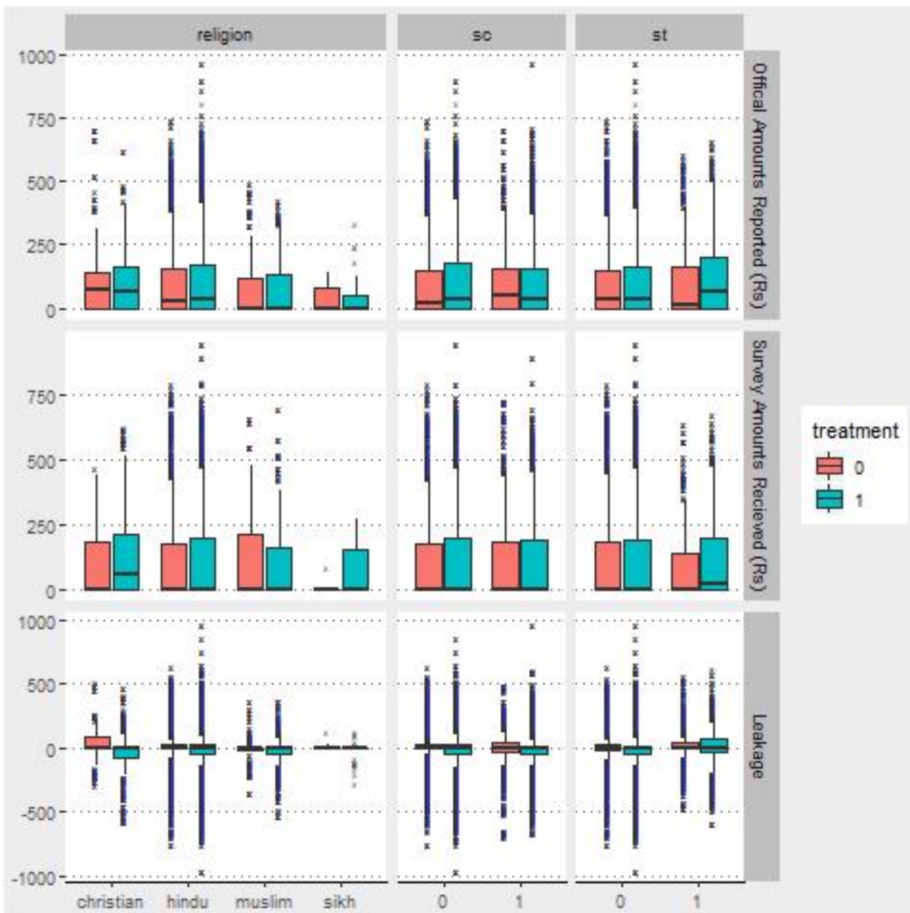

Figure 7: Boxplot matrix showing distribution of dependent variables across SC, ST, and Religion in Treatment (1) and Control (0) groups (NREGS)

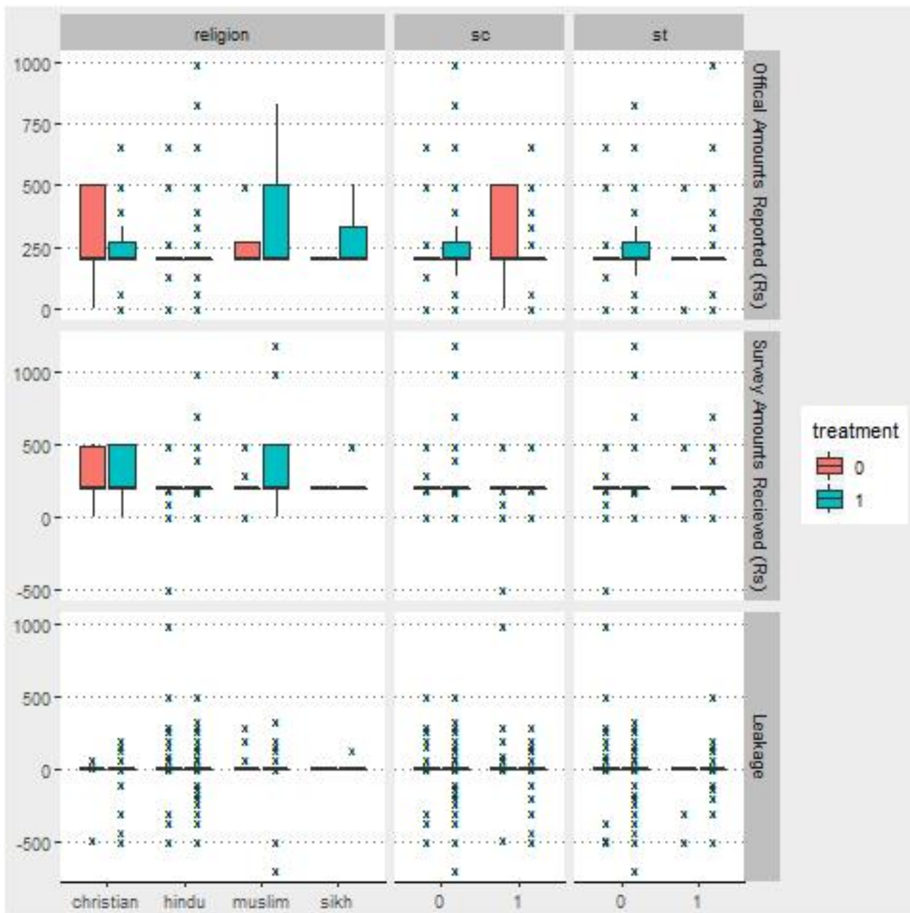

Figure 8: Boxplot matrix showing distribution of dependent variables across SC, ST, and Religion in Treatment (1) and Control (0) groups (SSP)

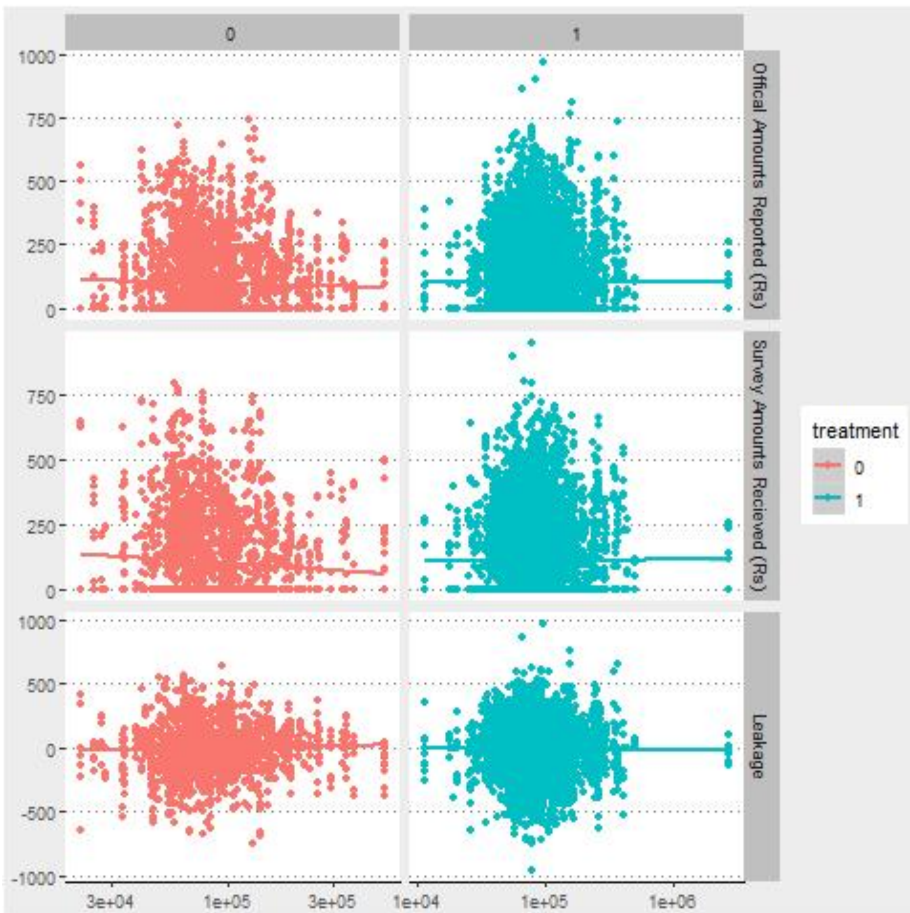

Figure 9: Boxplot matrix showing distribution of dependent variables across annual consumption in Treatment (1) and Control (0) groups (NREGS)

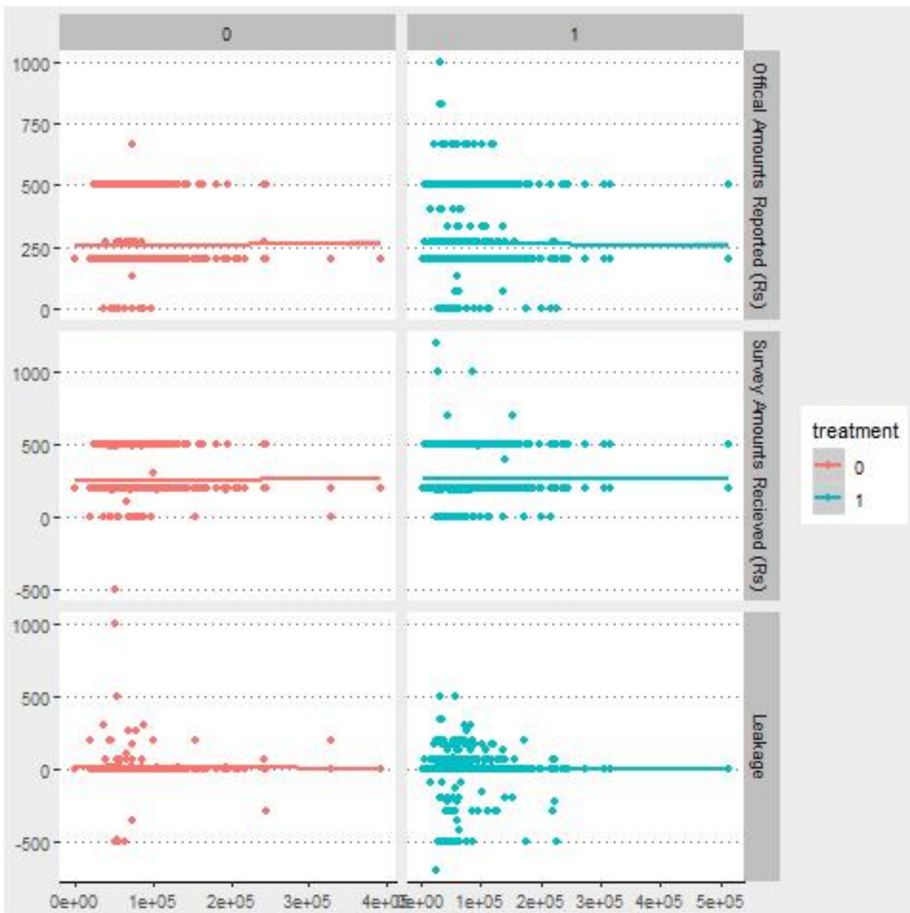

Figure 10: Boxplot matrix showing distribution of dependent variables across annual consumption in Treatment (1) and Control (0) groups (SSP)

that corresponds to the sex of individual i in mandal m, panchayat p, and district d. The base group for sex was male given the history of discrimination against women in India [Vaid, 2018]. Model 3 remains exactly the same as I described it in my econometrics section, except in the appendix version I also included language and sex as interaction variables (I_{ipmd}).

12.2.2 Expanded Heterogeneity Model Results

Table 6: Results of regressing expanded model 2 on change in official amounts reported paid, change in survey amounts reported paid, and change in leakage between Baseline and Endline surveys.

	Dependent variable:					
	Official Amounts		Survey Amounts		Leakage	
	NREGS	SSP	NREGS	SSP	NREGS	SSP
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	1.803	3.719**	13.991***	8.355***	−12.209***	−5.170***
	(1.194)	(1.641)	(1.652)	(1.741)	(1.516)	(0.897)
Annual Consumption (Rs)	−0.00001***	−0.00003**	−0.00001***	−0.00002	0.00001*	0.00001
	(0.00000)	(0.00001)	(0.00000)	(0.00002)	(0.00000)	(0.00001)
Religion: Christian	7.061***	13.980***	2.046	29.846***	4.523	−13.966***
	(2.507)	(4.406)	(3.568)	(4.500)	(3.034)	(2.658)
Religion: Muslim	−16.035***	27.997***	−17.499***	26.192***	1.222	2.089
	(2.293)	(3.897)	(3.766)	(4.599)	(3.432)	(2.306)
Religion: Sikh	−22.066**	55.619***	−39.010***	57.860***	18.137*	−1.129
	(9.311)	(15.661)	(9.226)	(15.164)	(9.925)	(3.135)
Language: English	−0.310	2.028	−4.470	2.720	3.995	−1.938
	(3.942)	(4.956)	(5.344)	(5.793)	(5.269)	(2.738)
Language: Hindi	−6.141*	−2.489	−5.063	−1.617	−1.300	−1.785
	(3.201)	(5.317)	(5.542)	(5.524)	(5.149)	(2.054)
Language: Kanada	−0.870	0.606	−0.737	5.990	−0.249	−6.408*
	(3.609)	(5.199)	(5.268)	(6.636)	(4.898)	(3.661)
Language: Marathi	2.986	0.990	13.673**	8.826	−10.927*	−8.637**
	(4.114)	(5.420)	(6.690)	(7.142)	(6.343)	(4.219)
Language: Oriya	4.629	11.267*	8.419	15.628**	−3.886	−5.387
	(4.083)	(6.290)	(6.495)	(7.765)	(6.880)	(3.956)
Language: Tamil	−1.471	3.830	7.584	5.264	−9.212	−2.246
	(3.737)	(5.631)	(6.503)	(5.844)	(6.377)	(1.798)
Language: Urdu	2.708	7.460	1.621	13.265*	0.971	−6.652*
	(3.906)	(5.638)	(5.367)	(6.839)	(4.867)	(3.457)
Sex: Female	0.297	−2.668*	−1.543	−2.020	1.832	−0.801
	(1.112)	(1.554)	(1.622)	(1.607)	(1.487)	(0.844)
Scheduled Caste	4.581***	2.191	15.714***	−0.924	−10.958***	3.295**
	(1.364)	(1.950)	(2.158)	(2.125)	(2.089)	(1.450)
Scheduled Tribe	15.432***	−18.402***	11.846***	−23.880***	3.621	5.694***
	(1.946)	(2.567)	(2.511)	(2.477)	(2.229)	(0.963)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,408	38,505	58,408	38,505	58,408	38,505

Note: *p<0.1; **p<0.05; ***p<0.01

**All quantities reported reflect change in rupees (Rs) between baseline (2010) and endline (2012) studies. Though not displayed in the table, this regression included the Gram Panchayat-level mean of the dependent variables taken during the baseline study period, to increase precision of the regressions and assess sensitivity to randomization imbalances, the principal component of a vector of mandal characteristics used to stratify randomization of treatment assignment, clustered standard errors at the mandal level, and District level fixed effects*

Table 7: Results for interaction of treatment on language and sex for both panels.

	Dependent variable:					
	Official Amounts		Survey Amounts		Leakage	
	NREGS	SSP	NREGS	SSP	NREGS	SSP
	(1)	(2)	(3)	(4)	(5)	(6)
A) Language:						
Treatment	3.248**	1.409	12.666***	5.645***	−9.451***	−4.974***
	(1.329)	(1.818)	(1.820)	(1.918)	(1.614)	(1.020)
English	3.915	1.733	−11.947	0.547	15.594*	0.220
	(6.259)	(7.566)	(8.158)	(7.795)	(8.998)	(2.656)
Hindi	−8.129*	1.156	−11.287	5.821	2.917	−5.786***
	(4.694)	(8.601)	(7.797)	(8.880)	(7.568)	(2.137)
Kanada	5.626	3.158	−5.774	4.693	11.149**	−2.164
	(5.618)	(7.896)	(6.048)	(7.905)	(5.363)	(2.562)
Marathi	8.308	−8.400	14.895	−8.413	−7.069	−1.043
	(6.261)	(7.548)	(11.382)	(7.823)	(11.875)	(2.542)
Oriya	16.356**	2.924	5.190	2.911	10.790	−0.464
	(7.350)	(8.597)	(9.858)	(9.198)	(9.874)	(3.169)
Tamil	−1.372	−3.488	−11.164	0.859	9.530	−3.844**
	(6.037)	(7.640)	(6.952)	(8.053)	(6.051)	(1.939)
Urdu	11.707	−4.806	−15.467**	−1.658	26.883***	−4.253
	(7.154)	(8.424)	(6.129)	(8.615)	(6.904)	(2.795)
Treatment*English	−7.428	5.756	5.882	6.011	−13.204	−0.575
	(7.899)	(9.793)	(10.503)	(11.323)	(10.842)	(5.346)
Treatment*Hindi	1.582	2.286	4.559	−6.913	−3.021	9.878***
	(6.186)	(10.659)	(10.499)	(10.986)	(9.829)	(3.648)
Treatment*Kanada	−9.026	3.211	4.904	7.134	−13.777	−4.406
	(7.222)	(10.317)	(9.361)	(12.935)	(8.541)	(6.995)
Treatment*Marathi	−6.653	23.384**	−4.222	33.904**	−2.074	−9.893
	(8.127)	(10.729)	(13.843)	(13.700)	(13.779)	(7.678)
Treatment*Oriya	−16.489*	23.898*	0.339	28.728*	−16.493	−5.454
	(8.735)	(12.275)	(12.539)	(15.102)	(12.890)	(7.579)
Treatment*Tamil	−1.954	21.021*	20.456*	13.198	−22.341**	5.842*
	(7.536)	(11.087)	(10.699)	(11.588)	(10.109)	(3.275)
Treatment*Urdu	−14.486*	27.079**	17.231*	28.528**	−31.539***	−0.803
	(8.454)	(11.155)	(8.924)	(13.067)	(8.877)	(6.255)
B) Sex:						
Treatment	4.540***	2.962	15.524***	6.260**	−11.024***	−4.057***
	(1.676)	(2.511)	(2.369)	(2.620)	(2.136)	(1.240)
Female	4.066**	−3.060	0.171	−3.573	3.824	0.282
	(2.031)	(2.823)	(2.739)	(3.008)	(2.412)	(1.497)
Treatment*Female	−5.440**	0.735	−2.825	2.341	−2.529	−1.526
	(2.425)	(3.392)	(3.382)	(3.574)	(3.030)	(1.812)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,493	38,580	58,493	38,580	58,493	38,580

Note: *p<0.1; **p<0.05; ***p<0.01

**All quantities reported reflect change in rupees (Rs) between baseline (2010) and endline (2012) studies. Though not displayed in the table, this regression included the Gram Panchayat-level mean of the dependent variables taken during the baseline study period, to increase precision of the regressions and assess sensitivity to randomization imbalances, the principal component of a vector of mandal characteristics used to stratify randomization of treatment assignment, clustered standard errors at the mandal level, and District level fixed effects*