Whose Right Is It Anyway? Welfare Implications of Food Security Programs

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Abstract: Governments worldwide implement food security programs to combat malnutrition, but there is a debate about which implementation strategy is more effective in developing countries: a universal approach, under which households of all income categories have access to the benefits of the program, or a targeted approach, under which only poor households are eligible. I address this question in the context of the world's largest food security program, the Indian Public Distribution System (PDS). The PDS provides grains at highly subsidized rates to the poor, and the extent of targeting differs from state to state within India. This provides an ideal quasi-experimental setting in South India to analyze the impact of universal versus targeted food security programs on vulnerability to poverty using a geographic regression discontinuity design. I use household survey data from the India Human Development Survey-II (IHDS II), 2011-12, for the empirical analysis. The results indicate that a more universal approach to food security is more successful in poverty reduction, and the effects are greater for the most marginalized groups. Households use the subsidy from the PDS to make various types of risk averse investments, all of which protect them in contingencies and reduce their vulnerability to poverty. They also increase their labor supply in their primary occupation and reduce the number of casual jobs they take up, thereby reducing variability in income and making them less vulnerable to poverty. These results indicate, that not only are food security measures sufficient for poverty alleviation, but a more universal approach is more effective, at least in the context of developing countries like India.

JEL: H53, I32, I38, J22, J28

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1 | Introduction

According to the FAO, one in 9 people worldwide suffer from chronic malnourishment, which make them less productive workers. As figure 1 shows, there is a strong correlation between malnourishment rates and poverty. Hence, food security programs may help improve living conditions, while reducing malnourishment prevalence, by giving the poor access to food at subsidized rates and allowing them to spend their money on other items. In practice, however, it is often unclear whether food security programs work as well as other anti-poverty programs, and how they should be implemented to be most effective.

The question of the best implementation strategy of a welfare program for the poor is a much debated topic, and empirical evidence on this question is scarce. Under a universal program everyone can claim the benefits of the program, whereas in a targeted program the benefits are delivered selectively to those in need. A targeted system tends to receive greater public support because it costs less in terms of expenditure on benefits and due to expectations of higher quality. However, determining eligibility for targeted programs is costly, difficult, and imperfect. This is especially true in developing countries which do not have the required administrative sophistication and capacity for identifying the poor with precision. The major advantage of universal programs on the other hand is that they are easy to administer. Arguments of proponents of a more universal system (Dreze & Khera 2010, Abreu et al 2011) are based on the premise of minimizing errors of wrong exclusion,[1] which is heightened under a targeted system. The current emphasis on targeting around the world, however, does not take into account the experience from many advanced countries, which suggests that universal systems may have underappreciated long term effects.[2]

[1] exclusion of the people that the government would most like to aid

[2] The experience of many European countries, for instance, suggests that universal provisioning of social services served as an important instrument for development and nation building. Many European countries, for example, introduced flat-rate pensions at a comparatively early stage of welfare state development, when these countries had the same per capita incomes that Latin American countries had in the 1980s and 1990s (Mkandawire 2005)

What is the ideal design of a food security program? This is the question addressed in this paper through an analysis of India's Public Distribution System (PDS). India spends significant resources on its core safety net programs[3] - over 2% of GDP in recent years. The PDS, which has been around since the 1940s, is a government distribution network that incorporates a food subsidy and absorbs substantial public resources at approximately 1% of GDP. Currently, the generosity of the coverage and benefits extended under the PDS in India differs from state to state. In South India,[4] Tamil Nadu and Andhra Pradesh run a nearly universal PDS while in the neighboring states it is strictly targeted. The long border between South-eastern (Tamil Nadu and Andhra Pradesh) and South-western (Kerala, Karnataka, Maharashtra) parts of the country provide an ideal quasi-experimental setting for a geographic regression discontinuity (RD) design for evaluation of differing forms of the PDS, in the spirit of Dell (2010). Specifically, I examine the impacts of a more generous PDS on vulnerability to poverty of the population in South India.[5] This can then also shed light on the broader question of the impacts of universal versus targeted food programs on poverty alleviation.

To provide some intuition for the expected empirical impacts of a more generous PDS, I set up a social welfare maximization model. In the model, the subsidy and probabilities of errors of targeting are known but exogenous to the state, and the income cutoff for targeting the food security program is the policy parameter. The model implies that the larger the probability of errors of wrong exclusion is, the more universal a food security program should be. That is, countries should choose policies of universal access in early stages of development when poverty is widespread, which is consistent with historical evidence from developed countries. It suggests, that in countries like India, strict targeting might be unnecessary and

[3]PDS, Mahatma Gandhi National Rural Employment Guarantee scheme (MGNREG), Indira Awaas Yojana (IAY), and Indira Gandhi National Old Age Pension Scheme (IGNOAPS) among others

[4]Tamil Nadu (TN), Andhra Pradesh (AP), Kerala (KL), Karnataka (KA) and Maharashtra (MH)

[5]Vulnerability to poverty is the ex-ante risk that a household will, if currently non-poor, fall below the poverty line, or if currently poor, will remain in poverty (Chaudhuri et al 2002). See section 3 for more details.

administratively too costly.

My empirical results corroborate the model's predictions. They indicate that a household's ability to mitigate risk and cope with shocks is enhanced with a quasi-universal PDS,[6] through direct and indirect channels. Households use the subsidy from the PDS to make various types of risk averse investments, such as increasing their asset base or investing in property and livestock, all of which protect them in contingencies and make them less vulnerable to poverty. They also increase their labor supply in their primary occupation and reduce the number of casual jobs they take up, thereby reducing variability in income and making them less vulnerable to poverty. A more generous PDS reduces overall household vulnerability to poverty by around 9% for the full sample compared to a less generous PDS. The impacts are largest for the most marginalized group in my sample (SC /ST), a reduction of about 12% in the probability of becoming poor, indicating that the PDS seems to be working in the right direction. The direct impacts of an expanded PDS, on consumption and health, are less prominent though. These results indicate, that not only are food security measures sufficient for poverty alleviation, but a more universal approach is more effective, at least in the context of developing countries like India.

My paper extends the general literature on food security programs and also the debate over universal and targeted programs. Evidence on food security programs elsewhere, such as Food For Education in Bangladesh, indicates that they have performed well, even while adopting different targeting methods (Ahmed et al 2001, Meng and Ryan 2007, Alderman et al 2010). However, these studies are usually in field survey settings where external validity may be low and scaling up differences not accounted for. The PDS is a very large program affecting millions of people in the context of a large developing country, and hence the results in this paper have greater external validity. Also, the empirical literature on the debate over universal and targeted programs has mostly concentrated on the effectiveness of different

[6] I am categorizing a program as universal when there are no income cutoffs for eligibility (TN). A quasi-universal system would be a program with a relatively high income cutoff (AP).

types of targeting (for instance, community based versus proxy means tested) rather than on a direct comparison of the two types of systems (Coady et al 2004, Alatas et al 2012, Bigman et al 2000, Benfield 2007). Despite the centrality of targeting in these studies, we know little about the relative effects of targeted and universal welfare policy for poverty and this paper fills this gap in the literature. The closest empirical study to this paper is Brady et al (2012), who look at the impacts of targeted versus universal social policy on single-mother poverty with a multilevel analysis across 18 affluent Western democracies. They do this by constructing an index of welfare generosity on a standardized scale based on public expenditures on various social programs as a percentage of GDP. In contrast, this paper looks at the actual eligibility criteria of a particular program to classify states as universal or targeted. This is closer to the heart of the debate since even programs with very strict rules for eligibility (and hence would be termed as 'targeted') could have very high levels of welfare expenditure.

My paper also contributes to the active literature on the PDS in India in three respects: the choice of outcome variable, the method, and the research question itself. Whereas evaluations of other programs in India, such as the NREGS, show that it is not ineffective in altering the situation of the poor despite low take up (Zimmermann 2015), the PDS has not received similarly positive reviews from economists.[7] Yet it is the most far reaching welfare program operational in India currently, in terms of coverage as well as public expenditure.[8] Existing empirical analyses on the PDS have mainly focused on consumption, nutritional and price gains and found minimal impacts (Bhalotra 2002, Kochar 2005, Tarozzi 2005, Krishnamurthy

[7]Extensive research on the subject has shown (Planning Commission 2005, Advisor To The Commissioners Of The Supreme Court, West Bengal 2010, Jha and Ramaswami 2010, Khera 2011, among others), that the PDS is plagued by numerous issues in implementation, with leakages and inaccurate identification of poor households. Other studies have revealed that nearly 44 to 60% or more of the needy population are wrongly excluded in the relatively backward states of Bihar, Madhya Pradesh, Rajasthan and Uttar Pradesh (Khera 2008, Swaminathan 2008).

[8]As Khera (2011) notes,for BPL households in many states, the implicit subsidy from PDS food grains alone is roughly equivalent to a week's NREGA wages (without having to work) every month, and hence, the PDS has the potential to improve the living standards of many more. However, it is a historical institution in the country and changes were made to its functioning in an adhoc manner, which makes empirical assessments of its role difficult.

et al 2013). A few studies have estimated the impact of the PDS on poor households, in terms of reductions in the incidence and severity of poverty (Radhakrishna et al 1997, Tritah 2003), but have been unable to detect substantial effects. In contrast, by concentrating on South India, where errors in the functioning of PDS is low, I am able to isolate significant impacts on vulnerability to poverty, which may be swamped in other parts of the country. This is also the first paper to use geographic RD to study the PDS to estimate causal effect of PDS generosity, and focus on generosity differences of PDS. The geographic RD in this paper gives estimates that have greater internal validity as statistical theory shows that a correctly implemented and analyzed regression discontinuity design gives unbiased effect estimates at the discontinuity. Thus, this paper adds value to our understanding of the PDS and like Khera (2011),[9] paints a more positive picture of the PDS than most existing papers do.

The rest of the paper is organized as follows. Section 2 gives the background of the PDS and the debate, section 3 gives a theoretical model and describes my measure of poverty, section 4 provides an overview of the methodology, section 5 describes the data and empirical specification, section 6 provides a summary of the results and discusses mechanisms and sources, section 7 discusses robustness checks, section 8 provides a Cost Effectiveness Analysis and finally, section 9 concludes.

2 | Background

2.1 Institutional Details

In terms of availability of food, India is a food surplus nation where buffer stocks are more than two times what is required for food security (Table 4). Between 1950-51 and 2006-

[9] Khera (2011) gives a more positive outlook on the PDS. She finds that respondents in an exhaustive nine-state PDS survey received 84-88% of their full entitlement and attributes this revival to a move towards universalism.

2007, production of food grains (comprising rice, wheat, coarse cereals and pulses) in the country increased at an average annual rate of 2.5% compared to the growth of population, which averaged 2.1% during this period (Swaminathan 2008). Yet, according to the Food and Agricultural Organization, India alone accounts for over 400 million poor and hungry people. The Public Distribution System (PDS) in India is a large scale producer price support-cum-consumer subsidy program that evolved in the wake of extensive food shortages and fluctuating high food prices in the 1940s. By the 1980s its reach widened considerably. Working alongside the free market, it provides rice, wheat, edible oils, sugar and kerosene at subsidized prices through 489,000 fair price shops in rural and urban areas across the country. The subsidy implied by the program has grown significantly over the years (Table 5), from Rs. 2,850 crore in 1991-92 to about Rs. 72,823 crore in 2011-12, an increase of over 25 times in 21 years. In 2011-12, the food subsidy implied by the program amounted to approximately 34% of total central government subsidies under non-plan expenditure and approximately 5.8% of agricultural GDP (Sharma 2012).

The government redesigned the PDS to form the Targeted Public Distribution System (TPDS) in 1997 due to poor assessments of the PDS and growing fiscal deficits. The new system distinguished between households that fall 'below the poverty line' (BPL) and those who are 'above the poverty line' (APL), and reduced subsidies to the latter, while increasing those to the former. Eligibility for APL and BPL ration cards[10] is based on the economic status of the household. Table 6 gives the procedure for identification of BPL households and distribution of ration cards for lifting the subsidized food. Food grains are allocated to states by the central government as per the proportion of BPL families fixed by the Planning Commission. As Table 6 shows, The Ministry of Rural Development uses the Planning Commission's state-wise estimates of BPL household numbers to come out with the criteria

[10]A Ration Card is a document issued under an order or authority of the State Government, as per the Public Distribution System, for the purchase of essential commodities from fair price shops. They are an important subsistence tool for the poor as they provide proof of identity and a connection with government databases.

for classification of BPL families based on parameters like size of land holding, assets owned, e.t.c. Many states in India rejected the Planning Commission's norms and expanded the PDS well beyond the BPL list, like Chhattisgarh in the north and Andhra Pradesh and Tamil Nadu in the south. Table 7 shows the key characteristics of the PDS in South India, in terms of the eligibility and entitlements of BPL ration cards. While it is voluntary to obtain ration cards in India, states have different exclusion norms for granting BPL ration cards. Typically, to obtain a ration card, the applicant needs to present proof of identity, address and income.

For categorizing universal and targeted PDS states I employ the definitions in Vanneman & Dubey (2011). They identify middle class families as those with incomes above half and below twice the all-India median, between Rs. 6,809 and Rs. 27,235 and affluent families as those with incomes more than twice the Indian median, an average equivalence income of Rs. 54,451 annually. The middle class they identify would still be relatively poor, while the affluent class would be a more recognizable middle class with comfortable existence in the Indian context. Hence, I term the system in a state to be 'more generous' if the income exclusion cutoff is above Rs. 27,235 per annum. The rationale for using this income cutoff is the fact that India's national poverty line is too low to be acceptable in middle-income and richer countries.[11] The 'middle class' line in Vanneman & Dubey (2011) is also closer to the international poverty line of $1.25 a day in 2011. Secondly, I also look at the actual subsidy received by a household with a ration card in these states. As can be seen from the extensive margins in Table 7, TN follows a universal PDS where anyone can get a BPL ration card. AP also has a quasi-universal system with very lenient eligibility criteria and covering over 80% of the population. These 2 states also provide substantially larger subsidies as can be

[11] As Choudhury (2011) says, even compared to less developed regions, India's poverty line is too low. For instance, the three poverty lines in South Africa - food, middle and upper - are all higher than that of India. The food poverty line in Indian rupees was Rs. 1,841 per capita per month in 2010, middle poverty line was at Rs. 2,445 and upper poverty line was at Rs. 3,484. Per capita poverty line of a rural adult Rwandian in Indian terms comes out to be Rs. 892 per month, slightly more than Rs. 816 for a person in rural India, even though food is cheaper in Rwanda.

seen from Table 3. Hence I define these 2 states as having a more generous form of PDS (as a proxy for a universal food security program), while the other 3 are said to run a less generous PDS (as a proxy for a targeted food security program).

To reasonably rule out that any negligible impacts on the poor are due a dysfunctional PDS, it is necessary to concentrate on an area with a well-functioning PDS, so that it can be assumed that the subsidies are reaching the intended beneficiaries mostly. Thus, to determine the states where the PDS is working well, I focus on trends in diversion of food grains, as this has been one of the areas of major concerns for the PDS. While grains could be lost in transportation or due to poor storage, e.t.c., the general consensus has been that the grains are sold illegally on the open market. Khera (2011) finds that states can be divided into those with a functioning, reforming and languishing PDS, in terms of per capita purchase of wheat and rice and proportion of grain diverted. The states I include in my analysis (South India) are all functioning states where leakage of food grains from the PDS is not a major concern (see Table 7).

2.2 Lessons Learned from Targeting

The shift away from universalistic policies towards targeted welfare programs began in the 1980s with the rise of the neoliberal ideological shift in industrialized countries, which gave more importance to individual responsibility and promoted a limited role for the state (Mkandawire 2005). Perhaps the most serious of the criticisms levelled against universalism is that it is not redistributive unlike a targeted program which is said to generate a pro-poor distribution of social services in society. However, as Korpi and Palme (1998) argue, though targeted programs may be more redistributive *per unit of money spent*, other factors are likely to make universal programs more redistributive. This can be illustrated by means of a simple example (an extension on the work of Rothstein 2001), as shown in Tables 2 and 3. Though targeting assumes that it is possible to precisely identify the poor on the basis of factors like land and income, a targeted welfare program tends to suffer from 2 types of errors in general due to imperfect measurement. Type I errors, or errors of wrongfully excluding genuinely deserving households from a program, and Type II errors, or errors of inclusion of privileged households ineligible for the program. Excluding privileged households implies significant risk of exclusion for poor households in a targeted program. When these errors are factored in, a targeted program may not be as redistributive as desirable. As can be seen from Tables 2 and 3, under a universal program, only 40% of the taxes raised are distributed to the poor, compared to a targeted program which results in 60-100% redistribution to the poor. When targeting is absolutely precise (Table 3 column 5), the reduction in inequality is greater under a targeted program than a universal program. However, even the strongest supporters of targeting would contend that its accuracy is unlikely to be perfect. When factoring in a leakage to non-poor households of 40% (which is typical in developing countries), the resulting reduction in inequality is less than that under a universal system (Table 3 Column 7).

Another point not often highlighted in these debates is that targeting also suffers from the problem of substantial administrative and transaction costs, which may overshadow the cost of subsidies under a universal system, if the objective is to fight poverty. Accurately identifying and maximizing coverage among the poor, controlling leakage (while maintaining high rates of efficiency) and implementing well-developed fraud control, can turn out to be a very expensive process. While the exact differences in costs between targeted and universal provision is not clear, it has been argued that targeting often signifies a substantially higher cost.[12]

In the Indian context, Dreze and Sen (2013) note that India's experience with targeting has been far from encouraging, while many public policies based on the principles of universalism

[12] In low-income countries, total administrative costs for targeted programs comes to about 30% of total costs, compared to 15% for running a universal program. Comparisons between universal and targeted programs in the United Kingdom indicated administrative costs of 3.5% for universal programms and about 10% for means-tested targeted programs. Studies from the United States found similar results (2.5% universal versus 13% targeted) - Dutrey (2007)

with 'self-selection' (like mid day school meals and NREGA) have performed comparatively well. They contend that the problems of exclusion and divisiveness inherent in targeted programs are exacerbated by the fact that India's official poverty lines are too low.

3 | Theory & Measure

3.1 A Stylized Model

The government plans to put a program in place to provide food subsidy (FS), s, to the population below a certain income cutoff. Let the information to the government be that consumption (c) is distributed uniformly over the interval (0,1). Let v be the income (consumption expenditure) cutoff to get a subsidy of s. Let us consider the null hypothesis that the consumer is below the income cutoff.

Then, Type I Error (Reject null when it is true)= $p^I = P(FS = 0|c < v)$.

And, Type II Error (Fail to reject null when it is false) = $p^{II} = P(FS = s|c > v)$.

Then cost of subsidy to the government = $(1 - p^I)vs + p^{II}(1 - v)s =$ y.

Total cost of program (including administrative costs, etc) = $\gamma(y)$ with $\gamma' > 0$ and $\gamma'' > 0$.

Let the utility of an individual consumer be given by, U(c), with $U' > 0$ and $U'' < 0$.

Then, government's goal is to maximize social welfare:[13]

$$\Omega = \int_0^v U(c+s)dF(c) + \int_v^1 U(c)dF(c) - p^I \int_0^v [U(c+s) - U(c)]dF(c) + p^{II} \int_v^1 [U(c+s) - U(c)]dF(c) - \gamma(y).$$

Here, s, p^I, p^{II} are exogenous. v is the policy parameter.

Then, FOC (using Leibniz's rule):

$$\frac{\partial \Omega}{\partial v} = U(v+s) - U(v) - p^I[U(v+s) - U(v)] - p^{II}[U(v+s) - U(v)] - \gamma' s(1 - p^I - p^{II}) = 0$$

$$\Rightarrow [U(v+s) - U(v)](1 - p^I - p^{II}) - \gamma' s(1 - p^I - p^{II}) = 0$$

[13] a 'welfarist' approach rather than 'fairness' approach, Kaplow and Shavell (2001)

$$\Rightarrow [U(v+s) - U(v)] = \gamma' s \tag{1}$$

This is simply saying that the marginal benefit of the program should equal the marginal cost.

And, SOC is satisfied:

$$\frac{\partial^2 \Omega}{\partial v^2} = -\gamma'' s^2 (1 - p^I - p^{II})^2 < 0.$$

Then,

$$\frac{\partial^2 \Omega}{\partial v \partial p^I} = -[U(v+s) - U(v)] + \gamma' s + \gamma'' s^2 v.$$

Substituting (1), we have:

$$\frac{\partial^2 \Omega}{\partial v \partial p^I} = \gamma'' s^2 v > 0 \tag{2}$$

Similarly,

$$\frac{\partial^2 \Omega}{\partial v \partial p^{II}} = -\gamma'' s^2 (1 - v) < 0 \tag{3}$$

Thus, (2) implies that, where probability of type I error is high it is optimal to make the income cutoff as high as possible, that is, a more universal approach. (As p^I rises, marginal cost of program falls, so v needs to rise so that the marginal benefit falls and equation (1) holds.)

And, (3) implies that, where probability of type II error is high it is optimal to make the income cutoff as low as possible, that is, a more targeted approach. (As p^{II} rises, marginal cost of program rises, so v needs to fall so that the marginal benefit rises and equation (1) holds.)

In a cross-country study of nine countries, Cornia and Stewart (1993) note that the poorer a society, the more serious will be errors of omission or undercoverage relative to the costs of leakage. Table 1 provides support for this intuition. It lists 8 countries with different targeted welfare programs, in ascending order of GDP per capita (that is, poor to rich). As we can see from columns 3, the benefits share of the poorest quintile in total subsidies under a program rises steadily as a country gets richer. Column 6 indicates that these also translate into lower exclusion rates for richer countries. That is, the severity of undercoverage (or type I errors) of the poor in Zambia in sub saharan Africa (a less developed country) is much more than in Brazil (a developing country). Further, in developed countries, like Chile and the United States, the problem is more one of leakage (Type II error), rather than undercoverage. Thus, we can say, in developing countries, it is more likely that p^I will be high due to corruption and other inefficiencies, hence a universal approach makes more sense. Whereas in developed nations p^{II} is likely to be high, such that a targeted program makes more sense.

As inferred by Cornia and Stewart (1993), the exclusion errors are indeed very high for most states under the targeted PDS regime in India, a developing country. As per Planning Commission Report 2005, about 58% of subsidized grains issued from the Central Pool do not reach the target group, BPL households (type I error) and another 21% reaches APL households (type II error). This indicates that a universal approach to food security should be more effective for poverty alleviation in India. Also, studies show that there might be important spillover benefits of including more households under a social welfare program (that is, higher type II errors), especially if non-participation is the result of a 'stigma' or disutility associated with participation. For instance, Kochar (2005) finds that take-up rates by BPL households increase with the level of benefits provided to the non-poor under the PDS. Greater public awareness regarding consumer rights is another example of such a spillover effect, as another reason for the poor not using the PDS could be lack of awareness regarding their entitlements. For instance, Mooij (1994) examines the PDS in Kerala prior to the introduction of targeting and finds that public awareness coupled with grass roots organisations to channel consumer complaints provided an effective check and control on the functioning of the PDS, and the state had a successful system in place. Complaints by card holders are also usually taken more seriously by officials if there are greater numbers. This goes back to the argument of Korpi and Palme (1998), that encompassing institutions pool the risks and resources of all citizens and thus create converging definitions of interest which targeting might fail to achieve.

3.2 Vulnerability to poverty

I refrain from using the usual measures of poverty and concentrate on a relatively broader and more dynamic measure of deprivation - vulnerability to poverty, which incorporates the destitution of individuals from future shocks. Vulnerability is the prospect that an individual will fall below some norm or benchmark of welfare at a given time in the future, where the time period and welfare measure are sufficiently general. It is an ex-ante measure of a household's well-being (unlike poverty, which is an ex-post measure).[14] The literature proposes three alternative approaches to assessing vulnerability (Hoddinott and Quisumbing 2003): vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU) and vulnerability as uninsured exposure to risk (VER). VEP and VEU approaches measure vulnerability at the individual level as a probability and summing up over all households gives a measure of aggregate vulnerability. VER measures do not construct probabilities, but rather assess ex post whether observed shocks generate welfare losses at the aggregate level. VEU approaches are problematic because the unit of measurement is units of utility, which many policymakers might not be familiar with and may be difficult to understand. The appropriate measure for this paper would be an ex-ante individual measure of poverty that is easy to understand. Also, a measure of vulnerability that takes account of poverty levels seems preferable. Hence, following the VEP approach in Chaudhuri et al. (2002), I define vulnerability as "the ex-ante risk that a household will, if currently non-poor, fall below the poverty line, or if currently poor, will remain in poverty."

Formally, the vulnerability level of a household h at time t is defined as the probability that

[14]Poverty and vulnerability, though correlated, are conceptually different as depending on whether a household has secure income sources, a household above the poverty line may be vulnerable, or one just below the poverty line may not be vulnerable. The presence of risk or uncertainty about the future distinguishes the two concepts. A household faces multiple sources of risk which makes its future uncertain, like weather shocks, health shocks, e.t.c. Without this risk, the two concepts would be identical. Figure 2 shows how a vulnerable population need not be poor and vice versa.

the household will find itself consumption poor[15] at time t+1:

$$v_{ht} = Pr(c_{h,t+1} \leq z)$$

where $c_{h,t+1}$ is the household's per-capita consumption level at time t+1 and z is the appropriate consumption poverty line. The procedure for estimating household vulnerability follows from Chaudhuri et al. (2002) (see Appendix).

An advantage of this vulnerability measure is that it can be estimated with cross-sectional data and the possibility of poverty traps and other non-linear dynamics are implicitly built in. However, it assumes that the distribution of consumption across households, given the household characteristics at time t, represents time-series variation of household consumption. Thus, a large sample is required for this measure in which some households experience positive shocks and others negative shocks. It also assumes economic stability and does not incorporate the possibility of aggregate shocks.

4 | Geographic Regression Discontinuity Design

The Geographic Regression Discontinuity (RD) design leads to identification of the local treatment effect at the boundary of treated and control areas, like a standard RD design with multiple forcing variables (Keele & Titiunik, 2014). I exploit a geographic RD design that is based on four borders (KR & TN, KA & TN, KA & AP, MH & AP) between the adjacent South Indian states (see Figure 2(a)) The idea is to interpret the distance to the closest state border as an assignment variable that decides about the more generous versus less generous PDS 'treatment'. In implementing the geographic RD design, I use a 'naive'

[15]According to the World Bank (2000), "poverty is pronounced deprivation in wellbeing." The main focus here is on whether households have enough resources to meet their consumption needs. Poverty is then measured by comparing households' consumption with some defined threshold below which they are considered to be poor. Poverty is largely seen in monetary terms, via consumption expenditure.

measure of distance, that is, the shortest or perpendicular distance to the nearest border of the opposite group from the district centroid, for computational ease. Note that the type of distance measure does not influence the geographic RD results, because in a local region of the border they would be highly correlated (Agrawal 2015). Districts with a negative distance to the border are located on the more generous PDS side from various state borders. The treatment effects are then estimated by pooling the data around the common boundary.

The use of distance can be justified as follows. Rice and wheat are the staple food grains of the people in India. The deltaic tracts of the rivers Krishna, Kaveri and Godavari are major rice producing regions in South India (see Figure 2(b)). While differences in rice production may not be much when distance increases marginally, as Figure 6 shows, rice yield per hectare is a monotonically decreasing function of the distance from the deltas when we take distance between district centroids. Conversely, we would also expect the average cost of procuring rice to increase monotonically with distance from the deltas. Hence, while regions on either side of the boundary would have similar climatic conditions, the treatment states (TN & AP) are characterised by a relative abundance of rice as compared to the control states (KL, KA & MH). Since the grains each state receives from the Central Pool for distribution through the PDS depends on the estimates of BPL population in each state, this would mean that a state which wishes to follow a more generous system would need additional means of procuring extra grains. But for districts in control states far away from the boundary it will be expensive for the state government to buy rice locally, whereas for districts within treatment states it will be much cheaper. Thus, we can hypothesize, that state governments in treatment states optimally introduced a more generous PDS than control states because the average cost of procuring additional rice is much lower. However, while distance from the deltas increases monotonically, the boundaries between states is random (that is, independent of rice production) in the sense that they were determined by The States Reorganisation Act, 1956, which organized the provinces under British India along linguistic lines.[16] This would mean that we can think of the distance measure intuitively as an instrument for PDS generosity, with the border acting as a line of 'random cutoff', so that it would be simply luck which determines whether a household ended up getting the more generous PDS.

Another concern that arises in the case of geographic RD designs is whether to assume that treatment assignment occurs at the individual level or at a more aggregated level of geography, analogous to the choice between the unit of randomization versus the unit of analysis in a randomized experiment. In this case, while the treatment is administered at the level of the state, the treatment status units are households. A more disaggregated unit of analysis gives more power. Since households choose to live on one side of the boundary by chance, an individual-level assignment mechanism can be applied here. Figures 4 and 5 show the discontinuous jump at the boundary in the two proxies for generosity at the individual level that can be used - the proportion of BPL ration card holders and the average PDS subsidy received by the household in the district. The second, the PDS subsidy the household is getting, is a more direct measure of generosity, since it captures the actual assistance extended by the PDS. The first, whether a household has a BPL ration card, is a more indirect measure of generosity. But it captures both the ease with which a poor household can get subsidized food in a state and also the entitlements (so both the intensive and extensive margins), and hence I use the ration card information. Figure 1 shows that, on average, the proportion of BPL ration card holders increase by roughly 0.4 at the boundary. Relative to the level at the less generous side, this translates approximately to an 80% increase. Since the jump is not from 0 to 1, the appropriate method would be a fuzzy RD.

The assumptions for a geographic RD framework to be valid are analogous to those in a

[16] When India gained independence in 1947, the grouping of the states was done more on the basis of historical and political principles, involving the reduction of princely states from 571 to 27. Language was decided as the basis on which India's states were to be reorganised due to popular demand and also because linguistic regions were geographically contiguous and this made them easily governable. The States Reorganization Act was passed by parliament in November 1956. It provided for fourteen states and six centrally administered territories. The state of Bombay was further split into two states, viz, Maharashtra and Gujarat, in 1960.

regular RD model. First, given that treatment assignment in a spatial RD design is non-random, households must not sort conditional on generosity of PDS. This is unlikely here, since obtaining a BPL ration card and availing subsidized rations in a state requires one to be a resident of the state, along with other eligibility criteria (Table 7) and the markets are segregated. Also, as can be seen from Table 8, the mean years a household has resided in a place is over 70 in all states and the expansion of the PDS in India began around 2006-07 in most states. Checking the sample for migration statistics, this assumption seems valid. About 6% of the sample migrated from another state or country (177 households). Out of this, only about 26% (45 households) have been in place for less than 20 yrs (that is migrated after 1997, when targeting was introduced). Out of this only 12 households migrated to AP or TN (the more generous states). So a strategic move due to a difference in PDS generosity is not likely to be a concern.

Second, in a standard RD design, beyond the treatment status variable, no other relevant variable should change discontinuously at the boundary. However, in a geographic RD design, we are often confronted with the problem of compound treatments, where extraneous factors also change discontinuously at the border such that isolating the effect of the treatment of interest becomes impossible. To assess the validity of the identifying assumptions, Figure 7 provides graphical evidence on placebo tests that explore possible discontinuities in key observable household characteristics which could be driving the results. The graphs indicated that my conjecture on the similarity of South Indian states is correct since these variables appear to be quite continuous at the border. This does not rule out that there are differences on some unobservables between the states, but this is likely to be minimal since I have isolated the southern states which are comparable on geographic, demographic and development indicators, while the differences between the north and the south in India on these parameters are much more. These states have similarly high incomes per capita and net state domestic product per capita, infrastructure, advantageous location in terms of access to sea, primary language spoken belong to the same language family (Dravidian), and each state has at least two dominating political parties. However, as Figures 4 and 5 show, we have discontinuities in two potential treatments for the generosity of the PDS at the boundary. Since the results change only marginally with the use of either treatment status variable, we can say that the Compound Treatment Irrelevance assumption (Keele & Titiunik 2015) holds here and identification is possible. That is, I can assume that there is no separate subsidy effect on outcomes, so that the generosity of PDS impacts can be exactly reduced to the BPL ration card treatment. Another possibility of compound treatments arises when two or more geographic boundaries coincide, such as a county and an electoral district. In India, however, parliamentary and district borders overlap but do not coincide exactly, and parliamentary borders do not cross state borders. Further, since I am looking at state borders, this is not a concern here since moving from a district located at the border of one state into a district on the other side of the border in a different state, would still give us the effect of the state. Thus, it seems unlikely that there is systematic sorting into treatment and we can be reasonably confident that the identifying assumptions are fulfilled.

5 | Data & Empirical Specification

5.1 Data

The analysis uses the India Human Development Survey 2012 (IHDS II) data, which was collected between January 2011 and March 2013. It is a nationally representative, multi-topic survey of 42,152 households in 384 districts, 1420 villages and 1042 urban neighborhoods across India. Two one-hour interviews in each household covered health, education, employment, economic status, marriage, fertility, gender relations, and social capital. Children aged 8-11 completed short reading, writing and arithmetic tests. These data are mostly re-interviews of households interviewed for IHDS-I in 2004-05. The sample for IHDS-I was drawn using stratified random sampling and contains 13,900 rural households who were interviewed in 1993-94 in a previous survey by NCAER and 28,428 new households. IHDS II re-interviewed 83% of the original households as well as split households residing within the village and an additional sample of 2134 households. IHDS was jointly organized by researchers from the University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi.

I restrict my sample to the five South Indian states, TN, AP, KR, KA and MH which generates a sample of 12,929 households. I also use Census 2011 data for generating community characteristics for estimating vulnerability. These were aggregated to district level from village level data released under the Census, and then merged with the main data. I use the 2011-12 state wise poverty lines based on MRP consumption published by the Reserve Bank of India, as they are the most recent estimates available. Lastly, I use the 2011 Consumer Price Index (base year 2010) from Ministry of Statistics and Program Implementation, India, to deflate consumption and poverty lines.

5.2 Empirical Specification

In estimating treatment effects at the cutoff, the preferred way in the literature is to run local linear or polynomial regressions on a restricted sample of observations close to the cutoff.[17] The main concerns with estimating the model is to choose the size of the bandwidth within which to restrict the model to find an optimal balance between precision and accuracy. Using a larger bandwidth yields more precise estimates, since more data points are used in the regression. However, the linear specification is less likely to be accurate, which can lead to bias when estimating the treatment effect. A solution is to try more flexible specifications by adding higher order polynomials in the running variable.

The two main types of RD design considered in the literature are the sharp and fuzzy RD

[17] Estimation of RD designs have been increasingly viewed as a nonparametric estimation problem, starting with Hahn et al (2001), since misspecification of the functional form can induce large bias in RD estimates of treatment effects.

designs (Lee & Lemieux 2010). With a sharp design, the treatment variable x_i depends in a deterministic way on some observable variable z_i, such that $x_i = f(z_i)$, where z_i takes on a continuum of values and there is a known point of discontinuity in the function, z_0. With a fuzzy design, x_i is a random variable given z_i, where the conditional probability $f(z_i) = E[x_i|z_i = z] = Pr[x_i = 1|z_i = z]$ has a discontinuity at point z_0. Unlike the sharp design, in the fuzzy design, there are additional unobserved variables that determine treatment and treatment assignment is not a deterministic function of z_i. The common feature in the two designs is that the the probability of receiving treatment, $Pr[x_i = 1|z_i]$, viewed as a function of z_i, has a discontinuity at z_0 (Hahn et al 2001). In other words, in a sharp design, the probability of treatment jumps from 0 to 1 when z_i crosses the threshold z_0, whereas a fuzzy design allows for a smaller jump in the probability of treatment. Since the probability of receiving a BPL ration card jumps by less than 1 at the threshold, in this case, the appropriate model would be a fuzzy RD design.

When the identifying assumptions hold, estimating the treatment effect in the fuzzy RD design is analogous to the 'Wald' formulation in an instrumental variables setting using two-stage least-squares (Berger et al. 2015). Specifically, the fuzzy RD design can be described by the following 2 equations:

$$bpl_{ij} = \lambda_0^g + \delta^g D_j + \sum_{k=1}^{\bar{k}} \lambda_k^g dist_j^k + \sum_{k=1}^{\bar{k}} \zeta_k^g (D_j \times dist_j^k) + \epsilon_{ij}^g \tag{4}$$

$$y_{ij} = \lambda_0^y + \delta^y D_j + \sum_{k=1}^{\bar{k}} \lambda_k^y dist_j^k + \sum_{k=1}^{\bar{k}} \zeta_k^y (D_{ij} \times dist_j^k) + \epsilon_{ij}^y \tag{5}$$

where the subscripts refer to household i in district j, y is an outcome variable of interest, bpl is an indicator variable for whether a household has a BPL ration card, D is a dummy variable indicating whether a district is located on the more generous PDS side of the boundary, $dist$ is the distance to the nearest border. Here, we are instrumenting bpl with D and (2) is just the reduced form equation. Both equations include trends in distance (up to polynomial degree $\bar{k}$), which will capture any unobserved factors that vary with the distance and potentially influence outcomes. We can then obtain the Wald estimator for the local average effect of generosity of PDS on outcome y as:

$$\beta^{RD} = \frac{\delta^y}{\delta^g}$$

The literature provides alternative methods for bandwidth selection,including plug-in rules and cross-validation procedures. I implement the bandwidth procedures proposed by Imbens and Kalyanaraman (2012)[18] and Calonico et al. (2014)[19], respectively. Since these might lead to bandwidth choices that are too large for conventional confidence intervals to be valid, for robustness checks, I use a simple but ad-hoc procedure to select a smaller bandwidth than the 'optimal' bandwidth (Keele & Titiunik, 2015) and check the consistency of my results. Another approach is to fit higher order polynomial regressions in a wide window. I incorporate both of these. For the local linear regressions, I restrict my model to a smaller window than the 'optimal' bandwidth. Then I increase window with the degree of the polynomial. The results do not vary substantially.

6 | Results

6.1 Main Results

Tables 10 to 12 and Figure 8 to 9 give the results for the impact of the generosity of the PDS on the full sample and 2 sub groups which can be identified as relatively weaker sections of the society. The sub groups are - Scheduled Castes(SC)/Scheduled Tribes (ST) and Other Backward Class (OBC).[20] From Table 9, we can see that SC / ST are the more vulnerable

[18]optimal bandwidth selection procedure by asymptotic mean squared error minimization for local-linear estimators

[19]alternative asymptotic approximation for bias-corrected local polynomial estimators

[20]These are official designations given by the GOI to various groups of historically, socially and educationally disadvantaged people in India who are the primary beneficiaries of many reservation policies under

group of the two and they have significantly lower wealth. Though OBC is categorized as a more vulnerable group in society, in the data we find that they are similar in characteristics to the average household in the full sample. As a result, the impacts on this group is similar to that of full sample. Hence, I omit a separate discussion of the impacts on this group. In all tables, one observation is a household.

Table 10 gives the impacts of generosity of PDS for the 3 samples and demonstrates that a more generous PDS has a relatively large impact on household vulnerability to poverty: the typical estimate is negative and relatively large in magnitude and statistically significant. Each row presents the impact of generosity of PDS on vulnerability for a different parametric functional form of the running variable. I concentrate on summarizing the results for polynomial of degree two[21] and bandwidth choice by Calonico et al.(2014). Column 1 looks at the estimates for the full sample and the coefficient in row 2 indicates that a more generous PDS leads to a reduction of household vulnerability by 0.085 percentage points. This suggests that being in a state with more universal approach to PDS reduces the average households probability of becoming poor within the next year by approximately 9%. This translates into a reduction of 51% in poverty since mean household vulnerability for the full sample is 0.168, and the effect is statistically significant at the 1% level. Column 2, row 2, of Table 10 reveals that the generosity of PDS impact on vulnerability of SC /ST is negative and statistically significant at the 10% level. A more generous PDS leads to a reduction of household vulnerability of the SC /ST group by 12%. This translates into a substantial reduction of 57% in poverty since mean household vulnerability for the full sample is 0.205. As

the Constitution in education, scholarship, jobs, and so on. Ancient Indian society was divided into four varnas, or categories, high to low they are: Brahmin (priests), Kshatriya (warriors), Vaishya (merchants or traders), and Shudras (laborers). An unofficial fifth category were the Dalits, or untouchables, a group so low that its members were assigned jobs like cleaning latrines, sweeping the streets, tanning hides and handling the remains of the dead. Untouchable castes became a category as avarnas (without varna). These ancient categories are not the same thing as the caste system, but they undergrid it. In 1935, the new term "scheduled castes" replaced the use of the term "untouchable". OBC comprises the non-untouchable communities who are socially and educationally (rather than historically) disadvantaged or "backward" in comparison to the higher castes (typically, these households would be from Shudra and Vaishya castes). The scheduled tribes are aboriginals, criminal tribes, nomads, e.t.c. (Wikipedia).

[21] since this gives the most consistent results for a wide range of bandwidths

SC /ST is the most marginalized group of the three, we would expect that a more generous PDS would ideally have the largest impact on this group, and this seems to be the case.

Table 11 gives an occupational decomposition of the impacts of the generosity of PDS on vulnerability for the full sample. I consider seven separate groups by occupation, all of which have mean vulnerability greater than average for the full sample. In the table, these occupations are listed in order of mean vulnerability, high to low. The impact of the generosity of PDS ranges from 4 - 35% across groups, but there is no clear pattern visible. In almost all cases the impacts are larger than the average impact on the full sample, indicating that the PDS is indeed reaching the weaker sections of society. However, agricultural wage laborers are an exception. This is the most vulnerable group and yet the impacts are lowest here at 1% and also not statistically significant. The second most vulnerable group are landless construction workers and here we find the largest impacts of a more generous PDS. A more generous PDS leads to a reduction of household vulnerability of landless construction workers by 37%, and the impact is statistically significant at the 10% level. Comparing the first two groups, with a marginal difference in mean vulnerability, what stands out is the extent of urbanization. Agricultural wage laborers are mostly concentrated in rural areas, whereas a large proportion of the second group is living in urban areas (a difference of over 30% in extent of urbanization). One explanation is the commonly held belief that the PDS in India has a strong urban bias (for instance, it could be that rural areas have much fewer fair price shops than urban areas). However, from Howes & Jha (1992), we see that for the South Indian states, the average urban dweller does not seem to gain more than the average rural dweller from the PDS. Then, the second explanation could be that urban areas provide access to infrastructure facilities and other opportunities, that complement the effects of the food subsidies. It is possible that urban areas provide easier access to fundamental infrastructure facilities (like basic sanitation facilities and clean water), which is required for the effects of proper food intake to come through. The trend can be noticed in other occupations as well. Non-agricultural wage laborers and automobile drivers are largely concentrated in urban areas, and the impacts on them are large and significant (12% and 26% respectively).

Table 12 decomposes the impacts of the generosity of PDS on vulnerability by poverty thresholds.[22] I consider the impacts on thresholds around two poverty lines - the national poverty line of Rs. 12,000 per annum and an approximate international poverty line ($1.25 a day) of Rs. 27,235 per annum. The mean income per capita in my sample is Rs. 30,655, and households are concentrated closer to the international poverty line. Thus, the income bands I consider are larger around the international poverty line (± 10,000) and smaller around the national poverty line (± 5,000). Comparing the first two columns of the table (Threshold 1 and 2) gives us the lower and upper income bands around the international poverty line. The estimates are more precise here than around the national poverty line (Thresholds 3 and 4). Two things stand out. Firstly, the impacts across all thresholds are larger for SC / ST /OBC, which is consistent with the findings of Table 10. Secondly, if we order the thresholds according to income distribution, we find the largest impacts are on the middle income groups (Thresholds 1 and 4), rather than the top and bottom of the distribution (19 - 23% for SC / ST /OBC). Also, the impact at the bottom of the distribution is larger than at the top of the distribution for SC / ST / OBC (16% versus 14%). Thus, a more generous PDS seems to be having the largest impacts on the "middle poor".

These results show that the impacts of a more generous PDS on poverty reduction is significantly larger than a less generous system, with the largest impacts being on more vulnerable groups in urban areas. This indicates that lack of access to basic infrastructure facilities might hinder the effects of food subsidies, and swamp the impacts of the PDS in other areas of the country. For instance, where there are no clinics or hospitals available, or where lack of roads or bridges makes them inaccessible, people cannot access the medical services that they require to be healthy and productive, even if they have access to adequate food. This indicates that while it is important to ensure that leakages in the PDS are curtailed in other parts of India, the development of fundamental infrastructure facilities, that complement

[22] SC/ST/OBC have been combined here as one group due to insufficient data points.

the functions of food, is equally important. These results also corroborate my theoretical model's predictions, that is, in a developing country like India, a more universal approach to food security is more welfare enhancing.

6.2 Mechanisms

The above results show empirical evidence regarding *what* effect the generosity of PDS has on vulnerability to poverty. Here, I will explore *how* the generosity of PDS affects vulnerability, that is, the potential channels through which the effects operate.

From Table 13 we see that PDS subsidy only marginally impacts consumption and savings (less than 0.5%), and the impacts are not statistically significant. Hence we can infer that the gains of the food subsidy is being transferred elsewhere. This could be either towards paying off outstanding debt or in some form of investment. For those households repaying loans (19% of sample), the average debt size in the data is Rs. 10,503 and the average monthly rate is 2.4%, which implies a monthly payment of around Rs. 252.[23] The average PDS subsidy in the generous states is Rs. 380 (about $6) per household per month. Hence, at a minimum, households must be investing around Rs. 128 (about $2) in the generous states per month. However, 81% of the sample is not repaying loans, and hence would be investing almost the entire amount of the subsidy.

From the data, I find significantly positive impacts on certain types of asset accumulation. With only 58.7% households with access to formal banking services as of 2011 (RBI Report 2013) the poor in India have to resort to creative ways of saving their spare cash, like keeping money with relatives or neighbours. Though all 5 states have a moderate to high degree of financial inclusion (51% of households have bank accounts in the sample), it is possible that most bank accounts lie dormant as has been seen in previous research (Dupas and Robinson 2013). Columns 3 - 5 of Table 15 looks at impacts of the generosity of PDS on three different

[23] assuming the household only pays the interest accruing on the loan each month

modes of saving typically used by the poor in India, and finds significant impacts on all three. The variable 'Wealth' is a wealth index calculated using data on a household's ownership of selected assets (such as television and cooler, materials used for housing construction, types of water access, sanitation facilities, e.t.c) by the method of Principal Component Analysis. The variable 'Investment' is an indicator variable for whether the household has bought property or expanded property or invested in Pension Fund/LIC/Other savings schemes. The variable 'Livestock' gives the number of draft animals, goats, and poultry owned by the household. The impacts on the full sample are given in row 1. Column 3 indicates that households in the states with more generous PDS increase their wealth holding by 2.1%, and this is significant at the 1% level. The coefficient in Column 4 indicates that being in a state with more generous PDS increases the average household's probability of making investments by 19.9 percentage points. This translates into an increase of 71% since mean investment is 0.281, and the effect is statistically significant at the 1% level. Finally, the coefficient in Column 5 indicates that households in states with more generous PDS increase their livestock holding by 2.686 animals, and this is significant at the 1% level. This translates into an increase of 99% since mean livestock holding is 2.72 animals. As Banerjee and Duflo (2011) observe, decisions to save require a certain amount of self control from rich and poor alike. However, while the rich have a variety of tools at their disposal, like banks and financial advisors, to aid them in the process, the poor have to do a much harder job from their limited resources. Hence, investing in relatively illiquid assets, like livestock, durable goods, property, e.t.c., makes it easier for the poor to forgo "temptation" spending (like alchohol, cigarettes, tea, snacks) and force them not to be "myopic" about the future. All of the above are also relatively risk free forms of investment. This makes sense since poor people are very likely to be risk-averse, since losing money could mean starving as they have limited access to sources of credit. Thus, a more generous PDS seems to be aiding in the process of resource allocation towards relatively low-risk investments, which in turn is protecting the poor from shocks in income, and hence reducing their vulnerability to poverty.

One of the criticisms levelled against welfare programs, no matter how broadly targeted, is that of "perverse incentives" created by changes in the behaviour of households attempting to become beneficiaries of welfare policies, especially through disincentive effects on the labour supply of the poor. Households may avoid activities that improve their living standards in order to remain eligible for public support. To test for this under a more generous regime of the PDS, I look at the impact of the generosity of the PDS on labor supply and casual employment. The variable 'Labor Supply' is the number of hours in a day worked by an individual in a household in their primary occupation. The variable 'Casual Jobs' is the number of casual jobs (casual daily, casual piecework, contract < 1 year). The typical individual in a household in the sample works 109 days a year (or 3.6 months) for 7 hours a day. Averaging over a year, the mean hours worked by an individual comes to be 2 hours. About 75% of the households have at least one casual job and about 5% have more than 3. The mean number of casual jobs taken up by households is 1.4. Table 13 Columns 6 and 7 give the coefficients of interest. The coefficient in Column 6 indicates that a more generous PDS induces households to supply 0.668 hours of a day (40 minutes) more of work, and this is significant at the 1% level. This translates into an increase of 33% in labor supply or the number of hours worked in average. Over the 3 and a half months work window, this translates into an average increase of roughly 2 hours of work, leading to a daily average labor supply of 9 hours. At the same time, a more generous PDS induces households to reduce casual employment by 0.365 jobs, and this is significant at the 1% level (Column 7). This translates into a decrease of 26% in casual employment. Ghose (2004) shows that a combination of low wage and high underemployment generates the the highest incidence of poverty among casual labourers across employment categories. Thus, a more generous PDS is making it possible for households to allocate their time more efficiently, when they don't have to worry about putting food on the table. In 2011-12, the average daily earnings of a casual worker stood at Rs. 156 ($2.26), compared to Rs. 372 ($5.40) for a regular worker (India Labour and Employment Report 2014). Hence, taking up less casual employment and allocating more time to a regular job implies a gain of \$3.14 per day. Taken over the 3.6 month window, an additional 2 hours in regular employment translates into a gain of Rs. 1,962 (\$29) at a minimum. Spending more time in the primary occupation also implies gaining more expertise at the job, which would imply greater productivity, and hence better jobs and higher wages down the road. Hence, I find no evidence of "perverse incentives" created by a more generous PDS. If anything, with greater food security, households become more proactive in terms of work, which generates a more steady source of income and make them less vulnerable to poverty.

The impacts on SC / ST of the generosity of the PDS are largely similar to that of the full sample. Row 2 of Table 13 give the coefficients of interest. As for the full sample, the impacts on consumption and savings are marginal and not significant. The largest impact is on livestock holdings at an 154% increase over the mean, and the effect is significant at the 10% level (Column 5). The impact on the probability of making investments is similarly quite large - an increase of 97% over the mean, and this is significant at the 1% level (Column 4). A more generous PDS also leads to higher wealth holdings by 1.16% and the effect is significant at the 5% level. The impact on labor supply is smaller and on casual employment is larger than that of the full sample and significant at the 5% level. The coefficient in Column 6 indicates that a more generous PDS induces households to supply 0.509 hours in a day (31 minutes) more of work, which translates into an increase of 24% over the mean. The typical individual in a SC / ST household in the sample works 117 days a year (or 3.9 months) for 7 hours a day. Over the 3.9 months work window, this translates into an average increase of roughly 1.6 hour of work, leading to a daily average labor supply of 8.6 hours. A more generous PDS also induces households to reduce casual employment by 0.471 jobs, which translates into a reduction of 24% in casual employment. Taken over the 3.9 month window, an additional 1.6 hours in regular employment translates into a gain of Rs. 1,685 (\$25) at a minimum. Hence, for all groups we can say that the resource allocation channel is more prominent than the time allocation channel in making the households less vulnerable to poverty with a more generous PDS.

6.3 Sources

In this section I will explore *why* the generosity of PDS affects vulnerability, that is, the potential sources through which poverty is impacted.

The impact on vulnerability in my main result section can be decomposed into higher benefits at the intensive and extensive margins. That is, the sources are both better/more reliable benefits under the universal system and giving more people access to the program. Since entitlements across states are similar, 'better/more reliable benefits' would translate into higher take up of rations under a universal system presumably due to less stigma associated with the program. Thus, total improvement of universal over targeted system equals the average of ***(a) Higher utilization:*** people under income v covered under both systems but better off under universal system AND ***(b) Lower Type I errors:*** people under income v who get excluded under a targeted system, but get the benefits under a universal system AND ***(c) Higher eligibility:*** people above income v who wouldn't be eligible for a BPL card under the targeted system but get the benefits under a universal system. The first is the impact at the intensive margin, while the latter two are the impacts at the extensive margin.

It is not possible to decompose these effects through my main empirical specification. Hence I use a propensity score matching technique to construct valid treatment and control groups and estimate the average treatment effect on the treated (ATT). Matching relies on the assumption of conditional independence of potential outcomes and treatment given observables, that is, the selection into the treatment should be driven by factors that can be observed. I use variables that most likely affect both treatment and the outcome variable to minimize selection bias. I first determine the probability of being selected into treatment (that is, obtaining a BPL ration card) by a logit equation and then use this probability (propensity score) to match households on either side of the border, filtering by the criteria for margin.[24]

Table 14 gives the results of interest for the full sample, SC / ST and OBC. All estimates are significant at the 1% level. Firstly, the overall ATT effect of the generosity of the PDS (that is, matching without filtering by criteria) by this method comes out to be 6%. This is very close to my linear geographic RD impact on vulnerability, and hence this serves as a good robustness check for my main results. We should expect the impacts at the 3 margins to average out to this number, and that appears to be the case. Column 1 gives the impacts for the full sample. Row 1 gives the impact of a more generous PDS on vulnerability due to higher utilization and the impact is 5%. Row 2 gives the impact of a more generous PDS on vulnerability due to lower Type I errors and the impact is 9%. Row 3 gives the impact of a more generous PDS on vulnerability due to higher eligibility and the impact is 3%. Thus, the intensive margin effect (a) is 5%, while the extensive margin effect (b+c) is 12%. This suggests that the bulk of the effect is coming from giving more people access to the program rather than better/more reliable benefits under the universal system. The impacts of the different sources on SC / ST (Column 2) are roughly similar.

These results also tie up well with my theoretical model. My model suggests that the driving force behind the welfare benefits under a universal system is lower Type I errors and this is consistent with my empirical finding. Thus, universal inclusion under a food security program might be the way forward for developing countries.

[24]a) HH has a BPL ration card and consumption is less than cutoff, v b) HH on the generous side of the border has BPL ration card OR HH on the generous side of the border does not have a BPL ration card due to bureaucratic reasons OR HH on the less generous side of the border does not have a BPL ration card due to bureaucratic reasons AND consumption is less than cutoff, v c) consumption is greater than cutoff, v.

7 | Robustness Checks

Firstly, to further analyze the primary aim of the PDS of ensuring food security to poor households, I examine the impact of the generosity of PDS on malnutrition by my main nonparametric approach for the entire border. Table 17 gives the impacts of generosity of PDS for the 3 samples and demonstrates that a more generous PDS has a limited impact on malnutrition: the typical estimate is negative but relatively small in magnitude and statistically insignificant. For a polynomial of degree 2 and bandwidth choice by Calonico et al.(2014), the impacts range between 3 - 4%. This finding is consistent with previous studies which indicate that the impact of the PDS on household food security is limited.

Secondly, I employ a few alternative methods to test how robust the main results in my analysis are. As a first check, I apply the parametric approach in Dell(2010), which uses a polynomial in latitude and longitude.[25] As a secondary check, I use the same polynomial, but augment it with an Instrumental Variable approach (similar to the fuzzy GRD). As a third test, I employ a standard difference in difference approach based on the multiple discontinuities, in income cutoff and border. Since the income threshold which defines generosity (Rs. 27,235) would create another discontinuity in the targeted states, above which ideally no household should have a BPL ration card (while in the universal states they would). Hence, I can then look at the impact on the households below the income threshold in the generous states by applying a difference in difference approach. The fourth test simply augments the third approach by including the polynomial in latitude and longitude as a control. Lastly, I bootstrap my standard errors for my main nonparametric approach. The results are given in Tables 18 and 19. The impacts on the full sample range from 4 - 9%, which is consistent with my main results.

[25]See Dell(2010) for the specification

8 | Cost Effectiveness Analysis

One way to encourage policymakers to use the scientific evidence from program evaluations in their decision making is to present evidence in the form of a cost-effectiveness analysis (CEA), which measures the ratio of the costs of a program to the effects it has on one outcome. This is different from a cost benefit analysis (CBA), which gives the ratio of costs to monetary value of effects on all outcomes. The advantage of CEA over CBA is its simplicity, since there is no need for making judgments on monetary value of all the benefits. It also allows the researcher to choose an objective outcome measure (Dhaliwal et al 2012).

There are 2 ways to do a CEA - a) Measure the cost for a given level of effectiveness (e.g.,cost to increase school attendance by 1 year) and b)measure the level of effectiveness for a given cost (e.g.,years of additional attendance induced by spending \$100). Here I focus on the first method of CEA, that is the cost to reduce the absolute number of the poor by 1 household. The calculation is done using Borel's law of large numbers, which implies that in the long term, proportion of poor is equal to the average vulnerability of the group. Hence, taking the impacts of a more generous PDS, we can calculate the number of households saved from poverty, for the group of poor by international standards.

8350 households have income per capita less than Rs. 27,235. A more generous PDS reduces vulnerability of this group by 7% (from Table 10). Thus, 585 households (7% of 8350) would be saved from poverty by Borel's law. Average PDS subsidy per household per month(assuming 35 kgs of rice is distributed per household free of cost. Price of rice is the CIP of GOI): Rs. 5.65*35 = Rs. 198= \$4. Total subsidy per month under universal coverage = K = Total sample (12,929 households) * \$4. Total stream of subsidy under universal scheme in the long would equal $\frac{K}{1-r}$, where r is the real discount rate for the US. Taking a real discount rate of 10% (as per Dhaliwal et al 2012), this comes out to be \$52,238. Thus, average cost of subsidy per household saved from poverty comes out to be = $\frac{\$52{,}238}{585}$ =

$89.

Thus, the food subsidy cost to the government to reduce the absolute number of the poor by 1 household is $89. The cost calculation here only includes the cost of the subsidy and not other costs, like transportation, storage, e.t.c., so the above number will likely be higher. However, this can be taken as a minimum bound on the cost of poverty eradication through food security.

9 | Conclusion

Using a geographic regression discontinuity design, this paper has analyzed the impacts of the generosity of the Public Distribution System (PDS) in India on vulnerability to poverty. The results suggest that the impacts of the generosity of the PDS on poverty reduction are positive and significant, but the effects on consumption and health are small and insignificant. The general qualitative pattern is robust across a wide range of empirical specifications, and shows that a more generous PDS is more effectively improving living standards of the poor. There is also some evidence that the PDS is working best in areas which have better infrastructure facilities. The results support the findings in Khera (2011) of the revival in the functioning of the PDS in recent years. The recommendation of the paper is that the Government of India should seriously consider the alternative to the Below Poverty Line Census proposed in Dréze and Khera (2010).

The results indicate that the generosity of the PDS is impacting poor households through indirect channels rather than directly through consumption. A more generous PDS induces households to allocate their additional resources towards relatively risk averse investments, like durable goods, property and livestock, which make them less vulnerable to poverty. Households in generous states also allocate their time more efficiently by reducing casual employment and increasing time spent in their primary occupation, which protects them from slipping into poverty.

At a more macroeconomic level, this paper sheds light on the debate over targeted versus universal welfare programs. Currently, the primary concerns regarding a more universal welfare program is whether it would be as redistributive as a targeted program and also one of cost efficiency. This paper provides evidence that a more universal approach is more welfare enhancing, in the context of the world's largest food security program. If taken seriously, the results would then justify expanding the reach of food security measures as a necessary means of income support and social protection for the poor in India as well as other developing countries.

Finally, there is the question of the viability of sustaining a near universal food security program in the long run. The cost of the implementation of the National Food Security Act in India is estimated to be $22 billion (1.25 lac crore), approximately 1.5% of GDP, with projected import of food grains of about 62 million tonnes annually. As Olivier De Schutter, United Nations Special Rapporteur on the right to food, said on the eve of a high-level WTO summit in Bali, Indonesia in December 2013, "Supporting local food production is the first building block on the road to realizing the right to food, and trade must complement local production, not justify its abandonment.....They must develop ambitious and innovative food security policies that support their own production base, building on successful experiences in a growing number of countries....Food reserves are a crucial tool, not just in humanitarian crises, but in the everyday struggle to provide stable income to farmers and to ensure a steady flow of affordable foodstuffs for poor consumers, many of whom lack a basic social safety net". Hence, there is a need for policy changes at the high level, that will allow developing countries the freedom to use strategic grain reserves to help secure the right to food without the threat of sanctions under World Trade Organization (WTO) rules.

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Table 1: Targeting Accuracy Of Poorest Quintile Across Countries

Country (1)	Program (2)	Benefits share (%) (3)	GDP per capita ($) (4)	Income share (%) (5)	Exclusion Rate (%) (6)	Error Type (7)
Zambia	Social Fund Program	25	1,310	3.81	68	Undercoverage
Sri Lanka	Food Stamps	28	3,926	7.27	31	Undercoverage
Jamaica	Food Stamps	31	5,138	5.28	30	Undercoverage
Colombia	SHIR	34	6,056	3.35	37	Undercoverage
Brazil	Bosla Escola	40	8,539	3.28	20	Undercoverage
Mexico	Oportunidades	58	9,009	4.86	-21	Leakage
Chile	SUF	66	13,384	4.63	-55	Leakage
United States	Food Stamps	80	55,837	5.1	-391	Leakage

Note: Column (6) calculated on the basis of the income transfer required to bring the poorest quintile to the international poverty line of $1.90 a day. It is calculated as follows: $(6) = [100 * \frac{1.90 - \frac{(4)*(5)}{100*365}}{1.90}] - (3)$

Source: Coady et al (2004), Castañeda et al (2005), World Bank.

Table 2: The redistributive effects of a universal program

Group (1)	Average Income (2)	Tax (40%) (3)	Transfers (4)	Final Income (5)
A (20%)	1000	400	240	840
B (20%)	800	320	240	720
C (20%)	600	240	240	600
D (20%)	400	160	240	480
E (20%)	200	80	240	360
Inequality	5	(=1200)	(=1200/5 = 240)	2.3

Table 3: The redistributive effects of a targeted program

Group (1)	Average Income (2)	Tax (20%) (3)	Transfers 1 (4)	Final Income 1 (5)	Transfers 2 (6)	Final Income 2 (7)
A (20%)	1000	200	0	800	64	864
B (20%)	800	160	0	640	64	704
C (20%)	600	120	0	480	64	544
D (20%)	400	0	240	640	144	544
E (20%)	200	0	240	440	144	344
Inequality	5	(=480)	(=480/2 = 240)	1.8		2.5

Note: Inequality = Ratio of incomes between groups A and E. Final Income is the income after deducting taxes and adding transfers. Source of Table 2: Rothstein (2001). Table 3 assumes a proportional tax system of 20%, where the bottom 2 quintiles are not taxed. The target for transfers are groups D and E. Column (6) assumes that targeting is imperfect, that is there is a leakage of 40% to non-poor groups (A, B and C), and the poor (D and E) get only 60% of the transfers.

Table 4: Stock Position of Wheat and Rice in the Central Pool vis-à-vis Minimum Buffer Norms

(lakh tonnes)

As on	WHEAT		RICE		TOTAL	
	Minimum Buffer Norms	Actual Stock	Minimum Buffer Norms	Actual Stock	Minimum Buffer Norms	Actual Stock
January 2009 #	112	182.12	138	175.76	250	357.88
April	70	134.29	142	216.04	212	350.33
July	201	329.22	118	196.16	319	525.38
October	140	284.57	72	153.49	212	438.06
January 2010	112	230.92	138	243.53	250	474.45
April	70	161.25	142	267.13	212	428.38
July	201	335.84	118	242.66	319	578.50
October	140	277.77	72	184.44	212	462.21
January 2011	112	215.40	138	255.80	250	471.20
April	70	153.64	142	288.20	212	441.84
July	201	371.49	118	268.57	319	640.06
October	140	314.26	72	203.59	212	517.85
January, 2012	112	256.76	138	297.18	250	553.94

Table 5: Quantum of Food Subsidies Released by Government Of India

Year	Food Subsidy (Rs. crore)	GDP (Rs. Crore)	% of GDP	Annual Growth (%)
2004-05	25,746.45	2,971,464	0.87	2.33
2005-06	23,071.00	3,253,073	0.71	-10.39
2006-07	23,827.59	3,564,364	0.67	3.28
2007-08	31,259.68	3,896,636	0.80	31.19
2008-09	43,668.08	4,158,676	1.05	39.69
2009-10	58,242.45	4,516,071	1.29	33.38
2010-11	62,929.56	4,918,533	1.28	8.05

Source: Department of Food and Public Distribution. World Bank. A lakh equals 100,000. A crore equals ten million.

Table 6: Process for identification of BPL families

Authority	Role	Details [26]
NSSO	Conducts sample survey of consumer expenditure every five years.	Consumer expenditure is the expenditure of a household on some basic goods and services. The expenditure on this basket of goods is the basis for the poverty line.
Planning Commission	Estimates state-wise poverty, i.e., the number of people below the poverty line.	Uses NSSO household expenditure data.
Central Government	Allocates food grains to each state based on state-wise poverty estimates of Planning Commission and population projections of the Registrar General of India as of March 2000.	The number of BPL families has been calculated using 1993-94 poverty estimates by Planning Commission. This number has not been revised despite the release of new poverty estimates by the Planning Commission in 2004-05 and 2011-12.
Ministry of Rural Development	Comes out with criteria for inclusion and exclusion from BPL list as part of its BPL Census.	Criteria for classification of BPL families, as per BPL Census 2002, include parameters like size of land holding, clothing owned, food security, means of livelihood etc.
State Governments	Identify eligible households.	Based on above criteria.

[26] *Sources: Department of Food and Public Distribution; Planning Commission; Ministry of Rural Development; PRS. (Rajendran & Reddy 2015)*

Table 7: Statewise PDS characteristics

Generosity of PDS [27]						
Criteria		TN	AP	KL	KA	MH
I. Intensive Margin (Entitlements)	Max Qty per card (Rice & Wheat, kgs.)	30	30	32	23	35
	PDS Price of Rice(Rs.)	Free	1	1	3	6
	Subsidy on Rice (using CIP of GOI, Rs./kg.)	5.65	4.65	4.65	2.65	-0.35
	Subsidy on Rice (using retail prices, Rs./kg.)	24	21	31	19	19
II. Extensive Margin (Exclusion Norms)	Income per annum (> Rs.)	None	Urban 75,000 Rural 65,000	21,000	Urban 17,000 Rural 12,000	15,000
	Land (> acres)	None	2.5 wet 5 dry	1 (excluding STs)	3	2.9 rain fed 2.5 semi-irrigated 1.2 irrigated
	Income tax payers	None	None	None	Exclude	Exclude
	Government Employees	None	Exclude ones with permanent positions	Exclude	Exclude	Exclude doctors, advocates, architects and chartered accountants
	Four wheelers owned	None	Exclude (other than provided under govt. schemes)	Exclude	Exclude	Exclude
	Residential telephone owned	None	None	None	Exclude	Exclude
III. Implementation	% of population with access to PDS (All India : 50.03)	94.68	89.26	85.02	76.06	48.12
	% with BPL ration cards (All India: 37.92)	87.81	85.07	28.76	62.99	27.07
	% Diversion of PDS grain (All India : 43.9)	4.4	19.2	16.2	41	42.5
	% HHs consuming rice from PDS (All India : 45.81)	89.65	86.36	79.64	75.02	44.22
	Implicit Income Transfer (Rs.) per HH per month (All India: 85.21)	218.25	121.56	129.18	104.38	60.16

[27] *Sources: Reports of Justice Wadhwa Committee on Public Distribution System, State Food and Civil Supplies portals, Khera 2011, Masiero 2012, Rahman 2014*

Table 8: Statewise Summary Statistics

Variable	TN	AP	KL	KA	MH
Vulnerability	0.163	0.143	0.118	0.153	0.237
Wealth	0.886	-0.431	2.018	-0.742	-0.334
Malnutrition	0.952	0.953	0.894	0.957	0.931
Consumption per capita (Rs)	2,467	2,750	3,098	2,515	2,042
Households	1,982	2,203	1,570	3,865	3,309
Years in Place	70	76	71	81	73
Income (Rs. lakh)	1.245	0.858	1.744	1.223	1.335
Population density (per km^2)	555	308	859	319	365
Net Domestic Product Per Capita (Rs.)	89,050	64,773	82,753	68,053	93,281
% land under rice cultivation	13.32	10.68	4.73	4.81	1.28
PDS Subsidy (Rs.) per household	426.990	339.064	204.174	205.877	39.603
Distance (kms)	80.105	102.723	32.730	73.791	268.496

Table 9: Sub Groups Summary Statistics

Variable	SC/ST	OBC	All
Vulnerability	0.205	0.155	0.168
Wealth	-1.375	0.256	0.000
Malnutrition	0.943	0.944	0.941
Consumption per capita (Rs)	1,890	2,572	2,497
Households	3,288	6,490	12,929
Income (Rs. lakh)	0.988	1.227	1.256
BPL ration card holders (%)	75.24	63.45	59.72

Generosity of PDS impacts: Vulnerability

Table 10

Specification	Full Sample	SC/ST	OBC
	(1)	(2)	(3)
(a)Polynomial degree 1 (linear model)			
τ_{IK}	-0.056***	-0.079	-0.054***
	(0.018)	(0.051)	(0.020)
τ_{CCT}	-0.069***	-0.076	-0.054***
	(0.019)	(0.051)	(0.020)
(b)Polynomial degree 2 (quadratic model)			
τ_{IK}	-0.078***	-0.115*	-0.065***
	(0.019)	(0.062)	(0.022)
τ_{CCT}	-0.085***	-0.117*	-0.081***
	(0.020)	(0.062)	(0.022)
(c)Polynomial degree 3 (cubic model)			
τ_{IK}	-0.102***	-0.126*	-0.056**
	(0.028)	(0.067)	(0.025)
τ_{CCT}	-0.085***	-0.162**	-0.098***
	(0.022)	(0.074)	(0.025)

Note: Estimates using a triangular kernel. Subscripts *IK* and *CCT* denote bandwidth choices according to Imbens and Kalyanaraman (2012) and Calonico et al.(2014) respectively. Standard errors are reported in parentheses. ***,**,* indicates significance at the 1%, 5%, 10%-level, respectively.

Generosity of PDS impacts: Vulnerability Across Occupational Groups

Table 11

Occupational Group	Mean	Urban %	τ_{IK}	τ_{CCT}
	(1)	(2)	(3)	(4)
Ag wage lab (landless)	0.225	12	-0.031	-0.010
	(0.134)		(0.096)	(0.103)
Construction workers (landless)	0.208	46	-0.373*	-0.373*
	(0.135)		(0.194)	(0.194)
Construction workers	0.203	33	-0.276**	-0.178*
	(0.134)		(0.117)	(0.093)
Other	0.201	72	-0.128	-0.058
	(0.145)		(0.402)	(0.129)
Non ag wage lab (landless)	0.200	62	-0.143***	-0.121**
	(0.132)		(0.049)	(0.053)
Automobile Drivers	0.188	56	-0.234**	-0.261**
	(0.134)		(0.107)	(0.106)
Unemployed	0.171	41	-0.028	-0.055
	(0.137)		(0.057)	(0.063)

Note: Category 'Other' includes shoemakers, maids, carpenters & caretakers. Estimates using a triangular kernel and a functional specification of polynomial degree 2. Subscripts IK and CCT denote bandwidth choices according to Imbens and Kalyanaraman (2012) and Calonico et al.(2014) respectively. Standard errors are reported in parentheses. ***,**,* indicates significance at the 1%, 5%, 10%-level, respectively.

Generosity of PDS impacts: Vulnerability Across Poverty Thresholds

Table 12

	Threshold 1	Threshold 2	Threshold 3	Threshold 4
	(1)	(2)	(3)	(4)
Full Sample	-0.176** (0.068)	-0.113*** (0.044)	-0.151* (0.086)	-0.093 (0.069)
SC/ST/OBC	-0.185** (0.078)	-0.139*** (0.050)	-0.157* (0.090)	-0.231** (0.113)

Note: Thresholds are as follows - Threshold 1: 17,235 < income < 27,235; Threshold 2: 27,235 < income < 37,235; Threshold 3: 7000 < income < 12,000; Threshold 4: 12,000 < income < 17,000. Estimates using a triangular kernel and a functional specification of polynomial degree 2. Bandwidth choices according to Calonico et al.(2014). Standard errors are reported in parentheses. ***,**,* indicates significance at the 1%, 5%, 10%-level, respectively.

Generosity of PDS impacts on Vulnerability: Channels

Table 13

	Consumption	Savings	Wealth	Investment	Livestock	Labor Supply	Casual Jobs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Full Sample	-0.038	0.293	2.090***	0.199***	2.686***	0.668***	-0.365***
	(0.077)	(0.194)	(0.393)	(0.056)	(0.969)	(0.129)	(0.137)
SC/ST	-0.037	0.441	1.161**	0.213***	4.337*	0.509**	-0.471**
	(0.100)	(0.320)	(0.559)	(0.077)	(2.503)	(0.229)	(0.233)
OBC	-0.060	0.282	2.416***	0.140**	1.654*	0.676***	-0.322**
	(0.100)	(0.247)	(0.557)	(0.069)	(0.914)	(0.161)	(0.156)

Note: Estimates using a triangular kernel and a functional specification of polynomial degree 2. Bandwidth choices according to Calonico et al.(2014). Standard errors are reported in parentheses. ***,**,* indicates significance at the 1%, 5%, 10%-level, respectively.

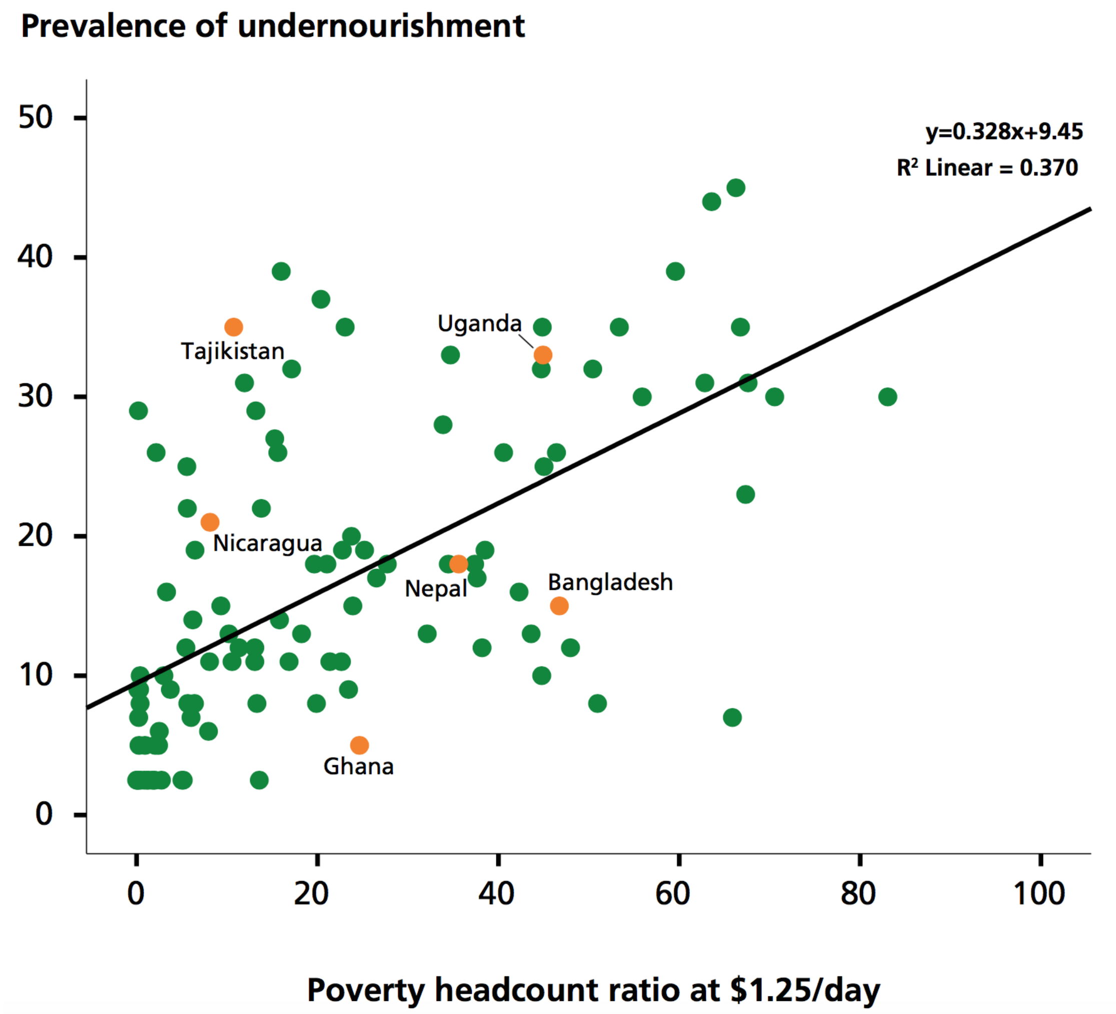
Generosity of PDS impacts on Vulnerability: Sources

Table 14

Source	Full Sample (1)	SC/ST (2)	OBC (3)
(a)Intensive Margin	-0.047 (0.005)	-0.050 (0.008)	-0.031 (0.007)
(b) Extensive Margin 1	-0.085 (0.007)	-0.093 (0.014)	-0.068 (0.010)
(c) Extensive Margin 2	-0.026 (0.004)	-0.026 (0.010)	-0.018 (0.006)

Note: ATT estimates using propensity score matching with Caliper 0.005. All impacts are significant at the 1% level. *Intensive Margin* is higher utilization, *Extensive Margin 1* is lower Type I errors and *Extensive Margin 2* is higher eligibility.

Figure 1: **Correlation of Poverty and Undernourishment At the Country Level**



Source: FAO (2013).

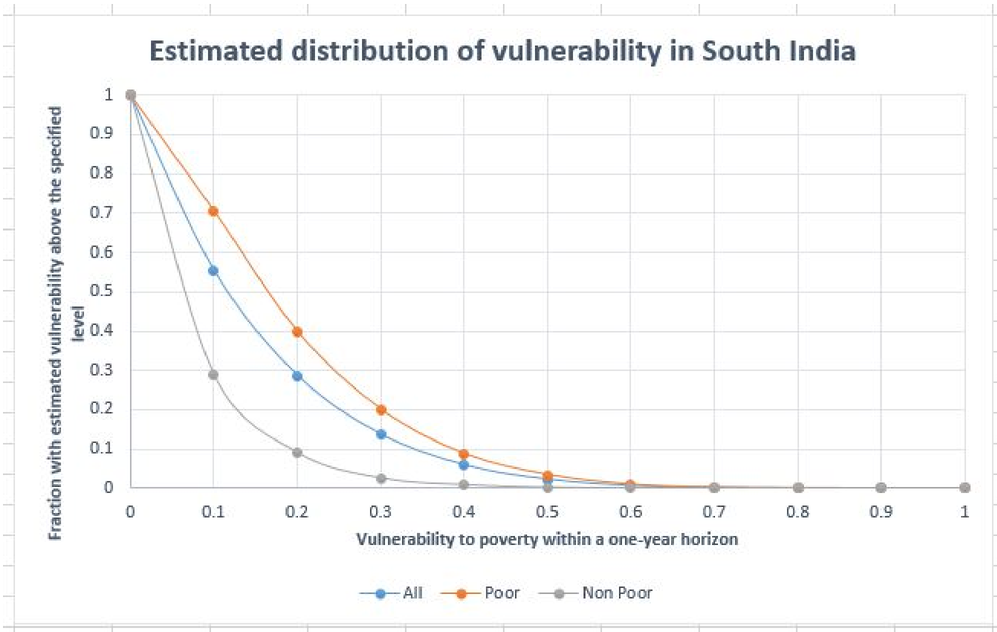
Note: Undernourishment is 'a state, lasting for at least one year, of inability to acquire enough food, defined as a level of food intake insufficient to meet dietary energy requirements'. In the FAO report 'hunger' is synonymous with 'chronic undernourishment'.

Figure 2: **South India**

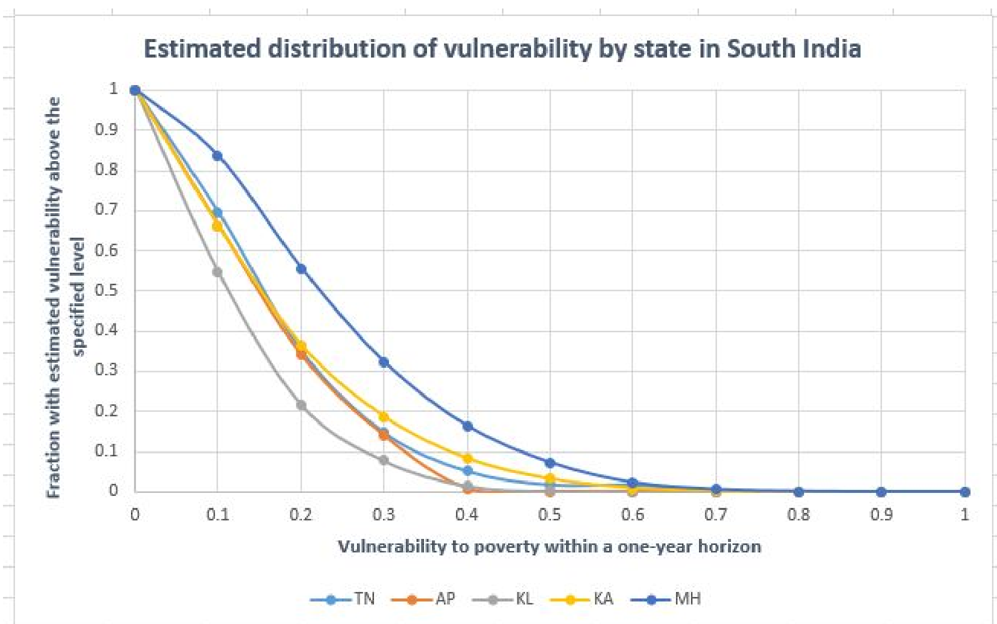
(a) The quasi-experimental border

(b) Rivers of Peninsular India

Figure 3: **Distribution of Vulnerability**



(a)



(b)

Discontinuity of treatment status

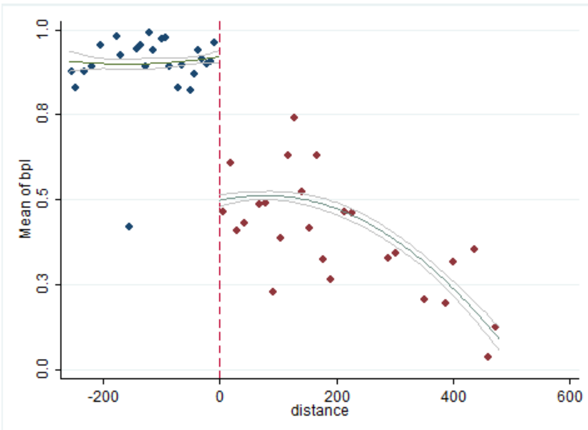


Figure 4: BPL ration card holders

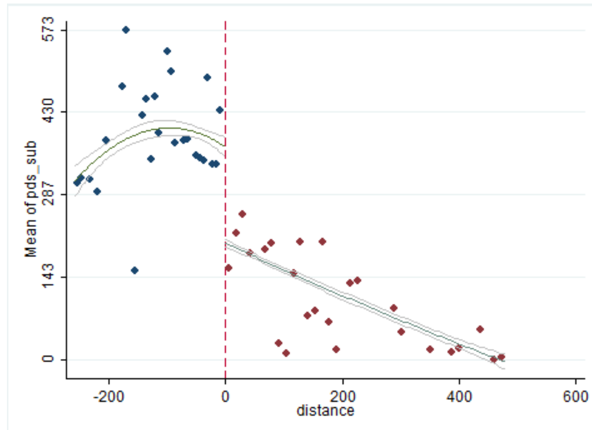


Figure 5: PDS Subsidy

Correlation of distance with rice production

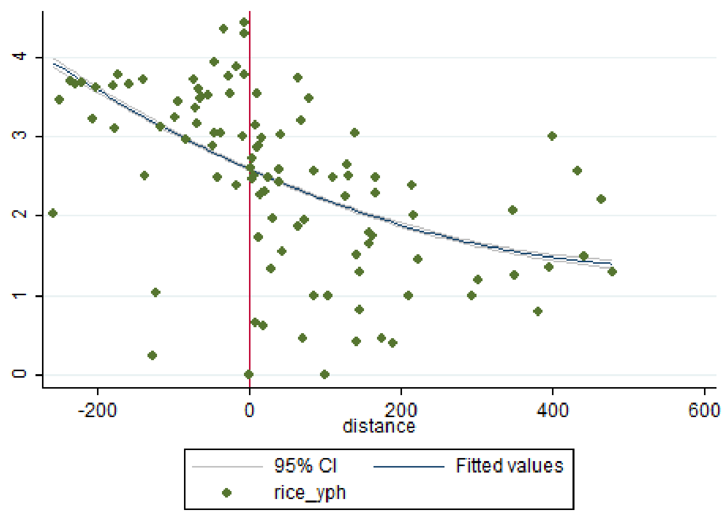
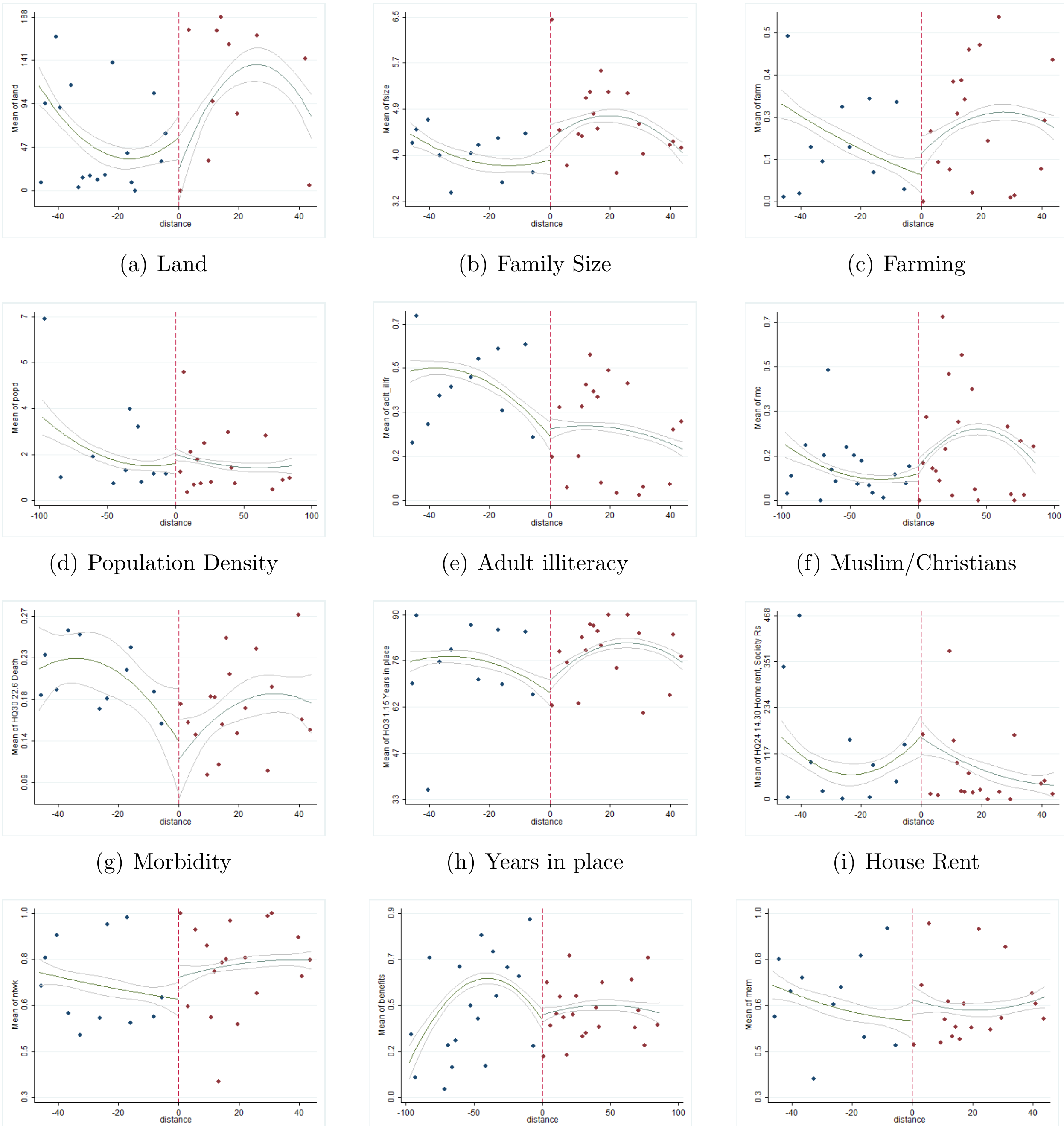


Figure 6: Rice yield per hectare

Note: Districts with a negative [positive] distance are located on the more [less] generous side of a border.

Figure 7: **Distribution of household characteristics**



(a) Land (b) Family Size (c) Farming

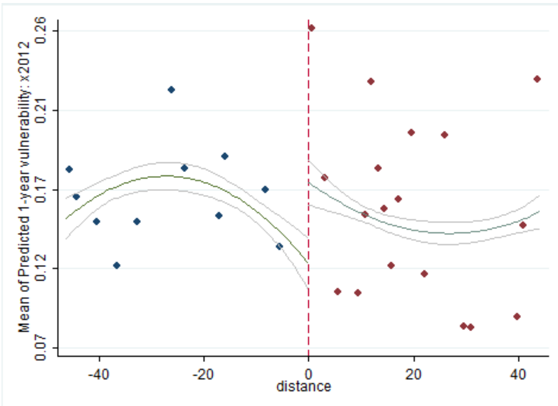
(d) Population Density (e) Adult illiteracy (f) Muslim/Christians

(g) Morbidity (h) Years in place (i) House Rent

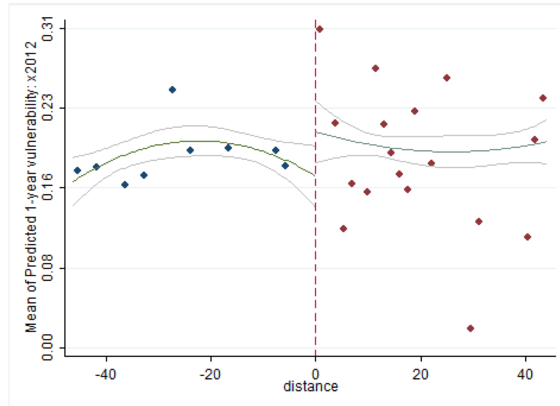
(j) Networks (k) Benefits (l) Memberships

Note: The figure illustrates the distribution of several key variables among households in districts within a 50-100 km distance to the closest state border in the main sample. Districts with a negative [positive] distance are located on the more [less] generous side of a border.

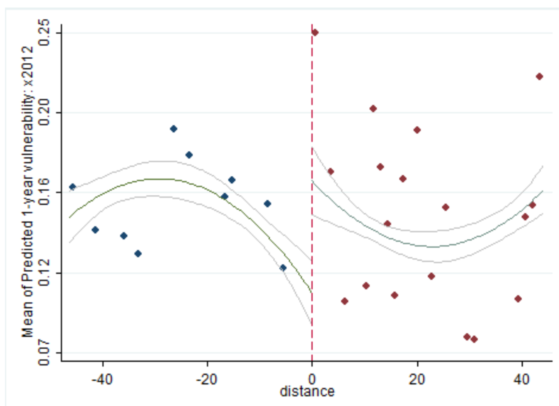
Figure 8: **Generosity of PDS Impacts: Vulnerability**



(a) Full Sample



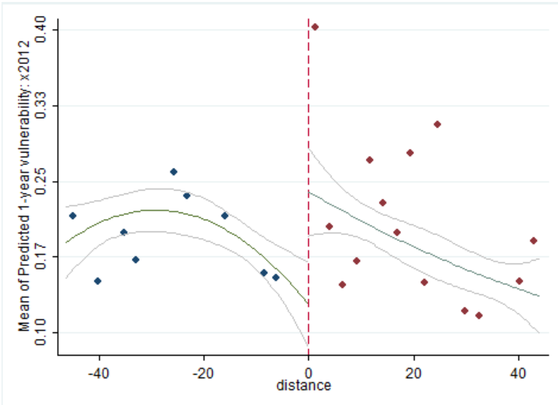
(b) SC/ST



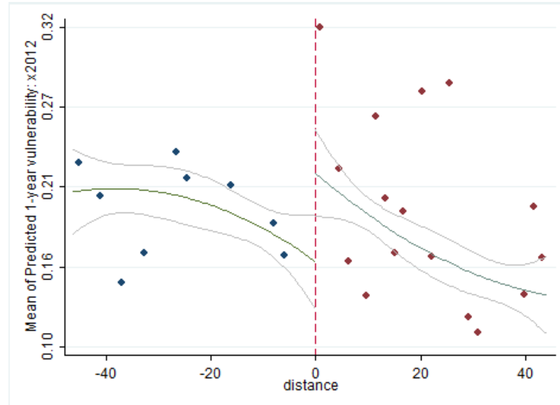
(c) OBC

Note: Districts with a negative [positive] distance are located on the more [less] generous side of a border.

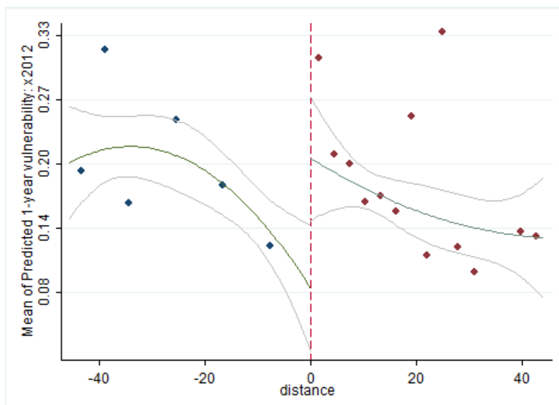
Figure 9: **Generosity of PDS Impacts: Vulnerability Across Occupational Groups**



(a) Construction Workers (landless)



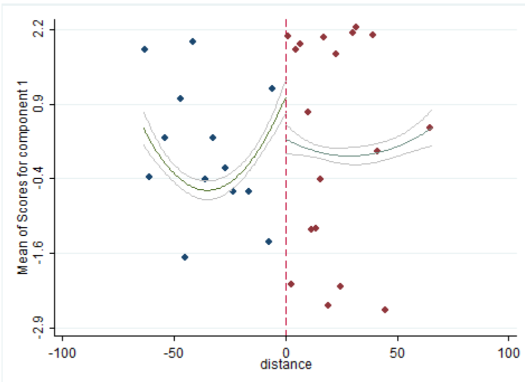
(b) Non ag wage lab (landless)



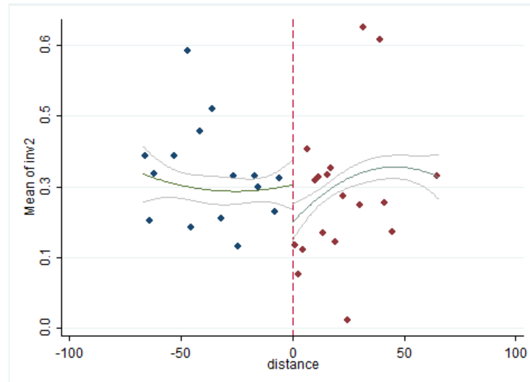
(c) Automobile Drivers

Note: Districts with a negative [positive] distance are located on the more [less] generous side of a border.

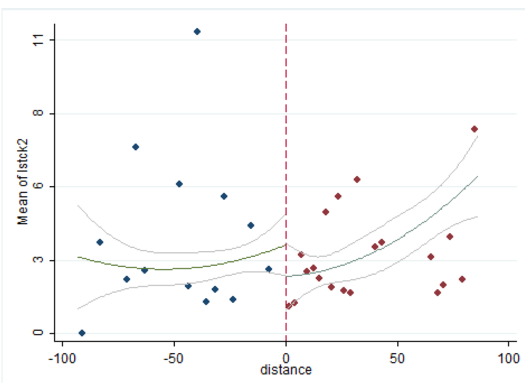
Figure 10: **Channels (Full Sample)**



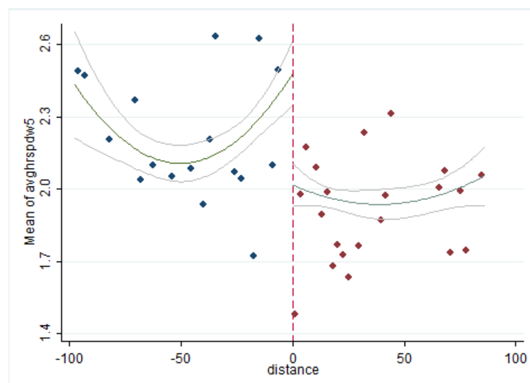
(a) Wealth



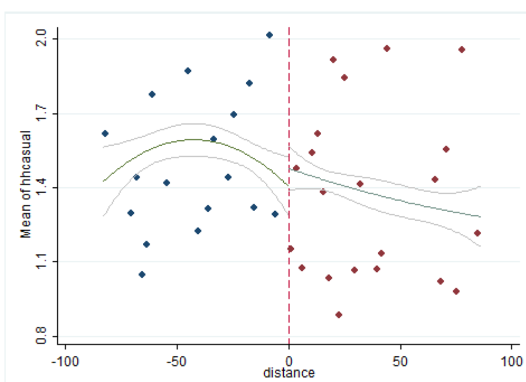
(b) Investment



(c) Livestock



(d) Labor Supply



(e) Casual Jobs

Note: Districts with a negative [positive] distance are located on the more [less] generous side of a border.

Appendix

Vulnerability to Poverty Estimation

The vulnerability level of a household h at time t is defined as the probability that the household will find itself consumption poor at time t+1:

$$v_{ht} = Pr(c_{h,t+1} \leq z)$$

where $c_{h,t+1}$ is the household's per-capita consumption level at time t+1 and z is the appropriate consumption poverty line. The procedure for estimating household vulnerability is as follows (Chaudhuri et al. (2002)).

The stochastic process generating the consumption of a household h is given by:

$$lnc_h = X_h\beta + e_h$$

where, c_h is per capita consumption expenditure, X_h represents selected observed household and community level characteristics, β is a vector of parameters, and e_h is a mean-zero disturbance term that captures idiosyncratic factors (shocks) that contribute to different per capita consumption levels for households that are otherwise observationally equivalent. X_h includes:

A: A set of variables indicating household characteristics, such as (i) Family size and squared (ii) Dependency ratio - child (0-14), teen (15-20) and old (60+) (iii) Proportion of adults (21-60) (iv) Age of head and squared (v) Proportion of adults illiterate (vi) Proportion of adults with primary education (vii) Proportion of adults with secondary education (viii) Proportion of adults with some higher education (ix) Dummy for male head, whether head is married, single or divorced, self-employed with some assistance, self-employed with no assistance, salaried worker (x) Dummy for whether farming is main livelihood (xi) Per capita land area owned and squared (xii) Dummy for whether household has access to a clean water source, indoor piped drinking water, electricity, flush toilet and hand wash after defecation (xiii) Electricity hours.

B: A set of variables indicating community characteristics (at district level), such as (i) Number of public banks per 1000 households (ii) Number of private banks per 1000 households (iii) Proportion of villages with cooperative banks (iv) Proportion of villages with public buses (v) Proportion of villages with pucca (concrete) roads (vi) Proportion of villages with railways (vii) Proportion of villages with power supply.

The variance of e_h (and hence of ln c_h) is allowed to depend upon observable household characteristics in some parametric way. The estimates ($\sigma^2_{e,h}$) are generated assuming the following functional form:

$$\sigma^2_{e,h} = X_h \theta$$

β and θ are estimated using a three-step feasible generalized least squares (FGLS) procedure. Using the estimates $\hat{\beta}$ and $\hat{\theta}$ that are obtained, expected log consumption and the variance of log consumption can be directly estimated as follows:

$$\hat{E}[lnc_h|X_h] = X_h \hat{\beta}$$

$$\hat{V}[lnc_h|X_h] = \hat{\sigma}^2_{e,h} = X_h \hat{\theta}$$

for each household h. By assuming that consumption is log-normally distributed (i.e., that ln c_h is normally distributed), these estimates can then be used to form an estimate of the probability that a household with the characteristics, X_h, will be poor, i.e, of the household's vulnerability level.

$$\hat{v}_h = Pr(lnc_h < lnz|X_h) = \Phi(\frac{lnz - X_h\hat{\beta}}{\sqrt{X_h\theta}})$$

Generosity of PDS impacts: Malnutrition

Table 17

Specification	Full Sample	SC/ST	OBC
	(1)	(2)	(3)
(a)Polynomial degree 1 (linear model)			
τ_{IK}	-0.015	-0.059	-0.013
	(0.033)	(0.095)	(0.038)
τ_{CCT}	-0.016	-0.047	-0.014
	(0.032)	(0.107)	(0.036)
(b)Polynomial degree 2 (quadratic model)			
τ_{IK}	-0.023	-0.003	-0.031
	(0.039)	(0.125)	(0.047)
τ_{CCT}	-0.026	-0.040	-0.033
	(0.039)	(0.119)	(0.046)
(c)Polynomial degree 3 (cubic model)			
τ_{IK}	-0.014	0.020	-0.017
	(0.045)	(0.140)	(0.053)
τ_{CCT}	-0.025	0.018	-0.043
	(0.046)	(0.145)	(0.050)

Note: Estimates using a triangular kernel. Subscripts IK and CCT denote bandwidth choices according to Imbens and Kalyanaraman (2012) and Calonico et al.(2014) respectively. Standard errors are reported in parentheses. ***,**,* indicates significance at the 1%, 5%, 10%-level, respectively.

Generosity of PDS impacts: Vulnerability (Robustness)

Table 18

	Dell	Dell Modified	Diff-in-Diff 1	Diff-in-Diff 2
	(1)	(2)	(3)	(4)
genrs	**-0.042*****		0.018*	-0.004
	(0.012)		(0.010)	(0.011)
pbpl		**-0.088*****		
		(0.023)		
polydist	0.000***	0.000***		0.000***
	(0.000)	(0.000)		(0.000)
cutoff			0.128***	0.121***
			(0.007)	(0.008)
cutoff*genrs			**-0.045*****	**-0.035*****
			(0.009)	(0.010)
constant	-0.061	0.014	0.088***	-0.103*
	(0.063)	(0.065)	(0.008)	(0.055)
R^2	0.030	0.038	0.162	0.177

Note: 'genrs' is a dummy variable indicating whether a district is located on the more generous PDS side of the boundary. *'pbpl'* is the proportion of households with a BPL ration card. *'polydist'* is the polynomial in latitude and longitude. *'cutoff'* is a dummy variable for whether household per capita consumption is less than Rs. 27,235. In specification 2 (Dell Modified), *'pbpl'* is instrumented with *'genrs'*. Figures in bold give the relevant impact estimates. Robust clustered (at district level) standard errors are reported in parentheses. ***,**,* indicates significance at the 1%, 5%, 10%-level, respectively.

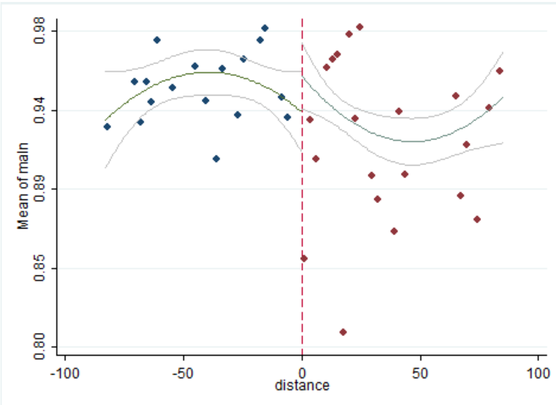
Generosity of PDS impacts: Vulnerability (Bootstrapped Standard Errors)

Table 19

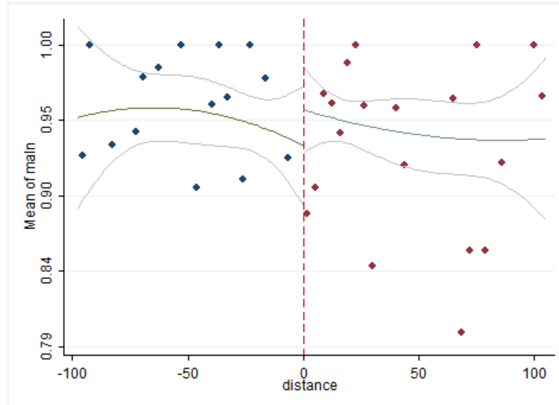
Sample	τ_{IK} (1)	τ_{CCT} (2)
Full Sample	-0.078*** (0.018)	-0.085*** (0.020)
SC/ST	-0.115** (0.057)	-0.117 (0.078)
OBC	-0.065*** (0.021)	-0.081*** (0.024)

Note: Estimates using a triangular kernel and a functional specification of polynomial degree 2. Subscripts *IK* and *CCT* denote bandwidth choices according to Imbens and Kalyanaraman (2012) and Calonico et al.(2014) respectively. Bootstrapped standard errors are reported in parentheses. ***,**,* indicates significance at the 1%, 5%, 10%-level, respectively.

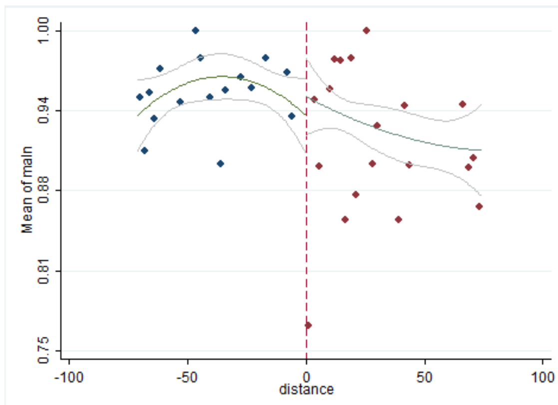
Figure 11: **Generosity of PDS Impacts: Malnutrition**



(a) Full Sample



(b) SC/ST



(c) OBC

Note: Districts with a negative [positive] distance are located on the more [less] generous side of a border.