Labor Market Effects of In-Kind Food Subsidies

Aditya Shrinivas*† Kathy Baylis† Ben Crost†

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Abstract

We estimate the effect of a large in-kind food subsidy program in India on labor supply and wages. Our empirical analysis exploits state-level changes to the generosity of the subsidy after the passage of Indias National Food Security Act in 2013. Using household monthly labor supply data for men and women and village-level wage data from 30 villages in India, we find that increases in the generosity of in-kind food subsidies led to lower labor supply and higher wages, mostly in the low-skilled casual labor market. This effect was particularly strong in years with late monsoon onset, a rainfall shock associated with reduced agricultural productivity. Our results suggest that in-kind food subsidies can play an important role in preventing the vicious cycle of low wages and high labor supply that afflicts poor households in bad years.

*Corresponding author: Aditya Shrinivas (shriniv2@illinois.edu)

†University of Illinois Urbana-Champaign, Department of Agricultural and Consumer Economics, Urbana, IL 6180

1 Introduction

Many developing countries use in-kind food subsidies, which offer a rationed quantity of staple food to the needy at a highly subsidized price, to improve food security and reduce poverty. In-kind food subsidies are an important part of social assistance programs that support poor and vulnerable persons. About 44% of individuals on social assistance programs around the world receive in-kind transfers (World Bank, 2015). Some of the largest programs are Raskin in Indonesia (62 million people), Public Distribution System in India (800 million people) and Ration cards and Baladi Bread programs in Egypt (150 million people). In-kind food subsides[1] have been shown to affect food consumption and nutrition of recipients (Hoynes and Schanzenbach, 2009; Jensen and Miller, 2011). Recent studies have shown that in-kind food subsidies can also affect non-recipients in different forms. For instance, in-kind food subsidies lower local consumer prices (Cunha et al., 2011).

A potentially important but less studied question is whether in-kind food subsidies affect labor supply and wages. Policy-makers and the public are often concerned that social assistance programs discourage work and enable the "lazy poor". Economists, on the other hand, have pointed out that a reduction in the labor supply of poor households in the private sector could drive up low-skilled wages and thus have an additional poverty-reducing effect in general equilibrium (Imbert and Papp, 2015; Berg et al., 2012). Recent studies suggest that the poverty-reducing effects of social assistance programs can be substantially underestimated if these kinds of general equilibrium effects are not taken into account (Cunha et al., 2011; Muralidharan et al., 2017).

In theory, the effect of in-kind subsidies on labor supply is ambiguous. Under the standard theory of household utility maximization over goods and leisure, with households facing time and budget constraints, an in-kind subsidy will affect both consumption and labor allocation. The net effect of in-kind subsidies on labor supply depends on the complementarity of the subsidized good and leisure. If the subsidized good and leisure are Hicks substitutes and leisure is a normal good, then an increase in in-kind transfer would reduce the demand for leisure and thereby increase labor supply. However, if the subsidized good and leisure are complements, the subsidy will reduce labor supply. In the latter case, we would expect wages to increase in order to bring the reduced labor supply into equilibrium with demand.

The ambiguous predictions for the labor supply effect of in-kind food subsidies make empirical evidence particularly valuable. However, the literature has thus far mostly focused on programs in industrialized countries and found limited effects. For instance, a large number of studies of the U.S. Food stamp program have found either no, or very

[1] A limiting case of an in-kind food subsidy is a free in-kind transfer, which can be thought of as a 100% subsidy. The two terms are used interchangeably hereafter.

small, effects on the labor supply of beneficiaries (Hoynes and Schanzenbach, 2012; Currie, 2003; Fraker and Moffitt, 1988; Hagstrom, 1996). This evidence may not generalize to developing countries where poor households are much closer to subsistence levels and food makes up a large part of their total expenditure. In developing country settings, studies of labor market effects of social assistance programs have so far focused almost exclusively on cash transfers. In a recent review, Banerjee et al. (2017) conclude that there is no systematic evidence that cash transfers reduce the labor supply of poor households. While this is important evidence, it does not necessarily imply that the same is true for in-kind food subsidies. If there is strong complementarily between the in-kind good and leisure (or non-market labor), an in-kind food subsidy may have stronger disincentive effects on labor supply, relative to cash. (Gahvari, 1994; Munro, 1989; Leonesio, 1988).[2]

In this paper, we estimate the labor market effects of the worlds largest in-kind food subsidy- Indias Public Distribution System (PDS) using ICRISATs panel data from 30 villages in India between 2010-2015. Our empirical strategy exploits state-level expansions of PDS subsidies that followed the National Food Security Act of 2013. Crucially for our study, the ICRISAT panel contains data on the amount of labor supplied for each individual in the sample households, as well as on their eligibility for the PDS subsidy. It also contains information on wages for different kinds of activities at the village level. This data allows us to estimate the effect of the PDS subsidy on labor supply at the household level separately for men and women and the equilibrium wage at the village-level in a regression that controls for household and time fixed effects.

We show that increases in the generosity of the PDS subsidy reduce household labor supply and raise the equilibrium wage. When we disaggregate the effects, based on gender and type of labor market, we find the wage effects are highest for the segments with the largest labor supply effects. In all, we find the highest incidence of PDS subsidy on the casual unskilled labor, which in principle is the desired population that PDS is targeted towards.

We further explore whether in-kind food subsidies can provide a buffer against the labor market effects of negative economic shocks. Previous studies have found that poor households increase labor supply to buffer negative shocks, so that wages deteriorate precisely at times when the poor are most dependent on labor income (Kochar, 1999; Jayachandran, 2006; Ito and Kurosaki, 2009; Rose, 2001). By reducing the dependence of poor households on labor income, PDS subsidies might therefore have particularly beneficial labor market effects in years with bad economic shocks. Consistent with this intuition, we find that the effect of PDS subsidies on labor supply and wages is particularly large during years with late monsoon onset, a rainfall shock associated with reduced agricultural production. This result suggests that in-kind food subsidies can play an

[2] As shown in Munro (1989), this implication holds, if the recipient is on the edge of the constrained consumption or if the constraint on consumption is small.

important role in preventing the vicious cycle of low wages and high labor supply that afflicts poor households in bad years.

Our estimates provide novel evidence for a labor market effect of in-kind food subsidies, based on plausibly exogenous policy variation in a panel framework with household and village fixed effects. The most closely related previous evidence comes from Sahn and Alderman (1996) who examine the labor supply effects of Sri Lankas rice subsidy program using cross-sectional data and an instrumental variables approach that instruments subsidy levels with household characteristics such as asset ownership and house size.

Our results differ from the literature on labor market effects of social assistance programs in developed countries. Studies in this have generally found very small if any work disincentives of the United States food stamp program (Hoynes and Schanzenbach, 2012; Currie, 2003; Fraker and Moffitt, 1988; Hagstrom, 1996), Medicaid program (Gruber, 2000; Buchmueller et al., 2015) and housing programs (Jacob and Ludwig, 2012; Collinson et al., 2015). Our results suggest that this evidence does not necessarily generalize to a developing country context.

Our results also contrast with recent evidence that cash transfers have no significant negative effects on labor supply (Banerjee et al., 2017; Jones and Marinescu, 2018; Salehi-Isfahani and Mostafavi, 2016). This disparity suggests that cash and in-kind transfers may not be equivalent with respect to their labor supply effects, perhaps because of complementarities between food consumption and leisure. Instead, our results suggest that the labor market effects of in-kind food subsidies are more similar to those of public works programs, which have been found to have considerable effects on labor supply in the private sector and consequently on equilibrium wages (Imbert and Papp, 2015; Berg et al., 2012; Muralidharan et al., 2017).

Our study also contributes to the literature on wage determination in rural labor markets in developing countries (Kochar, 1999; Jayachandran, 2006; Kaur, 2014). We show that large increases in the in-kind food subsidy can raise wages for casual low-skilled workers in the private sector. In-kind food subsidies can thus improve the welfare of the poor through a labor market effect in addition to their direct effect on food consumption and nutrition. Our results also highlight the important of accounting for local general equilibrium effects in program evaluation (**?**). Ignoring the general equilibrium effects on labor market would lead us to underestimate the impact of PDS program on the welfare of the poor.

Credible estimates of the benefits of the PDS program is particularly important in light of the Indian policy debate around the effectiveness of the program. Proponents have argued that PDS should be expanded as it improves welfare of the poor by improving their food security. Critics have objected on the grounds that the program is poorly targeted and may have little impact on nutrition. Our results suggest that PDS subsidies have additional benefits for the poor that have so far received little attention in this debate.

2 Public Distribution System of India

The PDS has been in existence prior to India's independence. It was initially established as a rationing system by the British Government during World War II to ensure workers in a few urban centers received food supplies (Nawani, 1994). The program later evolved in the early 1970s, as a welfare program with a primary objective to provide food security to vulnerable households, with the advent of green revolution and growth of domestic supply. Since its inception, the PDS primarily supplied rice and wheat at subsidized prices. The program was gradually expanded to provide pulses, sugar, edible oils, as well as kerosene. In this study, we focus on rice and wheat, the two predominant food items distributed under PDS.

The Food Corporation of India (FCI), a central government agency, is the primary stakeholder in the PDS supply chain[3]. The agency procures food grains directly from farmers and stores them in government operated warehouses. The state governments then procure grain stocks from FCI, distribute them to retail outlets known as fair price shops , and also control the functioning of fair price shops. With more than 532,000 fair price shops spread across the country, the PDS supply chain operates at a massive scale, covering 85% of villages in India, rendering PDS as the most far reaching of all social safety nets in the country.[4]

In most states in India, the PDS subsidy is targeted towards the poor and is available only for those who hold a PDS ration card. Beneficiary households are broadly classified into three ration card types based on an official state-defined poverty line: Above poverty line (APL), Below poverty line (BPL), and Anthodaya Anna Yojana (AAY). The Anthodaya Anna Yojanaa (AAY) is a central government scheme started in 2000 that identifies the poorest of the poor households from amongst the BPL population. Extremely vulnerable households headed by widows, disabled, or destitute households with no assured means of subsistence are identified as AAY. The value of PDS benefits are targeted towards the poor and hence is the lowest for APL households[5] and highest for AAY households, where the central government assures AAY households a minimum PDS entitlement of 35kg of rice and/or wheat. The PDS entitlement for AAY households

[3]See (Alderman et al., 2018, Chapter 2) for a more detailed description of the stakeholders in the PDS supply chain.

[4]In 2011, there were 506,198 PDS ration shops Government of India (2011b) in 597,608 inhabited villages Government of India (2011a). This suggests that as many as 85% of Indian villages were covered under the PDS. The coverage has since increased. In 2016, there were 532,000 FPs Government of India (2016)

[5]APL households in most states do not receive any PDS grain.

has been mostly constant and uniform across all states since its introduction in 2002. The benefits for BPL households, which form the majority of the population receiving PDS, differ across states and have increased over time.

The PDS subsidy for BPL households are different in each state as the fiscal expenditures towards the PDS are borne both by the central and state governments and hence are contingent on the state's outlays on PDS. In particular, the difference between FCI's cost of procuring food grains from farmers and the price at which the supplies are sold to the states, also called as the central issue price, is subsidized by the central government. The state governments can further boost the subsidy by providing an additional discount over the central issue price or by increasing the central issued quota. Not all states provide an additional subsidy. The final subsidy is therefore the sum of central and state's outlays on PDS and differs across states as it depends on the state's outlays on PDS.

Furthermore, in the pursuit of food security, the Indian central government substantially increased the outlays on the PDS program under the National Food Security Act in 2013. The Act mandated that the food grains under the PDS be converted to a legal "entitlement" for beneficiaries (or the "right to food") (NFSA, 2013) and the onus was on the State governments to enforce and provide the food entitlements. The NFSA prescribed a national standardized minimum entitlement of 2kg rice and 3kg of wheat per individual at Rs 3/kg and Rs 2/kg respectively. The adoption of NFSA by states, however, was not uniform, as NFSA permitted states to continue their state-specific PDS programs (Gulati and Saini, 2013). Therefore, since 2013, due to renewed political interest, several state governments significantly expanded their PDS programs either under NFSA or through their own state-level PDS programs such as Karnataka, Madhya Pradesh, Maharashtra and Bihar, whereas other states such as Gujarat and Jharkhand did not expand. These expansions in the PDS program, were either through increase in PDS quota or a decrease in PDS price, hereafter jointly referred to as PDS entitlements.

3 Data

We use the new wave of ICRISAT's VDSA panel data[6] of 1300 households observed over 60 months from June 2010 to July 2015. The VDSA data cover 30 villages spread

[6]ICRISAT's Village level studies (VLS) are longitudinal surveys collected between 1975 to 1985 in six villages in the semi-arid tropics of India. Data collection was restarted from 2001 in the same six villages, tagged as the second generation of VLS (VLS2). However, the frequency of household surveys from 2001 to 2004 was limited to annual observations based on the availability of funds, and was increased to monthly data in 2005-06. It was only after 2009, with the funding from the Gates foundation, the VLS was expanded significantly and was renamed as the Village Dynamics in South Asia (VDSA). In 2009, 12 villages in the semi-arid tropics, in addition to the 6 old VLS villages, and 10 more villages from east India were included; summing to a total of 30 villages across India. The data for panel year 2009, however, has many gaps, especially in the consumption module, and is inconsistent with the subsequent panel years. Accordingly, this paper uses data beginning from panel year 2010 until 2014.

across eight states in India. The states covered are Andhra Pradesh[7], Bihar, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maharashtra and Orissa; with 4 villages in each state, except Madhya Pradesh that has only 2. The geographical locations of the villages are shown in Appendix figure A4. Similar to the old VLS, households in each village are randomly selected to represent households in four land-holding classes: large, medium, small and landless.

The VDSA panel data are geographically divided into 18 villages in the Semi-Arid Tropics (SAT) and 12 villages in the Eastern region of India. The data follows the agricultural cycle in India from June to July. Endowment and household characteristics such as household size and landholding size are collected annually at the beginning of every panel year in June. Transactions, sales, market price, food and non-food expenditure data are collected every month. Market price data for commodities including rice and wheat are documented in the Monthly Price Schedule. Labor supply and wages data are reported in Employment module. Food expenditures are collected under the Transaction Module and are recorded item-wise along with information about the source of each food item, whether from home consumption or market purchase or from gifts. PDS rice and wheat are recorded as separate food items in the consumption module and are collected every month.

Ration card status of households from 18 villages in SAT and 12 villages in East India come from different sources. In East India, the ration card status is reported in the General Endowment Schedule (GES), and is collected at the beginning of every panel year in June. As for SAT, the ration card status is collected only during two periods - the beginning of panel year in 2009 and during a Household Census Survey (HCS) conducted separately by the VDSA team during 2014. Comparison of the ration card status between the two-time periods, do not reveal any significant changes in ration card status. We therefore use a time-independent ration card status of households in 2009 for SAT villages over the entire sample period. We also conduct robustness test of using 2014 ration card data. All the 30 villages have a fair price shop. The corresponding author of this study visited most of these SAT villages in person and conducted extensive fieldwork. The operation of PDS ration shops in each village, validation of ration card status and perception of PDS among beneficiaries were all documented.

Rainfall data are from the Indian Meteorological Department, defined at a fine spatial resolution of a 0.25 x 0.25 grid cell size. Daily rainfall data for the ICRISAT villages are obtained by mapping the village co-ordinates to each grid cell polygon. No two villages fall within the same grid cell and hence the spatial gridded rainfall data uniquely identifies the village locations. In summary, a rainfall shock corresponds to the monsoon start date and

[7] Two villages are in Telangana, a state formed in 2014. As our dataset begins before the formation of the new state, and for the purpose of consistency, the 2 villages in Telangana are considered as part of Andhra Pradesh

is measured annually for each village. As the effect of monsoon (or the harvest season) in India commences from September, the annual monsoon data for each village are merged with the monthly ICRISAT data such that the annual monsoon rainfall corresponds to monthly data from September to August.

[Insert Table 1]

Table 1 shows the summary statistics. We drop households with less 48 months of data and households whose head lives outside the village. The final sample consists of 1217 households.

3.1 Value of PDS Subsidy transfer

During our time frame, certain states expanded their PDS entitlements for the BPL population, either by increasing the rationed quantity of grain or by reducing the subsidized price. In total, there are 11 policy changes in the PDS entitlements, that correspond to the eight states in the ICRISAT data. Appendix Table A1 cleanly organizes and documents these changes.

We quantify the increases in the generosity of the PDS subsidy by considering the value of the transfer, calculated as the product of the quantity and price discount (difference between the market and PDS price):

$$Subs_{st} = \overbrace{Q_{st}^{pds\,rice}\left[\overline{P}_{st}^{Market\,rice} - P_{st}^{pds\,rice}\right]}^{RiceSubsidy} + \overbrace{Q_{st}^{pds\,wheat}\left[\overline{P}_{st}^{Market\,wheat} - P_{st}^{pds\,wheat}\right]}^{WheatSubsidy} \tag{1}$$

where $Q_{st}^{pds\,rice}$ is the statutory PDS quota set by state s in month t for rice, $\overline{P}_{st}^{Market\,rice}$ is the average market price of rice over the sample period in state s and $P_{st}^{pds\,rice}$ is the statutory PDS price set by state s in month t. The market price corresponds to a comparable variety of PDS rice and wheat. We use a state-level time invariant average market price to define the PDS subsidy value to ensure that any variation in the subsidy measure is derived solely from changes in the PDS program parameters (or "entitlements"), not changes in market conditions, or household consumption. Consequently, the implicit subsidy value in month t may not represent the value of the income transfer corresponding to the actual market price in month t.

[Insert Figure 1]

Figure 1 shows the gradual increase in the PDS subsidy value in each state after July 2013. Among the eight states, the NFSA was first implemented in Maharashtra and Bihar in February 2014 and later in Madhya Pradesh from April 2014. In addition to the phased rollout of the NFSA, certain states such as Karnataka and Madhya Pradesh expanded their PDS subsidy by initiating their own state-level PDS programs. For instance, in June 2013, the chief minister of Karnataka introduced the "Anna Bhagya Scheme", essentially doubling the PDS transfer value. Similarly, the chief minister of Madhya Pradesh introduced the "Mukhyamantri Annapurna Scheme" in June 2013, thereby increasing the PDS transfer value. In contrast, Jharkhand and Gujarat did not expand their PDS programs during the study period. However, Jharkhand already had the most generous PDS program with the highest transfer value even before NFSA. In summary, Figure 1 shows that there is tremendous variation, both temporally and spatially, in the PDS program parameters.

4 Labor Market Effects of PDS

4.1 Estimation Strategy

We examine the impact of PDS on labor supply and wages:

$$LS_{ivt} = \alpha_i + \lambda_t + \delta_i t + \beta_1 Subs_{vst} + \epsilon_{ivt} \quad (2)$$

$$W_{vt} = \alpha_v + \lambda_t + \delta_v t + \beta_1 Subs_{vst} + \epsilon_{vt} \quad (3)$$

where LS_{ivt} represents the labor supplied (number of days in a month) by household i in village v and month t with household and month fixed effects and W_{vt} represents daily wages, averaged to the year-level, in village v and year t with village and year fixed effects. δ_i and δ_v are the household and village-specific time trends. Standard errors are clustered at the village level. The consecutive time fixed effects absorb any aggregate time shocks that may affect the labor market, including any price effects or changes in the government policies. β_1 is the main coefficient of interest.

The model exploits both cross-sectional and temporal variation in the PDS program. The temporal variation comes from the 11 policy changes in the PDS entitlements during the study period. The cross-sectional variation comes from the difference in PDS entitlements across states and the differential expansion in the PDS entitlements for BPL households. The above fixed effects specification is akin to a triple difference-in-difference methodology, wherein the first difference is between households who receive PDS Subsidy and those who dont, the second difference is between households who were exposed to a more generous and a less generous PDS expansion and the third difference is between households before and after the PDS expansion.

4.2 PDS decreases labor supply

The effect of PDS on household labor supply is meticulously examined separately for men and women, and by the type of labor - whether for own or market, farm or non-farm (Casual unskilled, salaried job, business, etc.). Each component is examined as an outcome variable in equation (2). Table (2) reports the coefficient estimates on the PDS subsidy value β_1. Estimates are reported separately for men, women and for both in columns and each column is segregated in rows based on whether the labor was supplied to the market or for own purpose. The category market labor is further segmented into the type of labor, whether farm, casual labor, business, salaried job, etc. Each coefficient estimate comes from a separate estimation of equation (2) with different sources of household labor supply as the outcome variables and the PDS Subsidy value as the regressor. Standard errors are clustered at the village level. To interpret the significance of the estimates, we hereafter consider a policy experiment of increasing the PDS subsidy value by 70 rupees per adult-equivalent per month an amount equivalent to the PDS expansion in Karnataka in June 2013.

The results for total market supply of labor clearly shows that a more generous PDS subsidy decreases total supply of labor: 70 rupees increase in PDS subsidy value translates to 2.45 (=70*0.035) days decrease in total labor supplied by a household in a month. As the sample average labor supply is 43 days, the PDS program decreases the total household labor supply by 5.7% (=2.45/43). This estimate is significantly larger than previous estimates of the labor supply effects of welfare programs (Imbert and Paap 2015; Muralidharan, Niehaus and Sukhantar, 2018). One of the possible reasons could be that, we are estimating the direct effects of the program on the treated households, whereas previous studies have estimated the aggregate effects of the exposure of the program at a much large geographical scale (either district or state level).

The disaggregated results show that the PDS subsidy has the largest effect on non-farm labor supply, especially in the casual unskilled labor market for both men and women: 70 rupees increase in PDS Subsidy value decreases total casual labor supply by 0.7 days (=70*0.01) in a month, which translates to 2.7% decrease, as the sample average casual labor supply is 26 days. As expected, PDS subsidy has no effect on the number of days worked on salaried jobs. However, it is interesting to note that PDS subsidy has a marginal negative effect on the supply of labor to business enterprises in the informal sector such as running transport vehicles, handicraft shops, toddy or beedi making, selling milk, rice and flour milling etc. In regards to own labor supply, the results suggest that PDS subsidy has no significant effects, expect a small effect on own livestock.

4.3 PDS increases wages

Table (3) provides results from estimating the effect of PDS on village wages. As we are interested in the impact of the program on the equilibrium wages, the relevant level of analysis is the village-year, not the household-month. In addition, there may be rigidities in wage response or lag effects of the program with monthly data. Each coefficient estimate comes from a separate estimation of equation (3) with different types of wages (farm or non-farm; men or women) as the outcome variables and the PDS Subsidy value as the regressor. Appendix Table A1 provides the disaggregated results based on the wage categories. Standard errors are clustered at the village level.

The results suggest that PDS subsidy increases the equilibrium wage. In particular, the estimates on farm wages are statistically significant for men and women: A 70 rupees increase in PDS Subsidy value increases daily farm wages by approximately Rs. 15 (=70*0.211), which translates to a 10% increase in yearly wage rates (as the sample average farm daily wages is Rs. 150). Consistent with the results on labor supply, the PDS subsidy has the largest effect on non-farm casual wages rates of men: A 70 rupees increase in PDS Subsidy value increases daily casual wages of men by approximately Rs. 34 (=70*0.484), which translates to a 13.4% increase in yearly wage rates (as the sample average farm daily wages is Rs. 253). Although some of the wage effect estimates are not statistically significant at the 10% level, the standard errors on these estimates are not huge. Overall, the results provide suggestive evidence that PDS Subsidy increases equilibrium wages.

To investigate whether the magnitude of the wage increase is reasonable given the fall in the labor supply, we compute labor demand elasticity in the casual unskilled labor market, under the assumption that the market is competitive. The elasticity of demand is given by the ratio of the percentage change in labor supply over the percentage change in wages. From the above results, we know that PDS program decreased casual labor supply by 3% and increased wages by 13%. Hence, the elasticity of labor demand is $\tilde{\epsilon_d} = \frac{3}{13} \approx 0.23$, which is comparable to the 0.31 estimated by Imbert and Papp (2015) and lies at the lower end of the 0.25 to 0.4 range estimated by Evenson and Binswanger (1980) for farm employment in India. In comparing our estimates with previous studies, it is also important to note that our estimates measure local effects at the household or village level, as compared to labor market effects at the district or state-level, hence may represent the effect on the treated, rather than just the exposure of the program. Furthermore, about 75% of the casual labor in our dataset is supplied by BPL households who receive the PDS subsidy. Hence, our 3% estimate represents the labor supply effect mostly on the BPL households. If there were more non-BPL households covered in our labor market dataset, the effect on aggregate labor supply would have been less than 3% and the elasticity of demand would be lower.

5 Can PDS buffer productivity shocks on the labor market

5.1 Rainfall as a measure of productivity risk

Rainfall patterns are a crucial determinant of agricultural production in India, and the monsoon season is particularly important for agricultural returns. The impact of monsoon rainfall on agricultural returns has been studied extensively (Gine, 2007; Jacoby and Skoufias, 1997; Rosenzweig and Binswanger, 1993). In particular, the timing of the onset of monsoon (first phase of monsoon accompanied by an increase in rainfall relative to earlier months) is a crucial predictor of agricultural profits (Rosenzweig and Binswanger, 1993), since it provides the soil moisture necessary for the early stages of plant growth.

In this paper, we consider monsoon onset as a measure of productivity risk, measured as the first day after June 1 with more than 20 mm of rain, following Rosenzweig and Binswanger (1993).[8] In Appendix table, we show that monsoon onset is highly correlated with alternative rainfall measures. In Table 2, we also show how monsoon onset impacts agricultural yield, production and price at the village level. The results shows that a late monsoon decreases village yield, production, sold quantity and price. Therefore, these results validate the use of monsoon onset as a proxy for local productivity shock at the village level.

5.2 Estimation strategy

The ICRISAT data provide a unique setting to test the proposition that the PDS has beneficial labor market effects in years with adverse rainfall shocks. First, a majority of households in the data are vulnerable to rainfall shocks. About 78% of the sampled households are dependent on agriculture as the basis of their livelihood and only 32% of the sampled households have full irrigation. Second, and more importantly, the ICRISAT data has substantial variation in both rainfall and PDS subsidy value, meeting the critical data requirements to identify the buffer effect of PDS. Appendix B provides a detailed description of the variation in monsoon onset and PDS subsidy value in the ICRISAT data.

We empirically test the buffer effect of PDS on labor market outcomes by considering the interaction between the PDS subsidy value and monsoon onset:

$$Y_{ivt} = \alpha_i + \lambda_t + \delta_i t + \beta_1 R_{vy} + \beta_2 Subs_{vst} + \beta_3 R_{vy} Subs_{vst} + \epsilon_{ivt} \tag{4}$$

[8] As the effect of monsoon (or the harvest season) in India commences from September, the annual monsoon data for each village are merged with the monthly ICRISAT data such that the annual monsoon rainfall corresponds to monthly data from September to August. For instance, monsoon in 2013 (first day after June 1st 2013 with rainfall greater than 20 mm) would correspond to monthly labor supply from September 2013 to August 2014.

where $Y_{ist} = LS_{ivt}$ for the labor supply equation with household and month fixed effects and $Y_{ist} = W_{vt}$ for the wage equation with village and year fixed effects. R_{vy} is the monsoon start date in village v in crop-year y. We include a time trend term δ_s at the state-level, as trends at a more disaggregated level such as the village or household level soak up significant variation in the rainfall variable. For the wage equation, a late monsoon would have a negative effect $\beta_1 < 0$ and a more generous PDS subsidy would have a positive effect $\beta_2 > 0$. As the marginal effect of monsoon onset on wages is $\beta_1 + \beta_3 Subs_{vst}$, the coefficient β_3 can be interpreted as the extent to which the PDS attenuates the impact of rainfall on wages and hence is the coefficient of interest. $\beta_3 > 0$ implies that the PDS moderates the negative effect of rainfall shocks on wages. For the labor supply equations, the opposite effects are expected.

Equation (4) is akin to a triple difference-in-difference design. For the wage equation, the first difference is between villages that were exposed to a more generous and a less generous PDS expansion, the second difference is between villages before and after PDS expansion, and the third difference villages that faced a late monsoon and an early monsoon onset. The identifying variation is derived from villages with similar rainfall and a differential exposure to the PDS program. A more detailed explanation of the estimation approach with identifying examples from the data is provided in Appendix B.

5.3 PDS has larger effects on the labor market during a late monsoon

We empirically test whether PDS has greater labor market effects during negative economic shocks. In particular, we estimate the interaction between monsoon onset and PDS subsidy value, as specified in equation (4). The coefficient estimates for labor supply and wages are reported in Tables 4 and 5 respectively. Standard errors are clustered at the village level. The average effects of PDS and monsoon onset, provided in Appendix Tables A2 and A3, validate that they have opposite effects on labor supply and wages. We focus more on the interaction effects.

Results in Table 4 show that PDS subsidy reduces labor market supply to a greater degree during a late monsoon onset. The direction of the interaction term is negative for most of the outcomes and is statistically significant for the total market labor supply. The estimates on total labor market supply suggest that, when monsoon is delayed by 10 days (25th percentile in data), a 70 rupees increase in PDS subsidy decreases total market labor supply by 2.1 days (=0.028*70-0.000159*70*10); whereas, when monsoon is delayed by 70 days (90th percentile in the data), a 70 rupees increase in PDS subsidy decreases total market labor supply by 2.8 days (=0.028*70-0.000159*70*70). The disaggregated results, based on gender, suggest that the buffer effect from the PDS is the larger for women in the farm labor sector.

Results in Table 5 show that PDS subsidy raises wages to a greater extent during a delayed monsoon. Even though the interaction term is statistically insignificant for total wage rate, the estimates provide suggestive evidence for a positive interaction effect. The disaggregated results are consistent with the results on labor supply. We find larger effect on wages especially in the labor sectors that has the larger effect on labor supply the farm labor sector for women. Further disaggregated results, not shown here, suggest that the largest effect within the farm labor sector is for weeding which is primarily performed by women in India. These results are also consistent with the findings that households face excess labor supply at weeding time when rains are scarce (Fafchamps, 1993). The estimates on farm wages for women suggest that, when monsoon is delayed by 10 days (25th percentile in data), a 70 rupees increase in PDS subsidy increase daily wages by Rs. 23.7 (=0.29*70+0.005*70*10); whereas, when monsoon is delayed by 70 days (90th percentile in the data), a 70 rupees increase in PDS subsidy increases daily wages by Rs. 45 (=0.29*70+0.005*70*70).

Overall, our results imply that increases in the generosity of the PDS subsidy are effective in moderating the impact of a delayed monsoon on the labor market. In simple parlance, suppose two villages are hit by an adverse monsoon shock of a similar magnitude and only one of the village is exposed to a more generous PDS expansion, then the results imply that the village that was exposed to a more generous PDS subsidy was able to moderate the impact of the monsoon shock on the local labor market. These results are consistent with the findings in Jayachandran (2006), that productivity shocks translate into a larger change in the equilibrium wage if workers are closer to subsistence and more credit constrained because such workers supply labor less elastically. However, when credit constraints are relaxed and consumption is better smoothed, as in the case with in-kind transfers, labor can be supplied more elastically and consequently wages would be less sensitive to production shocks.

6 Conclusion

In this study, we estimate the effect of Indias food subsidy program, the PDS, on labor supply and wages. Using state-level changes in the program that occurred after the National Food security Act of 2013, we show that increases in the generosity of the in-kind food subsidy led to lower labor supply and higher wages. The disaggregated results suggest that the effect of PDS was larger for the casual unskilled labor market, which in principle is the desired population that PDS is targeted towards. Further, we find that the effect was particularly strong in years with late monsoon onset, a rainfall shock associated with reduced agricultural productivity. This buffer effect was greater for women in farm labor. Our results suggest that in-kind food subsidies can thus improve the welfare of the poor through a labor market effect in addition to their direct effect on food consumption and nutrition. Our results highlight the importance of accounting for local general equilibrium effects; ignoring these effects would lead us to underestimate the impact of PDS on the welfare of the poor.

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Table 1: Summary Stats

	AAY	BPL	APL/NoCard	Total
Number of HHs	105	579	533	1217
Number of members in the HH	4.706	4.724	5.040	4.861
	(2.125)	(2.238)	(2.377)	(2.296)
Nutrient and Calorie intake				
Calorie intake (Kcals)	2115.7	2032.5	2009.1	2029.7
	(740.9)	(794.8)	(746.3)	(770.1)
Protein intake (gms)	56.61	52.06	54.04	53.31
	(22.43)	(21.92)	(21.18)	(21.69)
Fat intake (gms)	39.21	37.92	46.74	41.84
	(19.53)	(35.99)	(25.96)	(31.07)
Consumption Quantity (in Kgs)				
Total Staple Cereals	12.82	11.46	10.43	11.13
	(5.886)	(5.546)	(5.608)	(5.648)
Quantity of pds grain consumed	7.259	5.400	1.183	3.742
	(3.905)	(3.883)	(2.511)	(4.067)
Pulses	1.066	1.035	0.964	1.007
	(0.704)	(0.811)	(0.677)	(0.748)
Expenditure and Income (in 2010 value)				
Food expenditure	558.2	596.7	715.6	644.7
	(236.4)	(305.3)	(359.1)	(330.6)
Non-food expenditure	518.7	667.3	757.5	693.4
	(1708.2)	(3221.9)	(3394.4)	(3197.9)
Total expenditure	1077.3	1264.7	1475.6	1339.4
	(1760.8)	(3278.9)	(3477.1)	(3267.4)
Implict PDS Subsidy	198.9	127.1	10.54	83.05
	(131.2)	(69.42)	(22.64)	(91.77)
Income total	1567.4	2243.5	2680.4	2375.9
	(4128.6)	(16946.8)	(13784.3)	(14878.5)

Standard deviation in parentheses. All values, except number of HHs and household size, represent the adult equivalent per household. Nutrient and Calorie intake is measured daily per-adult equivalent. Consumption quantity, expenditure and income is measured monthly per-adult equivalent.

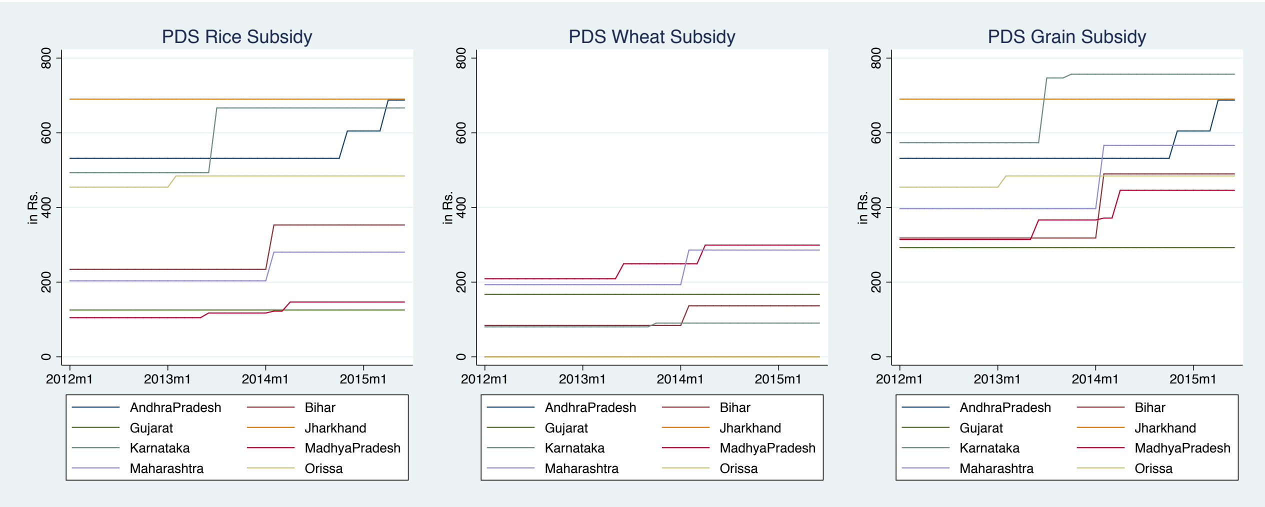

Figure 1: PDS implicit subsidy entitlement for BPL households from 2012 to 2015

Table 2: Effect of PDS subsidy on household labor supply (N=68910)

	Effect of PDS Subsidy		
	Men	Women	Total
Total Labor Supply (Own+Market)	-0.023***	-0.012**	-0.035***
	(0.008)	(0.006)	(0.011)
Segregated Results:			
Market Labor Supply total	-0.023***	-0.006	-0.029**
(Farm + Non-farm)	(0.008)	(0.006)	(0.012)
Farm	-0.004	-0.003	-0.007
	(0.005)	(0.003)	(0.007)
Non-farm	-0.019***	-0.003	-0.022**
(Casual+Job+Business+Others)	(0.006)	(0.004)	(0.008)
Casual labor	-0.008*	-0.002**	-0.010**
	(0.004)	(0.001)	(0.005)
Salaried Job	-0.005	-0.001	-0.007
	(0.004)	(0.001)	(0.004)
Business	-0.003*	-0.003**	-0.006**
	(0.002)	(0.001)	(0.003)
Others	0.001	0.001	0.002
	(0.004)	(0.002)	(0.006)
Own Labor Supply total	-0.004	-0.007*	-0.011
(Farm+Livestock+Others)	(0.004)	(0.004)	(0.007)
Own Farm	-0.001	-0.003	-0.003
	(0.004)	(0.003)	(0.006)
Own Domestic	-0.002	-0.038***	-0.041***
	(0.004)	(0.011)	(0.013)
Own Livestock	-0.005	-0.006*	-0.011*
	(0.003)	(0.003)	(0.005)

Standard errors in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor variable, row and column headings together describing the outcome variables.

Table 3: Effect of PDS subsidy on village wages (N=72724)

	Effect of PDS Subsidy		
	Men	Women	Total
Total Wage rate	0.265	0.223*	0.237
	(0.211)	(0.118)	(0.196)
Farm	0.262**	0.225**	0.211*
	(0.111)	(0.101)	(0.120)
Non-farm	0.401	0.329*	0.277
	(0.468)	(0.182)	(0.252)
Casual non-farm	0.484**	0.339	0.219
	(0.231)	(0.254)	(0.282)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor variable, row and column headings together describing the outcome variables.

Table 4: Effect of PDS subsidy on household labor supply, during a late monsoon onset (N=68910)

	Men			Women			Total		
	PDS Subsidy	Monsoon onset	Interaction	PDS Subsidy	Monsoon onset	Interaction	PDS Subsidy	Monsoon onset	Interaction
Total Labor Supply	-0.022871**	0.021922*	-0.000011	-0.009470*	0.027745**	-0.000069*	-0.032340**	0.049666***	-0.000080
(Own +Market)	(0.009045)	(0.012859)	(0.000078)	(0.005136)	(0.010594)	(0.000038)	(0.012616)	(0.017416)	(0.000085)
Segregated results:									
Market Labor supply total	-0.020313**	0.016244	-0.000068	-0.008133*	0.024729**	-0.000091**	-0.028446**	0.040973**	-0.000159*
(Farm+Non-farm)	(0.009444)	(0.013164)	(0.000066)	(0.004526)	(0.009103)	(0.000042)	(0.012712)	(0.017114)	(0.000084)
Farm	-0.003574	0.002179	-0.000001	-0.006284***	0.012256*	-0.000072	-0.010049	0.015117*	-0.000064
	(0.004990)	(0.003969)	(0.000027)	(0.002052)	(0.007159)	(0.000048)	(0.006182)	(0.008114)	(0.000068)
Non-farm	-0.016715***	0.014072	-0.000069	-0.001644	0.011742	-0.000028	-0.018359**	0.025814	-0.000097
	(0.005323)	(0.012688)	(0.000054)	(0.003641)	(0.007864)	(0.000036)	(0.007855)	(0.016686)	(0.000060)
Own Labor supply total	-0.005945	0.018677*	0.000036	-0.002646	0.011471	0.000012	-0.008591	0.030148**	0.000048
	(0.003912)	(0.010819)	(0.000059)	(0.003243)	(0.008989)	(0.000037)	(0.006340)	(0.014561)	(0.000075)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each set of coefficient estimates is from a separate regression with PDS subsidy value, monsoon onset and their interaction as the regressor variables, row and column headings together describe the outcome variables.

Table 5: Effect of PDS subsidy on village wages, during a late monsoon onset (N=68265)

	Men			Women			Total		
	PDS Subsidy	Monsoon onset	Interaction	PDS Subsidy	Monsoon onset	Interaction	PDS Subsidy	Monsoon onset	Interaction
Total Wage rate	0.3446	-0.0199	0.0001	0.2908	-0.3726	0.0033**	0.3342	-0.0690	0.0008
	(0.2612)	(0.2796)	(0.0020)	(0.1772)	(0.2263)	(0.0015)	(0.2817)	(0.2050)	(0.0016)
Farm	0.2566	-0.2175	0.0019	0.2885	-0.5749**	0.0050***	0.2517	-0.4236**	0.0037**
	(0.2341)	(0.2098)	(0.0015)	(0.1849)	(0.2135)	(0.0015)	(0.2292)	(0.2009)	(0.0013)
Non-farm	0.3413	0.1320	-0.0009	0.6103	1.4439	-0.0091	0.2732	0.1292	-0.0008
	(0.3991)	(0.4474)	(0.0032)	(0.3816)	(0.9294)	(0.0060)	(0.2769)	(0.5181)	(0.0036)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each set of coefficient estimates is from a separate regression with PDS subsidy value, monsoon onset and their interaction as the regressor variables, row and column headings together describe the outcome variables.The estimations on Non-farm wages of women have 56223 observations.

Appendix A

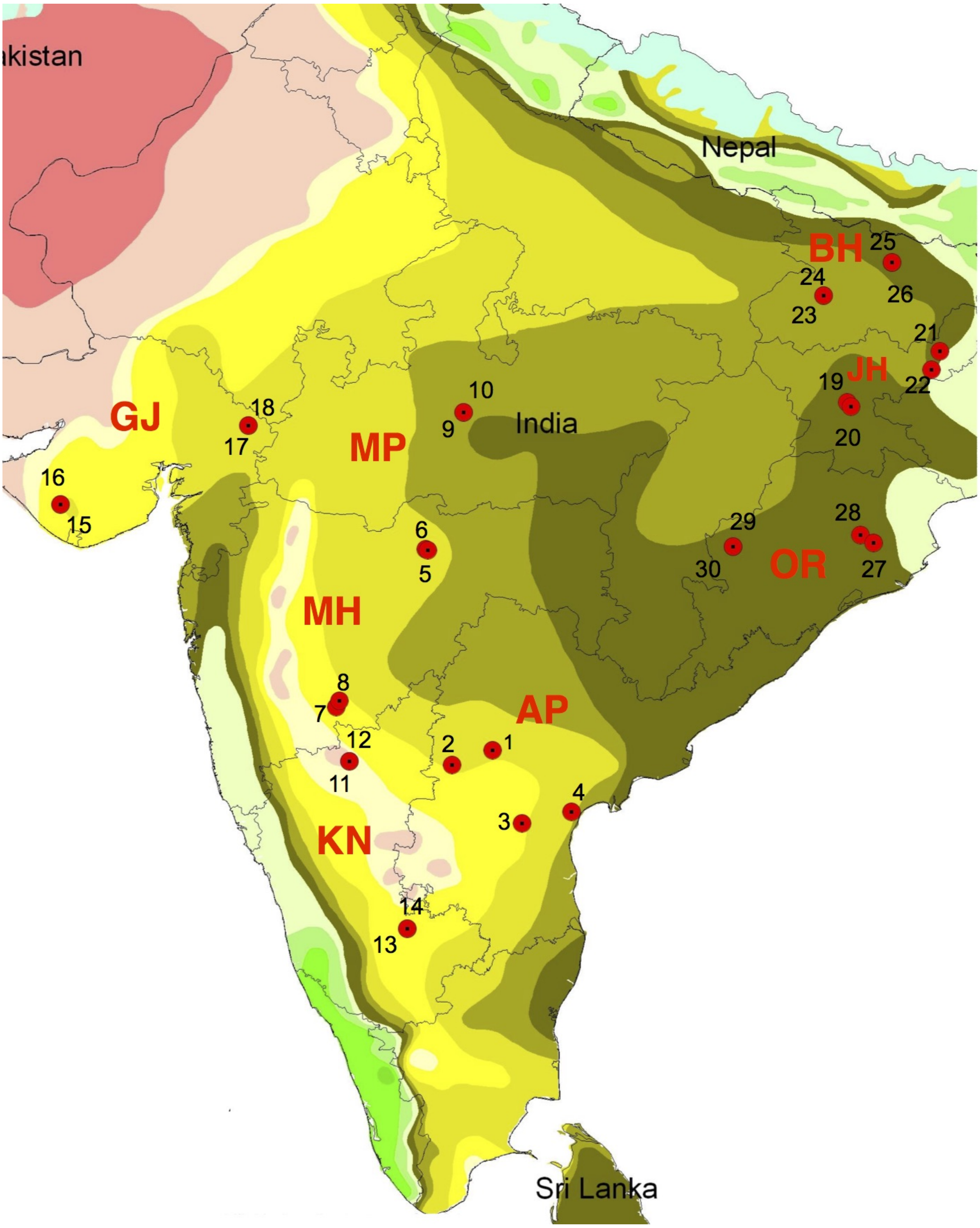

Figure A1: Location of ICRISAT VDSA villages 30 villages across 8 states

Table A1: Effect of PDS subsidy on village wages (N=72724)

	Effect of PDS Subsidy	Observations
Farm Wages (Operation-wise)		
Harvest	0.147	61305
	(0.175)	
Harvest Male	0.179	55079
	(0.149)	
Harvest Female	0.208	60559
	(0.131)	
Weeding	0.263	57921
	(0.174)	
Weeding Male	-0.833	30595
	(1.417)	
Weeding Female	0.138	56985
	(0.112)	
Sowing	0.350	59085
	(0.320)	
Sowing male	0.511**	52605
	(0.234)	
Sowing female	0.104	51677
	(0.133)	
Non-Farm Wages (Operation-wise)		
Casual	0.219	56575
	(0.282)	
Casual Male	0.484**	55555
	(0.231)	
Casual Female	0.339	37116
	(0.254)	
Construction	0.159	55528
	(0.338)	
Construction male	0.292	55138
	(0.422)	
Construction female	0.042	38897
	(0.145)	
Others	0.402	44156
	(0.405)	
Others male	0.779	39800
	(0.559)	
Others female	0.264**	21846
	(0.101)	

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor variable, row and column headings together describing the outcome variables.

Table A2: Monsoon Onset and alternative rainfall shock variables (N=180)

	Rainfall quantity during rainy season	Total rainfall quantity over the year	Rainfall Index	Rainfall Shock
Monsoon Onset	-3.521***	-4.181***	-0.005***	-0.012***
	(1.152)	(0.923)	(0.002)	(0.003)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Rainfall index is percentage deviation from long term average levels in the main rainy season relevant for consumption data (ratio of current year rainfall over long-run mean). Rainfall Shock (as defined in Jayachandran (2006)) =1 if RF > 80th percentile and =-1 if RF< 20th percentile

Table A3: Effect of Monsoon Onset on Yield and Production

		N=70410			
	Yield	Production Qty	Sold Qty	Market price	N
Rice	-0.840	-1.748*	-4.272**	0.024*	69719
	(0.899)	(0.870)	(1.830)	(0.013)	
Wheat	-1.599***	-7.308**	-1.858	0.006	69719
	(0.579)	(3.301)	(1.861)	(0.005)	
Staple Cereal	-2.182**	-4.068**	-6.602***	0.015*	69719
	(0.989)	(1.906)	(2.343)	(0.008)	
Pigeonpea	-0.239	-1.618	-1.160	-0.013	63245
	(0.758)	(1.190)	(0.712)	(0.034)	
Pulses	-0.272	-0.526	-1.630	0.009	67087
	(0.579)	(0.339)	(2.069)	(0.030)	
Coarse	-0.686	2.664	0.227	-0.019**	49491
	(0.616)	(1.933)	(1.522)	(0.007)	
Food	-0.832	-0.405	2.177		
	(0.584)	(0.370)	(1.632)		
Cash	32.021	-5.756	-3.396		
	(23.009)	(3.641)	(2.021)		
Crop total	16.171	-7.276	-2.171		
	(14.155)	(4.454)	(1.659)		

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each coeffcient estimate is from a separate regression with monsoon onset as the regressor and village-average production shocks as outcome variables. In calculating village average yield, production and sold quantity, households with 100% irrigation are left out

Table A4: Average effects of PDS subsidy and monsoon onset on household labor supply (N=68910)

	Men		Women		Total	
	PDS Subsidy	Monsoon onset	PDS Subsidy	Monsoon onset	PDS Subsidy	Monsoon onset
Total Labor Supply	-0.023**	0.021*	-0.011**	0.021*	-0.034***	0.041**
(Own +Market)	(0.009)	(0.011)	(0.005)	(0.010)	(0.012)	(0.019)
Segregated results:						
Market Labor supply total	-0.022**	0.009	-0.010**	0.015	-0.032**	0.024
(Farm+Non-farm)	(0.010)	(0.010)	(0.005)	(0.010)	(0.013)	(0.017)
Farm	-0.004	0.002	-0.008***	0.005	-0.011*	0.009
	(0.005)	(0.004)	(0.002)	(0.009)	(0.006)	(0.012)
Non-farm	-0.018***	0.007	-0.002	0.009	-0.020**	0.016
	(0.006)	(0.009)	(0.004)	(0.008)	(0.008)	(0.015)
Own Labor supply total	-0.005	0.022**	-0.002	0.013*	-0.008	0.035**
	(0.004)	(0.009)	(0.003)	(0.007)	(0.007)	(0.014)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each set of coefficient estimates is from a separate regression with PDS subsidy value, monsoon onset and their interaction as the regressor variables, row and column headings together describe the outcome variables.

Table A5: Average effects of PDS subsidy and monsoon onset on village daily wages (N=68265)

	Men		Women		Total	
	PDS Subsidy	Monsoon onset	PDS Subsidy	Monsoon onset	PDS Subsidy	Monsoon onset
Total Wage rate	0.3453	-0.0132	0.3250	-0.0279	0.3429	0.0193
	(0.2623)	(0.1378)	(0.1970)	(0.1431)	(0.2702)	(0.1182)
Farm	0.2763	-0.0189	0.3398*	-0.0578	0.2898	-0.0399
	(0.1926)	(0.1128)	(0.1845)	(0.1407)	(0.1785)	(0.1264)
Non-farm	0.4242	-0.1394	0.4250	0.2726	0.2121	-0.0208
	(0.5855)	(0.1636)	(0.2618)	(0.2316)	(0.2995)	(0.1863)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each set of coefficient estimates is from a separate regression with PDS subsidy value, monsoon onset and their interaction as the regressor variables, row and column headings together describe the outcome variables.The estimations on Non-farm wages of women have 56223 observations.

Appendix B

Monsoon onset and PDS subsidy value in ICRISAT data

The ICRISAT data has substantial variation in both rainfall and PDS subsidy value, meeting the critical data requirements to identify the buffer effect of PDS.

Figure A2 and A3 show graphs of deviations in annual monsoon onset for all the 30 villages during the study period 2010-15. In figure A3, all the 30 villages are marked on the X-axis, with SAT villages on the left and East India villages on the right. As shown in Figure A2, in a particular village, the monsoon onset is more delayed in certain years (temporal variation). Most villages experienced a delayed monsoon during 2012 and 2014, and an early monsoon in 2013. For instance, in Bhagakole village in Bihar (BH-3 in Figure A3), monsoon arrived ahead by 22 days in 2013, but was delayed by 12 days in 2012 and 2014, relative to their local average. Similarly, in any particular year, the monsoon onset may be more delayed in some villages (cross-sectional variation). As villages in the data are spread across different geo-climatic regions (shown in Figure A1), there is significant variation in the onset of monsoon between villages in a particular year relative to the local average. As shown in Figure A3, villages in Karnataka, Gujarat, Maharashtra and Jharkhand experienced substantial deviations in monsoon onset. For instance, in 2014, monsoon onset in Shirapur and Kanzara villages in Maharashtra was delayed by 58 days and 32 days in comparison to monsoon that arrived ahead by 10 and 15 days in Makhilaya and Karamdichingariya villages in Gujarat, all relative to their local average.

In conjunction with rainfall, the ICRISAT data has considerable spatial and temporal variation in PDS subsidy value. In a particular month, BPL households in certain states were exposed to a more generous PDS subsidy than the average BPL household in our sample (cross-sectional variation). For instance, in 2014, PDS subsidy value for BPL households in Jharkhand was about 2.3 times greater than in Gujarat. Similarly for BPL households in certain states, PDS value increased after 2013 (temporal variation). For instance, PDS subsidy value in Karnataka increased by about 75% in June 2013. The spatial and temporal in PDS subsidy value are clearly depicted in Figure 1. After 2013, PDS subsidy value increased in Karnataka, Maharashtra, Bihar and Madhya Pradesh; whereas it did not change in Gujarat, Jharkhand and Orissa. In addition, the increase in PDS subsidy value was greater in Karnataka as compared to Madhya Pradesh or Andhra Pradesh. For the sake of interpretation, let the time period before and after 2013 be referred to as pre and post-NFSA and suppose the villages can be grouped into two sets - with and without PDS expansion. Figure A4 shows the distribution of the monsoon onset deviations from local average, across the four identified cells Pre and Post NFSA, and With and without Expansion. The histogram shows that the distribution of monsoon onset deviation is similar across pre and post NFSA years for both set of villages (with and without PDS expansion) and hence forms the rationale for our identification strategy.

Triple difference design

The triple difference approach compares, among villages with similar rainfall, villages that were exposed to a more generous PDS program with villages that were exposed to a less generous PDS program. Consider two pairs of villages V1-V2 and V3-V4 in two time periods T1 and T2 and one of the villages in each pair, say V2 and V4, is exposed to a generous PDS expansion in T2. Suppose the village pairs face different rainfall shocks, say V1-V2 face an early monsoon and V3-V4 face a late monsoon in both time periods. A standard difference-in-difference comparison of before and after PDS expansion within each pair would give the impact of PDS expansion during an early monsoon onset (for pair V1-V2) and during a late monsoon onset (for V3-V4). The difference between these difference-in-differences estimates would give the triple-difference estimate.

For example, Figure A5 shows three examples of two village pairs. In each example, one of the village pair faced a late monsoon onset whereas another pair faced an early monsoon in 2014. Furthermore, within each pair, one of the villages was exposed to a more generous PDS expansion whereas the other village was either exposed to a less generous PDS expansion (Example 3) or no PDS expansion (Examples 1 and 2). For instance, in example 1, the pair Babrol village in Gujarat and Bhagakole in Bihar experienced delayed monsoons in 2012 and 2014 and an early monsoon in 2013. However, in 2014, Bhagakole was exposed to a more generous PDS expansion under NFSA, but there was no PDS expansion in Babrol. The difference-in-difference estimate between these two villages may be interpreted as the effect of PDS expansion during a late monsoon. Similarly, the other pair - Makhilaya village in Gujarat and Aurepalle in Andhra Pradesh - experienced early monsoons in 2013 and 2014. However, in 2014, Aurepalle was exposed to a more generous PDS program, but there was no expansion in Makhilaya. Accordingly, the difference-in-difference estimate between the latter village pair may be interpreted as the effect of PDS expansion during an early monsoon. The difference between the two village pairs would give the triple difference estimate.

Indeed, a second source of variation is derived from villages with similar PDS expansion and a differential monsoon onset distribution. In this case, the triple difference approach compares, among villages with similar PDS subsidy value, those that experienced a more delayed monsoon with those that experienced a less delayed monsoon. For instance in Example 2 in Figure A5, the village pair - Kanzara and Kinkhed in Maharashtra - were exposed to the same PDS subsidy expansion in 2014; but Kanzara faced a delayed monsoon in 2014 and Kinkhed faced a relatively early monsoon in 2013 and 2014. And the other pair Chatha in Gujarat and Ainlatunga in Orissa did not experience any expansion in the PDS subsidy in 2014; but Chatha faced a delayed monsoon and Ainlatunga faced an early monsoon in 2014.

In summary, the interaction between PDS subsidy value and monsoon onset accounts for both the variation in monsoon onset, conditional on PDS subsidy value and the variation in PDS subsidy value, conditional on monsoon onset. A simple triple difference model treats the two sources of variation symmetrically and the interaction term would be the weighted average of both the effects.

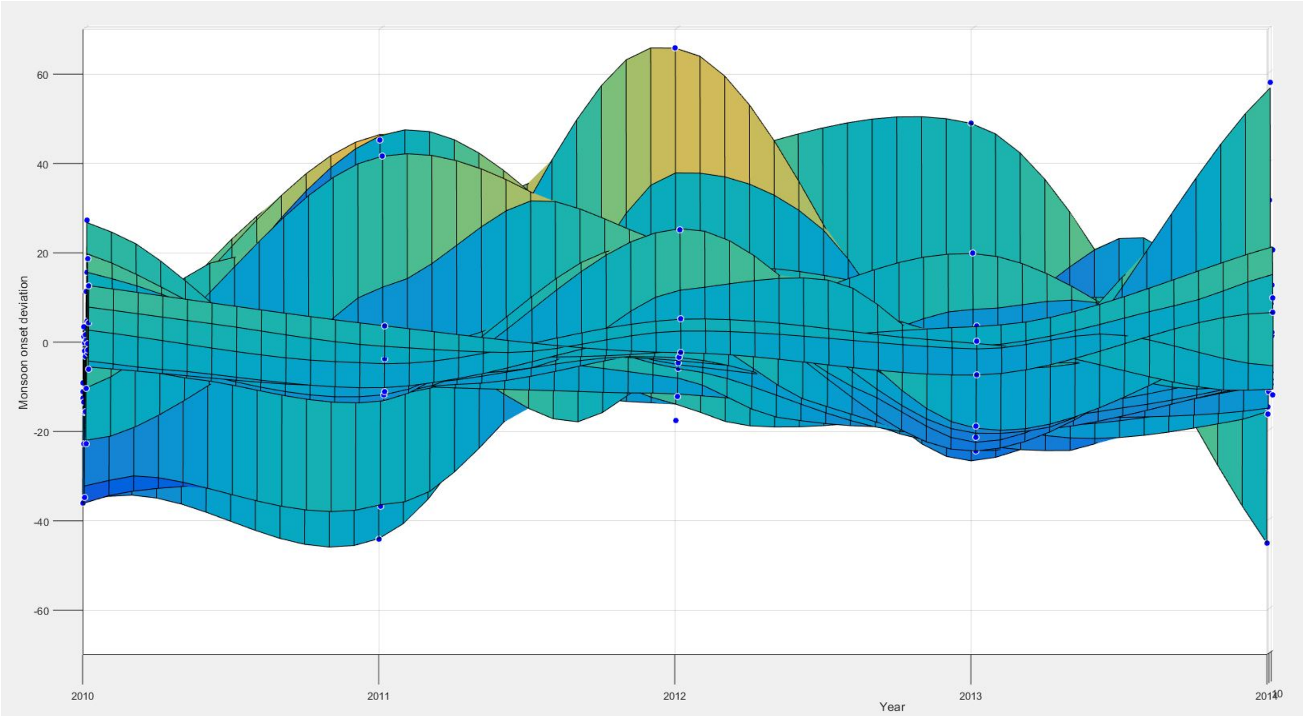

Figure A2: Monsoon onset deviation, within and between villages, from 2010-2015

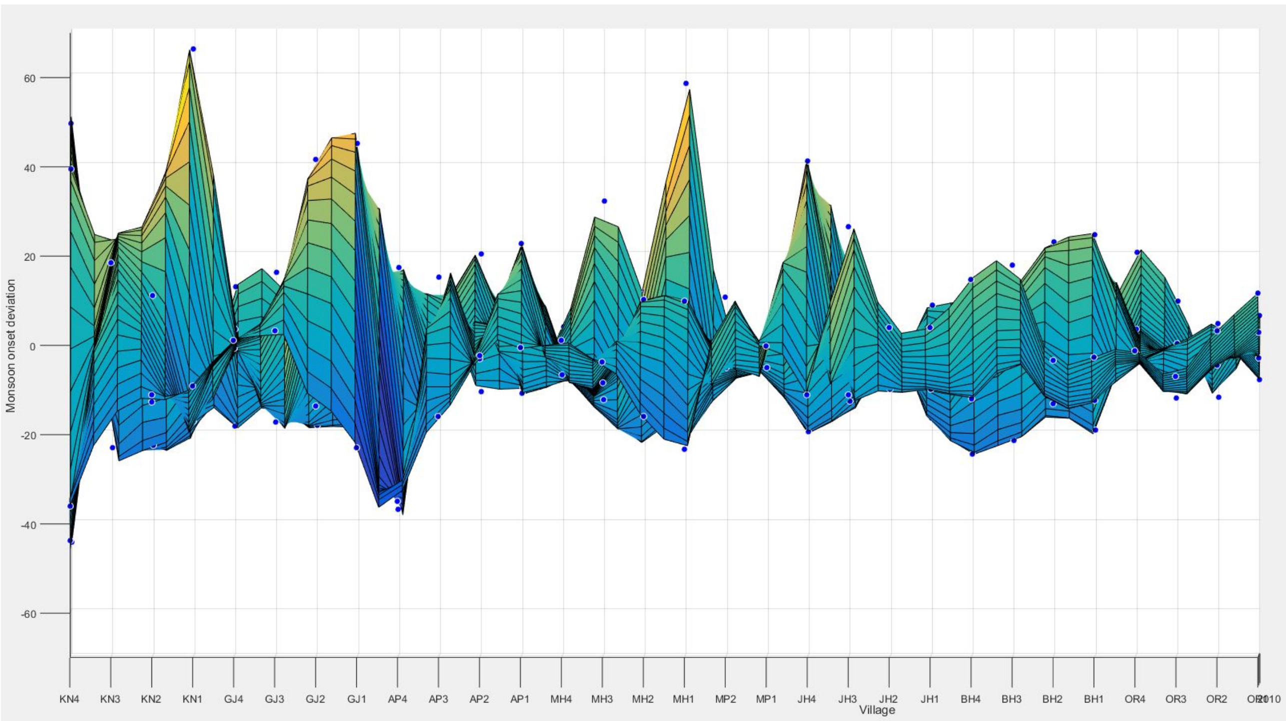

Figure A3: Monsoon onset deviation, within and between villages, from 2010-2015

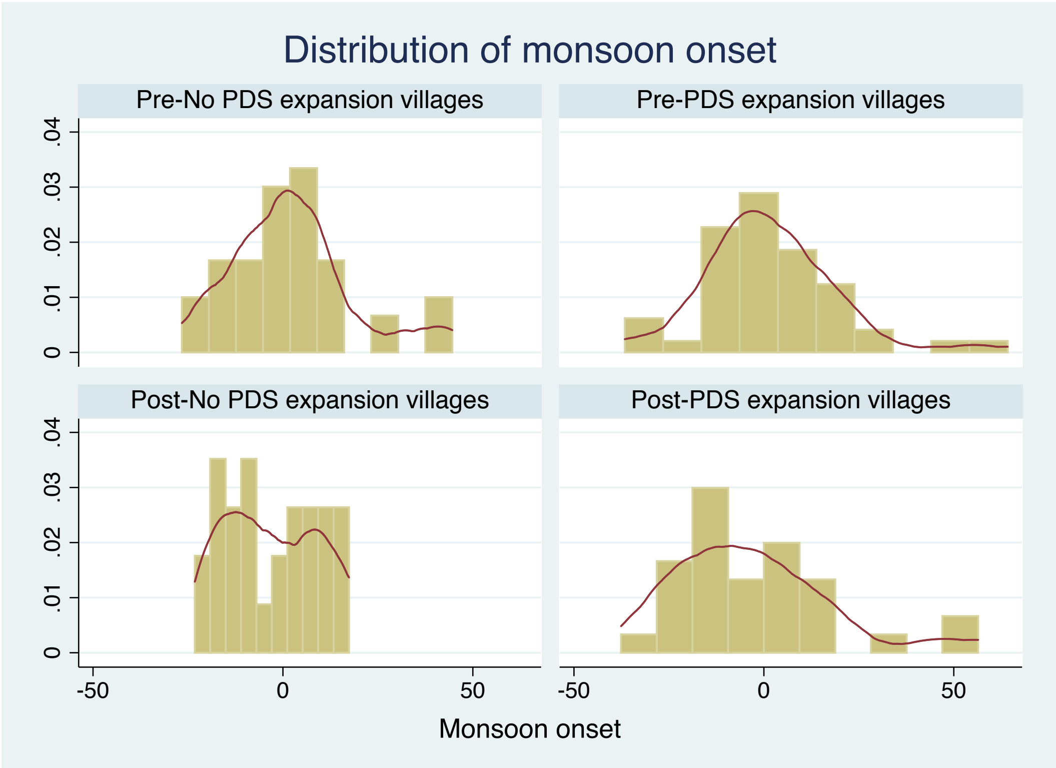

Figure A4: Histogram of monsoon onset deviation from local average, across 4 cells Pre and Post, With and without expansion

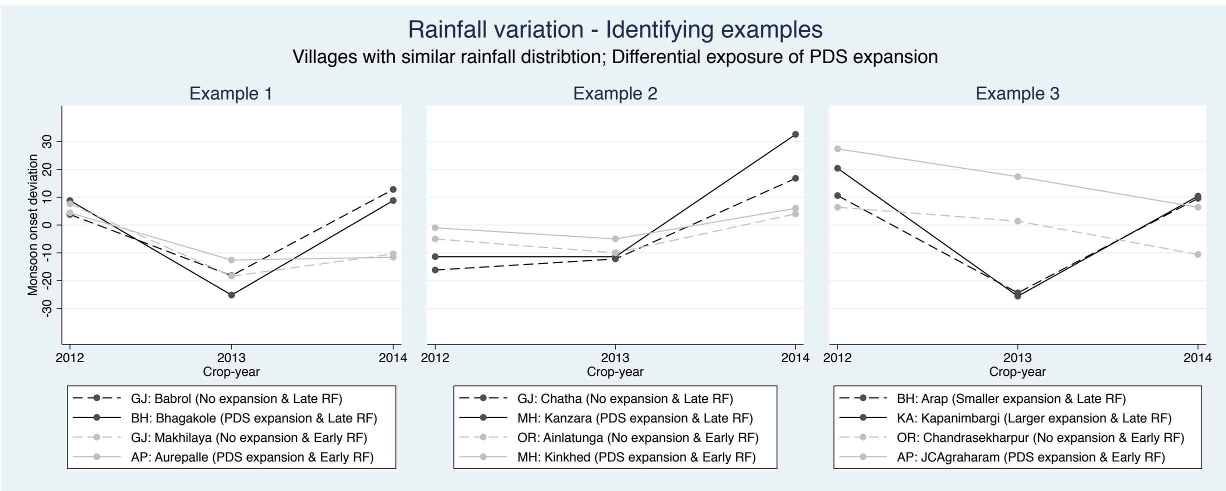

Figure A5: Villages pairs with similar rainfall; Differential exposure of PDS expansion