

Final report

In-kind transfers as insurance

Lucie Gadenne
Samuel Norris
Monica Singhal
Sandip Sukhtankar

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Price Risk and In-Kind Transfers*

Lucie Gadenne[†]
Warwick University

Samuel Norris[‡]
Northwestern University

Monica Singhal[§]
UC Davis

Sandip Sukhtankar[¶]
University of Virginia

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Abstract

Developing countries often rely on in-kind transfers to redistribute to poor households, although more recently governments have been shifting towards cash transfers. In this paper we consider one potential advantage of in-kind transfers: the ability to provide insurance against price shocks. Poorly integrated markets in many developing countries mean that poor households face substantial exposure to commodity price risk. Theoretically, however, price volatility is not necessarily welfare-reducing for consumers. In the context of India, we show that price shocks for food commodities are negatively associated with caloric intake and meeting minimal caloric requirements, suggesting that households are not able to insure against these shocks. We develop a model which shows that in-kind transfers can be welfare improving relative to cash in a world with price risk. Finally, we find that policies that expand the generosity of the Public Distribution System (PDS) - India's in-kind food subsidy program - are associated with increased caloric intake by households as well as reduced sensitivity of calories to local prices, suggesting that the PDS provides insurance against food price risk.

JEL codes: H42; H53; I38; O12; Q18

Keywords: in-kind transfers, cash transfers, price risk, Public Distribution System, India

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[†]Warwick University and Institute for Fiscal Studies, L.Gadenne@warwick.ac.uk.

[‡]Northwestern University, norris@u.northwestern.edu.

[§]University of California-Davis and NBER, msinghal@ucdavis.edu.

[¶]University of Virginia, JPAL, and BREAD. sandip.sukhtankar@virginia.edu.

1 Introduction

In-kind transfers have historically been an important way in which developing countries transfer resources to poor households. Governments may provide commodities directly or allow highly subsidized purchase of goods such as food and fuel by poor households. Large examples include the Raskin program in Indonesia (17.5 million households (Banerjee et al., forthcoming)) and the Public Distribution System in India (65.3 million households (Nagavarapu and Sekhri, 2016)). The World Bank estimates that 44% of individuals on social safety net programs around the world receive in-kind transfers (Honorati, Gentilini and Yemtsov, 2015). In recent years, however, there has been increasing interest among academics and policymakers in moving toward unconditional cash transfers. A recent review of evaluations of unconditional cash transfers concludes that the early evidence is promising and notes that “[e]merging-market governments have also begun to shift away from expensive, regressive, and distortionary subsidies of basic commodities such as food or fuels and instead are giving cash to the poor” (Blattman et al., 2017). This shift is consistent with standard economic models, which generally predict that cash transfers are (weakly) preferable to in-kind.

In this paper, we consider one potential advantage of in-kind relative to cash transfers: in-kind transfers can provide insurance against commodity price risk. A common feature of markets in many developing economies is a lack of integration. Trade across areas is often be hindered by high transportation costs and limited information and communication. As a result, there is substantial variation in prices for basic commodities across space, even within local geographic areas (Atkin, 2013; Allen, 2014). Lack of integration implies that households face substantial risk from local supply shocks. If a harvest is poor in a particular village, food prices in that village can rise suddenly and substantially. Self-insurance is likely to be limited: credit constraints may limit borrowing and saving, and stockpiling goods is challenging in practice. Informal insurance will be ineffective if the price shock hits an entire area simultaneously. The value of cash transfers will be eroded when prices rise. In theory, the government could provide price indexed cash transfers, providing larger transfers to households in periods of high prices. In reality, this is likely to be extremely difficult, since it would require the government to have the ability to measure local prices at a high level of frequency. In this context, in-kind transfers can provide partial insurance against risk: the effective value of the transfer rises automatically with local prices. Understanding the potential insurance value of in-kind transfers is therefore important for the larger ongoing debate around the world regarding the appropriate design of social protection programs.

Exposure to price risk and its consequences have received surprisingly little systematic attention in the literature, particularly relative to income risk. Theoretically, the impact of

price variability on households is unclear. Price fluctuations could actually be beneficial for households if they can purchase a commodity when its price is low and substitute toward other commodities when its price is high (Waugh, 1944; Turnovsky, Shalit and Schmitz, 1980). Meanwhile, price increases could help rather than hurt households who are net producers rather than consumers of food. Gaining a more nuanced understanding of price risk (e.g., how correlated prices are, the degree to which substitution is possible, and net spending on food commodities for poor households) is therefore critical for understanding how it affects household welfare. A comprehensive review of research on food security emphasizes the importance of risk as an important component of food security but notes that “most of the literature nevertheless fails to address issues of risk and uncertainty” (Barrett, 2002).

The limited literature that has focused on such issues has assessed the welfare effects of price risk relative to price stabilization. While stabilization policies and dual pricing policies are still used, many critics have argued that they are both expensive and ineffective (Rashid, 2009). To the best of our knowledge, previous studies have not considered the possibility of insuring against rather than attempting to reduce price variability.

We examine price risk and the role of in-kind transfers in the context of India. India provides an attractive context to examine these questions: local markets are not well-integrated (Atkin, 2013) and are subject to price volatility arising from weather shocks (Rosenzweig and Udry, 2014). The largest in-kind transfer system in India is the Public Distribution System (PDS). The PDS provides wheat, rice, sugar, and kerosene at significantly subsidized rates to eligible households via a widespread network of Fair Price Shops (FPS). The PDS provides subsidized basic food and fuel commodities to over 65 million households per year and comprises 1.3% of GDP (Nagavarapu and Sekhri, 2016). A commonly mentioned policy rationale for this program is that it protects the poor against price shocks (Dreze, 2011). However, we do not know whether this is true in practice, particularly given that there is substantial evidence that the PDS suffers from high levels of corruption (Khera, 2011). Similar issues are highly relevant across the developing world.

We begin by providing a detailed empirical examination of household exposure to price risk. We measure local prices from two sources: direct measures of local prices from the Indian Rural Price Survey (RPS) and imputed measures of prices from the National Sample Survey (NSS), a nationally representative survey that asks households for information on expenditures and quantities consumed for a wide range of commodities. We find that households are subject to substantial variation in the prices of basic food commodities. The variation over time within area is as large as the (substantial) cross-sectional variation in prices across areas. Food commodities comprise a substantial share of the total household budget, and we document that food prices are quite correlated. This implies that price vari-

ability is likely to have negative welfare effects, particularly for poor households. We also examine a direct proxy for welfare: household caloric intake. We find that higher local food prices are generally associated with lower caloric intake and a lower probability of households meeting recommended minimum calorie requirements.

We next develop a model to consider the welfare effects of in-kind and cash transfers in a world with price risk. We begin by demonstrating that as long as households are sufficiently risk averse, the optimal transfer policy involves higher cash transfers to households when prices are high. However, this policy is likely to be infeasible in practice. We therefore compare un-indexed cash transfers and in-kind transfers. We show that in a world with price risk, infra-marginal in-kind transfers are not equivalent to cash transfers and in fact can be welfare improving relative to cash because they better approximate the optimal policy.

Finally, we examine the effects of the PDS empirically, utilizing newly collected administrative data on PDS policy changes. We show that expansions of PDS generosity are associated with both higher caloric intake by households as well as reduced sensitivity of calories to local prices. The latter finding is consistent with the PDS providing insurance against commodity price risk.

This project contributes to several literatures. The empirical literature on price risk is sparse at best; the most prominent recent paper on this topic notes that “our theoretical and empirical toolkits for understanding the relationship between price volatility and household welfare remain puzzlingly dated and limited, especially when it comes to empirical applications” (Bellemare, Barrett and Just, 2013). Their paper studies whether households value price stability by calculating households’ willingness to pay for price stability using longitudinal data on agricultural households in Ethiopia. They estimate that the average Ethiopian household is willing to pay 18% of their income for full price stabilization of the 7 most consumed commodities. Barrett (2002) reviews the literature on food security in general, of which price risk is a component. An older literature has also considered food price risk and poorly integrated markets as a driver of farmers’ aversion to cash crops (Fafchamps, 1992).

We also add to the literature on the optimal design of social protection programs. Previous work has proposed other potential rationales for in-kind transfers: such transfers can potentially improve targeting to the poor (Nichols and Zeckhauser, 1982) and may improve well-being of non-targeted households by reducing market prices of transferred commodities (Cunha, De Giorgi and Jayachandran, 2011). However, to the best of our knowledge, we are the first to consider the potential insurance value of in-kind transfers. Gadenne (2016) models the PDS as a non-linear commodity tax system and calibrates the model to show that this system can improve welfare both through better targeting of the poor and by providing

insurance.

Finally, we note that the PDS is an important program in and of itself, and there has been relatively little work identifying the causal impact of this program on households, particularly work that focuses on recent periods and is comprehensive and well-identified. Kochar (2005) examines the effect of the PDS on nutritional outcomes of the rural poor in wheat-consuming states. The paper makes use of the switch from universal to targeted distribution in 1997, which increased the value of the program to eligible beneficiaries, combined with variation in program rules. It finds that the impact of the food subsidy on caloric intakes is “very low.” Similarly, Tarozzi (2005) finds no impact on nutritional status of a decline in generosity of PDS benefits in the state of Andhra Pradesh. On the other hand Kaul (2014), focusing on rice states, finds a substantial increase in the impact of the value of the subsidy on calories consumed, an impact that is twice the value of the implied impact on cereal consumption. Like our paper, this paper uses documented policy changes in the value of the PDS subsidy for identification, but is limited to six years and rice-consuming states.

The remainder of the paper proceeds as follows. Section 2 provides a motivating framework for examining the welfare effects of price risk. Section 3 discusses the context and data. Section 4 presents empirical evidence on price risk in India and its consequences for households. Section 5 develops a model for comparing the welfare effects of cash vs. in-kind transfers. Section 6 examines the effects of the PDS programs on households and Section 7 concludes.

2 Price Risk Framework

We begin by presenting a framework for thinking about the effect of price variability on household welfare in a simple and intuitive way. The insights here are by no means original - Turnovsky, Shalit and Schmitz (1980) model the welfare impact of price stabilization - but we reproduce the key result, the theoretically ambiguous relationship between price variation and welfare. Our model allows us to write down the utility ‘cost’ (or lack thereof) of price risk and compare our results regarding the relative welfare impact of cash and in-kind transfers to one type of policy that has been considered in the literature, stabilizing the varying price of a good around its mean. We will build on this theory in Section 5 to compare optimal non-indexed cash and in-kind transfers.

Households i are characterized by their indirect utility $v_i(p, \bar{y}_i)$ where p_i is the varying price of one good whose mean is \bar{p} , coefficient of variation is σ_p and density distribution $f(p)$. We assume the price of all other goods is fixed and income \bar{y}_i is non-stochastic. We can approximate $v_i(p, \bar{y}_i)$ as:

$$v_i(p, \bar{y}_i) = v_i(\bar{p}, \bar{y}_i) + v_{ip}(p - \bar{p}) + \frac{1}{2}v_{ipp}(p - \bar{p})^2 \quad (1)$$

Taking expectations over all values of p we find:

$$E(v_i(p, \bar{y}_i)) = v_i(\bar{p}, \bar{y}_i) + \frac{1}{2}v_{ipp}(\sigma_p \bar{p})^2 \quad (2)$$

To evaluate the utility cost of price risk in monetary terms, we consider the monetary transfer m_i that makes household i indifferent between a world with price risk and a world without price risk. Expected indirect utility in a world without price risk is thus given by:

$$E[v_i(\bar{p}, \bar{y}_i + m)] = v_i(\bar{p}, \bar{y}_i) + v_{iy}\bar{y}m_i \quad (3)$$

Equating (2) and (3) and re-arranging gives us

$$m_i = \frac{1}{2}\alpha [\varepsilon_i - \alpha_i[R_i - \eta_i]] \sigma_p^2 \quad (4)$$

where α is the budget share of the good, ε the (absolute value of the) price elasticity of demand, η the income elasticity of demand, R the coefficient of relative risk aversion and σ_p is the coefficient of variation of the price. Examination of this equation makes it clear that the value of price stabilization is ambiguous: a positive m_i indicates that the household's utility is higher in a world with price risk. Intuitively this result reflects the fact that price variation induces variation in real income (a welfare cost), but also allows the consumer the opportunity to substitute across commodities when they become relatively cheaper (a welfare gain). Overall households value price stabilization when R is large (the income risk is costly) and demand isn't too elastic with respect to prices or income (households cannot easily substitute consumption away from the good with varying price). The level of price risk does not affect whether households value or dislike price stabilization, it only affects the strength of their preference for price stabilization.

Note that a necessary (but not sufficient) condition for households to value price stabilization is $R_i > \eta_i$. Since food is clearly not a luxury good ($\eta < 1$), and most estimates of R are higher than 1, this condition is trivially met. Thus, households that spend a large share of their budget on the good are more likely to value price stabilization. Households are also more more likely to value price stabilization if the good has a low price elasticity.

When the government tries to stabilize the price of multiple goods, the analysis is very similar. Dropping the i 's for notational simplicity, if the utility-equalizing value of m for no stabilization versus the stabilization of goods 1 and 2 is

$$m = \frac{1}{2}\alpha_1 [\varepsilon_1 - \alpha_1[R - \eta_1]] \sigma_1^2 + \frac{1}{2}\alpha_2 [\varepsilon_2 - \alpha_2[R - \eta_2]] \sigma_2^2 + \alpha_1 [\varepsilon_{12} - \alpha_2[R - \eta_2]] \sigma_1\sigma_2\rho_{12} \quad (5)$$

where ε_{12} is the (absolute value) of the cross-price elasticity, ρ_{12} is the correlation in prices for goods 1 and 2, and the budget shares α , price elasticities ε and income elasticities η are indexed by good.¹ Unsurprisingly, the valuation of joint price stabilization is different from summing the valuations for the individual goods only if there is some price correlation. If prices are positively (negatively) correlated, price stabilization is more (less) valuable if the goods are substitutes and the budget shares are large.

3 Context and data

3.1 Context

The framework above suggests that the welfare cost of price variability is ambiguous; it depends on factors such as the budget share of food, the degree of price elasticity, and correlation between food prices. In order to gain a more nuanced understanding of the extent to which price variability matters, we narrow our focus to the context of India. The Indian context is ideal for studying these issues for a number of reasons: local markets are not well-integrated and are subject to price volatility arising from weather shocks (Rosenzweig and Udry, 2014); India has the highest number of undernourished people in the world²; and the flagship welfare program addressing food security is the large Public Distribution System (PDS), which provides in-kind transfers of staple foods to the poor.

The lack of integration of commodity markets, particularly those for food, is related to the poor functioning of transport infrastructure as well as myriad regulations related to internal trade in food. The World Bank estimates that a third of India's population lives in habitations at least two kilometers away from a paved road.³ Moreover, taxes and tariffs abound on intra-state trade.⁴ Regulations even determine where and who can sell wholesale food items, usually in official *mandis* or markets. In addition, the availability of price data is severely limited; no consistent retail data are available below the district level, and the best one can hope for are wholesale prices from the *mandis*, which are at the sub-district level

¹The third term of (5) appears asymmetric; Slutsky symmetry ensures that you can equivalently write the part before the price distribution components as $\alpha_2 [\varepsilon_{21} - \alpha_1[R - \eta_1]]$.

²According to the Food and Agriculture Organization of the United Nation (FAO) India has more undernourished people (194.6 million) than the entire population of Nigeria, the world's seventh most populous country (<http://www.fao.org/hunger/en/>, accessed May 31, 2017).

³<http://data.worldbank.org/data-catalog/rural-access-index>, accessed May 31, 2017.

⁴This has been true for the entirety of the period we study, although a unified Goods and Services Tax is to be effective as of July 1, 2017.

or above. A 2013 op-ed about agricultural markets in India put it succinctly: “our agrarian markets are still living in the past.”⁵ The result, as Atkin (2013) shows, is that substantial price differences persist across regions, and shocks to prices in a particularly region are not smoothed.

Such price shocks can mean that households face substantial risks to their food consumption. Households do not have access to formal insurance against these types of risks, and even when other types of formal insurance (e.g. weather insurance) is available, take-up has been extremely low (Banerjee and Duflo, 2011). Meanwhile, village-level informal insurance schemes will not work since shocks are correlated. Households may of course self-insure, but options here are limited due to credit constraints and the fact that most poor households are close to the subsistence level and unable to save. For these households, risk aversion is likely to be high.

Thus, despite years of relatively high economic growth, economic security remains tenuous for many households in India. As of 2012, 38% of households did not meet the Indian Council of Medical Research’s guidelines for subsistence caloric intake for low-exertion individuals. A full 66% did not meet the medium-exertion standard. Both of these numbers have been nearly flat since at least 2005, when the relevant shares were 42 and 68%. Similarly, the share of the population below the international poverty line of \$1.90 remains high, but has decreased from 38.2% in 2004 to 21.2% in 2011.⁶ This level of caloric deprivation has contributed to a child stunting rate of over 40% (Jayachandran and Pande, forthcoming).

We discuss the Indian government’s main attempt at solving this problem, the PDS, in greater detail in Section 6.1; for now we examine the data to determine the extent to which price risk is relevant in the Indian context.

3.2 Data

Our main sources of data are the 59th through 68th rounds of the National Sample Survey (NSS), covering the years 2003 to 2012. The NSS is an annual household survey, and asks households about their expenditure in each of about 400 categories. For a subset of these categories where the units are well-defined, it also records the quantity consumed. Finally, the survey records basic demographic information like household size and composition, religion, caste, assets, education and occupation. As is usual, we exclude Union Territories and Delhi from our analysis due to small samples sizes in these areas. In total, our sample includes 534,438 households.

⁵<http://www.thehindubusinessline.com/opinion/from-farm-mandi-to-bigger-things/article5278498.ece>, accessed May 31, 2017.

⁶World Bank data, using <http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx>, accessed May 31, 2017.

We use the NSS in two main ways. First, we follow Deaton and Tarozzi (2005) and construct unit values by dividing expenditure by quantities. We aggregate these at the level of the district to generate district-specific prices, which are necessary to quantify the value of the PDS. Second, we use the NSS to construct measures of caloric intake, which we use as an outcome. More details on data used are provided in the Appendix.

3.2.1 Unit values

For our time period, India lacks geographically granular measures of prices that are comparable across time and space. Since the PDS varies considerably between rural and urban areas, good measures of prices at the district level for urban and rural areas are necessary to understand the effect of the PDS.

To our knowledge, there is only one publicly-available survey that even tries to measure prices at a sub-district level. The Rural Price Survey (RPS) records prices at markets in rural areas over most of the country for many of the items in the NSS. There are two main reasons why the RPS is not adequate for our needs. First, and most glaringly, it covers only rural areas, rather than the whole country. Second, the RPS does not include prices for PDS goods.

Instead of using an external source of price information, we construct pseudo-prices using unit values calculated from the expenditure and quantity information in the NSS. Prices based on unit values differ from true prices when households respond to price changes by changing the quality of the goods they buy. Many of our goods are simple enough that there is relatively little scope for quality substitution, which makes this a relatively conducive setting for a unit values approach. In the Online Appendix, we validate our unit-values prices against the RPS, and show that there seems to be relatively little quality substitution in our data.

3.2.2 Calories

The 55th round NSS contains estimates of the caloric content of each item. Using these, we construct caloric intake measures at the household level (the NSS does not contain individual-level consumption data). Then, using age-gender-specific Indian Council of Medical Research guidelines for caloric requirements along with NSS demographic data, we estimate the total caloric requirements of the family. Relatively few households are meeting their caloric requirements; Figure 6 shows that even at median expenditure, only 60% are meeting the low-exertion requirement. There is also a considerable gradient of the likelihood of meeting caloric requirements with respect to income at median expenditure, highlighting the potential returns to programs that can increase food security. Moreover, caloric intake is divided unevenly in many Indian families, with first-born boys getting a disproportionate

share of calories (Jayachandran and Pande, forthcoming). Thus, even households who are just meeting their aggregate caloric threshold are unlikely to be meeting it for all members.

4 Evidence on Price Risk

In this section, we examine in detail household exposure to price risk. First, we report variation in prices across space and time for major food commodities. Next, we examine variation in expenditure shares for these commodities, as well as for food and fuel as categories. Finally, examine how variation in prices is correlated with calorie consumption by households. Note that for each of these categories, we report district-level means and medians; household level variation is clearly much higher.

4.1 Price and expenditure variability

We begin by examining major food staples - rice and wheat - and computing the average unit value for household h , commodity k , district-sector j , and time period t using households with non-zero consumption of the good:

$$\widetilde{MarketUV}_{jtk} = \sum_{h \in j,t} \frac{MarketUV_k^h}{\#h}$$

where $MarketUV_k^h$ is the market unit value for each commodity k .

The goal is to simply ask how much variation is there in the unit value of each good, and examine how this varies across and within periods. Figures 1 and 2 visually report this variation for rice and wheat respectively; across quarterly reporting periods from 2004-12, the variation appears substantial. Tables 1 and 2 report results in detail, and confirm the visual interpretation: with a mean of Rs. 9.74 per kilogram of rice, the standard deviation is Rs. 2.36, and the variation within districts across time is three-quarters of the variation across districts within the same time period. Moreover, this “within” variation is relatively constant even when controlling for time trends in an elaborate way, including quadratic x district-sector trends.

To get a better sense of price risk at the household level, we imagine that the household has perfect knowledge of the average year to year price change in its geographical region, as a percentage of the budget. However, it does not know the price changes for the goods separately. Deviations of the cost of the bundle from this expectation is then a measure of risk the household faces.

$$\widetilde{\Delta X}_{hjt} = \frac{p_{jt}q_{ht-1} - p_{jt-1}q_{ht-1}}{p_{jt-1}q_{ht-1}} - \frac{1}{n_j} \sum_{h \in j} \left\{ \frac{p_{jt}q_{ht-1} - p_{jt-1}q_{ht-1}}{p_{jt-1}q_{ht-1}} \right\}$$

Table 3 summarizes the mean price change, ΔX_{hjt} , in the first column. We then consider the household who knows what aggregate price change in the district will be, but does not know what the prices of the goods it consumes a lot of will do relative to that mean. The next three columns are the SD of the price change as a percent of budget, and the 5th and 95th percentiles of the distribution.

We calculate this price change year over year. The findings are stark: prices increase by, on average, about 13% of the budget. Even within a district, however, there is a lot of variation in how the size of the price change. The SD is nearly 30% of the budget. Concretely, a very lucky household (at the 5th percentile of price changes) would see their prices increase 12% less than the average for their district. An unlucky household (95th percentile) would have their prices increase 11% more than the average for their district.

Next, we examine more concretely how much real expenditure shares on key bundles of commodities (food & fuel) vary over time within and across areas. This is a first attempt to create a measure of risk at the household level by looking at how much budgets on “necessities” vary over time.

We define three sets of commodities K , food, fuel and food & fuel, a household by h , a commodity by k , an area (district-sector) by j , and a time period by t . For each household we define s_K^h , the share of total expenditures that is spent on the bundle K :

$$s_K^h = \sum_{k \in K} \frac{p_k^h * x_k^h}{y^h}$$

where p, x, y are as before. The variable we are interested in is the mean value of this share at the area-period(j, t) level:

$$\tilde{s}_{K,j,t} = \sum_{h \in j,t} \frac{s_K^h}{N_{j,t}}$$

where $N_{j,t}$ is the total number of households in the district-sector-period (weighted).

We find that food and fuel expenditures comprise a large 62% of household budgets (Table 4). The standard deviation of budget shares is 8%, with within and across district variation basically the same.

The above exercise takes into account actual variation after household adjust for price changes. We next examine how much expenditure shares on key bundles of commodities (food & fuel) vary over time within and across sectors, *assuming households do not react to changes in prices*. All variations in these *simulated* expenditure shares should now only come from changes in prices.

Ideally, we would like to consider each household’s expenditure shares assuming quantities

remain at their first period (t_0) level and applying current (t) prices. However we do not have a panel - cannot observe households over time. We therefore have to consider a ‘representative’ household at the j, t level: we compute, for each district-sector-period, the median unit value for each commodity k ($\bar{p}_{k,j,t}$) and the median quantity consumed for each commodity ($\bar{q}_{k,j,t}$). We then define the ‘simulated median’ total expenditure $\bar{y}_{j,t}$ as the sum over all commodities of $\bar{p}_{k,j,t} * \bar{q}_{k,j,t}$ in each period.⁷ And then we define the simulated expenditure shares as:

$$s0_{k,j,t} = \frac{\bar{q}_{k,j,0} * \bar{p}_{k,j,t}}{\bar{y}_{j,t}}$$

Intuitively, this is the expenditure share that the ‘median’ household in j, t would spend in each period if it kept consuming the same amounts. An alternative would be to use total expenditure in time 0 in all periods, but this leads to expenditure shares (often) being greater than 1. If real incomes increase rapidly we should see these simulated expenditure shares falling over time, but that is not what we see. As before, we are interested in expenditure shares on set of commodities K :

$$s0_{K,j,t} = \frac{\sum_{k \in K} \bar{q}_{k,j,0} * \bar{p}_{k,j,t}}{\bar{y}_{j,0}}$$

As expected, these simulated expenditure shares are higher than the actual expenditure shares (Table 5, with a mean share of 79% and standard deviation of 12%).

4.2 Price variability and calories consumed

Although the section above suggests that households are subject to considerable price risk, what this means for welfare is unclear. In practice, households might be able to self-insure against price risk and/or access subsidized staple commodities through the PDS system. One way to examine the net impact of price volatility is to determine whether total calories consumed vary with prices as well as how price variability is related to households’ ability to achieve minimum calorie requirements. The caloric value of various food goods is provided in the 55th round of the NSS and is consistent with other sources (e.g., Gopalan et al. 1980). Using data on household composition and calorie requirements by age and gender, we can calculate the degree to which a given household fails to meet minimum requirements.

Simple regressions of calories consumed on price fluctuations are obviously not well identified. However, most biases would preclude against finding a negative impact of prices on calories; for example, demand driven price variation would likely bias against finding an ad-

⁷Using the real median expenditure at that level does not insure that expenditure shares are below 1, and indeed often they are not.

verse impact of prices on calories. Nonetheless, any causal interpretation of the estimations below must be cautiously applied.

The main outcomes we consider are 1) total household calories for a month; 2) calories per capita; 3) whether the household met the IMCR-recommended medium-exertion subsistence level; 4) whether the household met the IMCR-recommended low-exertion subsistence level. We regress these outcomes on unit values of rice, wheat and a food price index, controlling for other sources of variation, including area (district-sector) fixed effects, price indices overall, household controls including size and asset index, survey year fixed effects, period fixed effects, agroclimatic zone \times season fixed effects, and area \times season fixed effects.

The food price index is based on Laspeyres and Paasche price indices for each commodity group (results are similar):

$$PriceIndex_{cjt} = \frac{\sum_{i \in c} \bar{p}_{itj} (\sum q_{ijt0})}{\sum_{i \in c} \bar{p}_{it0j} (\sum q_{ijt0})}$$

where c is the commodity group; j is district-sector; t is period; i is item. We use the first observed period for each district-sector as the base period (t_0) and take the weighted sum of t_0 quantities by district-sector-period-item. We calculate the denominator as the district-sector-period average t_0 unit values \times t_0 quantities. The numerator is calculated as t_0 quantities \times district-sector-period average unit values from the current period. In periods when that price is missing, we use the previous period's price.

We find that food prices are negatively associated with all our major caloric outcomes (Tables 7, 8, 9, 10). For example, a one unit change in the price index is associated with a 7.9% reduction in calories per capita, a 7.2% reduction in the likelihood of meeting the ICMR medium-exertion threshold, and a 10.7% reduction in the likelihood of meeting the ICMR low-exertion threshold for calories.

5 Insuring Against Price Risk: Theory

We return to the theoretical framework introduced in section 2 above to consider the welfare impact of policy responses to price risk. Price stabilization is not the only way households could be protected against price risk; price-indexed (state-dependent) transfers could provide households with perfect insurance without changing marginal prices. We start by characterizing these price-indexed transfers, and then consider two second-best policy options widely used by governments - cash and in-kind transfers.

5.1 Optimal insurance policy

We start by defining the insurance menu if households could perfectly insure against price risk. This menu specifies a set of (nominal) transfers x_i for each possible value of p , which we write $x_i(p)$. The expected value of these transfers ($\int_p x_i(p)f(p)dp$) must be equal to 0 (actuarially fair premium). The optimal level of transfer $x(p)$ for a given price p is thus the one that maximizes $\int_p v_i(p, \bar{y}_i + x_i(p))f(p)dp - \mu \int_p x_i(p)f(p)dp$, where μ is the marginal value of income. The first order condition tells us that the optimal menu equates the marginal value of income $v_{iy}(p, \bar{y}_i + x_i(p))$ in all states of the world:

$$v_{iy}(p, \bar{y}_i + x_i(p)) = \mu, \forall p \quad (6)$$

Households in developing countries typically do not have access to insurance against price risk but the government could achieve the same outcome with a price-indexed transfer policy: a different transfer $\tau_i(p)$ for each value of p . The optimal menu of transfers is the one that maximizes $\int_p v_i(p, \bar{y}_i + \tau_i(p))f(p)dp - \mu(\int_p \tau_i(p)f(p)dp - c)$ where c is the total value of the transfer. Trivially this optimal menu also equates the marginal value of income in all states of the world. Note that the optimal transfer is increasing in the price as long as the household is risk averse ($v(\cdot)$ is concave in y) and the marginal value of income is increasing in the price:

$$v_{iyp}(p, \bar{y}_i + \tau_i(p)) = \frac{v_{iy}(p, \bar{y}_i + \tau_i(p))}{p} \alpha_i(R_i - \eta_i) \quad (7)$$

As long as relative risk aversion is high compared to the income elasticity the optimal transfer policy transfers more to households facing high prices. Intuitively if the income elasticity is very large consumption of the good will drop substantially when prices increase, leading to a small income loss.

5.2 Cash vs in-kind transfers

In practice governments are unable to perfectly observe local prices at high frequency so this optimal transfer policy is not feasible. We consider instead the impact on household i 's utility of two widely used 'second-best' transfer policies - a cash transfer (price invariant) and an in-kind transfer of a fixed amount z of the good. Our aim is to compare the welfare impact of these two policies for a given budget constraint so we assume the cash transfer policy transfers an amount $z\bar{p}$ to the household. We assume the in-kind transfer is infra-marginal (the household consumes more than z of the good for all possible prices p) to abstract from the effect of the in-kind transfer on marginal prices and focus on its potential insurance value.

We start by taking a linear approximation of the marginal utility of income around the

mean price \bar{p} :

$$v_{iy}(p, \bar{y}_i) = v_{iy}(\bar{p}, \bar{y}_i) + v_{iyp}(\bar{p}, \bar{y}_i)(p - \bar{p}) \quad (8)$$

The welfare impact of introducing the cash transfer policy is given by:

$$W_{iC} = z\bar{p} \int_p v_{iy}(p, \bar{y}_i) f(p) dp = z\bar{p} v_{iy}(\bar{p}, \bar{y}_i) \quad (9)$$

Where the second equality is obtained by using (8).

The welfare impact of introducing the in-kind transfer policy is given by

$$W_{iK} = z \int_p v_y(p, \bar{y}_i) p f(p) dp \quad (10)$$

Using (8) and (7) we obtain

$$W_{iK} = W_{iC} + \bar{p}z \{ \alpha_i [R_i - \eta_i] \sigma_p^2 \} \quad (11)$$

This expression shows that, in the presence of price risk, the infra-marginal in-kind policy is not equivalent to the cash policy even though the expected monetary value of the transfer is the same for both policies. If $R > \eta$ the in-kind policy is welfare improving with respect to the cash policy because the former gives more to households when the price is high, and households value extra income more when the price is high. If this condition is met the difference between the two policies is higher for households which spend a large share of their budgets on the good, when the average price is high and when there is large price volatility.

6 Evidence from the PDS in India

The previous section suggests that in-kind transfers may be welfare improving due to their ability to protect households against price increases. In this section, we examine to what extent this is true empirically, focusing on the case of India's PDS, which provides heavily subsidized in-kind transfers of food to poor households across India. We begin with a brief introduction to the PDS, then describe the empirical strategy, and then the results.

6.1 How the PDS works

The Public Distribution System is one of India's oldest anti-poverty programs, dating back to several months before independence in 1947. The PDS provides wheat, rice, sugar, and kerosene at significantly subsidized rates to eligible households via a widespread network of Fair Price Shops (FPS). The program operates much like in-kind transfer programs across the

rest of the world: the government procures goods directly from producers,⁸ then sells them to households at below-market rates. State governments are responsible for transport and storage, while FPS generally owned by local elites handle final delivery of these commodities. The subsidized rates are fixed and don't vary across space or time other than by policy decision.

The PDS has undergone various nationwide policy changes. The Targeted Public Distribution System (TPDS) was initiated in 1997 to address some of the main concerns with the system and put a greater focus on targeting the poor. Eligibility during most of the period we study was restricted to poor households, in particular those considered to be "Below Poverty Line" (BPL); households must obtain "ration cards" which list names of family members as well as household entitlements. The TPDS provided subsidized grains up to a quota for BPL households and phased out subsidies for Above Poverty Line (APL) households. In 2000, the number of BPL households was increased by almost 6 million households when using a new population projection scheme. Also in 2000, Antyodaya cards (AAY) were initiated for the poorest of the poor household as a subset of BPL households. More recently, the National Food Security Act (NFSA) was passed in 2013, changing eligibility requirements drastically. Our focus is on the years 2003-2012, in between these major national events, but during a period of major expansions in some states.

Differences between market prices and the PDS prices are substantial; in 2012 the average price for PDS rice (wheat) was Rs 2.1 (Rs. 2.6), but the market price was Rs 9.5 (Rs. 7.1). Each household is limited in the quantity they can purchase; the average quantity in 2012 was 6.2kg of rice and 2.8kg of wheat and is generally higher for poorer households. In most states, there are different levels of ration cards, which entitle you to higher levels of purchases. In Andhra Pradesh, for example, AAY households get 35kg of rice at Rs.1/kg, BPL households get 4kg/capita (max 20kg/household) at Rs.1 and APL (Above the Poverty Line) households' entitlement is dependent on the BPL requirement shortfalls. APL households pay Rs.9/kg. There are asset and household composition tests for each of these cards, although the quality of monitoring is poor and there are many households with cards for which they do not technically qualify. In our sample, the average monthly transfer adds up to 39.8 rupees, and 49.9 rupees for below-median expenditure households (relative to monthly expenditures of 3,439 rupees and 2,082 rupees). Thus PDS provided goods, particularly rice and wheat, are infra-marginal for most households in our sample.

⁸One explicit goal of the PDS is to make a price floor for farmers selling agricultural products. Before the spring and winter harvests, the Commission for Agricultural Costs and Prices sets a guaranteed minimum price for key crops at which it will purchase from farmers if necessary.

6.2 Empirical strategy

Most PDS policy is set at the state level: while the federal government provides much of the funding for the baseline PDS, the state governments typically spend more money on top of that to increase program breadth or decrease PDS prices, meaning that the timing of the policy changes varies across states. The generosity of the PDS increased in most states over our study period. Figure 9 shows that PDS prices have decreased while quantities have increased. We use these expansions to determine the impact of the PDS on household welfare - as measured by caloric intake - and their ability to mitigate price risk.

The Foodgrain Bulletins record state-month-specific offtake and allocation of foodgrains. It also includes scattered mentions of PDS prices. We corroborate changes in quantities and prices by scouring newspapers and online sources for mentions of program changes. The relationship between program changes and changes in PDS consumption that we observe in the NSS is strong; Figure 10 shows the relationship for Andhra Pradesh. When PDS prices drop from Rs 5/kg to Rs 2/kg at the start of 2008 (see Figure 11), we see the same drop in the prices recorded in the NSS.

Having discovered policy expansions, we run regressions of the form

$$c_{ist} = \#_{ist}^{\text{policy}} \beta_1 + p_{ist} \beta_2 + \#_{ist} * p_{ist} \beta_3 + X \beta_4 \gamma_s + \varepsilon_{ist} \quad (12)$$

where $\#_{ist}$ is the number of policy changes observed in a given state up until that point. This is a straightforward generalization of a difference-in-differences approach; it assumes that the effect of each policy change on caloric intake is constant. The policies thus far all expand the PDS so the imposition of the same sign does not seem problematic; it may be an issue to assume they all have the same effect on caloric intake. We also control for all prices p_{ist} and the interaction of prices with policy changes; in the tables we show only the rice price effect and interaction. We include state fixed effects, and cluster standard errors at the state level. In all regression tables, household controls X include: household size, owns more than 0.2 hectares of land, scheduled tribe/caste, owns dwelling, non-rudimentary cooking/light fuel, and urban dweller. Tables in this section show pooled regressions; individual regressions by state are available on request.

6.3 Results

Table 12 suggests that each rice policy reform, expanding the generosity of the PDS, increases caloric intake by about 2% per capita. The results are not statistically significant after including state-year fixed effects, but this is not surprising since nearly all our policy variation is at the state-year level. This is a significant increase in calories given the levels

of undernutrition prevalent in India. Table 13 does this analysis by subsample and shows us that the effect is concentrated among the landless and especially the poor. The differences in impact between the landless and landowners, as well as those below and above median expenditure, are statistically significant. This is important confirmation that the impacts are indeed coming from expansions in PDS generosity, since the PDS during our period of study was restricted to poor households.

The results above are likely a function increased income from the PDS expansion. To the extent that they increase food security, PDS reforms should also decrease caloric sensitivity to price changes. The next part of the analysis regresses calories on prices, policy, and prices X policy. As expected, Table 14 shows that price sensitivity is lower after the reform. Table 15 runs the same regression by subsample. There is a larger effect on caloric price sensitivity for poor/landless groups, although in this case the results are not statistically significant.

7 Conclusion

Households in developing countries can be subject to substantial price variability as a result of poor local market integration and other barriers to trade. We provide a detailed examination of price risk in India and show that such risk is substantial and has negative effects on households. This has important implications for the design of optimal government policy. In particular, cash transfers – increasingly advocated by researchers and policymakers – may have an important limitation: the effective value of these transfers is eroded when market prices rise. In contrast, in-kind transfers can provide partial insurance against commodity price risk. We demonstrate that in a world with price risk, inframarginal in-kind transfers can therefore be welfare improving relative to cash transfers. Empirically, we demonstrate that expansions of the Public Distribution System in India are associated with both increased caloric intake by households and reduced sensitivity of calories to local prices.

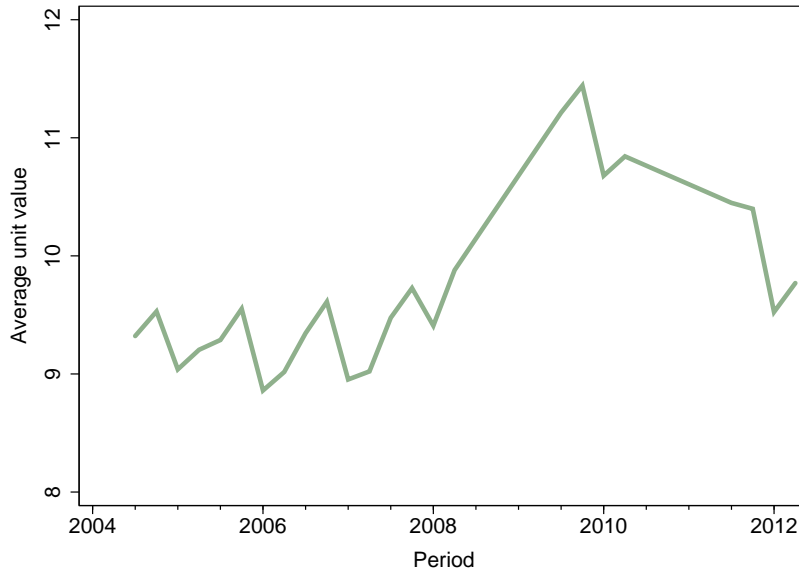
It is important to note that there are other potential differences between cash and in-kind transfers not considered here. For example, many have argued that in-kind transfers may be more subject to corruption, especially as mechanisms such as electronic transfers have reduced corruption in cash transfers. In the context of price risk, corruption in in-kind programs is particularly problematic since incentives for corruption rise when market prices are high (Hari, 2016), thereby potentially undermining the insurance value of such programs. However, our results indicate that the relationship between the form of transfers and price risk is an important factor that should be taken into consideration in the design of social protection programs.

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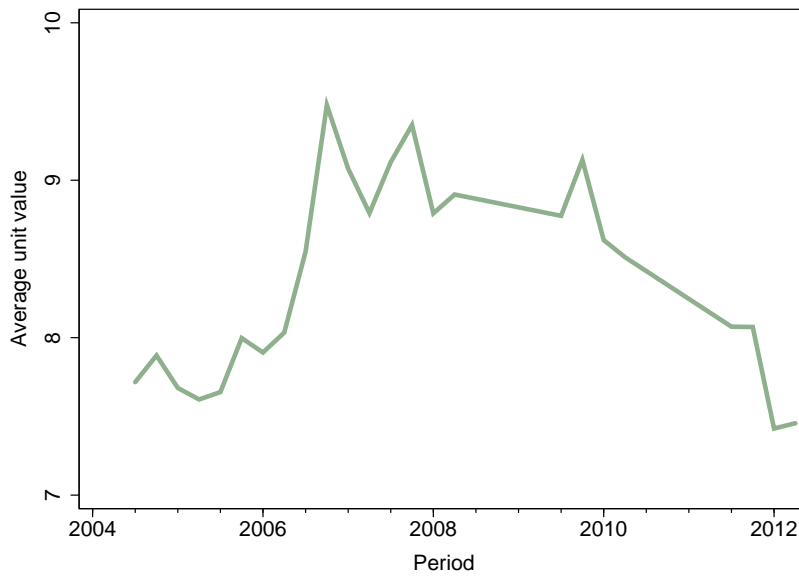
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Figure 1: Market Rice: unit values



Notes: $\widetilde{MarketUV}_{jtk} = \sum_{h \in j,t} MarketUV_k^h$, the average of the district-sector-period average unit values for all of India are shown.

Figure 2: Market Wheat: unit values



Notes: $\widetilde{MarketUV}_{jtk} = \sum_{h \in j,t} MarketUV_k^h$, the average of the district-sector-period average unit values for all of India are shown.

Figure 3: Food & fuel: real expenditure shares

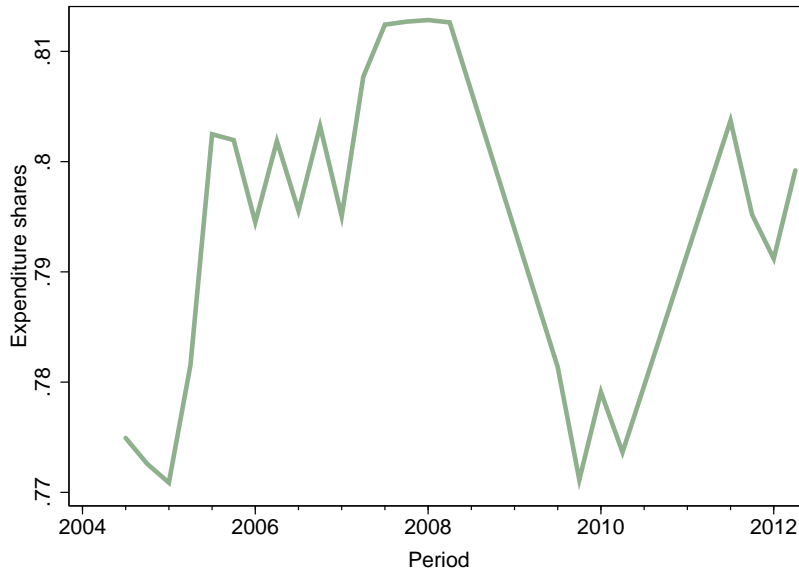
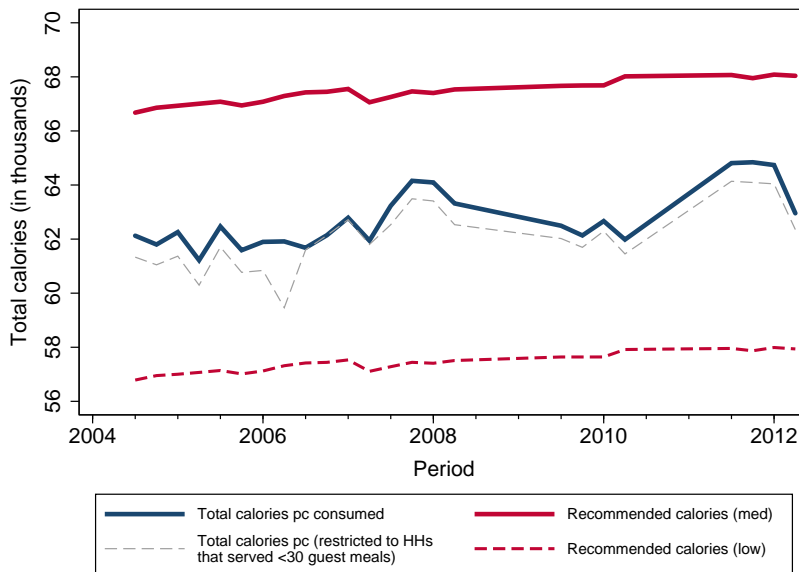
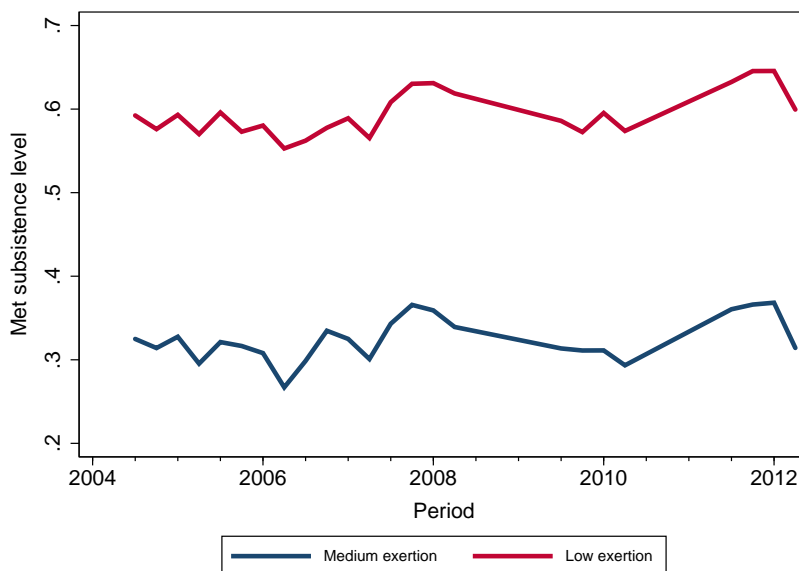


Figure 4: Total & recommended calories per capita



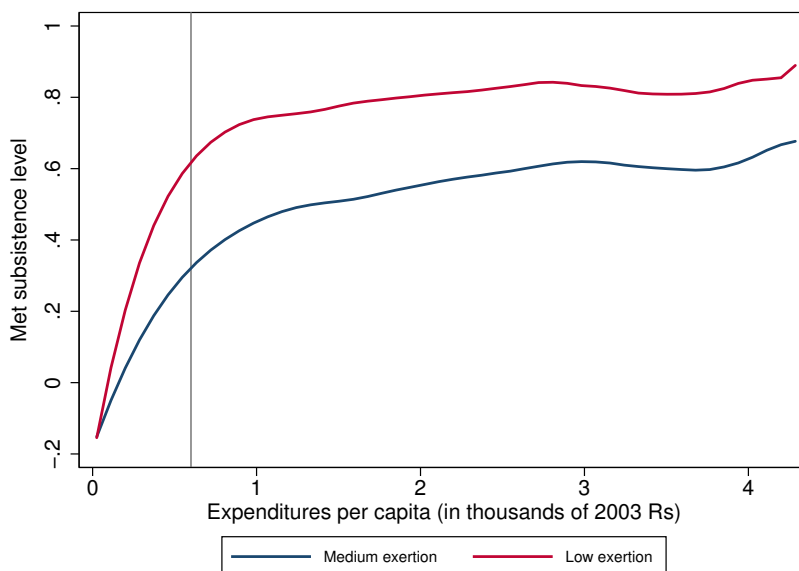
Notes: The average monthly calories and recommended caloric level per capita for subsistence is based on medium exertion.

Figure 5: Met caloric needs for subsistence



Notes: The figure plots the % of households that met the recommended subsistence level based on medium exertion and low exertion.

Figure 6: Expenditures per capita & subsistence



Notes: Expenditures per capita are in thousands of 2003 Rs. and are deflated using the district-sector laspeyres index. Expenditure per capita are capped at the 99th percentile, and the median across rounds is about 600 Rs (2003), or 1500 Rs (2015) (indicated by the vertical line). We use kernel-weighted local polynomial smoothing to estimate meeting the subsistence level on expenditure per capita.

Figure 7: Share of total calories: Market & PDS goods

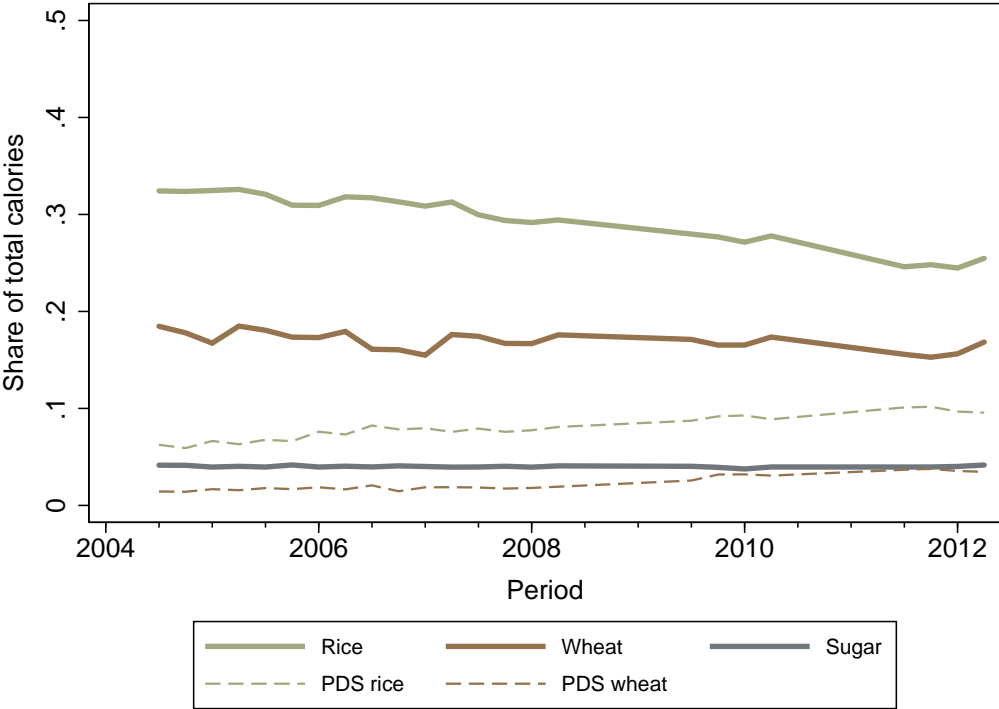


Figure 8: Value of PDS Rice and Wheat Transfers

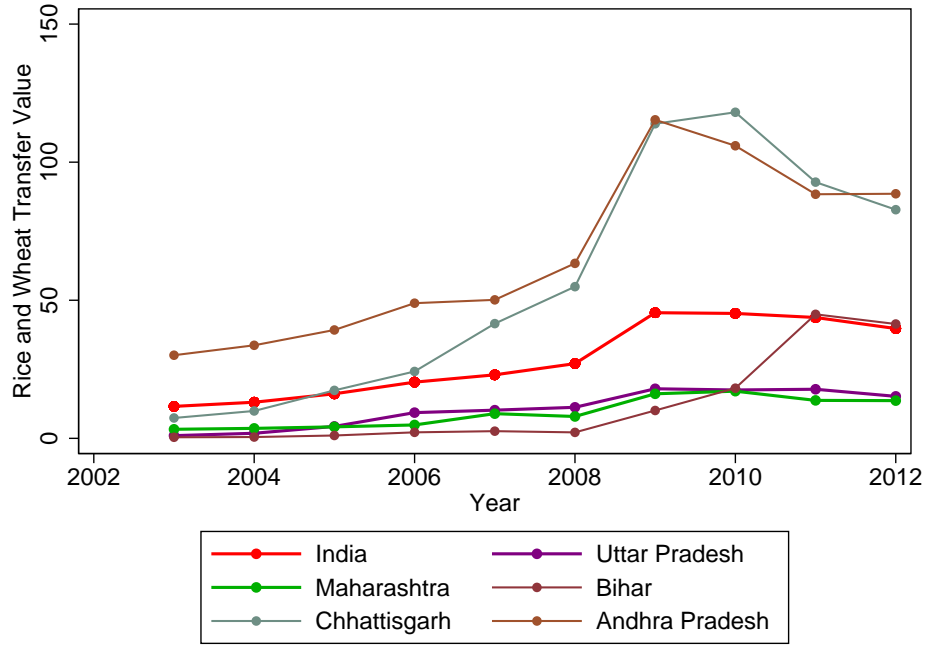


Figure 9: PDS Rice and Wheat Quantity and Transfer Value Over Time

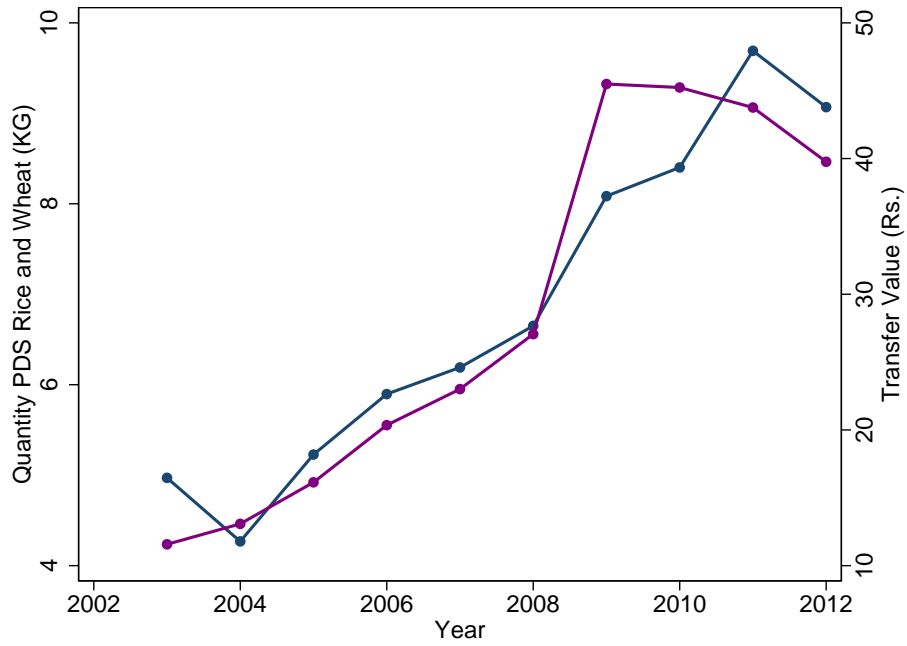


Figure 10: Andhra Pradesh PDS rice prices: 2-month trailing avgs

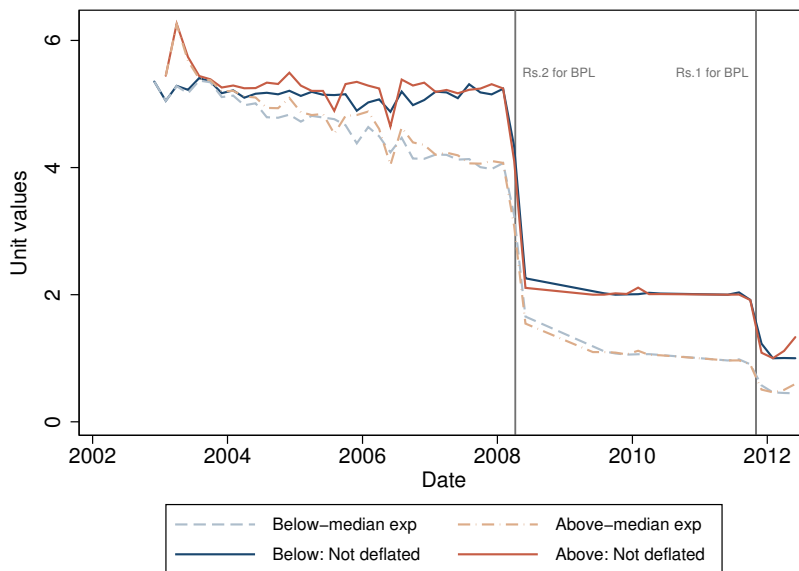


Figure 11: Andhra Pradesh Fair Price Shop Rice Prices

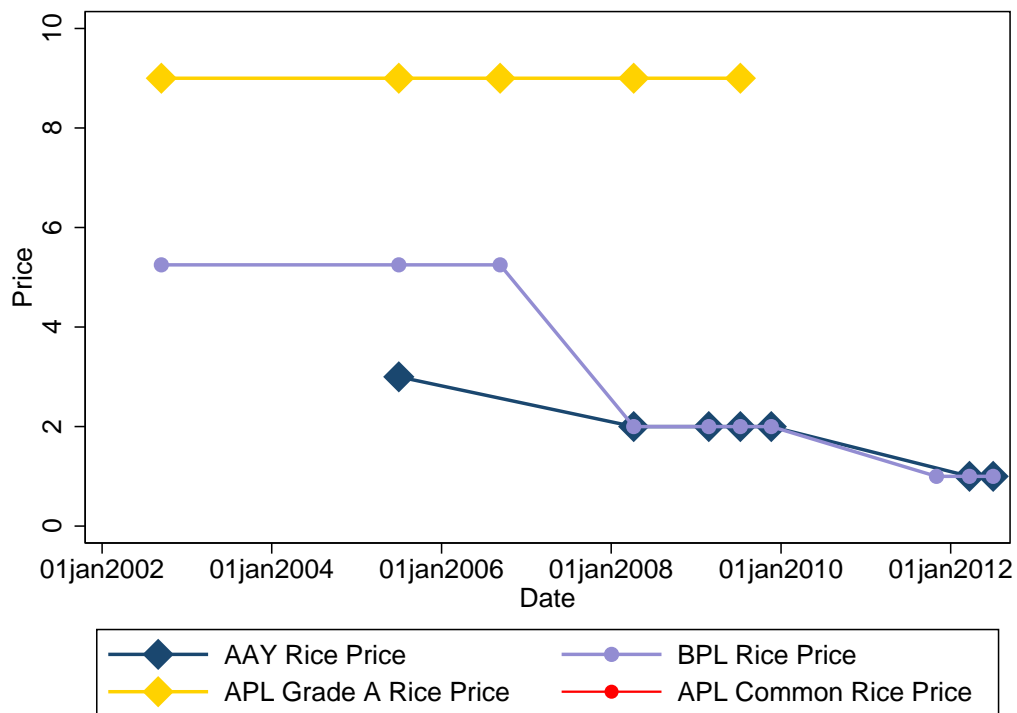


Table 1: Summary Statistics: Market Price of Rice

	<i>Market rice unit values</i>			
	Mean	S.D.	Median	95% CI
Overall	9.74	(2.36)	9.26	5.12 - 14.37
Within district-sectors (across periods)		(1.40)		7.00 - 12.48
Across district-sectors (within periods)		(1.91)		6.00 - 13.49
Rural	8.91	(1.83)	8.61	5.31 - 12.50
Within areas		(1.19)		6.57 - 11.24
Across areas		(1.64)		5.69 - 12.12
Urban	11.54	(2.37)	11.22	6.90 - 16.18
Within areas		(1.76)		8.09 - 14.99
Across areas		(1.81)		7.99 - 15.08
Below 25% income	8.36	(1.55)	8.16	5.32 - 11.41
Within areas		(1.05)		6.31 - 10.42
Across areas		(1.98)		4.48 - 12.25
Above 25% income	10.11	(2.41)	9.68	5.40 - 14.82
Within areas		(1.47)		7.23 - 12.99
Across areas		(1.91)		6.37 - 13.85
Below-median income	8.79	(1.84)	8.48	5.18 - 12.41
Within areas		(1.17)		6.51 - 11.08
Across areas		(1.88)		5.11 - 12.48
Above-median income	10.56	(2.44)	10.25	5.78 - 15.34
Within areas		(1.55)		7.53 - 13.59
Across areas		(1.91)		6.82 - 14.30

Notes: $\widetilde{MarketUV}_{jtk} = \sum_{h \in j,t} MarketUV_k^h$, the district-sector-period average unit values are shown.

Table 2: Summary Statistics: Market Price of Wheat

	<i>Market wheat unit values</i>			
	Mean	S.D.	Median	95% CI
Overall	8.36	(2.43)	7.91	3.59 - 13.12
Within district-sectors (across periods)		(1.12)		6.16 - 10.55
Across district-sectors (within periods)		(2.25)		3.94 - 12.77
Rural	7.86	(2.29)	7.42	3.37 - 12.35
Within areas		(1.15)		5.61 - 10.11
Across areas		(2.30)		3.35 - 12.37
Urban	9.22	(2.43)	8.70	4.46 - 13.99
Within areas		(1.07)		7.13 - 11.32
Across areas		(2.20)		4.91 - 13.54
Below 25% income	7.24	(1.72)	7.05	3.88 - 10.61
Within areas		(1.10)		5.09 - 9.40
Across areas		(2.24)		2.85 - 11.64
Above 25% income	8.59	(2.50)	8.11	3.69 - 13.50
Within areas		(1.12)		6.40 - 10.79
Across areas		(2.25)		4.18 - 13.01
Below-median income	7.57	(1.95)	7.31	3.74 - 11.40
Within areas		(1.10)		5.41 - 9.73
Across areas		(2.22)		3.22 - 11.92
Above-median income	8.91	(2.57)	8.41	3.87 - 13.95
Within areas		(1.11)		6.72 - 11.09
Across areas		(2.26)		4.48 - 13.33

Notes: $\widetilde{MarketUV}_{jtk} = \sum_{h \in j,t} MarketUV_k^h$, the district-sector-period average unit values are shown.

Table 3: Price changes as a percent of budget, year on year

	Mean change	<i>Within district-period</i>		
		S.D.	5%	95%
Overall	0.1398	6.4399	-0.1678	0.1118
Rural	0.1726	7.4178	-0.1567	0.1125
Urban	0.0474	1.8254	-0.1879	0.1103
Below 25% income	0.1795	5.6694	-0.1705	0.1366
Above 25% income	0.1264	6.6801	-0.1672	0.1039
Below median income	0.1763	6.5838	-0.1576	0.1195
Above median income	0.1025	6.2894	-0.1758	0.1050
Agricultural HH	0.1980	8.1422	-0.1560	0.1100
Non-agricultural HH	0.0847	4.2399	-0.1751	0.1139

Mean change is mean ΔX_{hjt} , within district period measure is $\Delta \widetilde{X}_{hjt}$

Table 4: Food and Fuel Real Expenditure Shares

	<i>Food & fuel</i>			
	Mean	S.D.	Median	95% CI
Overall	0.62	(0.08)	0.62	0.46 - 0.78
Within district-sectors (across periods)		(0.05)		0.51 - 0.72
Across district-sectors (within periods)		(0.06)		0.51 - 0.73
Rural	0.64	(0.07)	0.65	0.50 - 0.79
Within areas		(0.05)		0.54 - 0.75
Across areas		(0.05)		0.55 - 0.74
Urban	0.56	(0.07)	0.56	0.42 - 0.70
Within areas		(0.06)		0.45 - 0.67
Across areas		(0.05)		0.47 - 0.65
Below 25% income	0.68	(0.08)	0.69	0.53 - 0.84
Within areas		(0.07)		0.55 - 0.82
Across areas		(0.06)		0.57 - 0.80
Above 25% income	0.60	(0.08)	0.60	0.45 - 0.76
Within areas		(0.06)		0.49 - 0.72
Across areas		(0.05)		0.51 - 0.70
Below-median income	0.67	(0.07)	0.68	0.54 - 0.81
Within areas		(0.06)		0.56 - 0.78
Across areas		(0.05)		0.58 - 0.76
Above-median income	0.57	(0.08)	0.57	0.41 - 0.73
Within areas		(0.07)		0.44 - 0.70
Across areas		(0.05)		0.48 - 0.66

Notes: Descriptive stats of the mean expenditure shares at the area-period level.

Table 5: Food and Fuel Simulated Expenditure Shares

	<i>Food & fuel</i>			
	Mean	S.D.	Median	95% CI
Overall	0.79	(0.12)	0.82	0.57 - 1.02
Within district-sectors (across periods)		(0.09)		0.62 - 0.97
Across district-sectors (within periods)		(0.07)		0.65 - 0.94
Rural	0.79	(0.11)	0.82	0.57 - 1.02
Within areas		(0.09)		0.62 - 0.97
Across areas		(0.07)		0.66 - 0.93
Urban	0.80	(0.12)	0.82	0.56 - 1.03
Within areas		(0.08)		0.63 - 0.96
Across areas		(0.07)		0.65 - 0.94
Below 25% income	0.83	(0.08)	0.84	0.68 - 0.99
Within areas		(0.06)		0.71 - 0.96
Across areas		(0.07)		0.69 - 0.98
Above 25% income	0.79	(0.12)	0.82	0.55 - 1.03
Within areas		(0.09)		0.62 - 0.97
Across areas		(0.08)		0.64 - 0.94
Below-median income	0.82	(0.09)	0.83	0.64 - 0.99
Within areas		(0.07)		0.68 - 0.95
Across areas		(0.06)		0.70 - 0.94
Above-median income	0.80	(0.12)	0.82	0.56 - 1.04
Within areas		(0.09)		0.62 - 0.97
Across areas		(0.07)		0.65 - 0.94

Notes: Descriptive stats of the mean expenditure shares at the area-period level.

Table 6: Summary Statistics: Caloric Consumption

	Total calories consumed (in thousands)	Total calories per capita (in thousands)	Recommended caloric needs	Met sub- sistence level (medium exertion)	Met sub- sistence level (low exertion)
Overall	273.642 (147.041)	62.776 (19.150)	301.533 (147.485)	0.325 (0.468)	0.596 (0.491)
Rural	285.105 (153.332)	62.861 (19.363)	309.222 (147.101)	0.342 (0.474)	0.611 (0.487)
Urban	248.648 (128.799)	62.590 (18.676)	284.767 (146.932)	0.289 (0.453)	0.562 (0.496)
Above-median exp	265.658 (155.683)	69.709 (21.218)	270.661 (138.630)	0.434 (0.496)	0.714 (0.452)
Below-median exp	282.253 (136.591)	55.299 (12.999)	334.824 (149.493)	0.208 (0.406)	0.469 (0.499)
Above 25% exp	271.607 (151.316)	66.322 (19.522)	286.640 (142.750)	0.380 (0.485)	0.662 (0.473)
Below 25% exp	280.328 (131.810)	51.129 (11.936)	350.445 (152.136)	0.146 (0.353)	0.377 (0.485)
Non-agricultural HH	256.637 (136.036)	62.602 (19.408)	287.247 (144.963)	0.313 (0.464)	0.586 (0.493)
Agricultural HH	296.186 (157.669)	63.005 (18.800)	320.471 (148.663)	0.341 (0.474)	0.609 (0.488)

Notes: The observation is the household.

Table 7: Effect of Market Prices on Caloric Consumption

	<i>Log calories</i>				<i>Log calories per capita</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market rice log UVs	-0.093*** [0.018]	-0.035*** [0.013]	-0.035*** [0.013]	-0.037*** [0.013]	0.011 [0.012]	-0.023** [0.012]	-0.023* [0.012]	-0.021* [0.012]
Market wheat log UVs	-0.112*** [0.014]	-0.041*** [0.010]	-0.040*** [0.010]	-0.038*** [0.010]	-0.008 [0.010]	-0.029*** [0.009]	-0.029*** [0.009]	-0.026*** [0.009]
District-sector FEs	Yes	Yes	Yes	No	Yes	Yes	Yes	No
All prices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Period FEs	No	No	No	No	No	No	No	No
Agroclimatic region \times quarter FEs	No	No	Yes	No	No	No	Yes	No
District-sector \times quarter FEs	No	No	No	Yes	No	No	No	Yes
Observations	534,120	534,120	534,120	534,120	534,120	534,120	534,120	534,120

Table 8: Effect of Market Prices on Ability to Meet Caloric Subsistence Levels

	<i>Met medium-exertion subsistence level</i>				<i>Met low-exertion subsistence level</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market rice log UVs	0.036** [0.015]	0.016 [0.015]	0.016 [0.015]	0.020 [0.015]	0.000 [0.016]	-0.024 [0.015]	-0.024 [0.015]	-0.019 [0.016]
Market wheat log UVs	-0.030** [0.012]	-0.056*** [0.012]	-0.055*** [0.012]	-0.051*** [0.012]	-0.025* [0.014]	-0.051*** [0.013]	-0.050*** [0.013]	-0.045*** [0.013]
District-sector FEs	Yes	Yes	Yes	No	Yes	Yes	Yes	No
All prices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Period FEs	No	No	No	No	No	No	No	No
Agroclimatic region \times quarter FEs	No	No	Yes	No	No	No	Yes	No
District-sector \times quarter FEs	No	No	No	Yes	No	No	No	Yes
Observations	534,120	534,120	534,120	534,120	534,120	534,120	534,120	534,120

Notes: Standard errors are clustered by district-sector and are shown in brackets. District-sector-period average log UVs are used and the observation is the household. HH controls include household size, owns more than 0.2 hectares of land, scheduled tribe/caste, owns dwelling, non-rudimentary cooking/light fuel, and per capita expenditure.

Table 9: Effect of Food Index on Caloric Consumption

	<i>Log calories</i>				<i>Log calories per capita</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Food index	-0.157*** [0.023]	-0.072*** [0.018]	-0.059*** [0.020]	-0.052*** [0.020]	0.036* [0.019]	-0.102*** [0.016]	-0.086*** [0.018]	-0.079*** [0.018]
District-sector FEs	Yes	Yes	Yes	No	Yes	Yes	Yes	No
HH controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Period FEs	No	No	No	No	No	No	No	No
Agroclimatic region \times quarter FEs	No	No	Yes	No	No	No	Yes	No
District-sector \times quarter FEs	No	No	No	Yes	No	No	No	Yes
Observations	534,120	534,120	534,120	534,120	534,120	534,120	534,120	534,120

Table 10: Effect of Food Index on Ability to Meet Caloric Subsistence Levels

	<i>Met medium-exertion subsistence level</i>				<i>Met low-exertion subsistence level</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Food index	-0.029 [0.023]	-0.114*** [0.026]	-0.090*** [0.028]	-0.072** [0.029]	-0.035 [0.023]	-0.137*** [0.023]	-0.116*** [0.024]	-0.107*** [0.025]
District-sector FEs	Yes	Yes	Yes	No	Yes	Yes	Yes	No
HH controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Period FEs	No	No	No	No	No	No	No	No
Agroclimatic region \times quarter FEs	No	No	Yes	No	No	No	Yes	No
District-sector \times quarter FEs	No	No	No	Yes	No	No	No	Yes
Observations	534,120	534,120	534,120	534,120	534,120	534,120	534,120	534,120

Notes: Standard errors are clustered by district-sector and are shown in brackets. District-sector-period average laspeyres index is constructed for all food items.

Table 11: Dates On Which Documented PDS Policy Changes Increased Program Generosity

State	Policy Change 1	Policy Change 2
Andhra Pradesh	April 7, 2008	-
Bihar	August 1, 2009	-
Chhattisgarh	April 30, 2007	July 8, 2009
Jharkhand	October 1, 2010	-
Karnataka	June 17, 2004	-
Kerala	February 1, 2006	April 16, 2011
Odisha	August 1, 2008	-
Tamil Nadu	December 31, 2004	June 3, 2006

Notes: These dates create the dummy variable 'Rice Policy Change' in the subsequent tables.

Table 12: Effect of Increases in PDS Generosity on Caloric Consumption

	<i>Log calories</i>				<i>Log calories per capita</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rice policy change	0.014*** [0.004]	0.013*** [0.004]	0.016*** [0.004]	0.005 [0.007]	0.019*** [0.004]	0.020*** [0.004]	0.023*** [0.004]	0.007 [0.007]
State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time control	None	Linear year	Year FEs	State-year	None	Linear year	Year FEs	State-year
Observations	534,120	534,120	534,120	534,120	534,120	534,120	534,120	534,120

Table 13: Effect of Increases in PDS Generosity on Caloric Consumption by Group

Sample	<i>Log calories</i>				<i>Log calories per capita</i>			
	Landless	Landowner	Below- median exp	Above- median exp	Landless	Landowner	Below- median exp	Above- median exp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rice policy change	0.025*** [0.008]	0.008 [0.005]	0.025*** [0.007]	0.001 [0.004]	0.034*** [0.008]	0.012** [0.005]	0.031*** [0.007]	0.009** [0.004]
State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Equality p-value		0.0843		0.0098		0.0200		0.0132
Observations	191,906	342,214	209,947	324,173	191,906	342,214	209,947	324,173

Notes: Standard errors are clustered by district-sector and are shown in brackets. “Rice policy change” represents successive policy changes related to PDS rice in each state.

Table 14: Effect of Increases in PDS Generosity and Market Price on Caloric Consumption

	<i>Log calories</i>				<i>Log calories per capita</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market rice log UVs	-0.040*** [0.012]	-0.040*** [0.012]	-0.042*** [0.013]	-0.031** [0.013]	-0.032*** [0.011]	-0.032*** [0.011]	-0.033*** [0.011]	-0.021* [0.011]
Market rice × Rice policy change	0.033** [0.014]	0.033** [0.014]	0.033** [0.014]	0.023 [0.015]	0.035*** [0.014]	0.035*** [0.014]	0.038*** [0.014]	0.024 [0.015]
Rice policy change	-0.644 [1.669]	-0.643 [1.669]	-0.811 [1.656]	-0.642 [1.666]	-2.590* [1.535]	-2.591* [1.534]	-2.708* [1.521]	-2.333 [1.526]
All prices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time control	None	Linear year	Year FEs	State-year	None	Linear year	Year FEs	State-year
Observations	534,120	534,120	534,120	534,120	534,120	534,120	534,120	534,120

Table 15: Effect of Increases in PDS Generosity and Market Price on Caloric Consumption by Group

Sample	<i>Log calories</i>				<i>Log calories per capita</i>			
	Landless (1)	Landowner (2)	Below- median exp (3)	Above- median exp (4)	Landless (5)	Landowner (6)	Below- median exp (7)	Above- median exp (8)
Market rice log UVs	-0.076*** [0.019]	-0.022* [0.013]	-0.074*** [0.024]	-0.107*** [0.024]	-0.054*** [0.017]	-0.021* [0.012]	-0.072*** [0.013]	-0.088*** [0.014]
Market rice × Rice policy change	0.054*** [0.016]	-0.000 [0.018]	0.009 [0.026]	0.039 [0.026]	0.048*** [0.016]	0.020 [0.018]	0.011 [0.016]	0.047*** [0.017]
Rice policy change	-3.189 [2.381]	1.806** [0.909]	-5.939 [5.126]	0.709 [1.814]	-4.438** [2.145]	0.110 [0.837]	-5.725 [4.349]	2.732** [1.217]
All prices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Equality p-value		0.0068		0.4317		0.1814		0.4833
Observations	191,906	342,214	324,173	209,947	191,906	342,214	324,173	209,947

Notes: Standard errors are clustered by district-sector and are shown in brackets. “Rice policy change” represents successive policy changes related to PDS rice in each state.

A Additional Notes on Data

A.1 Sample

Our data comes from the Household Consumer Expenditure schedules of 8 recent rounds of the Indian National Sample Survey. The expenditure survey was not administered in rounds 65 and 67, so we have a gap from July 2008 – June 2009 and July 2010 – June 2011. We exclude Union Territories and Delhi from our analysis, which gives 28 distinct states. In total, our sample includes 534,438 households.

Table 16: NSS data

NSS Rounds	Sample size	Time period
59	39,544	Jan 2003 – Dec 2003
60	28,626	Jan 2004 – Jun 2004
61*	121,158	Jul 2004 – Jun 2005
62	38,485	Jul 2005 – Jun 2006
63	61,149	Jul 2006 – Jun 2007
64	48,720	Jul 2007 – Jun 2008
66*	98,010	Jul 2009 – Jun 2010
68*	98,746	Jul 2011 – Jun 2012

Notes: Asterisks indicate thick rounds.

A.2 Consistency across rounds

Districts District codes are not consistent across all rounds of the NSS due to redistricting/splitting or poor documentation. Changes in district codes are not well-recorded by the NSS and at times the data does not match with the existing documentation. Cross-tabs of regions and districts by round and state show that the districts are not in the regions that they are supposed to be in. Rounds 57 and 58 appear to have the most problems (and lack relevant documentation), so we exclude these rounds from our analysis. We have also found some issues with weights over rounds – The NSS weights should be the same for most consecutive rounds because they are based on the census, and the census is updated infrequently. This technically means that for a given district weights should be the same for a while (5 to 10 rounds), then change and be the same for another 5 to 10 rounds. We have thoroughly cross-checked district codes and matched them across rounds.

Sampling issues Rounds 59 & 60 had a slightly different sampling process, which has resulted in a large number of missing district-sectors (mostly urban) in these rounds. Specifically, rural areas were identified using the 1991 census in rounds 59 and 60, whereas they were identified using the 2001 Census from round 61 on. This, in addition to differences in sub-stratification methods across rounds, resulted in district-sectors that were missing in

several rounds. In addition to rounds 59 and 60, we have dropped all district-sectors that are missing in at least one period to maintain a balanced panel for the exploratory summary statistics and time-series graphs. The total number of unique district-sectors in our balanced panel is 810.

Commodities The list of items on the expenditure survey differs slightly from round to round. Across rounds, some categories are broken down into more specific categories and/or commodities are combined to create a broader category of items. In order to standardize the commodities across all rounds, we combine categories in order to create a list of items that are available in all rounds. For example, in round 61, “air cooler” and “air conditioner” are listed as separate commodities, whereas they are listed as a single category in subsequent rounds. We combined these two commodities in round 61 to be consistent with other rounds. Combining items affects source codes if there are differences across the individual items. However, there are only a few food items that are combined to create larger categories, and none of our PDS items are among these. In all cases, we make sure that the combined commodities have similar unit values. In total, we have a list of 316 unique items.

Recall periods Some rounds had a recall period of 30 days in addition to 365 days for certain commodities. To maintain consistency across rounds, we use the recall period in each commodity category that is available for all rounds:

- *30 days*: Food, fuel, and miscellaneous/non-institutional medical items
- *365 days*: Clothing, bedding, footwear, education, institutional medical, durables

Inflation Time-series, state-level deflators for India are hard to find, so in most analyses, we deflate all prices using an all-India CPI obtained from the World Bank. Prices are in 1999 Indian Rs. We have also calculated state-level deflators from our NSS data using laspeyres price indices. (We also have other geographic levels available, see `make_cpi_laspeyres.do` in the `Dataprep_code` folder for more information.) Internally generated deflators are highly correlated with the World Bank’s CPI (97%) and preliminary analysis suggests using state-level deflators vs. all-India deflators doesn’t make much of a difference in our results.

Weights We use NSS-provided weights in all analyses. For tables and figures looking at unit values of individual commodities, weights are calculated conditional on consumption of the good.

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