# In-Kind Transfers as Insurance*

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**Abstract**

In recent years, there has been increasing academic and policy interest in cash as the preferred form of transfer to low income households. However, in-kind transfers remain prevalent throughout the developing world. 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. We develop a model which shows that in-kind transfers can be welfare improving relative to cash in a world with price risk. In the context of India, we show that price shocks for food commodities are negatively associated with caloric intake and meeting minimal caloric requirements. We then demonstrate 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

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# 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, thus eroding the value of cash transfers. Informal insurance will be ineffective if the price shock hits an entire area simultaneously, and self-insurance is likely to be limited: credit constraints may limit borrowing and saving, and stockpiling goods is challenging in practice. 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.

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 literature that has focused on such issues has assessed the welfare effects of price risk relative to price stabilization. Bellemare, Barrett and Just (2013) 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.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 research has 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 developing 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.

We next provide 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 significant variation in the prices of basic food commodities. The variation over time within area is as large as the 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 fairly correlated. This implies that price variability 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.

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). 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 with the exception of Gadenne (2016) who models the PDS as a non-linear commodity tax system that allows governments to redistribute and provide partial insurance against price risk when income tax and transfers are not available.

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 and section 5 examines the effects of the PDS programs on households and the extent to which it mitigates households' sensitivity to price risk.

# 2 Theoretical framework

In this section we present a framework for thinking about the effect of price variability on household welfare in a simple way. We derive the optimal insurance contract in a world with price risk, and show that in-kind transfers are typically welfare increasing compared to cash transfers. Intuitively, this result comes from the fact that an (infra-marginal) in-kind transfer has a higher value when prices are high; in a crude sense an in-kind transfer is price-indexed.

## 2.1 Optimal insurance policy

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 $\sigma_p$ and density distribution $f(p)$. We assume the price of all other goods is fixed and income $\bar{y}_i$ is non-stochastic. We consider first the optimal insurance policy: price-indexed (state-dependent) transfers. The optimal insurance menu specifies a set of (nominal) transfers $x_i$ for each possible value of $p$, which we write $x_i(p)$. We assume an actuarially fair premium so the expected value of these transfers ($\int_p x_i(p)f(p)dp$) must be equal to 0. The optimal 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 $\mu$ 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:

$$v_{iy}(p, \bar{y} + x_i(p)) = \mu, \forall p \tag{1}$$

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 $\int_p v_i(p, \bar{y}_i + x_i(p))f(p)dp - \mu(\int_p \tau_i(p)f(p)dp - c)$. 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 ($v(.)$ is concave in $y$) and the marginal value of income is increasing in the price:

$$v_{iyp}(p, \bar{y}_i + \tau_i(p)) = \frac{v_{iy}(p, \bar{y}_i + \tau_i(p))}{p}\alpha_i(R_i - \eta_i) \tag{2}$$

As long as relative risk aversion is high compared to the income elasticity the optimal transfer policy transfers more to households facing high prices. Since food is not a luxury good ($\eta < 1$) and most estimates of $R$ are higher than 1 this condition is trivially met. The lower the income elasticity the less the optimal transfer will increase with the price, intuitively if the income elasticity is very large consumption of the good will drop substantially when prices increase, leading to a smaller income loss.

## 2.2 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 price-invariant cash transfer 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 that both policies transfer an amount $z\bar{p}$ to the household in expectation. We also 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 $\bar{p}$:

$$v_{iy}(p, \bar{y}_i) = v_{iy}(\bar{p}, \bar{y}_i) + v_{iyp}(\bar{p}, \bar{y}_i)(p - \bar{p}) \tag{3}$$

Using this approximation we can write the welfare impact of introducing the cash transfer policy as:

$$W_{Ci} = z\bar{p}\int_p v_{iy}(p,\bar{y}_i)f(p)dp = z\bar{p}v_{iy}(\bar{p},\bar{y}_i) \tag{4}$$

Similarly the welfare impact of introducing the in-kind transfer policy is:

$$W_{Ki} = z\int_p v_y(p,\bar{y}_i)pf(p)dp \tag{5}$$

Using (3) and (2) we obtain

$$W_{Ki} = W_{Ci}[1 + \{\alpha_i[R_i - \eta_i]\sigma_p^2\}] \tag{6}$$

where $\alpha$ is the budget share of the good. 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. As long as $R > \eta$ 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. The difference between the two policies is higher for households which spend a large share of their budgets on the good and when there is large price volatility.

Households in developing countries are sometimes producers, as well as consumers, of food. Intuitively, this affects how they value the in-kind policy relative to the cash policy to the extent that higher prices will increase their income, lowering their marginal utility of income and hence the value of a transfer that is positively correlated with prices. Formally we can show that the welfare effect of the in-kind policy of a household endowed with an amount $\omega$ of the good that can be consumed or sold on the market at price $p$ is given by:

$$W_{Ki} = W_{Ci}[1 + \{(\alpha_i[R_i - \eta_i] - 2R_i\alpha_{\omega i})\sigma_p^2\}] \tag{7}$$

where $\alpha_{\omega i} = \frac{\bar{p}\omega_i}{y_i}$ is the share of the endowment in the household's total income.[1] This expression shows that the welfare benefit of the in-kind transfer is lower than that of the cash transfer for net producers (those for whom $\alpha < \alpha_\omega$), ie households whose income increases with the price. For households with no endowment of the good the in-kind transfer still dominates as long as $R > \eta$.

[1]We assume the endowment is fixed, in particular that it does not vary with the price. In practice we expect households to adjust their production of the good when its price varies but we abstract from these considerations here. This is coherent with our empirical setting as empirically we will consider whether the fact that a household is endowed with more land (a proxy for their capacity to produce food that does not vary with prices) affects the impact of the PDS.

# 3 Context and data

## 3.1 Context

### 3.1.1 Price risk in India

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 world;[2] 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 or above. A 2013 op-ed about agricultural markets in India put it succintly: "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 smoothened.

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

[2] According 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.

[4] This 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.

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

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).

### 3.1.2 India's Public Distribution System (PDS)

The government's main attempt at solving this problem, 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,[7] 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

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

[7] One 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.

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.

## 3.2 Data

Our main sources of data are the 59$^{\text{th}}$ through 68$^{\text{th}}$ 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.

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 $55^{\text{th}}$ 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 caloric requirement guidelines from the Indian Council of Medical Research along with NSS demographic data, we estimate the total caloric requirements of the family. Relatively few households are meeting their caloric requirements; Figure 1 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.

#### 3.2.3 Data on PDS policy changes

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. This has happened by both increasing generosity for existing users of the system and increasing the number of eligible households, either by relaxing eligibility or expanding the network of PDS shops to new areas. Figure 2 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.

Our main source of information regarding PDS policy changes comes from the government-produced Foodgrain Bulletings. It records allocation of foodgrains to each state at the monthly level as well as the prices at which the foodgrains are sold, we use this to measure the PDS price of rice in each state and period. We complement this with information on major policy changes for PDS rice by scouring newspapers and online sources for mentions of program changes at the state level. We find 11 major policy changes in 8 states, listed in Table 1. The relationship between program changes and changes in PDS consumption that we observe in the NSS is strong; Figure 3 shows the relationship for Andhra Pradesh. When PDS prices drop from Rs 5/kg to Rs 2/kg at the start of 2008 we see the same drop in the prices recorded in the NSS.

# 4 Price risk in India

In this section, we examine in detail household exposure to price risk. We first report variation in prices and expenditure shares across space and time for major food commodities then examine how variation in prices is correlated with calorie consumption by households, a proxy for household welfare. 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 by considering how the average unit value in each district-sector and period varies both over time and across district-sectors. Table 2 and 3 report results for rice and wheat in detail. There are relatively high levels of price risk: across the sample, the deflated mean price of rice is Rs 9.74/k.g. and the standard deviation 2.36. Strikingly, there is nearly as much variation within districts over time as there is 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 $\times$ district-sector trends.

Next, we examine 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 compute the within district-sector and period means and present distributions in Table Table 5. We find that food and fuel expenditures comprise a large share (62%) of household budgets. The standard deviation of budget shares is 8%, with both similar variation within districts over time and across districts.

The above exercise takes into account actual variation after households adjust for price changes and therefore under-estimate the variation in households' expenditures that is due to price risk. In the Appendix we 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 come from changes in prices.As expected, these simulated expenditure shares are higher that the actual expenditure shares, with a mean share of 79% and standard deviation of 12%, but results are otherwise very similar.

## 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. Most biases would probably preclude against finding a negative impact of prices on calories; demand driven price variation for example would likely bias against finding an adverse impact of prices on calories. Nonetheless, we do not interpret our estimates as causal effects but as evidence suggestive of the potential effect of price risk on welfare.

The main outcomes we consider are total household calories and household calories per capita. Summary statistics are contained in Table 6. We regress these outcomes on unit values of rice and wheat, 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 × season fixed effects, and area × season fixed effects.

We find that food prices are negatively associated with all our major caloric outcomes in Table 7. For example, a 10% increase in food prices decreases calories per capita by 0.2% for rice and 0.26% for wheat.

# 5 Empirical evidence on the role of in-kind-transfers

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.

## 5.1 Empirical strategy

As discussed in Section 3.2.3, there was significant aggregate expansion of the PDS over our study period. This section estimates the effect of this increase in the value of the in-kind PDS transfer on i) total calories consumed by households and ii) the extent to which calories vary with market prices, a proxy for households' vulnerability to price risk. We focus on the sale of rice through the PDS.

We quantify the household-level value of the PDS transfer as:

$$v_{igt} = (p^{mt} - p_{gt}^{PDS})q_{igt} \tag{8}$$

for household $i$ in district $g$ in period $t$. $p_{gt}^{PDS}$ is the average unit value at which rice is sold through the PDS in district $g$, $p_m$ is the average all India price in period $t$ and $q_{igt}$ is the amount of PDS rice consumed by household $i$. We therefore consider only variations in the value of the transfer that potentially come from the parameters of the PDS system (quota amounts and PDS price), not changes in market conditions.

In practice however the quota amounts households are able to access and the PDS price at which they buy it may vary for reasons unrelated to policy, including with market conditions (Hari, 2016). We therefore instrument $v_i$ by changes in states' PDS policies. Our first instrument is simply $\widetilde{q}_{gt}^{BPL}$, the PDS price of rice as set by states recorder in the Foodgrain Bulletins. Our second instrument is an indicator $P_{st}$ equal to 1 if household $i$ is in a state $s$ in which a major PDS expansion has occurred prior to year $t$; this allows us to also capture the effect of program expansions that are not necessarily accompanied by decreases in prices. A striking example of the importance of additionally using this variation is in Figure 4, where a reform design to improve targeting and expand coverage increased participation rates from less than 5% to 40% in two years.

Our two regressions of interest are

$$c_{igt} = \delta_1 v_{igt} + \delta X_{igt} + \lambda_s + \tau_t + e_{igt} \tag{9}$$

and

$$c_{igt} = \beta_1 p_{gt} + \beta_2 v_{igt} + \beta_3 p_{gt} \times v_{igt} + X_{igt}\beta + \lambda_s + \tau_t + e_{igt} \tag{10}$$

where $p_{igt}$ is the market price of rice and $v_{igt}$ is instrumented for using our two instruments (we present results obtained using each instrument in turn as a robustness check). We expect that $\delta, \beta_2 > 0$ (PDS expansion increases caloric intake), $\beta_1 < 0$ (demand curves slope down) and $\beta_3 \geq 0$ (the PDS reduces variability of caloric consumption with respect to market prices).

## 5.2 Identification

Identification of Equation 9 is straightforward in a diff-in-diff framework. Identifying the price and price interaction terms ($\beta_1$ and $\beta_3$) in Equation 10 is much more difficult. This is because prices are an equilibrium object, and in particular are increased by unobserved demand shocks that independently increase demand. In other words, $p_{igt}$ and $e_{igt}$ could be positively correlated, biasing estimates of both $\beta_1$ and $\beta_3$. The sign of the biases depends, respectively, on the sign of $\phi_1$ and $\phi_3$ in

$$e_{igt} = \phi_1 p_{gt} + \phi_2 v_{igt} + \phi_3 p_{gt} \times v_{igt} + X_{igt}\phi + \varepsilon_{igt} \tag{11}$$

where $v_{igt}$ and the price interaction are instrumented with PDS price and expansions. Positive correlation between demand shocks and equilibrium prices means that $\phi_1$ is weakly positive (and will be more positive as supply becomes less elastic). The sign of $\phi_3$ is less obvious. Because $v_{igt}$ is instrumented by PDS generosity, the relevant question is whether the equilibrium relationship between demand shocks and prices is stronger or weaker after PDS rollout. If supply is convex, then the lower demand for market rice after rollout implies a weaker relationship between prices and demand shocks. This suggests that $\phi_3$ is negative and $\beta_3$ is biased down, towards zero.

An alternative identification strategy would be to instrument for prices. However, it is difficult to imagine an instrument (or even an RCT) that affects prices but does not affect income.[8] If the increase in income is not fully observed, then the exclusion restriction would be violated — the change in income would independently affect calories consumed. Even more worrying, we show in Appendix Section B that this sort of bias is likely to exaggerate the extent to which the PDS ameliorates price shocks. We therefore use non-instrumented regressions that may result in slightly attenuated estimates.

## 5.3 Results

Panel A of Table 8 contains first stage results. Moving across the columns, we add quarter fixed effects, price controls, and finally demographic controls in column 4, our preferred

[8] The most common examples used in the literature is a rainfall shock, which affects farmer income directly and non-farmer income through wage adjustments in the labor market.

specification. We suppress the market price interactions for clarity. The coefficients for both instruments are significant and have the expected sign. Reducing the government-mandated BPL price by one rupee increases the value of the PDS transfer by one third to one half of a standard deviation, or 17-25 Rs/month. This is in line with entitlements of roughly 20-30 kg/month, allowing for some measurement error and incomplete fulfillment, though it likely also reflects expansions in coverage that took place at the same time as price reductions. The policy instrument is even more powerful. On average, one policy expansion/improvement increases the value of the PDS by 100 Rs/month (average total household expenditure is approximately Rs 2600).

In Panel B, we display the coefficients from a regression of calories on PDS value, instrumenting for PDS value with policy changes. PDS expansion increases calories per capita by approximately 2%. To the extent possible, Column 4 contains controls for permanent income (land and home ownership, cooking and lighting type, and household expenditure). That PDS expansion increases caloric intake conditional on these measures suggests that the direct provision of PDS foodgrains increases calories more than an income transfer of equivalent value.

Finally, we turn to the price interactions in Panel C. If the PDS provides households with insurance against price risk we should see that their caloric intake (a proxy for welfare) should become less sensitive to prices when the PDS is more generous; this is indeed what we see. In our preferred specification, the elasticity of calories per capita with respect to rice prices is high (-0.187). However, an extra SD of PDS value (or 52 Rs/month per household) reduces that sensitivity by 0.085. For high levels of PDS provision (100 Rs/month for example), the elasticity becomes very close to 0 and statistically insignificant.

Our theoretical framework suggests that the welfare effect of in-kind transfers will be smaller for households producing the commodities at home. Table 9 uses whether a household owns land as a proxy for its ability to produce the good at home and considers the effects separately for poor and non-poor, landless and land-owning households. [LG COMMENT: link to theory here could be strengthened but at least now it's mentionned!] In Panel B, the elasticity of calories with respect to PDS value is 4.9% and 2.4% for landless and landowning below-median expenditure households. For above-median expenditure households, the overall effect is very close to zero. This difference is not caused by imprecision resulting from low-powered instruments. The first stage is strong for both above-median expenditure populations and the second-stage coefficients are precisely estimated. Ration cards are relatively easy to obtain even for relatively well-off households that do not qualify for them and not all states target the PDS to poor households so above-median expenditure households do benefit from the PDS policy changes.

In Panel C of Table 9, we show caloric sensitivity to rice prices as a function of PDS generosity for each subgroup. For rich and poor landowners, there is a small and insignificant effect of PDS expansions on sensitivity. For non-landowners of any expenditure level, a more generous PDS significantly decreases caloric elasticity. For poor non-landowners, a one SD increase in PDS generosity from the average reduces the elasticity with respect to rice prices from 0.231 to 0.163; the gap is approximately the same size for rich non-landowners. Consistent with theory, our results suggest that the PDS provides households with protection against price changes only when these households do not have the option of producing the good at home.

In the Online Appendix, we include robustness checks with additional controls for district-sector fixed effects and the full vector of prices. We also consider log calories as the outcome, and using only the policy variable and only the PDS value as instruments. In all cases we find broadly similar results.

# 6 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.

# References

**Allen, Treb.** 2014. "Information frictions in trade." *Econometrica*, 82(6): 2041–2083.

**Atkin, David.** 2013. "Trade, tastes, and nutrition in India." *The American Economic Review*, 103(5): 1629–1663.

**Banerjee, Abhijit, and Esther Duflo.** 2011. *Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty.* PublicAffairs.

**Banerjee, Abhijit, Rema Hanna, Jordan Kyle, Benjamin Olken, and Sudarno Sumarto.** forthcoming. "Tangible Information and Citizen Empowerment: Identification Cards and Food Subsidy Programs in Indonesia." *Journal of Political Economy.*

**Barrett, Christopher B.** 2002. "Food security and food assistance programs." *Handbook of agricultural economics*, 2: 2103–2190.

**Bellemare, Marc F, Christopher B Barrett, and David R Just.** 2013. "The welfare impacts of commodity price volatility: evidence from rural Ethiopia." *American Journal of Agricultural Economics*, 95(4): 877–899.

**Blattman, Chris, Michael Faye, Dean Karlan, Paul Niehaus, and Chris Udry.** 2017. "Cash as Capital."

**Cunha, Jesse M, Giacomo De Giorgi, and Seema Jayachandran.** 2011. "The price effects of cash versus in-kind transfers." National Bureau of Economic Research.

**Deaton, A., and A. Tarozzi.** 2005. "Prices and Poverty in India." *The Great Indian Poverty Debate.* New Delhi:MacMillan.

**Dreze, Jean.** 2011. "The cash mantra." *Indian Express*, 11.

**Fafchamps, Marcel.** 1992. "Cash crop production, food price volatility, and rural market integration in the third world." *American Journal of Agricultural Economics*, 74(1): 90–99.

**Gadenne, Lucie.** 2016. "The Economics of Ration Shop Systems: Theory and an Application to India." Warwick University.

**Gopalan, CRBV, BV Rama Sastri, SC Balasubramanian, et al.** 1980. "Nutrition value of Indian foods."

**Hari, Siddharth.** 2016. "Markets, Subsidies, and Corruption: Evidence from India." New York University.

**Honorati, M, U Gentilini, and RG Yemtsov.** 2015. "The state of social safety nets 2015." *World Bank.*

**Jayachandran, Seema, and Rohini Pande.** forthcoming. "Why Are Indian Children So Short? The Role of Birth Order and Son Preference." *The American Economic Review.*

**Kaul, Tara.** 2014. "Household Responses to Food Subsidies: Evidence from India." *University of Maryland, College Park*.

**Khera, Reetika.** 2011. "Trends in diversion of grain from the public distribution system." *Economic and Political Weekly*, 106–114.

**Kochar, Anjini.** 2005. "Can targeted food programs improve nutrition? An empirical analysis of India's public distribution system." *Economic development and cultural change*, 54(1): 203–235.

**Nagavarapu, Sriniketh, and Sheetal Sekhri.** 2016. "Informal monitoring and enforcement mechanisms in public service delivery: Evidence from the public distribution system in India." *Journal of Development Economics*, 121: 63–78.

**Nichols, Albert L, and Richard J Zeckhauser.** 1982. "Targeting transfers through restrictions on recipients." *The American Economic Review*, 72(2): 372–377.

**Rashid, Shahidur.** 2009. *Food price stabilization policies in a globalizing world.* Cornell University Press.

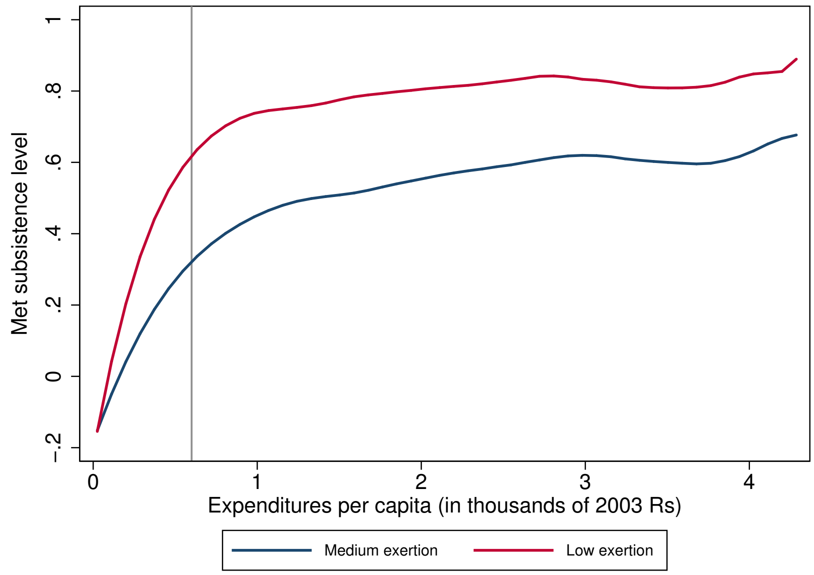
**Rosenzweig, Mark R, and Christopher Udry.** 2014. "Rainfall forecasts, weather, and wages over the agricultural production cycle." *The American Economic Review*, 104(5): 278–283.

**Tarozzi, Alessandro.** 2005. "The Indian Public Distribution System as provider of food security: Evidence from child nutrition in Andhra Pradesh." *European Economic Review*, 49(5): 1305–1330.

**Turnovsky, Stephen J, Haim Shalit, and Andrew Schmitz.** 1980. "Consumer's surplus, price instability, and consumer welfare." *Econometrica: Journal of the Econometric Society*, 135–152.

**Waugh, Frederick V.** 1944. "Does the consumer benefit from price instability?" *The Quarterly Journal of Economics*, 58(4): 602–614.

Figure 1: 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 2: Share consuming PDS good over time and value conditional on consumption

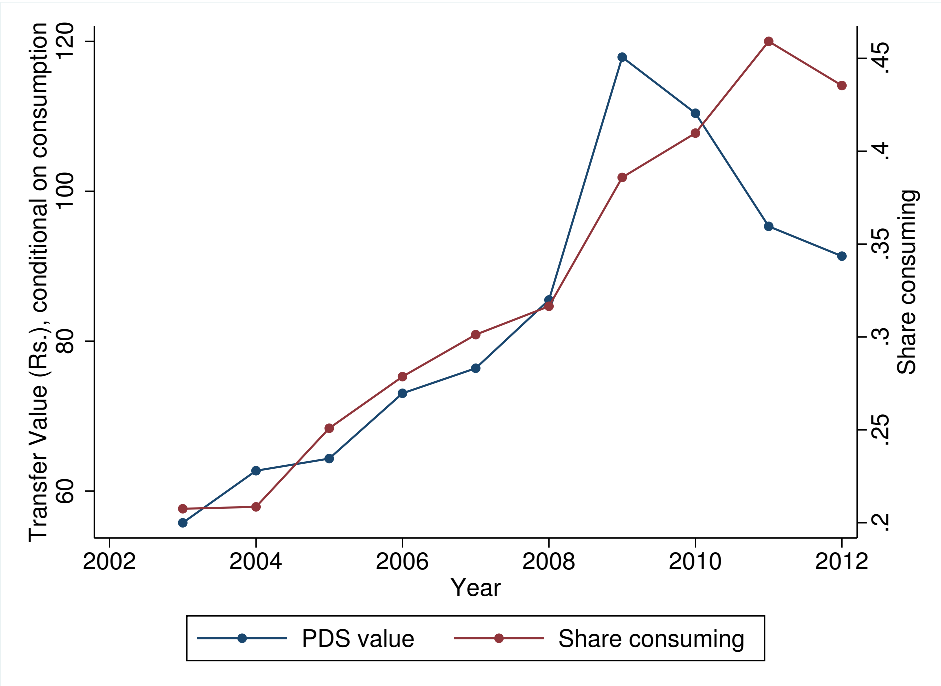


Figure 3: Andhra Pradesh PDS rice prices: 2−month trailing avgs

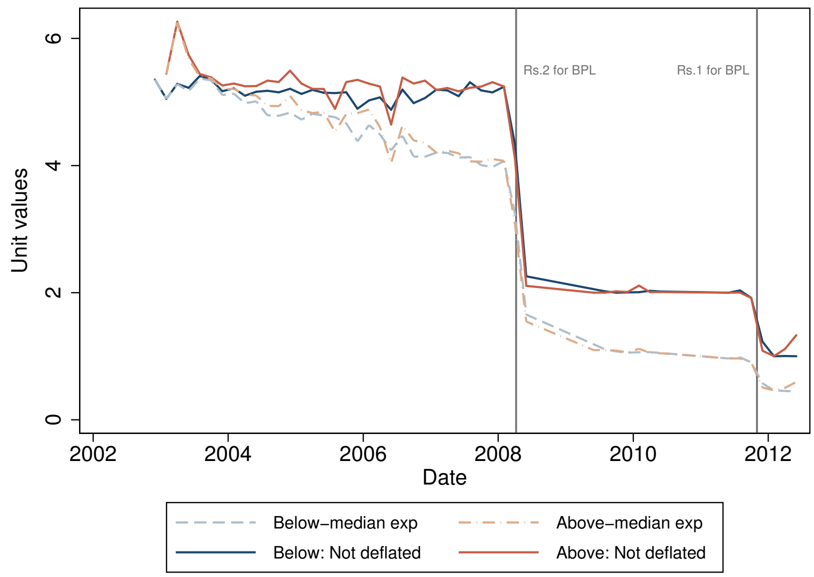


Figure 4: Share of households consuming PDS rice, Bihar

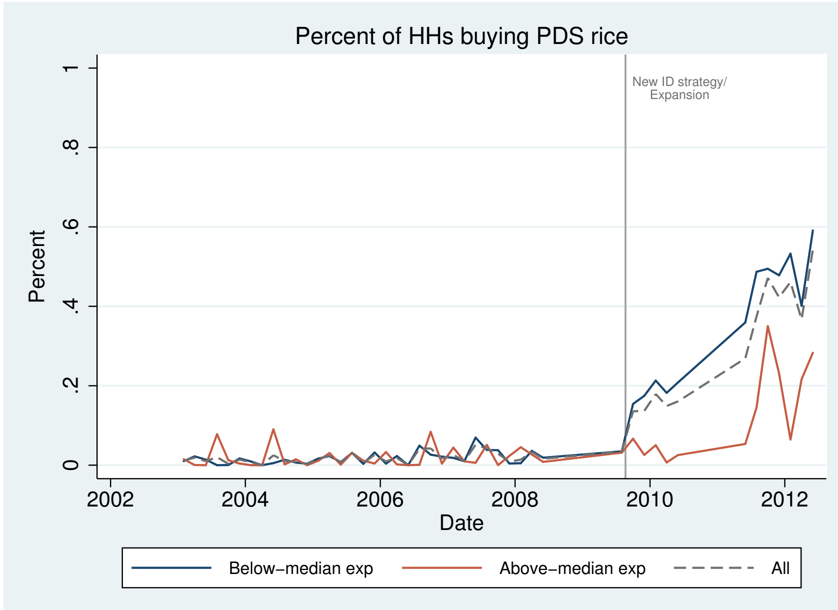


Table 1: Selected PDS Policy Changes

| 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 |

Table 2: Summary Statistics: Market Price of Rice

| | *Market rice unit values* | | | |
|---|---|---|---|---|
| | 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 3: Summary Statistics: Market Price of Wheat

| | *Market wheat unit values* | | | |
|---|---|---|---|---|
| | 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 4: Price changes as a percent of budget, year on year

| | | *Within district-period* | | |
|---|---|---|---|---|
| | Mean change | S.D. | 5% | 95% |
| Overall | 0.1398 | 0.1151 | -0.1442 | 0.1039 |
| Rural | 0.1726 | 0.1131 | -0.1302 | 0.1039 |
| Urban | 0.0474 | 0.1203 | -0.1712 | 0.1038 |
| Below 25% income | 0.1795 | 0.1153 | -0.1338 | 0.1248 |
| Above 25% income | 0.1264 | 0.1149 | -0.1471 | 0.0971 |
| Below median income | 0.1763 | 0.1142 | -0.1305 | 0.1090 |
| Above median income | 0.1025 | 0.1159 | -0.1576 | 0.0985 |
| Agricultural HH | 0.1980 | 0.1127 | -0.1272 | 0.0999 |
| Non-agricultural HH | 0.0847 | 0.1173 | -0.1581 | 0.1071 |

The first column calculates mean prices changes, $\Delta X_{hjt} = \frac{1}{n_j}\sum_{h\in j}\left\{\frac{p_{jt}q_{ht-1}-p_{jt-1}q_{ht-1}}{p_{jt-1}q_{ht-1}}\right\}$. The next three columns show summary statistics for the distribution of year-on-year price changes for households' baseline consumption bundle subtracting out district-sector mean changes, $\widetilde{\Delta X_{hjt}} = \frac{p_{jt}q_{ht-1}-p_{jt-1}q_{ht-1}}{p_{jt-1}q_{ht-1}} - \frac{1}{n_j}\sum_{h\in j}\left\{\frac{p_{jt}q_{ht-1}-p_{jt-1}q_{ht-1}}{p_{jt-1}q_{ht-1}}\right\}$.

Table 5: Food and Fuel Real Expenditure Shares

| | *Food & fuel* | | | |
|---|---|---|---|---|
| | 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 6: Summary Statistics: Caloric Consumption

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

*Notes:* The observation is the household.

Table 7: Effect of Market Prices on Caloric Consumption

| | *Log calories* | | | | *Log calories per capita* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Market rice log UVs | -0.093*** | -0.035*** | -0.035*** | -0.037*** | 0.011 | -0.023** | -0.023* | -0.021* |
| | [0.018] | [0.013] | [0.013] | [0.013] | [0.012] | [0.012] | [0.012] | [0.012] |
| Market wheat log UVs | -0.112*** | -0.041*** | -0.040*** | -0.038*** | -0.008 | -0.029*** | -0.029*** | -0.026*** |
| | [0.014] | [0.010] | [0.010] | [0.010] | [0.010] | [0.009] | [0.009] | [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 × quarter FEs | No | No | Yes | No | No | No | Yes | No |
| District-sector × 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 PDS program expansion on log calories per capita

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Panel A: First stage (dependent variable = SD of PDS value)* | | | | |
| BPL price | -0.523*** | -0.474*** | -0.465*** | -0.352*** |
| | (0.093) | (0.096) | (0.097) | (0.087) |
| Policy (=1) | 2.008*** | 1.835*** | 1.894*** | 2.067*** |
| | (0.325) | (0.332) | (0.338) | (0.290) |
| *Panel B: IV (dependent variable = log calories per capita)* | | | | |
| PDS value (SD) | 0.029*** | 0.019*** | 0.020** | 0.019*** |
| | (0.005) | (0.008) | (0.008) | (0.006) |
| Cragg-Donald F-stat | 165.25 | 167.42 | 165.90 | 167.77 |
| *Panel C: IV (dependent variable = log calories per capita)* | | | | |
| Market rice price, logged | 0.079*** | 0.076*** | 0.096*** | -0.187*** |
| | (0.014) | (0.014) | (0.016) | (0.015) |
| Market rice price X PDS value (SD) | 0.088*** | 0.087*** | 0.106*** | 0.081*** |
| | (0.019) | (0.019) | (0.020) | (0.018) |
| Cragg-Donald F-stat | 165.70 | 176.34 | 177.08 | 178.09 |
| Price controls | No | Yes | Yes | Yes |
| Quarter FE | No | No | Yes | Yes |
| Demographic controls | No | No | No | Yes |
| Observations | 524079 | 524079 | 524079 | 524079 |

One SD of PDS value is 52, compared to per-capita income of 712. PDS value for household $j$ is defined as $(p_m - p_{j,PDS})q_j$, where $p_m$ is the all-sample mean market price. All specifications include state fixed effects and rice price controls. Price control is Laspeyres index, and demographic controls are household size, SC/ST, home and land ownership, cooking/lighting fuel, urban dummy, and log per-capita income. Standard errors in parentheses and clustered at the district-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effect of PDS program expansion on log calories per capita

| | Below-median exp | | Above-median exp | |
|---|---|---|---|---|
| | Landless (1) | Landowner (2) | Landless (3) | Landowner (4) |
| *Panel A: First stage (dependent variable = SD of PDS value)* | | | | |
| BPL price | -0.123 | -0.218 | -0.231*** | -0.098 |
| | (0.111) | (0.160) | (0.079) | (0.104) |
| Policy | 0.763** | 1.620*** | 1.243*** | 0.909** |
| | (0.313) | (0.559) | (0.300) | (0.405) |
| *Panel B: IV (dependent variable = log calories per capita)* | | | | |
| PDS value (SD) | 0.049*** | 0.024*** | -0.001 | 0.008 |
| | (0.014) | (0.006) | (0.011) | (0.013) |
| Cragg-Donald F-stat | 196.83 | 70.56 | 118.20 | 82.40 |
| *Panel C: IV (dependent variable = log calories per capita)* | | | | |
| Market rice price, logged | -0.231*** | -0.158*** | -0.190*** | -0.128*** |
| | (0.029) | (0.018) | (0.017) | (0.015) |
| Market rice price X PDS value (SD) | 0.068*** | 0.014 | 0.085*** | 0.011 |
| | (0.016) | (0.014) | (0.024) | (0.024) |
| Price controls | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes |
| Cragg-Donald F-stat | 182.31 | 65.97 | 118.47 | 82.15 |
| Observations | 115481 | 91893 | 196422 | 120283 |

One SD of PDS value is 52 compared to per-capita income of 712. PDS value for household $j$ is defined as $(p_m - p_{j,PDS})q_j$, where $p_m$ is the all-sample mean market price. All specifications include state fixed effects and rice price controls. Price control is Laspeyres index, and demographic controls are household size, SC/ST, home ownership, cooking/lighting fuel, urban dummy, and log per-capita income. Standard errors in parentheses and clustered at the district-sector level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# A Theory Appendix

In this section we calculate the value of price stabilization, another commonly-considered method of insuring households against price risk, and finding that the welfare effect of price stabilization is ambiguous. This is by no means original - Turnovsky, Shalit and Schmitz (1980) model the welfare impact of price stabilization - but we reproduce the key result to demonstrate the similarities between our models.

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 $\sigma_p$ 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:

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

Taking expectations over all values of $p$ we find:

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

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:

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

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

$$m_i = \frac{1}{2} \alpha \left[ \varepsilon_i - \alpha_i [R_i - \eta_i] \right] \sigma_p^2 \tag{4}$$

where $\alpha$ is the budget share of the good, $\varepsilon$ the (absolute value of the) price elasticity of demand, $\eta$ the income elasticity of demand, $R$ the coefficient of relative risk aversion and $\sigma_p$ 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

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

where $\varepsilon_{12}$ is the (absolute value) of the cross-price elasticity, $\rho_{12}$ is the correlation in prices for goods 1 and 2, and the budget shares $\alpha$, price elasticities $\varepsilon$ and income elasticities $\eta$ 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.

# B Bias of PDS Effects From Income Shocks

As discussed in Section 5.2, the presence of correlated demand shocks for food commodities at the district-sector level will bias our price elasticities towards zero. Estimates of the ameliorating effect of the PDS will also be biased towards zero. An alternative approach would be to find instruments that affect prices through the supply side rather than the demand side. The problem with this approach is that it is difficult to imagine instruments (or even an RCT) that satisfies the exclusion condition. More concretely, supply shocks are likely to have income effects on households, independently affecting caloric consumption. Suppose that calories were related to PDS value $v_{igt}$ and income $y_{igt}$

$$c_{igt} = \beta_1 p_{gt} + \beta_2 v_{igt} + \beta_3 p_{gt} \times v_{igt} + \beta_4 y_{igt} + \beta_5 p_{gt} \times y_{igt} + X_{igt}\beta + \lambda_s + \tau_t + e_{igt} \quad (6)$$

but the regression was estimated without including income $y_{igt}$ and the price-income interaction $p_{gt} \times y_{igt}$, and instrumenting for PDS value with PDS program changes. Alternatively, the same logic holds if analogs of these controls (e.g., household expenditure) are included, but do not fully reflect the income change resulting from the supply shock. This would be true if, for example, there was saving or dissaving.

The bias of $\widehat{\beta}_3$ is equal to $\beta_4 \times \alpha_3 + \beta_5 \times \alpha_6$, where

$$y_{it} = \alpha_1 p_{gt} + \alpha_2 v_{igt} + \alpha_3 p_{gt} \times v_{igt} + X_{igt}\widetilde{\alpha} + \widetilde{\lambda}_s + \widetilde{\tau}_t + \varepsilon_{igt} \quad (7)$$

$$p_{it} \times y_{it} = \alpha_4 p_{gt} + \alpha_5 v_{igt} + \alpha_6 p_{gt} \times v_{igt} + X_{igt}\widetilde{\widetilde{\alpha}} + \widetilde{\widetilde{\lambda}}_s + \widetilde{\widetilde{\tau}}_t + u_{igt} \quad (8)$$

where $v_{igt}$ and $p_{gt} \times v_{igt}$ are instrumented with PDS program changes at the state-district-time level. Demand theory predicts that $\beta_4, \beta_5 > 0$. Because the instrument for $v_{igt}$ is over time, higher levels of program expenditure are associated with higher levels of income. This implies that $\alpha_6 > 0$. The sign of $\alpha_3$ is ambiguous but likely smaller in magnitude than $\alpha_6$, which reflects the direct relationship ($p_{it} \times y_{it}$ on $p_{gt} \times v_{igt}$) rather than the indirect ($y_{it}$ on

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

$p_{gt} \times v_{igt}$). There remains some ambiguity, but on balance this means that $\widehat{\beta}_3$ is likely biased up, or away from zero.

# C Additional Notes on Data

## C.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 A1: 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.

## C.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.

# D Robustness checks

## D.1 Evidence on price risk

Table A2 presents results regarding the simulated expenditure shares, assuming households do not adjust their consumption in response to change in prices. To construct these simulated shares we 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 ($\bar{q}_{k,i,t}$). 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.The simulated expenditure shares are thus:

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

As before, we are interested in expenditure shares on a set of commodities $K$:

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

Table A2: Food and Fuel Simulated Expenditure Shares

| | *Food & fuel* | | | |
|---|---|---|---|---|
| | 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.

## D.2 Evidence on impact of the PDS

We include five robustness checks of Table 9:

1. District-sector FEs rather than state FEs. All policy variation is at the state-quarter level, so additionally controlling for state-quarters does not affect the main results.

2. The full vector of prices rather than a price index to control for prices. We have information on prices for 123 consumption goods across India, but not all those goods are consumed in each district-period. This is a problem because it means that we have no estimate of the price for that good (recall that prices are constructed from unit values). An imperfect solution is to include both the log price and a dummy for missing price.

The Table is relatively similar, although above-median expenditure landless households no longer receive insurance value from PDS expansions.

3. Log calories instead of log calories per capita as the outcome variable. Since we include a control for household size in our main results, the differences are slight.

4. Using only the policy variable (and its interaction with market price) as an instrument, rather than policy and government-mandated PDS value and their interactions.

5. Using only government-mandated PDS value (and its interaction with market price) as an instrument, rather than policy and PDS value and their interactions.

Tables A3-A7 contain the results.

Table A3: Effect of PDS program expansion on log calories per capita, with district-sector fixed effects

| | Below-median exp | | Above-median exp | |
|---|---|---|---|---|
| | Landless (1) | Landowner (2) | Landless (3) | Landowner (4) |
| *Panel A: IV (dependent variable = log calories per capita)* | | | | |
| PDS value (SD) | 0.047*** | 0.026*** | 0.021* | 0.009 |
| | (0.013) | (0.005) | (0.011) | (0.013) |
| Cragg-Donald F-stat | 192.72 | 69.16 | 121.57 | 82.81 |
| *Panel B: IV (dependent variable = log calories per capita)* | | | | |
| Market rice price, logged | -0.148*** | -0.114*** | -0.051*** | -0.067*** |
| | (0.032) | (0.018) | (0.015) | (0.017) |
| Market rice price X PDS value (SD) | 0.035** | 0.010 | 0.085*** | 0.014 |
| | (0.015) | (0.015) | (0.020) | (0.026) |
| Price controls | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes |
| Cragg-Donald F-stat | 179.03 | 65.08 | 123.05 | 77.73 |
| Observations | 115477 | 91841 | 196422 | 120282 |

One SD of PDS value is 52, compared to per-capita income of 712. PDS value for household $j$ is defined as $(p_m - p_{j,PDS})q_j$, where $p_m$ is the all-sample mean market price. All specifications include district-sector fixed effects and rice price controls. Price control is Laspeyres index, and demographic controls are household size, SC/ST, home ownership, cooking/lighting fuel, urban dummy, and log per-capita income. Standard errors in parentheses and clustered at the district-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Effect of PDS program expansion on log calories per capita, with full vector of price controls

| | Below-median exp | | Above-median exp | |
|---|---|---|---|---|
| | Landless (1) | Landowner (2) | Landless (3) | Landowner (4) |
| *Panel A: IV (dependent variable = log calories per capita)* | | | | |
| PDS value (SD) | 0.040*** | 0.028*** | -0.019 | 0.006 |
| | (0.013) | (0.006) | (0.013) | (0.016) |
| Cragg-Donald F-stat | 212.92 | 78.64 | 138.15 | 82.88 |
| *Panel B: IV (dependent variable = log calories per capita)* | | | | |
| Market rice price, logged | -0.100*** | -0.083*** | -0.068*** | -0.064*** |
| | (0.029) | (0.015) | (0.015) | (0.018) |
| Market rice price X PDS value (SD) | 0.038** | 0.004 | 0.027 | -0.040 |
| | (0.018) | (0.015) | (0.022) | (0.026) |
| Price controls | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes |
| Cragg-Donald F-stat | 204.09 | 78.72 | 138.65 | 84.14 |
| Observations | 115481 | 91893 | 196422 | 120283 |

One SD of PDS value is 52, compared to per-capita income of 712. PDS value for household $j$ is defined as $(p_m - p_{j,PDS})q_j$, where $p_m$ is the all-sample mean market price. All specifications include state fixed effects and rice price controls. Price control is Laspeyres index, and demographic controls are household size, SC/ST, home ownership, cooking/lighting fuel, urban dummy, and log per-capita income. Standard errors in parentheses and clustered at the district-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Effect of PDS program expansion on log calories

| | Below-median exp | | Above-median exp | |
|---|---|---|---|---|
| | Landless (1) | Landowner (2) | Landless (3) | Landowner (4) |
| *Panel A: IV (dependent variable = log calories per capita)* | | | | |
| PDS value (SD) | 0.037** | 0.020*** | -0.019 | 0.003 |
| | (0.015) | (0.006) | (0.012) | (0.016) |
| Cragg-Donald F-stat | 196.83 | 70.56 | 118.20 | 82.40 |
| *Panel B: IV (dependent variable = log calories per capita)* | | | | |
| Market rice price, logged | -0.251*** | -0.112*** | -0.153*** | -0.076*** |
| | (0.032) | (0.019) | (0.022) | (0.021) |
| Market rice price X PDS value (SD) | 0.073*** | -0.003 | 0.070*** | -0.010 |
| | (0.017) | (0.015) | (0.026) | (0.032) |
| Price controls | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes |
| Cragg-Donald F-stat | 182.31 | 65.97 | 118.47 | 82.15 |
| Observations | 115481 | 91893 | 196422 | 120283 |

One SD of PDS value is 52, compared to per-capita income of 712. PDS value for household $j$ is defined as $(p_m - p_{j,PDS})q_j$, where $p_m$ is the all-sample mean market price. All specifications include state fixed effects and rice price controls. Price control is Laspeyres index, and demographic controls are household size, SC/ST, home ownership, cooking/lighting fuel, urban dummy, and log per-capita income. Standard errors in parentheses and clustered at the district-sector level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A6: Effect of PDS program expansion on log calories per capita, policy instrument only

| | Below-median exp | | Above-median exp | |
|---|---|---|---|---|
| | Landless | Landowner | Landless | Landowner |
| | (1) | (2) | (3) | (4) |
| *Panel A: IV (dependent variable = log calories per capita)* | | | | |
| PDS value (SD) | 0.045*** | 0.021*** | 0.003 | 0.007 |
| | (0.014) | (0.006) | (0.011) | (0.013) |
| Cragg-Donald F-stat | 178.37 | 55.26 | 111.16 | 78.98 |
| *Panel B: IV (dependent variable = log calories per capita)* | | | | |
| Market rice price, logged | -0.234*** | -0.159*** | -0.187*** | -0.125*** |
| | (0.030) | (0.018) | (0.016) | (0.015) |
| Market rice price X PDS value (SD) | 0.076*** | 0.022 | 0.083*** | 0.018 |
| | (0.017) | (0.014) | (0.024) | (0.024) |
| Price controls | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes |
| Cragg-Donald F-stat | 172.01 | 54.20 | 109.05 | 78.67 |
| Observations | 116443 | 92828 | 199675 | 123782 |

One SD of PDS value is 52, compared to per-capita income of 712. PDS value for household $j$ is defined as $(p_m - p_{j,PDS})q_j$, where $p_m$ is the all-sample mean market price. All specifications include state fixed effects and rice price controls. Price control is Laspeyres index, and demographic controls are household size, SC/ST, home ownership, cooking/lighting fuel, urban dummy, and log per-capita income. Standard errors in parentheses and clustered at the district-sector level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A7: Effect of PDS program expansion on log calories per capita, PDS value instrument only

| | Below-median exp | | Above-median exp | |
|---|---|---|---|---|
| | Landless (1) | Landowner (2) | Landless (3) | Landowner (4) |
| *Panel A: IV (dependent variable = log calories per capita)* | | | | |
| PDS value (SD) | 0.060*** | 0.030*** | -0.039** | 0.010 |
| | (0.020) | (0.007) | (0.017) | (0.018) |
| Cragg-Donald F-stat | 112.85 | 69.66 | 95.16 | 64.61 |
| *Panel B: IV (dependent variable = log calories per capita)* | | | | |
| Market rice price, logged | -0.219*** | -0.156*** | -0.199*** | -0.134*** |
| | (0.028) | (0.018) | (0.018) | (0.016) |
| Market rice price X PDS value (SD) | 0.044** | -0.003 | 0.083*** | -0.015 |
| | (0.019) | (0.018) | (0.031) | (0.030) |
| Price controls | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes |
| Cragg-Donald F-stat | 97.11 | 66.62 | 90.91 | 63.97 |
| Observations | 115481 | 91893 | 196422 | 120283 |

One SD of PDS value is 52, compared to per-capita income of 712. PDS value for household $j$ is defined as $(p_m - p_{j,PDS})q_j$, where $p_m$ is the all-sample mean market price. All specifications include state fixed effects and rice price controls. Price control is Laspeyres index, and demographic controls are household size, SC/ST, home ownership, cooking/lighting fuel, urban dummy, and log per-capita income. Standard errors in parentheses and clustered at the district-sector level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.