In-Kind Transfers as Insurance*

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Abstract

Recent debates about the optimal form of social protection programs have highlighted the potential for cash as a 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 commodity price risk. Many households face substantial price variation as a result of poorly integrated markets. We develop a model showing that in a world with price risk, in-kind transfers are welfare improving relative to cash if the covariance between marginal utility of income and price is positive. Using calorie shortfalls as a marginal utility proxy, we find that in-kind food transfers are empirically welfare improving relative to cash for Indian households, an effect driven entirely by poor households. We further show that policies that expand the generosity of the Public Distribution System (PDS)—India's in-kind food transfer program—are associated with increased caloric intake as well as reduced sensitivity of calories to prices, suggesting that the PDS does indeed provide insurance against food price risk.

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

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1 Introduction

A central question in the design of social protection programs is what form transfers to the poor should take. Historically, in-kind transfers have been the primary form of anti-poverty program and these transfers remain prevalent and important: approximately 44% of individuals on social safety net programs around the world receive in-kind transfers (Honorati, Gentilini and Yemtsov, 2015), and over 90% of low-income countries have social protection programs that include in-kind transfers (World Bank, 2014). In recent years, however, there has been a dramatic shift among academics and policymakers toward unconditional cash as the preferred form of transfer, spurred by the success of GiveDirectly in East Africa (Haushofer and Shapiro, 2016) and growing interest in Universal Basic Income programs worldwide (Banerjee, Niehaus and Suri, 2019).

The textbook rationale for cash transfers is that beneficiaries (weakly) prefer cash to in-kind. Justifications for in-kind transfers therefore rely on transfers meeting a social objective, such as pecuniary redistribution (Coate, Johnson and Zeckhauser, 1994) or targeting (Nichols and Zeckhauser, 1982), or on the belief that beneficiaries are maximizing the "wrong" utility function (either due to intra-household conflicts or simply a paternalistic view (Currie and Gahvari, 2008)). However, beneficiaries themselves often report a preference for in-kind to cash in survey contexts as varied as Ecuador, India, and Malawi (Hidrobo et al., 2014; Khera, 2014; Gentilini, 2016).

We demonstrate that in-kind transfers can be preferable to cash in the presence of commodity price risk. A common feature of many developing countries is lack of market integration (Atkin, 2013; Allen, 2014), implying that households may be subject to substantial variation in prices of basic consumption goods. In-kind transfers can provide implicit insurance against this risk since the value of the transfer rises automatically with the local market price of the transferred good. We derive a condition under which households prefer in-kind transfers, provide an empirical test of whether this condition applies in the context of India, and examine the effects of a large scale in-kind transfer program.

We begin with a simple model to demonstrate that the optimal policy will provide price-indexed cash transfers that equalize marginal utility of income across price states. The optimal policy does not imply smooth consumption: absent storage technology, households face a trade-off between the desire to consumption smooth and substitution toward cheaper consumption in low price states. Optimal transfers may therefore theoretically increase or decrease with respect to price.[1]

In practice, price-indexed transfers are often infeasible because local prices are difficult

[1] This results parallels prior work on welfare effects of price variability (Waugh, 1944) and price stabilization (Turnovsky, Shalit and Schmitz, 1980).

for governments to observe at high frequency. We therefore consider the choice between two commonly used second best alternatives: price-invariant cash transfers and in-kind transfers. We show that inframarginal in-kind and cash transfers with the same expected value have different effects on household welfare when prices vary. Note that we focus on the welfare effects to the beneficiary household; a full welfare analysis would require the social cost of provision. Households will prefer in-kind transfers as long as the high marginal utility states are also the high price states. Intuitively, in this case, in-kind transfers better approximate the optimal policy. Specifically, we show that households prefer in-kind to cash as long as a simple condition holds: the covariance between the marginal utility of income and price is positive.

Critically, an empirical test of this relationship does *not* rely on exogenous variation in prices: the condition holds regardless of whether there are income or other changes correlated with the change in price. The condition also takes into account the possibility of home production. If, for example, prices rise due to a positive local demand shock, producers of the good may have high income (and therefore low marginal utility) in the high price states of the world, making in-kind transfers relatively less attractive.[2]

A challenge when implementing this test is to find an appropriate empirical proxy for the marginal utility of income. Note that total (real) consumption is not an appropriate proxy in this case because households will not optimally smooth total consumption. Our primary measure is an indicator for falling below minimum calorie requirements. The assumption underlying this test is that the marginal utility of income rises when households fall below minimum requirements. We also examine calories per capita as an inverse proxy for marginal utility of income. A vast literature has documented the negative consequences of calorie shortfalls, demonstrating long-run effects of even short-term episodes. Undernutrition has been shown to worsen health, human capital accumulation, and earnings.[3] Calories have low substitutability across periods and are likely to have low substitutability with other types of (non-food) consumption goods. In addition, many governments care about nutrition and food security as a policy goal and as a motivation for in-kind transfers. Calories are therefore also an important outcome for the evaluation of in-kind transfer programs per se, not just relative to a cash counterfactual.

We examine in-kind transfers in the context of India, using data from over 500,000 observations in the National Sample Survey (NSS) across 28 states and ten years (2003-12).

[2]Conceptually, the parameter we are estimating is distinct from a direct causal effect of prices. Instrumenting for local prices with, for example global commodity prices or rainfall, is therefore not appropriate in this case, even if an instrument were to satisfy the exclusion restriction.

[3]For a summary of the medical literature see Victora et al. (2008); for literature in economics see Currie and Almond (2011).

India provides an attractive context to examine these issues: local markets are not well-integrated (Atkin, 2013) and are subject to substantial price volatility, for example from weather shocks (Rosenzweig and Udry, 2014). The average Indian household is exposed to substantial risk from food price fluctuations, as it spends 52% of its budget on food, with 9% spent on rice—the most commonly consumed food staple and the focus of our analysis—alone. To construct our outcome measure, we use an indicator for meeting minimum calorie requirements (MCR) put forth by the Indian Council on Medical Research (ICMR) as well as calories per capita as (inverse) proxies for the marginal utility of income.[4] A significant proportion of households in our sample—39.5%—fall short of minimum recommended calorie intake guidelines. In addition, 48% of children under the age of 5 were stunted, and 43% underweight according to the National Family Health Survey 2005-06 (National Family Healthy Survey, 2007).

We find that increases in price of rice are significantly negatively associated with caloric intake: a 10% increase in market price is associated with 1.1 percentage point fewer households (equivalent to 13 million individuals nationwide) meeting the MCR and a 0.7% decline in calories consumed by the average household. These results are robust to controlling for district-sector-season fixed effects, year-quarter and NSS round fixed effects, as well as various household controls. The results are entirely driven by households below median socio-economic status (SES)[5] and those living in rural areas. Rich households and those living in urban areas demonstrate no response to caloric intake in the face of rice price fluctuations, despite facing similar underlying variation in prices as poor and rural households. This is unlikely to be due to calorie satiation: in the cross-section, calories increase with respect to expenditure throughout the expenditure distribution. These results imply that in-kind transfers will result in higher expected utility for households than equal expected value cash transfers, particularly for the lower income households generally targeted by safety net programs.

In theory, therefore, a program that transfers foodgrains has the potential to benefit households in India. Indeed, India boasts one of the largest in-kind transfer programs in the world: the Public Distribution System (PDS) provides food transfers to up to 180 million eligible households (Balani, 2013). The program provides (primarily) rice and wheat every month at substantially below-market prices —set by states and periodically revised—through a network of over 500,000 specially designated shops. Previous analyses of the PDS's impact have focused on the levels of calories or other outcomes, not on the sensitivity of these

[4]We use MCR as shorthand for the ICMR's caloric guideline for the "sedentary" (lowest) level of exertion, separately by age and gender.

[5]We calculate SES as the predicted value from a regression of log expenditure per capita on permanent household characteristics such as demographics, education, land type, and housing characteristics.

outcomes to prices (Tarozzi, 2005; Kaul, 2014). Moreover, even evidence on the level impacts has been mixed, given widespread corruption in implementation (Nagavarapu and Sekhri, 2016; Niehaus et al., 2013). We examine the causal effects of the PDS on caloric intake and the price-calorie relationship, using newly collected administrative data on state-level PDS policy changes between 2003-12. We use this variation in the mandated PDS price as well as expansions in eligibility to instrument for actual value of the subsidy received ("PDS value")[6] reported by households (first stage F=37).

Increases in PDS value significantly increase the proportion of households meeting the MCR, and also increase log calories consumed per household. A Rs. 100 increase in PDS value (approximately the same size as the average non-zero PDS value of Rs. 109) leads to a 10.7 percentage point increase in households meeting the MCR and a 6.4% increase in calories per capita. As expected, these results are larger in magnitude for households that are below median SES as well as rural households. Overall, we estimate that PDS expansions led to 36 million additional individuals meeting MCR thresholds in the five year period post expansion. Meanwhile, pre-trends in our outcome variables are flat, and our results are robust to controlling for political cycles and generosity of the National Rural Employment Guarantee Scheme, India's other major anti-poverty program. While it is possible that increases in PDS value increases calories consumed because of its effect on market prices, we show that the impact of PDS value increases on market prices is too small—by at least two orders of magnitude—to explain our results.

Finally, we turn to the impact of the PDS on the sensitivity of calories to market prices. An increase in PDS generosity from zero to the average transfer reduces the sensitivity of calories to market prices by 22% for the average household; if the transfer value of the PDS were increased to Rs. 135, one third larger than the average non-zero transfer, this would reduce average price sensitivity to zero. This impact is seen for both above and below median households, and those living in urban and rural areas.

The results are consistent with the PDS providing insurance against food price risk. To be sure, insurance is only one aspect of the tradeoff between cash and in-kind transfers. Moreover, we do not explicitly consider the costs of procurement or relative costs of administering the PDS versus cash transfers. Nonetheless, our model formalizes, and our empirical results confirm, one of the policy community's long-held rationales for in-kind transfers (Kotwal, Murugkar and Ramaswami, 2011).[7]

This paper contributes to several literatures. First, understanding the potential insur-

[6]We define PDS value as the quantity of rice obtained from the PDS times the difference between the market price of rice and the PDS price paid by beneficiaries.

[7]For example, Dreze (2011) lists the fact that in-kind transfers are "inflation-proof" as the very first out of five advantages that they have over cash transfers.

ance value of in-kind transfers is important for the larger ongoing debate around the world regarding the appropriate design of social protection programs. Recent studies have highlighted the potential benefits of unconditional cash transfers (Haushofer and Shapiro, 2016; Banerjee, Niehaus and Suri, 2019), with a review of evaluations of cash transfers noting 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). The academic literature has proposed other potential rationales for in-kind transfers: they can potentially improve targeting to the poor (Nichols and Zeckhauser, 1982; Besley and Coate, 1991; Lieber and Lockwood, 2019), may improve well-being of non-targeted households by reducing market prices of transferred commodities (Coate, Johnson and Zeckhauser, 1994; Cunha, De Giorgi and Jayachandran, 2018), and may improve the efficiency of imperfectly competitive food markets under some conditions (Coate, 1989). However, the literature has mostly ignored the insurance rationale; the influential and comprehensive Currie and Gahvari (2008) review of cash versus in-kind transfers does not even mention it, and papers that empirically test the impact of different transfer modalities (Hidrobo et al., 2014) generally do not focus on mechanisms. One exception is Gadenne (2020) who models the PDS as a non-linear commodity tax system in which two potential advantages (relative to a linear commodity tax) are redistribution and insurance.

Second, we speak to a long literature on household exposure to price variability and its consequences. However, this literature has generally assessed the welfare effects of price risk relative to price stabilization (Waugh, 1944; Turnovsky, Shalit and Schmitz, 1980; Bellemare, Barrett and Just, 2013). While stabilization policies and dual pricing policies are still used, many critics have argued that they are both expensive and ineffective (Rashid, 2009; Bellemare, Barrett and Just, 2013). Moreover Bellemare and Lee (2016), in reviewing the theoretical and empirical literature on price risk, note that "there are only a handful of empirical studies on the topic." To the best of our knowledge, previous studies have not considered the possibility of insuring against rather than attempting to reduce price variability.

A related literature examines the specific issue of price shocks and food security.[8] Numerous papers show that positive food price shocks lead to worse nutrition (for example Brinkman et al. (2010) and the various World Food Programme studies cited therein). However, a significant number of careful analyses also find non-existent or positive relationships

[8]Barrett (2002) reviews the literature on food security in general, emphasizing the importance of risk as an important component of food security but noting that "most of the literature nevertheless fails to address issues of risk and uncertainty." An older literature has considered how producer choices may be distorted by food price risk and poorly integrated markets (Fafchamps, 1992; Saha and Stroud, 1994; Barrett, 1996).

(Jensen and Miller, 2008; Behrman, Deolalikar and Wolfe, 1988). Our study complements this literature by demonstrating the implications of this empirical relationship for the design of optimal social protection programs.[9]

Finally, we provide new evidence on the effects of the PDS, which is an important program in and of itself: it is India's flagship food security scheme, and directly affects three-quarters of a billion people. The program has been criticized for corruption and mistargeting (Niehaus et al., 2013; Dreze and Khera, 2015), but there is surprisingly little rigorous evidence of causal effects. What exists finds mixed evidence on the effects of the PDS on calories and nutritional status: Kochar (2005) and Tarozzi (2005) find little to no impact of policy changes, while Kaul (2014) finds a substantial impact of the value of the subsidy on calories consumed. Our results—finding that the PDS does improve nutrition by allowing households to reach minimum caloric requirements—suggest that the time period of study might be important (our paper and Kaul (2014) study later expansions as compared to the older findings). In addition, we highlight a previously unstudied effect of the PDS: reducing caloric sensitivity to local prices. These results suggest a perhaps bigger role for the PDS in providing food security than previously understood, and may help explain why large numbers of beneficiaries report preferring in-kind food transfers from the PDS over equivalent value cash transfers (Muralidharan, Niehaus and Sukhtankar, 2017*a*). Indeed, given the current Covid-19 crisis, the PDS has assumed an even more important role: not only as the flagship food security and social welfare program, but explicitly as a bulwark against local food price shocks.

The remainder of the paper proceeds as follows. Section 2 provides a framework for examining the welfare effects of cash versus in-kind transfers. Section 3 discusses the context and data. Section 4 presents empirical evidence on price risk in India and its consequences for households. Section 5 examines the effects of the PDS program on households and the extent to which it mitigates households' sensitivity to price risk. Section 6 concludes.

2 Theoretical framework

2.1 Optimal insurance policy

We begin with a simple model focusing on the welfare of a household faced with a varying price of one consumption good and a potentially varying source of income. We derive several key results. First, the optimal insurance policy consists of price-indexed transfers that equate the marginal utility of household income across states of the world. Second, optimal transfers

[9] Note again that our test does not require isolating a causal effect of prices on outcomes, a major challenge in this literature.

may theoretically be increasing or decreasing with respect to price. Third, if the government must instead choose between price-invariant cash or in-kind transfers, the household will prefer in-kind as long as the marginal utility of income is higher in the high price states of the world. We begin by assuming that household income is fixed and that government policy does not affect general equilibrium prices. We return to these assumptions below.

Consider a household consuming several goods and assume that the price p_j of one of the goods, good j, varies across states of the world with mean $\bar{p}_j$, coefficient of variation σ_{p_j} and density distribution $f(p_j)$. The price of all other goods is fixed but household income y potentially covaries with price p_j. The household's preferences are characterized by the indirect utility function $v(\cdot)$.

We start by characterizing the optimal insurance policy: price-indexed (state-dependent) transfers. The optimal break-even insurance menu specifies a set of transfers x for each possible value of p_j, which we write $x(p_j)$, such that the expected value of these transfers, $\int_{p_j} x(p_j)f(p_j)dp_j$, is equal to 0. The optimal transfer $x(p_j)$ for a given price p_j is thus the one that maximizes $\int_{p_j} v(p, y + x(p_j))f(p_j)dp_j - \mu \int_{p_j} x(p_j)f(p_j)dp_j$, where μ is the marginal value of income and p is the vector of all good prices. The first order condition tells us that the optimal menu equates the marginal value of income $v_y(p, y + x(p_j))$ in all states of the world:

$$v_y(p, y + x(p_j)) = \mu, \forall p_j \tag{1}$$

The optimal policy will transfer positive amounts to households in states with high marginal value of income and negative amounts in states with low marginal value of income. Optimal transfers $x(p_j)$ will therefore be increasing in the price level if the marginal value of income is itself increasing in the price.

Assuming income is fixed, we can write the derivative of the marginal value of income with respect to price in the following way:[10]

$$v_{yp}(p, y + x(p_j)) = \frac{v_y(p, y + x(p_j))}{p_j}\alpha(\gamma - \eta_j) \tag{2}$$

where α is the budget share the household spends on good j, γ is the coefficient of relative risk aversion, and η_j is the income elasticity of demand for good j. The sign of this expression will depend on $(\gamma - \eta_j)$. Intuitively, if households are not very risk averse, they prefer transfers in the low price state to take advantage of higher purchasing power. As risk aversion increases, the value of consumption smoothing increases, leading households

[10]This expression is obtained by taking the derivative of Roy's identity with respect to income y.

to prefer transfers in the high price state.[11] This result is related to Turnovsky, Shalit and Schmitz (1980), who show that households will be better off with varying prices than with price stabilization if their demand elasticities are high relative to their risk aversion. The amounts transferred across states of the world are increasing in α: the higher the budget share spent on the good, the greater the sensitivity of marginal utility to price.

2.2 Varying household income

Lack of market integration implies that local prices will be affected by local supply and demand conditions. Local prices may therefore be correlated with household income. Allowing household income to co-vary with prices we obtain the following expression for the marginal utility of income:

$$v_{yp}(p, y + x(p_j)) = \frac{v_y(p, y + x(p_j))}{p_j}[\alpha(\gamma - \eta_j) - \gamma \frac{\partial y}{\partial p_j} \frac{p_j}{y}] \tag{3}$$

The additional term on the right-hand side captures the effect of allowing income to be correlated with prices: a positive derivative implies that high price states of the world are also high income states of the world. If this term is positive and sufficiently large, the marginal utility of income will decrease with the price even if $\gamma > \eta_j$.

This formulation allows an arbitrary correlation between income and prices, which we might expect to be different between households who are net producers versus net consumers of the good. The form of optimal transfers continues to be determined by the derivative of the marginal utility of income with respect to price.

2.3 Cash versus in-kind transfers

In most contexts, governments are unable to perfectly observe local prices at high frequency so the optimal transfer policy described above cannot be implemented. We therefore consider the impact on the household'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 two equivalent expected value policies, so we assume that both policies transfer an amount $z\bar{p}_j$ to the household on average across all states of the world. We also assume the in-kind transfer is infra-marginal (the household consumes more than z of the good for all possible prices p_j).[12] Finally, we assume that prices are not affected by either cash or in-kind transfers.

[11] The higher the income elasticity η_j the more consumption of the good is increasing with income, making income in the low price states of the world relatively more attractive. η will also capture the possibility of substitution to other goods.

[12] This assumption holds for over 95% of households in our empirical context.

Assuming no general equilibrium price effects, the welfare effect of introducing a cash transfer can be written as:

$$W_C = z\bar{p}_j \int_{p_j} v_y(p, y) f(p_j) dp_j \tag{4}$$

and the welfare impact of the in-kind transfer as:

$$W_K = z\bar{p}_j \int_{p_j} v_y(p, y) f(p_j) dp_j + z \int_{p_j} v_y(p, y)(p_j - \bar{p}_j) f(p_j) dp_j \tag{5}$$

Plugging in (4) in (5) we obtain:

$$W_K = W_C + z \int_{p_j} v_y(p, y)(p_j - \bar{p}_j) f(p_j) dp_j \tag{6}$$

where the second term is simply the transfer amount z times the covariance between the marginal utility of income and prices. Using a linear approximation of $v_y(p, y)$ around $v_y(\bar{p}, y)$ we obtain:[13]

$$W_K \approx W_C + z v_{yp}(\bar{p}, y) \int_{p_j} (p_j - \bar{p}_j)^2 f(p_j) dp_j \tag{7}$$

Expression (6) shows that in the presence of price risk the in-kind transfer is not equivalent to the cash transfer from the household perspective, even though the expected monetary value of both transfers is the same. Moreover, as long as the covariance between the marginal utility of income and prices is positive (or, equivalently, as long as the derivative of the marginal utility of income with respect to price is positive—see expression (7)), the in-kind transfer is welfare improving with respect to the cash transfer. This is because the former effectively transfers more to the household in states of the world in which the price is high and it values extra income more: the in-kind transfer more closely approximates the optimal insurance contract.

We might expect cash and in-kind transfers to have differential effects on local prices. For example, Cunha, De Giorgi and Jayachandran (2018) show that in-kind transfers in Mexico reduced prices for that commodity by about 4%. However, as we demonstrate below, we find very small and insignificant effects of expansions of in-kind transfers on market prices in our empirical context. We therefore abstract away from this additional potential difference between cash and in-kind transfers to focus on the interaction between in-kind transfers and price risk.

Finally, a full welfare analysis of cash vs. in-kind would need to take into account

[13] Here $\bar{p}$ indicates the vector of prices when $p_j = \bar{p}_j$.

potential differences in the costs of provision. Such analysis would need to incorporate factors such as the structure of the tax system and interactions with other distortionary government policies, such as the procurement process and production-side subsidies, and is beyond the scope of this paper. Our analysis focuses on the effects of in-kind transfers from the point of view of the recipient household.

3 Context and data

3.1 Context

We examine the predictions of the model empirically in the context of India, focusing on variability in food prices. The Indian context is ideal for studying these issues for a number of reasons. First, as much prior research has documented, markets are not well-integrated: local prices are subject to volatility arising from weather shocks (Rosenzweig and Udry, 2014). Substantial price differences persist across regions, and temporary shocks to local prices are frequent over time (Atkin, 2013). Second, as we discuss below, a substantial share of the population is undernourished and fails to meet basic caloric requirements. Finally, India has a large in-kind transfer system: the Public Distribution System (PDS).

The PDS is one of India's oldest and most important anti-poverty programs, dating back to several months before independence in 1947. The PDS provides chiefly rice and wheat at significantly subsidized rates to eligible households via a widespread network of Fair Price Shops (FPS).[14] The program operates much like in-kind transfer programs across the rest of the world: the government procures goods directly from producers in a few agricultural states and then sells them to households at below-market prices.[15] Each household is eligible to buy up to a certain quantity of grains each month, although due to corruption and logistical failures the FPS may not always have enough for each household to purchase their entire allocation.

Most PDS policy is set at the state level. While the federal government provides significant funding for the PDS, states are responsible for transport and storage, and typically devote additional resources to increase program breadth or decrease prices. This means that the generosity of the program varies across states and over time.

[14] Other commodities such as sugar, salt, kerosene for cooking fuel as well as other local grains are occasionally also provided.

[15] One explicit goal of the PDS is to provide 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. Geographic centralization of production—in 2016-17, 78% of all rice procured was from the top 6 (out of 29) states (FCI, 2018)—means that effects of the PDS on producers are concentrated away from most of our sample. In Table 8 we show that our results are robust to excluding PDS-producing states.

In 1997, eligibility was largely restricted to poor households, in particular those considered to be "Below Poverty Line" (BPL); all households had to obtain ration cards which list entitlements. The PDS has grown more generous over the last twenty years, with large nation-wide expansions in 2000 and 2013. In 2000, 6 million households became newly eligible, and PDS generosity was increased for the very poorest households. In 2013, the National Food Security Act further expanded eligibility to 75% of the rural population. Between these two federal changes, many states expanded their own PDS generosity; we focus on this period in our empirical analysis.

3.2 Data

Our main source of data are the 59$^{\text{th}}$ through 68$^{\text{th}}$ rounds of the National Sample Survey (NSS), covering January 2003 through June 2012. This covers most of the period between 2000 and 2013, when the basic structure of the program stayed the same but generosity was dramatically increased in many states. We begin in 2003 because the NSS does not consistently identify many districts before the 59$^{\text{th}}$ round (see Section A.1 for further details).

The NSS surveys households about their expenditure in each of about 350 categories over the past 30 days. For a subset of these categories where the units are well-defined, it also records the quantity consumed. The survey also contains basic demographic information like household size and composition, religion, caste, landholding, assets, education and occupation. Individual households are not re-surveyed across rounds, so the data is a repeated cross-section of households. Each round takes place throughout the year, allowing us to identify observations at the year-quarter level.

The most granular geographic identifiers are districts, which could be interacted with an indicator for rural/urban sector; however, NSS data are not representative at this level, particularly in "thin" rounds with fewer observations where the data are not representative at even the district level, and further when we use data by year-quarters.[16] We therefore use NSS region interacted with a rural/urban indicator (hereafter "region-sector") as our geographic unit of aggregation for prices; NSS regions are groupings of "contiguous districts having similar geographical features, rural population densities and crop-pattern," which makes them appropriate for our analysis of price variation (Organization, 2001).

As is usual for empirical work in India, we exclude Union Territories and Delhi due to small sample sizes in these regions (see, for example, Imbert and Papp (2015)). The 65$^{\text{th}}$ and 67$^{\text{th}}$ rounds did not include the expenditure survey, so we do not observe household outcomes between July 2008 and June 2009, and July 2010 to June 2011. In total, our sample includes

[16] The average population of a district is about 2 million individuals or roughly 450,000 households. Meanwhile, at the district-sector-quarter level, the 10th percentile district-sector by size in our data has only 5 observations.

524,911 households in 140 region-sectors spread across 28 states.

We use the NSS in two main ways. First, we follow Deaton and Tarozzi (2005) and use unit values—expenditures divided by quantities—as the basis for our measures of local prices. Second, we use the NSS to construct measures of caloric intake, which we use as an outcome. Appendix A provides further details on the NSS and data construction.

3.2.1 Unit values

India lacks measures of prices that are (1) for individual items, (2) cover the entire country, and (3) vary at the local level. To overcome this challenge, we construct unit values from expenditure and quantity information: $UV_{ijt} = \frac{expenditure_{ijt}}{q_{ijt}}$ for good j in time t consumed by household i. After removing observations that appear to result from transcription or data errors, we measure local prices for each good using the region-sector-quarter mean unit value. Using unit values rather than prices is standard practice in the literature that uses the NSS (Subramanian and Deaton, 1996; Deaton and Tarozzi, 2005). See Section A.3 for more details.

One potential issue with using unit values is that households might consume different qualities of rice in response to price changes, attenuating the relationship between true prices and measured unit values. We address this in two ways. First, we calculate the unit values at the region-sector-year-quarter level, and find that different demographic groups—despite facing similar observed price variability—respond very differently.

Second, in Section A.3, we provide a more direct test of the validity of the unit values by directly comparing them to prices from the Rural Price Survey (RPS). The RPS is a market-level survey of prices for many of the goods in the NSS, although only in rural areas and only for a subset of the regions we study. As a result, the RPS only covers about 25% of our overall sample, so we do not use it for our main analysis; we do provide robustness checks using these data. Within the overlapping sample, the over-time correlations between RPS prices and unit values are nearly 0.60. We conclude that unit values do a good job of capturing underlying price variation.

3.2.2 Household characteristics

We use various household characteristics as controls and dimensions of heterogeneity to examine. We capture economies of scale in consumption using log household size. Religion and Scheduled Caste/Scheduled Tribe status, as well as the type of cooking fuel used all determine the type of food that households eat and therefore calories consumed. We use landholding as a proxy for ability to produce food commodities. We define landholding households as owning more than 0.01 hectare of land, which allows us to effectively categorize those with the ability to engage in agricultural production.

To proxy for household permanent income, we construct a socioeconomic status (SES) index by regressing log per-capita expenditure on caste, occupation, education of head, land possessed, and the number of household members in the 18 bins defined by the intersection of age (0-17, 18-54, 55+), gender, and education (below primary, primary, above primary). The SES index is the predicted value from this regression, standardized to have a mean of zero and a standard deviation of one.

3.2.3 Calorie requirements

The relevant empirical parameter for determining the welfare effects of in-kind relative to cash is the correlation between marginal utility of income and prices. If this relationship is positive, households will prefer an in-kind transfer to cash transfer with equal expected value. Our main empirical proxy for marginal utility of income is an indicator for whether the household fails to meet a minimum recommended caloric intake. We interpret an increased likelihood of failing to meet basic calorie requirements as associated with an increase in marginal utility of income.

Note that total consumption would not be an appropriate proxy for marginal utility of income in this context: optimizing households may prefer to have lower consumption in high price states in order to take advantage of the ability to purchase greater consumption in the low price states. However, it is very unlikely that an optimizing household will prefer to fall short of minimum calorie thresholds.

We estimate household-level caloric intake using the information on total consumption of each item combined with NSS estimates of the caloric value of each item (Gopalan et al., 1980). To contextualize caloric consumption, we rely on age $\times$ gender specific guidelines for caloric intake from the Indian Council of Medical Research (ICMR) and calculate the total household requirement (Rao and Sivakumar, 2010). The ICMR provides separate caloric guidelines for different levels of exertion: sedentary, moderate work, and heavy work. We focus on the lowest of these, the "sedentary" guideline or the minimum calorie requirement (MCR) by age and gender. On average, individuals consume 2,102 calories per day, while the ICMR estimates that 1,904 would be necessary on average given our NSS sample's age-gender composition. Average consumption of course obscures substantial heterogeneity; only 61% of households meet their caloric requirement, falling to 56% for households below the median SES and 55% for rural landless households (Table 1).[17]

[17] We do not have data on consumption by individual, hence are restricted to calculating calories at the household level (and reporting results per capita for convenience). Of course, calories may be unevenly distributed within households; this may mean that individuals do not meet MCRs even in households that consume sufficient calories overall (Brown, Calvi and Penglase, 2018).

3.2.4 PDS policy variation

There is no comprehensive data source for state PDS policies. We therefore construct measures of PDS generosity at the state-year level on both the price and quantity margins as follows. We observe statutory PDS prices in the Foodgrain Bulletin, an annual government report.[18] The Bulletin is not comprehensive, so we additionally surveyed newspaper databases to identify other policy changes and to get more exact information on the date of Bulletin price changes. Combined, we have as complete a dataset of PDS price changes as is possible.

The quantity component of the value of the PDS reflects both entitlements per eligible household as well as the number of eligible households. However, there is no consistent source of information on changes to entitlements or eligibility. To identify policy changes in eligibility, we use the data to find sharp breaks in observed PDS value received by households (as defined below), then check in newspapers and state records to see if there was a policy change at that time. We discuss this method in detail in Section A.4. As for changes in entitlements, there are very large numbers of small, ad-hoc changes at state and district levels, which are difficult to capture and establish as "policy changes" versus supply fluctuations, and which are sometimes announced and not followed on. Hence we do not consider such changes in our analysis.

4 Price risk in India

4.1 Price exposure and variability

The average Indian household faces considerable potential exposure to price risk. Table 1 shows that the average household spends 52% of its budget on food, and 9% on rice alone. In our empirical analysis, we focus on rice because it comprises a substantial portion of household food expenditure, is consumed throughout the country, and is one of the main goods provided through the PDS system.

We begin by examining how the region-sector rice price varies both over time and across areas (Table 2). The NSS distinguishes between market and PDS consumption; these prices reflect unit values for market rice. Only 4.4% of households in our sample consume grain from the PDS but not from private sources, so the averages incorporate market rice prices faced by the vast majority of households.

Deflating by the all-India CPI, the mean price of rice is Rs. 9.65 per kilogram.[19] Taking

[18] When different card types are charged different prices, we use the BPL price in all calculations. This is by necessity—our data do not list card type—but the vast majority of households using the PDS pay BPL prices (Niehaus et al., 2013).

[19] Authors' calculations from the NSS. We convert all nominal values to 1999 Rupees using the all-India

out district-sector fixed effects, the standard deviation of the residual is 0.83. Household characteristics do not explain this variation: the standard deviation is unchanged when we include household controls and the SES index. We then include year-quarter fixed effects to capture common shocks across areas.[20] The residual standard deviation decreases to 0.61. Including district-sector-season fixed effects reduces it further slightly to 0.59. In theory, the government could address price shocks that are common across areas as well as predictable seasonal variation using other policy instruments. We therefore use the residual variation in the final column to estimate caloric responses to price variability to focus on the type of price variability in-kind transfers are likely to be most suitable to address. In practice, this provides a conservative estimate of the true price risk faced by households since they may not actually be able to smooth common cross-area or seasonal variability.

The remaining rows of Table 2 show the same summary statistics by demographic groups. We continue to use the average price calculated using all households in a given region-sector, so the differences across subgroups will reflect differences in the composition of geographic locations of households in different subgroups. Unsurprisingly, the average prices faced by urban households are higher than rural households, as are average prices for above median SES households compared with below median.

4.2 Price variability and calories consumed

Our primary welfare proxy is an indicator for whether the household meets the minimum calorie requirement (MCR) given the age and gender composition of the household. We interpret a decrease in the likelihood of meeting the MCR as reflecting an increase in the marginal utility of income. We also examine calories per capita as an outcome.

In Table 3 we regress the calorie outcome c_{idrt} on log market rice prices p_{rt}:

$$c_{idrt} = \beta p_{rt} + X_{idrt}\lambda + \delta_{dq} + \tau_t + \phi_{round} + e_{idrt} \tag{8}$$

where i indexes households, d indexes district-sector, r indexes region-sectors, q indexes seasons (quarter of year), and t indexes the year-quarter in which the survey took place. We control for district-sector $\times$ season fixed effects (δ_{dq}) to account for place-specific agricultural cycles, as well as year-quarter fixed effects (τ_t) for national changes in policy and economic growth and NSS round fixed effects (ϕ_{round}). We additionally control for household characteristics X_{idrt} including log household size, religion and Scheduled Caste/Scheduled Tribe status, land ownership, cooking fuel used and the SES index. Standard errors are clustered

CPI from the World Bank. One US dollar was about 43 rupees in 1999.

[20] We also control for NSS round effects to account for any potential differences in survey procedure or instruments. Because not all households are surveyed within the scheduled time, NSS round FEs can be included separately from year-quarter FEs.

at the region-sector level, the level of our price variation.

We want our estimates to capture the empirical relationship between price variability on marginal utility of income, allowing income to co-vary with rice price and the ability to substitute across goods. We therefore do not control for current household expenditure or other commodity prices. In addition, these estimates will capture the average effect of price variation given any existing household smoothing mechanisms as well as access to social safety nets, including the PDS.

Column (1) shows our preferred specification, regressing the likelihood of meeting MCR on prices, controlling for district-sector-season fixed effects, year-quarter and NSS round fixed effects, the SES index, and household controls. A 10% increase in the price of rice decreases the likelihood that households meet the MCR by 1.1 percentage points, and this effect is significant at the 1% level. The SES index and household controls are meant to capture household permanent income and characteristics that are likely to affect diet and calories directly. However, if we exclude these, we still see a decrease in the likelihood of meeting MCR of 0.8 percentage points for every 10% increase in the rice price (column (2)). We lose some precision, but the estimates are still significant at the 10% level. In column (3), we include district-sector fixed effects but not district-sector $\times$ season fixed effects to allow seasonal variation in our price measure. The coefficient is almost identical to our baseline estimate, indicating that seasonal and non-seasonal sources of price variation have similar effects on caloric shortfalls. In column (4), we remove year-quarter and NSS round fixed effects. The coefficient increases in magnitude, suggesting that households are not easily able to smooth shocks that are common across areas.

Finally, we compare our estimates to estimates using prices from the Rural Price Survey. The RPS samples prices directly from markets and is not derived from household unit values. The RPS is conducted in a subsample of rural districts. Column (5) presents results using the baseline price measure, restricting the sample to the set of districts for which RPS data are available. Column (6) presents the baseline specification using the RPS price measure. Reassuringly, the estimates are almost identical and in both cases are statistically significant ($p<0.01$). The calorie-price sensitivity is also much higher for this sample: a 10% increase in price is associated with a 2.9 percentage point decrease in the likelihood of meeting the MCR.

We next examine heterogeneity in calorie-price sensitivity by demographic categories that are commonly used to target policy: SES status, rural vs. urban, and landowning (Table 4). We find that a 10% increase in rice price is associated with a 1.9 percentage point reduction in the likelihood of meeting MCR for below median SES households and a 1.8 percentage point reduction for rural households. These effects are statistically significantly larger than those for above median SES and urban households, for which the estimates are small and insignificant.[21] We then divide the rural sample into landless and landowning households. The estimate for landless households is larger in magnitude, but we cannot reject equality of effects between landless and landowning.

One possible explanation for the observed heterogeneity is that above median SES, urban households, and rural landowning households are further away from the MCR and therefore have lower sensitivity to falling below this threshold. To distinguish this explanation from underlying differences in caloric sensitivity to prices, we estimate effects using the log of calories per capita as our outcome variable (Table 5). Our baseline estimate for the full sample implies that a 10% increase in the market price is associated with a 0.7% reduction in calories per capita ($p<0.05$). We again see that the effects are concentrated among below median SES and rural households. This cannot be explained by differences in the average levels of prices or variability across the groups: in fact, as shown in Table 2, average prices and the residual standard deviations are higher for above median SES and urban households. It is also not the case that richer households have no sensitivity of calories to real income: within district-sector-quarters, log calories are increasing in log expenditure over the entire range of expenditure (see Figure 1). In contrast, the coefficients for rural landless and landowning are very similar, suggesting that the higher sensitivity of meeting the MCR for landless households reflects that they are closer to the calorie threshold. This is unsurprising, since landless households in rural areas are poorer than landholding households on average.

How do we interpret the magnitudes of these correlations? A 10% increase in rice prices is associated with 1.1 percentage points fewer households—or approximately 13 million individuals extrapolating India's population in our study period—meeting the MCR. Of course, the MCR is a somewhat arbitrary threshold; the density of households around the threshold also matters. For poor households who are already below the MCR thresholds, the calorie results indicate that they move even further away from meeting the threshold when prices increase. Moreover, these correlations exist despite all the efforts households make to smooth consumption as well as government welfare programs including the PDS, and after removing the effects of geography and season (which in practice households may not be able to insure against). Finally, as Chetty and Looney (2006) argue, the welfare consequences of risk are likely underestimated given the actions highly risk-averse households take to smooth consumption. Taken together, these results suggest that rice price variability is likely associated with substantial losses in welfare.

[21] The effect for rural households is smaller than for the RPS sample in Table 3. This may possibly reflect the fact that RPS data is collected from a fixed set of 603 villages/markets chosen because they are ones that "rural agricultural labourers visit;" see http://mospi.nic.in/price-collection-survey for more details.

Reflecting back on the model, our interpretation of the MCR as proxying for the marginal utility of income combined with the significant correlations between rice prices and the MCR/calories suggest that in our context in-kind transfers will improve welfare for the average household over equivalent cash transfers. This is certainly true for the poor, for rural households, and in particular the rural landless, but not the case for rich and urban households. These results have clear policy implications for the PDS, at least in theory; the rest of the paper explores the extent to which the implementation of the PDS in practice affects household nutrition.

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

In this section, we study the extent to which the PDS shields households from price variability. Section 4 indicates that in-kind transfers will improve welfare relative to cash transfers, particularly for poor and rural households.[22] However, the PDS—like other in-kind programs—may suffer from poor targeting, rationing, and leakage in practice. Each household is limited in the quantity it can purchase by the type of ration card it holds, but poor verification of assets and household composition mean that well-off households often purchase PDS goods even when they are not eligible to do so (Niehaus et al., 2013). Distribution failures and corruption often mean there is not enough rice delivered for all households to take their full allocation, and PDS dealers sometimes charge more than the statutory price. This is particularly concerning in our setting, because distribution may suffer (and dealer rents may increase) precisely during high-price periods (Hari, 2016). The goal of this analysis is to estimate the effects of the PDS "on the ground." To do this, we exploit significant state-level changes in PDS prices (mainly decreases) and coverage (mainly increases) over our study period, and use these to instrument for PDS generosity.

5.1 PDS versus market prices

We calculate the subsidy value v_{idrt} for each household using information on the observed market prices p_{rt}, (below-market) PDS prices p_{rt}^{PDS}, and observed PDS consumption q_{idrt}^{PDS}.[23] For inframarginal households, the value of the PDS rice subsidy can be written as:

$$v_{idrt} = (p_{rt} - p_{rt}^{PDS})q_{idrt}^{PDS}$$

[22]We do not attempt to quantify the welfare gain, which would require assumptions about how meeting the MCR and caloric consumption generally translate into marginal utilities.

[23]We define market prices and PDS prices by the mean region-sector-year-quarter unit values (the average unit value observed in a region-sector in each time period). The market unit value is based on the 88.3% of households that consume rice from the market; the PDS unit value is based on the 25.7% of households that consume rice from the PDS.

Differences between market prices and PDS prices are substantial, leading to a large transfer to households. The average price for PDS rice was Rs. 3.5 per kilogram, compared to a market price of Rs. 9.9. In our sample, the average monthly transfer adds up to Rs. 109 for rice beneficiaries (conditional on obtaining PDS rice), 4.9% of the Rs. 2,205 average monthly expenditure. This is likely the single largest government transfer for most households. Although our data do not contain information on NREGS—the other major social welfare program that provides rural employment—NREGS transfers made up only 1.8% of beneficiaries' expenditure in Andhra Pradesh in 2012 (Muralidharan, Niehaus and Sukhtankar, 2017*b*).

5.2 PDS policy changes

The "on the ground" observed generosity of the PDS increased dramatically over the study period. Panel A of Figure 2 shows that average real PDS prices more than halved over our study period, from over Rs. 5 to 2. Panel B shows that while quantities for beneficiaries stayed roughly constant, the number of beneficiaries more than doubled, from from 20% to 45% of households. This translated into a nearly 400% increase in the value of the PDS subsidy over the period (Panel C), from Rs. 14 to 55 (average across all households).[24]

To isolate changes in PDS value driven by policy changes, we instrument PDS value by changes in states' PDS policies. Our first instrument is simply p_{st}^{BPL}, the statutory PDS price of rice charged to families classified as BPL—the vast majority of PDS beneficiaries—in state s at time t. Our second instrument is an indicator E_{st} equal to 1 if household i is in a state s in which a major PDS eligibility increase 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 A2, where Odisha universalized the PDS in a poor region of the state in 2008, more than doubling PDS participation in one year.

As discussed in Section 3.2.4, there are no comprehensive data sources for statutory PDS policy. Our measures of statutory prices come from information reported in the Foodgrain Bulletin, supplemented with newspaper database surveys. To capture eligibility increases, we look for breaks in observed PDS value in the data and then examine newspapers and state records to verify policy changes. Specifically, we simulate potential policy changes for each state s and quarter t. We run regressions of PDS value on state and time fixed effects; controls for household characteristics and known policies; and an indicator for being in state

[24]Figure A1 plots the share of households consuming PDS grains against per-capita expenditure, deflated to the 1999 price level. We display this relationship for 2008 and earlier, before most of the big expansions in eligibility, and for 2009 and after. Households became more likely to access the PDS at all expenditure levels over time, but the gains were most pronounced for very poor households.

s after time t. Whenever the coefficient on the indicator was larger than Rs. 10 in absolute value, we checked newspapers and state records. If we found explicit, credible mention of an increase in eligibility we coded that period as an eligibility increase for the given state. We find 6 such eligibility increases, which we list in Table A4.

5.3 Empirical strategy

We examine the direct effect of PDS generosity on caloric outcomes as well as the effect of the PDS on the sensitivity of calories to market prices. Our first estimating equation is:

$$c_{idrst} = \alpha_1 v_{idrst} + \alpha_2 p_{rst} + X_{idrst}\lambda + \delta_{dq} + \tau_t + \phi_{round} + e_{idrst} \tag{9}$$

where s additionally indexes states, c_{idrst} is our calorie outcome measure, p_{rst} is the market price, and α_1 is the coefficient of interest. Standard errors are clustered at the state level, which is the level of PDS policy variation.[25] We instrument for observed PDS value v_{idrst} with three instruments: the statutory PDS price at the time the household was surveyed, an indicator for whether the household was surveyed after a major eligibility expansion in their state, and the interaction between the two.

To determine the effect of the PDS on caloric sensitivity to market prices, we estimate:

$$c_{idrst} = \beta_1 p_{rst} + \beta_2 p_{rst} \times v_{idrst} + \beta_3 v_{idrst} + X_{idrst}\lambda + \delta_{dq} + \tau_t + \phi_{round} + e_{idrst}. \tag{10}$$

We instrument for v_{idrst} as above and for $p_{rst} \times v_{idrst}$ using our three instruments as well as their interactions with market price. Our main coefficient of interest is β_2, which is identified by comparing the correlation between rice prices and calorie outcomes at different levels of instrumented PDS generosity.

The key identifying assumption is that policy changes in PDS generosity are not endogenous to local conditions or correlated with other unobserved changes which might affect calories or calorie-price sensitivity directly. For example, we might be concerned that expansions of the PDS occur during good economic times or in response to calorie shortfalls.

In Figure 3 we run an event-study specification of the eligibility expansion instrument, with the first stage in Panel A and the second stage in Panel B.[26] Consistent with our measures of expansions capturing the important state-level changes to the PDS, we see no

[25] de Chaisemartin and D'Haultfœuille (2020) decompose the two-way fixed effect estimand into a weighted average of treated area-period-specific effects, and point out that under heterogenous treatment effects the conventional estimand may be biased. We calculate the weights and find that they are all positive, meaning our main estimates are convex combinations of treatment effects, and hence unlikely to be biased.

[26] With small and frequent changes to PDS prices, our price instrument is not conducive to this type of graph; we show below that results go through with the expansion instrument only.

differential trends in the average PDS value in the years before the reform. However, PDS value v_{idrst} begins to increase immediately following the reforms. Five years after the reform, v_{idrst} has increased by Rs. 40, a larger increase than the average PDS transfer during our study period (Rs. 31).

Panel B of Figure 3 also provides no evidence of changes in caloric intake before a policy is implemented, supporting the parallel trends assumption. Finally, an interpretational issue is that the benefits of PDS expansions might come through reductions in market prices (Cunha, De Giorgi and Jayachandran, 2018), rather than through the transfer itself. We return to this issue in the following section, and show that, supporting the parallel trends assumption the PDS generosity expansions we study have no effect on market prices.

5.4 Results

Table 6 contains first stage results for Equation 9 for the overall sample and for our demographic subgroups. The coefficients for PDS price decreases and eligibility increases are both strongly significant and have the expected signs in the full sample and across all subgroups (F-stats range from 21 to 39). Reducing the government-mandated BPL price by one rupee increases the value of the PDS transfer by Rs. 9.7. On average, our increases in eligibility increase the value of the PDS by Rs. 51/month, 2% of average total household expenditure.[27]

Panel A of Table 7 presents our results on the effects of PDS generosity on the likelihood a household meets the MCR. An increase of Rs. 100 in PDS value leads to a 10.7 percentage point increase in the likelihood that the household meets the MCR. One way to gauge this magnitude is the following: Panel B of Figure 3 shows that the average PDS expansion increased the share of the population that meets the MCR by 12.8% after five years. The population of the states that expanded their PDS was 283 million in the 2011 Census. Our estimates therefore imply that the PDS expansions we study lifted 36 million individuals above the MCR threshold over five years.[28]

Panel B demonstrates that expansions in PDS generosity also decrease household sensitivity to market prices. The first row shows the implied effect of an increase in the market price for a household without any (instrumented) PDS consumption; the second row shows the interaction of market price and a Rs. 100 increase in PDS value; and the third row provides the predicted effect of market rice price at the mean PDS value. A 10% increase in prices for a household without any (instrumented) PDS consumption decreases the likelihood

[27] The first stage for Equation 10 (unreported) additionally includes interactions of these instruments with market price.

[28] This estimate is, if anything, conservative. Our baseline estimates of the effects of expansions on PDS value and of PDS value on the likelihood of meeting the MCR are at the lower end of the range of estimates obtained across our robustness checks.

the household meets the MCR by 2.43 pp. However, increasing the PDS value to the average amount (Rs. 29.6) decreases the effect to 1.9 pp. Our results imply that households' caloric intake would no longer be sensitive to market prices if they received a Rs. 137 transfer from the PDS, which is roughly one-third larger than the average non-zero transfer.

In Table 8, we find that these results are robust to various alternative choices of samples and controls. First, restricting the sample to only those states that are not major suppliers of rice to the PDS makes no qualitative difference to the results; the coefficients are very similar, suggesting that the results are not driven by procurement or unobserved positive shocks to supply. Next, adding controls related to election cycles as well as the rollout of the NREGS, the other big social welfare program, makes no observable difference to either coefficients or statistical significance. Examining the impacts of the price and eligibility instruments by themselves shows that the price instrument by itself does not directly affect calories consumed; however, the interaction effect remains positive and significant in both cases.

In-kind transfers like the PDS could directly affect market prices, as found by Cunha, De Giorgi and Jayachandran (2018) in a different context. We address this in Table A5, where we regress market rice prices on instrumented PDS value. Across specifications, we find very small effects of the PDS on prices. Using our baseline set of instruments, we find that an additional Rs. 100 of PDS generosity decreases market prices by an insignificant 0.6%. Using our estimate of the correlation between increases in prices and crossing the subsistence caloric threshold in Table 4 as given, this would imply a change in meeting subsistence of .07 pp. This is at least two orders of magnitude smaller than our estimated effect of a Rs. 100 increase in PDS generosity (see Panel A of Table 7). The potential effect of PDS expansions on market prices is therefore too small to explain our findings.

The above specifications return average impacts across demographic subgroups, which may be different in practice. Given that lower SES, rural, and rural landless households are more likely to be below the MCR threshold to begin with, it is not surprising that the impacts of increased PDS values on reaching MCR thresholds for these groups is higher (Table 7, Panel A). However, the impacts across subgroups do not tend to be different when considering simply calories per capita as the outcome (Table 9, Panel A). These results make sense when considering the fact that the IV estimate does not reflect differences in access to PDS across the groups; rather, it answers the question "if we were to hypothetically give 100 Rs. of PDS to a rich and poor household, would it have different effects on calories for these groups?" The calorie results are thus consistent with the nearly constant expenditure-calorie gradient seen in Figure 1.

Finally, increases in PDS value lead to lower sensitivity to market rice prices for all subgroups, and this is reflected in both outcomes we consider. The mitigating effects of the PDS on price risk are slightly (though insignificantly) larger for higher-SES and urban households, perhaps reflecting the local average treatment effect (LATE) captured by the IV: households in these sub-samples affected by our instruments may not be very different from lower-SES and rural households. For these richer and urban households, who are less sensitive to market prices to begin with, the additional impact of increases in PDS value reduces their sensitivity to basically zero (consistent with the results shown in Table 4).

These results are robust to various alternative specifications and data choices; in the interests of not overwhelming readers, we provide a full list of robustness checks in Appendix B.

6 Conclusion

Households in developing countries face substantial price variability as a result of poor local market integration and other barriers to trade. We demonstrate that in a world with price risk, inframarginal in-kind transfers can be welfare improving relative to cash transfers. Examining empirically the context of India, we show that increases in rice prices are negatively associated with caloric intake, particularly for poor as well as rural households. We also demonstrate that expansions of the Public Distribution System increase caloric intake by households and reduce sensitivity of calories to local prices.

Since the period that we consider in our analysis, the PDS has undergone various changes. Access has expanded with the National Food Security Act (2013) mandating eligibility for 75% of rural and 50% of urban households. Prices charged have gone down on average, targeting has improved, and corruption has declined (Drèze et al., 2019). More recently, the PDS has been a central component of the government's response to the Covid-19 crisis, with many claiming precisely that it will help protect the poor from price shocks.[29] Our results suggest that all of these changes are likely to prove beneficial in terms of caloric intake and food security.

More generally, our results have 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. Of course, we do not consider here the costs of delivering grains in-kind versus delivering cash transfers, nor the costs that households may face in accessing these two alter-

[29] See for example the following op-eds in major Indian newspapers: https://indianexpress.com/article/opinion/columns/india-coronavirus-lockdown-food-stock-supply-pds-scheme-6476514/ and https://www.hindustantimes.com/analysis/a-post-covid-19-social-protection-architecture-for-india/story-BCt1POzFojnKloCkHTsv9H.html.

natives; and there are other tradeoffs between cash and in-kind transfers that the literature has identified. Nonetheless, 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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Figure 1: Log calories per capita versus log expenditure per capita, within district-sector-quarters

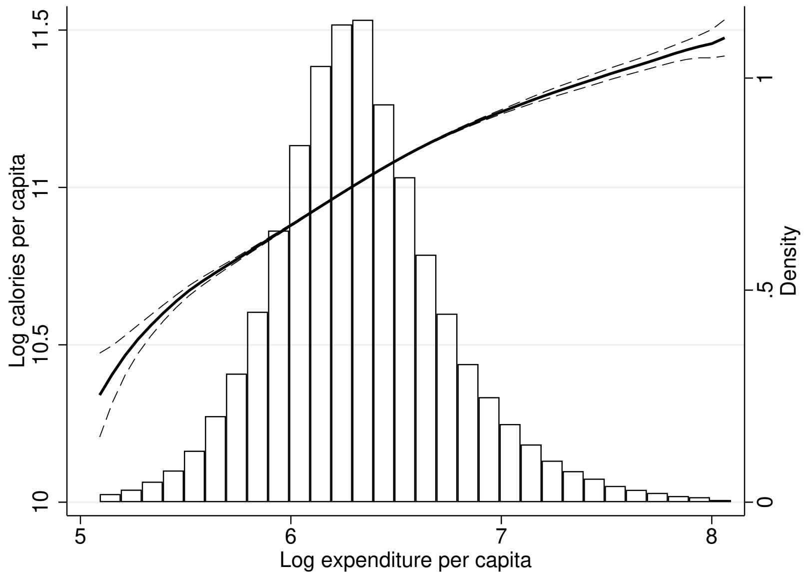
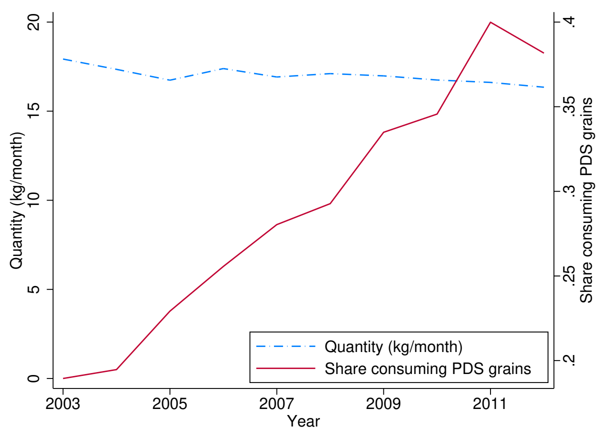


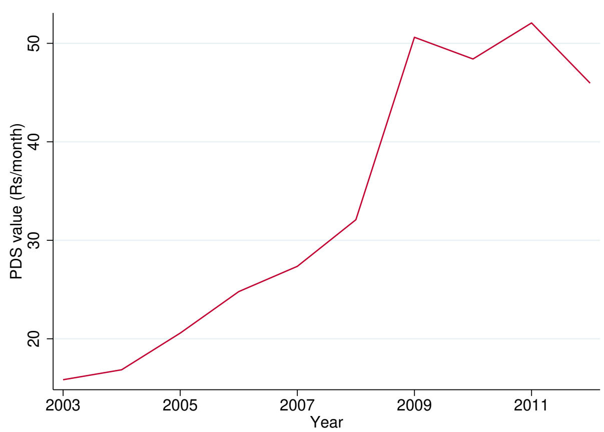
Figure shows histogram of household log expenditure per capita, and line represents nonparametric regression of log calories per capita on log expenditure per capita. Regression and histogram both condition on district-sector-quarter fixed effects to nonparametrically adjust for prices. Dashed lines represent 95% confidence interval, clustered at the area level.

Figure 2: PDS generosity and eligibility over time
(a) Market and PDS prices

(b) PDS quantities and reach



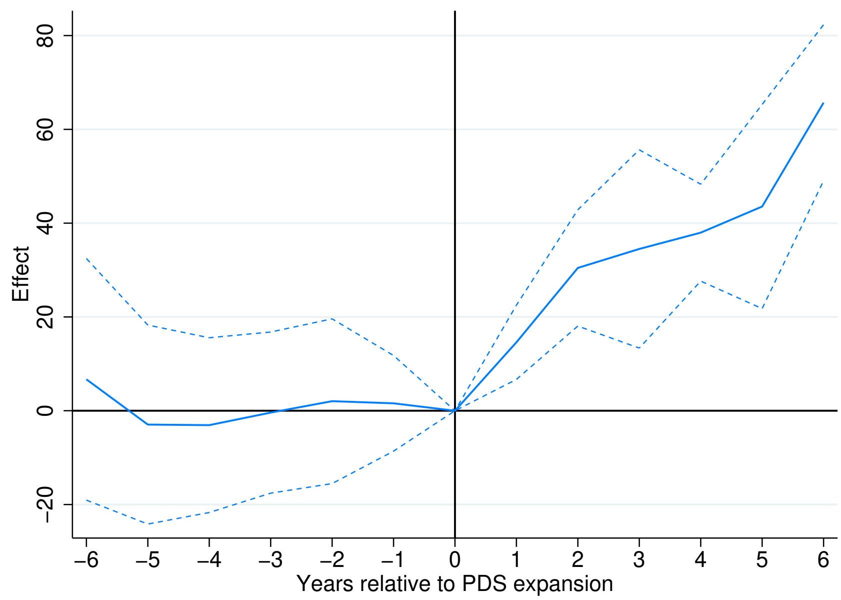
(c) Average PDS value



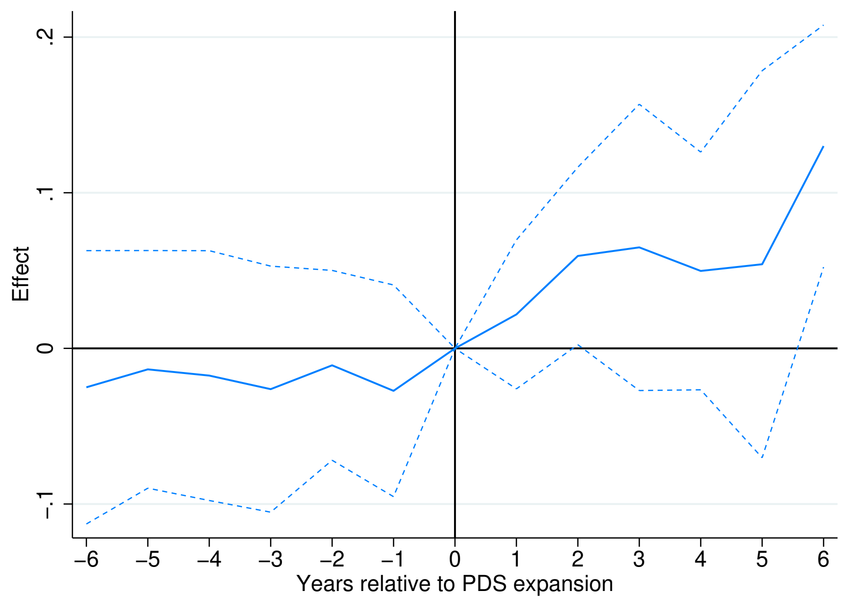
Panel A shows market and PDS mean unit values over time. Panel B shows PDS quantities for beneficiaries, and the total share of households who consume PDS goods. Panel C shows unconditional average monthly PDS generosity $(p_{rt}^{mkt} - p_{rt}^{PDS})q_{idrt}^{PDS}$. All units are deflated to 1999 rupees, which traded at 43 to 1 with the US dollar.

Figure 3: Effect of PDS expansions on PDS transfer value and caloric intake

(a) Effect on PDS transfer value



(b) Effect on meeting minimum calorie requirement



Shows event study coefficients from a regression of the outcome on time relative to policy expansion for individual i in area-season a, period t at time relative to expansion r, $y_{iat} = \sum_{r \neq 0} \beta_r \mathbb{1}_r + X_{iat}\alpha + \gamma_a + \varphi_t + \varepsilon_{iat}$, where controls include PDS rice price, and demographic controls are log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. All households owning 0.01 hectares of land or greater are classified as landowning. Household-level SES are the predicted values from a projection of log expenditure per capita on permanent household characteristics, with geographic unit, calendar, and NSS round fixed effects. Standard errors clustered at the state level.

Table 1: Summary statistics: daily caloric consumption

	Food share of expenditure (1)	Rice share of expenditure (2)	Total calories per capita (3)	Per capita MCR (4)	Met MCR (5)
Overall	0.52	0.09	2097	1904	0.61
	(0.13)	(0.09)	(632)	(231)	(0.49)
Below median SES	0.55	0.10	1976	1861	0.56
	(0.11)	(0.10)	(548)	(226)	(0.50)
Above median SES	0.47	0.06	2295	1974	0.69
	(0.13)	(0.06)	(707)	(222)	(0.46)
Rural	0.54	0.10	2097	1886	0.62
	(0.12)	(0.10)	(633)	(228)	(0.49)
Urban	0.45	0.06	2097	1952	0.57
	(0.13)	(0.06)	(632)	(232)	(0.49)
Rural Landless	0.54	0.09	2003	1877	0.55
	(0.12)	(0.09)	(636)	(245)	(0.50)
Rural Landowning	0.54	0.10	2135	1890	0.65
	(0.11)	(0.10)	(627)	(221)	(0.48)

Table shows summary statistics for daily household calorie consumption. Column (1) reports summary statistics for share of household-reported expenditure on all combined food items. Column (2) reports summary statistics for share of household-reported expenditure on market rice. Column (3) reports summary statistics for household calories per-capita, estimated from the quantity and average caloric content of all food items consumed by the household during the survey recall period. The upper and lower 0.1% of calories per-capita are trimmed to adjust for implausibly extreme calorie figures. Column (4) reports summary statistics for household average minimum calorie requirement (MCR), which is calculated as the average MCR of all household members based on the household demographic composition and recommended caloric intake guidelines published in 2012 by the Indian Council of Medical Research. Column (5) reports summary statistics for an indicator that the per-capita caloric consumption of the household met or exceeded its average MCR. Standard deviations in parentheses.

Table 2: Summary statistics for market rice prices

	Mean	SD			
	(1)	(2)	(3)	(4)	(5)
Overall	9.86	0.83	0.83	0.61	0.59
Below median SES	9.39	0.79	0.78	0.58	0.56
Above median SES	10.62	0.89	0.88	0.64	0.61
Rural	9.18	0.76	0.76	0.55	0.54
Urban	11.66	0.99	0.99	0.69	0.67
Rural Landless	9.33	0.79	0.79	0.56	0.54
Rural Landowning	9.12	0.75	0.74	0.54	0.52
District-sector FE		Yes	Yes	Yes	Yes
Controls		No	Yes	Yes	Yes
Period FE		No	No	Yes	Yes
District-sector-season FE		No	No	No	Yes

Table shows summary statistics for mean rice unit values. Unit values of rice are the unweighted means of deflated average rice expenditure per kilogram across all households from the same region-sector geographic unit and year-quarter time period. All unit values are measured in 1999 rupees. Controls include log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. All households owning 0.01 hectares of land or greater are classified as landowning. Household-level SES are the predicted values from a projection of log expenditure per capita on permanent household characteristics, with geographic unit and period fixed effects. Period fixed effects include calendar and NSS round fixed effects.

Table 3: Meeting minimum calorie requirement and market prices

	All districts				RPS districts	
	(1)	(2)	(3)	(4)	(5)	(6)
Market price rice, logged	-0.114***	-0.079*	-0.115***	-0.156***	-0.286***	-0.296***
	[0.041]	[0.044]	[0.041]	[0.042]	[0.076]	[0.080]
District-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
District-sector-season FE	Yes	Yes	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	No	Yes	Yes
HH controls	Yes	No	Yes	Yes	Yes	Yes
SES controls	Yes	No	Yes	Yes	Yes	Yes
Observations	524,911	524,911	524,911	524,911	175,065	175,065

Table displays regression of meeting minimum calorie requirement on log market prices for rice. Model (6) reports coefficients and standard errors on log Rural Price Survey (RPS) prices; all other models report on log NSS unit values. Household controls are log household size, SC/ST, land ownership, religion, and cooking fuel. All households owning 0.01 hectares of land or greater are classified as landowning. Household-level SES are the predicted values from a projection of log expenditure per capita on permanent household characteristics, with geographic unit and period fixed effects. Period fixed effects include calendar and NSS round fixed effects. Standard errors in parentheses and clustered at the region-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Meeting minimum calorie requirement and market prices by subsamples

	By median SES		By Census region		Rural by landowning	
	Below	Above	Rural	Urban	Landless	Landowning
	(1)	(2)	(3)	(4)	(5)	(6)
Log market rice price	-0.193***	-0.009	-0.182***	0.016	-0.284***	-0.152***
	[0.053]	[0.040]	[0.052]	[0.057]	[0.088]	[0.050]
Equality of effect (p-value)		0.00		0.01		0.12
Observations	262,654	262,257	316,234	208,677	63,614	252,620

Table displays regression of meeting minimum calorie requirement on log rice unit values. All specifications include area-season and period fixed effects. Demographic controls are log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. All households owning 0.01 hectares of land or greater are classified as landowning. Household-level SES are the predicted values from a projection of log expenditure per capita on permanent household characteristics, with geographic unit and period fixed effects. Period fixed effects include calendar and NSS round fixed effects. Standard errors in parentheses and clustered at the region-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Log calories per-capita and market prices by subsamples

	All	By median SES		By Census region		Rural by landowning	
		Below	Above	Rural	Urban	Landless	Landowning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log market rice price	-0.065**	-0.108***	-0.003	-0.105**	0.004	-0.122*	-0.111***
	[0.031]	[0.039]	[0.028]	[0.041]	[0.031]	[0.071]	[0.035]
Equality of effect (p-value)			0.01		0.03		0.86
Observations	524,911	262,654	262,257	316,234	208,677	63,614	252,620

Table displays regression of log calories per-capita on log market prices for rice. All specifications include area-season and period fixed effects. Demographic controls are log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. All households owning 0.01 hectares of land or greater are classified as landowning. Household-level SES are the predicted values from a projection of log expenditure per capita on permanent household characteristics, with geographic unit and period fixed effects. Period fixed effects include calendar and NSS round fixed effects. Standard errors in parentheses and clustered at the region-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: PDS value (in 100 Rs.) on eligibility expansions, statutory prices, and interaction

	All	By median SES		By Census region		Rural by landowning	
		Below	Above	Rural	Urban	Landless	Landowning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PDS price (Rs.)	-0.097***	-0.116**	-0.054**	-0.105**	-0.063**	-0.101***	-0.107**
	(0.035)	(0.043)	(0.023)	(0.039)	(0.026)	(0.033)	(0.042)
Eligibility increase (=1)	0.512***	0.576***	0.445***	0.525***	0.500***	0.481***	0.539***
	(0.102)	(0.117)	(0.098)	(0.114)	(0.106)	(0.122)	(0.127)
Eligibility increase × PDS price	-0.116***	-0.117**	-0.140***	-0.108**	-0.148***	-0.117**	-0.102**
	(0.038)	(0.048)	(0.030)	(0.045)	(0.030)	(0.045)	(0.048)
Weak IV F-stat	36.59	38.55	24.52	32.34	26.62	42.22	21.05
Observations	524,911	262,654	262,257	316,234	208,677	63,614	252,620

This table presents coefficients and standard errors from a regression of PDS transfer value on PDS statutory rice prices, PDS expansion indicator, and their interaction. PDS value is calculated as the difference between market and PDS rice prices multiplied by household-level PDS quantities (expressed in units of 100). Market and PDS prices are average unit values of market and PDS rice at region-sector-period level. Statutory rice prices are state-mandated prices per kilogram of PDS rice for households below the poverty line. Expansion indicates if a household is surveyed in an expansion state after the date of expansion of the PDS reported in Table A4. All prices are deflated to 1999 Rs. All specifications include region-sector-season and period (calendar quarter and NSS round) fixed effects. Controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Standard errors in parentheses and clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effect of PDS generosity on meeting minimum calorie requirement

	All	By median SES		By Census region		Rural by landowning	
		Below	Above	Rural	Urban	Landless	Landowning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: IV of meeting minimum calorie requirement on PDS value							
PDS Value (100 Rs.)	0.107*	0.127**	0.061	0.121**	0.083	0.178***	0.105**
	(0.052)	(0.055)	(0.045)	(0.054)	(0.055)	(0.060)	(0.048)
Weak IV F-stat	36.59	38.55	24.52	32.34	26.62	42.22	21.05
Panel B: IV of meeting minimum calorie requirement on PDS value							
Market rice price, logged	-0.243***	-0.395***	-0.077*	-0.344***	-0.131**	-0.477***	-0.277***
	(0.054)	(0.076)	(0.041)	(0.082)	(0.050)	(0.079)	(0.072)
Market rice price $\times$ PDS value	0.178**	0.191**	0.285**	0.162**	0.412**	0.110	0.113
	(0.066)	(0.075)	(0.133)	(0.073)	(0.165)	(0.086)	(0.093)
Predicted rice elasticity,	-0.190***	-0.323***	-0.030	-0.293***	-0.030	-0.435***	-0.244***
at mean PDS value	(0.051)	(0.082)	(0.030)	(0.076)	(0.053)	(0.085)	(0.061)
Weak IV F-stat	26.20	34.96	40.90	49.74	14.76	37.03	29.17
Mean PDS value	0.296	0.375	0.166	0.314	0.246	0.376	0.290
SD PDS value	0.604	0.651	0.492	0.592	0.632	0.632	0.574
1st percentile PDS value	0	0	0	0	0	0	0
99th percentile PDS value	2.56	2.63	2.30	2.41	2.73	2.56	2.36
Observations	524,911	262,654	262,257	316,234	208,677	63,614	252,620

Mean per-capita expenditure is 711 Rs. PDS value is measured in units of 100 Rs. All specifications include area-season and period fixed effects. Controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Weak IV F-stats are calculated with Kleibergen-Paap (2006). All households owning 0.01 hectares of land or greater are classified as landowning. Household-level SES are the predicted values from a projection of log expenditure per capita on permanent household characteristics, with geographic unit and period fixed effects. Period fixed effects include calendar and NSS round fixed effects. Coefficient on PDS value not shown in Panel B. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of PDS generosity on meeting minimum calorie requirement

	Baseline	No suppliers	Pol. econ. controls	Price inst. only	Expansion inst. only
	(1)	(2)	(3)	(4)	(5)
Panel A: IV of meeting minimum calorie requirement on PDS value					
PDS Value (100 Rs.)	0.107*	0.171***	0.109*	0.018	0.172**
	(0.052)	(0.053)	(0.054)	(0.085)	(0.068)
Weak IV F-stat	36.59	32.53	34.33	8.93	17.42
Panel B: IV of meeting minimum calorie requirement on PDS value					
Market rice price, logged	-0.243***	-0.231***	-0.252***	-0.229***	-0.282***
	(0.054)	(0.048)	(0.054)	(0.073)	(0.071)
Market rice price × PDS value	0.178**	0.170	0.192**	0.257**	0.131*
	(0.066)	(0.120)	(0.071)	(0.112)	(0.071)
Predicted rice elasticity, at mean PDS value	-0.190***	-0.184***	-0.195***	-0.153**	-0.243***
	(0.051)	(0.058)	(0.052)	(0.062)	(0.066)
Weak IV F-stat	26.20	22.27	30.58	4.40	8.59
Mean PDS value	0.296	0.280	0.296	0.296	0.296
SD PDS value	0.604	0.601	0.604	0.604	0.604
1^{st} percentile PDS value	0	0	0	0	0
99^{th} percentile PDS value	2.56	2.56	2.56	2.56	2.56
Observations	524,911	391,176	524,911	524,911	524,911

This table shows coefficients from regression of a dummy for meeting the minimum caloric requirement (MCR) on PDS value (in Panel A) and PDS value, market rice prices and their interaction (Panel B). In Panel A, PDS value is calculated as the difference between market and PDS rice prices multiplied by household-level PDS quantities (expressed in units of 100 Rs.), and instrumented for with state-level statutory PDS prices, a dummy for state-level PDS expansions, and their interaction. In Panel B, the same three instruments are included, as well as their interactions with market prices. Model (1) includes all PDS instruments, (2) includes all PDS instruments but excludes states supplying the majority of rice to the PDS, (3) includes all PDS instruments but controls for active NREGA program in district at the time of surveying as well as elections at the state-quarter level, (4) instruments for PDS value with statutory rice price instruments alone, and (5) instruments for PDS value with expansion instruments alone. For comparison, mean per-capita expenditure is 711 Rs. All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Weak IV F-stats are calculated with Kleibergen-Paap (2006).. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effect of PDS generosity on log calories per-capita

	All	By median SES		By Census region		Rural by landowning	
		Below	Above	Rural	Urban	Landless	Landowning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: IV of log calories per-capita on PDS value							
PDS Value (100 Rs.)	0.064	0.064	0.064*	0.067	0.068*	0.107**	0.051
	(0.039)	(0.040)	(0.036)	(0.043)	(0.033)	(0.049)	(0.031)
Weak IV F-stat	36.59	38.55	24.52	32.34	26.62	42.22	21.05
Panel B: IV of log calories per-capita on PDS value							
Market rice price, logged	-0.154***	-0.233***	-0.064*	-0.219***	-0.098**	-0.255***	-0.189***
	(0.033)	(0.052)	(0.033)	(0.058)	(0.036)	(0.069)	(0.056)
Market rice price $\times$ PDS value	0.137***	0.145***	0.238***	0.149***	0.273**	0.103	0.101
	(0.045)	(0.047)	(0.072)	(0.050)	(0.120)	(0.088)	(0.067)
Predicted rice elasticity,	-0.113***	-0.179***	-0.025	-0.173***	-0.030	-0.216**	-0.160***
at mean PDS value	(0.033)	(0.054)	(0.032)	(0.055)	(0.031)	(0.078)	(0.044)
Weak IV F-stat	26.20	34.96	40.90	49.74	14.76	37.03	29.17
Mean PDS value	0.296	0.375	0.166	0.314	0.246	0.376	0.290
SD PDS value	0.604	0.651	0.492	0.592	0.632	0.632	0.574
1^{st} percentile PDS value	0	0	0	0	0	0	0
99^{th} percentile PDS value	2.56	2.63	2.30	2.41	2.73	2.56	2.36
Observations	524,911	262,654	262,257	316,234	208,677	63,614	252,620

Mean per-capita expenditure is 711 Rs. PDS value is measured in units of 100 Rs. All specifications include area-season and period fixed effects. Controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Weak IV F-stats are calculated with Kleibergen-Paap (2006). All households owning 0.01 hectares of land or greater are classified as landowning. Household-level SES are the predicted values from a projection of log expenditure per capita on permanent household characteristics, with geographic unit and period fixed effects. Period fixed effects include calendar and NSS round fixed effects. Coefficient on PDS value not shown in Panel B. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Additional Notes on Data

A.1 Sample

Our data comes from the Household Consumer Expenditure schedules of the 59^{th} through 68^{th} rounds of the Indian National Sample Survey, covering January 2003 through June 2012. 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 523,435 households.

We considered including data from earlier rounds of the NSS. However, the 58^{th} and earlier rounds are based on the 1991 Census, rather than the 2001 Census. This presents two difficulties. First, the weights change drastically, because of large population changes between the two years, which presents difficulties in interpretation. Second, many district definitions change between the 58^{th} and 59^{th} rounds, mostly as a result of district splits. Creating consistent district identifiers would therefore mean using the larger 58^{th} round districts, limiting our geographic precision and reducing the number of unique districts by 17%. Given that all of our policy variation is after the 59^{th} round, we elected to use the smaller but more geographically precise data.

A.2 Consistency across rounds

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 reported consumption over the previous 30 and 365 days for some goods. 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

We then scale the consumption for the 365-day recall goods by $\frac{30}{365}$, and interpret consumption as over the previous 30 days.

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 Rupees. We have also calculated state-level deflators from our NSS data using Laspeyres price indices. 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.

A.3 Unit values as prices

We use unit values as measures of prices. There are two potential issues with this approach. First, that there are too few observations for precise estimates of the unit value, and second, that households substitute to lower-quality goods in the same category as prices rise.

Table A2 contains information on the number of observations per commodity for rice, wheat, sugar, and kerosene (the PDS goods), as well as over all items in the food and fuel categories. The median area area has 10 observations per quarter, and even the fifth percentile has 3.

A more direct test of the measurement error induced by a finite number of observations is to compare the NSS unit values directly against prices. We do this in Table A3, where we regress prices from the Rural Price Survey on NSS unit values. The Rural Price Survey is run separately from the NSS, and collects data on prices at markets in rural areas in India. For the subset of districts and quarters where the RPS overlaps with the NSS, the two price measures are measuring the same thing up to differences in how the RPS selects markets to survey (the RPS documentation is non-existent, so the extent to which this is true is very unclear). Nonetheless, the correlation between the two price measures is in the 0.7-0.8 range across all food groups, and 0.5-0.8 for rice and wheat. This suggests that the unit values are picking up most of the variation in prices, with the gap between the observed correlation and

1 (which we would estimate if the two prices measures were measuring the *exact* same thing) made up of some combination of measurement error in unit values, quality substitution, and different sampling procedures. We are agnostic about which is most important.

A.3.1 Detecting data errors in unit values

Before taking mean unit values to use as price measures, we remove some obvious data errors. The errors seem to be arising from errors in the unit measures. Most of the obvious outliers have quantities that are very small, which suggests that they may have been reported in different units. In some cases, the quantity appears to be 10x or 100x too small. We identify these using the following two methods;

We identify outliers for all our items using 2 methods:

- SD rule: We first trim the top and bottom 1% of UVs by item-round to create UV_{trim}. We then take the median and SD of UV_{trim} by item-round. The idea here is to get a close to accurate measure of the SD for every item, since some SDs are more skewed than others, depending on how much of an issue outliers are for the item. Once we trim the the unit values, the SDs generally become very small, indicating that a few very big outliers are causing the SDs to be skewed. We then identify outliers as UVs outside $15 \times SD_{trim}$ above/below the median. Using 10 or anything smaller as the threshold seems to capture observations that could be valid data. 12 and 15 produce similar results, so we use the less restrictive threshold.

- Factor rule: To deal with quantities that seem to have been reported in different units, we identify observations that are ... .08x-.12x, 8x-12x, 80x-120x ... greater than the item-round or area-period median.

A.4 PDS expansions and policy changes

We hand-collected changes in PDS eligibility by examining newspapers, online sources, and government documents. As discussed in the main text, we structured our search by first looking for changes in PDS generosity in each state-quarter. If we found evidence of a change larger than Rs. 10, we then looked for evidence that the change had actually occurred. In most cases, the change was very clear in the data—Figure A2 shows two examples that were obvious even without a direct confirmation.

B Robustness checks

We conduct the following robustness checks:

1. **FES:** Using region-sector-season FEs, rather than district-sector-season. The results are nearly unchanged.

2. **Clustering:** the results are similar when we cluster at the region level rather than the state. We also implement the wild-cluster bootstrap at the state level to account for the small number of states. The effect of the PDS on caloric levels for disadvantaged groups remains significant at the 10% level, while the interaction of prices and PDS remains significant at the 5% level.

3. While conditioning on contemporaneous expenditure over-controls for economic changes that affect caloric intake, we find that it has little effect on coefficient magnitude while slightly increasing precision.

4. Setting the threshold for landowning 0.20 hectares (rather than 0.01 hectares as in the paper) slightly increases the difference in effect sizes between landowning and non-landowning households.

C Appendix Exhibits

Figure A1: Share purchasing PDS by per-capita expenditure

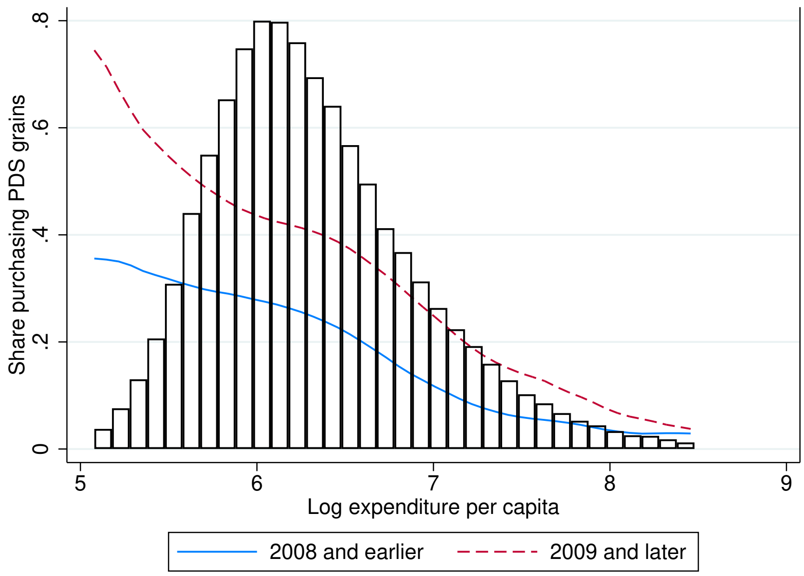


Figure shows share of households consuming PDS rice in the first and second half of the sample. The histogram shows the distribution of per-capita income, in 1999 rupees. The exchange rate was roughly 43 rupees to one USD.

Figure A2: PDS value and share of population consuming PDS for Odisha policy change

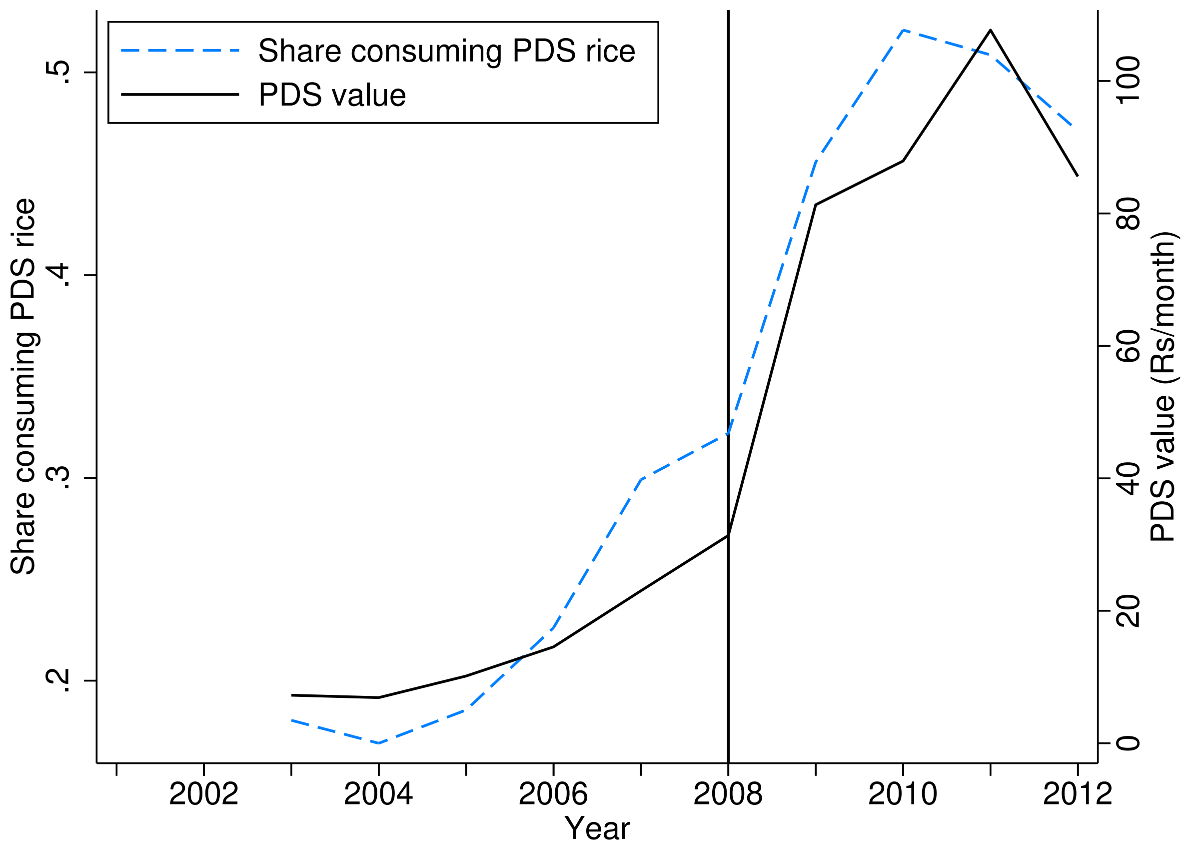


Figure shows share consuming PDS rice and average PDS value for Odisha in each year. Odisha reduced prices and expanded the number of PDS-eligible households in 2008.

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.

Table A2: Summary statistics for number of observations defining rice unit values

	Mean (SD)	Percentile				
		1%	5%	10%	25%	50%
Market rice	112.29 (103.55)	8	16	23	42	78
PDS rice	38.63 (56.20)	1	1	2	5	16

Table shows summary statistics and percentiles for number of observations defining unit values at region-sector-period level. Standard deviations in parentheses.

Table A3: Log RPS prices on log NSS unit values

	All	By Median SES		By Landowning	
		Below	Above	Landless	Landowner
	(1)	(2)	(3)	(4)	(5)
NSS rice unit value, logged	0.574***	0.556***	0.650***	0.578***	0.572***
	[0.063]	[0.065]	[0.065]	[0.076]	[0.062]
Observations	175,065	116,070	58,995	36,655	138,410

Standard errors in parentheses and clustered at the region-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: PDS major policy changes

State	Policy Change	Type
Andhra Pradesh	April 7, 2008	Entitlement change/price reduction
Chhattisgarh	April 30, 2007	Expansion
Chhattisgarh	July 8, 2009	Price reduction
Karnataka	June 1, 2008	Expansion
Kerala	February 1, 2006	Price reduction
Kerala	April 16, 2011	Expansion
Odisha	August 1, 2008	Expansion/price reduction
Tamil Nadu	December 31, 2004	Expansion
Tamil Nadu	June 3, 2006	Price reduction

Table A5: Effect of PDS generosity on logged rice prices

	All	By median SES		By Census region		Rural by landowning	
		Below	Above	Rural	Urban	Landless	Landowning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: PDS rice price instrument							
PDS Value (100 Rs.)	-0.026	-0.016	-0.065	-0.015	-0.065	-0.048	-0.005
	(0.057)	(0.048)	(0.095)	(0.054)	(0.084)	(0.086)	(0.048)
Weak IV F-stat	8.11	7.13	8.70	7.76	7.41	9.84	7.05
Panel B: PDS expansion instrument							
PDS Value (100 Rs.)	-0.008	-0.010	-0.001	-0.001	-0.022	-0.038	0.008
	(0.044)	(0.041)	(0.056)	(0.043)	(0.039)	(0.059)	(0.039)
Weak IV F-stat	17.72	18.46	11.35	19.92	10.84	13.81	19.54
Panel C: PDS rice price, expansion, and interaction instruments							
PDS Value (100 Rs.)	-0.006	-0.005	-0.007	0.002	-0.030	-0.018	0.009
	(0.030)	(0.029)	(0.031)	(0.032)	(0.019)	(0.036)	(0.033)
Weak IV F-stat	37.69	36.76	24.40	34.21	25.05	66.50	21.78
Observations	524,911	262,654	262,257	316,234	208,677	63,614	252,620

Panel A displays results of instrumental variables regression of log rice unit values on PDS value, instrumented by PDS rice price. Panel B displays results of instrumental variables regression of log rice unit values on PDS value, instrumented by PDS expansion. Panel C displays results of instrumental variables regression of log rice unit values on PDS value, instrumented by PDS rice price, PDS expansion, and their interaction. Weak IV F-stats are the effective F-stat of Montiel Olea-Pflueger (2013) in all panels. Controls include log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.