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 the preferred form of transfer to low income households. However, in-kind transfers remain prevalent throughout the world. We argue that beneficiaries themselves may prefer in-kind transfers because these transfers can provide insurance against price risk. Households in developing countries often face substantial price variation as a result of poorly integrated markets. We develop a model demonstrating that in-kind transfers are welfare improving relative to cash if the covariance between the marginal utility of income and price is positive. Using calorie shortfalls as a proxy for marginal utility, we find that in-kind transfers improve welfare relative to cash for Indian households, an effect driven entirely by poor households. We further show that expansions in the generosity of the Public Distribution System (PDS)—India's in-kind food transfer program—result not only in increased caloric intake but also reduced sensitivity of calories to prices.

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1 Introduction

A central question in the design of social protection programs is the optimal form of transfers to the poor. Historically, in-kind transfers have been the primary type of anti-poverty program. These transfers remain prevalent and important: approximately 44% of safety net beneficiaries 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 given cash will maximize the "wrong" utility function (either due to intra-household conflicts or simply a paternalistic view (see Currie and Gahvari, 2008)). However, in contrast to the textbook intuition, beneficiaries themselves often report a preference for in-kind relative to cash in contexts as varied as Ecuador, India, and Malawi (Hidrobo et al., 2014; Khera, 2014; Gentilini, 2016).

We demonstrate that in-kind transfers can be welfare improving relative to cash from the perspective of the beneficiary household in the presence of commodity price risk. A common feature of many developing countries is the lack of market integration (Atkin, 2013; Allen, 2014), and households often face substantial variation in prices of basic consumption goods.[1] In-kind transfers provide implicit insurance against this risk since the value of the transfer rises automatically with the local market price of the transferred good. Indeed, beneficiaries who prefer food transfers to cash frequently mention the fear of unstable prices as a reason for their preference (Khera, 2014).

We derive a condition under which households prefer in-kind transfers, provide an empirical test of whether this condition is satisfied in the context of India, and examine the effects of a large scale in-kind transfer program on households. Our focus is on questioning the fundamental premise that cash delivers higher expected utility to the recipient; a full

[1] In addition to these studies on India (Atkin, 2013) and the Philippines (Allen, 2014), a plethora of evidence exists on the lack of market integration and subsequent internal price variation in various other countries; for example Uganda (Gollin and Rogerson, 2014), Sierra Leone (Casaburi, Glennerster and Suri, 2013) and Peru (Sotelo, 2020). One way to gauge the extent to which integration matters is provided by Atkin and Donaldson (2015), who show that the effect of distance on trade costs in Ethiopia and Nigeria is four to five times that in the United States.

welfare analysis would also need to consider the relative social cost of provision.[2]

We begin with a simple model to demonstrate that when prices vary across states of the world, the optimal policy will provide price-indexed cash transfers that equalize marginal utility of income across states. Absent storage technology, households face a trade-off between the desire to smooth consumption and the gains from substitution toward cheaper consumption in low price states. Therefore, the marginal utility of income and optimal transfers may theoretically increase or decrease with respect to price.[3]

In practice, price-indexed transfers are often infeasible because local prices are difficult for governments to observe at high frequency and in real time.[4] We therefore consider the choice between two common 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. 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.

Indeed, the *reason* that marginal utility of income might be higher in high-price states is not relevant for our test. It might be because of higher prices directly, or because incomes tend to be lower in high-price states of the world, or for some other reason. This means that even if a causal estimate of the effect of prices on marginal utility were available, it would not be appropriate for determining whether an in-kind transfer would be preferred by the household. Instead, our test would still rely on the covariance between prices and marginal utility. This test is along the lines of a sufficient statistics approach (Chetty, 2009) and analogous to recent work estimating the welfare effects of Medicaid (Finkelstein, Hendren and Luttmer, 2019). Since the relevant relationship can be estimated without instruments for prices, our test can be applied in a wide variety of empirical settings.

A challenge when implementing this test is to find an appropriate empirical proxy for the

[2]Estimating the social cost is challenging: in-kind procurement often interacts with distortionary production subsidies and purchase guarantee schemes. In some cases, transfers may be financed externally through aid organizations. In addition, there may be differences in administrative costs or corruption (Banerjee et al., 2021). Finally, we note that certain behavioral models predict that households will misallocate cash transfers (Currie and Gahvari, 2008), or treat in-kind transfers as non-fungible, even when they are inframarginal (Hastings and Shapiro, 2018). These issues are outside the scope of this paper.

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

[4]It is well known that "community price surveys in developing economies are either absent or suffer quality problems" (Gibson and Rozelle, 2005). In the Indian case, Khera (2014) notes that "it is not 'technically simple' to index cash transfers; one needs to consider several factors—including local variation in prices, adequate infrastructure requirements to collect such information, and frequency of indexing the amount."

marginal utility of income. Our primary measure is an indicator for falling below minimum calorie requirements. The key assumption underlying this measure is that the marginal utility of income rises when households fall below minimum requirements. 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.[5] Calories have low substitutability across periods and with other types of (non-food) consumption goods, so the curvature of utility with respect to calories is likely to be high, particularly for households close to minimum requirements.[6]

We implement the model test in the context of India, using National Sample Survey (NSS) data from over 500,000 households across 28 states and ten years. 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 just on rice—the most commonly consumed food staple and the focus of our analysis. We use an indicator for meeting minimum calorie requirements (MCR) from the Indian Council of Medical Research (ICMR) as well as calories per capita as (inverse) proxies for the marginal utility of income.[7] Forty percent of households in our sample fall short of minimum recommended calorie intake guidelines.

Increases in the price of rice are significantly negatively associated with caloric intake: a 10% increase in the market price is associated with 1.1 percentage points fewer households (equivalent to 13 million individuals nationwide) meeting the MCR and a 0.7% decline in calories consumed by the average household. These findings are entirely driven by below-median socioeconomic status (SES) households. In the context of the model, these results demonstrate empirically that in-kind transfers are preferable to cash for poorer households—precisely the group generally targeted by safety net programs.

We next turn to providing direct causal evidence on the effects of India's flagship in-kind transfer program: the Public Distribution System (PDS). The PDS is one of the largest in-kind transfer programs in the world, providing food transfers to nearly a billion people in 180 million eligible households (Balani, 2013). The program provides (mainly) rice and wheat every month at substantially below-market prices through a network of over 500,000 designated shops. The primary goal of this analysis is to demonstrate that expansions in the PDS do in fact lead to decreased sensitivity of calories to prices "on the ground"—consistent with the insurance mechanism posited in the model—and to quantify the magnitude of these

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

[6] We do not attempt to construct a marginal utility measure using total real consumption because we lack local price measures for most non-food consumption.

[7] We use MCR as shorthand for the ICMR's caloric guideline for the "sedentary" (lowest) level of exertion calculated by age and gender and aggregated to the household level.

effects. To the best of our knowledge, previous work has not analyzed the effect of in-kind transfer programs on the sensitivity of outcomes to prices.

We examine the causal effects of the PDS on caloric intake and the calorie-price relationship using newly collected administrative data on state-level PDS policy changes between 2003-12, a period between major national policy changes. We use variation in the mandated PDS price as well as expansions in eligibility to instrument for *PDS value*: the actual value of the subsidy received by households, defined as the quantity of rice obtained from the PDS multiplied by the difference between the market price of rice and the PDS price paid by beneficiaries (first stage F=37).

We first document large effects of PDS expansions on the level of calories. A Rs. 100 increase in PDS value (the average non-zero PDS transfer) leads to a 10.7 percentage point increase in households meeting the MCR and a 6.4% increase in calories per capita. Overall, we estimate that PDS policy changes led to 40 million additional individuals meeting MCR thresholds over the study period.

Increases in PDS generosity also substantially reduce the sensitivity of calories to market prices. A Rs. 100 increase in PDS value reduces the sensitivity of calories to market prices by 73%, with estimated sensitivity for the average household reaching zero for a PDS transfer worth Rs. 135. This is only one-third larger than the average non-zero transfer, indicating that the PDS as implemented during our study period already provides a substantial amount of insurance against price risk.

To alleviate concerns about policy endogeneity and omitted variables bias, we demonstrate that trends in calories prior to eligibility expansions are flat. Our results are also robust to controlling for political cycles and generosity of the National Rural Employment Guarantee Scheme (India's other major welfare program), and are similar when we restrict the sample to states that are not major suppliers to the PDS or identify effects based solely on either price or quantity variation in the PDS. Finally, we demonstrate that the impact of the PDS on market prices is too small—by at least two orders of magnitude—to explain our results.

This paper contributes to several literatures. First, understanding the potential insurance value of in-kind transfers is important for the larger ongoing debate around the world regarding the appropriate design of social protection programs. Numerous recent studies have highlighted the benefits of unconditional cash transfers (Haushofer and Shapiro, 2016; Banerjee, Niehaus and Suri, 2019).[8] Previous studies have proposed other rationales for in-kind transfers: they can improve targeting (Nichols and Zeckhauser, 1982; Besley and Coate, 1991; Lieber and Lockwood, 2019), the well-being of non-targeted households by re-

[8]See also Blattman et al. (2017); Egger et al. (2019); Ghatak and Muralidharan (2020).

ducing market prices of transferred goods (Coate, Johnson and Zeckhauser, 1994; Cunha, De Giorgi and Jayachandran, 2018), and the efficiency of imperfectly competitive food markets under some conditions (Coate, 1989). However, although some in the policy community have highlighted the potential insurance benefits of in-kind transfers (Kotwal, Murugkar and Ramaswami, 2011; Dreze, 2011), this rationale has been largely unstudied in the academic literature. 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 longstanding literature on household exposure to price variability and its consequences. 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 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, the empirical literature on price risk is limited (Bellemare and Lee, 2016), and 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.[9] Numerous studies have examined the effect of food price shocks on nutrition, with mixed findings.[10] Our study complements this literature by demonstrating the implications of this empirical relationship for the design of optimal social protection programs *without* requiring an instrument for prices, a major challenge in this literature.

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 it directly affects two-thirds of the population. The program has been criticized for corruption and mistargeting (Niehaus et al., 2013; Dreze and Khera, 2015), while the (surprisingly) limited rigorous evidence on its causal effects is mixed (Kochar, 2005; Tarozzi, 2005; Kaul, 2014). Our results—finding that the PDS does improve nutrition by allowing households to reach

[9] 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).

[10] A number of 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 (Jensen and Miller, 2008; Behrman, Deolalikar and Wolfe, 1988).

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 that find little or no effect). 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, during the current Covid-19 crisis, the PDS has assumed an even more important role: not only as the main food security and social welfare program, but explicitly as a bulwark against local food price shocks (Roy, Boss and Pradhan, 2020).

The remainder of the paper proceeds as follows. Section 2 develops a framework for examining the welfare effects of cash versus in-kind transfers. Section 3 discusses the context and data. Section 4 presents evidence on price risk in India and provides an empirical test of the model. 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 unitary household facing a varying price in one of several consumption goods. We derive three key results. First, the optimal insurance policy consists of price-indexed transfers that equate the marginal utility of income across states of the world. Second, optimal transfers 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 if and only if the marginal utility of income is higher in the high-price states of the world. Consider a household consuming several goods and assume that the price p_j of one of the goods, j, varies across states of the world with mean $\bar{p}_j$ and density $f(p_j)$. The prices of all other goods are fixed. For simplicity, we abstract from potential effects of transfers on market prices.[11] The household has income y and preferences characterized by the indirect utility function $v(\cdot)$. We assume that y is fixed but relax this assumption below.

We first characterize the optimal insurance policy: price-indexed (state-dependent) transfers. The optimal break-even insurance menu specifies a set of transfers for each possible value of p_j, which we write $x(p_j)$, such that the expected value of these transfers,

[11] In some settings, in-kind transfers reduce market prices (Cunha, De Giorgi and Jayachandran, 2018; Jiménez-Hernández and Seira, 2021). However, we do not observe this in our empirical context (see Section 5.4).

$\int x(p_j)f(p_j)dp_j$, is equal to 0.[12] However, all the results derived below hold if the net expected value of the transfer is positive.

The optimal transfer $x(p_j)$ for a given price p_j is thus the one that maximizes $\int v(p, y + x(p_j))f(p_j)dp_j - \mu \int x(p_j)f(p_j)dp_j$, where μ is the marginal utility of income and p is the vector of all good prices. The first order condition tells us that the optimal menu equates the marginal utility 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 larger amounts to households in states with higher marginal utility of income. Optimal transfers $x(p_j)$ will therefore be increasing in the price if the marginal utility of income is itself increasing in the price. Taking the derivative of Roy's identity with respect to income, we can write the derivative of the marginal utility of income with respect to price in the following way:

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

where α_j 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 to prefer transfers in the high price state.[13] 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_j: the higher the budget share spent on the good, the greater the sensitivity of marginal utility to price.

2.2 Extending the model

A key advantage of this approach is that we do not need to explicitly specify all potential components of the utility function: because agents are optimizing, the derivative of marginal utility with respect to price will continue to be sufficient to assess the welfare effects of transfers.

[12]This policy replicates the outcome the household could achieve with access to complete Arrow-Debreu securities.

[13]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 also captures the possibility of substitution to other goods.

As an illustrative example, we consider the case in which income co-varies with local prices. This is likely, since local prices themselves will be affected by local supply and demand conditions if there is a lack of market integration. Allowing household income to co-vary with prices, we obtain the following expression for the derivative of the marginal utility of income with respect to price:

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

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 (for example) between households who are producers versus consumers of the good.

However, the form of optimal transfers continues to be determined solely by the derivative of the marginal utility of income with respect to price. Specifically, transfers will be increasing with respect to price if and only if this derivative is positive.

$$x'(p_j) > 0 \iff v_{yp}(p, y + x(p_j)) > 0 \tag{4}$$

v_{yp} reflects risk aversion and income elasticity and allows for price-income correlations. This derivative will also capture the effects of potential correlations between p_j and the prices of other goods,[14] as well as other dimensions of household behavior such as savings, storage, and home production.

2.3 Cash versus in-kind transfers

In practice, implementing the optimal state-contingent policy requires observing local prices in real time and at high frequency, which is infeasible in most developing country contexts (Gibson and Rozelle, 2005; Khera, 2014). 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 inframarginal (the household consumes more than z of the good for

[14] Until now, the j indexing on the derivative of marginal utility with respect to price has been implicit since only the price of the in-kind good has varied; to account for other prices varying as well, one would index the derivative v_{yp_j}.

all possible prices p_j).[15] Finally, we assume that prices are not affected by either cash or in-kind transfers.

The welfare effect of introducing a cash transfer can then be written as:

$$W_C = z\bar{p}_j \int v_y(p, y) f(p_j) dp_j \tag{5}$$

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

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

Plugging (5) into (6) we obtain:

$$W_K = W_C + z \int v_y(p, y)(p_j - \bar{p}_j) f(p_j) dp_j \tag{7}$$

where the second term is simply the transfer amount z multiplied by 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:[16]

$$W_K \approx W_C + z v_{yp}(\bar{p}, y) \int (p_j - \bar{p}_j)^2 f(p_j) dp_j \tag{8}$$

Expression (7) 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 (8)), the in-kind transfer is welfare improving with respect to the cash transfer. Therefore:

$$W_K > W_C \iff v_{yp}(p, y) > 0 \tag{9}$$

This is because the in-kind transfer effectively transfers more to the household in states of the world in which the price is high and it values extra income more: in other words, it more closely approximates the optimal insurance contract. In Appendix A1, we demonstrate that the in-kind transfer will be equivalent to the optimal transfer for particular parameter values, but in general will underperform the optimal transfer because it scales the transfer

[15] This assumption holds for 93% of households in our empirical context. Our results below will also hold if transfers are marginal but households can engage in resale at the market price. Otherwise, the welfare gain from in-kind transfers will be reduced as a result of distortion to the consumption bundle.

[16] Here $\bar{p}$ indicates the vector of mean prices.

value with respect to price only as a function of the in-kind transfer quantity, rather than as a function of the household's preferences.

2.4 Model implementation

In practice, we do not observe marginal utility of income directly and therefore rely on consumption-based measures as empirical proxies. Our main measure is an indicator for households failing to meet minimum calorie requirements. This allows us to capture total real food consumption—a substantial share of total consumption—in a single measure derived solely from quantity data. The identifying assumption is that an increased likelihood of failing to meet minimum requirements is associated with an increase in the marginal utility of income. This assumption is likely to be satisfied since calories have low substitutability (both intertemporally and with non-food consumption), and the curvature of the utility function with respect to calories near the threshold is likely to be high.

Note that we are unable to construct an accurate measure of total real consumption because we do not have local price measures for 25% of food consumption and 87% of non-food consumption. However, if we deflate expenditure by the limited price vector available and use this as an outcome, we find very similar results to the calorie results presented below (see Appendix A2.3 for a discussion of the data limitations and results).

An important interpretation consideration arises if the observed calorie gradient with respect to price reflects costly consumption smoothing mechanisms on the part of households (Chetty and Looney, 2006). In this case, observing a positive relationship between the likelihood of failing to meet caloric thresholds and price is a *sufficient* but *not necessary* condition for in-kind transfers to be welfare improving relative to cash. Observing no relationship could still be consistent with a preference for in-kind, if in-kind transfers better allow risk-averse households to be less reliant on costly smoothing behaviors.

3 Context and data

3.1 Context

We examine the predictions of the model empirically in the context of India. 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, and local prices are subject to volatility arising from (for example) weather shocks (Rosenzweig and Udry, 2014). Substantial price differences persist across regions, and temporary shocks to local prices are frequent (Atkin, 2013). Second, as we discuss below, a substantial share of the population fails to meet basic caloric requirements. Finally, India has one of the world's largest in-kind transfer programs:

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 goods such as rice at significantly subsidized rates to eligible households via a widespread network of Fair Price Shops.[17] 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.[18] Eligible households can buy up to a certain quantity of grains each month based on entitlements listed on ration cards, although in practice the PDS shops may not always have enough for each household to purchase its entire allocation.[19]

Before 2000, eligibility was largely restricted to poor households, in particular those considered to be Below Poverty Line (BPL). 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.

3.2 Data

Our main source of data is 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 our sample period in 2003 because the NSS does not consistently identify many districts before the 59$^{\text{th}}$ round. June 2012 is the end of the survey period for the 68$^{\text{th}}$ round.

The NSS is a repeated cross-sectional survey that asks 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. In addition, the

[17]The PDS also provides wheat, kerosene for cooking fuel, and less commonly sugar, salt, and other local grains.

[18]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 similar when we exclude PDS-producing states.

[19]Direct transfers of in-kind goods to households are rare outside of emergency relief situations. Accounting for a below-market price the household must pay for the in-kind good modifies the implicit transfer amount—from $z\bar{p}_j$ in our baseline model to $z(\bar{p}_j - p_j^{PDS})$—but does not affect the model test.

survey contains basic demographic information like household size and composition, religion, caste, landholding, assets, education and occupation. We categorize households by the year-quarter in which they were surveyed.

As is standard 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 in the periods July 2008 to June 2009 and July 2010 to June 2011. In total, our sample includes 524,911 households 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 to measure local rice prices. Second, we use the NSS to construct measures of caloric intake, which we use as outcome variables. Appendix A2 provides further details on the NSS and data construction.

3.2.1 Unit values

India lacks measures of prices that are for individual items, cover the entire country, and 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 consumed by household i in time t.[20] Using unit values rather than prices is standard practice in the literature that uses the NSS (Subramanian and Deaton, 1996; Deaton and Tarozzi, 2005) as well as in work on rural prices elsewhere (Sotelo, 2020). We remove observations that appear to result from transcription or data errors; see Appendix A2.2 for more details.

The smallest consistently-identified geographic units in the NSS are districts interacted with a rural/urban ("sector") indicator, and most of our analysis conditions on fixed effects at this level. However, for sample size reasons we measure local prices at a slightly higher level. Instead of districts we use NSS regions, groupings of "contiguous districts having similar geographical features, rural population densities and crop-pattern" that are likely to face similar price shocks. The 10$^{\text{th}}$ percentile region-sector-quarter has 23 consumers of market rice and the 25$^{\text{th}}$ percentile has 42; compared to 4 and 6 at the district-sector-quarter level (Table A1). There are 140 region-sectors, and we measure prices using the mean unit value at the region-sector-quarter level.

We test the validity of the unit-value measures of prices by comparing unit values 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. However, it covers only a limited subsample of rural areas, and a lack of documentation makes it impossible to determine the sampling frame. We therefore

[20]The NSS data includes both expenditure and quantity information for goods purchased from the market and the PDS, so we observe unit values separately for market goods and for goods purchased from PDS shops.

do not use it for our main analysis. However, within the overlapping sample (about 25% of the NSS sample areas), we find an over-time correlation in NSS unit values and RPS prices for rice of nearly 0.60 (see Table A2). Moreover, we show below that results using RPS prices are identical to those using NSS unit values in the overlapping sample.

3.2.2 Household characteristics

Since our object of interest is the price risk faced by individual households over time, we control for permanent household characteristics (indeed, if the same households appeared in the NSS in different rounds, we would control for household fixed effects). The most important of these is household permanent income, which we proxy for using a socioeconomic status (SES) index. We construct this index by regressing log per-capita expenditure on caste, occupation, education of household 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, education (below primary, primary, above primary), and district-sector-season, round, and period fixed effects. The SES index is the predicted value from this regression, standardized to have a mean of zero and a standard deviation of one. When we split the sample by above- and below-median SES, we construct the cutoff using NSS weights within state-rounds.

We use several other household characteristics as controls and as dimensions of heterogeneity to examine. We capture economies of scale in consumption using log household size. Religion and Scheduled Caste/Scheduled Tribe status (constitutional status for historically discriminated-against groups), 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 households' ability to produce food commodities. We define landholding households as owning more than 0.01 hectares of land, which allows us to proxy for the ability to engage in agricultural production.

3.2.3 Calorie requirements

As discussed above, the relevant 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 a 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 the marginal utility of income.

We estimate household-level caloric intake using the information on total consumption of each item (including consumption from the market, the PDS, and home production) combined with estimates of the caloric value of each item (Gopalan et al., 1980). To contextualize caloric consumption, we rely on age × gender specific guidelines for caloric intake from the Indian Council of Medical Research (ICMR) (Rao and Sivakumar, 2010) and calculate the total household requirement. 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, to define 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 the MCR, falling to 56% of households below the median SES (Table 1).[21]

4 Empirical tests of preference for in-kind transfers

4.1 Price exposure and variability

Indian households face considerable 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, it is consumed throughout the country, and it is one of the main goods provided through the PDS system. In line with our assumption of inframarginality in Section 2, only 6.6% of all households and 8.8% of below-median SES households consume rice from the PDS but not from private sources during the 30 day recall period.

We next examine variation in market rice prices over time and across areas (Table 2). Deflating by the all-India CPI, the mean price of rice is Rs. 9.86 per kilogram.[22] Taking 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.[23] 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

[21] 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, implying that individuals may not meet MCRs even in households that consume sufficient calories overall (Brown, Calvi and Penglase, 2018; D'Souza and Tandon, 2019).

[22] We convert all nominal values to 1999 Rupees using the all-India CPI from the World Bank. One US dollar was 43 rupees in 1999.

[23] 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 fixed effects can be included separately from year-quarter fixed effects.

price risk that the government can likely only address by using in-kind transfers. 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 shocks.

The remaining rows of Table 2 show the same summary statistics by demographic groups. 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 outcome measure is an indicator for the household falling below the MCR; we also examine calories per capita as an outcome. Ex ante, it is not obvious that high rice price states will be associated with lower caloric intake: high price states could also be high income states; households may be able to substitute toward other goods; and the relationship is estimated given existing anti-poverty programs and household smoothing mechanisms.

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

$$c_{idrt} = \beta p_{rt} + X_{idrt}\lambda + \delta_{da} + \tau_t + \phi_{round} + e_{idrt} \tag{10}$$

where i indexes household, d indexes district-sector, r indexes region-sector, a indexes agricultural season (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_{da}) to account for place-specific agricultural cycles, 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. Regressions are estimated using NSS weights, and standard errors are clustered at the region-sector level, the level of our price variation.

We want our estimates to capture the empirical relationship between market rice prices and the marginal utility of income, allowing covariance of income and prices as well as substitution across goods in response to changes in relative prices. We therefore do *not* control for current household expenditure or other commodity prices. These estimates will capture the average effect of price variation given any existing household insurance mechanisms as well as access to social safety nets, including the PDS.

Column 1 shows our preferred specification, regressing the likelihood of meeting the MCR on log market rice 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 × season fixed effects to allow for seasonal variation in our price measure. The coefficient is almost identical to our baseline estimate, indicating that caloric shortfalls have similar sensitivity to seasonal and non-seasonal sources of price variation. In column 4, we remove year-quarter and NSS round fixed effects. The coefficient increases in magnitude (though the difference is not statistically significant), suggesting that households are not easily able to insure against shocks that are common across areas.

Finally, we compare our main estimates to results using prices from the Rural Price Survey, which collects prices directly from markets. Column 5 presents results using the baseline price measure (NSS unit values), restricting to the subsample of rural districts where the RPS is conducted. 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 subsample: 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 versus urban, and landowning (Table 4). We find that a 10% increase in rice prices is associated with a 2.2 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.[24] 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 simply 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

[24]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.

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 ($p < 0.05$, column 1). We again see that the effects are concentrated among below-median SES and rural households (columns 2 and 4). 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 unlikely to be due to calorie satiation: in the cross-section, calories increase with respect to expenditure throughout the expenditure distribution (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 (columns 6 and 7). This is unsurprising, since landless households in rural areas are poorer than landholding households on average.

In the context of the theory, these results indicate that in-kind transfers will improve welfare for the average household relative to equal expected value cash transfers. This result is driven by poorer households, precisely those typically targeted by safety net programs. Although we do not observe a significant correlation between prices and caloric intake for above median households, we cannot rule out welfare gains from in-kind relative to cash transfers. Recall that if households are engaging in costly consumption smoothing behavior, our test provides a sufficient but not necessary condition for in-kind transfers to be welfare improving relative to cash.

What do these results imply about the costs of price risk to households? On average, our full-sample results indicate that a 10% increase in rice prices (1.2 SDs of the within-district-sector price variation; see Table 2) is associated with 1.1 percentage points fewer households—or approximately 13 million individuals extrapolating from India's population in our study period—meeting the MCR. Our results also indicate a negative calorie-price gradient for poorer households, implying that many households already below the MCR experience further shortfalls below minimum requirements when prices rise. Moreover, these correlations exist despite government welfare programs including the PDS. 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.[25] Taken together, these results suggest substantial losses in welfare from price variability.

[25]Indeed, there is a long tradition of documenting these actions in the context of India, for example the accumulation of bullocks (Rosenzweig and Wolpin, 1993) as well as female migration for marriage (Rosenzweig and Stark, 1989).

5 Empirical evidence on the role of in-kind transfers

We next turn to estimating the causal effect of in-kind transfers on household outcomes. Our goal in this section is not to compare in-kind and cash transfers: the results in Section 4 have already provided an empirical test of the welfare effect to the household of an equal expected value in-kind versus cash transfer, and a full welfare analysis would require the (unobserved) relative social cost of provision. Rather, the primary aim of this analysis is to show that expansions in in-kind transfers do in fact causally reduce sensitivity of calories to prices "on the ground"—consistent with the insurance mechanism posited in the model—and to determine the empirical magnitude of these effects.

To do this, we exploit policy variation in the PDS, India's flagship in-kind transfer program.[26] 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. The generosity of the program therefore varies across states and over time. We use this policy variation to instrument for observed PDS value and examine the effects of PDS generosity on household caloric intake and the sensitivity of calories to prices.

5.1 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.[27] 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 PDS value reflects both the number of eligible households and quotas per eligible household. However, there is no consistent source of information on changes to either. To identify policy changes in eligibility, we use NSS data to find sharp breaks in observed PDS value received by households and then check in newspapers and state records to see if there was a policy change at that time. Specifically, we simulated potential

[26] Analyzing the "on the ground" effects of the PDS is particularly relevant given potential problems with targeting, rationing and leakage (Government of India Planning Commission, 2005; Niehaus et al., 2013; Dreze and Khera, 2015). In addition, corruption in distribution might increase precisely during high-price periods (Hari, 2016).

[27] 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).

policy changes for each state s and year-quarter t in the following way. We ran regressions of PDS value on state and time fixed effects; controls for household characteristics and known policies; and an indicator for being in state 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 five such eligibility increases, which we list in Table A3. Changes in quotas for eligible households are often small and ad hoc and difficult to identify cleanly in the data. We therefore do not exploit this source of variation in our quantity instrument.

The generosity of the PDS as observed in the NSS increased dramatically over the study period. Panel A of Figure 2 shows that average real PDS rice 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 20% to 45% of households. This translated into a 300% increase in the value of the PDS subsidy over the period (Panel C), from Rs. 14 to 45 (average across all households). Figure A1 plots the share of households consuming PDS rice 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.

5.2 PDS value and instruments

We calculate the subsidy value v_{idrt} for each household using information on the observed market prices p_{rt}, PDS prices p_{rt}^{PDS}, and observed PDS consumption q_{idrt}^{PDS}.[28] The value of the PDS rice subsidy can be written as:

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

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: in comparison, transfers from the National Rural Employment Guarantee Scheme (NREGS),

[28] 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.

India's other major social welfare program made up only 1.8% of beneficiaries' expenditure in Andhra Pradesh in 2012 (Muralidharan, Niehaus and Sukhtankar, 2017*b*).

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. Panel A of Figure A2 shows a particularly striking example of changes in PDS prices, when Andhra Pradesh lowered the PDS rice price from Rs. 5 to 2 in 2008, and then to Rs. 1 four years later.

Our second instrument is an indicator E_{ist} equal to 1 if household i is in a state s in which a major PDS eligibility increase has occurred prior to the survey date. Panel B of Figure A2 shows the importance of additionally accounting for this variation, highlighting the increase in PDS value when Odisha universalized the PDS in a poor region of the state, approximately doubling PDS participation in one year.

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

$$c_{idrst} = \alpha_1 v_{idrst} + \alpha_2 p_{rst} + X_{idrst}\lambda + \delta_{da} + \tau_t + \phi_{round} + e_{idrst} \tag{11}$$

where s indexes states (other indices as previously defined), 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. All regressions are estimated using NSS weights. 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 its state, and the interaction between the two.[29]

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

$$c_{idrst} = \beta_1 p_{rst} + \beta_2 p_{rst} \times v_{idrst} + \beta_3 v_{idrst} + X_{idrst}\lambda + \delta_{da} + \tau_t + \phi_{round} + e_{idrst}. \tag{12}$$

We instrument for v_{idrst} as above and for $p_{rst} \times v_{idrst}$ using our three instruments as well

[29] 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 since those weights may be negative, under heterogeneous treatment effects the conventional estimand may be opposite-signed from the group-specific average treatment on treated effects. We calculate these weights in the differences-in-differences estimate of the effect of the expansions on outcomes in Figure A3 (the theory to compute these weights for continuous regressors does not yet exist), and find that all but 13 of the 2,756 treated area-periods have positive weights.

as their interactions with the 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 plot estimates obtained using an event-study specification for the eligibility expansion instrument, with the first stage in Panel A and the second stage in Panel B.[30] We see no 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. Within five years, v_{idrst} increases by Rs. 40 on average, approximately 40% of the mean PDS transfer received by beneficiaries during our study period. Panel B of Figure 3 also provides no evidence of changes in caloric intake before a policy is implemented, supporting the parallel trends assumption.

5.4 Results

Table 6 contains first stage results for Equation 11 for the overall sample and for below-median SES households (Table A4 contains the first stage for all demographic subgroups). The coefficients for PDS price decreases and eligibility increases are both strongly significant and have the expected signs in the full and below-median SES samples (F-stats 36.6 and 32.5 respectively). 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.

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 (column 1). Panel C of Figure 2 shows that PDS value increased by Rs. 30.1 over the study period; extrapolating to the entire population implies that the expansions in PDS generosity increased the number of people meeting the MCR by just over 40 million. Calories per capita also increase by 6% for every Rs. 100 of PDS value (column 3; marginally insignificant with p-values of 0.111).

Panel B of Table 7 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

[30] 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.

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 the household meets the MCR by 2.4 percentage points (column 1). However, increasing the PDS value to the average amount (Rs. 29.6) decreases the effect to 1.9 percentage points. 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. This also implies that the PDS as implemented during the study period provided households with substantial insurance against price risk. We observe similar patterns when we use log calories per capita as the outcome measure (column 3).

In columns 2 and 4, we restrict the sample to below median SES households. The point estimates imply larger impacts of the PDS for this group as compared to the full sample. These results should be interpreted as the effect of a hypothetical Rs. 100 increase in PDS value; in practice, poorer households are more likely to access the PDS.[31]

5.5 Robustness

In Table 8, we find that these results are robust to various alternative choices of samples and specifications. 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. We continue to see mitigating effects of PDS value on caloric sensitivity to prices when we instrument for PDS value using policy variation in prices alone (column 3) or eligibility expansions alone (column 4). . In Table A6 we include wild cluster bootstrap p-values at the state level and find almost no change in the effect of the PDS on caloric sensitivity (Panel B).

Finally, 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 A7, 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 insignif-

[31]Note that the complier population (those for whom increases in policy generosity lead to on the ground increases in PDS value) are different than for the full sample. In Tables A4 and A5 we show results for all subgroups. In brief, the PDS increases caloric intake and reduces sensitivity to market prices for all subsamples, and consistent with Table 4 reduces sensitivity of urban and rich households to basically zero.

icant 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 the MCR of 0.07 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), suggesting that the potential effect of PDS expansions on market prices is too small to explain our findings.

6 Conclusion

A recent and growing body of evidence documenting the success of unconditional cash transfers has changed the global debate about the optimal form of transfers to the poor, garnering much media and policy attention and influencing the ways in which donors choose to allocate funds.[32] While there are of course many potential differences between cash and in-kind transfer programs, the primary stated motivation for unconditional cash is that it is preferable from the beneficiary household point of view. It is thus puzzling that beneficiaries themselves often report a preference for in-kind transfers over cash.

We show that in a world in which households are exposed to commodity price risk—a common situation in many developing countries due to poor market integration—inframarginal in-kind transfers will be welfare improving relative to cash transfers from the household perspective if and only if the marginal utility of income is increasing with respect to price. Intuitively, in-kind transfers provide insurance since the value of the transfer rises automatically with the price of the transferred good. Testing this condition empirically in the context of India, we find that in-kind transfers are preferable to cash for below-median socioeconomic status households, precisely the group generally targeted by transfer programs. In addition, we provide the first evidence that in-kind transfers do in fact smooth household outcomes in the face of price fluctuations, demonstrating that expansions of the Public Distribution System not only increase caloric intake by households but also reduce sensitivity of calories to local prices.

We stress that our results do not imply that in-kind transfers necessarily dominate cash transfers: a full welfare analysis would need to take into account the social cost of provision, including potential differences in implementation. Nevertheless, they elucidate an important advantage of in-kind transfers that should be taken into consideration in the design of social protection programs as well as a possible explanation for why beneficiaries might report a preference for transfers in-kind. It is important to note that the relative benefits of in-kind vs. cash will vary geographically and over time, based on differences and changes in underlying market integration and resulting price volatility. In addition, this potential benefit of in-

[32]See, for example https://www.poverty-action.org/impact/cash-transfers-changing-debate-giving-cash-poor, accessed February 12, 2021.

kind transfers—mitigation of exposure to price risk—may be difficult to capture in existing randomized controlled trials, which generally measure (relatively) short run outcomes. We see this as an important area for future research, and a key advantage of the welfare test we propose is that it does not require exogenous variation in prices and can therefore be applied in a variety of settings.

More broadly, our results speak to the importance of considering household exposure to price risk in the design of safety net programs. While in-kind transfers are one way to provide insurance, they are not the only policy instrument that could improve welfare in the presence of price risk. For example, targeting rules for cash transfers may want to take into account local geographic price indicators, such as the average level of staple commodity prices or historical levels of price volatility, or proxies for household ability to smooth price variation. In addition, improvements in digital technology are rapidly changing the landscape for decentralized information collection, opening the possibility for (first-best) price-indexed cash transfers. We hope that our paper serves as a starting point for further work in this important area.

References

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

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

Atkin, David, and Dave Donaldson. 2015. "Who's getting globalized? The size and implications of intra-national trade costs." National Bureau of Economic Research Working Paper w21439.

Balani, Sakshi. 2013. "Functioning of the Public Distribution System: An Analytical Report." PRS Legislative Research Policy Discussion Paper.

Banerjee, Abhijit, Paul Niehaus, and Tavneet Suri. 2019. "Universal basic income in the developing world." *Annual Review of Economics.*

Banerjee, Abhijit, Rema Hanna, Benjamin Olken, Sudarno Sumarto, and Elan Satriawan. 2021. "Food versus food stamps: Evidence from an at-scale experiment in Indonesia." MIT Working Paper.

Barrett, Christopher B. 1996. "On price risk and the inverse farm size-productivity relationship." *Journal of Development Economics*, 51(2): 193 – 215.

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

Behrman, Jere R, Anil B Deolalikar, and Barbara L Wolfe. 1988. "Nutrients: impacts and determinants." *World Bank Economic Review*, 2(3): 299–320.

Bellemare, Marc F., and Yu Na Lee. 2016. "Attitudes to price risk and uncertainty: The earnest search for identification and policy relevance." *Canadian Journal of Agricultural Economics*, 64(4): 599–612.

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

Besley, Timothy, and Stephen Coate. 1991. "Public provision of private goods and the redistribution of income." *American Economic Review*, 81(4): 979–984.

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

Brinkman, Henk-Jan, Saskia De Pee, Issa Sanogo, Ludovic Subran, and Martin W Bloem. 2010. "High food prices and the global financial crisis have reduced access to nutritious food and worsened nutritional status and health." *Journal of Nutrition*, 140(1): 153S–161S.

Brown, Caitlin, Rossella Calvi, and Jacob Penglase. 2018. "Sharing the Pie: Undernutrition, Intra-household Allocation, and Poverty." SSRN Working Paper 3199129.

Casaburi, Lorenzo, Rachel Glennerster, and Tavneet Suri. 2013. "Rural roads and intermediated trade: Regression discontinuity evidence from Sierra Leone." SSRN Working Paper 2161643.

Chetty, Raj. 2009. "Sufficient statistics for welfare analysis: A bridge between structural and reduced form methods." *Annual Review of Economics*, 1(1): 451–488.

Chetty, Raj, and Adam Looney. 2006. "Consumption smoothing and the welfare consequences of social insurance in developing economies." *Journal of Public Economics*, 90(12): 2351–2356.

Coate, Stephen. 1989. "Cash versus direct food relief." *Journal of Development Economics*, 30(2): 199–224.

Coate, Stephen, Stephen Johnson, and Richard Zeckhauser. 1994. "Pecuniary redistribution through in-kind programs." *Journal of Public Economics*, 55(1): 19–40.

Cunha, Jesse M, Giacomo De Giorgi, and Seema Jayachandran. 2018. "The price effects of cash versus in-kind transfers." *Review of Economic Studies*, 86(1): 240–281.

Currie, Janet, and Douglas Almond. 2011. "Human capital development before age five." In *Handbook of Labor Economics*. Vol. 4, 1315–1486. Elsevier.

Currie, Janet, and Firouz Gahvari. 2008. "Transfers in cash and in-kind: Theory meets the data." *Journal of Economic Literature*, 46(2): 333–83.

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

de Chaisemartin, Clément, and Xavier D'Haultfœuille. 2020. "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects." *American Economic Review*.

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

Dreze, Jean, and Reetika Khera. 2015. "Understanding leakages in the Public Distribution System." *Economic and Political Weekly*, 50(7): 39–42.

D'Souza, Anna, and Sharad Tandon. 2019. "Intrahousehold nutritional inequities in rural Bangladesh." *Economic Development and Cultural Change*, 67(3): 625–657.

Egger, Dennis, Johannes Haushofer, Edward Miguel, Paul Niehaus, and Michael W Walker. 2019. "General equilibrium effects of cash transfers: experimental evidence from Kenya." National Bureau of Economic Research Working Paper w26600.

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

FCI. 2018. "Procurement Data for Current Marketing Season." *http://fci.gov.in/procurements.php?view=87*, Accessed: April 19, 2018.

Finkelstein, Amy, Nathaniel Hendren, and Erzo F.P. Luttmer. 2019. "The value of medicaid: Interpreting results from the Oregon health insurance experiment." *Journal of Political Economy*, 127(6): 2836–2874.

Gadenne, Lucie. 2020. "Can rationing increase welfare? Theory and an application to India's ration shop system." *American Economic Journal: Economic Policy.*

Gentilini, Ugo. 2016. *The Other Side of the Coin: The Comparative Evidence of Cash and in-Kind Transfers in Humanitarian Situations.* The World Bank.

Ghatak, Maitreesh, and Karthik Muralidharan. 2020. "An inclusive growth dividend: Reframing the role of income transfers in India's anti-poverty strategy." *India Policy Forum.*

Gibson, John, and Scott Rozelle. 2005. "Prices and unit values in poverty measurement and tax reform analysis." *World Bank Economic Review*, 19(1): 69–97.

Gollin, Douglas, and Richard Rogerson. 2014. "Productivity, transport costs and subsistence agriculture." *Journal of Development Economics*, 107: 38 – 48.

Gopalan, CRBV, BV Rama Sastri, SC Balasubramanian, et al. 1980. *Nutrition value of Indian foods.* National Institute of Nutrition, Indian Council of Medical Research.

Government of India Planning Commission. 2005. "Performance evaluation of Targeted Public Distribution System (TPDS)." The Programme Evaluation Organisation.

Hari, Siddharth. 2016. "Markets, subsidies, and corruption: Evidence from India." New York University Working Paper.

Hastings, Justine, and Jesse M Shapiro. 2018. "How are SNAP benefits spent? Evidence from a retail panel." *American Economic Review*, 108(12): 3493–3540.

Haushofer, Johannes, and Jeremy Shapiro. 2016. "The short-term impact of unconditional cash transfers to the poor: experimental evidence from Kenya." *Quarterly Journal of Economics*, 131(4): 1973–2042.

Hidrobo, Melissa, John Hoddinott, Amber Peterman, Amy Margolies, and Vanessa Moreira. 2014. "Cash, food, or vouchers? Evidence from a randomized experiment in northern Ecuador." *Journal of Development Economics*, 107: 144–156.

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

Imbert, Clement, and John Papp. 2015. "Labor market effects of social programs: evidence from India's employment guarantee." *American Economic Journal: Applied Economics*, 7(2): 233–63.

Jensen, Robert T, and Nolan H Miller. 2008. "The impact of food price increases on caloric intake in China." *Agricultural Economics*, 39: 465–476.

Jiménez-Hernández, Diego, and Enrique Seira. 2021. "Should the government sell you goods? Evidence from the milk market in Mexico." Stanford University Working Paper.

Kaul, Tara. 2014. "Household responses to food subsidies: Evidence from India." University of Maryland Working Paper.

Khera, Reetika. 2014. "Cash vs. in-kind transfers: Indian data meets theory." *Food Policy*, 46: 116–128.

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

Kotwal, Ashok, Milind Murugkar, and Bharat Ramaswami. 2011. "PDS forever?" *Economic and Political Weekly*, 72–76.

Lieber, Ethan MJ, and Lee M Lockwood. 2019. "Targeting with in-kind transfers: Evidence from Medicaid home care." *American Economic Review*, 109(4): 1461–85.

Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar. 2017*a*. "Direct benefits transfer in food: Results from one year of process monitoring in Union Territories." UCSD Working Paper.

Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar. 2017*b*. "General equilibrium effects of (improving) public employment programs: Experimental evidence from india." National Bureau of Economic Research Working Paper w23838.

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

Niehaus, Paul, Antonia Attanassova, Mariane Bertrand, and Sendhil Mullainathan. 2013. "Targeting with Agents." *American Economic Journal: Economic Policy*, 5(1): 206–238.

Rao, BSN, and B Sivakumar. 2010. "Nutrient requirements and recommended dietary allowances for Indians." National Institute of Nutrition, Indian Council of Medical Research Report.

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

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

Rosenzweig, Mark R, and Kenneth I Wolpin. 1993. "Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in India." *Journal of Political Economy*, 101(2): 223–244.

Rosenzweig, Mark R, and Oded Stark. 1989. "Consumption smoothing, migration, and marriage: Evidence from rural India." *Journal of Political Economy*, 97(4): 905–926.

Roy, Devesh, Ruchira Boss, and Mamata Pradhan. 2020. "How India's food-based safety net is responding to the COVID-19 lockdown." International Food Policy Research Institute Report.

Saha, Atanu, and Janice Stroud. 1994. "A household model of on-farm storage under price risk." *American Journal of Agricultural Economics*, 76(3): 522–534.

Sotelo, Sebastian. 2020. "Domestic trade frictions and agriculture." *Journal of Political Economy*, 128(7): 2690–2738.

Subramanian, Shankar, and Angus Deaton. 1996. "The demand for food and calories." *Journal of Political Economy*, 104(1): 133–162.

Sukhtankar, Sandip. 2017. "India's national rural employment guarantee scheme: What do we really know about the world's largest workfare program?" *India Policy Forum*.

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

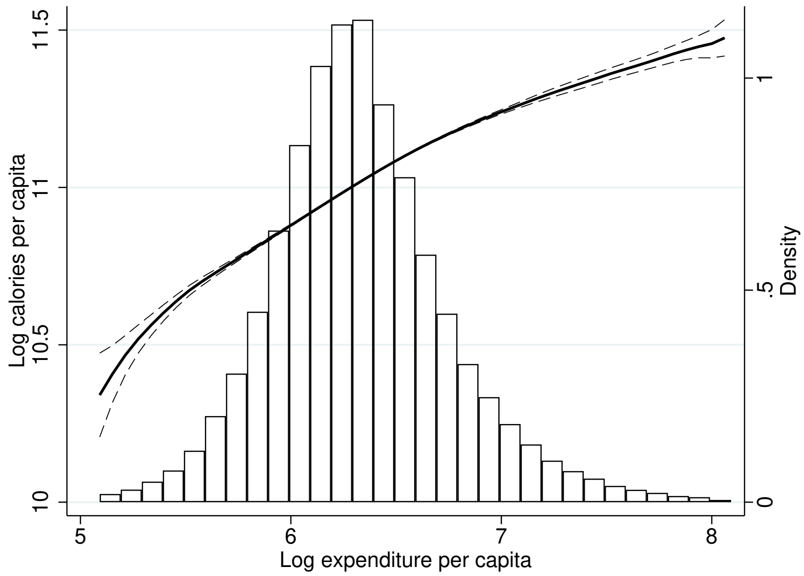
Turnovsky, Stephen J, Haim Shalit, and Andrew Schmitz. 1980. "Consumer's surplus, price instability, and consumer welfare." *Econometrica*, 135–152.

Victora, Cesar G, Linda Adair, Caroline Fall, Pedro C Hallal, Reynaldo Martorell, Linda Richter, Harshpal Singh Sachdev, Maternal, Child Undernutrition Study Group, et al. 2008. "Maternal and child undernutrition: consequences for adult health and human capital." *The Lancet*, 371(9609): 340–357.

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

World Bank. 2014. *The State of Social Safety Nets 2014.* The World Bank.

Figure 1: Log calories per capita versus log expenditure per capita

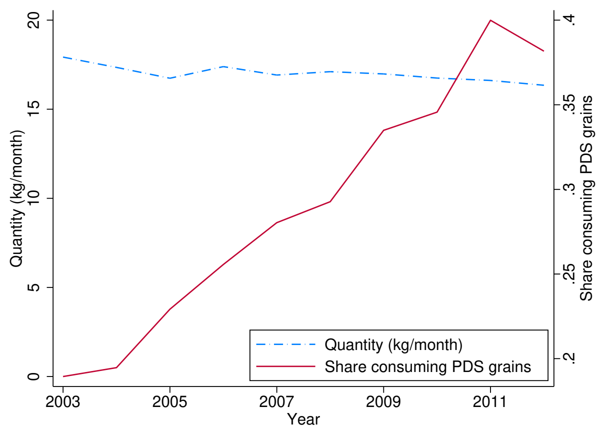


This figure plots a histogram of household log expenditure per capita (right axis) against a line representing a nonparametric regression of log calories per capita on log expenditure per capita (left axis), using data from the National Sample Survey 2003-12. Regression and histogram both condition on district-sector-quarter fixed effects to nonparametrically adjust for prices. Dashed lines represent 95% confidence interval, clustered at the district-sector level.

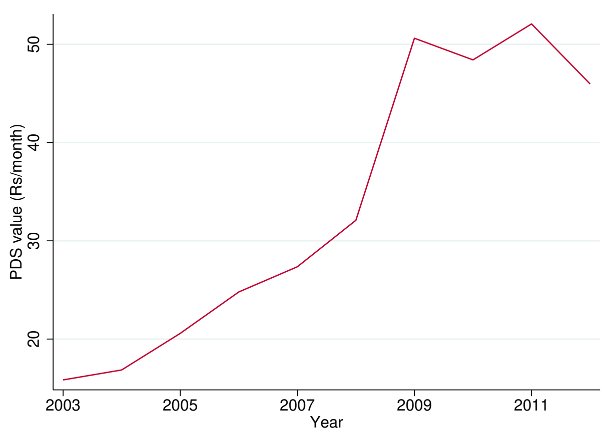
Figure 2: PDS generosity and coverage over time

(a) Market and PDS prices

(b) PDS quantities and reach



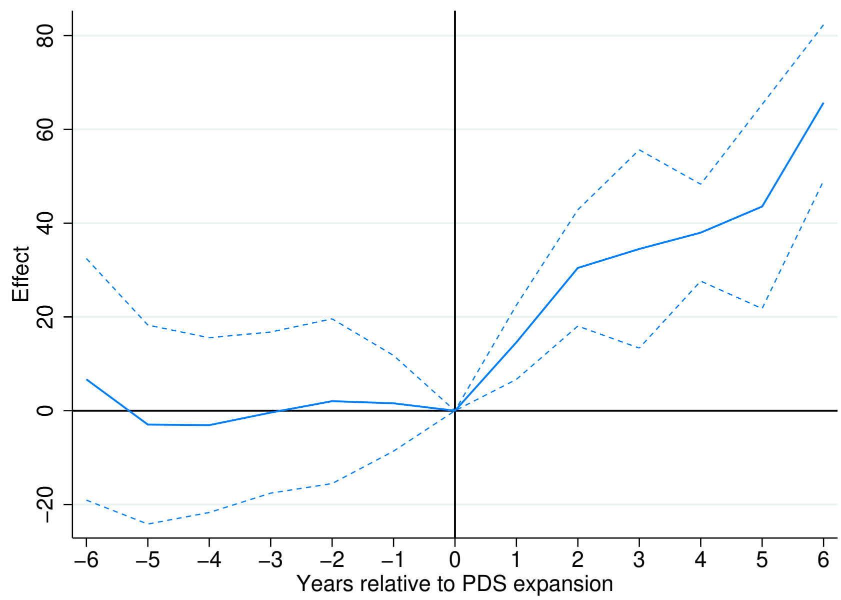
(c) Average PDS value



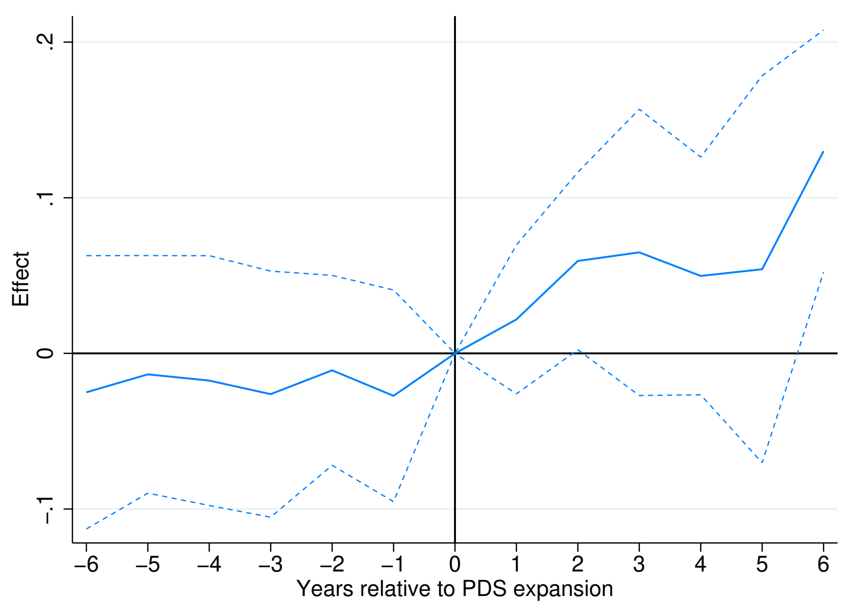
This figure shows the evolution of benefit generosity in the PDS using data from the National Sample Survey 2003-12. Panel A shows market and PDS mean unit values over time. Panel B shows PDS quantities for beneficiaries, and the total share of households who consume PDS goods. Panel C shows unconditional 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 eligibility expansions on PDS transfer value and caloric intake

(a) Effect on PDS transfer value



(b) Effect on meeting minimum calorie requirement



This figure shows event study coefficients from a regression of the outcome (PDS value in Panel (a) and an indicator for whether the household meets minimum calorie requirements in Panel (b)) on time relative to policy expansion: $y_{idt} = \sum_{\tau \neq 0} \beta_\tau \mathbb{1}_\tau + X_{idt}\alpha + \gamma_d + \varphi_t + \varepsilon_{iat}$, for household i in district-sector-season d, year-quarter t at time relative to expansion τ, where controls include PDS rice price, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. Standard errors clustered at the state level.

Table 1: Summary statistics: food expenditure and 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	2,097	1,904	0.61
	(0.13)	(0.09)	(632)	(231)	(0.49)
Below median SES	0.55	0.10	1,976	1,861	0.56
	(0.11)	(0.10)	(548)	(226)	(0.50)
Above median SES	0.47	0.06	2,295	1,974	0.69
	(0.13)	(0.06)	(707)	(222)	(0.46)
Rural	0.54	0.10	2,097	1,886	0.62
	(0.12)	(0.10)	(633)	(228)	(0.49)
Urban	0.45	0.06	2,097	1,952	0.57
	(0.13)	(0.06)	(632)	(232)	(0.49)
Rural landless	0.54	0.09	2,003	1,877	0.55
	(0.12)	(0.09)	(636)	(245)	(0.50)
Rural landowning	0.54	0.10	2,135	1,890	0.65
	(0.11)	(0.10)	(627)	(221)	(0.48)

This table shows summary statistics for household food expenditures and calorie consumption from NSS survey data 2003-12. Column (1) reports expenditure on all combined food items as a share of total expenditure. Column (2) reports expenditure on market rice as a share of total expenditure. Column (3) reports mean 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 the 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 by the Indian Council of Medical Research. Column (5) reports means for an indicator that the per-capita caloric consumption of the household met or exceeded its average MCR. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. 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

This table shows mean unit values for rice from NSS survey data 2003-12. Unit values of rice are the means of deflated average rice expenditure per kilogram across all households from the same region-sector-quarter. In reporting subgroup prices we use the same overall region-sector-quarter mean; the differences across these rows therefore reflect differences in the places and times where different groups reside. All unit values are measured in 1999 rupees. Controls include log household size, SC/ST, land ownership, religion, cooking fuel, and socioeconomic status (SES) index. All households owning 0.01 hectares of land or greater are classified as landowning. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season and period fixed effects. Period fixed effects include year-quarter and NSS round fixed effects.

Table 3: Meeting the minimum calorie requirement and market prices

	All districts				RPS districts	
	(1)	(2)	(3)	(4)	(5)	(6)
Log market price rice	-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
Household 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

This table displays regressions of an indicator for meeting minimum calorie requirement on log market prices for rice from NSS survey data 2003-12. Column (6) measures prices using the Rural Price Survey (RPS); all other columns use mean NSS unit values. Columns (5) and (6) are restricted to districts in which RPS data are available. Household controls are log household size, SC/ST, land ownership, religion, and cooking fuel. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season and period fixed effects. Period fixed effects include year-quarter 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 the 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	-0.219***	-0.018	-0.182***	0.016	-0.284***	-0.152***
	[0.055]	[0.039]	[0.052]	[0.057]	[0.088]	[0.050]
Equality of effect (p-value)		0.00		0.01		0.12
Observations	211,772	313,139	316,234	208,677	63,614	252,620

This table displays regressions of an indicator for meeting minimum calorie requirement on log rice unit values from NSS survey data 2003-12. All specifications include district-sector-season and period fixed effects. Household controls are log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Median SES defined using survey weights, so observation counts are different across above and below median groups. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season and period fixed effects. Period fixed effects include year-quarter and NSS round fixed effects. All households owning 0.01 hectares of land or greater are classified as landowning. 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**	-0.120***	-0.016	-0.105**	0.004	-0.122*	-0.111***
	[0.031]	[0.039]	[0.029]	[0.041]	[0.031]	[0.071]	[0.035]
Equality of effect (p-value)			0.00		0.03		0.86
Observations	524,911	211,772	313,139	316,234	208,677	63,614	252,620

This table displays regressions of log calories per-capita on log market prices for rice from NSS data 2003-12. All specifications include district-sector-season and period fixed effects. Household controls are log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Median SES defined using survey weights, so observation counts are different across above and below median groups. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season and period fixed effects. Period fixed effects include year-quarter and NSS round fixed effects. All households owning 0.01 hectares of land or greater are classified as landowning. Standard errors in parentheses and clustered at the region-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: First stage of PDS value (in 100 Rs.) on instruments

	All (1)	Below median SES (2)
PDS price (Rs.)	-0.097***	-0.126***
	(0.035)	(0.043)
Eligibility increase (=1)	0.512***	0.540***
	(0.102)	(0.114)
Eligibility increase × PDS price	-0.116***	-0.099*
	(0.038)	(0.049)
Weak IV F-stat	36.59	32.54
Observations	524,911	211,772

This table regressions 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 A3. All prices are deflated to 1999 rupees. All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Household controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. 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 caloric outcomes

	Meets MCR		Log calories per capita	
	All	Below median SES	All	Below median SES
	(1)	(2)	(3)	(4)
Panel A: IV of outcomes on PDS value				
PDS value (100 Rs.)	0.107*	0.136**	0.064	0.063
	(0.052)	(0.063)	(0.039)	(0.039)
Weak IV F-stat	36.59	32.53	36.59	32.53
Panel B: IV of outcomes on PDS value and market prices				
Log market rice price	-0.243***	-0.453***	-0.154***	-0.251***
	(0.054)	(0.087)	(0.033)	(0.057)
Market rice price × PDS value	0.178**	0.210***	0.137***	0.141***
	(0.066)	(0.075)	(0.045)	(0.045)
Predicted rice elasticity, at mean PDS value	-0.190***	-0.368***	-0.113***	-0.194***
	(0.051)	(0.095)	(0.033)	(0.057)
Weak IV F-stat	26.20	30.24	26.20	30.24
Mean PDS value	0.296	0.401	0.296	0.401
SD PDS value	0.604	0.668	0.604	0.668
1^{st} percentile PDS value	0	0	0	0
99^{th} percentile PDS value	2.56	2.69	2.56	2.69
Observations	524,911	211,772	524,911	211,772

This table shows coefficients from regressions of an indicator for meeting the minimum calorie requirement (MCR, columns 1 and 2) or log calories per capita (columns 3 and 4) 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. 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 price, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. 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 caloric outcomes: robustness

	All				Below median SES			
	No suppliers	Pol. econ. controls	Price inst. only	Expansion inst. only	No suppliers	Pol. econ. controls	Price inst. only	Expansion inst. only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: IV of meeting minimum calorie requirement on PDS value								
PDS Value (100 Rs.)	0.171***	0.109*	0.018	0.172**	0.225***	0.136**	0.058	0.198**
	(0.053)	(0.054)	(0.085)	(0.068)	(0.066)	(0.065)	(0.078)	(0.090)
Weak IV F-stat	32.53	34.33	8.93	17.42	69.86	29.86	9.05	16.70
Panel B: IV of meeting the minimum calorie requirement on PDS value and prices								
Log market rice price	-0.231***	-0.252***	-0.229***	-0.282***	-0.422***	-0.453***	-0.461***	-0.475***
	(0.048)	(0.054)	(0.073)	(0.071)	(0.075)	(0.085)	(0.093)	(0.110)
Market rice price $\times$ PDS value	0.170	0.192**	0.257**	0.131*	0.163	0.203**	0.326**	0.128
	(0.120)	(0.071)	(0.112)	(0.071)	(0.119)	(0.073)	(0.118)	(0.081)
Predicted rice elasticity,	-0.184***	-0.195***	-0.153**	-0.243***	-0.360***	-0.372***	-0.331***	-0.424***
at mean PDS value	(0.058)	(0.052)	(0.062)	(0.066)	(0.108)	(0.092)	(0.094)	(0.118)
Weak IV F-stat	22.27	30.58	4.40	8.59	25.96	29.86	4.95	8.26
Mean PDS value	0.280	0.296	0.296	0.296	0.380	0.401	0.401	0.401
SD PDS value	0.601	0.604	0.604	0.604	0.667	0.668	0.668	0.668
1^{st} percentile PDS value	0	0	0	0	0	0	0	0
99^{th} percentile PDS value	2.56	2.56	2.56	2.56	2.67	2.69	2.69	2.69
Observations	391,176	524,911	524,911	524,911	160,154	211,772	211,772	211,772

This table shows coefficients from regression of an indicator 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. No suppliers excludes Andhra Pradesh, Chhattisgarh, Haryana, Orissa, Punjab, and West Bengal, which together supply the majority of rice to the PDS. Pol. econ. controls includes controls for active NREGS program in district at the time of surveying (data from Sukhtankar (2017)) as well as elections at the state-quarter level, Price inst. only instruments for PDS value with statutory rice price instruments alone, and Expansion inst. only instruments for PDS value with expansion instruments alone. For comparison, mean per-capita expenditure is Rs. 711. 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. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix for *In-Kind Transfers as Insurance*

A1 Comparing the optimal and in-kind transfer

In this section, we show that in-kind transfers will not equal the optimal transfer except in special cases. As a result, the in-kind transfer will generally not provide the same welfare benefit as the optimal transfer. Intuitively, the in-kind transfer provides insurance in proportion to the in-kind transfer quantity, rather than the individual's preferences.

To highlight this intuition, we focus on the simple case where income is fixed and only the price of the in-kind good varies. Equation 1, restated here, tells us that the optimal transfer $x(p_j)$ equates the marginal value of income for all prices p_j, or all states of the world:

$$v_y(p, y + x(p_j)) = \mu$$

Taking the derivative with respect to p_j,

$$v_{yp} + v_{yy}x'(p_j) = 0$$

Rearranging and taking advantage of the fact that $\frac{v_{py}}{v_y} = \frac{\alpha_j}{p_j}[\gamma - \eta_j]$ and $\frac{v_{yy}}{v_y} = \frac{-\gamma}{y}$,[1] we have that

$$x'(p_j) = \frac{q_j[\gamma - \eta_j]}{\gamma} \tag{A1}$$

where q_j is consumption of the in-kind good. In contrast, for the in-kind transfer $p_j z$, the marginal change in the transfer with respect to p_j is z. The in-kind transfer therefore emulates the optimal transfer if and only if $z = \frac{q_j[\gamma-\eta_j]}{\gamma}$. Otherwise, it will provide either too much or too little insurance.

[1]These expressions follow from taking the derivative of Roy's identity with respect to p_j, and from the definition of the coefficient of relative risk aversion respectively.

A2 Additional notes on data

A2.1 Sample

Our data come from the Household Consumer Expenditure schedules of the 59$^{\text{th}}$ through 68$^{\text{th}}$ 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 524,911 households.

We considered including data from earlier rounds of the NSS. However, the 58$^{\text{th}}$ 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$^{\text{th}}$ and 59$^{\text{th}}$ rounds, mostly as a result of district splits. Creating consistent district identifiers would therefore mean using the larger 58$^{\text{th}}$ round districts, limiting our geographic precision and reducing the number of unique districts by 17%. Table A8 provides a full list of the rounds included in our analysis, and periods they cover.

A2.2 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 two 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.

We use this procedure when we calculate the rice prices in our main analysis, and for all prices when we construct the Laspeyres index in Section A2.3.

A2.3 Real consumption

An alternative to using calories as an outcome would be to instead use real consumption. The main difficulty with this approach is measuring local prices for all consumption categories. While the NSS records expenditure in each category, for we can measure prices only for those categories that record quantities and are relatively homogenous.[2] We are able to construct unit-value prices for 73.7% of food expenditure, but only 16.7% of non-food expenditure (food and non-food are each about half of the budget). The vast majority of the non-food consumption for which we observe prices is fuel.

Using unit values for food and fuel, we construct a region-sector-quarter level Laspeyres price index. We also measure nominal expenditure, imputing the level of consumption for PDS goods at the level of the market price in line with our inframarginality assumption and including consumption from home production as valued by the NSS surveyors. Combining these, we construct a measure of real consumption.[3]

In Tables A9 and A10 we reproduce our main results using log real consumption as the dependent variable. Table A9 shows that real consumption is lower when market rice prices are high, indicating that higher prices are not fully offset by higher expenditures. Similarly as in our calorie results, we observe a negative relationship between market rice prices and log real consumption for below-median SES households, but not for above-median SES households. Panel A of Table A10 shows the effect of the PDS on real consumption; a Rs. 100 increase in the value of the PDS increases consumption by 5.5 percent overall, and 6.5 percent for below-median SES households. Panel B regresses log real consumption on market prices, PDS value, and their interaction (with PDS value and the price interaction instrumented as discussed in Section 5). In line with our calorie results, higher prices are associated with lower consumption but this relationship is attenuated by higher PDS transfers.

[2] For example, "other tobacco products" measures quantities in grams, but could include different products in different times and places.

[3] We considered using only food and fuel nominal expenditure to match the price index, but this would overstate the extent to which real consumption drops when prices are high as households substitute away from food and fuel consumption.

A3 Appendix Exhibits

Figure A1: Share purchasing PDS by per-capita expenditure

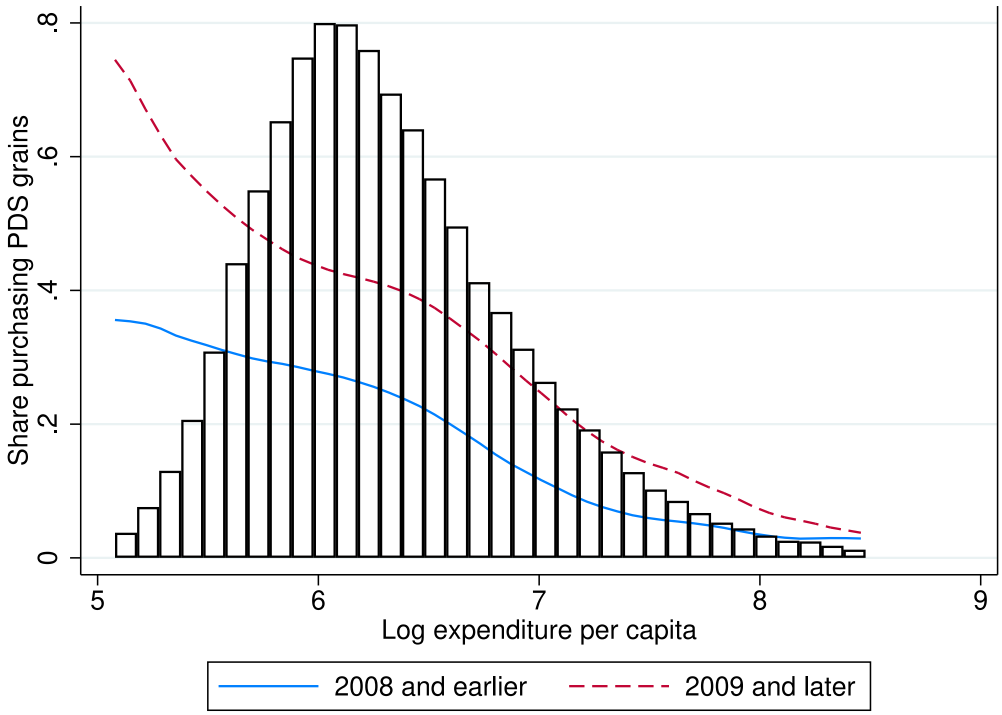
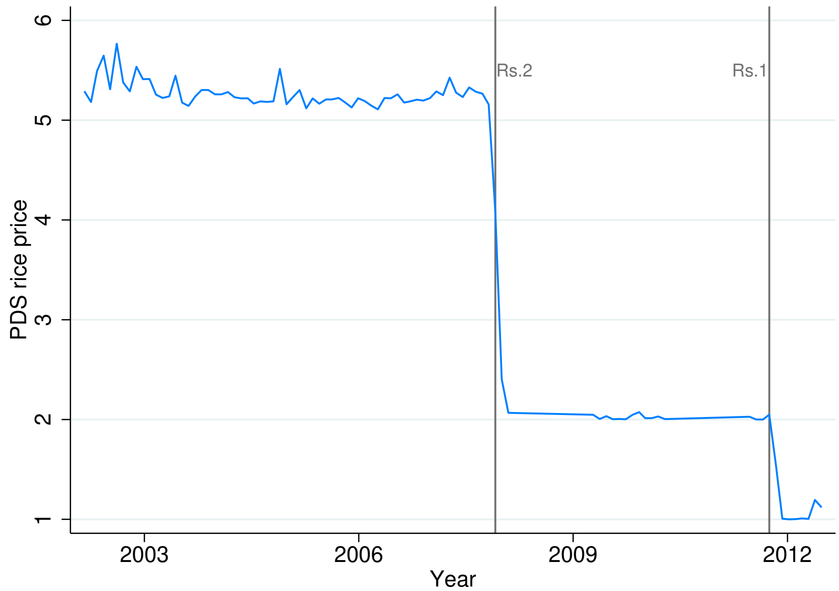


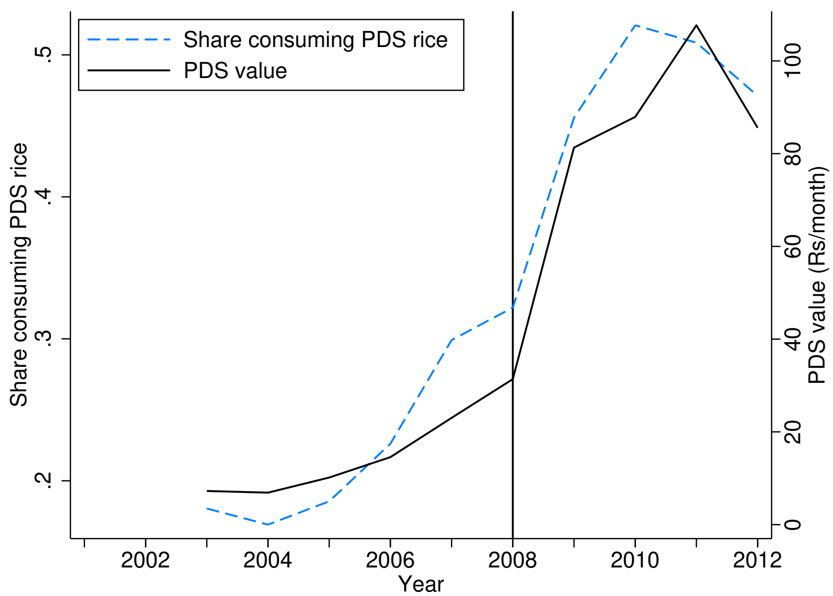
Figure shows share of households consuming PDS rice before and after 2008. The histogram shows the distribution of per-capita income, in 1999 rupees. The exchange rate was 43 rupees to one USD.

Figure A2: Example PDS policy changes

(a) Statutory PDS rice prices in Andhra Pradesh

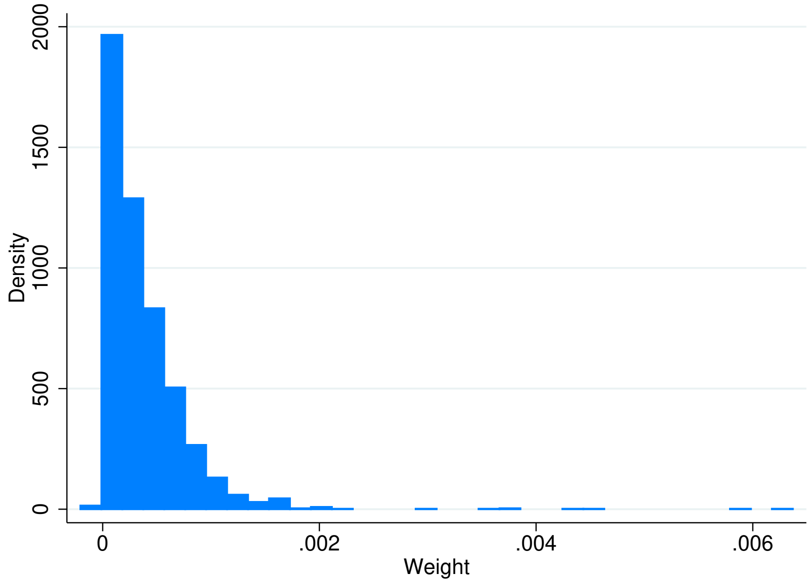


(b) Share of population consuming PDS in Odisha



Panel A shows monthly average PDS rice prices in Andhra Pradesh, measured using NSS unit values. Vertical lines highlight two statutory price reductions.Panel B shows the share of households consuming PDS rice (left axis) and average PDS value (right axis) in Odisha in each year in our sample period, with the vertical line representing a reform that reduced prices and expanded the number of PDS-eligible households in 2008.

Figure A3: Distribution of weights on district-sector-time effects



This figure shows the histogram of weights on the district-sector-period-specific treatment effects in a difference-in-differences estimate of the effect of the PDS eligibility expansions. 13 of 2,756 treated district-sector-periods have negative weights. Calculated using de Chaisemartin and D'Haultfœuille (2020).

Table A1: Summary statistics for number of observations defining rice unit values

	Mean (SD)	Percentile				
		1%	5%	10%	25%	50%
Panel A: Region-sector-quarter level						
Rice UV, unweighted	112.29	8	16	23	42	78
	(103.55)					
PDS rice	38.63	1	1	2	5	16
	(56.20)					
Panel B: District-sector-quarter level						
Rice UV, unweighted	14.93	1	3	4	6	10
	(15.81)					
PDS rice	7.82	1	1	1	2	4
	(9.86)					

This table shows summary statistics and the number of observations available to define unit values at various percentiles of the region-sector-quarter level (Panel A) and district-sector-quarter level (Panel B). Standard deviations in parentheses.

Table A2: Log RPS prices on log NSS unit values

	All	By median SES		By landowning	
		Below	Above	Landless	Landowner
	(1)	(2)	(3)	(4)	(5)
Log NSS rice unit value	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

This table shows regressions of log rice prices from the Rural Price Survey (RPS) on log rice unit values from the National Sample Survey from 2003-12. All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. All households owning 0.01 hectares of land or greater are classified as landowning. Standard errors in parentheses and clustered at the region-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: PDS eligibility expansions

State	Policy Change	Type
Tamil Nadu	December 31, 2004	Expansion
Chhattisgarh	April 30, 2007	Expansion
Karnataka	June 1, 2008	Expansion
Odisha	August 1, 2008	Expansion/price reduction
Kerala	April 16, 2011	Expansion

This table shows the major expansions in PDS eligibility used in our analysis, as noted in Section 5.1.

Table A4: First stage of PDS value (in 100 Rs.) on instruments

	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***	-0.126***	-0.063**	-0.105**	-0.063**	-0.101***	-0.107**
	(0.035)	(0.043)	(0.025)	(0.039)	(0.026)	(0.033)	(0.042)
Eligibility increase (=1)	0.512***	0.540***	0.449***	0.525***	0.500***	0.481***	0.539***
	(0.102)	(0.114)	(0.093)	(0.114)	(0.106)	(0.122)	(0.127)
Eligibility increase × PDS price	-0.116***	-0.099*	-0.120***	-0.108**	-0.148***	-0.117**	-0.102**
	(0.038)	(0.049)	(0.026)	(0.045)	(0.030)	(0.045)	(0.048)
Weak IV F-stat	36.59	32.54	31.15	32.34	26.62	42.22	21.05
Observations	524,911	211,772	313,139	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 A3. All prices are deflated to 1999 Rs. All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Household controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. Standard errors in parentheses and clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Effect of PDS generosity on meeting minimum calorie requirement

	All	By median SES		By sector		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*	0.136**	0.079	0.121**	0.083	0.178***	0.105**
	(0.052)	(0.063)	(0.049)	(0.054)	(0.055)	(0.060)	(0.048)
Weak IV F-stat	36.59	32.53	31.18	32.34	26.62	42.22	21.05
Panel B: IV of meeting the minimum calorie requirement on PDS value							
Log market rice price	-0.243***	-0.453***	-0.105**	-0.344***	-0.131**	-0.477***	-0.277***
	(0.054)	(0.087)	(0.046)	(0.082)	(0.050)	(0.079)	(0.072)
Market rice price × PDS value	0.178**	0.210***	0.274**	0.162**	0.412**	0.110	0.113
	(0.066)	(0.075)	(0.104)	(0.073)	(0.165)	(0.086)	(0.093)
Predicted rice elasticity,	-0.190***	-0.368***	-0.053	-0.293***	-0.030	-0.435***	-0.244***
at mean PDS value	(0.051)	(0.095)	(0.038)	(0.076)	(0.053)	(0.085)	(0.061)
Weak IV F-stat	26.20	30.24	30.89	49.74	14.76	37.03	29.17
Mean PDS value	0.296	0.401	0.191	0.314	0.246	0.376	0.290
SD PDS value	0.604	0.668	0.512	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	2.69	2.32	2.41	2.73	2.56	2.36
Observations	524,911	211,772	313,139	316,234	208,677	63,614	252,620

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. For comparison, mean per-capita expenditure is 711 Rs. All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Household controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Caloric intake on market prices and PDS generosity, with wild bootstrap p-values

	Meets MCR		Log calories per capita	
	All	Below median SES	All	Below median SES
	(1)	(2)	(3)	(4)
Panel A: IV of outcomes on PDS value				
PDS value (100 Rs.)	0.107*	0.136**	0.064	0.063
	(0.052)	(0.063)	(0.039)	(0.039)
Wild bootstrap p-value	0.127	0.054	0.205	0.132
Panel B: IV of outcomes on PDS value and market prices				
Log market rice price	-0.243***	-0.453***	-0.154***	-0.251***
	(0.054)	(0.087)	(0.033)	(0.057)
Market rice price × PDS value	0.178**	0.210***	0.137***	0.141***
	(0.066)	(0.075)	(0.045)	(0.045)
p-value, market price	0.487	0.459	0.483	0.459
p-value, market price × PDS	0.017	0.001	0.013	0.001
Observations	524,911	211,772	524,911	211,772

This table shows coefficients from regression of outcome in header 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. For comparison, mean per-capita expenditure is 711 Rs. All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Household controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: 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	-0.010	-0.057	-0.015	-0.065	-0.048	-0.005
	(0.057)	(0.044)	(0.085)	(0.054)	(0.084)	(0.086)	(0.048)
Weak IV F-stat	8.11	8.29	7.65	7.76	7.41	9.84	7.05
Panel B: PDS expansion instrument							
PDS value (100 Rs.)	-0.008	-0.006	-0.012	-0.001	-0.022	-0.038	0.008
	(0.044)	(0.040)	(0.053)	(0.043)	(0.039)	(0.059)	(0.039)
Weak IV F-stat	17.72	15.46	12.76	19.92	10.84	13.81	19.54
Panel C: PDS rice price, expansion, and interaction instruments							
PDS value (100 Rs.)	-0.006	-0.000	-0.016	0.002	-0.030	-0.018	0.009
	(0.030)	(0.029)	(0.033)	(0.032)	(0.019)	(0.036)	(0.033)
Weak IV F-stat	37.69	30.19	31.45	34.21	25.05	66.50	21.78
Observations	524,911	211,772	313,139	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. All specifications include district-sector-season and period (calendar and NSS round) fixed effects. Household controls include log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: 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

This table presents details on the National Sample Survey rounds used in our analysis. Asterisks indicate thick rounds which are representative at the district level. Thin rounds are only representative at the NSS region level.

Table A9: Log real consumption 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	-0.112***	-0.169***	-0.068	-0.142**	-0.032	-0.055	-0.170***
	[0.042]	[0.057]	[0.043]	[0.055]	[0.050]	[0.073]	[0.056]
Equality of effect (p-value)			0.08		0.14		0.08
Observations	519,573	210,138	309,435	313,031	206,542	62,848	250,183

Table displays regressions of log real consumption on log market rice prices. See Section A2.3 for details on the measurement of real consumption. All specifications include district-sector-season and period (calendar and NSS round) fixed effects. Household 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 is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, 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 A10: Effect of PDS generosity on log real consumption

	All	Below median SES
	(1)	(2)
Panel A: IV of log real expenditure on PDS value		
PDS value (100 Rs.)	0.055*	0.065*
	(0.032)	(0.033)
Weak IV F-stat	37.92	32.18
Panel B: IV of log real expenditure on PDS value		
Log market rice price	-0.202***	-0.294***
	(0.050)	(0.064)
Market rice price × PDS value	0.156**	0.127***
	(0.057)	(0.037)
Predicted rice elasticity,	-0.155***	-0.243***
at mean PDS value	(0.042)	(0.060)
Weak IV F-stat	28.42	30.24
Mean PDS value	0.300	0.405
SD PDS value	0.608	0.671
1^{st} percentile PDS value	0	0
99^{th} percentile PDS value	2.56	2.69
Observations	519,573	210,138

This table shows coefficients from regression of log real consumption on PDS value (in Panel A) and PDS value, market rice prices and their interaction (Panel B). See Section A2.3 for details on the measurement of real consumption. 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. For comparison, mean per-capita expenditure is 708 Rs. All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Household controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Household-level SES is the predicted value from a regression of log expenditure per capita on permanent household characteristics, with district-sector-season, year-quarter, and NSS round fixed effects. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.