In-Kind Transfers as Insurance*

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Abstract

Households in developing countries often face variation in the prices of consumption goods. We develop a model demonstrating that in-kind transfers will provide insurance benefits against price risk 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 this condition holds for low-income Indian households. Expansions in India's flagship in-kind food transfer program not only increase caloric intake but also reduce caloric sensitivity to prices. Our results contribute to ongoing debates about the optimal form of social protection programs.

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A common feature of many developing countries is variation in the prices of staple commodities across space and over time. Price variation may leave households, particularly those with low incomes, vulnerable to risk in their ability to meet even basic consumption needs. In this paper, we consider the implications of price risk for the design of social protection programs, with a particular focus on the role of in-kind transfers. In-kind transfers are a critical component of social protection around the world: approximately 44% of safety net beneficiaries 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). We explore a novel benefit of such transfers by demonstrating both conceptually and empirically that when local commodity prices vary, in-kind transfers can deliver welfare gains to beneficiary households by providing insurance value in addition to pure redistribution. More broadly, our results highlight the importance of considering insurance in the design of social safety net policies.

Variation in local commodity prices in developing countries has been well documented. For example, prices can vary due to weather-related shocks to local production, often exacerbated by a lack of market integration (Atkin, 2013; Allen, 2014).[1] The implications of this price risk for households and for optimal policy, however, is less clear. As prior work (e.g., Waugh (1944)) has demonstrated, the welfare consequences of price variability are theoretically ambiguous. Intuitively, absent storage technology, households face a trade-off between the cost of smoothing consumption when prices are high and the gains from substitution towards cheaper consumption when prices are low. In addition, other factors such as income may covary with prices, affecting the welfare consequences of price volatility.

We begin with a simple model to demonstrate that when prices vary across states of the world, the optimal policy will provide price-indexed transfers that equalize marginal utility of income across states. The marginal utility of income and therefore optimal transfers may theoretically increase or decrease with respect to price. Households will prefer transfers that increase with respect to price as long as a simple condition holds: the covariance between the marginal utility of income and price is positive.

We next demonstrate that when this condition holds, in-kind transfers will provide positive insurance value to the beneficiary household in addition to the welfare gain from pure redistribution. This occurs because the value of in-kind transfers rises automatically with

[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), Kenya (Burke, Bergquist and Miguel, 2019), 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.

the local market price of the transferred good. These insurance benefits may be particularly relevant when there are logistical constraints—such as a lack of high frequency local price data—that preclude price-indexed cash transfers.[2]

Importantly, 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 the optimal form of social protection program. Instead, our test would still rely on the covariance between prices and marginal utility, 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). The correlation of interest is therefore unconditional: we do not seek to control for income shocks or other factors potentially correlated with prices. Indeed, since in some places incomes are likely to be higher in periods with high prices, it is easy to imagine settings where marginal utility is *lower* in high-price periods and in-kind transfers would be welfare-reducing relative to a constant-value transfer. A key advantage of our approach is that it does not require instruments for prices, and so can be applied in a wide variety of settings to understand when transfers should increase with local prices.

A challenge when implementing this test is to find an appropriate empirical proxy for the 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.[3] 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.[4]

We implement the 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

[2]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."

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

[4]We lack the local price measures for most non-food consumption needed to construct an accurate marginal utility measure based on total real consumption; see Section 2.4 for further discussion.

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.[5] 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 1.3 percentage points fewer households (equivalent to 16 million individuals nationwide) meeting the MCR and a 0.7% decline in calories consumed by the average household. These findings are driven entirely by below-median socioeconomic status (SES) households. These results demonstrate empirically that high-price states are also high marginal utility states for poorer households. In the context of the model, this positive covariance of marginal utility and price implies that one of the benefits of in-kind transfers is that they can provide positive insurance value, helping households smooth consumption in the face of price risk.

To what extent do in-kind transfer programs deliver such insurance benefits in practice, and how large would transfers need to be to smooth caloric sensitivity to prices fully? To answer these questions, we turn to an evaluation 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 ("PDS prices") through a network of over 500,000 designated shops. However, the program has been criticized for corruption and mistargeting (Niehaus et al., 2013; Dreze and Khera, 2015), and the limited rigorous evidence on its causal effects is mixed (Kochar, 2005; Tarozzi, 2005; Kaul, 2018; Shrinivas et al., 2018).[6]

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 and 2012, a period between major national policy changes. The PDS became a more important part of the social safety net over this period (Khera, 2011). Expansions in eligibility doubled the number of households receiving PDS grains, while decreases in PDS prices increased the real value of the transfer for each household. We use variation in the mandated PDS price as well as expansions in eligibility to instrument for *PDS value*: 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.

[5]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.

[6]See also Li (2021) for evidence of the effects of PDS expansions on home production and Shrinivas, Baylis and Crost (2019) for evidence of small effects on labor supply.

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.[7] Overall, we estimate that PDS policy changes led to 40 million additional individuals meeting MCR thresholds over the study period.

We next examine the—previously unstudied—role of the PDS in reducing caloric sensitivity to local prices. A Rs. 100 increase in PDS value reduces the sensitivity of calories to market prices by 68%, with estimated sensitivity for the average household reaching zero for a PDS transfer worth Rs. 147. This is only one-half 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 the best of our knowledge, this is the first study examining the effect of transfer program receipt on the sensitivity of outcomes to prices. These results suggest a perhaps bigger role for the PDS in providing food security than previously understood, and may be one reason 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*; Das and Sethi, 2023). Indeed, during the Covid-19 crisis, the PDS 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).

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 the 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.

Finally, we provide empirical evidence against alternatives to the insurance mechanism, demonstrating that income effects, flypaper effects, and general equilibrium price effects are orders of magnitude too small to explain the observed findings. Our results on the effect of in-kind transfers in reducing caloric sensitivity to prices thus complement our sufficient statistics approach by providing direct support for the insurance mechanism posited in the model and by quantifying the magnitude of these effects.

This paper contributes to several literatures. First, 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; Massell,

[7]These results suggest that the time period of study might be important. Our paper, Kaul (2018) and Shrinivas et al. (2018) find positive effects on nutrition and study later expansions as compared to the older studies that find little or no effect.

1969; Turnovsky, Shalit and Schmitz, 1980; Finkelshtain and Chalfant, 1991; Bellemare, Barrett and Just, 2013).[8] 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. In addition, while the previous literature has taken a structural approach to estimate price risk preferences (see, e.g., (Deaton, 1989)), we follow the sufficient statistics literature in deriving a test that requires the estimation of a simple empirical parameter. This allows us to determine whether households value insurance without directly parameterizing risk aversion or other components of the economic environment, such as price-income correlations, access to credit or storage, or home production.

Second, 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 *without* requiring an instrument for prices, a major challenge in this literature. Since our test does not rely on exogenous variation in prices, it can be easily generalized to other empirical contexts.

Third, we propose a novel rationale for in-kind transfers. Previous studies have proposed other motivations 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 reducing 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; Jiménez-Hernández and Seira, 2021). Others have argued that in-kind transfers are beneficial if beneficiaries given cash will maximize the "wrong" utility function, either due to intra-household conflicts or simply a paternalistic view (Currie and Gahvari, 2008; Cunha, 2014; Batista, Silverman and Yang, 2015). However, although some in the policy community have highlighted the potential insurance benefits of in-kind transfers (Kotwal, Murugkar and Ramaswami, 2011; Dreze,

[8]One exception is Newbery (1989) who compares price stabilization to rations (in-kind transfers).

[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." A large literature has considered how producer choices may be distorted by food price risk and poorly integrated markets (see for example Fafchamps, 1992; Saha and Stroud, 1994; Barrett, 1996) and Fackler and Goodwin (2001) for a review of this literature.

[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) and welfare losses (Attanasio et al., 2013). However, a significant number of careful analyses also find non-existent or positive relationships (Jensen and Miller, 2008; Behrman, Deolalikar and Wolfe, 1988).

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 have not considered insurance as a potential mechanism (Hidrobo et al., 2014; Moffitt, 1989; McIntosh and Zeitlin, 2021; Siu, Sterck and Rodgers, 2021). 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. Understanding the insurance benefits of in-kind transfers is critical because of their global prevalence and importance.[11]

Finally, our findings have implications for larger ongoing debates regarding the appropriate design of social protection programs. While in-kind transfers remain common around the world, numerous recent studies have highlighted the benefits of unconditional cash transfers (Haushofer and Shapiro, 2016; Banerjee, Niehaus and Suri, 2019).[12] One important rationale for cash transfers is the textbook argument that beneficiaries themselves will be indifferent between cash and in-kind if transfers are inframarginal and will prefer cash if in-kind transfers are marginal and distort the consumption bundle. We contribute to this literature by demonstrating that inframarginal in-kind and cash transfers with the same expected value have different effects on household welfare when prices vary. Interestingly, and 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, Malawi, Kenya, and Ethiopia (Hidrobo et al., 2014; Khera, 2014; Ghatak, Kumar and Mitra, 2016; Gentilini, 2016; Shapiro, 2019; Hirvonen and Hoddinott, 2021). While there are many possible explanations for these stated preferences, beneficiaries who prefer food transfers to cash do frequently mention the fear of unstable prices as a reason for their preference (Khera, 2014; Sabates-Wheeler and Devereux, 2010).[13] More generally, our findings highlight the important potential role of price risk for vulnerable households and the importance of designing social protection programs that mitigate exposure to this risk, through in-kind transfers or other policy tools such as indexing cash transfers to prices.

The remainder of the paper proceeds as follows. Section 2 develops a framework for

[11]Interestingly, Fetzer (2020) shows that NREGA (workfare) transfers eliminate the relationship between rainfall shocks and conflict in India. His idea that workfare can help households insure against adverse income shocks complements our more general argument regarding the insurance value of in-kind transfers.

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

[13]There are of course many other reasons in-kind and cash transfers may differ from both the beneficiary and policymaker perspective. For example, stated household preferences may reflect differences between cash and in-kind in allocation mechanisms or intrahousehold dynamics. There may also be differences in administrative costs or corruption (Banerjee et al., 2021) or differences in whether the transfer affects not only the level but also diversity of food intake (see, e.g., Hidrobo et al. (2014), Ahmed et al. (2022), and Leroy et al. (2010)).

examining social protection programs in the context of price risk. Section 3 discusses the empirical setting 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

In this section, we present a simple theoretical model to examine the potential role of insurance in the presence of price variability. Our model builds on a well-established literature considering the welfare effects of price risk. Pioneering work by Waugh (1944); Massell (1969); Deschamps (1973); Hanoch (1977); Turnovsky, Shalit and Schmitz (1980); Newbery and Stiglitz (1981) studies theoretically the effect of commodity price risk on consumer welfare as well as the impact of price stabilization policies. More recent work generalizes their findings by considering households as both consumers and producers and extending to the multi-commodity case (Finkelshtain and Chalfant, 1991, 1997; Barrett, 1996; Bellemare, Barrett and Just, 2013). Our contribution to this literature is two-fold. First, we consider price risk in the context of the design of social protection programs, with a particular focus on in-kind transfers. Second, we derive an empirically testable statistic that can be used to determine the welfare effects of state-contingent and in-kind transfers without the need to specify the structural parameters of the model.

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, in-kind transfers will deliver positive insurance value if and only if the marginal utility of income is higher in the high-price states of the world.

We 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 and assume that households treat inframarginal in-kind transfers as fungible.[14]

[14] In-kind transfers may reduce market prices (Cunha, De Giorgi and Jayachandran, 2018; Jiménez-Hernández and Seira, 2021) and cash transfers increase them (Filmer et al., 2021) though in practice effects may be small (see Egger et al., 2019); and behavioral households could exhibit flypaper effects in spending from in-kind transfers (Hastings and Shapiro, 2018). However, we find that both effects are negligible in our empirical context (see Section 5.6).

The household has income y and preferences characterized by the indirect utility function $v(\cdot)$. For expositional purposes 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 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, $\int x(p_j)f(p_j)dp_j$, is equal to 0. 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.[15] This result parallels 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.

[15] 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.

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.

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:

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

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 $\gamma > \eta_j$. Intuitively, if price and income are positively correlated, a dollar in the high-price state generates less marginal utility than in the baseline framework. 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,[16] as well as other dimensions of household behavior such as savings, storage, and home production.

[16]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}.

2.3 In-kind transfers

We now examine the role of in-kind transfers, which are both a key component of social protection programs in practice and may be of particular importance when governments face challenges in implementing the optimal state-contingent policy due to logistical constraints in the measurement of local prices.[17] To determine the insurance value of in-kind transfers, we compare them to a fixed benchmark transfer that provides pure redistribution. We model the in-kind transfer as providing a fixed amount z of the good to the household, while the benchmark transfer provides the same amount $z\bar{p}_j$ to the household across all states of the world. Both transfers thus provide the same transfer to the household in expectation. For simplicity, we assume the in-kind transfer is inframarginal (the household consumes more than z of the good for all possible prices p_j).[18] Finally, we assume that prices are not affected by the form of the transfer. We use the term "welfare" to refer to the expected utility of the household. We acknowledge, however, that a social planner might also want to consider the social cost of provision, which could differ based on the form of the transfer.[19]

The welfare effect of the benchmark transfer can then be written as:

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

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:

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

where the term on the right-hand side is simply the transfer amount z multiplied by the covariance between the marginal utility of income and prices. Using a linear approximation of $v_y(p, y)$ with respect to prices around the vector of mean prices $\bar{p}$, we obtain:

[17] Previous work has argued, for example, that observing local prices in real time and at high frequency is often infeasible in many developing country contexts (Gibson and Rozelle, 2005; Khera, 2014).

[18] 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 total welfare gain from in-kind transfers will be reduced as a result of distortion to the consumption bundle.

[19] 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, in-kind transfers may be administratively costly to implement or prone to corruption (Banerjee et al., 2021).

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

Expression (7) shows that in the presence of price risk the in-kind transfer is not equivalent to the benchmark 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 benchmark. Therefore:

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

This is because when the covariance is positive, the household's optimal insurance menu is one in which transfers are increasing with respect to price. The in-kind transfer provides this insurance function by delivering more purchasing power in the high-price states, thereby better approximating the optimal policy than a state-invariant transfer which provides pure redistribution. 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 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 directly observe marginal utility of income 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 interpretational 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 improve household welfare through an insurance channel: observing no relationship could still be consistent with in-kind transfers allowing 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 in the context of India, which 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 below-market rates to eligible households via a widespread network of Fair Price Shops.[20] 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.[21] The effective transfer is substantial: for example, the PDS price for rice was 35% of the market price on average over our study period and 10% today.[22] Eligible households can buy up to a certain quantity

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

[21]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.

[22]Accounting for a below-market price the household must pay for the in-kind good modifies the implicit transfer amount—from $z\overline{p}_j$ in our baseline model to $z(\overline{p}_j - p_j^{PDS})$—but does not affect the model test. In practice, the PDS prices are so low that the system is close to free distribution (see Figure 2(a)); it is extremely rare for households to not be able to afford "co-pays." Rather, the main reasons for not getting PDS grains are related to technical/bureaucratic issues, and conditional on getting grain beneficiaries obtain 94% of their entitlements (Muralidharan, Niehaus and Sukhtankar, 2023).

of grains each month based on entitlements listed on ration cards, although in practice the PDS shops may not always have enough for all households to access their allocations.

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^{th} through 68^{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^{th} round. June 2012 is the end of the survey period for the 68^{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 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^{th} and 67^{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.[23] 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 A2). There are 140 region-sectors, and we measure prices using the mean unit value at the region-sector-quarter level.

A natural measure of prices is place- and time-specific average unit values. However, this approach is susceptible to bias arising from measurement error in either expenditure or quantities. In particular, classical measurement error in quantities would affect the left hand side (caloric intake) and the right hand side (average unit value) in opposite directions, resulting in negative bias. Alternatively, household income shocks that increase caloric consumption might also increase measured prices due to quality upgrading. This would cause positive bias.

To avoid a mechanical correlation between unobservable income of taste shocks that affect both outcomes and prices, we instead use a leaveout measure of prices:

$$p_{-i,jt} = \frac{1}{N_{r(i)} - 1} \sum_{k \in R(i) \setminus i} UV_{kjt} \tag{10}$$

where $R(i)$ is the collection of households in the region-sector in which household i is located and $N_{r(i)}$ is the total number of households in i's region-sector. The correlation between this leaveout price measure and the simple average $p_{ijt} = \frac{1}{N_{r(i)}} \sum_{k \in R(i)} UV_{kjt}$ is extremely high; the coefficient on $p_{-i,jt}$ in a regression of p_{ijt} on leaveout prices and our baseline set of controls is 0.994. As a result, there is nearly no difference in the results if we use the non-leaveout price measures.[24]

Although our price measures are by construction uncorrelated with individual-level demand shocks, one possible remaining concern is that unobserved region-sector-level taste or

[23] The NSS data separately records 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.

[24] An alternative would be to instrument for p_{ijt} with $p_{-i,jt}$. However, given the first stage of 0.994, the results are nearly indistinguishable.

income shocks affect both demand and quality. In the most likely scenario, unobserved income shocks cause higher caloric intake and substitution into higher-quality rice, leading to upwards-biased coefficients. To assess whether unit-value prices accurately capture changes in the prices faced by households, we therefore turn to the Rural Price Survey. The RPS is a survey of vendors at local markets and covers many of the same goods as the NSS. Unfortunately, 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 do not use it for our main analysis. Nonetheless, 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 A4). To more directly assess the robustness of our results, we also show below that our 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 scheduled caste/scheduled tribe status, fuel used at home, home ownership, occupation and education of household head, land possessed, 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 optimal form of transfers is the correlation between marginal utility of income and prices. If this relationship is positive, (1) households will prefer transfers that increase with respect to price; and (2) in-kind transfers will therefore deliver welfare gains to households relative to a fixed equal expected value cash transfer by providing insurance benefits. 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 also examine calories per capita as an additional outcome.[25]

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.[26] To contextualize caloric consumption, we rely on age $\times$ 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.[27] On average, individuals consume 2,097 calories per day, while the ICMR estimates that 1,904 would be necessary on average given our NSS sample's age-gender composition. On average, only 61% of households meet the MCR (69% of above median SES households and 56% of below median, see Table 1).[28]

[25]As discussed above, we cannot construct an accurate measure of real total consumption because the price vector for non-food consumption is highly incomplete. However, the consumption results using the limited available price information are very similar to our calorie results; see Appendix A2.3.

[26]These estimates are included by the NSS in the 55$^{\text{th}}$ round data release (NSSO, 2001), who adopted them from Gopalan et al. (1989).

[27]Eli and Li (2020) show that caloric requirements vary across seasons in our context. Using the lowest recommended caloric intake defined by the ICMR for 'sedentary' exertion ensures that decreases in calories around that threshold are associated with lower utility regardless of the actual type of work undertaken by household members.

[28]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; we also show results per adult equivalent in Appendix Tables A5 and A13, which are similar to the per capita results). 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).

4 Empirical test of optimal form of transfers

4.1 Price exposure and variability

Indian households face considerable potential exposure to price risk because budget shares of staple goods are large. 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.[29]

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. 9.73 per kilogram.[30] Taking out district-sector-season fixed effects, the standard deviation of the residual is 1.17. We then include year-quarter fixed effects to capture common shocks across areas.[31] The residual standard deviation decreases to 1.03. Household characteristics do not explain any of the remaining variation: the standard deviation is unchanged when we include household controls and the SES index. In our main specifications, we use the residual variation in the final column to estimate caloric responses to price variability to focus on the component of variation that is idiosyncratic across time and space. 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, and we provide specifications with varying sets of fixed effects below.

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 Empirical specification and results

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

[29] This is true throughout our period: even after the expansion of PDS generosity beginning in 2008, 89.2% of below-median SES households were inframarginal.

[30] 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.

[31] 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.

rice price states will be associated with lower caloric intake: high-price states could also be high-income states and households may be able to substitute toward other goods. In addition, the relationship is estimated given existing anti-poverty programs and household smoothing mechanisms, such as self-insurance (for example, drawing down savings) and informal insurance. Finding a non-zero relationship implies that these smoothing mechanisms cannot fully insure price risk, leaving a role for state-contingent transfers. The sign of this relationship—which in turn will determine whether households prefer transfers that increase with respect to price and consequently whether in-kind transfers deliver insurance benefits —is therefore an empirical question.

In Table 3 we regress the calorie outcome c_{it} on log leaveout market rice prices $p_{-i,rt}$:

$$c_{it} = \beta p_{-i,rt} + X_{it}\lambda + \delta_{da} + \tau_t + \phi_{round} + \varepsilon_{it} \tag{11}$$

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_{it} 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 correlation between prices and our proxy for the marginal utility of income given any existing household insurance mechanisms as well as access to social safety nets, including the PDS.

Column 1 of Table 3 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 is associated with a decrease in the likelihood that households meet the MCR by 1.31 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 1.12 percentage points for every 10% increase in the rice price (column 2). We lose some precision, but the estimates are still significant at the 5% 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 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 able to easily insure against shocks that are common across areas.

Finally, we compare our main estimates to results using prices from the Rural Price Survey (RPS). Again, we do not use the RPS for our main analysis because it is only conducted in a selected subsample of rural areas and because documentation on the sampling methodology is incomplete. However, it has two important advantages in addressing concerns both about measurement error in prices and potential substitution across rice quality varieties. First, prices are measured in local markets by surveyors and are not derived from household expenditure or quantity data. Second, the RPS is used to construct consumer price indices and is therefore meant to capture a quality-constant bundle of commodities over time. In particular, we use the RPS price measure for "medium grade" rice throughout.[32]

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. The point 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 3.04 percentage point decrease in the likelihood of meeting the MCR. The robustness of our results to using the RPS is reassuring and alleviates concerns about potential bias from measurement error or quality substitution in our unit value measure of local prices.

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 2.33 percentage point reduction in the likelihood of meeting MCR for below-median SES households and a 1.90 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.[33] Table 4 also reports estimates that divide the rural sample

[32] https://mospi.gov.in/sites/default/files/publication_reports/Report_TACon%20SPCL_on_BaseRevision_CPI_4mar15.pdf, accessed October 9, 2023.

[33] 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.gov.in/price-collection-survey for more

into landless and landowning households. The estimate for landless households is larger in magnitude, but the difference is only statistically significant at the 10% level.

We also examine caloric sensitivity by more granular SES categories. Figure A4 re-estimates Equation 11 with interactions between log price and indicators for households belonging to each of the SES quintiles. Caloric sensitivity decreases substantially throughout the SES distribution; a 10% increase in prices would decrease the likelihood of meeting the MCR for 1.9 percentage points for the poorest households but by only 0.1 percentage points for the upper quintile.

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 using log 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 nearly the same 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).

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 (about 1 SD of the within-district-sector-season price variation; see Table 2) is associated with 1.31 percentage points fewer households—or approximately 16 million individuals extrapolating from India's population in our study period—meeting the MCR. However, it is important to note that households near the MCR threshold are not the only ones facing welfare losses from price risk. Our results also indicate a negative calorie-price gradient for poorer households, implying that many households *already* below the MCR (close to half of below median households) 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

details.

the actions highly risk-averse households take to smooth consumption.[34] Taken together, these results suggest substantial losses in welfare from price variability.

In the context of the theory, these results imply that households would benefit from policy tools that provide insurance against price risk, such as indexed transfers that increase with local prices or in-kind transfers. This result is driven by poorer households, precisely those typically targeted by safety net programs.[35] Intuitively, the fact that households fall below the MCR in high-price states—despite allowing potential substitution to other goods, price-income correlations, and available smoothing technologies—implies that the marginal utility of a dollar for households is high in these states and that they would value an insurance menu in which transfers increase with respect to price. In-kind transfers provide such this type of insurance (relative to fixed cash transfers) since the value of in-kind transfers rises automatically when local prices rise.

5 An evaluation of India's in-kind transfer program

Having demonstrated the benefit to households from in-kind transfers, we next turn to a policy evaluation of India's flagship in-kind transfer program: the PDS. The goal of this analysis is to determine whether the PDS actually targets the households that would benefit from in-kind transfers and the extent to which these transfers mitigate caloric sensitivity to prices. 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; Banerjee et al., 2021). In addition, corruption in distribution might increase precisely during high-price periods (Hari, 2016). We use policy variation in PDS generosity to instrument for observed PDS value and estimate the causal effects of the PDS on household caloric intake and the sensitivity of calories to prices. We conclude by providing evidence against alternatives to the insurance mechanism.

5.1 PDS policy variation

PDS commodities are procured by the central government and made available to state governments at significantly discounted prices. States purchase these commodities at the discounted price, transport them to a network of shops, and sell them to beneficiaries. The federal gov-

[34] 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).

[35] Note that 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 a fixed cash transfer. 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 deliver benefits through an insurance mechanism.

ernment sets minimum guidelines for the program by determining maximum prices at which PDS goods can be sold, minimum entitlements per household, and mandated categories of eligible beneficiaries. However, states can and do use state resources to lower prices further and expand entitlements and eligibility beyond these federal requirements (see Balani (2013) for details on the functioning of the PDS). Therefore, the generosity of the PDS varies across states and over time, and we exploit this source of variation to estimate the causal effects of the PDS. We address potential policy endogeneity in detail below.

There is no comprehensive data source for state PDS policies.[36] 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.[37] 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 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 A6. 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. We provide more information on the political context in which states' PDS policies changed as well as study the determinants of reform in Appendix A3.

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 doubled from 20% to 38%

[36] For PDS policy changes in select states see Khera (2011).

[37] 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).

of households. This translated into a 300% increase in the value of the PDS subsidy over the period (Panel C), from Rs. 16 to 47 (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_{irt} for each household using information on the leaveout market prices $p_{-i,rt}$, PDS prices $p^{PDS}_{-i,rt}$, and observed PDS consumption q^{PDS}_{it}.[38] The value of the PDS rice subsidy can be written as:

$$v_{irt} = (p_{-i,rt} - p^{PDS}_{-i,rt})q^{PDS}_{it}$$

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), 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^{BPL}_{st}, 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.

[38] As discussed above, we define market prices and PDS prices by the mean region-sector-year-quarter leaveout unit values. 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.

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

$$c_{ist} = \alpha_1 v_{irt} + \alpha_2 p_{-i,rt} + X_{it}\lambda + \delta_{da} + \tau_t + \phi_{round} + \varepsilon_{ist} \tag{12}$$

where s indexes states (other indices as previously defined), c_{ist} is our calorie outcome measure, $p_{-i,rt}$ is the leaveout 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_{irt} 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.[39]

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

$$c_{ist} = \beta_1 p_{-i,rt} + \beta_2 p_{-i,rt} \times v_{it} + \beta_3 v_{irt} + X_{it}\lambda + \delta_{da} + \tau_t + \phi_{round} + \varepsilon_{ist}. \tag{13}$$

We instrument for v_{irt} as above and for $p_{-i,rt} \times v_{irt}$ using our three instruments as well 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.

To assess this possibility, we estimate event-study specifications for the dynamic effect of the eligibility expansion instrument on PDS transfer value and meeting the MCR.[40] We use an imputation approach that uses only pre- and never-treated observations to predict counterfactual non-treated outcomes (Borusyak, Jaravel and Spiess, 2021), although our results look similar if we use a conventional two-way fixed effects specification (see Figure A6).

[39] 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 district-sector-quarters have positive weights.

[40] 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.

Figure 3 displays the results, with the first stage effect of the expansion on PDS value in Panel A and the reduced form effect on meeting the MCR in Panel B. We see no differential trends in average PDS value in the years before the reform. However, PDS value v_{irt} begins to increase immediately following the reforms. Within five years, v_{irt} increases by Rs. 50 on average, approximately 50% of the mean PDS transfer received by beneficiaries during our study period. Panel B of Figure 3 also provides no evidence of changes in whether households meet the MCR before a policy is implemented—supporting the parallel trends assumption—but a sharp increase after PDS expansion, indicating that the PDS substantially improved caloric consumption.

5.4 Results

Table 6 contains first stage results for Equation 12 for the overall sample and separately for below- and above-median SES households (Table A7 contains the first stage for all demographic subgroups). We present throughout the robust effective F-statistic (Montiel Olea and Pflueger, 2013), which can accommodate both heteroskedasticity and multiple excluded instruments, and report the critical values for when the worst-case bias of two-stage-least squares exceeds 10% of the worst case bias of OLS.[41] The coefficients for PDS price decreases and eligibility increases are both strongly significant and have the expected signs. In the full sample, 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. These coefficients are broadly similar and again strongly significant in the below and above median subsamples.

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 4; $p = 0.121$). We find a positive and significant effect on the likelihood of meeting the MCR for below median households and a positive

[41] Our effective F stats are above the critical values in the main sample, and slightly under these critical values in the sub-samples. We note that in a setting like ours with multiple excluded instruments case these effective F statistics could be compared to either a value of 10 or the Montiel Olea and Pflueger (2013) critical values we report Andrews, Stock and Sun (2019). In practice both the critical values and the effective F stats are always clearly above 10 so reporting these critical values is the conservative approach. Unfortunately, there is no method to produce weak-instrument robust F stats in the multiple endogenous regressor case of panel B in Tables 7 and 8—see Andrews, Stock and Sun (2019) for a discussion. However, the results for the single endogenous regressor case are reassuring, and suggest that our instruments in the multiple endogenous regressors case are likely to be of similar strength.

but insignificant effect for above median households. The point estimates for log calories per capita are very similar (but insignificant) for both subgroups. These results suggest that an increase in PDS has a similar effect on calories for the two groups (consistent with the relatively constant calorie-income gradient we document in Figure 1) but a larger effect on meeting the MCR for below median households who are on average more likely to be just below the minimum calorie threshold.[42]

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 shows the interaction of market price and a Rs. 100 increase in PDS value. We also provide 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 2.6 percentage points (column 1). However, every Rs. 100 of PDS value reduces this drop by 1.8 percentage points. Our results imply that households' caloric intake would no longer be sensitive to market prices if they received a Rs. 147 transfer from the PDS, which is roughly one-half larger than the average non-zero transfer. We observe similar patterns when we use log calories per capita as the outcome measure (column 4).

The remaining columns show the results separately for below and above median SES households. We see larger calorie-price sensitivity at mean PDS levels for below median households (consistent with our results in Tables 4 and 5), but interestingly we see that both below and above median households would experience caloric sensitivity to prices at zero (imputed) PDS. For both groups, higher PDS transfers reduce price sensitivity. These results imply that the PDS as implemented during the study period provided households with substantial insurance against price risk, both for below and above median households.

In Tables A7 and A8 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.

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

[42]Note, however, that the complier population (those for whom increases in policy generosity lead to on the ground increases in PDS value) are different across these subgroups.

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).[43] In Table A9 we include wild cluster bootstrap p-values at the state level and find little change in our inference on the effect of the PDS on caloric sensitivity (Panel B).

5.6 Mechanisms

The decline in caloric sensitivity to prices resulting from expansions in in-kind transfers is consistent with the insurance mechanism posited in the model. We now turn to investigating other mechanisms through which expansions in in-kind transfers could potentially affect household responses to price risk.

First, caloric price sensitivity might decline after PDS expansions merely because households are richer or face lower liquidity constraints. While we know of no experimental or quasi-experimental research on the effect of unconditional cash transfers on price sensitivity, we exploit cross-sectional variation in a measure of permanent income in our sample to estimate the observational effect of income on price-calorie sensitivity. These estimates will provide an upper bound on the causal effect of the income channel on price sensitivity if higher-income households have access to better smoothing technologies, as seems likely.

Specifically, we use the exponent of predicted log consumption per capita from our SES measure as a rupee-denominated measure of permanent income, and add an interaction with prices to our baseline regression of meeting the MCR on prices in Equation 12. We find that caloric sensitivity to prices declines by 0.013 per additional Rs. 100 of permanent income, consistent with our results on above and below median households in Section 4.2. However, this gradient is relatively small compared to the causal effect of the PDS, where an additional Rs. 100 of PDS value decreases caloric sensitivity by 0.177. This suggests that the income channel accounts for only a small share of the observed effect.[44]

Second, households could exhibit flypaper effects in spending from in-kind transfers (Hastings and Shapiro, 2018), resulting in a higher marginal propensity to consume calories from the PDS than from an equivalent cash transfer. Households with higher caloric intake could in turn exhibit reduced caloric sensitivity to prices. To address this concern, we

[43]We note that results obtained using only one source of variation at a time have low effective first-stage F statistics and should be interpreted with caution.

[44]In Figure A4 we more flexibly estimate the relationship between permanent income and price elasticities by interacting prices with indicators for the five quintile groups. Price elasticities are higher for poorer groups, and statistically significant for the bottom three quintiles.

compare our estimates to Weaver et al. (2023) who provide randomized cash transfers to households in Jharkhand, a state in northeast India. They find a log per capita calorie impact of a Rs. 500 per month transfer of 0.084. Scaling and normalizing to 1999 Rs. gives an estimate of 0.059, extremely close to our estimate of 0.064 (Table 7), indicating a negligible role for flypaper effects in this context.[45]

A potential caveat to the cash transfer estimates is that the study included a mild framing toward maternal and child nutrition. In practice, this took the form of phone call reminders that connected with less than 50% of the group; moreover, nutrition impacts on those with phones and without phones are not statistically distinguishable. Nonetheless, for added reassurance we also perform a similar test to the income effect test above, estimating the cross-sectional gradient of calorie-price sensitivity to a measure of predicted caloric intake based on the same fixed household characteristics we use to construct our SES measure. An additional log point of predicted calories increases the coefficient on log market price by 0.511 (Table A12). Multiplying this gradient with the estimates of the effect of Rs. 100 of PDS transfer on caloric intake (0.064, see Panel A of Table 7), we find an implied PDS effect on price sensitivity of 0.033, roughly a fifth of our baseline estimate (0.177, Panel B of Table 7). This implies that the increase in the level of caloric intake arising from PDS expansions (even if partially driven by flypaper effects) is too small to account for the magnitude of reduction in calorie-price sensitivity we observe.

Third, in-kind transfers could have general equilibrium effects on local market prices, as found by Cunha, De Giorgi and Jayachandran (2018) in a different context. If caloric sensitivity to prices is nonlinear with respect to the market price, such general equilibrium price effects could theoretically affect observed caloric smoothing. We address this possibility in Table A10, where we regress market rice prices on instrumented PDS value. Across specifications, we find very small effects of the PDS on prices. Using our baseline set of instruments, we find that an additional Rs. 100 of PDS generosity decreases market prices by an insignificant 0.6%. Given the negligible effect of expansions on market prices, these effects cannot explain the smoothing effects.

These muted price effects are consistent with evidence in Shrinivas, Baylis and Crost (2019), who also find no effect of PDS expansions on market prices. This difference with Cunha, De Giorgi and Jayachandran (2018) may be because the transfers they study are much larger than the PDS transfers. Rescaling their estimates implies a decrease of market

[45] IGDP per capita in the Weaver et al. (2023) sample and our (inflation-adjusted) all-India sample are very comparable: Rs. 79,873 (Jharkhand) and Rs. 82,979 (all-India). Sources: https://mospi.gov.in/data; https://finance.jharkhand.gov.in/pdf/Economic_Survey_2020_21/Jharkhand_Economic_Survey_2020_21.pdf. Accessed July 6, 2023.

price of only 1.6% per Rs. 100 of PDS, broadly comparable to our estimate.[46]

Finally, increased PDS generosity could theoretically result in a reduction in the variation of market prices, which could reduce sensitivity to observed price variation if, for example, households are better able to smooth small price shocks than large price shocks. However, we find that the effects of PDS expansions on price variability are small and insignificant (Figure A5).

6 Conclusion

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 provide insurance value to households in addition to pure redistribution. 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.

These results have important implications in the context of ongoing global debates about the optimal form of social protection programs. In particular, a recent and growing body of evidence documenting the success of unconditional cash transfers has garnered much media and policy attention and influenced the ways in which donors choose to allocate funds.[47]

We stress that our results do not imply that in-kind transfers necessarily dominate fixed cash transfers from a social planner perspective: a full welfare analysis would need to take into account the social cost of provision, including potential differences in implementation costs (see, e.g., Banerjee et al. (2021), Gentilini (2016), Margolies and Hoddinott (2015)). 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 themselves might value in-kind transfers.

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-kind transfers—mitigation

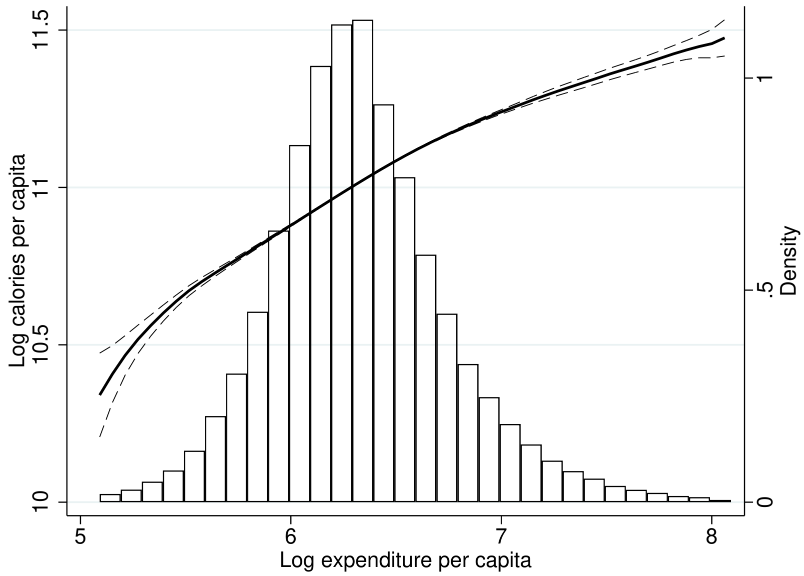
[46] A Rs. 100 transfer represents only 3.5% of expenditure, while the Cunha, De Giorgi and Jayachandran (2018) were 10% of expenditures. Rescaling their 4% estimate implies a $(10/3.5) \times 4\% = 1.6\%$ effect.

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

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.

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

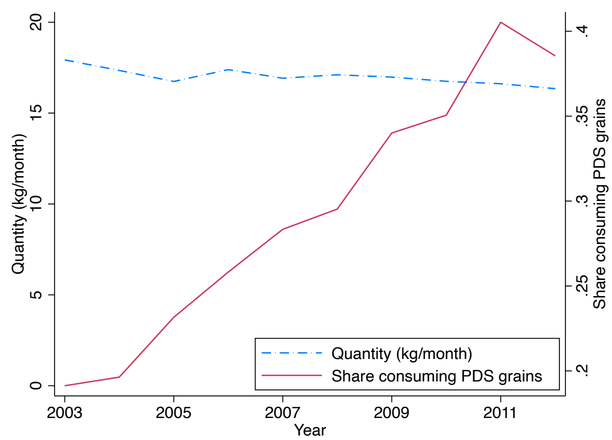


This figure plots a histogram of household log expenditure per capita (right axis) against a line representing a nonparametric regression of log calories per capita on log expenditure per capita (left axis), using data from the National Sample Survey 2003-12. Regression and histogram both condition on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

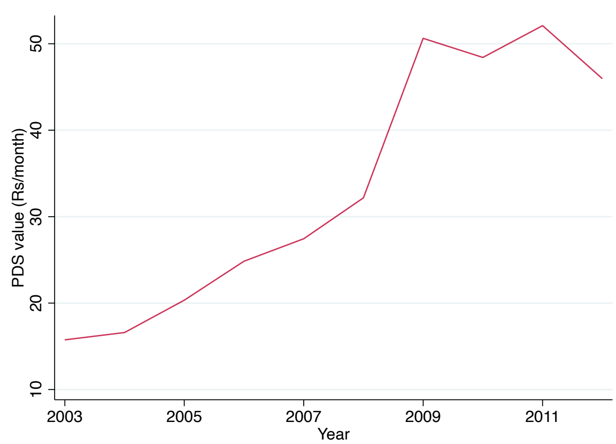
Figure 2: PDS generosity and coverage over time

(a) Market and PDS prices

(b) PDS quantities and reach



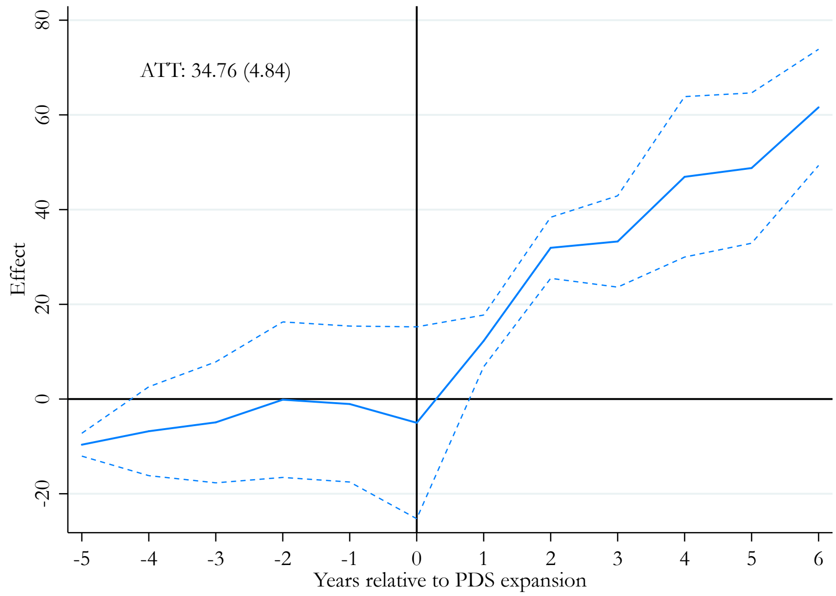
(c) Average PDS value



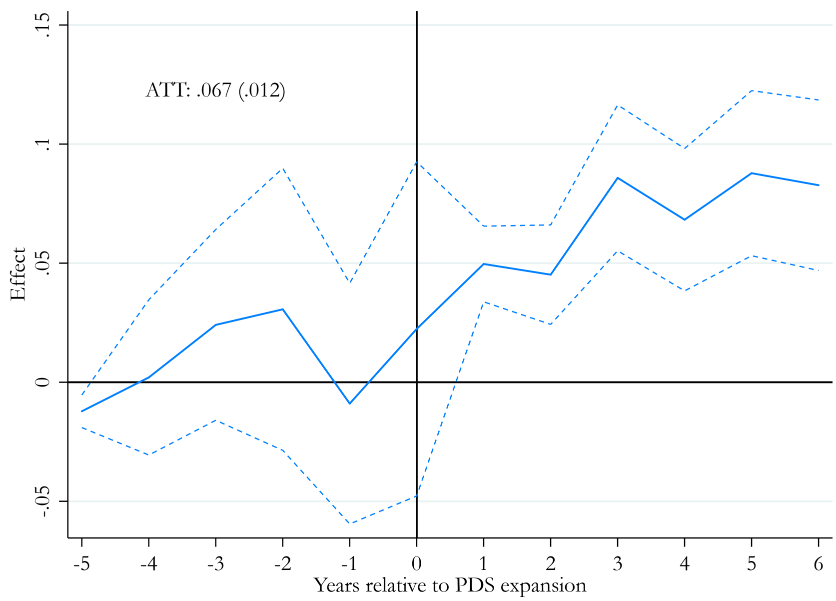
This figure shows the evolution of benefit generosity in the PDS using data from the National Sample Survey 2003-12. Panel A shows market and PDS mean unit values over time. Panel B shows PDS quantities for beneficiaries, and the total share of households who consume PDS goods. Panel C shows unconditional 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: $y_{idt} = \sum_{\tau} \beta_{\tau} \mathbb{1}_{\tau} + X_{idt}\alpha + \gamma_d + \varphi_t + \varepsilon_{iat}$, for household i in district-sector-season d and year t at year 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. Models are estimated using the imputation approach of Borusyak, Jaravel and Spiess (2021). Standard errors clustered at the state level.

Table 1: Summary statistics: daily caloric consumption

	Food share of expenditure (1)	Rice share of expenditure (2)	Total calories per capita (3)	Per capita MCR (4)	Met MCR (5)
Overall	0.52	0.09	2097	1904	0.61
	(0.13)	(0.09)	(633)	(231)	(0.49)
Below median SES	0.55	0.10	1976	1861	0.56
	(0.11)	(0.10)	(549)	(226)	(0.50)
Above median SES	0.47	0.06	2295	1974	0.69
	(0.13)	(0.06)	(708)	(222)	(0.46)
Rural	0.54	0.10	2097	1886	0.62
	(0.12)	(0.10)	(633)	(228)	(0.49)
Urban	0.45	0.06	2097	1952	0.57
	(0.13)	(0.06)	(633)	(232)	(0.49)
Rural landless	0.54	0.09	2003	1877	0.55
	(0.12)	(0.09)	(637)	(245)	(0.50)
Rural landowning	0.54	0.10	2135	1890	0.65
	(0.11)	(0.10)	(628)	(221)	(0.48)

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

Table 2: Summary statistics for market rice prices

	Mean	SD			
	(1)	(2)	(3)	(4)	(5)
Overall	9.73	2.25	1.17	1.03	1.03
Below median SES	9.38	2.07	1.14	1.02	1.02
Above median SES	10.31	2.40	1.19	1.01	1.01
Rural	9.37	2.12	1.14	1.02	1.02
Urban	10.68	2.31	1.25	1.05	1.05
Rural landless	9.59	2.02	1.15	1.01	1.01
Rural landowning	9.28	2.15	1.11	1.00	1.00
District-sector-season FE		No	Yes	Yes	Yes
Period FE		No	No	Yes	Yes
Controls		No	No	No	Yes

This table shows mean unit values for rice from NSS survey data 2003-12. Unit values of rice are the leaveout 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)
Market price rice, logged	-0.131***	-0.112**	-0.131***	-0.165***	-0.300***	-0.304***
	(0.041)	(0.044)	(0.041)	(0.042)	(0.077)	(0.081)
District-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
District-sector-season FE	Yes	Yes	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	No	Yes	Yes
HH controls	Yes	No	Yes	Yes	Yes	Yes
SES controls	Yes	No	Yes	Yes	Yes	Yes
Observations	524,911	524,911	524,911	524,911	175,065	175,065

This table displays regressions of an indicator for meeting minimum calorie requirement on log leaveout unit value market rice prices 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. 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 subsample

	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	-0.233***	-0.036	-0.190***	-0.025	-0.301***	-0.157***
	(0.056)	(0.039)	(0.053)	(0.058)	(0.090)	(0.049)
Equality of effect (p-value)		0.00		0.04		0.09
Observations	211,795	313,116	316,234	208,677	63,614	252,620

This table displays regressions of an indicator for meeting minimum calorie requirement on log leaveout unit value market rice prices 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. 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 subsample

	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	-0.073**	-0.130***	-0.028	-0.112**	-0.016	-0.138*	-0.119***
	(0.031)	(0.041)	(0.030)	(0.042)	(0.032)	(0.082)	(0.035)
Equality of effect (p-value)			0.01		0.07		0.79
Observations	524,911	211,795	313,116	316,234	208,677	63,614	252,620

This table displays regressions of log calories per-capita on log leaveout unit value market rice prices 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 6: First stage of PDS value (in 100 Rs.) on instruments

	All	Below median SES	Above median SES
	(1)	(2)	(3)
PDS price (Rs.)	-0.097***	-0.126***	-0.064**
	(0.035)	(0.043)	(0.025)
Eligibility increase (=1)	0.513***	0.542***	0.449***
	(0.103)	(0.114)	(0.093)
Eligibility increase × PDS price	-0.116***	-0.099*	-0.120***
	(0.038)	(0.049)	(0.025)
Effective F-stat	19.07	17.03	16.36
10% bias crit. val.	18.66	17.84	18.87
Observations	524,911	211,795	313,116

This table reports 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 A6. 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	Above median SES	All	Below median SES	Above median SES
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV of outcomes on PDS value						
PDS value (100 Rs)	0.107**	0.136**	0.078	0.064	0.062	0.069
	(0.052)	(0.063)	(0.048)	(0.040)	(0.039)	(0.041)
Equality of effects (p-value)			0.049			0.690
Effective F-stat	19.07	17.03	16.36	19.07	17.03	16.36
10% bias crit. val.	18.66	17.84	18.87	18.65	18.15	18.85
Panel B: IV of outcomes on PDS value						
Log market rice price	-0.260***	-0.467***	-0.123***	-0.166***	-0.260***	-0.106***
	(0.054)	(0.086)	(0.044)	(0.033)	(0.057)	(0.030)
Market rice price × PDS value	0.177**	0.208***	0.274**	0.149***	0.143***	0.247***
	(0.066)	(0.075)	(0.105)	(0.049)	(0.045)	(0.073)
Equality of effects (p-value)						
Log market rice price			0.000			0.011
Market rice price × PDS value			0.435			0.026
Pred. rice elasticity at mean PDS	-0.207***	-0.383***	-0.071*	-0.122***	-0.203***	-0.059**
	(0.051)	(0.094)	(0.036)	(0.033)	(0.058)	(0.027)
Mean PDS value	0.30	0.40	0.19	0.30	0.40	0.19
SD PDS value	0.604	0.668	0.512	0.604	0.668	0.512
1^{st} percentile PDS value	0.000	0.000	0.000	0.000	0.000	0.000
99^{th} percentile PDS value	2.556	2.685	2.325	2.556	2.685	2.325
Observations	524,911	211,795	313,116	524,911	211,795	313,116

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. Pred. rice elasticity is taken at mean PDS value. 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. Effective F-stat calculated using Montiel Olea-Pflueger (2013). Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

	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)	0.170***	0.109*	0.017	0.171**	0.224***	0.136**	0.058	0.198**
	(0.053)	(0.054)	(0.085)	(0.068)	(0.066)	(0.065)	(0.078)	(0.090)
Effective F-stat	25.05	19.12	8.94	17.43	20.54	16.79	9.07	16.73
10% bias crit. val.	21.05	18.57	23.11	23.11	19.60	17.80	23.11	23.11
Panel B: IV of meeting minimum calorie requirement on PDS value								
Log market rice price	-0.253***	-0.269***	-0.246***	-0.298***	-0.441***	-0.465***	-0.472***	-0.487***
	(0.047)	(0.053)	(0.074)	(0.070)	(0.074)	(0.084)	(0.093)	(0.108)
Market rice price × PDS value	0.171	0.190**	0.256**	0.129*	0.163	0.201**	0.322**	0.128
	(0.119)	(0.071)	(0.112)	(0.074)	(0.117)	(0.073)	(0.117)	(0.082)
Pred. rice elasticity at mean PDS	-0.205***	-0.212***	-0.170**	-0.260***	-0.379***	-0.384***	-0.343***	-0.436***
	(0.057)	(0.052)	(0.063)	(0.066)	(0.106)	(0.091)	(0.094)	(0.117)
Mean PDS value	0.28	0.30	0.30	0.30	0.38	0.40	0.40	0.40
SD PDS value	0.603	0.606	0.606	0.606	0.669	0.670	0.670	0.670
1^{st} percentile PDS value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
99^{th} percentile PDS value	2.581	2.559	2.559	2.559	2.698	2.700	2.700	2.700
Observations	391,176	524,911	524,911	524,911	160,154	211,772	211,772	211,772

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

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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 A1 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 A3 and A11 we reproduce our main results using log real consumption as the dependent variable. Table A3 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 stronger negative relationship between market rice prices and log real consumption for below-median SES households than for above-median SES households. Panel A of Table A11 shows the effect of the PDS on real consumption; a Rs. 100 increase in the value of the PDS increases consumption by 5.4 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 PDS policy changes

A3.1 Institutional and political context

The PDS has a long history, with antecedents in British times related to public food distribution to avoid famines. In the modern era, the Central Government, through the Food Corporation of India, procures foodgrains from farmers via a vast network of intermediary agencies. These grains are stored in FCI warehouses across the country. State governments obtain grain from these warehouses and distribute it locally via Fair Price Shops (FPSs, or "ration shops"), of which there are over half a million across the nation. Households are assigned to local FPSs, from whom they obtain grains at the last mile after paying the subsidized price (in some cases, like in the state of Tamil Nadu, there is no charge for obtaining PDS rice).

PDS policy is set at the national level by the Central Government, with state governments supplementing national benchmarks with their own policies. The Central Government sets what is called the "Central Issue Price," the highly subsidized rate at which state governments can procure grains from the central pool and distribute to citizens. In addition, the central government also determines quotas for the number of people who are eligible to receive PDS grains.

For the era that is relevant to our study, the main national policy reform was the introduction of the Targeted PDS (TPDS) in 1997, which was further revised in 2000-01. Under TPDS, households were categorized as Above Poverty Line (APL), Below Poverty Line (BPL), or Antyodaya (poorest of the poor). For the most part, APL households were effectively ineligible for the TPDS since the PDS price set for them was often higher than the market price for equivalent grains. Meanwhile, there were very few officially sanctioned Antyodaya households; for this reason, we mainly focus on BPL households and the PDS policies relevant for these households (as does most of the literature). In 2014, the National Food Security Act was passed, which completely overhauled the functioning of the PDS; we therefore study the period between 2003-12, which falls between the two major national policy changes and corresponds to available NSS data in that period.

As part of the introduction of the TPDS, the Central Government used poverty rates from 1993-94 to determine the number of BPL households (eligible for PDS subsidies) in each state. This was the number of households whose PDS entitlement—at Central Government-set PDS prices—the Central Government committed to pay for in each state.

However, state governments were free to use their own revenues to supplement Central Government subsidies, by either expanding the number of households eligible for the PDS, and/or reducing the rates charged. There are many such instances of state government policies, which is what we exploit in our analysis. For example, Khera (2011) notes that "since 2003, many state governments have felt that the caps on BPL cards imposed by the central government are too stringent," going on to set their own eligibility numbers. The same article goes on to point out the "renewed political interest" in the PDS in the mid-aughts, resulting in both increased eligibility and reduced prices for PDS grains.

A3.2 Reform determinants

The motivation for these state level policy changes was mainly political—indeed, in a democratic system, to some extent all policy reforms are politically motivated. State governments or opposition parties would often advertise these reforms before elections, making them part of their platforms. However, they are of course not always able to implement these promises, and moreover incumbent governments are restricted in implementing big policy changes right before elections by the election commission.

In Table A14 we consider whether states which reformed the PDS at some point during our period of study (either through an expansion or a statutory price change) had different characteristics at the start of the period. We find that households in these states were of similar SES status and faced similar market conditions (in particular no difference in the market price of rice) as states in which no reforms happened. The only difference we observe is that states which made their PDS system more generous over 2003-2012 already had slightly more generous PDS systems to start with: a higher share of the population purchased rice from the PDS, and when they did they paid a slightly lower price than in states which never had a reform. To reflect these slight differences across the control and treatment locations, in our main analysis we control throughout for district-sector fixed effects which capture time-invariant state characteristics such as baseline PDS characteristics that could affect outcomes.

We also consider whether observable state characteristics can explain the timing of the reforms, by looking at the evolution of these characteristics prior to the reform in reforming states in Table A15. Specifically, for the period prior to the reform we regress these characteristics on an indicator for the six months immediately before the reform, conditioning on state and period fixed effects. We include the non-reform states to help identify the period fixed effects.

Here again, we see no evidence that reforming states were on a different trajectory prior to implementing reforms. There are no large or statistically significant changes in market rice prices, PDS generosity, or measures of caloric intake. We view these results as consistent with the event study graphs in Figure 3, which find flat pre-trends in PDS value and meeting the MCR in the years before the reforms.

A3.3 Other potential confounders

It is also possible that other concurrent factors, including other social welfare programs, may drive our results. First, we confirm that political cycles—which could perhaps coincide with price cycles—are not driving our results. We do so by including controls for electoral cycles, as shown in Table 8. As is clear from Column 2, including these cycles does not make any qualitative difference to our results.

Since the PDS is a large and expensive program, and local governments are restricted in their revenue raising capacities (Rao, 2019), these policy changes are unlikely to be linked to other programs or changes at the local level. However, during the course of our study period the National Rural Employment Guarantee Act (NREGA) was passed, setting up India's other large social protection program (see Sukhtankar (2017) for more details on NREGA). NREGA entitles rural households to 100 days of paid employment on demand, doing manual labor at minimum wages, and state programs were rolled out from 2005-07. Given that the rollout was at the district level, and the policy changes we exploit were at the state level, it is unlikely that the rollout affects our estimates. Nonetheless, given the size of the program and the targeting of the poor, we also check that the NREGA rollout is not driving our results, by including indicators for the rollout at the district level as controls. Again, Table 8 shows that our results are robust to the NREGA rollout.

A4 Appendix Exhibits

Figure A1: Share purchasing PDS by per-capita expenditure

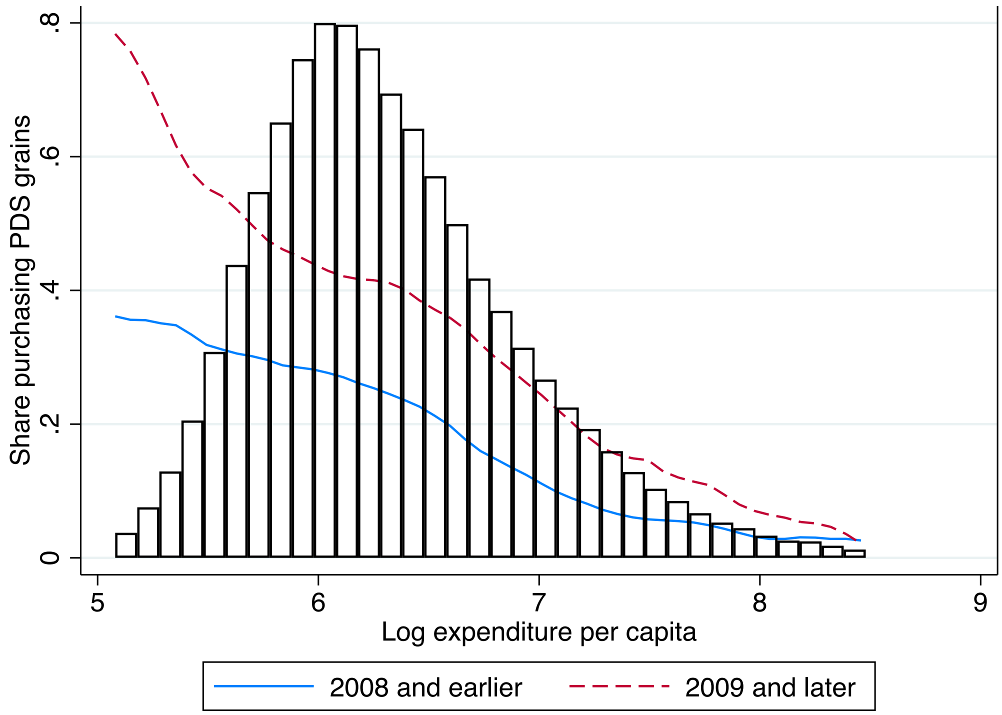
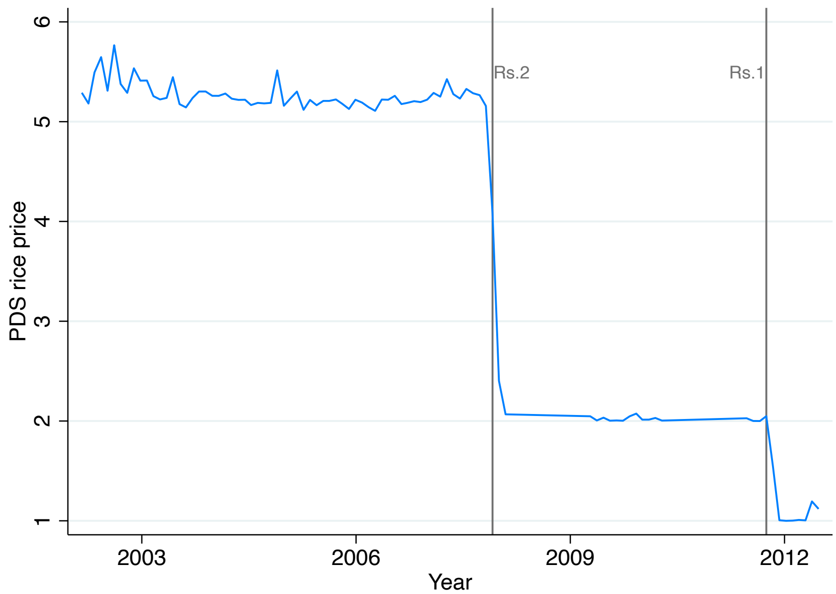


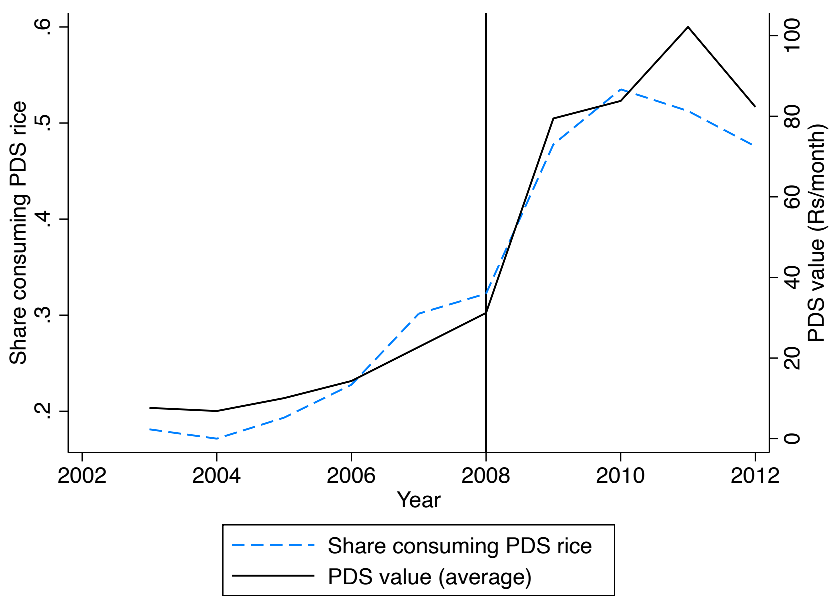
Figure shows share of households consuming PDS rice before and after 2008. The histogram shows the distribution of per-capita income, in 1999 rupees. The exchange rate was 43 rupees to one USD.

Figure A2: Example PDS policy changes

(a) Statutory PDS rice prices in Andhra Pradesh

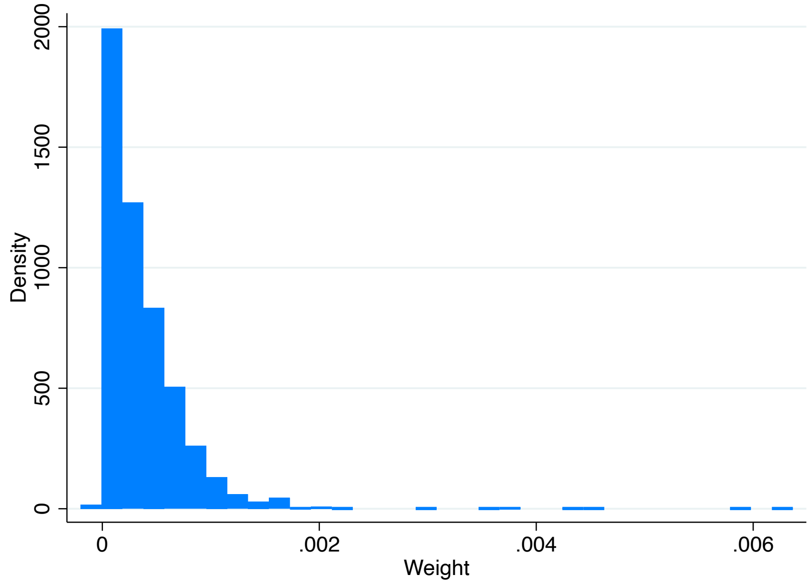


(b) Share of population consuming PDS in Odisha



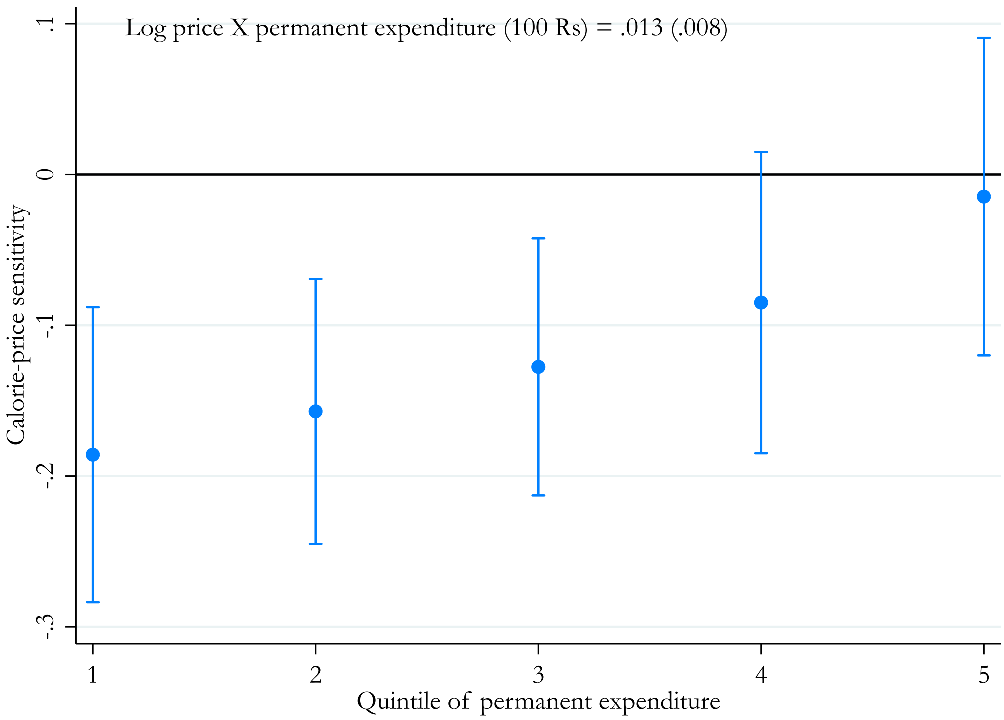
Panel A shows monthly average PDS rice prices in Andhra Pradesh, measured using NSS unit values. Vertical lines highlight two statutory price reductions.Panel B shows the share of households consuming PDS rice (left axis) and average PDS value (right axis) in Odisha in each year in our sample period, 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



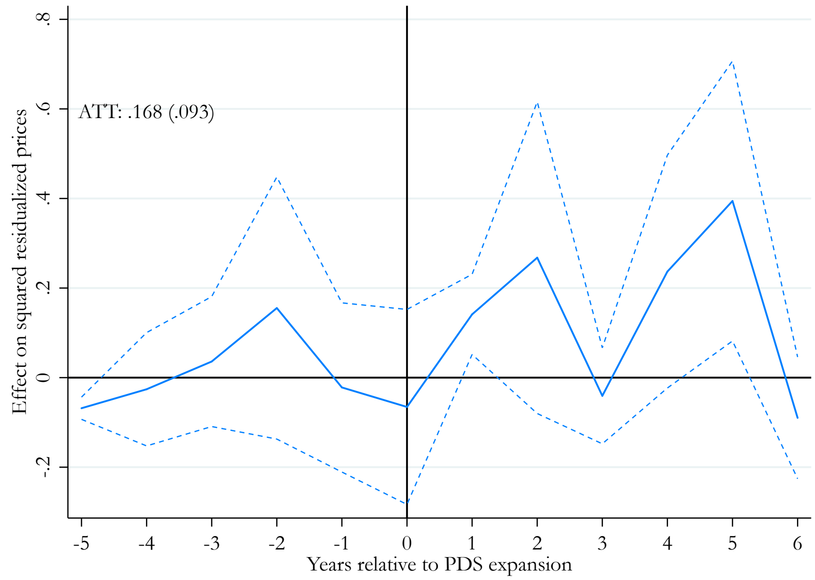
This figure shows the histogram of weights on the district-sector-period-specific treatment effects in a difference-in-differences estimate of the effect of the PDS eligibility expansions. 13 of 2,756 treated district-sector-periods have negative weights. Calculated using de Chaisemartin and D'Haultfœuille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

Figure A4: Sensitivity of meeting the MCR on prices by SES quintile



This figure shows the coefficients from a regression of meeting the MCR on prices interacted with groups for each quintile of the within-state-year household SES distribution. 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. Overlaid coefficient comes from the analogous regression of meeting the MCR on price and predicted SES interacted with price.

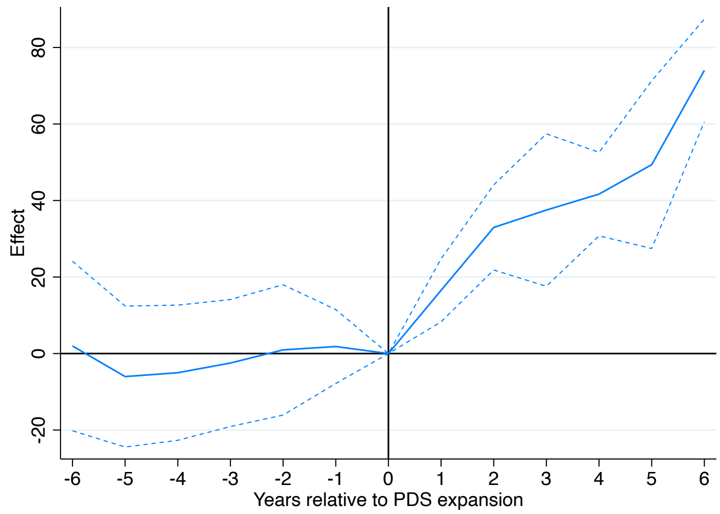
Figure A5: Effect of PDS eligibility expansions on market rice price variability



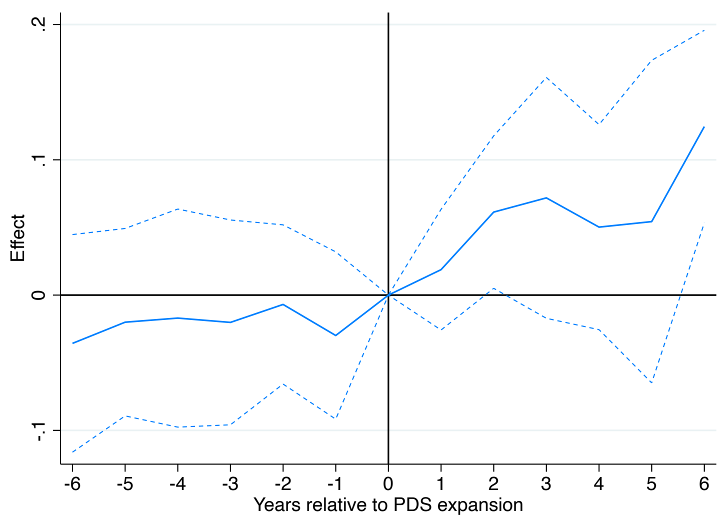
This figure shows event study coefficients from a regression of price variability on time relative to policy expansion: $y_{idt} = \sum_{\tau \neq 0} \beta_\tau \mathbb{1}_\tau + X_{idt}\alpha + \gamma_d + \varphi_t + \varepsilon_{iat}$, for household i in district-sector-season d and year t at year relative to expansion τ. Residualized market prices constructed from state-region-sector-specific regressions of prices on a quintic polynomial in quarter of surveying. 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. Models are estimated using the imputation approach of Borusyak, Jaravel and Spiess (2021). Standard errors clustered at the state level.

Figure A6: Effect of PDS eligibility expansions on PDS transfer value and caloric intake (two-way fixed effects estimation)

(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 and year-quarter t at year 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. Models are estimated using two-way fixed effects and contain year-quarter fixed effects, but are otherwise identical to Figure 3. Standard errors clustered at the state level.

Table A1: NSS data

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

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

	Mean (SD)	Percentile				
		1%	5%	10%	25%	50%
Panel A: Region-quarter level						
Rice UV, unweighted	112.29	7	16	23	42	78
	(103.53)					
PDS rice	38.63	1	1	2	5	16
	(56.19)					
Panel B: District-quarter level						
Rice UV, unweighted	14.94	1	3	4	6	10
	(15.81)					
PDS rice	7.82	1	1	1	2	4
	(9.86)					

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

Table A3: Log 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	-0.167***	-0.198***	-0.145***	-0.175***	-0.144***	-0.088	-0.203***
	(0.041)	(0.057)	(0.042)	(0.055)	(0.051)	(0.072)	(0.055)
Equality of effect (p-value)			0.36		0.68		0.07
Observations	519,573	210,162	309,411	313,031	206,542	62,848	250,183

Table displays regression of log calories per-capita on log market prices for rice. All specifications include district-sector-season and period fixed effects. Demographic controls are log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. All households owning 0.2 hectares of land or greater are classified as landowning. Household-level SES are the predicted values from a projection of log expenditure per capita on permanent household characteristics, with geographic unit and period fixed effects. Period fixed effects include calendar and NSS round fixed effects. Standard errors in parentheses and clustered at the region-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Log RPS prices on log NSS unit value prices

	All	By median SES		By landowning	
		Below	Above	Landless	Landowner
	(1)	(2)	(3)	(4)	(5)
Log market rice price	0.575***	0.558***	0.653***	0.582***	0.573***
	[0.063]	[0.065]	[0.068]	[0.075]	[0.062]
Observations	175,065	117,815	57,250	36,655	138,410

This table shows regressions of log rice prices from the Rural Price Survey (RPS) on log market rice leaveout mean unit values from the National Sample Survey from 2003-2012. 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. 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 A5: Log calories per adult equivalent and market prices by subsample

	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	-0.078**	-0.143***	-0.021	-0.119***	-0.001	-0.154**	-0.119***
	(0.030)	(0.039)	(0.030)	(0.041)	(0.032)	(0.074)	(0.034)
Equality of effect (p-value)			0.00		0.02		0.60
Observations	524,911	211,795	313,116	316,234	208,677	63,614	252,620

Table displays regression of log calories per adult equivalent on log market prices for rice. All specifications include district-sector-season and period fixed effects. Demographic controls are log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. All households owning 0.2 hectares of land or greater are classified as landowning. Household-level SES are the predicted values from a projection of log expenditure per capita on permanent household characteristics, with geographic unit and period fixed effects. Period fixed effects include calendar and NSS round fixed effects. Standard errors in parentheses and clustered at the region-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: 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 A7: 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***	-0.064**	-0.106**	-0.063**	-0.102***	-0.107**
	(0.035)	(0.043)	(0.025)	(0.039)	(0.026)	(0.033)	(0.042)
Eligibility increase (=1)	0.513***	0.542***	0.449***	0.525***	0.501***	0.481***	0.540***
	(0.103)	(0.114)	(0.093)	(0.114)	(0.107)	(0.122)	(0.127)
Eligibility increase × PDS price	-0.116***	-0.099*	-0.120***	-0.108**	-0.148***	-0.117**	-0.103**
	(0.038)	(0.049)	(0.025)	(0.045)	(0.030)	(0.045)	(0.049)
Effective F-stat	19.07	17.03	16.36	17.30	16.48	15.19	15.57
10% bias crit. val.	19.02	17.36	18.87	19.20	19.73	20.12	17.49
Observations	524,911	211,795	313,116	316,234	208,677	63,614	252,620

This table reports 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 A6. 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 leaveout 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 A8: 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	0.120**	0.081	0.176***	0.106**
	(0.052)	(0.063)	(0.048)	(0.054)	(0.055)	(0.060)	(0.048)
Effective F-stat	19.07	16.99	16.36	17.30	16.48	15.19	15.57
10% bias crit. val.	18.66	17.86	18.88	18.14	19.84	20.14	17.79
Panel B: IV of meeting minimum calorie requirement on PDS value							
Log market rice price	-0.260***	-0.465***	-0.125***	-0.351***	-0.175***	-0.491***	-0.281***
	(0.054)	(0.086)	(0.044)	(0.083)	(0.045)	(0.083)	(0.072)
Market price × PDS value	0.177**	0.208***	0.275**	0.160**	0.422**	0.108	0.112
	(0.066)	(0.074)	(0.105)	(0.073)	(0.170)	(0.085)	(0.093)
Pred. rice elasticity at mean PDS	-0.207***	-0.382***	-0.073*	-0.301***	-0.070	-0.450***	-0.249***
	(0.051)	(0.094)	(0.036)	(0.077)	(0.049)	(0.091)	(0.061)
Mean PDS value	0.30	0.40	0.19	0.31	0.25	0.38	0.29
SD PDS value	0.606	0.670	0.513	0.594	0.636	0.634	0.575
1^{th} percentile PDS value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
99^{th} percentile PDS value	2.559	2.700	2.330	2.416	2.733	2.564	2.367
Observations	524,911	211,660	313,251	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. Model (1) includes all PDS instruments, (2) includes all PDS instruments but excludes states supplying the majority of rice to the PDS, (3) includes all PDS instruments but controls for active NREGA program in district at the time of surveying as well as elections at the state-quarter level, (4) instruments for PDS value with statutory rice price instruments alone, and (5) instruments for PDS value with expansion instruments alone. For comparison, mean per-capita expenditure is 711 Rs. All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Effect of PDS generosity on caloric outcomes

	Meets MCR			Log calories per capita		
	All (1)	Below median SES (2)	Above median SES (3)	All (4)	Below median SES (5)	Above median SES (6)
Panel A: IV of outcomes on PDS value						
PDS value (100 Rs)	0.107**	0.136**	0.078	0.064	0.062	0.069
	(0.052)	(0.063)	(0.048)	(0.040)	(0.039)	(0.041)
Equality of effects (p-value)			0.049			0.690
Effective F-stat	19.07	17.03	16.36	19.07	17.03	16.36
10% bias crit. val.	18.66	17.84	18.87	18.65	18.15	18.85
Wild bootstrap p-value	0.142	0.086	0.338	0.270	0.098	0.322
Panel B: IV of outcomes on PDS value						
Log market rice price	-0.260***	-0.467***	-0.123***	-0.166***	-0.260***	-0.106***
	(0.054)	(0.086)	(0.044)	(0.033)	(0.057)	(0.030)
Market rice price × PDS value	0.177**	0.208***	0.274**	0.149***	0.143***	0.247***
	(0.066)	(0.075)	(0.105)	(0.049)	(0.045)	(0.073)
Equality of effects (p-value)						
Log market rice price			0.000			0.011
Market rice price × PDS value			0.435			0.026
Pred. rice elasticity at mean PDS	-0.207***	-0.383***	-0.071*	-0.122***	-0.203***	-0.059**
	(0.051)	(0.094)	(0.036)	(0.033)	(0.058)	(0.027)
Mean PDS value	0.30	0.40	0.19	0.30	0.40	0.19
SD PDS value	0.604	0.668	0.512	0.604	0.668	0.512
1^{st} percentile PDS value	0.000	0.000	0.000	0.000	0.000	0.000
99^{th} percentile PDS value	2.556	2.685	2.325	2.556	2.685	2.325
Wild bootstrap p-value, market price	0.492	0.482	0.494	0.450	0.504	0.442
Wild bootstrap p-value, market price × PDS	0.016	0.004	0.002	0.000	0.004	0.000
Observations	524,911	211,795	313,116	524,911	211,795	313,116

See notes to Table 7. This table includes wild bootstrap p-values, in addition to asymptotic standard errors but is otherwise the same as Table 7.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: 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	-0.016	-0.064	-0.051	-0.004
	(0.057)	(0.044)	(0.085)	(0.054)	(0.084)	(0.086)	(0.048)
Effective F-stat	8.10	8.31	7.63	7.78	7.34	9.88	7.06
10% bias crit. val.	23.11	23.11	23.11	23.11	23.11	23.11	23.11
Panel B: PDS expansion instrument							
PDS value (100 Rs)	-0.008	-0.006	-0.012	-0.002	-0.022	-0.039	0.008
	(0.044)	(0.040)	(0.053)	(0.043)	(0.039)	(0.058)	(0.040)
Effective F-stat	17.75	15.56	12.73	19.99	10.74	13.88	19.60
10% bias crit. val.	23.11	23.11	23.11	23.11	23.11	23.11	23.11
Panel C: PDS rice price, expansion, and interaction instruments							
PDS value (100 Rs)	-0.006	-0.000	-0.016	0.002	-0.029	-0.020	0.010
	(0.030)	(0.029)	(0.033)	(0.032)	(0.019)	(0.036)	(0.033)
Effective IV F-stat	17.20	14.51	16.33	15.55	15.77	12.61	14.77
10% bias crit. val.	17.99	16.77	19.01	16.82	19.99	20.57	16.88
Observations	524,911	211,795	313,116	316,234	208,677	63,614	252,620

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

Table A11: Effect of PDS generosity on log real expenditure, food/fuel-deflated

	All (1)	Below median SES (2)	Above median SES (3)
Panel A: IV of log real expenditure on PDS value			
PDS value (100 Rs)	0.054*	0.065*	0.040
	(0.031)	(0.032)	(0.035)
Effective F-stat	19.02	16.85	16.79
10% bias crit. val.	18.75	17.50	19.05
Panel B: IV of log real expenditure on PDS value			
Log market rice price	-0.258***	-0.324***	-0.223***
	(0.047)	(0.065)	(0.051)
Market rice price × PDS value	0.159**	0.128***	0.288***
	(0.060)	(0.039)	(0.102)
Pred. rice elasticity at mean PDS value	-0.210***	-0.272***	-0.166***
	(0.039)	(0.061)	(0.045)
Mean PDS value	0.30	0.41	0.19
SD PDS value	0.609	0.672	0.518
1^{st} percentile PDS value	0.000	0.000	0.000
99^{th} percentile PDS value	2.564	2.704	2.337
Observations	519,573	210,162	309,411

This table shows coefficients from regression of log real expenditure 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 708 Rs. All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Controls include log market rice unit value, log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Effect of market rice prices on caloric outcomes, by predicted caloric intake

	Meets MCR			Log calories per capita		
	All	Below median SES	Above median SES	All	Below median SES	Above median SES
	(1)	(2)	(3)	(4)	(5)	(6)
Log market rice price	-0.136***	-0.213***	-0.074**	-0.075**	-0.115**	-0.022
	(0.040)	(0.064)	(0.036)	(0.029)	(0.053)	(0.029)
Market rice price × pred. calories	0.511**	0.331	0.517**	0.283*	0.276	0.042
	(0.234)	(0.234)	(0.248)	(0.150)	(0.233)	(0.184)
Implied price × PDS effect	.033	.021	.037	.018	.017	.003
Observations	524,911	211,795	313,116	524,911	211,795	313,116

This table shows coefficients from regression of meeting the MCR and log calories per capita on log market rice prices and their interaction with predicted caloric intake. Predicted caloric intake comes from a regression of caloric intake on the SES predictors. The implied price × PDS effect comes from multiplying the log market rice prices × predicted calorie coefficient by the effect of the an extra 100 Rs of PDS value (from Panel A of Table 7). All specifications include district-sector-season and period (calendar quarter and NSS round) fixed effects. Controls include log household size, SC/ST, land ownership, religion, cooking fuel, and SES index. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Effect of PDS generosity on caloric outcomes

	Meets MCR			Log calories per adult equiv.		
	All	Below median SES	Above median SES	All	Below median SES	Above median SES
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV of outcomes on PDS value						
PDS value (100 Rs)	0.107**	0.136**	0.078	0.082*	0.077*	0.094**
	(0.052)	(0.063)	(0.048)	(0.041)	(0.039)	(0.043)
Equality of effects (p-value)			0.049			0.290
Effective F-stat	19.07	17.03	16.36	19.07	17.03	16.36
10% bias crit. val.	18.66	17.84	18.87	18.67	17.96	18.84
Panel B: IV of outcomes on PDS value						
Log market rice price	-0.260***	-0.467***	-0.123***	-0.188***	-0.292***	-0.109***
	(0.054)	(0.086)	(0.044)	(0.037)	(0.054)	(0.039)
Market rice price × PDS value	0.177**	0.208***	0.274**	0.167***	0.151***	0.245***
	(0.066)	(0.075)	(0.105)	(0.054)	(0.046)	(0.074)
Equality of effects (p-value)						
Log market rice price			0.000			0.003
Market rice price × PDS value			0.435			0.040
Pred. rice elasticity at mean PDS	-0.207***	-0.383***	-0.071*	-0.139***	-0.232***	-0.062*
	(0.051)	(0.094)	(0.036)	(0.039)	(0.059)	(0.035)
Mean PDS value	0.30	0.40	0.19	0.30	0.40	0.19
SD PDS value	0.604	0.668	0.512	0.604	0.668	0.512
1^{st} percentile PDS value	0.000	0.000	0.000	0.000	0.000	0.000
99^{th} percentile PDS value	2.556	2.685	2.325	2.556	2.685	2.325
Observations	524,911	211,795	313,116	524,911	211,795	313,116

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. Pred. rice elasticity is taken at mean PDS value. 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. Effective F-stat calculated using Montiel Olea-Pflueger (2013). Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Difference in baseline characteristics, by whether ever reformed PDS

	Ever expanded eligibility			Ever lowered PDS prices		
	Reform (1)	No reform (2)	Difference (3)	Reform (4)	No reform (5)	Difference (6)
Caloric intake (per capita)	2000.0	2109.1	-109.2	2033.2	2147.0	-113.8**
	[653.2]	[650.0]	(50.5)	[638.7]	[663.6]	(45.5)
Meets MCR	0.50	0.64	-0.13	0.55	0.68	-0.12***
	[0.50]	[0.48]	(0.049)	[0.50]	[0.47]	(0.044)
PDS value (100 Rs.)	0.44	0.070	0.37	0.26	0.030	0.23**
	[0.63]	[0.23]	(0.17)	[0.50]	[0.14]	(0.10)
PDS value > 0	0.40	0.12	0.28	0.29	0.063	0.22***
	[0.49]	[0.33]	(0.11)	[0.45]	[0.24]	(0.077)
Market rice price	10.0	9.79	0.26	9.83	9.87	-0.037
	[2.19]	[2.17]	(0.94)	[2.02]	[2.35]	(0.87)
PDS rice price	4.97	5.55	-0.58	5.19	5.70	-0.51
	[1.42]	[2.90]	(0.61)	[1.81]	[3.38]	(0.43)
Statutory PDS rice price	4.39	5.08	-0.69	4.56	5.37	-0.82**
	[0.88]	[0.75]	(0.39)	[0.95]	[0.26]	(0.31)
Monthly expenditure (per capita, deflated)	677.2	635.9	41.3	654.4	634.2	20.2
	[678.9]	[630.8]	(85.6)	[685.1]	[585.1]	(74.4)
SES index	-0.10	-0.17	0.070	-0.16	-0.16	0.0020
	[1.01]	[0.92]	(0.25)	[0.94]	[0.94]	(0.21)
Urban (=1)	0.27	0.26	0.0099	0.27	0.26	0.011
	[0.44]	[0.44]	(0.047)	[0.44]	[0.44]	(0.053)
Landless (rural only)	0.00079	0.0067	-0.0059	0.0036	0.0076	-0.0040
	[0.028]	[0.082]	(0.0025)	[0.060]	[0.087]	(0.0040)
Observations	8,678	30,150		19,057	19,771	

Columns (1) and (3) show the weighted mean and standard deviations in [] of the characteristic for reform states; columns (2) and (5) the mean for non-reform states. Columns (3) and (6) show the difference with standard errors in () clustered by state. Means calculated for the first round each state appears in the NSS. Reform defined as having either reduced PDS prices by at least 1 Rs.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Within-state differences in household characteristics, by time relative to reform

	Expanded eligibility			Lowered PDS prices		
	Two qrtrs. before (1)	Earlier (2)	Difference (3)	Two qrtrs. before (4)	Earlier (5)	Difference (6)
Caloric intake (per capita)	2031.3	2102.0	41.3	2052.4	2111.8	23.7
	[640.5]	[633.9]	(24.7)	[620.7]	[639.0]	(18.8)
Meets MCR	0.53	0.61	0.043	0.55	0.63	0.0047
	[0.50]	[0.49]	(0.024)	[0.50]	[0.48]	(0.013)
PDS value (100 Rs.)	0.60	0.19	0.0043	0.34	0.13	0.033
	[0.71]	[0.44]	(0.038)	[0.53]	[0.33]	(0.019)
PDS value > 0	0.48	0.22	-0.013	0.38	0.18	0.018
	[0.50]	[0.42]	(0.023)	[0.48]	[0.38]	(0.014)
Market rice price	9.92	9.78	-0.25	10.0	9.66	-0.14
	[1.68]	[2.09]	(0.12)	[1.78]	[2.16]	(0.098)
PDS rice price	2.97	3.76	-0.13	3.87	4.02	0.11
	[0.50]	[2.11]	(0.22)	[1.18]	[2.14]	(0.12)
Statutory PDS rice price	2.70	3.94	-0.26	3.84	4.32	0.19
	[0.95]	[1.27]	(0.15)	[0.67]	[0.89]	(0.10)
Monthly expenditure (per capita, deflated)	847.1	697.3	115.9	726.7	677.3	27.3
	[1095.7]	[719.7]	(64.6)	[839.2]	[697.1]	(37.4)
SES index	0.088	-0.031	0.054	-0.023	-0.083	-0.0067
	[1.13]	[0.99]	(0.045)	[1.03]	[0.99]	(0.028)
Year preceding an election	0.21	0.19	0.16	0.23	0.21	0.055
	[0.41]	[0.39]	(0.12)	[0.42]	[0.41]	(0.073)
Year following an election	0	0.18	-0.25	0.16	0.19	-0.078
	[0]	[0.38]	(0.065)	[0.36]	[0.40]	(0.098)
Observations	8,019	459,811		14,492	385,232	

Columns (1) and (3) show the weighted mean and standard deviations in [] of the characteristic for the two quarters before the reform; columns (2) and (5) the mean prior to that. Columns (3) and (6) show the difference with standard errors in () clustered by state-year-quarter. Columns (3) and (6) adjust for state and quarter fixed effects, and includes non-reform states to help estimate the quarter effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.