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Self-targeted food subsidies and voice: Evidence from the Philippines ☆

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ABSTRACT

This paper studies the targeting outcomes of a self-targeted rice subsidy program in the Philippines. We find modest within-community targeting outcomes, but weak between-community targeting. This appears to be because, controlling for the direct influence of household characteristics, participation was lower in poorer communities. These inter-community differentials are strongly correlated with several proxies for citizen "voice", including education, income, and access to other public services. This suggests that self-targeting outcomes are not simply a function of the good selected for subsidy, but are also influenced by variations in communities' access to usable services; that these variations favor richer communities; and that efforts to enhance consumer voice in disenfranchised communities would facilitate targeting improvements.

Introduction

Governments often self-target food subsidies or other transfer payments. Self-targeting can be attractive when it is difficult or costly to identify who should be eligible to receive benefits (Houssou and Zeller, 2011; Swaminathan and Misra, 2001), or politically challenging to exclude people from the program (e.g., Adams, 2000; Tuck and Lindert, 1996). The standard approach to self-targeting food is to select products that are nutritionally sound, but have low or even negative income elasticities of demand (e.g., Ahluwalia, 1993; Alderman and Lindert, 1998). This encourages greater use of the program by poor households than by rich households. These income elasticities of demand can be further reduced by imposing higher costs of participation on richer buyers of subsidized products through queuing or work requirements (Rogers and Coates, 2002). Unfortunately, despite these efforts to ensure negative income elasticities, self-targeted transfer programs tend to have higher targeting errors than programs that use most other targeting mechanisms (Coady et al., 2004).

One possible reason for these higher overall targeting errors is that, *ceteris paribus*, a household's propensity to participate in the program may be lower if it resides in a poorer community. This would weaken the program's geographic targeting outcomes. Such regressive variations in participation proclivities could occur for many reasons. Subsidized food outlets may be unevenly distributed, with more outlets or more convenient outlets available in rich communities. Alternately, if the per capita food allocation is not sufficiently higher in more vulnerable communities, then higher excess demand in vulnerable communities will lead to more rationing, and more frequent stock-outs. The quality of food and customer service (for example, the length of queues or store hours) may also be lower in poorer communities. Each of these regressive tendencies could be driven or exacerbated by a regressive distribution of political "voice" across communities, which may limit the ability of more vulnerable communities to demand better service (Hirschman, 1970, Ch. 3).

We examine this possibility by studying the targeting performance of a national rice subsidy program administered by the Philippines National Food Authority (NFA) prior to 2008. After demonstrating that the program did not successfully target the most vulnerable provinces and communities, we investigate the prediction that, holding constant all the usual determinants of food subsidy utilization, a household's tendency to participate in the program was higher if it resided in a community that was richer and had greater voice. We know of no previous study that has studied this prediction.

These concerns about access to usable distribution services, self-targeting and voice resonate with three sets of findings from previous work. First, studies have shown that limited access to usable food distribution services influences program uptake in

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several ways. Unintentional differences in the quality of food and service between the subsidized and private markets influence household demand for subsidized and unsubsidized food (Balakrishnan and Ramaswami, 1997; Ramaswami and Balakrishnan, 2002). Even where demand for the subsidized product is robust, supply-side constraints on program access can prevent consumers from utilizing their entire quota of subsidized food (Khera, 2011a). Targeting studies, which show significant failures in geographic targeting of programs by central authorities often allude to such constraints (e.g., Galasso and Ravallion, 2005; Murgai and Zaidi, 2005). In this vein, the current paper is focused on anti-poor patterns of participation between communities that appear to reflect unintended variations in program quality and access.

Second, studies of transfer programs have shown that systematic variations between potential beneficiaries in variables that are not usually considered in the design of these programs can create targeting errors. For example, Barrett and Clay (2003) show that variations in reservation wages across households can detract from the targeting outcomes of food for work programs, and Ravallion (2009) argues that decentralizing eligibility requirements can reduce targeting effectiveness if poorer local governments set more restrictive criteria for access. Similarly, we examine the possibility that effective targeting is hindered by differences in communities' access to usable services, which result from local institutional processes, but are not directly considered in program design.

Third, voice is an important theme in the literatures on both food security and public services delivery. There are many excellent studies of the role of political processes and citizen voice in preventing famines (e.g., Dreze and Sen, 1989; Rubin, 2011). Improvements in transparency and citizen voice are found to reduce corruption in the delivery of subsidized food (Khera, 2011b) and other public services (Reinikka and Svensson, 2004a,b). Such evidence, and case studies of institutional reforms, give rise to the widely accepted argument that measures to enhance voice significantly improve access to subsidized food programs (Dreze and Khera, 2010). International comparisons of the targeting outcomes of transfer programs are consistent with this argument, showing that national measures of voice are correlated with better targeting outcomes (Coady et al., 2004). The 2004 World Development Report (World Bank, 2004) summarizes a voluminous body of research showing that unintentional variations between communities in access to quality education and health services influence utilization, and that these variations are driven by disparities in citizen voice. Our work does likewise for a self-targeted food subsidy.

The NFA subsidy program provides, in several respects, a suitable case study of the relationship between voice, access to usable services, and self-targeting outcomes. First, the program was self-targeted by design. It was universal – all consumers could access it, and officially unrationed – no rules limiting per consumer purchases were prescribed. Second, prices were set below market clearing so that rationing mechanisms had to be devised locally, and some of them clearly reduced access to quality services. Third, there is evidence that excess demand was indeed higher in poorer communities. Fourth, the program was administered by the same body according to the same rules across the country. This permits a relatively clean examination of between-community variations in participation. Fifth, the Philippines government collects the appropriate data for investigating such variations. We use a large geographically stratified and clustered survey dataset that should capture the diversity of local conditions, and were able to match these data to a wide range of proxies for voice and local market conditions from two other databases. Finally, our analysis and previous work (Reyes et al., 2009) both suggest that NFA rice had a negative income elasticity of demand, so weak self-targeting outcomes require an explanation.

The remainder of this paper is structured as follows: The next two sections describe our data and the NFA program. The following section and Appendix A set up the problem empirically, showing that poorer and more vulnerable provinces experienced higher food price inflation, but were not much more likely to benefit from the program. The remaining sections ask whether these weak geographic targeting outcomes can be attributed to variations in access to usable services. We begin that analysis by presenting a targeting decomposition which shows that while program targeting outcomes are progressive, especially within communities, there is significant unmet potential for between-community targeting. We argue that this weak geographic targeting involves more than simple administrative decisions about where to situate outlets. Next, we show that, controlling for the direct influence of household characteristics and retail rice prices, participation was lower in poorer communities, which helps to explain why self-targeting works better within communities than between communities. We also show that these inter-community differentials are strongly correlated with several proxies for citizen voice. Appendix B provides some circumstantial evidence that rationing of subsidized rice was more acute in needier communities. We conclude by discussing the implications of our findings.

Data

We combine three data sources in this paper. The first, the 2006 Family Income and Expenditure Survey (FIES) is a multi-stage stratified random sample covering 38,483 households collected by the Philippines National Statistical Office (NSO). Each household was visited twice, once in July 2006 and once in January 2007, responding each time to the same survey instrument. The publicly released FIES data-sets contain only annual aggregates of household variables based on these two samples. Each household was asked to self-report the average weekly consumption of each major food type, as well as unit prices. Unfortunately, the unit price data are not distributed to the public, and we are therefore constrained to work with data on NFA rice expenditures.

The Philippines has 17 regions, divided into 85 provinces. The FIES sampling frame contains 1567 geographic strata, delineated by province, urbanity, the proportion of dwellings that are permanent structures, the importance of agricultural employment, and average income. This ensures maximal representation of the population geographically, in terms of livelihoods, local government, and in terms of community income. Each stratum was divided into primary sampling units (PSUs, or "communities", as we will refer to them), each of which is comprised of either one Barangay of 500 households or more, or multiple smaller Barangays put together to reach that figure. The Barangay is the smallest unit of governance in the Philippines. Between two and seven PSUs were sampled at random within each stratum, implying randomization with respect to local governance. We have approximately ten sampled households from each PSU. All of the above is important because our key independent variables are local market conditions and community-level proxies for "voice" and vulnerability to food price shocks. These community-level proxies are estimated from average values of household variables at the PSU level. The stratification scheme implies that the distribution in the data of these conditions and their underlying political influences will be nationally representative. Regression estimates account for probability weights, stratification, and clustering at the PSU level.

The FIES sampling scheme excludes some extremely remote areas that account for 0.4% of the population. Some figures for the National Capital Region (NCR) were imputed after a fire destroyed a large share of one round of the completed surveys, so we drop all observations from the NCR. Our dataset is representative of the rest of the country.

Table 1
Summary statistics.

	All communities[a]		Baseline sample[b]	
	Mean	Std. dev.	Mean	Std. dev.
A Variables from FIES 2006				
Do you buy NFA rice? (1 = yes, 0 = no)	0.14	0.34	0.27	0.44
Per capita expenditures on NFA rice (pesos/year)	123.50	438.87	244.05	592.61
HH Per capita income (000s of pesos/year)	35.87	45.79	32.71	44.77
Below the poverty line? (1 = yes, 0 = no)	0.301	0.458	0.348	0.476
# of persons in HH	4.89	2.18	4.94	2.22
Expenditures on food as share of total	0.51	0.14	0.52	0.14
HH head's years of schooling	7.49	3.80	7.28	3.81
Female HH head (0 = no, 1 = yes)	0.18	0.38	0.17	0.37
Is the HH head employed? (0 = no, 1 = yes)	0.85	0.36	0.86	0.35
HH head is a working woman (0 = no, 1 = yes)	0.11	0.31	0.11	0.31
Age of HH head	48.78	14.02	48.82	14.09
HH head is a farmer (0 = no, 1 = yes)	0.16	0.36	0.17	0.37
# of non-relatives in HH	0.01	0.05	0.01	0.05
Fraction of HH members aged 1–6	0.11	0.16	0.12	0.16
Fraction of HH members aged 7–14	0.18	0.19	0.18	0.19
Fraction of HH members aged 15–24	0.17	0.20	0.16	0.20
Fraction of HH members aged 25–59	0.41	0.23	0.40	0.23
Fraction of HH members aged > 60	0.12	0.25	0.12	0.25
TV ownership (0 = no, 1 = yes)	0.66	0.47	0.61	0.49

	Mean	Std. dev.	No. of Obs.
B. Province-level variables			
Average annual retail rice price (pesos/kg)	21.24	1.36	81
Retail rice price inflation (% increase 2003–2007)	0.22	0.06	80
Density of road network (km of road/km^2 area)	0.12	0.07	76
Population density (persons/km^2)	0.30	0.32	81
Functional literacy rate	81.01	9.53	81
Share of households with access to safe drinking water	83.26	16.10	85
Student–teacher ratio: primary school	33.33	7.07	85
Student–teacher ratio: secondary school	37.66	6.78	85
Expenditures on social services (% of total provincial expenditure)	27.37	15.49	79
Human Development Index (HDI)	597.96	98.56	81
Population density	0.30	0.32	81
Road density	0.12	0.07	76

[a] The sample of all communities includes 2604 communities, and 34,029 households.
[b] The baseline sample is restricted to households residing in PSUs in which at least one household consumes NFA rice. It includes observations on 18,178 households in 1335 communities.

We also use data on regional/provincial food prices and disappearance from the Philippines Bureau of Agricultural Statistics (BAS), as well as measures of regional GDP per capita, fiscal resources, provincial road density, the Human Development Index (HDI), and provision of other public services from the National Statistical Coordination Board (2008).

Table 1 summarizes the dataset. In some analyses in this paper it will be useful to examine subsamples restricted to communities in which some minimum fraction of the households consume NFA rice. To examine the possible biases introduced by this restriction, household level variables are summarized for the full sample, and also for a "baseline" sample which excludes all households residing in communities that include no sampled NFA rice consumers. There are almost no major differences in household characteristics, other than NFA uptake, between NFA consuming and non-consuming communities.[1] The only exception is that the baseline sample is slightly poorer, indicating that communities with no sampled NFA consumers are richer than average. These results provide some comfort that such restrictions will not introduce large selection biases.

The NFA rice subsidy program

The NFA's responsibilities have been undergoing a radical overhaul as the Philippines transitions towards cash-based consumer safety nets. In the interests of brevity, the descriptions that follow concern arrangements for distribution of subsidized rice at the time that our data were collected.[2]

During the period of our study, the NFA sold rice through accredited retailers at a fixed price that was approximately 15–25% below the regular market price of rice. The retailers received a fixed margin on NFA sales. Customer purchases of NFA rice were not officially rationed, meaning that all Filipinos were eligible to purchase it. It was distributed through a variety of channels, including licensed retailers, church groups, mobile stores, local governments, and school feeding programs. Other than the school feeding programs, which accounted for some 5% of total rice distribution (NFA, 2006) and should not appear in our survey, the NFA did not publish any rules for rationing its subsidized rice.

No published information exists on geographically disaggregated subsidized rice supplies. Mehta and Jha (2012) were able to obtain a spreadsheet showing allocations for 2006 disaggregated by 15 regions, and compare this information to the same FIES data used in this paper to determine how much rice went missing. They report a roughly 48% disappearance rate. They find per capita

[1] For 14 out of 19 of the household level variables listed in Table 1, t-tests reject the null that the variable has the same mean in NFA consuming and non-consuming communities. However in terms of economic significance the differences are small.

[2] See Jha and Mehta (2010) for a wider literature review of NFA operations at the time of our study, Clarete (2008) for an institutional history of the NFA, and Ambat (2011) for a more recent update.

regional allocations uncorrelated with average incomes or poverty rates, but note that poorer regions did receive slightly more rice per capita because a smaller share of their allocations disappeared. Thus, supply and rationing outcomes upstream of consumers are different at different points along the supply chain, and, the data to characterize them empirically are not publicly available. Only the amounts reaching consumers may be estimated from the FIES data.

Not only are data on supplies along the supply chain unavailable, information on how these supplies are decided is limited as well. The only public statement we could find on this states that the allotment of rice to dealers was officially based on several criteria, including “stock inventory, rice allocation, distribution target, supply/demand situation, commercial stocks and prices, etc.”[3] Thus matching supply to demand at the subsidized price was only one objective of many and extensive anecdotal and circumstantial evidence suggests that the objective was not met.

Unsurprisingly, then, ad hoc rationing mechanisms were used. NFA rice consumers with whom we have spoken (albeit beginning in 2008) all reported experiencing queuing, maximum purchase limits, and stock-outs. None indicated that they could purchase NFA rice in unlimited quantities. Consistent with this, our household survey data from 2006 indicate that over 85% of households obtained less than 10% of their rice purchases from the NFA. One NFA agent queried on rationing mechanisms indicated that they received NFA rice every Wednesday, that their allocation usually sold out within a day, that in 2006 they limited each household to 5 kilograms per store visit, and that consumers were required to purchase one kilogram of commercial rice in order to qualify to purchase two kilograms of NFA rice. None of these practices or outcomes were explicitly prescribed or described by the NFA. It therefore appears that significant discretion was exercised at the local level in the rationing of NFA rice, and that many of these rationing mechanisms shifted costs from retailers onto consumers.

While the above implies significant scope for variations in the degree to which communities could access usable NFA services, there is also ex-ante evidence that this variation exists and a suggestion that it favors richer locations. The World Bank (2001), provides survey evidence that some households opted not to consume NFA rice because it was unreliable and otherwise undesirable. The NFA expends significant effort to tackle physical quality variability, as demonstrated by the technical studies it conducts on the subject (e.g., De Dios et al., 2002; Ramirez et al., 2003). The same World Bank report also notes a widespread practice of mixing low and high quality grain stocks in response to availability and demand. It notes that access to NFA outlets was more limited in poorer regions of the country, and that a larger share of poor consumers reported the quality of rice to be low. NFA rice is also widely reported to be adulterated with inferior broken rice, inadequately protected from the elements, or stored beyond its sell-by date. The current paper examines the targeting implications of these variations.

The geography of vulnerability vs. geographic targeting

An assessment of the evolution of hunger and food prices in the Philippines underscores the importance of targeting subsidized food to the most vulnerable communities. Data from the country’s Social Weather Survey[4] show that self-reported hunger roughly quadrupled nationwide between 2003 and 2008. Most of this increase predated the 2008 price shock, and hunger has oscillated around 2008 levels since. The World Development Indicators similarly indicate an increase in under-five malnutrition (weight for age) rates from 20.7% to 26.2% between 2003 and 2008.[5] Appendix A shows that increases in self- reported hunger in the Philippines between 2003 and 2007 cannot be attributed to lower per capita rice availability, falling average incomes, worsening income distribution, or rising average rice prices nationwide.

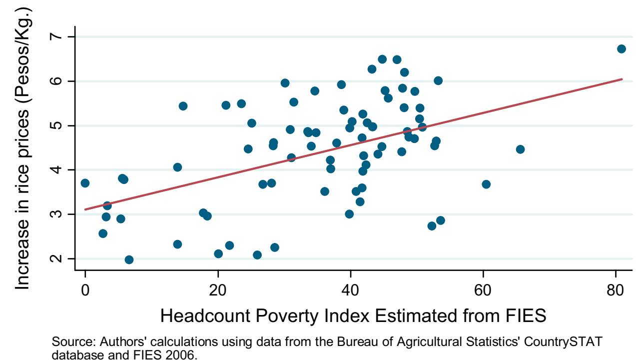

Fig. 1. Retail rice price change (2003–2007) vs. poverty rate (2006) (by Province, Population Weighted). *Source*: Authors’ calculations using data from the Bureau of Agricultural Statistics’ CountrySTAT database and FIES 2006.

On the other hand, Fig. 1 shows that retail rice prices rose much faster in provinces with higher poverty rates.[6] The first column of Table 2 confirms that rice price inflation between 2003 and 2007 was higher in provinces with lower income, education, functional literacy, and human development index levels; and whose households were larger, devoted a larger share of expenditures to food and were more likely to be below the poverty line. (The only helpful trend for food security was that inflation was lower in provinces with more unemployed household heads.) Taking these variables as proxies for voice and vulnerability, this implies that rice price inflation was geographically concentrated in provinces whose populations are more vulnerable and lacking in voice.

This concentration of inflation in vulnerable geographic areas complements findings by Son (2008) and Reyes et al. (2009) that rice-price inflation in the Philippines hurts the poor more because rice is a necessary good, accounting for a larger share of poor households’ expenditures; our data show that rice prices also hit the poor because they rose faster in more vulnerable locations. This geographic correlation between poverty, lack of voice, and rice-price inflation underscores the importance of targeting food-subsidies to poor and less powerful communities.

To shed light on the NFA’s geographic targeting outcomes, Table 2 also provides correlations of provincial indicators with the NFA participation rate (the share of households who report purchasing non-zero quantities of NFA rice), and with households’ mean expenditures per capita on NFA rice. Because the price of NFA rice was essentially constant nationally, NFA expenditures provide a good proxy for the per capita quantity of NFA rice consumed. In stark contrast with rice price inflation, the correlation between these measures of NFA uptake and the usual proxies for vulnerability are weak. Participation is correlated only with mean household size, and marginally correlated with poverty, while expenditures are not correlated with any vulnerability measure. On the other hand, both measures of NFA uptake are lower in provinces with high student:teacher ratios at the primary and second-

[3] NFA Distribution Flowchart. http://www.nfa.gov.ph/image/distribution.jpg. Accessed 3 June 3, 2009.

[4] http://www.sws.org.ph/pr20121001.htm, accessed 4 January 2013.

[5] Accessed July 2010.

[6] It is not hard to explain why this happened. In a nation of over 7000 islands, the increase in fuel prices between 2003 and 2007 would have increased transport costs, raising the geographic dispersion of retail prices (Baulch, 1997). Moreover, more remote, isolated and inaccessible regions of the Philippines – those with higher transport costs – tend to be poorer.

Table 2
Across province correlations with rice price inflation and NFA uptake.

Correlates (measured in 2006)	Rice price inflation (2003–2007)	NFA participation rate	Per capita expenditures on NFA rice	No. of observations
Market conditions				
Average annual retail rice price	0.186*	0.203*	0.173	81
Household conditions from survey data				
Mean per capita income	−0.489***	−0.030	0.113	81
Expenditures on food as share of total	0.390***	−0.024	−0.171	81
Poverty headcount index	0.505***	0.197*	0.007	81
Average household head years of schooling	−0.416***	−0.047	0.105	81
Average household size	0.279**	0.254**	0.124	81
Employment rate of household heads	0.457***	0.348***	0.278**	81
Provincial development indicators				
Share of households with access to safe drinking water	−0.077	0.140	0.172	81
Functional literacy rate	−0.411***	0.056	0.134	77
Student–teacher ratio: primary school	−0.057	−0.301***	−0.438***	81
Student–teacher ratio: secondary school	−0.062	−0.419***	−0.519***	81
Expenditures on social services (% of total provincial expenditure)	−0.113	0.009	0.039	75
Human Development Index (HDI)	−0.539***	−0.157	0.001	77
Population density	−0.279**	−0.184	−0.199*	81
Road density	−0.121	0.402***	0.444***	76

Sample size for correlations with rice price inflation is one province less than the listed number of observations.
*** 1% significance.
** 5% significance.
* 10% significance.

ary levels, consistent with the idea that voice may play a similar role in accessing services from the NFA and other public services. They are also lower in provinces with more roads, suggesting that ease of access may be an explicit or implicit criterion effecting geographic targeting, and in provinces with higher employment rates.

These results imply that the geographic targeting outcomes of the program were progressive, but weak. The remainder of this paper assesses this weakness relative to certain benchmarks, and considers the plausibility of different explanations for it.

Targeting decompositions

We examine targeting outcomes using a decomposition of a targeting differential based on the work of Galasso and Ravallion (2005). The exercise is best explained with reference to Table 3. Let H be the headcount poverty rate and P be the participation rate in some population. Each member of the population can then be placed into one of four groups depending on whether they participated in the program (bought NFA rice) and whether they were poor. The fraction of the population that was poor and participated is n_{11}, a fraction n_{12} was not poor but did participate, and so forth.

The targeting differential is defined as the difference between the fraction of the poor who participated and the fraction of the non-poor who participated:

$$T \equiv n_{11}/H - n_{12}/(1 - H).$$

If a poor person was as likely to participate as a non-poor person, the targeting differential is zero; if all of the poor participated and none of the non-poor did, it is one; and if none of the poor did and all the non-poor did, it is negative one. One important benchmark is the program's best possible targeting performance *given its size* (i.e. holding the fraction of the population that participates constant). This is achieved if only the poor participate. In this case, if the program covered too few participants to include all the poor ($P < H$), the maximum achievable targeting differential was P/H.[7]

Table 4 analyzes the targeting differential. The four columns provide results from sequentially nested subsamples. The first column involves the households from all communities, the baseline subsample is restricted to those communities in which at least one household purchased some NFA rice, and the conservative (most conservative) subsamples include only those communities in which at least 10% (20%) of sampled households purchased some NFA rice. We examine this sequence of subsamples because we do not have information on whether a universally accessible NFA store was available within a reasonable distance of any given community. Increasing the threshold participation rate for inclusion in a subsample gives us a higher degree of confidence that such a store was available. Analysis of increasingly truncated samples permits us to describe targeting outcomes in sets of communities whose participation rates are increasingly like to reflect household decisions.[8] For brevity, we will henceforth refer to more conservatively selected subsamples of communities as "more clearly served."

In the case of our full sample, only 24.6% of the poor participated, implying a high under-coverage rate, while only while 8.9% of the non-poor participated (Table 4, rows 1–2), implying a targeting differential of 0.246–0.089 = 0.157 (row 5). Given the 13.6% overall participation rate (row 3) and 30% poverty headcount

Table 3
Components of a targeting decomposition.

		Poor?		
		Yes	No	Total
Program participant?	Yes	n_{11}	n_{12}	P
	No	n_{21}	n_{22}	$1 - P$
	Total	H	$1 - H$	

[7] Of course, if the number of participants exceeds the poverty headcount, a targeting differential of P/H is not obtainable, and the maximum achievable is one (see the fourth column of Table 4).

[8] This is a more empirically conservative approach than has been applied previously. For example, Dutta and Ramaswami (2001) study demand for subsidized food in India by assuming that participation signals demand if a community has at least one sampled household that reports consuming subsidized food. Our claim is weaker: we only claim greater confidence that participation can be used to uncover trends in household participation decisions as more low-participation communities are excluded. This claim rests on the understanding that communities lacking nearby NFA stores are more likely to have low participation rates.

Table 4
Targeting decompositions.

	Sample			
	All communities	Baseline	Conservative	Most conservative
Participation rates				
(1) Among the poor	0.246	0.419	0.516	0.614
(2) Among the non-poor	0.089	0.187	0.256	0.353
(3) Overall (*P*)	0.136	0.268	0.354	0.463
Poverty incidence				
(4) Poverty headcount rate (*H*)	0.301	0.348	0.379	0.420
Total targeting differential				
(5) Achieved	*0.157*	*0.232*	*0.260*	*0.261*
(6) Maximum possible (min [*P*/*H*,1])	0.451	0.770	0.936	1.000
(7) Achieved as share of maximum possible [(5)/(6)]	0.349	0.301	0.277	0.261
Decomposition of the acheived targeting differential				
(8) Within community	0.080	0.146	0.178	0.199
(9) Between community	0.078	0.086	0.081	0.062
(10) *Total [(5)]*	*0.157*	*0.232*	*0.260*	*0.261*
Benchmarks for between community differentials:				
(11) Optimal between-community differential	0.332	0.309	0.298	0.284
(12) Size constrained optimal between-community differential	0.150	0.238	0.279	0.284
Achieved between-community differential as share of:				
(13) Optimal between-community diff. [(9)/(11)]	0.234	0.278	0.273	0.217
(14) Size constrained optimal between-community diff. [(9)/(12)]	0.518	0.361	0.292	0.217
No. of communities	2604	1335	988	687
No. of households	34,029	18,178	12,944	8915

Note: Decompositions and benchmarks are calculated per Eqs. (1), (2) and (3).

(row 4), the maximum targeting differential was 0.136/0.30 = 0.45 (row 6), and the program achieved just over one third of this figure (row 7).

An obvious question is whether this weak targeting arises because needy communities do not have access to NFA outlets. To shed light on this question, we ask whether the outcomes are better in the most clearly served communities, where we are more confident that such outlets exist. Participation rates (row 3) are higher by construction in more clearly served communities. Headcount poverty rates also rise across columns (row 4), suggesting that the program is geographically progressive. However, while the achieved targeting differential (row 5) becomes larger as we shift attention to more clearly served communities, the potential differential rises even more sharply (row 6), so that there is *more* unmet potential for targeting in the set of communities that we are *most* confident had access to an NFA outlet (row 7). This finding suggests that the location of outlets is not an adequate explanation for the inadequate targeting outcomes, and is somewhat puzzling for a self-targeted program distributing an inferior good.

A natural follow-on question is whether targeting is bad because food is targeted to the wrong communities, or to the wrong people within communities. To shed light on this, we follow Galasso and Ravallion in decomposing the targeting differential into within-community (W) and between-community components (B). Denote the fraction of the subpopulation from each community (i) by α_i, the components of Table 3 within each community by H_i, P_i, $n_{11,i}$, etc., and the targeting differential within community i by T_i. It is then straightforward to split the targeting differential into components driven by the targeting performance within communities, and by higher participation rates in poorer communities (the between-communities component):

$$T \equiv \overbrace{\sum\nolimits_i \frac{\alpha_i T_i (1-H_i) H_i}{H(1-H)}}^{\text{Within Communities}} + \overbrace{\sum\nolimits_i \frac{\alpha_i (P_i - P)(H_i - H)}{H(1-H)}}^{\text{Between Communities}} = W + B \qquad (1)$$

The within-communities component will be large if targeting differentials within communities are large, as we expect to be the case for a self-targeted inferior good. The between-communities component will be positive if participation rates are higher in poorer communities. In other words, B is a measure of the geographic progressivity of the program. It should be large for a self-targeted inferior good if rich and poor communities enjoy similar access to usable distribution services.

The results indicate that W is higher in more clearly served sets of communities (row 8). This is consistent with the intuition that subsidized food is more likely to freely available in communities with high participation rates and that this facilitates self-targeting which increases targeting differentials. In contrast, B is lower in more clearly served sets of communities (row 9). Thus, the decomposition shows that unmet targeting potential is high, and is higher in the subsets of communities that are more likely to have NFA stores, because *between*-community targeting is not better in these communities.

We consider two possible explanations for the fact that between-community targeting is weaker amongst the most clearly served communities. We compare the between-community differential (B) to two benchmarks that we have developed to explore these possibilities.

First, poverty rates may not vary much amongst the most clearly served communities, reducing the scope for differentiation between more and less poor communities. The relevant benchmark in this case is:

$$\widetilde{B} = \frac{\sum_i \alpha_i (H_i - H)^2}{H(1-H)} = \frac{Var_i(H_i)}{H(1-H)}; \qquad (2)$$

where $Var_i(H_i)$ is the variance of poverty rates across communities, and $H(1-H)$ is the total variance of poverty in the subpopulation. This benchmark is derived as the between-sector differential that would be achieved if targeting were perfect. In this case all of the poor and none of the rich would be covered, so that $P = H$, $P_i = H_i$, and $T = T_i = 1$. Substituting these optimal values into the expression for B in identity (1) yields (2). The benchmark tells us that the between sector differential is limited by the share of the variance of poverty that is between communities. $\widetilde{B}$ is 0.33 in the full sample, and falls monotonically to 0.28 in the most plausibly self-targeted sample (row 11). However the achieved between community differential trends similarly (row 9), so that even relative to this benchmark the unmet potential for geographic targeting remains highest in the most clearly served communities (row 12).

The second possible explanation is that, because poverty rates are so much higher in more clearly served communities, the program is not large enough to achieve the optimal between-community differential ($\widetilde{B}$). The relevant benchmark, once this further limitation is acknowledged, is:

$$\overline{B} = \left(\frac{P}{H}\right)\left(\frac{Var_i(H_i)}{H(1-H)}\right) = \left(\frac{P}{H}\right)\widetilde{B}. \tag{3}$$

This benchmark acknowledges that that scope for between-community targeting is further reduced if the program is too small to cover all of the poor (i.e. if H exceeds P). It is calculated as the between-sector differential that would be achievable, holding P fixed, if the probability of a poor person participating in the program were independent of which community they lived in (i.e. if $P_i/H_i = P/H < 1, \quad \forall i$).[9] $\overline{B}$ is only 0.15 in the full sample, but rises rapidly to 0.284 among the most clearly served communities (row 12) because participation grows faster across columns than poverty. It follows that when assessed relative to this more realistic benchmark, the unmet potential for geographic targeting increases even faster as we turn to more clearly served communities (row 14).

The decomposition analysis therefore reveals significant unmet potential for targeting, especially amongst communities that we are relatively confident have NFA outlets. This suggests that the geographic distribution of outlets is not the reason for weak between-community targeting. Comparison with our benchmarks also shows that this higher unmet potential in more clearly served sets of communities does not arise because they feature a more uniform distribution of poverty across communities or because they have a lower participation:poverty ratio. The remainder of the paper therefore asks why, although within-community targeting becomes better as we turn to more clearly served communities, between-community targeting does not. We will argue that this is at least partly because more vulnerable communities, lacking voice, had less access to usable services. As we have seen in Table 1 and in row 4 of Table 4, the most clearly served communities are selected to include more vulnerable households.

Regression analyses

The preceding sections have demonstrated that the NFA program's geographic targeting outcomes were progressive, but only weakly so. Table 2 shows this at the provincial level, while Table 4 confirms the finding at the community level and also shows significant unmet potential for between-community targeting amongst even the most clearly served communities. These results leave two questions unanswered.

The first question is whether the apparent lack of progressivity arises simply because we have not controlled for other determinants of vulnerability and need. For example, while it is well known that India's Public Distribution Systems distribute more grain per-capita in cities, where poverty rates tend to be lower, there has been much debate regarding what this apparently regressive urban bias means for policy. The debate arises, at least in part, because rural farm communities presumably have less need for purchased grain in the first place, so that it is not clear that urban bias should be viewed as a policy failure (Dev and Suryanarayana, 1991; Howes and Jha, 1992, 1994; Suryanarayana, 1994).[10] Similarly, our geographic targeting outcomes must be conditioned on other variables that could influence a community's need for subsidized food before they are interpretable as targeting failures. The second question is why the geographic targeting outcomes are weak. The next two subsections present regression analyses designed to answer these two questions.[11] A final subsection reconciles these regression results with those to the bivariate analyses in Tables 2 and 4.

Does weak measured between-community targeting result from omitted variables?

Table 5 presents the results of community-level Tobit regressions of the fraction of sampled households who report non-zero NFA rice consumption levels. We include regressions on only community poverty rates, and on poverty and other controls to see whether evidence of progressivity is stronger once we condition on other community characteristics. The regressions allow for censoring at zero and one. [12] Once more, we conduct the analysis on nested subsets of communities in which we are increasingly confident that an NFA outlet was available. Our purpose in using nested samples is to understand whether tightening the selection criteria is likely to alter the relationships between community characteristics and participation. If it is not, then results from regressions using the most conservative subsamples are more likely to be generalizable.

Consistent with findings from our targeting decompositions, the results provide mild indications of progressivity. For example, the first short regression indicates that a one percentage point difference in the poverty rate is associated with a 0.386 percentage point higher participation rate. This is an underestimate of the relationship, because the poverty rates are subject to sampling error, causing attenuation. However, this seems unlikely to explain why, consistent with our previous findings, there is no indication of greater progressivity in the most clearly served communities (where poverty is closer to 50% and attenuation bias should be reduced). Most importantly, this relationship is not strengthened by the inclusion of other controls, indicating that omitted variables do not account for weak between-community targeting outcomes.

Most control variables are not individually significant. Among those that are: participation rises with household size but falls with TV ownership rates in most subsamples. It also rises with the unsubsidized local retail rice price for much of the observed price range – a reasonable result given that subsidized and unsubsidized rice are presumably substitutes. Participation is higher in communities located in provinces with better road networks and lower population densities.

[9] Proof: Applying $\sum_i \alpha_i P_i = P$,$\sum_i \alpha_i H_i = H$, and the definition of the between-community differential (B) from (1) yields: $B = \sum_i \alpha_i (P_i H_i - PH_i - P_i H + PH)/[H(1-H)] = \sum_i \alpha_i P_i H_i/[H(1-H)] - P/(1-H)$. Then imposing $P_i/H_i = P/H, \forall i$, we have: $\overline{B} = \frac{1}{H(1-H)} [\sum_i \alpha_i (P/H) H_i^2] - \frac{P}{(1-H)} = \frac{P[\sum_i \alpha_i H_i^2 - H^2]}{H^2(1-H)} = \frac{P[E_i(H_i^2) - E_i^2(H_i)]}{H^2(1-H)}$.

[10] In the case of the PDS, the debates also involve disagreements over the objectives of the PDS, with those finding strong urban bias evaluating it as a transfer program, and those finding no such evidence treating it primarily as a nutritional program. The disputes over the correct normalized indicators to assess its targeting outcomes flow from this disagreement.

[11] Both sets of regression analyses are confined to participation decisions, excluding consideration of expenditures on NFA rice. Appendix B presents a double-hurdle model (Cragg, 1971) that jointly models household participation and NFA rice expenditures to examine the possibility that subsidized rice is more subject to rationing in vulnerable communities. The results are inconclusive – the coefficients take on the signs expected in the presence of rationing, but statistical significance is weak. Estimates from the double-hurdle model and those to the community-level regressions, indicate that the effects of household characteristics on household participation decisions are very similar to their effects on expenditures on NFA rice.

[12] We have conducted two other sets of similar, community-level regressions. One takes the community's per capita expenditures on NFA rice as the dependent variable (censored at zero), and the other is simply a Probit regression of whether the community contains any sampled NFA rice consumers. Results are not qualitatively different from those presented here.

Table 5
Determinants of community-level NFA paricipation rates. (Tobit models censored at zero and one.)

	Sub-sample							
	All communities		Baseline		Conservative		Most conservative	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Community characteristics (All fractions between 0 and 1)								
Fraction of HH's that are poor	0.386***	0.172***	0.268***	0.129***	0.272***	0.090*	0.233***	0.113*
HH head's average years of schooling		−0.350***		−0.114		−0.087		−0.067
Average age of HH Head		0.003		0.000		0.002		0.001
Fraction of HH heads female		0.063		0.096		0.170		0.251*
Fraction of HH Heads Employed		0.371**		0.057		0.055		−0.010
Fraction of HH heads that are working women		−0.205***		−0.118**		−0.102*		−0.126**
Fraction of HH heads that are farmers		0.246		−0.013		−0.352		−0.657
Average # of non-relatives in HH		0.031*		0.027*		0.030*		0.024
Aveage # of persons in HH		−0.004		−0.007		−0.008		−0.006
Fraction of HH members aged 1–6		0.477		0.243		0.254		0.331
Fraction of HH members aged 7–14		−0.114		0.028		0.151		−0.140
Fraction of HH members aged 15–24		−0.070		0.069		0.063		−0.002
Fraction of HH members aged 25–59		−0.355		−0.216		−0.145		−0.324
Fraction of HH members aged > 60		−0.036		0.210		0.320		0.405
Fraction of HH owning TVs		−0.150***		−0.069		−0.092*		−0.052
Constant	−0.105***	12.144***	0.182***	11.313***	0.258***	9.090***	0.369***	6.860**
Prices and access								
Average annual retail rice price (pesos/kg)		−1.182***		−1.059***		−0.864***		−0.637**
Average annual retail rice price – squared		0.028***		0.025***		0.020***		0.015***
Retail price × urbanity dummy		−0.013		−0.005		−0.015		−0.042***
Urban? (0 = no, 1 = yes)		0.288		0.096		0.284		0.851**
Density of provincial road network (km of road/km^2 area)		0.886***		1.069***		0.958***		0.728***
Provincial population density (persons/km^2)		−0.186***		−0.141***		−0.117***		−0.059
Sample sizes (# of communities)								
Total sample, of which:		2477		1271		936		640
Zero Participation		1206		0		0		0
Full Participation		35		35		35		35
Derivatives with respect to the market price of rice								
Slope when price = 19 pesos/kg, rural areas		−0.102***		−0.112***		−0.090***		−0.065**
Slope when price = 25 pesos/kg, rural areas		0.239***		0.188***		0.0155***		0.116***
Price of zero slope (pesos/kg), rural areas		20.80		21.24		21.20		21.15

Standard errors are robust.
*** 1% significance.
** 5% significance.
* 10% significance.

Usefully, the relationship between community level variables other than poverty and participation appears to be quite similar across the samples, providing little indication that sample selection will seriously limit the generalizability of qualitative results from conservative subsamples. We have already shown (section 'Data') that the distribution of control variables across NFA-consuming and non-consuming communities is not very different.

Why is between-community targeting weak?

The coefficients on poverty in the above community-level regression analysis reflect a combination of the *direct* and *indirect* effects of local poverty on program participation rates. We will show that these effects have opposing effects. Direct effects arise because needier households are more likely to participate than their less needy neighbors within the same community. Indirect effects arise because needier households live in communities that tend to receive worse access to usable services, perhaps because they suffer from a lack of voice, differential administrative attention and so forth. We demonstrate this using a three step procedure.

The first step regresses household participation decisions on household controls and community fixed effects. The fixed effects correct for between-community differences in access to usable services, so that coefficients on household variables capture their direct effects on participation. The estimated fixed are estimates of participation proclivities that have been purged of the effects of household characteristics. In the second step we regress these fixed effects on rice prices, proxies for the ease with which the NFA could reach these communities, and community poverty rates. This captures the indirect effect of poverty on participation. If, controlling for price and ease of access, poverty rates are negatively associated with participation, this would indicate that access to usable services is regressively distributed across communities, and would help to account for the significant unmet potential for between-community targeting. Third, we ask whether the fixed effects, once they have been purged of any possible effect of prices and the ease of reaching communities, are correlated with measures of voice and vulnerability. This sheds light on how the indirect effects are to be interpreted.

Within-community regression

Table 6 presents estimates of linear probability (LP) models of household participation allowing for community fixed-effects. This yields estimates of the direct effects of household characteristics on demand. LP models are preferred because they yield readily interpretable fixed effects.

Switching to the conditional Logit model resulted in no qualitative changes to the results, and a Hausman test rejects a LP model with random community effects in favor of one with fixed effects (p-value = 0.000). The probabilities of NFA rice consumption predicted by the linear probability model are almost all (92–93%) in the unit interval in the conservative subsamples, and 89% of them

Table 6
Determinants of household NFA participation rates, with local fixed effects.

Linear probability models	Sub-sample		
	Baseline	Conservative	Most conservative
Sample characteristics			
Local participation rate	>0	>10%	>20%
No. of households	18,178	12,944	8915
No. of local markets	1335	988	687
Regression coefficients			
HH per capita income ('000s of pesos/year)	−0.0007***	−0.0009***	−0.0011***
Below the poverty line? (1 = yes, 0 = no)	0.1412***	0.1670***	0.1787***
HH head's years of schooling	−0.0105***	−0.0133***	−0.0156***
Age of HH head	−0.0004	−0.0007	−0.0010*
Female HH head (0 = no, 1 = yes)	−0.0183	−0.0264	−0.0463
Is the HH head employed? (0 = no, 1 = yes)	0.0094	0.0108	0.0124
HH head is a working woman (0 = no, 1 = yes)	0.0382**	0.0398	0.0624*
HH head is a farmer (0 = no, 1 = yes)	−0.0596***	−0.0692***	−0.0595***
# of non-relatives in HH	−0.0501	−0.1482**	−0.1201
# of persons in HH	0.0032	0.0053**	0.0065*
Fraction of HH members aged 1–6	0.0939	0.1543*	0.1403
Fraction of HH members aged 7–14	0.1460**	0.2200***	0.2428**
Fraction of HH members aged 15–24	0.1172*	0.1894**	0.2095*
Fraction of HH members aged 25–59	0.1086*	0.1857**	0.1984*
Fraction of HH members aged > 60	0.0792	0.1502*	0.17
TV ownership (0 = no, 1 = yes)	−0.0817***	−0.0962***	−0.1059***
Constant	0.2640***	0.2971***	0.4053***
Magnitude of community fixed effects			
Std. dev. of local fixed effects	0.222	0.240	0.239
Local probability of consuming NFA rice	0.268	0.354	0.463
Local coefficient of variation	0.828	0.678	0.518
Diagnostic statistics			
Fraction of predicted probabilities < 0	0.091	0.049	0.017
Fraction of predicted probabilities > 1	0.022	0.034	0.051

We use robust standard errors.
*** 1% significance.
** 5% significance.
* 10% significance.

are in the unit interval for the baseline subsample. A fixed effects model cannot be identified on a sample that includes observations from communities that have no sampled NFA consuming households.

In line with our regression strategy, the list of household controls aims to be comprehensive, and includes variables intended to capture income, education, employment, gender differences in nutritional preferences or access to public programs, household demographics, the presence of "non-relatives" (who could be servants), access to food from home-production, and social status. Measured prices are uniform across households in the same local market, so their effects are subsumed by the community fixed effects.

The coefficients on household characteristics, when significant, are consistent in sign across the subsamples. Households are more likely to purchase subsidized rice if they are headed by non-farmers, have more mouths to feed - especially teenage ones, or do not possess a television. Employment has no significant effect on participation among male headed households, but (applying the delta method) increases participation among female headed households. This is suggestive of a greater role of employment in empowering women to access social programs.

Usefully, given that the program is supposed to be self-targeted, lower income and poor households were more likely to participate than their richer neighbors. Thus, as indicated in section 'Targeting decompositions', self-targeting appears to work fairly well within communities. Also, consistent with section 'Targeting decompositions', these results are stronger in more clearly served sets of communities. If one assumes that households in the most clearly served communities all have the option of purchasing NFA rice, it implies that NFA rice is an inferior good.[13]

Table 6 also provides information on the magnitude of the community fixed-effects. It shows that the standard deviation across communities of the probability that a household will demand NFA rice is in the range 0.22–0.24. This works out to between 52% and 83% of the mean local participation rate.

Between-community regression

Table 7 provides results from OLS regressions of the estimated community fixed effects on community-level variables.[14] Three specifications are examined for each subsample. The first (columns 1, 4 and 7) captures the effects of local prices, approximated by provincial prices, their square and an interaction between the provincial price and an urban dummy. The second specification (columns 2, 5 and 8) introduces a correction for the community's poverty rate. This specification captures the indirect effects of poverty on community participation rates, and permits us to test the hypothesis that, controlling for a wide array of household characteristics and prices, a household is less likely to participate simply by virtue of living in a poorer community. If this alternate hypothesis is accepted against the null that community fixed effects are unrelated to poverty rates, we take this as an indication that poorer locations have lower access

[13] Unlike previous work (Ramadan and Thomas, 2011), we have no information on whether or how tightly households are rationed, and so cannot use expenditure data to estimate parameters of demand systems.

[14] While it is more efficient to use weighted least squares when using an estimated dependent variable, the FIES sampling design held sample sizes almost constant across PSUs, implying little gain from weighting.

Table 7
Determinants of local tendencies to participate.

	Sub-sample								
	Baseline			Conservative			Most conservative		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Average annual retail rice price (pesos/kg)	−0.982***	−0.982***	−1.011***	−1.049***	−1.048***	−0.896***	−0.741***	−0.729***	−0.792***
Average annual retail rice price – squared	0.023***	0.023***	0.024***	0.025***	0.025***	0.021***	0.018***	0.017***	0.019***
Retail price × urbanity dummy	0	−0.001	0	0	−0.002**	−0.001	0.001	−0.002	−0.001
Poverty rate		−0.054**	−0.057**		−0.128***	−0.114***		−0.199***	−0.156***
Density of provincial road network (km of road / km^2 area)			1.075***			1.009***			0.825***
Provincial population density (persons/ km^2)			−0.142***			−0.123***			−0.051
Constant	10.314***	10.333***	10.638***	11.020***	11.054***	9.466***	7.739***	7.708***	8.435***
Sample size	1335	1335	1271	988	988	936	687	687	640
R-squared	0.052	0.055	0.111	0.065	0.081	0.118	0.046	0.089	0.122
Derivatives with respect to the market price of rice									
Slope when price = 19 pesos/kg	−0.095***	−0.095***	−0.104***	−0.103***	−0.101***	−0.094***	−0.070***	−0.069***	−0.088***
Slope when price = 25 pesos/kg	0.185***	0.185***	0.182	0.196***	0.198***	0.159***	0.142***	0.140***	0.134***
Price of zero slope (pesos/kg)	21.05	21.03	21.18	21.06	21.03	21.24	20.99	20.97	21.39

Standard errors are robust.
* $p < .l.$
** $p < .05$.
*** $p < .01$.

to usable services. Such systematically differentiated access will detract from the program's geographic targeting outcomes. To the extent that focusing on communities with high participation rates eliminates households facing the tightest supply constraints, results from the most conservative sample are more likely to reflect self-targeting. We note that the coefficient on the local poverty rate may be biased towards zero due to attenuation bias, increasing our confidence, from a rejection of the null, that poverty detracts from a communities' propensity to participate. The third specification (columns 3, 6 and 9) introduces proxies for the ease with which the NFA can reach these communities in order to check whether this accounts for variations in access to usable services.

The results indicate that higher prices in the regular rice market increase demand for NFA rice over most of the range of observed prices. However, a comparison of the R^2 statistics across specifications indicate that price variations capture only a small fraction of explainable demand differences across local markets. Poverty rates are negatively associated with participation, and this tendency is the strongest in the most clearly served set of communities. To give a sense of magnitude: communities at the 10th and 90th percentiles of the distribution of local poverty rates would have poverty rates of 0 and 74%, respectively. Based on the coefficient estimates in the conservative subsample (column 8), which are biased towards zero, observationally equivalent households in the poorer of these two communities would have 15% lower participation rates than those in the richer one. Finally, participation is higher in communities located in provinces with denser road networks and less dense populations. This might indicate easier access in places where it is easier or cheaper to deliver rice to stores. However, introducing these variables does not change the result that poorer communities have lower participation propensities. This suggests that these lower participation propensities in poorer communities (especially in the most clearly served subsample) reflect genuine differences in access to usable services across communi-

Table 8
Correlations of local participation propensities with proxies for voice.

Correlate	Sub-sample, correcting for:						
		Baseline		Conservative		Most conservative	
	Level	Price (1)	Price and access (2)	Price (3)	Access (4)	Price (5)	Price and access (6)
Poverty rate	Local	−0.048	−0.047	−0.116***	−0.094***	−0.192***	−0.136***
Per capita income (000's of pesos/year)	Local	0.065**	0.045	0.117***	0.089***	0.174***	0.138***
Human Development Index	Provincial	0.010	−0.001	0.060	0.013	0.142***	0.032
Average years of schooling amongst HH heads	Local	0.066**	0.06**	0.093***	0.087***	0.154***	0.133***
Functional literacy rate	Provincial	0.067**	0.031	0.091***	0.045	0.17***	0.095**
Urban (1 = year, 0 = no)	Local	0.001	0.000	0.003	0.001	0.006	0.004
Employment rate amongst HH heads	Local	0.002	−0.003	−0.021	−0.016	−0.059	−0.041
TV ownership rate	Local	0.033	0.046	0.079**	0.077**	0.16***	0.125***
% of provincial expenditures on social services	Provincial	0.015	0.037	0.059	0.067**	0.09**	0.079
Share of households with access to safe drinking water	Provincial	0.102***	0.084***	0.075**	0.073**	0.082**	0.066
Student–teacher ratio: primary school	Provincial	−0.084***	0.002	−0.104***	−0.029	−0.117***	−0.044
Student–teacher ratio: secondary school	Provincial	−0.211***	−0.132***	−0.213***	−0.169***	−0.223***	−0.183***
Max possible # of communities		1335	1271	988	936	687	640

* Correlations are different from zero at 10% significance.
*** Correlations are different from zero at 1% significance.
** Correlations are different from zero at 5% significance.

ties that are not explained by differences in the ease of delivering to different locations.

Why do households in rich communities participate more?

The residuals from the regressions in columns 1, 4 and 7 of Table 6 capture the propensity of a community to participate in the NFA program *purged of the direct effects of household composition and local prices.* To test the idea that these propensities are driven by endogenous differences in access to usable services and voice, columns 1, 3 and 5 in Table 8 provide the bivariate correlation coefficient between these propensities and a range of proxies for citizen voice. In addition, we have estimated propensities that are purged of the effects of ease of access (using the residuals from regressions of the fixed effects on prices, road density and population density), and present correlations between these and proxies for voice in Table 8, columns 2, 4, and 6. This third stage of the analysis utilizes bivariate correlations rather than regressions because there is, for example, no need to control for education levels when assessing whether lower income communities have lower propensities to participate. If access to usable services were uniform, the propensities should not be correlated with any community characteristic.

We use proxies for voice intended to capture wealth (poverty rate, per capita income), general development (the Human Development Index), education (years of schooling and functional literacy), possible access to networks offering information and redress (urbanity, employment, TV ownership), and the availability of other quality social services (public expenditure share on social services, access to clean drinking water, student:teacher ratios). Many of these proxies are significantly correlated with community participation propensity, and every significant correlation coefficient has the sign that would be expected if voice influenced access to usable services. These results indicate that observationally equivalent households living in communities that have less voice are less likely to be users of the program.

Reconciliation

This paper has examined the "progressivity" of the program along four dimensions. Unsurprisingly, conclusions about the program's progressivity depend upon the dimension under consideration. We have shown that: (i) Program participation was progressive across people nationwide, in the sense that poor people had a higher probability of participating in it (Table 4, row 5). (ii) Participation outcomes were also progressive across people within communities, in the sense that, holding community constant, poorer and more vulnerable households were more likely to participate (row 8 of Table 4; Table 6). (iii) Participation rates across geographic locations – provinces or communities – were at best mildly progressive (Table 2; Table 4 row 9; Table 5). (iv) Finally, we have argued that this weak geographic targeting occurred at least in part because *access to usable services* was regressively distributed across communities (Tables 7 and 8).

The distinction between dimensions (iii) and (iv) deserves further clarification, given that both result from different forms of "between-community" analysis: (iv) concerns variations in targeting outcomes that remain after conditioning on variables that determine how much households need the program (specifically, household characteristics and local rice prices); on the other hand, (iii) derives from analyses of targeting outcomes that have not been purged of the differences in households need to participate using a first-stage household-level regression. Thus, the mild between-community progressivity reported as (iii) reflects a combination of need and constraints on access. It is only these constraints on access (iv) that are regressively distributed.

Discussion

We have examined the targeting outcomes of an (officially) self-targeted food subsidy program in the Philippines. Our findings are as follows: Tackling hunger in the Philippines requires solid geographic targeting outcomes as it appears to have been driven by local price volatility. Unfortunately, there was significant unmet potential for geographic targeting, and, curiously, this unmet potential was higher when we restricted attention to subsets of communities that we are more confident had access to NFA stores. This suggests that something other than the presence/absence of NFA outlets was behind the weak geographic targeting outcomes. Finally, the poor geographic targeting outcomes occurred partly because the program did not provide equal access to usable services in communities that were the most vulnerable and lacking in voice. This is counterbalanced by the fact that, within communities, more vulnerable households did elect to use the program more often. The net result was targeting outcomes that were progressive, but less progressive than they should have been.

These results are quite consistent with theoretical expectations. Neoclassical theory predicts that, in the absence of explicit targeting or rationing rules for dealing with excess demand, distribution agents have incentives to devise allocative methods of their own. We have described some such methods which rationed or otherwise limited access to NFA rice, or which reduce the quality of food or service. Such approaches to limiting excess demand will need to be more forcefully applied in more food insecure communities if their per capita receipts of subsidized food are not commensurately higher – and we have shown that per capita deliveries were quite unresponsive to local conditions under the NFA program. Institutional approaches emphasizing voice predict that the costs of ad hoc mechanisms to limit excess demand are more likely to be shifted onto consumers in communities that lack political clout or access to redress.

Together, these theory-consistent results therefore indicate that good self-targeting outcomes are not assured simply by choosing a product that has a low or negative income elasticity of demand. Differences in access to usable services across communities that detract from targeting outcomes are likely, and can be exacerbated by disparities in vulnerability and citizen voice. Such an explanation of the poor targeting outcomes of self-targeted programs emphasizes the importance of measures to enhance citizen voice, proper systems for filing and monitoring grievances, and a serious effort to allocate supplies so as to minimize excess demand in vulnerable communities.

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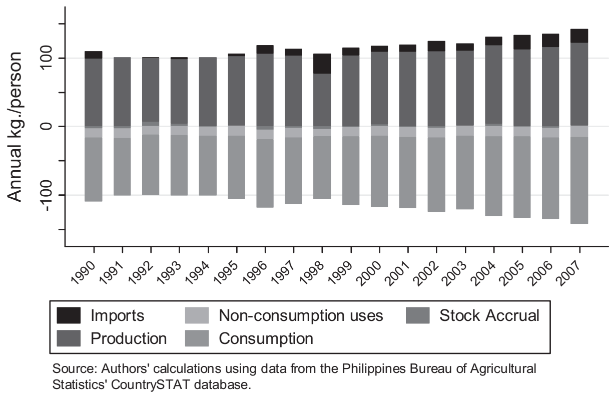

Fig. A1. Per-capita rice balances. *Source*: Authors' calculations using data from the Philippines Bureau of Agricultural Statistics' CountrySTAT database.

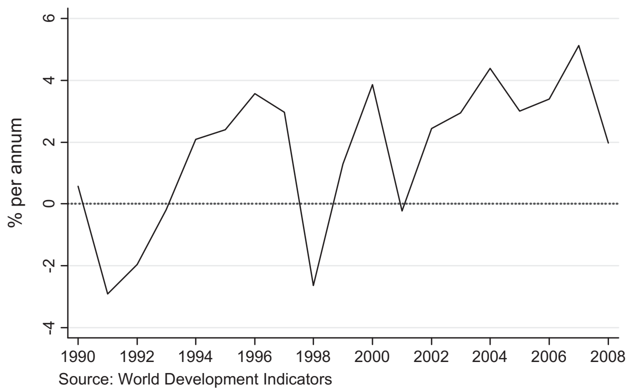

Fig. A2. Per-capita GDP growth. *Source*: World Development Indicators.

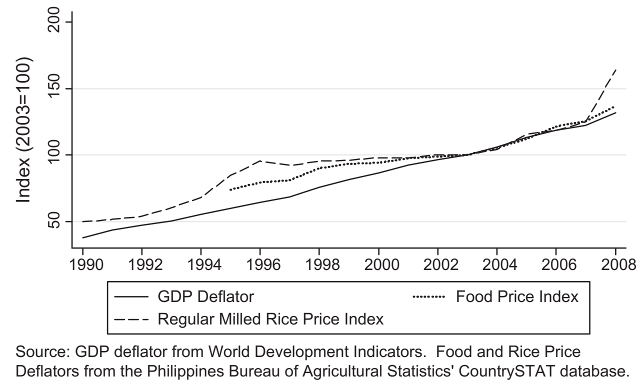

Fig. A3. Comparison of price indices (National Aggregates). *Source*: GDP deflator from World Development Indicators. Food and Rice Price Deflators from the Philippines Bureau of Agricultural Statistics' CountrySTAT database.

Appendix A. Factors that do not explain rising food insecurity in the Philippines

Fig. A1 summarizes national per-capita rice balances. Rice supplies are depicted above the line, and utilization is depicted below it. It shows that hunger did not rise due to declines in per capita rice consumption, which trended upwards. This trend was facilitated by both rising per capita production and imports. Average per capita real-income grew robustly between 2001 and 2008, so there was no growth collapse to explain the rise in hunger either (Fig. A2). While rising mean incomes could mask declines in income for the poor, incomes of the poor would have to decline sharply to push the share of households going hungry from 4% to 19% between 2003 and 2007 (as indicated by the Social Weather Stations data reported in section ‘The geography of vulnerability vs. geographic targeting’) while mean income grew robustly. Such a large deterioration is implausible: the Gini coefficient fell from 0.4605 in 2003 to 0.4564 in 2006.[15]

We can also rule out the possibility, prior to 2006, that food prices received insufficient weight in the GDP deflator and that rising average national food prices actually drove real incomes down. The food price index and the price of regular milled rice (rice being the main staple) rose no faster than the GDP deflator prior to 2007 (Fig. A3). Son (2008) confirms this, showing that even price indices that give greater weight to those commodities whose prices determine expenditure levels of the poor (i.e. food in general and rice in particular) registered inflation rates that are smaller than general inflation until 2005. This said, rising rice prices almost certainly explain much of the increase in hunger in 2007 and 2008, when they outstripped other components of the GDP deflator – a trend apparent in Fig. A3 and Son’s tables. However the increase in hunger to 2006 has no apparent explanation other than the regressive widening of the distribution of rice prices that we document in section ‘The geography of vulnerability vs. geographic targeting’.

Appendix B.

Here we examine the household and community-level determinants of households’ NFA rice consumption. We use Cragg’s (1971) double-hurdle model to jointly consider a household’s decision to participate in the program (i.e. to buy a non-zero amount of NFA rice) and its expenditures per household member on subsidized rice. Joint modeling is necessary to allow for truncation of the expenditure data that arises because some households and communities do not participate in the program.[16] Two samples are included to allow for the possibility that the determinants of participation in the full sample reflect a different combination of supply and demand constraints.

The model includes variables measured at the household level to capture within-community determinants of program uptake, and variables measured at the community and province levels to capture between-community determinants of uptake. Given that food is distributed to local markets quite frequently (typically weekly) we expect participation to be less curtailed by rationing than expenditures. This exercise rejects the null that there is no rationing if some variable that strongly predicts participation also predicts lower expenditures when measured at the community level. There is some evidence of this type in Table B1 – poor households are more likely to participate in the program, but, controlling for household poverty, living in a poor community reduces per capita expenditures. No other sign-switches that could signal rationing involve statistically significant coefficients in both equations. The regressions also show that whenever a household characteristic is significant in both the participation and expenditure equa-

[15] Source: National Statistical Office, Family Income Expenditure Survey 2006 press-release.

[16] An alternative approach would be to use a Heckit model. The Heckit model has the advantage that it does not assume participation and expenditures to be independent of each other. However, it requires an exclusion restriction for proper identification– a variable that influences participation but not expenditures. We could not propose any variable that we are convinced play this role. However, Heckit results obtained by excluding household television ownership from the expenditure equation, yield qualitatively similar results to those from the Cragg model.

Table B1
Cragg's (1971) double hurdle model of household expenditures on NFA rice.

	Full sample		Baseline sample	
	Participation	Expenditure	Participation	Expenditure
Household variables				
HH income per capita	−0.007***	−4.513	−0.008***	−4.513
Poor	0.267***	638.470***	0.348***	638.469***
Female HH head	−0.115**	−124.844	−0.097	−124.844
Age of HH head	−0.001	−5.022	−0.001	−5.022
HH head is employed	0.020	431.723	0.047	431.723
HH head is a working woman	0.173***	297.148	0.152**	297.147
HH head is a farmer	−0.237***	−130.154	−0.226***	−130.154
# of non-relatives in HH	−0.056	987.167	−0.156	987.166
# of persons in HH	0.001	−182.638***	0.002	−182.638***
HH head's years of schooling	−0.026***	−53.245**	−0.032***	−53.245**
Share of HH aged 1–6	0.288	3567.911**	0.278	3567.906**
Share of HH aged 7–14	0.324*	5231.080***	0.423*	5231.074***
Share of HH aged 15–24	0.297	7158.014***	0.388*	7158.005***
Share of HH aged 25–59	0.230	6198.185***	0.309	6198.178***
Share of H Hover 60	0.229	6165.364***	0.290	6165.356***
HH owns a TV	−0.161***	−417.921**	−0.204***	−417.920**
Province level variables				
Regular retail rice price	−2.874***	1178.232	−2.861***	1178.231
Regular retail rice price squared	0.069***	−25.262	0.067***	−25.262
Retail price × urbanity dummy	−0.033*	91.458	−0.013	91.458
Provincial road density	3.423***	8427.945***	3.727***	8427.936***
Provincial population density	−0.590***	−3427.684***	−0.522***	−3427.680***
Community level variables				
Average local HH per capita income	0.002***	−6.378	0.002***	−6.378
Local poverty	0.062	−2764.855***	−0.122	−2764.852***
Average HH head years of schooling	0.017**	−63.939	0.011	−63.938
Average local HH size	0.119***	−118.566	0.090***	−118.566
% of Local HH heads employed	0.279***	−92.767	0.125	−92.767
Local TV ownership rate	−0.173***	−1458.155***	−0.021	−1458.153***
Urban area? (1 = yes)	0.698*	−1179.574	0.212	−1179.573
Derivatives with respect to the market price of rice				
Slope when price = 19 pesos/kg	−0.25	218.26	−0.30	218.26
Slope when price = 25 pesos/kg	0.57	−84.89	0.51	−84.89
Price of zero slope (pesos/kg)	20.84	23.32	21.23	23.32
Sample size	32,380		17,332	

*** Correlations are different from zero at 1% significance.
** Correlations are different from zero at 5% significance.
* Correlations are different from zero at 10% significance.

tions, it takes the same sign in both. This suggests that it is reasonable, in the interests of brevity, to focus on only participation, rather than analyzing both participation and expenditures throughout the paper.

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