View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Apollo

UNIVERSITY OF
CAMBRIDGE

Cambridge Working Papers in Economics

Neighbourhood Effects in Consumption: Evidence from Disaggregated Consumption Data

Teodora Boneva

CWPE 1328

Neighbourhood Effects in Consumption: Evidence from Disaggregated Consumption Data

Teodora Boneva[*,†]

University of Cambridge

May 2013

Abstract

This paper identifies neighbourhood effects in consumption using the randomized nature of the Progresa programme. Recent studies establish that the programme affects the consumption of both eligible and neighbouring ineligible households but the underlying mechanism of the spillovers is not fully understood. I use disaggregated consumption data to distinguish between changes in consumption which result from changes in neighbourhood consumption and changes in consumption which are a result of income transfers between households. Using a flexible demand model that accounts for total expenditure, prices and household characteristics, I find that neighbourhood consumption has a substantial effect on household consumption choices.

JEL categories: D12, H23, I38, O12

Keywords: Social interactions, consumption, field experiments, Progresa

[*] I am grateful to Thomas F. Crossley, Hamish Low and Orazio Attanasio whose suggestions substantially improved the paper and to Peter Blair, Nicola Dehnen, Esther Duflo, Steven Durlauf, Jane Cooley Fruehwirth, Christina Gravert, James J. Heckman, Pramila Krishnan, Alice Kuegler, David Phillips, Moritz Roth, Cath Sleeman, seminar participants at the University of Cambridge and at the INET Summer School on Socio-economic Inequality at the University of Chicago. I also thank the ESRC for funding my research (ES/J500033/1).

[†] Faculty of Economics, University of Cambridge, Sidgwick Avenue, Cambridge, CB39DD, tbb25@cam.ac.uk

1 Introduction

The utility an individual derives from the choice of a particular consumption bundle might not only depend on the individual's own preferences over certain goods but it might also be affected by the consumption choices of other people in the community. For example, it might well be that the consumption of a certain good seems more desirable if more people in the community are consuming it. Understanding whether neighbourhood effects in consumption exist is relevant for many questions. For example, it can help us understand how targeted welfare programmes affect the consumption choices of both welfare recipients and their neighbours.

The identification of neighbourhood effects in consumption is a challenging task (Manski, 1993). Angelucci and De Giorgi (2009) and Kuhn et al. (2011) make important contributions to the literature by exploiting random variation in neighbourhood income levels to identify spillover effects.[1] In both studies, within randomly selected communities a predetermined subset of households received an exogenous income shock. As a consequence, households which received the income shock increased their consumption expenditure. Interestingly, both studies find that neighbouring households also increased their expenditure on different consumption categories.

There are two competing explanations for the observed spillover effects. First, households which received the income shock might have shared their increases in income with neighbouring households, possibly due to a risk sharing motive, which allowed the latter to consume more (*income effect*). Alternatively, neighbouring households might have directly reacted to the increased consumption in the community by choosing to increase their spending as well (*neighbourhood effect in consumption*). To finance the additional expenditure they might have decided to accept more transfers from their neighbours, to take up more loans or to reduce their savings.[2]

If we only investigate the level of total expenditure, or if we only investigate the level of expenditure on a certain good in isolation, it seems difficult to differentiate between the two competing explanations even if we perfectly observed transfers. We cannot separately identify changes in consumption which occur due to an income effect from changes in consumption which occur due to changes in neighbourhood consumption behaviour.

[1]Early studies which investigate whether the consumption choices of a reference group affect own consumption (e.g. Kapteyn et al., 1989, and Alessie and Kapteyn, 1991) did not use exogenous variation in reference group consumption and might therefore suffer from endogeneity bias.

[2]Arrow and Dasgupta (2009) provide a theoretical argument for when relative consumption concerns affect the intertemporal consumption decision. Frank (1999) also discusses the possibility that relative concerns might lead to suboptimal overborrowing.

In this paper, I suggest using disaggregated expenditure data to investigate changes in the *composition* of household spending. Since the two competing explanations yield different predictions concerning the way households allocate their spending across different goods, this allows us to separately identify the two effects.

First consider a model in which eligible households share their increases in income with neighbouring ineligible households. Since households have non-homothetic preferences, we expect the neighbouring ineligible households to change the composition of their expenditure once they receive transfers from their neighbours. Essentially, we expect them to slide along their Engel curves. More importantly, if income sharing was the *only* mechanism we would not expect to see an additional effect of neighbourhood consumption expenditure on the allocation decision.

Second, consider a model in which household consumption is additionally affected by the consumption choices of households in the neighbourhood. Again we expect an income effect due to increased expenditure levels, but this time we also expect neighbourhood expenditure changes to affect the household's consumption choices in a very specific way. In particular, if a household derives a higher utility from consuming a good which is consumed to a greater extent in the neighbourhood we expect the *compositional change* in expenditure to mimic the compositional change in the neighbourhood.

To better understand the intuition behind this argument it is important to make the following observation. Those households which receive an exogenous income shock do not only increase their total consumption expenditure but since their preferences are non-homothetic they also change the composition of their spending. Or, put differently, they disproportionately increase their spending on certain consumption categories compared to others. Hence, from the perspective of a neighbouring household this constitutes an exogenous shock to the *composition* of neighbourhood consumption spending. We can now test whether this compositional change in neighbourhood expenditure is reflected in the way neighbouring households allocate their spending across different goods. In particular, after controlling for the income effect a neighbourhood effect in consumption implies that neighbouring households also consume disproportionately more of those goods which are now consumed disproportionately more in the neighbourhood.

To separately identify income effects from neighbourhood effects in consumption I use data from the Mexican conditional cash transfer programme Progresa. The unique design of the programme coupled with the detailed food expenditure data allows me to separate the two effects. Progresa was randomly phased in across villages and within each village only a subset of households was eligible to receive the grant. We can exploit this feature of the data in several ways to obtain exogenous variation in neighbourhood food expenditure. Moreover, the availability of disaggregated food expenditure data makes it possible to model the food budget allocation decision of ineligible households with the help of a flexible demand system. Since this approach allows us to directly control for the total food expenditure of the household, we can isolate the effect of neighbourhood consumption behaviour. Additionally, I also control for local prices and household characteristics which might be important determinants of demand. This is important since these variables might also change as a result of the intervention.

By simply comparing eligible households across treatment and control villages I find that eligible households in treated villages spend a larger fraction of their food budget on fruit and vegetables, animal products and wheat, while they spend lower fractions on pulses and the category "other foods" which includes sweets, carbonated beverages, coffee, sugar and oil. Estimating the demand system for ineligible households reveals that there are sizeable neighbourhood effects in consumption which cannot be explained by income transfers between households. Due to changes in neighbourhood consumption ineligible households change their consumption behaviour in a way which mimics the changes observed in the neighbourhood. This change in consumption behaviour is consistent with an interpretation according to which ineligible households find those goods more desirable which are consumed to a greater extent in the community.

This paper is organized as follows. Section 2 explains the design of the Progresa programme and the data used in the analysis. Section 3 provides the theoretical framework and derives the testable predictions. Section 4 discusses the different identification strategies, while section 5 presents the results. Section 6 concludes.

2 Progresa

2.1 Programme Design[3]

Progresa is a conditional cash transfer programme in rural Mexico aimed at improving the education, health, and nutrition levels of the poor. Since its start in 1997 more than 5 million households have benefited from the programme. Eligible households received a cash transfer conditional upon the children attending classes at least 85 percent of the time, family visits to health centres, and women's participation in workshops on health and nutrition issues. The transfers were of substantial size. For the average family the grant constituted about 10 percent of total household expenditures (Bobonis and Finan, 2009).

Access to the programme was randomly phased in at the village level. The experimental data contains

[3]See Hoddinott and Skoufias (2004) and the welfare programme's website http://www.oportunidades.gob.mx/index.html for more detailed information.

506 rural villages out of which 320 were randomly selected to participate from the beginning of 1998, while the other villages only participated from the end of 1999. Behrman and Todd (1999) perform formal balancing tests on the baseline survey and conclude that the two samples were balanced in terms of observable characteristics.

Eligibility was determined in each village based on a constructed poverty measure (Skoufias et al., 1999). Initially, about 52 percent of the households were classified as being eligible (poor) in 1997 and almost all of these households also received the transfer in the treated villages (97 percent). A few months after the initial classification, but before the beginning of the programme, the formula used to determine eligibility was revised and the cutoff was increased (Skoufias et al., 2001). After this 'densification process' 78 percent of the households were eligible to receive the grant. However, because of administrative problems 60 percent of these reclassified households did not receive the transfer (Angelucci and De Giorgi, 2009). For the purpose of this analysis which focuses on the consumption choices of ineligible households, I classify all those households as eligible that were classified as being eligible at any time of the intervention.

Taken together we have data on four groups: Eligible households in treatment villages (who should have received the transfer), eligible households in control villages (who would have received the transfer had their village been selected), ineligible households in treatment villages and ineligible households in control villages. The fact that we have information on eligibility status in both treatment and control villages is crucial to the instrumental variable strategy. Moreover, note that the fraction of eligible households in a village varies considerably across villages (figure 1). This variation will be exploited to achieve the identification of the neighbourhood effect.

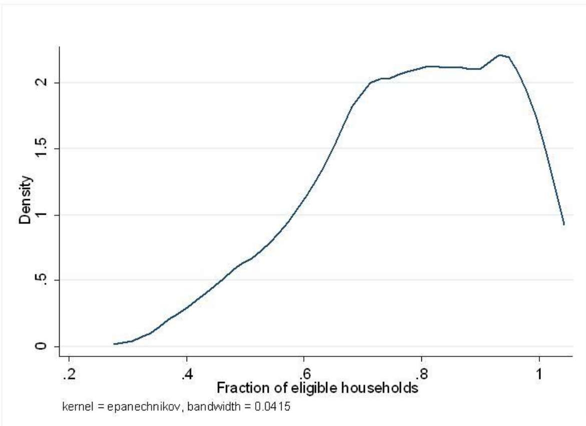

Figure 1: Variation in the fraction of eligible households across villages

2.2 The Data

All households in the 506 villages were interviewed twice before the programme started (September 1997, March 1998) and three times after the beginning of the payments in the treated villages (November 1998, May 1999, November 1999). This analysis is performed using the May 1999 data. The questionnaire includes very detailed questions on household characteristics and on consumer behaviour.[4] The expenditure data contains information on 36 items of food and drink. To make the estimation of the demand system feasible, I follow Attanasio et al. (2009) and group the 36 items into 8 groups: rice, corn, wheat, pulses, fruits and vegetables, animal products, other foods, and other starches (table 1).[5] We can calculate the value spent on each category of food and also the total amount spent on food using this data.

Table 1: The different components of the food groups

Group	Components
Rice	Rice
Corn	Maize tortilla, maize grain, breakfast cereals
Wheat	White bread, sweet bread, loaf of bread, wheat flour, biscuits
Pulses	Beans
Fruit and Vegetables	Tomatoes, onions, potatoes, carrots, leafy vegetables, oranges, bananas, apples, lemons, prickly pears
Animal Products	Chicken, beef and pork, goat and sheep, fish, tinned fish, eggs, milk, cheese, lard
Other Foods	Sweets, carbonated beverages, coffee, sugar, vegetable oil
Other Starches	Potatoes, pasta soup

To estimate the demand system we also need information on local prices. While no reliable price data is directly available from the survey we can construct a proxy for prices from the household expenditure data following the procedure in Attanasio et al. (2009).[6] First, the unit value is computed for each item by dividing the average weekly expenditure on the item by the quantity purchased during this period.[7] Once unit values are calculated for each household, a median unit value at the village level is computed to proxy for the price faced by a representative household in the village. If too few households report

[4]The baseline surveys do not contain detailed questions on consumption which is why I cannot make use of pre-treatment data.

[5]Alcohol purchases are omitted because of data inconsistencies.

[6]The price data from the existing local shop survey turns out not to be useful for this analysis because local shops do not offer the full range of items the households purchase. Also, the categories of food for which local shop prices are recorded differ from the ones in the expenditure questionnaire (Attanasio et al., 2009).

[7]Households were allowed to report their purchases in different units (e.g. kg, g, pieces), so quantities need to be converted to make the unit values comparable. All quantities are converted into kg or l using specific conversion factors for each item. See Attanasio et al. (2009) for more details on how the conversion procedure is implemented.

buying a good or the village median price is implausibly high, the median is computed at the municipality or state level.[8]

An advantage of using median unit values as opposed to mean unit values is that this procedure is robust to outliers. Using the median unit values we can also check the data for inconsistencies. In particular, the data reveals that the implied household unit values sometimes differ considerably from the median unit values. While there might be several reasons for this variability like differences in quality (Crawford et al., 2003) or non-linear price schedules (Attanasio and Frayne, 2006), the observed differences might also be a result of measurement error. If for some product a household's reported consumption implies prices that are more than 10 times the median village price, I consider the consumption entries of this household as implausible and treat the consumption data for this household as missing.

To estimate the demand system described in the following section, we need to compute the Stone price indices for the eight commodity groups. Each group price index is constructed as a weighted sum over all log prices of the food items in the group, where the weights for each item reflect the relative importance of this item in the group budget. Moreover, to compute the value of real total food expenditure we need a price index reflecting all village prices. To construct this overall Stone price index, I compute a weighted average of the Stone price indices of all commodity groups, where the weights are determined by the relative importance of the food group in the total food budget.

Overall, we have consumption information on a total of 18,671 households, out of which 4,066 were classified as being ineligible. The demand system estimation uses 3,875 of these ineligible households as some households have not responded to all relevant questions in the questionnaire. Out of these 3,875 ineligible households, 2,362 live in treatment villages while 1,513 live in control villages. Depending on the identification strategy I either use all ineligible households in both treatment and control villages, or ineligible households in treatment or control villages only.

Panel A of table 2 presents the mean values of several household characteristics for both eligible and ineligible households. The differences-in-means between treatment and control villages are reported by eligibility status. While most characteristics seem to be balanced between treatment and control groups there are some variables for which we find significant differences. In particular, the household heads of eligible households in treatment villages seem to be younger, and tend to have slightly more children aged 0-9 and slightly fewer children aged 10-19 compared to their control counterparts. For ineligible households, all characteristics seem to be balanced except for the household size. In particular, ineligible

[8] Village-level unit values were only used if at least 8 households reported purchasing the good. The threshold for plausible unit values was set at 100 pesos for most goods, with the exception of certain meat products. This threshold was only found to be binding in a few cases (Attanasio et al., 2009).

households in treatment villages seem to be smaller on average than ineligible households in control villages.

Table 2: Mean Comparisons

	Ineligible Households				Eligible Households			
	Mean [SD]	Treatment	Control	Difference	Mean [SD]	Treatment	Control	Difference
A: Household Characteristics								
Head of household's gender (male)	0.885 [0.319]	0.881	0.890	-0.009 (0.010)	0.894 [0.307]	0.893	0.896	-0.003 (0.005)
Head of household's age (years)	52.05 [15.38]	52.06	52.03	0.030 (0.496)	46.59 [16.70]	46.22	47.16	-0.935*** (0.284)
Head of household's ethnicity (indigenous)	0.192 [0.394]	0.190	0.194	-0.004 (0.013)	0.380 [0.485]	0.376	0.386	-0.010 (0.008)
Household size	5.28 [2.67]	5.17	5.45	-0.286*** (0.086)	6.00 [2.829]	5.98	6.05	-0.073 (0.048)
Number of young children (0-9)	1.09 [1.39]	1.09	1.11	-0.017 (0.045)	1.948 [1.746]	1.97	1.91	0.060** (0.030)
Number of old children (10-19)	1.22 [1.40]	1.20	1.26	-0.061 (0.045)	1.542 [1.538]	1.52	1.57	-0.053** (0.026)
Fraction of poor in village	0.673 [0.142]	0.671	0.674	-0.004 (0.005)	0.813 [0.144]	0.813	0.813	0 (0.002)
B: Household Expenditure								
Total food exp. (adult equivalent)	190.95 [116.30]	196.46	182.19	14.28*** (3.74)	167.13 [96.94]	174.60	155.39	19.21*** (1.64)
Rice share	0.021 [0.024]	0.020	0.022	-0.002** (0.001)	0.022 [0.028]	0.022	0.021	0.001*** (0.001)
Corn share	0.289 [0.153]	0.290	0.288	0.002 (0.005)	0.317 [0.164]	0.305	0.336	-0.031*** (0.003)
Wheat share	0.030 [0.047]	0.031	0.029	0.002 (0.002)	0.027 [0.046]	0.030	0.024	0.006*** (0.001)
Pulses share	0.110 [0.070]	0.110	0.109	0.001 (0.002)	0.114 [0.075]	0.112	0.115	-0.003** (0.001)
Fruit and vegetable share	0.115 [0.065]	0.117	0.112	0.005** (0.002)	0.111 [0.067]	0.114	0.106	0.009*** (0.001)
animal products share	0.200 [0.132]	0.197	0.204	-0.007* (0.004)	0.177 [0.129]	0.184	0.165	0.019*** (0.002)
other foods share	0.188 [0.100]	0.187	0.190	-0.002 (0.003)	0.189 [0.100]	0.188	0.192	-0.005*** (0.002)
other starches share	0.046 [0.041]	0.047	0.046	0.001 (0.001)	0.043 [0.041]	0.045	0.040	0.004*** (0.001)

*The Progresa data from May 1999 is used. Standard deviations of variables are reported in brackets. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

When investigating food expenditure behaviour it is important to take these differences into account. To make household food expenditure comparable across households I compute the food expenditure per adult equivalent which accounts for the variation in household size and the fact that children consume less than adults (Di Maro, 2004).[9] Using this measure of food expenditure we find a 13 percent increase in

[9] Di Maro (2004) finds that children consume about 73 percent of adults.

spending among eligible households as a result of the intervention. In particular, their food expenditure (per adult equivalent) rises from an average of 155 monthly pesos to an average of 175 monthly pesos. Interestingly, we also find a significant increase of about 8 percent among ineligible households. Their average food expenditure (per adult equivalent) increases from 182 monthly pesos to 196 monthly pesos.

Panel B of table 2 also presents the changes in the composition of food expenditure. Eligible households spend a higher fraction of their food budget on fruit and vegetables, animal products, other starches, rice and wheat while they spend a lower fraction on corn, pulses, and the category "other foods". For the ineligible group most of the differences are insignificant with the only exceptions being the fruit and vegetables share and the animal products share. To establish whether we have evidence for neighbourhood effects in consumption we need to estimate a demand system which carefully controls for changes in total food expenditure, prices and household characteristics since changes to those factors might have also affected the composition of the food budget.

3 Theoretical Framework

This section derives an estimable consumer demand model for the allocation of the total food budget across the different food categories. Household expenditure behaviour is assumed to be decided in three stages. First, households choose how to allocate expenditure across time periods. Taking this inter-temporal allocation as given, households then decide how to allocate the expenditure across food and non-food commodities.[10] Finally, the households choose how to divide the total food expenditure across the different food components - taking total food expenditure as given.[11] We can now model the household allocation of total food expenditure across the eight different categories of food as a function of food prices and total food expenditure without taking the prices of non-food items or the value of non-food expenditure into account (Deaton and Muellbauer, 1980). Additionally, we can allow for preference heterogeneity by conditioning on household and village characteristics. More specifically, the allocation is modelled as a function of (1) local prices of all food groups, $p_1, \ldots, p_8$; (2) real total food expenditure of the household (squared), X_r; and (3) household demographics including the age, sex and ethnicity of the household head, the household size (squared), and the number of young and old children in the household, Z. To allow for neighbourhood effects the demand system is augmented with the average

[10] This assumes inter-temporally separable preferences which rules out the presence of habit formation. Several studies have investigated the importance of habits in consumption choices (see for example Dynan, 2000, or Browning and Collado, 2007) but evidence remains mixed.

[11] This assumes that the utility derived from the consumption of food is separable from the utility derived from the consumption of all other goods (Deaton and Muellbauer, 1980). While separability might be regarded as a strong assumption, the available data does not permit to extend the analysis to also include non-food items.

total food expenditure of the other households residing in the same village, $\bar{c}$. Moreover, the fraction of poor people, π, is directly controlled for since households living in poorer villages might systematically differ from households living in relatively wealthier villages.

We can use the almost ideal demand system (AIDS) proposed by Deaton and Muellbauer (1980) or its extension, the quadratic almost ideal demand system (QUAIDS), proposed by Banks, Blundell and Lewbell (1997) to model demand. This class of demand systems has the advantage that it can be derived from a general indirect utility function which represents consumer preferences. This ensures that adding-up, homogeneity, and symmetry can all be satisfied.[12] Compared to the AIDS, the QUAIDS includes the square of log total expenditure which allows Engel curves to be quadratic.[13] This extension is preferable since empirical analyses have found Engel curves to be non-linear (e.g. Atkinson et al., 1990, Blundell et al., 1993).

Assuming that households make their consumption choices taking other people's consumption as given, the following share equations can be derived for a utility maximising household:[14]

$$w_i = \alpha_i + \beta_{0i} \ln X_r + \beta_{1i} (\ln X_r)^2 + \sum_j \gamma_{ij} \ln p_j + \delta_{0i} Z + \boldsymbol{\delta_{1i} \bar{c}} + \delta_{2i} \pi + u_i \; \forall i,$$

where w_i is the share of total food expenditure spent by the household on food group i, and α_i and u_i are the equation-specific constant and error term. The neighbourhood coefficient of interest in each equation is δ_{1i}. Preference heterogeneity across consumers is allowed by including a linear function of the household-level variables into the intercept of the share equation.[15]

For the demand system to be consistent with consumer theory, several restrictions need to be satisfied. Estimating the model using least squares automatically ensures that the adding-up restrictions hold (Deaton and Muellbauer, 1980):

$$\sum_i \alpha_i = 1, \sum_i \beta_{0i} = 0, \sum_i \beta_{1i} = 0, \sum_i \gamma_{ij} = 0 \; \forall j, \sum_i \delta_{0i} = 0, \sum_i \delta_{1i} = 0, \sum_i \delta_{2i} = 0.$$

[12]The adding-up and the homogeneity condition follow from the fact that consumers face a budget constraint and Marshallian demands exist, while the symmetry of the Hessian of the expenditure function follows from utility maximisation (Deaton and Muellbauer, 1980).

[13]The inclusion of the extra term is not only consistent with utility maximisation but it also turns out that the resulting demand system has the highest possible rank which is consistent with theory in the class of perfectly aggregable systems (Gorman, 1981).

[14]The subscript for the household is suppressed to make the notation more comprehensible.

[15]See Pollak and Wales (1980) for more details on the linear demographic translation method and for a review of the different methods which can be used to incorporate demographic variables into theory-consistent demand systems.

Symmetry is imposed by including the following parameter restrictions:

$$\gamma_{ij} = \gamma_{ji} \; \forall i, j.$$

To impose homogeneity, log prices are normalised by subtracting the log price of the "other starches" category. Using this specification we formulate two testable hypotheses.

HYPOTHESIS 1: In the absence of neighbourhood effects, $\delta_{1i} = 0$ for all food groups i. Or, put differently, once we control for the total food budget and other relevant factors determining demand, neighbourhood consumption should have no direct effect on the allocation of the total food budget across the different food components. If we reject this hypothesis we can perform a second test.

HYPOTHESIS 2: If ineligible households find those goods more desirable which eligible households spend a larger fraction on, we expect the following pattern. $\delta_{1i} \geq 0$ for all food groups i on which eligible households choose to spend a higher share once they receive the grant, and $\delta_{1i} \leq 0$ for all food groups i on which eligible households choose to spend a lower share.

4 Identification

To identify the neighbourhood effects of interest we need to overcome the problem that neighbourhood consumption is endogenous (Manski, 1993). In particular, we might be worried that households living in the same village have common characteristics and face similar environments, which makes them more likely to consume similar goods. Also, since consumption choices are simultaneously determined it might well be that the estimation of the demand system suffers from simultaneity bias. To estimate the parameters of interest we need an exogenous shock to neighbourhood consumption levels.

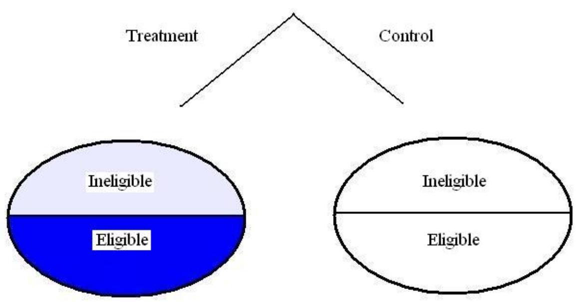

Figure 2: Using treatment status as an IV (IV1)

Village-level access to Progresa exogenously changes the income and consumption levels of eligible households in treated villages. From the perspective of an ineligible household residing in a treated village this constitutes an exogenous change to average neighbourhood consumption behaviour. Hence, to identify the effect we can estimate the demand system for ineligible households only and instrument neighbourhood consumption levels with the treatment status of the village, T (figure 2). While it is possible that eligible households share their income with neighbouring ineligible households this should not affect the estimates of the neighbourhood parameters. The reason is that the demand system directly controls for total food expenditure which allows us to disentangle the two effects. Moreover, prices are allowed to change with the instrument without affecting the neighbourhood estimates since they are also controlled for in the analysis.

This approach relies on the assumption that there are no unobserved Progresa-specific shocks to the environment which affect the ineligible households' consumption choices. To check the robustness of the estimates we can use a second instrumental variables strategy which exploits the fact that the fraction of eligible households varies within treated villages, π (figure 3).[16] The rationale behind this instrument is that in villages where the eligibility rate is high, the intensity of treatment is higher. Hence, we expect average food expenditure in the village to rise by more once the village gets access to the programme.

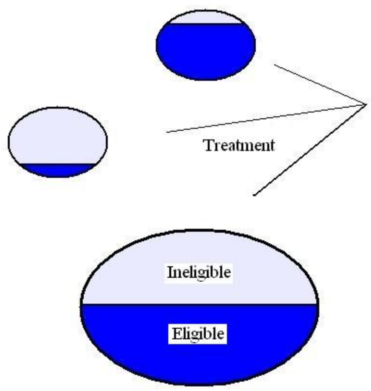

Figure 3: Using intensity of treatment as an IV (IV2)

For this approach to be reliable treatment intensity needs to be exogenous and should not affect the households' consumption choices directly. However, while programme eligibility is pre-determined at the time of the intervention the eligibility rate within each village is not randomly determined. Villages with a higher intensity of treatment are inevitably poorer since eligibility is determined on the basis of a poverty measure. This poses a problem since households living in poorer villages might differ systematically from

[16]Similar identification strategies have been used by Bobonis and Finan (2009) and Lalive and Cattaneo (2009) who estimate neighbourhood effects in the schooling decision using the same data set.

those living in relatively wealthier villages. They might have different characteristics and face different environments which might be important determinants of demand.

If we only had data on households in treated villages we could therefore not use the intensity of village treatment as an instrument. It would be impossible to disentangle the direct effect of the eligibility rate from the indirect effect which comes through the differential change in village-level food expenditure. Since we also have data from control villages, however, we can use an alternative strategy to circumvent this problem. In particular, we can estimate the demand system for ineligible households living in *both* treatment and control villages. This time we instrument neighbourhood consumption with the interaction of the village treatment status and the eligibility rate, $T \times \pi$, while directly controlling for the eligibility rate in the demand system, π. Like in the previous approach, the exogenous variation in neighbourhood consumption is induced by the variation in the eligibility rate across treatment villages. However this time, we can additionally identify the direct effect of the eligibility rate since this variable also varies within control villages (figure 4).

Essentially, this approach is similar to a difference-in-difference strategy. We compare the behaviour of ineligible households in poor treated villages to the behaviour of those in relatively wealthier treated villages, and use data from the untreated villages to control for the differences in consumption choices between poor and rich villages in the absence of treatment.

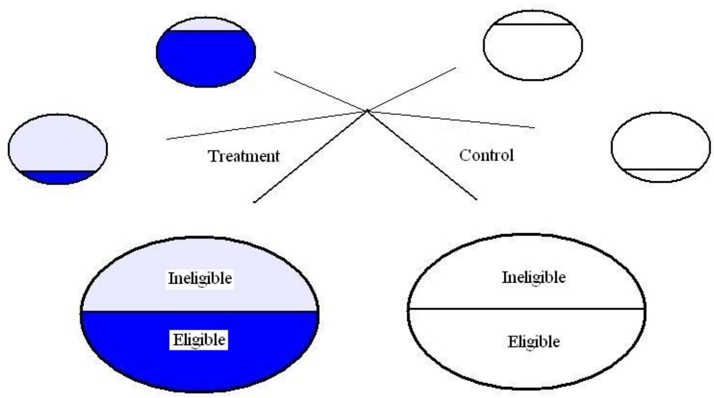

Figure 4: Using the interacted design (IV3)

Summing up, we can either instrument neighbourhood expenditure using the treatment status of the village (IV1), using the eligibility rate (IV2), or using the interacted design (IV3). Comparing the results of the different estimation strategies is informative about the potential sources of biases in the different approaches.

5 Results

This section presents the least squares and instrumental variables estimates of the demand system specified in section 3. In every estimation the dependent variables are the shares of rice (w_1), corn (w_2), wheat (w_3), pulses (w_4), fruit and vegetables (w_5), animal products (w_6), and other foods (w_7).

Table 3: Estimates of Neighbourhood Effects

	(1) Rice	(2) Corn	(3) Wheat	(4) Pulses	(5) Fruit and Vegetables	(6) Animal Products	(7) Other Foods
A: Treatment status across villages (IV1)							
Average food expenditure/1000	-0.0398	-0.110*	0.0909***	-0.139***	0.166***	0.109**	-0.116**
	(0.0245)	(0.0622)	(0.0218)	(0.0482)	(0.0416)	(0.0466)	(0.0588)
Household and price controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for fraction of poor	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,875	3,875	3,875	3,875	3,875	3,875	3,875
B: Treatment intensity within villages (IV2)							
Average food expenditure/1000	0.0427	0.0186	0.158***	-0.385**	0.167**	0.258***	-0.277**
	(0.0663)	(0.143)	(0.0418)	(0.158)	(0.0778)	(0.0812)	(0.149)
Household and price controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for fraction of poor	No	No	No	No	No	No	No
Observations	2,362	2,362	2,362	2,362	2,362	2,362	2,362
C: Treatment status x Treatment intensity (IV3)							
Average food expenditure/1000	-0.0379***	-0.0995	0.0918***	-0.158***	0.166***	0.118**	-0.115*
	(0.0190)	(0.0859)	(0.0208)	(0.0509)	(0.0462)	(0.0463)	(0.0644)
Household and price controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for fraction of poor	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,875	3,875	3,875	3,875	3,875	3,875	3,875
D: LS							
Average food expenditure/1000	0.0171***	-0.139***	0.0248**	0.0239*	0.0317**	0.0476*	-0.00836
	(0.00568)	(0.0263)	(0.00960)	(0.0141)	(0.0159)	(0.0278)	(0.0180)
Household and price controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for fraction of poor	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,513	1,513	1,513	1,513	1,513	1,513	1,513

*Bootstrapped standard errors in parentheses (99 replications), *** p<0.01, ** p<0.05, * p<0.1.
**Progresa data from the May 1999 wave is used. The dependent variables are the food budget shares of rice (1), corn (2), wheat (3), pulses (4), fruit and vegetable (5), animal products (6), and other foods (7). The equation for the category 'other starches' is excluded. Prices (in logs) are normalised by subtracting the log price of the 'other starches' category to impose homogeneity. Symmetry is imposed by including parameter restrictions. Average expenditure refers to the average expenditure of the other households within the same village. Household controls are the age, sex and ethnicity of the household head, the household size (squared), and the number of young and old children in the household. See tables in the Appendix for more details.

Panel A of table 3 shows the demand system estimates using treatment status of the village as an instrument for neighbourhood consumption (IV1).[17] This estimation uses data on ineligible households living in both treatment and control villages. We can reject the null of having weak instruments. The F-statistic of the first-stage regression has a value of 110 which exceeds the critical value of 16 (Stock and Yogo, 2005).

The estimates reveal that the level of average food expenditure in the village substantially affects the allocation of the food budget across the different food components, i.e. we can reject hypothesis 1. Since prices and the total food budget are directly controlled for these effects cannot be attributed to income sharing between households or village level changes in prices. If income sharing was the only mechanism underlying the spillovers of the programme we would expect households to increase their overall expenditure on food. This might change the allocation of their food budget across the different food components because preferences are non-homothetic. However, once we allow for this effect by conditioning on the total food budget we do not expect the allocation decision to be additionally affected by neighbourhood consumption levels.

The effects are substantial in size (panel A, table 3). For example, an increase in average food consumption by 1 monthly peso increases the share of fruit and vegetables by 0.017 percentage points. Access to Progresa increased average household food expenditure by 65 monthly pesos, which translates into an increase in the fruit and vegetables share by 1.1 percentage points. Given that the average fruit and vegetables share in control villages is only about 10.6 percent this is an effect of considerable size.

Interestingly, the results are consistent with the hypothesis that ineligible households find those goods more desirable which are consumed disproportionately more by eligible households. As noted earlier, eligible households in treated villages consume substantially higher shares of wheat, fruit and vegetables and animal products, while they consume lower shares of corn, pulses and other foods.[18] When we investigate the signs of the coefficients across the different commodities we find the following pattern. Due to changes in overall food expenditure ineligible households also spend a higher fraction of their food budget on wheat, fruit and vegetables and animal products, while they spend less on corn, pulses and other foods. The compositional changes which we can attribute to changes in neighbourhood consumption mimic the way eligible households reallocate their food budget across the different goods. This finding is consistent with the idea that ineligible households find the consumption of a good more desirable if it is consumed to a greater extent in the community.

As noted earlier a concern with the first estimation strategy is that there might be unobservable

[17]The Appendix contains more detailed tables.

[18]They also consume a slightly higher share of rice, but the effect is very small in comparison to the other effects.

village level characteristics which change as a result of the intervention. To check the robustness of the findings we can compare the estimates to those obtained from the other two identification strategies.[19]

While the estimates differ substantially from the ones obtained using the IV2 approach (panel B, table 3), they are very much in line with the estimates using the IV3 approach (panel C, table 3). In the IV2 approach I use data from the treated villages only and use the intensity of village treatment as an instrument. As noted earlier, however, this approach does not allow us to directly control for the fraction of eligible households in the village. From the estimated regression coefficients of the first identification strategy (table 4, see Appendix) it becomes apparent that directly controlling for the fraction of eligible households is important. A higher percentage of poor households is associated with higher shares of wheat and lower shares of other foods. The magnitudes of the effects are non-negligible. For example, someone living in a village with a 75 percent eligibility rate has a wheat expenditure share which is by 0.6 percentage points higher than the wheat expenditure share of a household residing in a village with a 25 percent eligibility rate (ceteris paribus). Omitting the fraction of eligible households from the equation and using it as an IV seems to lead to estimates that are severely biased.

It is reassuring that the estimates using the first estimation strategy are not significantly different from the ones obtained using the third identification strategy which uses the intensity of treatment in treated villages as an IV, but also controls for the fraction of eligible households. As explained in the previous section, we can isolate the two effects since the fraction of eligible households also varies within control villages. Not only are the signs of the effects the same, but the estimated coefficients are also similar in magnitude. The similarity of the estimated coefficients suggests that changes in unobserved village-level characteristics which result from the intervention do not confound the estimates from the first estimation strategy.

Finally, we can compare the IV estimates from the two preferred strategies (IV1 and IV3) to the ones obtained using LS. The demand system presented in panel D of table 3 does not account for endogeneity and it is estimated using ineligible households living in control villages only. The estimated coefficients differ substantially from the IV estimates and a formal Hausman test rejects the null of having equal coefficients. This suggests that LS estimates are biased and that accounting for endogeneity is important.

[19] In both cases we can reject the null of weak instruments.

6 Conclusion

The identification of neighbourhood effects in consumption is an interesting but challenging task. Previous studies have documented that an exogenous shock to the income of a subset of households in a neighbourhood can have substantial spillover effects on neighbouring households. This paper sheds more light on the mechanism underlying these spillovers. In particular, I isolate changes in consumption which are due to changes in neighbourhood consumption behaviour from changes in consumption which occur due to changes in available income.

If we only examine total food expenditure the two mechanisms are observationally equivalent. This paper develops a test which uses the idea that an increase in available resources due to income transfers should only affect the composition of food expenditure through changes in the total food budget. However, once we condition on the total food budget, neighbourhood expenditure levels should not have an additional direct effect on the allocation of this budget across different goods.

To perform this test I augment a structural demand system with neighbourhood consumption behaviour and make use of the exogenous variation generated by the randomised phase-in of the Progresa programme to identify the neighbourhood parameters of interest. I find evidence for substantial neighbourhood effects which cannot be explained by income transfers between households. The results are consistent with the interpretation that households find those goods more desirable which other households in the community consume to a greater extent. Possible reasons for this behaviour might be that households can obtain more information on the product or they can infer something about the quality of the product from the fact that it has become more popular. Alternatively, households might like to conform to their neighbours' consumption choices (Bernheim, 1994, Akerlof and Kranton, 2010), or they might want to keep up with their neighbours by consuming the more desirable goods (Veblen, 1899). Future research should aim at understanding the behavioural reasons underlying the identified neighbourhood consumption effects.

References

[1] Akerlof, G.A. and Kranton R.E. (2010), *Identity Economics: How our Identities shape our Work, Wages and Well-being*, Princeton University Press

[2] Alessie, R. And Kapteyn, A. (1991), 'Habit Formation, Interdependent Preferences and Demographic Effects in the Almost Ideal Demand System', *The Economic Journal*, 101, pp. 404-419

[3] Angelucci, M. and De Giorgi, G. (2009), 'Indirect Effects of an Aid Program: How Do Cash Transfers Affect Ineligibles' Consumption?' *American Economic Review*, 99(1), pp. 486–508

[4] Arrow, K.J. and Dasgupta, P.S. (2009), 'Conspicuous Consumption, Inconspicuous Leisure', *Economic Journal*, 119:541, pp. 497-516

[5] Atkinson, A.B., Gomulka, J. and Stern, N.H. (1990), 'Spending on Alcohol: Evidence from the Family Expenditure Survey 1970-1983', *Economic Journal*, 100, pp. 808-827

[6] Attanasio, O., Di Maro, V., Lechene, V., and Phillips, D. (2009), The Welfare Consequences of Increases in Food Prices in Rural Mexico and Colombia, Draft 2009

[7] Attanasio, O.P., and Frayne, C. (2006), Do the Poor Pay More? Draft 2006.

[8] Banks, J., Blundell, R. and Lewbel, A. (1997), 'Quadratic Engel Curves and Consumer Demand', *The Review of Economics and Statistics*, 79(4), pp. 527-539

[9] Behrman, J.R. and Todd, P.E. (1999), 'Randomness in the Experimental Samples of PROGRESA', International Food Policy Research Institute Report

[10] Bernheim, B.D. (1994), 'A Theory of Conformity', *Journal of Political Economy*, 102, 841-877

[11] Blundell, R.W., Pashardesa, P. and Weber, G. (1993), 'What Do We Learn about Consumer Demand Patterns from Micro-Data?', *American Economic Review 83*, pp. 570-597

[12] Bobonis, G.J. and Finan, F. (2009), 'Neighborhood Peer Effects in Secondary School Enrollment Decisions', *Review of Economics and Statistics*, 91(4): 695–716.

[13] Browning, M.J. and Collado, L. (2007), 'Habits and Heterogeneity in Demand: A panel data analysis', *Journal of Applied Econometrics*, 22, pp. 625-640

[14] Crawford, I., Laisney, F. and Preston, I. (2003), ‘Estimation of household demand systems with theoretically compatible Engel curves and unit value specifications’, *Journal of Econometrics*, 114, 221-41

[15] Deaton, A. and Muellbauer, J. (1980), *Economics and Consumer Behaviour*, Cambridge University Press

[16] Di Maro, V. (2004), Evaluation of the Impact of PROGRESA on Nutrition: Theory, Econometric Methods and an Approach to deriving individual welfare findings from household data, UCL mimeo, Sep 2004

[17] Dynan, K.E. (2000), ‘Habit Formation in Consumer Preferences: Evidence from Panel Data’, *American Economic Review* 90(3), pp. 391-406

[18] Frank, R.H. (1999), *Luxury Fever: Why Money Fails to Satisfy in an Era of Excess*’, New York: The Free Press

[19] Gorman, W.M. (1981), *Some Engel Curves*, In: The Theory and Measurement of Consumer Behaviour, A. Deaton ed. Cambridge, Cambridge University Press

[20] Hoddinott, J. and Skoufias, E. (2004), ‘The Impact of PROGRESA on food consumption’, *Economic Development and Cultural Change*, pp. 37-61

[21] Kapteyn, A., van de Geer, S., van de Stadt, H. and Wansbeek, T. (1989), Interdependent preferences: an econometric analysis, CentER Discussion paper no. 8954, Tilburg University

[22] Kuhn, P., Kooreman, P., Soetevent, A. and Kapteyn, A. (2011), ‘The Effects of Lottery Prizes on Winners and Their Neighbours: Evidence from the Dutch Postcode Lottery’, *American Economic Review*, 101, pp. 2226-2247

[23] Lalive, R. and Cattaneo, M.A. (2009), ‘Social Interactions and Schooling Decisions’, *Review of Economics and Statistics*, 91(3), pp. 457-77

[24] Manski, C.F. (1993), ‘Identification of Endogenous Social Effects: The Reflection Problem’, *Review of Economic Studies*, 60, pp. 531-542

[25] Pollak, R.A. and Wales, T.J. (1980), ‘Comparison of the Quadratic Expenditure System and Translog Demand Systems with Alternative Specifications of Demographic Effects’, *Econometrica*, 48 (3), pp. 595-612

[26] Skoufias, E., Davis, B. and Behrman, J. (1999), 'An Evaluation of the Selection of Beneficiary Households in the Education, Health and Nutrition Program (Progresa) of Mexico', Research Report prepared as part of the Progresa Evaluation Project of the International Food Policy Research Institute. International Food Policy Research Institute, Washington, D.C.

[27] Skoufias, E., Davis, B. and de la Vega, S. (2001), 'Targeting the Poor in Mexico: An Evaluation of the Selection of Households into Progresa', *World Development* 29, 1769-1984

[28] Stock, J.H. and Yogo, M. (2005), *Testing for Weak Instruments in IV Regression*, In: Identification and Inference for Econometric Models: A Festschrift in Honor of Thomas Rothenberg. Donald W. K. Andrews and James H. Stock, eds. Cambridge University Press, pp. 80-108

Appendix

Table 4: Demand system estimation for ineligible households (IV1)

	(1) Rice	(2) Corn	(3) Wheat	(4) Pulses	(5) Fruit and Vegetables	(6) Animal Products	(7) Other Foods
Average food expenditure/1000	**-0.0398** **(0.0245)**	**-0.110*** **(0.0622)**	**0.0909***** **(0.0218)**	**-0.139***** **(0.0482)**	**0.166***** **(0.0416)**	**0.109**** **(0.0466)**	**-0.116**** **(0.0588)**
Real food expenditure (ln)	0.00887 (0.0122)	0.0726 (0.0713)	0.0658*** (0.0204)	-0.102*** (0.0348)	-0.0835** (0.0415)	0.278*** (0.0604)	-0.302*** (0.0435)
Real food expenditure sq. (ln)	-0.00122 (0.00138)	-0.00279 (0.00789)	-0.00622*** (0.00228)	0.00775** (0.00368)	0.00538 (0.00447)	-0.0225*** (0.00664)	0.0276*** (0.00466)
Fraction of poor	-0.00172 (0.00424)	-0.0168 (0.0197)	0.0127** (0.00553)	0.00409 (0.0102)	0.00666 (0.00901)	0.00508 (0.0146)	-0.0241** (0.0126)
Price rice (ln)	0.0261*** (0.00914)	0.00446 (0.00529)	-0.00120 (0.00216)	-0.00922 (0.0103)	-0.00303 (0.00559)	0.00417 (0.00458)	-0.0144** (0.00609)
Price corn (ln)	0.00446 (0.00529)	0.0524*** (0.0201)	-0.0309*** (0.00672)	0.00416 (0.0146)	0.017 (0.0104)	0.0218 (0.0140)	-0.0795*** (0.0154)
Price wheat (ln)	-0.00120 '(0.00216)	-0.0309*** (0.00672)	0.00990*** (0.00278)	0.00774* (0.00494)	-0.0107** (0.00453)	0.00155 (0.00448)	0.00782 (0.00540)
Price pulses (ln)	-0.00922 (0.0103)	0.00416 (0.0146)	0.00774 (0.00494)	0.0380* (0.0213)	0.00716 (0.0132)	-0.0432*** (0.0107)	-0.0289** (0.0148)
Price fruit and vegetables (ln)	-0.00303 (0.00559)	0.017 (0.0104)	-0.0107** (0.00453)	0.00716 (0.0132)	-0.023 (0.0152)	-0.00188 (0.00834)	0.00834 (0.0130)
Price animal products (ln)	0.00417 (0.00458)	0.0218* (0.0140)	0.00155 (0.00458)	-0.0432*** (0.0107)	-0.00188 (0.00834)	0.0488*** (0.0138)	-0.0154 (0.0131)
Price other foods (ln)	-0.0144** (0.00609)	-0.0795*** (0.0154)	0.00782 (0.00540)	-0.0289** '(0.0148)	0.00834 (0.0130)	-0.0154 (0.0131)	0.117*** (0.0204)
Observations	3,875	3,875	3,875	3,875	3,875	3,875	3,875

*Bootstrapped standard errors in parentheses (99 replications), *** p<0.01, ** p<0.05, * p<0.1.
**Progresa data from the May 1999 wave is used. The dependent variables are the food budget shares of rice (1), corn (2), wheat (3), pulses (4), fruit and vegetable (5), animal products (6), and other foods (7). The equation for the category 'other starches' is excluded. Log prices are normalised by subtracting the log price of the 'other starches' category to impose homogeneity. Symmetry is imposed by including parameter restrictions. Average expenditure refers to the average expenditure of the other households within the same village. Age, sex and ethnicity of the household head, the household size (squared), and the number of young and old children in the household is additionally controlled for.

Table 5: Demand system estimation for ineligible households in treatment villages (IV2)

	(1) Rice	(2) Corn	(3) Wheat	(4) Pulses	(5) Fruit and Vegetables	(6) Animal Products	(7) Other Foods
Average food	**0.0427**	**0.0186**	**0.158*** **	**-0.385** **	**0.167** **	**0.258*** **	**-0.277** **
expenditure/1000	**(0.0663)**	**(0.143)**	**(0.0418)**	**(0.158)**	**(0.0778)**	**(0.0812)**	**(0.149)**
Real food	0.0416***	0.113	0.0786***	-0.150**	-0.107	0.319***	-0.346***
expenditure (ln)	(0.0138)	(0.0948)	(0.0281)	(0.0639)	(0.0658)	(0.0526)	(0.0655)
Real food	-0.00527***	-0.00888	-0.00843***	0.0151**	0.00848	-0.0288***	0.0344***
expenditure sq. (ln)	(0.00190)	(0.0103)	(0.00316)	(0.00754)	(0.00724)	(0.00582)	(0.00731)
Price rice (ln)	0.0375***	-0.0108	-0.00371	-0.0359**	0.000764	-0.00103	0.00634
	(0.00952)	(0.0183)	(0.00467)	(0.0165)	(0.0101)	(0.00911)	(0.0203)
Price corn (ln)	-0.0108	0.00218	-0.0535***	0.0693*	0.00823	-0.0209	-0.0138
	(0.0183)	(0.0343)	(0.0116)	(0.0418)	(0.0199)	(0.0255)	(0.0376)
Price wheat (ln)	-0.00371	-0.0535***	0.0113***	0.0124	-0.00237	-0.00299	0.0188**
	’(0.00467)	(0.0116)	(0.00414)	(0.0111)	(0.00700)	(0.00537)	(0.00943)
Price pulses (ln)	-0.0359**	0.0693*	0.0124	0.113**	-0.0237	-0.0472*	-0.0868**
	(0.0165)	(0.0418)	(0.0111)	(0.0518)	(0.0283)	(0.0244)	(0.0413)
Price fruit and	0.000764	0.00823	-0.00237	-0.0237	-0.0118	0.00913	0.00863
vegetables (ln)	(0.0101)	(0.0199)	(0.00700)	(0.0283)	(0.0230)	(0.0122)	(0.0208)
Price animal	-0.00103	-0.0209	-0.00299	-0.0472*	0.00913	0.0611***	0.00288
products (ln)	(0.00911)	(0.0255)	(0.00537)	(0.0244)	(0.0122)	(0.0209)	(0.0242)
Price other	0.00634	-0.0138	0.0188**	-0.0868**	0.00863	0.00288	0.0676
foods (ln)	(0.0203)	(0.0376)	(0.00943)	(0.0413)	(0.0208)	(0.0242)	(0.0414)
Observations	2,362	2,362	2,362	2,362	2,362	2,362	2,362

*Bootstrapped standard errors in parentheses (99 replications), *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
**Progresa data from the May 1999 wave is used. The dependent variables are the food budget shares of rice (1), corn (2), wheat (3), pulses (4), fruit and vegetable (5), animal products (6), and other foods (7). The equation for the category ’other starches’ is excluded. Log prices are normalised by subtracting the log price of the ’other starches’ category to impose homogeneity. Symmetry is imposed by including parameter restrictions. Average expenditure refers to the average expenditure of the other households within the same village. Age, sex and ethnicity of the household head, the household size (squared), and the number of young and old children in the household is additionally controlled for.

Table 6: Demand system estimation for ineligible households (IV3)

	(1) Rice	(2) Corn	(3) Wheat	(4) Pulses	(5) Fruit and Vegetables	(6) Animal Products	(7) Other Foods
Average food expenditure/1000	**-0.0379*** (0.0190)**	**-0.0995 (0.0859)**	**0.0918*** (0.0208)**	**-0.158*** (0.0509)**	**0.166*** (0.0462)**	**0.118** (0.0463)**	**-0.115* (0.0644)**
Real food expenditure (ln)	0.00911 (0.0115)	0.0743 (0.0635)	0.0660*** (0.0196)	-0.105*** (0.0326)	-0.0836** (0.0415)	0.279*** (0.0608)	-0.303*** (0.0468)
Real food expenditure sq. (ln)	-0.00126 (0.00128)	-0.00309 (0.00675)	-0.00625*** (0.00217)	0.00819** (0.00355)	0.00540 (0.00437)	-0.0228*** (0.00657)	0.0276*** (0.00503)
Fraction of poor	-0.00149 (0.00413)	-0.0157 (0.0219)	0.0128** (0.00575)	0.00212 (0.00994)	0.00674 (0.00854)	0.00596 (0.0199)	-0.0241* (0.0132)
Price rice (ln)	0.0265*** (0.00828)	0.00439 (0.00630)	-0.00139 (0.00217)	-0.0104 (0.0103)	-0.00262 (0.00613)	0.00392 (0.00565)	-0.0138** (0.00670)
Price corn (ln)	0.00439 (0.00630)	0.0490** (0.0207)	-0.0313*** (0.00646)	0.00773 (0.0153)	0.0177 (0.0110)	0.0190 (0.0145)	-0.0778*** (0.0181)
Price wheat (ln)	-0.00139 (0.00217)	-0.0313*** (0.00646)	0.00984*** (0.00333)	0.00837 (0.00542)	-0.0107*** (0.00403)	0.00115 (0.00494)	0.00805 (0.00578)
Price pulses (ln)	-0.0104 (0.0103)	0.00773 (0.0153)	0.00837 (0.00542)	0.0404 (0.0247)	0.00454 (0.0118)	-0.0406*** (0.0120)	-0.0336** (0.0144)
Price fruit and vegetables (ln)	-0.00262 (0.00613)	0.0177 (0.0110)	-0.0107*** (0.00403)	0.00454 (0.0118)	-0.0223* (0.0136)	-0.00141 (0.00906)	0.00896 (0.0127)
Price animal products (ln)	0.00392 (0.00565)	0.0190 (0.0145)	0.00115 (0.00494)	-0.0406*** (0.0120)	-0.00141 (0.00906)	0.0465*** (0.0152)	-0.0137 (0.0116)
Price other foods (ln)	-0.0138** (0.00670)	-0.0778*** (0.0181)	0.00805 (0.00578)	-0.0336** (0.0144)	0.00896 (0.0127)	-0.0137 (0.0116)	0.118*** (0.0230)
Observations	3,875	3,875	3,875	3,875	3,875	3,875	3,875

*Bootstrapped standard errors in parentheses (99 replications), *** p<0.01, ** p<0.05, * p<0.1.
**Progresa data from the May 1999 wave is used. The dependent variables are the food budget shares of rice (1), corn (2), wheat (3), pulses (4), fruit and vegetable (5), animal products (6), and other foods (7). The equation for the category 'other starches' is excluded. Log prices are normalised by subtracting the log price of the 'other starches' category to impose homogeneity. Symmetry is imposed by including parameter restrictions. Average expenditure refers to the average expenditure of the other households within the same village. Age, sex and ethnicity of the household head, the household size (squared), and the number of young and old children in the household is additionally controlled for.

Table 7: Demand system estimation for ineligible households in control villages (LS)

	(1) Rice	(2) Corn	(3) Wheat	(4) Pulses	(5) Fruit and Vegetables	(6) Animal Products	(7) Other Foods
Average food expenditure/1000	**0.0171*** (0.00568)**	**-0.139*** (0.0263)**	**0.0248** (0.00960)**	**0.0239* (0.0141)**	**0.0317** (0.0159)**	**0.0476* (0.0278)**	**-0.00836 (0.0180)**
Real food expenditure (ln)	-0.0200 (0.0217)	0.0432 (0.101)	0.0462 (0.0301)	-0.0538 (0.0464)	-0.0632 (0.0577)	0.234*** (0.0892)	-0.258*** (0.0878)
Real food expenditure sq. (ln)	0.000995 (0.00219)	0.00113 (0.0108)	-0.00310 (0.00328)	0.000927 (0.00492)	0.00385 (0.00608)	-0.0163* (0.00963)	0.0209** (0.00928)
Fraction of poor	0.00386 (0.00415)	-0.0437 (0.0288)	0.0102 (0.00875)	0.0340** (0.0140)	0.00964 (0.0112)	-0.000355 (0.0263)	-0.0298* (0.0168)
Price rice (ln)	0.0342*** (0.0109)	-0.00936** (0.00473)	-0.00518* (0.00295)	-0.0143 (0.0132)	0.0152** (0.00647)	-0.00734 (0.00503)	-0.00253 (0.00480)
Price corn (ln)	-0.00936** (0.00473)	0.0487** (0.0212)	-0.0183** (0.00736)	-0.0112 (0.0125)	0.0525*** (0.0111)	0.0393** (0.0167)	-0.116*** (0.0111)
Price wheat (ln)	-0.00518* (0.00295)	-0.0183** (0.00736)	0.0103*** (0.00391)	0.00798 (0.00727)	-0.0183*** (0.00560)	0.00889 (0.00677)	-0.00166 (0.00717)
Price pulses (ln)	-0.0143 (0.0132)	-0.0112 (0.0125)	0.00798 (0.00727)	-0.0586** (0.0284)	0.0387*** (0.0149)	-0.0246* (0.0142)	0.0207* (0.0118)
Price fruit and vegetables (ln)	0.0152** (0.00647)	0.0525*** (0.0111)	-0.0183*** (0.00560)	0.0387*** (0.0149)	-0.0590*** (0.0130)	0.00960 (0.00792)	-0.0262*** (0.0100)
Price animal products (ln)	-0.00734 (0.00503)	0.0393** (0.0167)	0.00889 (0.00677)	-0.0246* (0.0142)	0.00960 (0.00792)	0.00986 (0.0198)	-0.0148 (0.0131)
Price other foods (ln)	-0.00253 (0.00480)	-0.116*** (0.0111)	-0.00166 (0.00717)	0.0207* (0.0118)	-0.0262*** (0.0100)	-0.0148 (0.0131)	0.150*** (0.0155)
Observations	1,513	1,513	1,513	1,513	1,513	1,513	1,513

*Bootstrapped standard errors in parentheses (99 replications), *** p<0.01, ** p<0.05, * p<0.1.
**Progresa data from the May 1999 wave is used. The dependent variables are the food budget shares of rice (1), corn (2), wheat (3), pulses (4), fruit and vegetable (5), animal products (6), and other foods (7). The equation for the category 'other starches' is excluded. Log prices are normalised by subtracting the log price of the 'other starches' category to impose homogeneity. Symmetry is imposed by including parameter restrictions. Average expenditure refers to the average expenditure of the other households within the same village. Age, sex and ethnicity of the household head, the household size (squared), and the number of young and old children in the household is additionally controlled for.