Nutrition and Child Care Choices

Evaluating a Community Nursery Programme in Rural Colombia*

Orazio P. Attanasio♣ and Marcos Vera-Hernández♦

November 2004, Revised March 2007

Abstract

We evaluate the effects of a large nutrition programme in rural Colombia. The intervention we study is a community nursery programme that provides nutrition and child care for the children of poor households. In the first part of the paper, we use an Instrumental Variable approach to estimate the impacts of the programme on children's nutritional status and female employment. In the second part, we frame these results within a model in which the community nurseries are seen as an input in the production function of human capital that poor households can choose along side other inputs. The theoretical framework serves several purposes. First, it justifies the use of the specific instrument we use. Second, it provides an interpretation for the results we obtain. With the help of the model we point out that, because some of the alternative inputs in the process of human capital accumulation might be unobserved, we need relatively strong assumption to give our impact estimates a sensible interpretation, even when the instruments we use are 'exogenous'. We find that the programme has very large and positive impacts. Dealing with the endogeneity of treatment is crucial, as the children with otherwise worse nutritional status tend to select into the programme. We also validate our evaluation strategy by considering the effect of the programme on pre-intervention variables. Further, we explore the heterogeneity of the impact of the programme. Finally, our structural estimates show that the programme has important direct effects, over and above the indirect effects that might arise through the large effects observed on female employment.

JEL: C21, I12, I38

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* We are very grateful to Erich Battistin, Jere Behrman, Samuel Berlinski, Tim Besley, Pedro Carneiro, Emla Fitzsimons, Luis Carlos Gomez, Alejandro Gaviria, Beatriz Londoño, Costas Meghir, Jairo Nuñez, Aureo de Paula, Adam Rosen, Mark Rosenzweig, Jim Smith, Petra Todd and seminar audiences at LSE and UCL development seminar, Stanford, Universidad de Los Andes (Bogotá), INRA (Paris), University of Toulouse, CEMFI, the World Bank, the London School of Hygiene and Tropical Medicine, Yale, Rand and UCLA, the 8th World Congress, the Bocconi-Penn conference and the Policy Evaluation workshop in Seville for many useful comments and suggestions. We are particularly grateful to the staff of *Instituto Colombiano de Bienestar Familiar (*ICBF), including Maria Francisca Concha, Ana Maria Peñuela and Yaneth Romero, for answering many questions about the details of the programme *Hogares Comunitario* programme. The authors acknowledge financial support from the Economic and Social Research Council - Department for International Development 2006-2009, Grant reference Number RES-167-25-0124 "Human Capital Accumulation and Poverty Reduction in Developing Countries". Finally, the extremely useful comments of the editor and four anonymous referees are gratefully acknowledged.

♣ UCL, IFS and NBER

♦ UCL, and IFS

1. Introduction

Malnutrition is a dramatic problem in developing countries. According to Onis *et al.* (2000) about one third of children less than five years old are stunted in growth. There is evidence that inadequate nutrition affects educational attainment (Behrman 1996, Strauss and Thomas 1998, Glewwe *et al.* 2001, Maluccio *et al.* 2006) which then affects productivity later in life (Strauss and Thomas 1998, Schultz 2005, and Maluccio *et al.* 2006). A recent review by Walker *et al* 2007 identifies stunting, inadequate cognitive stimulation, iodine deficiency, and iron deficiency anaemia as the four key risk factors where the need for intervention is urgent to prevent children living in developing countries from not achieving their development potential.

Because of the importance of malnutrition, several different types of nutritional programmes have been proposed in the developing world and have received considerable attention in recent years. Given the scarcity of resources and the abundance of different interventions, it is crucial to understand what interventions work, where they work and, most importantly, how they work.

Some interventions have been evaluated. A programme providing a nutritional supplement in Guatemala has been shown to have effects both in the short run nutritional status of children and in the long run on the same individuals as they become adults (Martorell *et al.* 1995; Maluccio *et al.* 2006). Conditional Cash Transfer (CCT) programmes provide mothers with cash transfers if their young children are kept up to date with vaccines and preventive health care visits. The Mexican CCT programme, PROGRESA, was shown to have an effect on the height of children younger than 12 months (Rivera *et al.* 2004) as well as in children aged 12 to 36 months (see Behrman and Hoddinott, 2005; Gertler 2004). The Colombian CCT programme, *Familias en Acción*, increased the height of children aged 0 to 2 years old living in rural areas, but had limited effects on older children or on all children living in the urban centres of the municipalities targeted by the programme (Attanasio *et al.* 2005). On the other hand, the Brazilian CCT programme failed to improve children nutritional status (Morris *et al.* 2004). In this paper, we analyze the *HC* programme that is very different from both nutritional supplementation and CCT programmes regarding both the channels through which the programme affects nutritional status as well as the motivation that drives mothers to enrol their children in the programme. In the survey that we use in this paper, almost half of the mothers of children below 5 years old report that their child is not enrolled in the *HC* programme because there is someone at home that can take care of the child. This indicates that looking for childcare could be one of the reasons why mothers enrol their children into the programme. Consequently, the effects of the programme on labour supply are potentially important as well as the effects that labour supply might have on child nutrition. More generally, the heterogeneity of the results obtained in the evaluations that exist stresses the need to go beyond the simple impact evaluation and study the mechanisms through which a programme operates.

The contribution of this paper is twofold. First, we estimate the impact of a large nutrition programme in rural Colombia, called *Hogares Comunitarios de Bienestar Familiar (HC* from now on*)*. This is a large intervention based on community nurseries where poor children receive food (purchased by the government) and child care from one of the mothers in the community. We want to measure the effects of this programme on the nutritional status of young children, as well as on female employment. The focus of our analysis is ultimately on the nutritional status of children. However, we also study the effect of the programme on female employment because the programme, in addition to food, provides childcare, which might allow some women to work. The explicit consideration of the programme effect on female employment will allow us to shed light on the mechanisms through which the programme affects child nutritional status.

These considerations bring us to the second contribution of our paper, which is to use a structural model to interpret our impact estimates, shed light on the mechanisms through which the programme operates, and inform our empirical analysis. In our model, *HC* participation is seen as an input of a production function for nutritional status, as in Rosenzweig and Schultz (1983) and, more recently, Todd and Wolpin (2003). This approach allows us both to justify the use of specific instruments, to state the conditions under which a standard Instrumental Variable strategy is valid and to suggest an alternative empirical strategy should some of these conditions fail. We extend Rosenzweig and Schutz (1983) in that we consider the case in which some important inputs are not observed in the data. In such a situation, we show that even if the chosen instrument is distributed across households independently of other individual and household characteristics, individual choices of input mixes could induce important biases in the results. The importance of this finding extends more generally to other situations where the cost of participating in a programme is used as an instrument for participation in the program.

Although several programmes similar to *HC* exist, we are aware of only two studies that analyze their effects. They both compare children who attend a nursery to children who do not, using a matching approach, that is, trying to control for a large number of observable characteristics. Behrman, Cheng and Todd (2003) study a programme in Bolivia called PIDI. This study is particularly relevant for us because PIDI is remarkably similar to *HC*. These authors show that, given the assumption of selection on observables, the programme has no positive effect on child height. Conditional on participation, however, they find some moderate positive effect of length of exposure. Ruel *et al.* (2000) study a programme very similar to *Hogares Comunitarios*, implemented in Guatemala City. They follow a "case study" methodology that only included 250 participant children and find that participant children consume 20% more calories than non participants.

The impact evaluation approach taken in this paper is different from that used in these papers, as it is based on an IV approach rather than on matching. We exploit a large and high quality data base recently collected to evaluate *Familias en Acción*, a programme introduced by the Colombian government in 2001.[1] In particular, we use information on the children living in the towns where the new programme did not operate to evaluate the effect of *HC*. In all these towns the *HC* has been available for some time. We estimate its effects by comparing children who attend (or have attended) *HC* to children who do not. Here we follow a standard IV approach and identify variables (fees, distance to the HC nursery) that are important determinants of participation to *HC* and yet, plausibly, do not have a direct effect on children's nutritional status, especially if we control for other 'location' variables. As always, this type of assumption is debatable: in what follows we discuss it at length and present several arguments and pieces of evidence to justify it in our context. We find that the programme has important effects on the nutritional status of young children. We also find important effects on female labour supply.

In the second part of the paper, we introduce a structural model where households make investment choices. Attendance to one *HC* is a possible input available to households to develop their children's human capital. Other inputs are available, like food and maternal child care, and other variables are chosen simultaneously by the household, like female labour supply and overall consumption. We show that the identification strategy implied by the standard instrumental variable approach that we take the first part of the paper is valid

[1] The data are publicly available at http://www.dnp.gov.co/paginas_detalle.aspx?idp=760

only under specific assumptions on the utility function and, possibly, the production function of nutritional status. The model leads us to estimate a more complete empirical specification where we allow for the effect of food and female labour supply on the development of human capital. When we estimate this more complex model, we find that the HC programme has a direct effect on child nutrition over and above the effects mediated by changes in female labour supply.

From a substantive point of view, the results we present are relevant in the context of the recent literature that highlights the importance of early child development (see for instance Currie 2001, Heckman and Masterov, 2005 and Grantham-McGregor *et al.* 2007). It is argued that early childhood is the most cost effective period in a person's life to invest (Carneiro, P. and Heckman, J. 2005a; Heckman and Masterov 2005; Engle *et al.* 2007). Evaluations of the Head Start programme in the US have shown that large scale pre-school programs can have impacts on later educational attainment (Currie and Thomas 1995 and 1999; Garces, Thomas, and Currie 2002). Our work is also related to different types of interventions that influence female labour supply in the developing world (Field 2006; Berlisnki and Galiani 2005). The programme that we analyze is targeted towards the poorest children. This is important as recent research has shown that the targeting of an intervention is very important for its success (Banerjee *et al*. 2006; Glewwe, Kremer and Sylvie 2006).

The rest of the paper is organized as follows. In Section 2, we describe the operation of the programme. In Section 3, we present the data we use and some descriptive statistics. Section 4 presents the results of our IV based impact evaluation. We discuss at length the robustness of these results and the plausibility of our identification assumptions. We also test for heterogeneous effects of the program. In section 5 we present a model of human capital accumulation where *HC* is one of many inputs in a production function. In Section 6, we present some additional empirical evidence based on the model developed in Section 5 and interpret our previous results in the light of the model and the additional evidence. Section 7 concludes. The definitions of control variables and the full set of results are relegated to the Appendix.

2. The *Hogares Comunitarios* programme

In the late 1970s, the Colombian government legislated a new nutrition intervention targeted towards poor families. The programme, called *Hogares Comunitarios de Bienestar Familiar,* was legislated in 1979 as the development of previous initiatives that focussed on community participation and initiatives to target nutrition and child development.

At the beginning of the programme, which started between 1984 and 1986 and is run by the *Instituto Colombiano de Bienestar Familiar (ICBF)*, the ICBF regional office targeted poor neighbourhoods and localities and encouraged eligible parents with children aged 0 to 6 to form 'parents associations'. Households belonging to the so called SISBEN levels 1 to 3 can participate.[2] After a few meetings with programme officials, the parents association was registered with the programme and elected a *madre comunitaria* (or community mother). This mother had to satisfy some criteria, such as having basic education and a large enough house and would be certified by the regional office of the ICBF. The *madre comunitaria* would then receive in her house the children aged 0 to 6 of the parents belonging to the associations. Each family would pay a small monthly fee (roughly the equivalent of four US dollars), which would be used to pay a small salary to the *madre comunitaria.* Each *madre* would receive up to 15 children. The average number of children is around 12. The parents association would then receive funds from the government to purchase food. The food would be delivered weekly at the house of the *madre comunitaria* who would keep it in her fridge. The menu varies regionally and is established by a nutritionist in the regional office of ICBF. In addition to the food included in the regional menu, the children would also be given a nutritional beverage called *bienestarina.* Children are fed three times daily: lunch and two snacks. According to ICBF, the food received by the children (including the beverage) would provide them with 70% of the recommended daily amount of calories.

Therefore, in exchange for the small monthly fee, the parents would obtain child care and some food for the children. The programme objectives included the improvement of the

[2] In Colombia most welfare programs are targeted through the SISBEN indicator. This indicator is computed using a number of different indicators of economic well-being. SISBEN is constructed on the basis of an index that is the first principal component of a number of variables related to poverty. Depending on the value of the index, each household is assigned to one of six levels. Information on the variables used in the construction of SISBEN is collected periodically. For most welfare programs, only households belonging to level 1 and 2 are deemed eligible. FA households are in SISBEN 1.

nutritional status of poor children as well as the provision of child care that could stimulate labour force participation of women and the generation of additional income.

The program, whose cost is financed with a 3% tax on the wage bill, expanded very rapidly in Colombia. It is now the largest welfare programme in the country: there are roughly 80,000 HC across the country and more than a million children that attend one. The cost of the programme is approximately 250 million US$, or almost 0.2% of GDP.

As we discuss below, the location of the *HC* plays an important role in our identification strategy. After the start of the programme and its rapid growth, the turnover among the *madre comunitarias* was substantial. According to officials of the ICBF, between 10 and 15% of the existing *HC* are relocated in each year, in that a *madre comunitaria* ceases to be such and a new *madre* starts to operate it. Moreover, if a household moves to a certain neighbourhood, it can normally register its children in an existing *HC*. It seems that over time, the *HC* have evolved into relatively mobile and informal nurseries and have lost some of the tight connection with the original parents association. In rural and very dispersed areas, an apparently common problem is the difficulty to set up a new *HC* because the ICBF does not register new *HC's* unless there are a sufficient number of children that want to attend. This 'integer' constraint seems to be binding in many communities.

3. The data

The data we use in this paper were collected to evaluate *Familias en Acción,* a new welfare programme perceived as an alternative to *Hogares Comunitarios*. For this reason, the sample we use is concentrated in a certain type of community. In this section we first describe the nature of the data set and then present some descriptive statistics of the sample.

3.1. The Familias en Acción programme and the evaluation database.

Between 2001 and 2002, the Colombian government started a conditional cash transfer programme in towns with less than 100,000 inhabitants, modelled after the PROGRESA programme in Mexico and financed with a loan from the World Bank and the Inter American Development Bank. This program, called *Familias en Acción* (FA from now on) has an education, and a health component and is directed to the poorest families living in the municipalities targeted by the program. As in the case of PROGRESA, the targeting of the programme is first done at the community level and then, within the chosen communities, at the individual level. The targeted communities were chosen on the basis of several criteria. First, they had to be relatively small towns (less than 100,000 inhabitants and no departmental capitals). Moreover, given that *FA* is a conditional cash transfer program, a town could be included only if it had enough education and health infrastructure. Finally, for security reasons in delivering the payments, the presence of a bank in the municipality was also a condition for qualifying.[3] At the individual level, the programme was targeted to households with children aged 0 to 17 belonging to the lowest level of the so called SISBEN index (see footnote 1).

The nutrition component of *FA* consists of a cash subsidy that is given to the mother of children aged 0 to 6 living in beneficiary households. The subsidy is about 15 US dollars per month and is conditional on certain behaviours. Clearly such a programme is very different from *Hogares Comunitarios* and, indeed, is widely perceived as a substitute for it. While *HC* provides childcare, in-kind transfers and up to a certain extent nutritional insurance, *FA* relies on monetary transfers conditional on visits to health care professionals. Moreover, in the targeted municipalities, households entitled to the nutrition component of *FA* have to choose between that programme and *HC,* in that they cannot send their children to an *HC* if they register for *FA*.

When the *FA* programme started, the government commissioned a large scale evaluation of its impact. A large data collection project was undertaken in 122 municipalities, 57 of which were targeted by the programme. The remaining 65 were chosen as 'comparison town'. While the assignment of the programme to municipalities was not random, the comparison towns were chosen so be as similar as possible to the random sample of 57 'treatment' municipality. In practice, most of the comparison towns satisfy most of the conditions imposed by the programme with the exception of the bank presence.[4] The first wave of data was collected in the summer of 2002. The same households were interviewed twice more: the second wave was collected between July and November 2003, while the third took place

[3] An additional condition (that turned out to be binding in some situations) was that the mayoral office had to process some documents and have a list of potential beneficiaries ready.

[4] The municipalities were classified in 25 strata according to geographical region, population size living in the urban part of the municipality, the value of synthetic index for quality of life (QLI) as well as education and health infrastructure. Two treatment municipalities were randomly selected within each stratum among the municipalities participating in *Familias en Acción*. For each treatment municipality, a control municipality was chosen as the most similar to the treatment municipality in terms of population size, population living in the urban part of the municipality, and QLI among the set of municipalities not participating in *Familias en Acción* but belonging to the same stratum than the treatment municipality.

between December 2005 and March 2006. Attrition rates were reasonable low (6% between the first and second wave and an additional 10% in the third wave).

The households included in the survey had to satisfy the eligibility rules of *Familias en Acción,* that is they had to be registered as SISBEN 1 as of December 1999 and have children aged 0 to 17. This implies that our sample is representative of the poorest households in small towns. In addition to a very large number of questions covering consumption, income, school attendance, labour supply and a variety of other variables, every child aged 0 to 6 was weighed and measured. The questionnaire included a number of questions about current and past attendance of each child to a *HC*. In particular, for each child, we know whether he or she is currently attending a *HC*, and, for each year of the child's life, how many months he or she had attended a *HC*. Finally, and importantly for our identification strategy, if a child is attending a HC centre, we know the distance from the household to the HC centre. If the child is not attending a HC centre, we know the distance to the nearest *HC*. For each child that has ever attended a *HC* centre, we also ask for the fee that they currently pay or that they used to pay when they attended. We also know at what ages they attended a *HC* centre.

As we are interested in evaluating the impact of the *HC* programme and we want to avoid contaminations by the new programme (*FA*), in what follows we focus on the towns where *Familias en Acción* was not implemented. In the first and second wave, there are 65 municipalities where FA was not implemented. Between the second and third wave of data, the FA programme started in 13 municipalities that were part of the comparison group in the first and second wave. So, only 52 municipalities are used in the third wave of data. As a consequence the third wave includes considerably less children than the first two.

The fee paid for attending a *HC* centre and municipality wages as reported by the town major were collected in the second and third wave of data but not in the first one. For the first wave, we use the values collected in the second wave. We do not think that this is a major problem as the first and second wave were collected only 12 months apart. The distance to the health centre and school was collected for the whole sample in the second and third wave, but only for users of these services in the first wave. Using only observations with non missing information in the distance to the health centre and school in the first wave would select the sample according to our outcome of interest, which we want to avoid. Consequently, for the first wave of data, we use distance to the health centre, and school collected in the second wave of data. However, in the first wave, we do not use 384 children whose household moved between the first and second wave of data as the distance to the nearest school and health centre might have changed. Note however that we obtain very similar results if we include these 384 children and use, for the first wave, the distance to the nearest school and health centre measured in the second wave.

3.2. Descriptive Statistics.

Here we provide some basic information about our sample. More descriptive statistics are provided in Table B1 of Appendix B. The towns in our sample are reasonably small: the average (median) population in 2001 was 25k (20k) and even the town at the 75^{th}% percentile had less than 30k inhabitants. However, the area over which these municipalities extend is at times substantial: the average size in square kilometres is 674. Typically, there is a substantial fraction of the population that lives in the so called 'cabecera municipal' (the main town) (the average is 14k) while the rest is dispersed in the country side.

The population of our sample is very poor. The average family size is 7. Average consumption is about 114 US dollars per month, which includes our estimates for consumption of food produced or acquired as remuneration of work.[5,6] The average share of food consumption in total consumption is 73%. The education level of household heads and spouses is very low: in our sample, 15% of the children have a mother with no education.

Following the literature, we do not use height directly, but we construct the so-called z-scores for these variables standardizing them by age and sex according to the World Health Organization/Centre for Disease and Control (WHO/CDC) reference population.[7] In particular, the z-score for height per age is obtained from the height of a child, subtracting the median height of the WHO/CDC reference population of the same age and gender and dividing by the standard deviation of height of the WHO/CDC reference population of the same age and gender. Acceptable values of the z-scores range from -6 to 6. Chronic malnourishment in children is typically defined in terms of height per age. A child is defined

[5] The data base contains information on the quantities of 98 types of food consumed and on prices of each of these commodities at the town level.

[6] According to the 2003 Quality Life Survey, the average consumption in Colombia is $432, excluding consumption in kind.

[7] This reference population is mostly formed by the population of children living in the US in 1975. At the moment this is the reference population most widely used. The World Health Organization is working on a project to build a true international reference population.

as 'chronically malnourished' if is her or his Z-score for height per age is less than -2 standard deviations from the median of the WHO/CDC reference population of the children of the same age and gender.

The children in our sample have a deficit in height. The average height is -1.25 while it should be zero in a healthy sample. Moreover, 23.80% of children are chronically malnourished. However, they do not have a deficit of weight for the height nor problem of obesity.[8] This is why we focus our paper on the impact of the programme on child height which is an indicator of long run nutritional status.

Table 3.1

Percentage of children attending *Hogares Comunitarios*

Age	Girls	Boys
0	3	4
1	21	16
2	39	47
3	46	44
4	36	34
5	16	21
6	7	8

In Table 3.1 we report the percentage of children who attend a *HC*. Two features are worth stressing. First, attendance rates have an inverted U shape, being highest at age 3. They are particularly low for very young children. Second, the programme does not seem to be extremely popular. Even for age 3 children, attendance rates do not achieve 50%.

For each child that does not attend an *HC* we ask the main reason for not attending. In Table 3.2, we report the percentages reporting a specific reason, for different age groups. The most popular reason for not attending is the availability of child care at home. As to be expected, this is particularly relevant for the youngest children. For the oldest children, the importance of the 'other' reasons is explained by the fact that a significant proportion of these children are in school. Interestingly for our analysis, the distance from the nearest *HC*

[8] The percentage of children acutely malnourished –their weight is too low for their height- is only 1.33%. The percentage of obese children is 1.87%.

and the fee that has to be paid to attend a HC centre appear as important reasons for not attending a *HC*.

Table 3.2

Main Reason for not attending a *HC*

	Age: 0-1	Age:2-4	Age:5-6
Available caregiver at home	63%	39%	16%
No *Hogar* or too far away	16%	26%	13%
Cannot afford fee	4%	8%	3%
Does not like food	1%	4%	3%
Other	16%	23%	65%

4. The impact of *Hogares Comunitarios*

Although the *HC* programme is the largest welfare programme in Colombia, it has barely been studied. Besides some early internal studies, which considered mainly the operation of the program, the only attempt at measuring the effect of the programme was Siabato *et al* (1997) an internal study that used a relatively large survey designed for the explicit purpose of evaluating the *HC* programme. However, that study only measured children that were attending a *HC* centre. No measurements were taken of children not attending the programme. While the study provides a wealth of useful statistics and observations about the children and the *madres comunitarias,* the basic (and implicit) evaluation strategy is to compare the anthropometric measures of *HC* children with those of children of *similar socio-economic background* (observed in other surveys). The most striking observation was that participant children's standardized height was worse than in children with 'similar socio-economic background'.

In this section, we estimate the impact of *HC* using a standard impact evaluation approach. We focus on the nutritional status of children, as measured by their standardized height per age. We also consider other outcomes that could be affected by the program, such as female labour supply. As we discuss below formally, these impacts can be informative about the mechanisms through which the programme might be operating.

Like in the evaluation of most social interventions, the fact that a programme is not assigned randomly, can create substantial problems. A comparison of children attending a *HC* to children not attending one, even if we control for observed characteristics, can yield very misleading results as it ignores the endogeneity of the participation decisions: the children whose parents decide to send to a *HC,* are in all likelihood very different from the children that are not sent to a *HC*.

This section, which is a prelude to the structural analysis that follows, takes the standard programme evaluation approach to estimate how much child's height (or female labour supply) changes in average due to exposure to the *HC* program. Here, we do not make explicit any economic model. However, rather than using a matching approach to the estimation of the impact, we use instrumental variables, implicitly assuming a model of participation to the program. Thus we estimate the following equation

$$H_i = \beta' q_i + \gamma A_i + u_i \tag{1}$$

where H_i is child's height, q_i is a vector of exogenous covariates, A_i is a treatment variable, and u_i is an error term, probably correlated with A_i. We consider several alternative definitions of 'treatment'. First, for children younger than 6, we define treatment on the basis of current attendance to a *HC*. However, we also define what we label as 'exposure' as the number of months in which the child has attended a *HC* between ages 0 and 6 divided by the child's age in months, therefore defining treatment as the fraction of his or her life spent in a *HC*. This indicator considers the intensity of treatment as in Angrist and Imbens (1995). In the case of female labour supply, we define a mother as 'treated' if she has at least one of her children attending a *HC*.

As instruments we consider variables that affect the availability and cost of the *HC* and that can be assumed as exogenous to the household: the distance from the household to the nearest *HC* nursery,[9] and the median fee paid in the municipality to attend a *HC* nursery. Identification is based on the exclusion restrictions that state that the instrumental variables are uncorrelated with the residuals of equation (1). As is often the case, these assumptions

[9] Distance to college has been used as an instrument for schooling by Card (1993), Kling (2001), and Cameron and Taber (2004).

can be questioned. In section 4.4 below, we discuss our identification strategy in detail. In Section 5 we discuss a model that can give rise to equation (1) and that would justify our estimation strategy.

The sample includes several children from the same household, different households from the same municipality, and the same children and households might be observed at different waves. The standard errors are clustered at the municipality level, which allows for arbitrary intra-cluster dependence and arbitrary heteroskedasticity (see Pepper 2002).

We start our analysis of the impact of *HC* from the first stage regressions that model the take-up of the programme. We then present the results on the effect of the programme on child's height. We conclude this section by discussing the robustness of our identification strategy and with a test for heterogeneous effects.

4.1. *First stage regressions*

We start by reporting, in Table 4.1, some of the statistics of the distribution of travel distances to the nearest *HC* and the median monthly fee paid in the municipality to attend a HC centre. As can be seen there is a substantial amount of variation in distances, especially in rural areas. [10] In urban areas, however, the variation is much more limited. As expected, participants tend to live close to HC centres and live in municipalities with lower fees.

We report the results of the first stage for exposure and attendance in Table 4.2. As mentioned above we use two sets of instruments. First, for each child, regardless of whether he or she attends a *HC*, we consider the distance to the nearest *HC* from the child's household residence in minutes and its square. We use both the distance in the current wave as well as the distance in the first wave of data. Past distance is correlated with exposure as well as with current attendance, due to probably some inertia in the participation decision. Second, in each town, we compute the median fee paid to participate in a *HC* nursery.[11] Again we consider both the level and the square of this variable.

[10] Distance is commonly measured in time in Colombia. In the third wave of the survey we asked respondents how they travel (or would travel) to the nearest HC. 87% of the respondents stated by walking.

[11] The average fee paid is computed using the fee that participants currently pay as well as the fee that used to be paid by children that were enrolled in the past. This question is only available for the second and third wave of data. Exchange rate of 2600 peso to the US dollar. Average per capita household consumption in our sample is 83427 Colombian pesos.

Table 4.1
Distribution of Excluded Variables

	Entire sample				Participants in the HC program			
	Travel distance in minutes from the household to the nearest HC centre			Median monthly fee. Colombian pesos	Travel distance in minutes from the household to the nearest HC centre			Median monthly fee. Colombian pesos
	All	Rural	Urban		All	Rural	Urban	
25th percentile	5	5	3	1650	3	3	3	1000
Median	10	20	5	3000	5	5	5	3000
Mean	23	38	9	3807	10	13	9	3008
75th percentile	30	60	10	5254	15	15	10	4000

Table 4.2
First stage regression results

	Exposure	Attendance
Distance in the first wave	-0.156 (0.034)	-0.197 (0.060)
(Distance in the first wave)^2.	0.053 (0.013)	0.076 (0.023)
Distance in current wave	-0.121 (0.029)	-0.264 (0.058)
(Distance in current wave)^2.	0.041 (0.012)	0.076 (0.024)
Median fee	-0.027 (0.009)	-0.028 (0.013)
(Median fee) ^2	0.001 (0.0005)	0.001 (0.001)
F-statistic for distance [P-Value]	14.30 [0.000]	14.43 [0.000]
F-statistic for Fee [P-Value]	7.21 [0.002]	4.34 [0.018]
F-stat. for Distance and Fee [P-Value]	16.83 [0.000]	1426 [0.000]
N1	2409	2445
N2	2450	2502
N3	972	974

Standard errors in parentheses are clustered at the town level. P-values are reported in square brackets

These results are consistent with those reported in Table 3.2 on the self-reported reasons not to attend a *HC* nursery: "being too far away" was the second most important reason not to attend, and "cannot afford the fee" the third. We find that the distance from the household to the HC nursery is a very important determinant of both attendance and exposure. The average fee paid in the municipality is also an important determinant of our two definitions of treatment. The F-statistics for distance are high enough to rule out a problem of weak instruments. The F-statistic for the average fee is also strongly statistically significant for exposure. For attendance, the fee and its square term are statistically significant different from zero at the 5% level, although this F-statistic (4.34) is the lowest. Consequently, the results for attendance that use only the fee as an instrument must be interpreted with caution.

4.2. The effect of the programme on children's height

In Table 4.3, we present our 2SLS estimates of equation (1), using the distance to the nearest HC nursery and the average fee in the municipality as variables omitted from the vector of covariates q_i. The left hand side of equation (1) is the Z-score for height per age. While in the Table we report only the estimates of the programme's impacts, the vector q_i include a large set of covariates at the individual, household, and community level. In particular, as mentioned above, we include distance from the household to the nearest school, and nearest health centre. The full results of the regressions are given in Appendix B.

Table 4.3
Effect of HC on height per age

	OLS	IV: Distance and Fee	IV: Distance	IV: Fee
Exposure	-0.001 (0.083)	0.897 (0.394)	0.924 (0.541)	0.764 (0.597)
Attendance	-0.090 (0.041)	0.590 (0.256)	0.535 (0.306)	0.749 (0.532)

Standard errors in parentheses are clustered at the town level. P- values for over-identification restriction test is 0.43 for Exposure and 0.27 for Attendance

The OLS estimates are negative and the one for attendance is statistically different from zero. On the other hand, the IV estimates are always positive and statistically different from zero at the 5% when both instruments are used.[12] If only distance is used as an instrument, the estimates are statistically different from zero at the 10%. The effects we report are large. Current attendance is estimated to have an effect of 0.59 standard deviations on the Z-score. This effect corresponds to 2.86 centimetres for a boy (2.90 for a girl) aged 72 months.[13]

The fact that the OLS estimates are negative is an interesting result in its own right. This piece of evidence is consistent with the evidence from the internal study done by Siabato *et al.* (1997) previously mentioned, which found that children attending *HC* were shorter than children of 'similar socio-economic background'. The negative bias of the OLS estimates relative to the IV ones is consistent with self-selection into the programme by those individuals with poor nutritional status. This might indicate that the programme is well targeted, in that the households most in need seem to self-select as *HC* customers.

As we mentioned above, all specifications include a large set of controls, including the distance from the household to the health centre, and school, as well as town level variables. The reason for our un-parsimonious specification of this respect is our worry that our instruments could capture some unobserved feature of the environment where the households live and have a direct effect on the outcome of interest. While such an identification assumption is clearly un-testable, we will provide indirect evidence of the validity of our approach in section 4.4.

4.3. Female labour supply

In Table 4.4, we report our estimates of the effect of the programme on female employment rate. This might be important, as the childcare aspect of the programme could allow mothers to work and earn additional resources that might benefit the child. In particular, we estimate the effect of the programme on the probability that mothers work in the week prior to the interview. We define a treatment dummy variable that takes value one if the mother has at least one child currently attending *HC,* and takes value zero otherwise. The Table reports the results obtained by using a simple Probit, which ignores the endonegeity of the treatment. In

[12] We also tried to include a square term in exposure but the P-value of the hypothesis that the estimate is different from zero is 0.91.

[13] The standard deviation of height in the reference population for a boy aged 72 months is 4.8573 cms and 4.917 for a girl.

the third column, instead, treatment is modelled jointly with employment using a Bivariate Probit. Consistent with our IV strategy, the distance variable and the average fee in the municipality enter the participation decision, but not the labour supply equation.[14] We find that the programme increases by 0.31 the average probability that mothers work in the week previous to the interview.[15]

Table 4.4
Effect of HC on the probability to work in the week previous to the interview

	Probit	Bivariate Probit
Current attendance dummy variable	0.327	0.813
	(0.056)	(0.242)
Change in the average probability of working due to participating the program	0.116	0.31
N. 1st wave	1495	
N. 2nd wave	1544	
N. 3rd wave	642	

Standard errors in parentheses are clustered at the town level.

4.4. Is the identification strategy credible?

The credibility of the results we present relies on the plausibility of our instruments as exogenous variables that determine participation but are not related directly to nutritional outcomes. In the next section we discuss a model that delivers these predictions. In this section, we present some evidence that justifies our identifying strategy.

There are several reasons why the distance from the nearest *HC* centre could be considered endogenous to the outcome of interest: (i) individual households who care about their children needs or need more help could locate closer to a *HC* centre; (ii) the households who live near a *HC* centre could be systematically different from those who live far for other

[14] A Bivariate Probit model requires that both the participation and outcome equation are correctly specified. That is why we include both instruments jointly, and we do not report results with each instrument separately.

[15] In order to compute the change in probability, we average across the sample the difference in the predicted probability of working if the treatment variable takes value 1 and if the treatment variable takes value 0.

reasons; (iii) the allocation of the programme across areas could reflect an attempt by the central government to target areas most in need. We analyze each of these issues in turn.

Table 4.5.
Results of regression of distance to the nearest HC centre (minutes)

	Without additional covariates	With distance to other facilities as covariates
Moved (1 if household moved address, 0 otherwise)	-2.20 (1.86)	0.453 (1.511)

Sample size is 3095. Standard errors shown in parenthesis are clustered at the town level

(i) Given the evolution of the *HC* programme, we believe that the distance from the household to the nearest HC is a good instrument. First, conversations with programme officials indicated that, especially in isolated rural areas, which make up a substantial proportion of our sample, there might be severe supply restrictions induced by the need of a minimum number of children for ICBF to register a new *HC*. Moreover, after the first few years of the program, the turn over of *madres comunitarias,* induced by a variety of factors, contributed to substantially weaken the link between the original parent association and the location of the *HC.*[16] It seems that many of the current clients of *HC* are households that move to a given neighborhood and access an existing *HC*. Second, we can provide evidence that households do not move with the purpose to be closer to a HC. Those households that moved location between two consecutive waves but were found and interviewed were asked the reason for changing address. Although 'moving closer to a HC' was explicitly listed as a possible reason to move, only one of the 596 households that moved chose it as an answer.[17] Moreover, comparing the distance from the nearest HC for the movers and those who did not move, (which is done in Table 4.5 conditionally and unconditionally), we do not find any statistically significant difference. Finally, among the households who moved, we compare

[16] It is possible that the quality of the new HC available in a place is related to the density of children in need of a *HC*. This would be reflected in heterogeneity of impacts, which we investigate below.

[17] Responses to the reasons to move are "to find a better equipped house" (32%), "for work related reasons" (14%), to be closer to a relative (8%), to be closer to a school (3%), violence related (2.68%), to be closer to the town centre (0.5%), and to be closer to a HC centre (0.17%), and other reasons (39%).

those who have children less than 7 to those who do not, as the latter are not eligible to participate. Once again the distance to the nearest HC is not statistically different for the two groups. All these pieces of evidence indicate that households do not seem to move to be closer to a HC centre, which could be partly explained because of the high turnover of *madres comunitarias* that we described in section 2.

(ii) The identification assumption we make states that the variables we use as instruments are uncorrelated with the residuals of equation (1). To provide a sense of the plausibility of such an assumption, it is useful to check whether our instruments are correlated, conditional on controls, with some observable indicators that are likely to be correlated with the outcome of interest. This type of exercise also stresses the importance of controlling for certain variables. In Table 4.6, we report the P-values of a regression of the distance from the nearest *HC* centre on several variables that might be indicators of household wealth and might be correlated with the nutritional status of children and report the p-value of the significance of these variables. In the first column, we do not control for other location factors, while in the second we control for important location variables: the distance from the nearest hospital and nearest school. The evidence in the Table 4.6 is illuminating. First of all, the distance from the nearest *HC* centre is related to the distance from the nearest school and health centre. Furthermore, it is also related to several other variables, such as parental education. However, once we control for the distance from the nearest school and health centre, all other variables, including mother's education, become statistically insignificant. These results indicate that controlling for these location variables is essential for our identification strategy to be credible.

(iii) Our identification strategy would also be invalid if the programme administrators followed a compensatory rule and provided more resources for the HC in poorer municipalities. In this case, households living in poorer municipalities would be closer to a *HC* centre or they might have to pay less to attend a HC centre. If that were the case, our identifying assumption would be invalid unless our set of covariates was rich enough so as to control for this. In order to examine this issue, we estimate the impact of the HC controlling for municipality fixed effects, and using only distance from the household to the HC as instrument. The results, shown in Table 4.7, show that the pattern of estimates using municipality fixed effects is similar to the ones without municipality fixed effects (Table 4.3) though the standard errors of the estimates with municipality fixed effects are much larger.

Table 4.6
P-Values of joint significance of certain variables in a regression of distance to the nearest HC from the household

	Not controlling for distance to health centre, and school	Controlling for distance to health centre, and school
Distance to nearest school and health centre[a]	-	0.000
Child age and gender	0.045	0.127
Birth order	0.723	0.349
Mother's height	0.778	0.782
Head of household's education	0.241	0.286
Mother's education	0.012	0.378
Mother's and head of household's age	0.695	0.932
Several municipality variables[b]	0.380	0.314
Region dummies	0.001	0.065
Municipality wages	0.007	0.998
Altitude	0.583	0.922

a. It also includes the average distance to a school in the municipality
b. Presence of hospital, coverage of sewage and piped water network, percentage of families with health insurance in the municipality

Finally, as an additional check on the validity of our instrumental variables we estimate the impact that *HC* has on two variables on which it should not have an effect: children's birth weight[18] and mother height. If we were to find that current attendance or exposure to *HC* has an effect on birth weight or mother height, one would suspect that the instruments we are using are correlated with unobservable factors and are therefore invalid. It could be that children from households that live closer to a *HC* are healthier (and therefore heavier at birth and taller at later ages) for some reason other than the exposure or participation into *HC*. It could also be that the mothers of children living closer to a *HC* are healthier what would generally imply that their children are also healthier and generally taller.

[18] We refer to birth weight of the same children for whom we have estimated the impact of HC on anthropometrics.

Table 4.7
Effect of HC on height per age using municipality fixed effects

Exposure		Attendance	
OLS	IV	OLS	IV
-0.086	0.617	-0.125	0.335
(0.093)	(0.639)	(0.047)	(0.350)

Standard errors in parentheses are clustered at the town level

Table 4.8
Assessing the validity of the instruments.
Effect of HC on birth weight and mother's height

	Birth Weight (Kilos)	Mother's Height (Metres)
Exposure	0.818	-0.031
	(0.843)	(0.034)
Attendance	.4566	-0.011
	(0.492)	(0.013)
Sample	1423	1879

Standard errors in parentheses are clustered at the town level.
The P-Values of the overidentification restriction tests are 0.73 for birth weight and 0.40 for mother's height

In table 4.8, we report the results we obtain by 2SLS using the same instruments used to obtain Table 4.3. Given that neither birth weight nor mother's height are time variant, we only use only one observation for each child or mother. As for those covariates that are time variant, we use the average across the different waves. None of the estimates are statistically different from zero at 5%. Moreover, the coefficient on birth weight is positive while the coefficient on mother's height is negative. These results support our claim that once we have controlled for other covariates such as distance to the health centre and school, variation in distance to the nearest HC centre is not related to other time invariant determinants of child nutrition.

4.5. Testing for heterogeneous effects

The recent literature on policy evaluation has highlighted the role of heterogeneous effects on the identification and estimation of treatment effects. If the benefits of a programme are heterogeneous in the population and people select into the programme on the basis of their idiosyncratic benefit, then there is not a single "effect" of the programme but a variety of parameters that are informative about the effect of the programme on different individuals. For instance, if heterogeneity was an issue, the IV estimates presented before would not identify the average treatment effect, but a Local Average Treatment Effect (Imbens and Angrist, 1994). In the presence of heterogeneity in the benefits of the program, the Marginal Treatment Effect (MTE), introduced in Bjorklund and Moffitt (1987) and extended in Heckman and Vytlacil (1999, 2000), is very important as different parameters related to the effect of the programme can be expressed as weighed averages of the MTE, where different parameters correspond to different weights (Heckman, 1997; Heckman and Vytlacil 2000).[19]
In this subsection, we follow Carneiro *et al.* (2005b) and Heckman *et al.* (2006a and 2006b) to test for the presence of heterogeneous effects. Testing for heterogeneous effects implies testing whether the function *K(P(w))* is linear in the following regression:

(2) $$H_i = \pi_0 + \beta_0 q_i + \beta_1 q_i P(w_i) + K(P(w_i)) + u_i$$

where the vector q_i represent the covariates of individual *i*, $P(w_i)$ is the estimated probability of attending a HC centre as a function of the distance, the median fee paid in the municipality, and q_i , as before, are the control variables.
The simplest way to test for the non-linearity of $K(P(w_i))$ is to approximate $K(P(w_i))$ with a polynomial in $P(w_i)$, that is, $\sum_{j=0}^{J} \phi_j [P(w_i)]^j$. The hypothesis of homogenous effects is rejected if ϕ_j is different from zero for any *j* larger than one. The P-Values for the hypothesis that the terms ϕ_j are jointly zero for any *j* larger than one are 0.43 in the model with the second degree polynomial, 0.33 for the third degree, 0.15 for the fourth degree, and 0.27 for the

[19] The MTE is the limit form of LATE. The limt form of LATE was introduced by Heckman (1997), and Angrist et al. (2000).

fifth degree.[20] The lack of evidence on the non-linearity of $K(P(w_i))$ implies that we cannot reject the hypothesis that the benefits of the programme are homogenous, or if they were heterogeneous, individuals do not select into the programme on the basis of their idiosyncratic benefit of the program. This could occur if they are unaware of those benefits or if they use the programme as a safety net and decide to participate when they are hit by an adverse shock.[21] The lack of heterogeneous effects could also be due to the fact that our sample includes only individuals that are classified in SISBEN 1, the lowest socio-economic level in Colombia.

4.6. Sensitivity analysis

In this section, we assess the robustness of our results to deviations from the identifying assumption that the instruments are not correlated with the error term of the outcome equation (1).[22] In particular, we want to assess the bias arising from different degrees of correlation between the instruments we use and the residuals. Operationally, this is somehow problematic because we exclude six variables: the distance from the house to the *HC* in the first wave of data, the current distance from the house to the *HC*, the median fee in the municipality, and the square terms of these three variables. To overcome this problem, we collapse these six instrumental variables into one predicted instrument. When we consider the impact of attendance on child height, we use as instrument the predicted probability that a child is attending a HC centre using a Probit model. The regressors of the Probit model are the six variables that we exclude from the outcome equation. In an analogous way, when we consider the impact of exposure on child height, we use as an instrument the predicted exposure using a Tobit model estimated using as regressors the six variables that we exclude from the outcome equation.

Re-writing equation (1) in matrix form, we have:

[20] In the model with the fourth order polynomial, the coefficients on the polynomial terms are individually different from zero at the 5%. However, they seem to cancel out in the relevant range of the propensity score. The estimated function by the model with the fourth degree polynomial is line and increasing until it reaches 0.67 when it decreases. However, only 1.3% of the observations have a propensity score larger than 0.67.

[21] Notice for instance that Carneiro et al (2005b) reject the null of no heterogeneity in their model where family background is not used as an exclusion restriction but they cannot reject the null for the model where family background is used as an exclusion restriction.

[22] Imbens (2003) and Altonji, Elder and Taber (2005) assess the robustness of their conclusions to the violation of the conditional independence assumption. Their benchmark assumption is the opposite of ours, that there is no correlation between the treatment variable and the error term of the outcome equation.

(2) $$H = S * \beta + U,$$

where $S = [Q \vdots A]$ has dimension *nxk*; *H*, *A* and *U* have of dimension *nx1, n* is the number of observations, Q are *k-1* exogenous covariates and $\beta' = [\alpha' \vdots \gamma]$ has dimension *1xk*. The 2SLS estimator can be written as:

(3) $$\hat{\beta}_{2SLS} - \beta = [S'P_w S]^{-1}[S'W(W'W)^{-1}W'U],$$

where the last component *W'U* includes the correlation between the instrument $\hat{A}$ and the error term *U*.

As a first exercise, using (3), one can compute different values for γ that would correspond to the 2SLS estimates and different assumptions about *corr(*$\hat{A}$,U). As is often the case, the bounds we obtain by varying the relevant correlation are extremely wide and not very informative, including both positive and negative values. Positive values of corr($\hat{A}$,*U)*, which are more plausible as households who live far from a *HC* are also more likely to have poor nutritional outcomes, imply a positive bias in the estimate of the programme impact. Even small positive values of the correlation imply a substantial bias that can reverse the sign of the estimated impact.

However, following Ashley (2007), one can obtain more informative bounds using information on the difference between OLS and 2SLS estimates. Some straightforward algebra yields:

(4) $$[S'P_w S]^{-1}[S'W(W'W)^{-1}W'U] = \hat{\beta}_{2SLS} - \hat{\beta}_{OLS} + [S'S]^{-1}[S'U]$$

The terms *W'U* and *S'U* include the correlation of the predicted instrument, $\hat{A}$, with the error term, and of *A* with the error term, respectively. Under the maintained assumption that the exogenous variables *Q* are uncorrelated with the error term *U,* for each possible value of the correlation between actual *A* and *U,* one can solve for the correlation between $\hat{A}$ and *U* that is implicit in equation (4). This correlation between $\hat{A}$ and *U* can then be used to compute the implied estimate of the bias of the 2SLS estimator, and the implied value of γ using equation (3). We report the results of this procedure in Table 4.10. For the sake of brevity, we only report results in the case where the predicted instrument is computed using distance only.

The first interesting result from Table 4.10 is that even relatively large correlations between the treatment variable *A* and the error term imply small correlations between the predicted instrument and the error term. This is driven by equation (4) that includes the difference between the 2SLS and the OLS estimates.

Table 4.10.

Values of γ for different values of the correlation between the treatment variable and the error term. Predicted instrument is computed using distance only

Corr(A,*U*)	A=Exposure		A=Attendance	
	corr($\hat{A}$,*U*) implied by equation (4)	Value of γ implied by (2) and corr($\hat{A}$,*U*)	corr($\hat{A}$,*U*) implied by equation (4)	Value of γ implied by (2) and corr($\hat{A}$,*U*)
0.30	0.067	-1.564	0.066	-0.921
0.20	0.053	-1.043	0.053	-0.644
0.10	0.038	-0.522	0.039	-0.367
0.05	0.031	-0.262	0.032	-0.223
0.01	0.025	-0.05	0.027	-0.118
0.00	0.024	-0.001	0.026	-0.090
-0.01	0.022	0.051	0.025	-0.063
-0.03	0.019	0.155	0.021	-0.007
-0.05	0.016	0.259	0.019	0.048
-0.10	0.09	0.519	0.012	0.186
-0.20	-0.005	1.041	-0.001	0.463
-0.30	-0.020	1.562	-0.013	0.740

We focus on the case of a negative correlation between participation and the error term of the equation (1). There are several pieces of evidence that point in this direction. First, according to the official guidelines, the programme is targeted towards children that suffer economic vulnerability. Second, a Probit regression, available upon request, shows that children whose mothers have more education are less likely to attend a HC centre. Third, the OLS point estimates reported in Tables 4.3 and 4.7 are negative and statistically different from zero. We find it easier to believe that this negative coefficient is due to children with poor nutritional status selecting into the programme rather than the programme having a negative impact on children's height. Fourth in a similar programme in Bolivia, the poorest children were also the ones that were more likely to participate (Behrman *et al.* 2004).

If the correlation between participation and the error term, *corr(A,U)*, is negative, we should focus on the results reported in the middle to bottom rows of Table 4.10. At the same time, *corr(A,U)* cannot be smaller than -0.20, because if it were then the correlation between $\hat{A}$ and U implied by equation (4) would be negative, which would also be hard to believe. Therefore, if we focus on the region where *corr(A,U)* is between -0.01 and -0.20 for exposure and between -0.03 and -0.25 for attendance, then the value of γ would be positive, even if the predicted instrument is positively correlated with the error term.[23] Clearly there are positive values of corr($\hat{A}$,*U)* that would imply that the bias of our 2SLS estimate is large enough so that γ could be positive while the actual value of γ will be negative. However, given the difference between the 2SLS and the OLS estimates, these values of corr($\hat{A}$,*U)* would not be consistent with our hypothesis about the sign of *corr(A,U)*, and consequently, of what type of individuals selects into the program.

5. A model of Human Capital Investment

In this section we consider the *Hogares Comunitarios* programme within a behavioural model of child nutrition. The theoretical model allow us to analyze under what assumptions we can give a structural interpretation to the parameters estimated in section 4, and what alternative empirical strategies are available.

We view the *Hogares Comunitarios* programme as one of several inputs that enter into the production function that yields child nutritional status as an output, in the spirit of Rosenzweig and Schultz (1983) and, more recently, Todd and Wolpin (2003). As in Rosenzweig and Schultz (1983), we consider that the inputs of such a production function, including the use of the programme, are chosen by the household decision maker taking into account their cost and their productivity. It is therefore likely that the households that choose to use the programme are those for whom the programme is most effective or least costly. For this reason, a simple comparison between participants and non-participants is problematic if we want to infer the productivity of the programme. If there are two sets of reasons for a household to choose to use the programme, its benefits and its costs, we will

[23] Notice that a positive correlation between the predicted instrument and the error term implies that distance from the household to the HC centre is negative correlated with the error term.

want to compare households that differ in the latter rather than in the former, given that costs can be thought of as varying exogenously to the household. It is this intuition that our model formalizes.

Given our context, we pay particular attention to the case where some of the inputs might not be observable. This issue is discussed at length in Todd and Wolpin (2003), who also discuss the difference between the estimation of the impact of a policy (which we presented in Section 5) and the knowledge of the production function.

Let's consider a household that maximizes a utility function that depends on child nutritional status, *H,* on children food consumption, *F,* on household consumption other than child food, x and on female leisure, 1-l. Total household consumption, *C*, is given by $x+pF$. The maximization problem is given by the following:

$$
\begin{aligned}
& \underset{x,F,l,A}{Max}\, U(H,x,F,1-l) = \underset{C,F,l,A}{Max}\, U(H,C-pF,F,1-l) \\
& s.t. \\
(5)\qquad & H = H(A,F,l,e) \\
& C + zA = w(l - DA - M(1-A)) + Y \\
& 0 \le A \le 1;\ 0 \le l \le 1
\end{aligned}
$$

where A is participation in the *HC* programme, e is a vector of observable and unobservable variables that affect nutritional status *H,* p is the price of child food, z the fee to attend a *HC* (which we have measured as the median fee paid in the municipality). *D* is the distance (in time) from the *HC* and *M* is the amount of time the mother needs to spend with a child if the child does not attend a *HC*. The household chooses $x,F,l,$ and *A*. Here we consider *A* as a continuous variable and think of it as the fraction of time (possibly over a horizon of several years) a child spends in the *HC*. The dependence of the utility function on *H,* on l and on x is natural. We also let it depend on *F* for the sake of generality.

The first of the constraints is the main object of interest: the nutritional status production function. We assume that *H* is a function of the child's intake of food *F*, the fraction of time he or she spends in a *HC,* female labour supply l and other variables e. These variables could include for example mother height or mother education. The dependence of *H* on l is justified by substantial evidence on the impact of maternal care on the growth and development of young children.

The second constraint in problem (5) is the budget constraint. On the left-hand-side we have expenditures: household consumption other than child food, child food and the fee for the *Hogar Comunitario.* On the right hand side we have other income *Y* and female earnings. *M,* the amount of time the mother needs to spend with a child if the child does not attend a HC, can be household specific: if a particular child has access to alternative child care at home (for instance older siblings or other adults), *M* can be very low and, as a consequence, attendance to a *Hogar Comunitario* becomes less attractive.[24]

The first order conditions for problem (5) are:

$$(6)\qquad \begin{aligned} C:&\quad U_x = \mu \\ F:&\quad U_H H_F - pU_x + U_F = 0 \\ A:&\quad U_H H_F = \mu(z - w(D - M)) \\ L:&\quad -U_L + U_H H_L = -w\mu \end{aligned}$$

where we have ignored the possibility of corner solutions in the choice of *A* and *l.* These could be easily added, so that the third and fourth conditions in (6) would be inequalities.

Suppose first that we can observe *F, x, A* and *l.* Then we can solve the first order conditions in (6) and obtain *F, l* and *A* as a function of *w, D, z, p* and *Y*. Several observations on the reduced form for *F, l* and *A* are in order:

Both *D* and *z* represent the cost to attend a *HC.* High levels of *D* imply low levels of *A.* The same is true of z, the difference being that the effect of *D* on attendance is mediated through *w,* the labour market opportunity. Ceteris paribus, for women with a positive (*D-M*), those with high wages would be the most discouraged from using *HC.* On the contrary, if *(D-M)* is negative (these are women living close to a *HC* and with little alternative sources of child care), those with higher wages are more likely to use a *Hogar Comunitario.*

If one had data on *F,* one could solve the endogeneity problem discussed by Rosenzweig and Schultz (1983), by using *w, D, z* and *Y* as instruments for *F, l* and *A* in a regression of *H* on *F, A* and possibly other control variables. The identification assumption that the instruments do not enter the production function directly and are not correlated with the unobserved component *e* does therefore, in principle, hold. While one could suspect that variables such as *M* and *Y* might be correlated with *e,* this is less likely to be a worry for *z, D*

[24] This would be consistent with some of the answers we observe in the data to the question on why a child does not attend a *Hogar Comunitario.*See Table 3.2.

and *w*. Under this assumption it is possible to identify the parameters of the production function.

The approach above is very demanding in terms of data because one needs to observe *F,* child specific food consumption at home. This would not be available in most household surveys. We address the problem that we do not observe individual food intakes by using two alternative strategies. The first conditions children nutritional status on female labour supply, while the second also conditions on total household consumption. In particular, our first strategy is to use the first order conditions for *x, F* and *l* to eliminate the multiplier μ and solve for F and x as a function of *H, l, p* and *w*. We can then substitute *F* out of the production function and obtain *H* as a function of *A*, *l, w* and *p*. Such a relationship can then be estimated, appropriately instrumenting for A and *l*. In particular, after linearization, we would be considering an equation of the following type:

(7) $$H_i = \beta' q_i + \gamma A + \alpha l_i + u_i$$

where the vector *q* includes *p* and *w* as well as other variables we might think relevant for the function *H* in (5). This implies that the wage, *w,* cannot be used as an exclusion restriction anymore, because it enters directly in (7). We can only rely on *z* and *D* as instruments.[25] It should be stressed that the coefficient γ does not represent the marginal productivity of *HC* in the production function in (5) but takes into account the behavioural responses in other variables induced by the program. In Appendix A, we report the expression for the parameters γ and α. The overall effect of the programme on the nutritional status can be computed from estimates of (7) by computing its effect on female labour supply and then using the estimates of α and γ.

Equation (7) can be estimated with most household surveys, as not even household consumption is required to estimate it. However, a second strategy can be followed if household consumption is observed. We can solve the first order condition for *F* as a function of *l, C, H* and *p* and substitute *F* out of the production function. We will then obtain *H* as a function of *C, A, l* and *p*. This relationship can be estimated, appropriately instrumenting for *C, A* and *l*. In particular we would have an equation of the following type:

[25] We are reluctant to use *M* or *Y* as excluded regressors as they could conceivably enter the function *H* directly. This is particularly true for *M* which reflects the availability of child care at home.

(8) $H_i = \theta' q_i + \psi A + \phi l_i + \delta C + u_i$

Where the vector of controls *q* now does not include *w,* which can then be used as an instrument, along with *z* and *D*. Once again, the coefficient on *A,* ψ *,* does not reflect only the marginal productivity of A. In this case, one can show that:

(9)
$$\psi = \left(1 - \frac{\alpha_1}{\alpha_2}\right)^{-1} \left(H_A + \frac{\alpha_5}{\alpha_2}\right), \phi = \left(1 - \frac{\alpha_1}{\alpha_2}\right)^{-1} \left(H_L + \frac{\alpha_4}{\alpha_2}\right), \delta = \left(1 - \frac{\alpha_1}{\alpha_2}\right)^{-1} \frac{\alpha_3}{\alpha_2}$$

where

$$\alpha_1 = H_F U_{HH} + PU_{XH};\ \alpha_2 = U_H H_{FF} - P^2 U_{XX};\ \alpha_3 = \mathrm{H_F U_{HX} + PU_{XX}};$$
$$\alpha_4 = \mathrm{U_H H_{FL} - U_{HL} H_F - U_{XL}};\ \alpha_5 = U_H H_{FA}$$

The two approaches behind equations (7) and (8) are obviously quite similar, as they are derived from a different expression of the same underlying model. In the case of equation (7) the relationship we can uncover between *A* and *H,* controlling for *l*, would not be reflecting only the direct effect of *A* on *H* , but would also include the indirect effect that the availability of *A* would have on *F,* mediated by the effect that *F* has on *H*. This is an interesting parameter, as it would consider both the directs and indirect effects of the program, but it is different from the partial derivative of *H* with respect to *A*. Analogous considerations apply to equation (8). Notice that the advantage of expression (7) versus (8) is that is less demanding in terms of required data, and moreover, does not require using wages as an exclusion restriction.

Notice that neither equation (7) nor equation (8) corresponds to the equation that we have estimated in Section 4. To obtain a specification similar to the one we used, we would need to impose additional restrictions on the utility function *U(.)* and/or the production function *H(.)*. A sufficient condition that delivers the specification we estimated is to assume that the utility function is additively separable in *H* and linear in consumption and that *l* does not enter the production function *H(.)*. In this case, we can use the f.o.c. for *F* in (9) to solve for *F* as a function of H and prices and substitute that out of the production function. Alternatively, if we want to allow female labour supply to enter the production function *H(.)*, to obtain a specification like the one estimated in Section 4 we need to assume additive separability of *H* and of labour supply and that the utility function is linear in *x* and *l*. If this is the case, we can then substitute F and l in the production function as a function H and prices and still have valid exclusion restrictions.

In the more general case in which these functional form assumptions are violated, if we do not condition on l and F, the exclusion restrictions that D and z do not enter equation (1) will not be valid. This can be seen clearly if we solve for F and l as a function of A,P,w,D, and z and substitute into the production function to obtain:

(10) $$H=H[A,G_F(A,P,w,D,z),G_L(A,P,w,D,z),\varepsilon].$$

Notice that the bias induced in the specification estimated in Section 4 by the problem just discussed arises even when D and z are distributed completely randomly across households. It is induced by the fact that, even among participants, differences in distance or fee might induce changes in labour supply behaviour and food intakes, which in turn, directly or indirectly, have an effect on nutritional status. The extent to which these biases are important in practice depends, apart from the form of the utility function, on other factors such as the type of variation in D and z. For instance, if among participants variations in D are not large and do not induce large changes in labour supply, the bias should not be too important. This is likely in our setting. Table 4.1 above shows that the 75th percentile of distance, *among participants,* is only 15 minutes. Consequently, participants live close enough to HC centres so that travel distance might not be an important variable that affects the amount of labour supplied. In section 6, we report the results of estimating equation (7) and (8), which are immune to the potential problem just mentioned.

6. A theoretically consistent empirical specification.

In this section, we present estimates of equation (7) and (8) discussed above and relate these results to those obtained in Section 4. As in Section 4, we use two different definitions of 'treatment', current participation and exposure. As for female labour supply we consider either employment in the previous week or the number of hours worked in the previous month.

Before presenting our structural results, however, we show the first stage results for consumption and labour supply. In particular, in Table 6.1, we report the F-statistics of joint significance of the variables excluded from equations (7) and (8). The complete set of results is shown in Tables B11 and B13 of Appendix B. Notice that wages are excludedfrom equation (8) but they are not excluded from equation (7).[26] We notice that the instruments do a better job at predicting female employment than consumption. For the latter, distance does not seem significant (after conditioning for all the controls) and we need to rely on the variation in fees and in wages.

Table 6.1
F-statistics for excluded variables in Equations 7 and 8

	Equation 7		Equation 8	
	Any paid work last week by mother	Monthly hours worked by mother	Log of food consumption per capita	Log of total consumption per capita
F-statistic for distance	5.76	4.09	0.71	1.15
[P-Value]	[0.001]	[0.006]	[0.586]	[0.342]
F-statistic for Fee	17.4	4.84	4.37	0.28
[P-Value]	[0.000]	[0.012]	[0.017]	[0.758]
F-stat. for Wages	not excluded	not excluded	8.73	4.95
[P-Value]			[0.000]	[0.010]

Table 6.2 reports the estimates of equation (7), which relate child height to the HC programme conditioning on female employment. As discussed above, we uss distance and the median fee in the municipality as instruments. The estimates on exposure and attendance are similar to those in Table 4.3, and the estimate of the coefficient of female labour supply is very close to zero. The interpretation of the labour supply coefficient is complex, and its exact definition can be found in the Appendix A. It is difficult to predict its sign because it combines the effect of the programme on income obtained through female labour supply with the effect of female labour supply in the human capital production function. While the first is probably positive, the second is probably negative. The fact that the estimate of the coefficient of the programme is very similar to that in Table 4.3 means that the type of bias that we discussed at the end of section 5 is probably not important in our setting. Consequently, the estimates in Table 4.3 could be interpreted as the overall effect of the programme including both direct and indirect effects. At the end of this section we present

[26] In our previous analysis, we have conditioned on female wages as reported by the town mayor. However, as instruments for total and food consumption, we use average male wages in the municipality computed using the survey response because their F-statistic is considerably higher.

some calculations of the overall impact of the programme based on the estimates in Table 6.2.

Table 6.2
Height per Age over Attendance and Female Labour Supply (Equation 7)

	Exposure & N. Hours	Exposure & Participation	Attendance & N. Hours	Attendance & Participation
Exposure	0.945	0.981		
	(0.410)	(0.428)		
Attendance			0.541	0.605
			(0.262)	(0.279)
Monthly number of hours worked by the mother divided by 100	0.032		0.168	
	(0.318)		(0.337)	
Dummy variable if mother worked in the week previous to the interview		-0.080		-0.008
		(0.267)		(0.282)
Sample Size				
N. 1st wave	2365	2398	2401	2434
N. 2nd wave	2433	2439	2485	2491
N. 3rd wave	946	947	948	949

As with the impact analysis, we also perform some robustness exercises. In particular, we consider alternative outcomes, such as birth weight and mothers height. These results, that are not reported for the sake of brevity, indicate, once again, that the programme and female labour supply have no effects on these outcomes.

Table 6.3 reports the results obtained estimating equation 8, using distance, the median fee, and wages as the excluded instruments. We only show the results for number of hours because the ones that condition on participation in the labour market give very similar results. This table confirms that the programme has a positive effect on children nutritional status over and above the effect that the programme can have on household resources. Using the expression in equation (9), the coefficient on female labour supply is proportional to $H_L + a_4/a_2$ and hence its sign cannot be determined a priori from the model.

As in Table 6.2, the effect of female employment is not statistically different from zero, while the effect of consumption is marginally so, especially when we use food consumption (rather than total consumption).

Table 6.3

Height per Age over Attendance, Consumption and Female Labour Supply (Equation 8)

	Exposure, N. Hours & Food	Attendance, N. Hours & Food	Exposure, N. Hours & Consumption	Attendance, N. Hours & Consumption
Exposure	0.836		1.467	
	(0.371)		(0.662)	
Attendance		0.478		0.771
		(0.216)		(0.331)
Monthly number of hours worked by the mother divided by 100	0.181 (0.287)	0.302 (0.302)	-0.362 (0.494)	-0.100 (0.434)
ln (Total Household Consumption per capita)			0.718 (0.475)	0.626 (0.435)
ln (Household Food Consumption per capita)	0.491 (0.247)	0.537 (0.263)		
N. 1st wave	2470	2507	2470	2507
N. 2nd wave	2496	2549	2507	2560
N. 3rd wave	960	962	963	965

To conclude this section, we compute the overall effect of the programme based on the estimates obtained from Table 6.2 and the impact on labour supply results reported in Section 4.3. The standard errors are computed using 500 bootstrap replications. This computation would evaluate the total effect of the programme at 0.958 for exposure with a standard error of 0.652, and 0.603 for attendance with a standard error of 0.386. The estimates are very similar to the estimates obtained in Table 4.3, except for the larger standard errors. This seems to indicate that the overall impact estimates of the programme obtained in section 4 do not present significant biases. According to our theoretical model, this can be either because the assumption on the utility function discussed in section 5 hold or because distance to the HC centre does not constitute a burden for the quantity of labour supplied by the mothers of children participating in the HC program. As we mentioned, this would be the case if participants live close enough to a HC centre. Of course, how close it must be is an empirical issue that cannot be ascertain without estimating the theoretically based model that was discussed in section 5.

7. Conclusions

In this paper we have studied one of the largest welfare programme in Colombia. *Hogares Comunitarios¸* a community nursery programme, absorbs about 250 million US$ per year and, although it has been running since the mid 1980s, had never been systematically evaluated. In the first part of the paper, we propose an Instrumental Variable approach based on comparing participant and non-participant children and using the distance of the house of residence to the nearest *HC* and the median fee to attend a HC centre in the municipality as an instrument for participation. The result we find is that, unlike the OLS estimates, the IV results show important effects of the program. In particular, a 72 months old boy (girl) that has attended a HC during all his life will be 4.36 (4.41) centimetres taller than if he had not attended a HC at all. The negative bias that characterizes OLS estimates is a consequence of the fact that the children with poorest nutritional status are those that select into the program. The program, therefore, seems to be well targeted and to help maintain the nutritional status of the poorest children.

We show what believe to be credible evidence on the reliability of our instrument: when we perform the same exercise on birth weight and mother height we do not obtain any effect of the program. We also estimate positive effects of the programme on mothers employment rates..

In the second part of the paper we consider the empirical results obtained in the first part within the framework of a structural model where the programme is considered as an input in the production function of nutritional status that might be chosen among others. Our model serves several purposes. First, it makes clear under what conditions our identification strategy works: the instruments we use, distance from and cost of an HC are potentially legitimate because reflect costs of the input that might be exogenous to the household. Second, the model is useful to show that in our context, because of the presence of unobservable inputs, even truly 'exogenous' instruments do not guarantee unbiased estimates of the impact. We state the conditions on utility and technology that make our IV results unbiased estimates of the impact of the programme and suggest an alternative econometric strategy that can be used when these conditions fail. The results we obtain under this strategy confirm those obtained in the first part. Moreover, we find that the programme has an important effect on children's nutrition over and above the effect that female labour supply could have.

This evidence is important as the Colombian government is currently considering the possibility of scrapping the *HC* programme in favour of conditional cash subsidies. What we have shown should give an element of caution in implementing these plans.

There is much work that still needs to be done. First, it should be stressed that our results cannot be extrapolated to different contexts. The large majority of *HC* in Colombia operates in large cities and urban areas: our results are from a sample of small towns with an important rural component. Second, as we have evidence on the effectiveness of the alternative programmes being considered, it would be interesting to compare them explicitly and model impact heterogeneity, especially in terms of child ages. It might be that the two programs, rather than being substitutes, are complements. It might be that the youngest children are best targeted by the conditional cash subsidies, while children aged 2 to 4 might benefit more from the *HC* programme.

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Appendix A Parameters of equation (7)

Straightforward but tedious algebra yields that the parameters of equation (7) are given by the following expressions:

$$\gamma = \Theta[H_A(\theta_{12}\theta_{23} - \theta_{13}\theta_{22}) + H_F(\theta_{22}\theta_{15} - \theta_{12}\theta_{25})]$$
$$\alpha = \Theta[H_L(\theta_{12}\theta_{23} - \theta_{13}\theta_{22}) + H_F(\theta_{22}\theta_{14} - \theta_{12}\theta_{24})]$$
$$where:$$
$$\Theta = (\theta_{12}\theta_{23} - \theta_{13}\theta_{22} - H_F\theta_{11}\theta_{22} + H_F\theta_{12}\theta_{21})^{-1}$$
$$\theta_{11} = H_F U_{HH} - PU_{XH} + U_{FH}$$
$$\theta_{12} = H_F U_{HX} - PU_{XX} + U_{FX}$$
$$\theta_{13} = H_F U_{HF} - PU_{XF} + U_{FF} + U_H H_{FF}$$
$$\theta_{15} = U_H H_{FA}$$
$$\theta_{21} = H_L U_{HH} - wU_{XH} - U_{LH}$$
$$\theta_{22} = H_L U_{HX} - wU_{XX} - U_{LX}$$
$$\theta_{23} = U_H H_{LF} - U_{LF} + H_L U_{HF}$$
$$\theta_{24} = U_H H_{LL} + wU_{XL} - H_L U_{HL} - U_{LL}$$
$$\theta_{25} = U_H H_{LA}$$

Appendix B. Detailed Tables

Table B1. Variable definitions and descriptive statistics

Variable Name	Definition	Mean	Sd.	25th Perc.	75th Perc.
age_head	Household head's age in years divided by 100	0.39	0.11	0.32	0.45
age_mot	Mother's age in years divided by 100	0.32	0.07	0.27	0.37
age_m	Child age in months	48.84	23.28	30.91	69.09
altitude	Altitude in thousand meters	0.45	0.68	0.3	0.6
birth_w	Birth weight in kilograms	3.44	0.80	3	3.8
cons	Logarithm of per capita monthly household consumption in Colombian pesos (December 2003)	11.10	0.57	10.73	11.47
edu_h345	1 if household head has completed primary education or more, 0 otherwise	0.34	0.47	0	1
edu_m345	1 if mother has completed primary education or more, 0 otherwise	0.41	0.49	0	1
female	1 if child is female, 0 if child is male	0.49	0.50	0	1
food	Logarithm of per capita monthly food consumption in Colombian pesos (December 2003)	10.57	0.64	10.22	10.99
haz	Child's height. Unit: z-scores	-1.25	1.11	-1.96	-0.54
hc_fee	Median fee to attend a HC nursery in the municipality	3.81	3.18	1.65	5.25
height_mot	Mother's height in metres	1.54	0.06	1.50	1.58
hosp	1 if there is a hospital in the town, 0 otherwise	0.71	0.48	0	1
insur_mun	Proportion of children with formal health insurance in the municipality	0.62	0.22	0.46	0.81
ln_age_head	Logarithm of household head's age in years divided by 100	-0.96	0.26	-1.14	-0.80
ln_age_mot	Logarithm of mother's age in years divided by 100	-1.17	0.22	-1.31	-0.99
ln_order	Logarithm of order of kid in the household	1.15	0.53	0.69	1.61
order	Order of kid in the household	3.61	1.74	2	5
pipe	Percentage of households with pipe water in the municipality	0.85	0.14	0.82	0.95
region_2	1 if household lives in the Eastern region, 0 otherwise	0.19	0.39	0	0
region_3	1 if household lives in the Central region, 0 otherwise	0.25	0.43	0	1
region_4	1 if household lives in the Pacific region, 0 otherwise	0.13	0.34	0	0
rural	1 if household lives in the rural part of the municipality, 0 otherwise	0.49	0.50	0	1
sewage	Percentage of households with sewage connection in the municipality	0.44	0.37	0.03	0.84
time_hc	Distance (minutes divided by 100) to the nearest HC for those that are not attending a HC centre and actual distance for those that attend	0.23	0.37	0.05	0.30

time_hc_b	same as time_hc but in the first wave of data	0.25	0.39	0.05	0.30
time_hea	Distance in minutes to the nearest health care provider, divided by 100	0.44	0.63	0.1	0.6
time_sch	Distance in minutes to nearest school, divided by 100	0.14	0.15	0.05	0.2
time_sch_mun	Average of *time_sch* in the municipality	0.10	0.06	0.05	0.15
time2	Time dummy for second wave of data	0.42	0.49	0	1
time3	Time dummy for third wave of data	0.17	0.37	0	0
wage_fr	Rural female wage in pesos as indicated by the town major divided by 1000 in Colombian pesos (December 2003)	0.91	0.35	0.7	1.2
wage_fu	Urban female wage in pesos as indicated by the town major divided by 1000 in Colombian pesos (December 2003)	0.98	0.34	0.8	1.2
wage_m	Mean male wages in the municipality computed using the survey, divided by 1000 in Colombian pesos (December 2003)	0.961	0.25	0.75	1.14

Table B2. Comparing descriptive statistics of those living "close" and "far" from the nearest HC centre. See also Table 4.6 in the text.

Variable Name	Average for those living close	Difference: Far-Close	S.E of the difference	P-Value
age_head	0.392	0.014	0.008	0.08
age_mot	0.317	0.002	0.003	0.47
age_m	49.639	-3.046	0.962	0.00
altitude	0.389	0.241	0.108	0.03
edu_h345	0.383	-0.163	0.025	0.00
edu_m345	0.456	-0.180	0.029	0.00
female	0.487	0.028	0.025	0.27
height_mot	1.542	-0.011	0.006	0.09
hosp	0.712	0.002	0.074	0.98
insur_mun	0.614	0.007	0.056	0.90
order	3.55	0.24	0.12	0.05
pipe	0.846	0.015	0.020	0.44
region_2	0.145	0.179	0.073	0.02
region_3	0.210	0.165	0.083	0.05
region_4	0.135	-0.019	0.043	0.66
rural	0.360	0.494	0.041	0.00
sewage	0.416	0.091	0.070	0.19
time_hea	0.315	0.472	0.090	0.00
time_sch	0.103	0.152	0.014	0.00
time2	0.431	-0.041	0.022	0.06
time3	0.166	0.002	0.021	0.94
wage_fr	0.931	-0.051	0.047	0.28
wage_fu	0.976	0.028	0.042	0.68

Living far is defined as living more far away than the average distance (23 minutes). Living close is defined as living closer than the average distance

Table B.3. FIRST STAGE REGRESSION for program participation

See Table 4.2 in the Text

	OLS for Exposure	OLS for Attendance
time_hc	-0.121**	-0.265**
	[0.029]	[0.058]
time_hc2	0.041**	0.076**
	[0.012]	[0.024]
time_hc_b	-0.156**	-0.197**
	[0.035]	[0.060]
time_hc_b2	0.053**	0.076**
	[0.013]	[0.023]
hc_fee_med	-0.028**	-0.028*
	[0.009]	[0.013]
hc_fee_med2	0.001*	0.001
	[0.001]	[0.001]
female	-0.003	0.01
	[0.008]	[0.010]
age_m	0.009**	0.023**
	[0.001]	[0.002]
age_m2	-0.007**	-0.027**
	[0.001]	[0.002]
ln_age_h	-0.033	-0.022
	[0.019]	[0.030]
ln_age_m	-0.014	-0.047
	[0.022]	[0.036]
height_mot	0.008	0.06
	[0.077]	[0.124]
ln_order	0.028*	0.023
	[0.010]	[0.014]
edu_h345	0.009	0.014
	[0.011]	[0.017]
edu_m345	0.012	-0.013
	[0.010]	[0.016]
time2	-0.021**	-0.013
	[0.005]	[0.011]
time3	-0.025	-0.027
	[0.013]	[0.017]
rural	-0.008	-0.017
	[0.021]	[0.030]
time_hea	-0.005	0.017
	[0.017]	[0.032]
time_hea2	0.008**	0.007
	[0.003]	[0.006]
time_sch	-0.041	-0.067
	[0.056]	[0.099]
time_sch2	0.102*	0.125
	[0.050]	[0.094]
time_sch_mun	-0.159	-0.751
	[0.298]	[0.484]
time_sch_mun2	0.653	1.94
	[0.747]	[1.179]
time_hea_sch	-0.060**	-0.054
	[0.022]	[0.040]
hosp	0.01	0.01
	[0.017]	[0.027]

pipe	-0.016	-0.001
	[0.081]	[0.130]
sewage	-0.006	-0.036
	[0.027]	[0.039]
region_2	0	0.055
	[0.034]	[0.056]
region_3	0.002	0.052
	[0.032]	[0.050]
region_4	0.043	0.096
	[0.041]	[0.063]
altitud	-0.062	-0.043
	[0.039]	[0.057]
altitud2	0.014	0.011
	[0.017]	[0.027]
insur_mun	0.063	0.125
	[0.163]	[0.274]
insur_mun2	0.008	0.007
	[0.137]	[0.228]
wage_fu	0.02	0.028
	[0.032]	[0.046]
wage_fr	-0.007	-0.042
	[0.029]	[0.036]
Constant	-0.028	-0.149
	[0.148]	[0.191]
Observations	5831	5921

* significant at 5%; ** significant at 1%

Table B4. Effect of Exposure on Child's Height
See Table 4.3 in the Text

	OLS	t: Distance and F	Inst: Distance	Inst: Fee
exposure	-0.001	0.897*	0.924	0.764
	[0.083]	[0.394]	[0.541]	[0.597]
female	0.147**	0.149**	0.150**	0.149**
	[0.034]	[0.032]	[0.032]	[0.033]
age_m	-0.028**	-0.036**	-0.037**	-0.035**
	[0.003]	[0.004]	[0.006]	[0.006]
age_m2	0.025**	0.031**	0.031**	0.030**
	[0.003]	[0.004]	[0.005]	[0.005]
ln_age_h	0.269**	0.297**	0.298**	0.293**
	[0.082]	[0.085]	[0.086]	[0.088]
ln_age_m	0.322**	0.340**	0.341**	0.338*
	[0.117]	[0.125]	[0.126]	[0.127]
height_mot	5.704**	5.711**	5.711**	5.710**
	[0.448]	[0.443]	[0.449]	[0.448]
ln_order	-0.282**	-0.312**	-0.313**	-0.307**
	[0.038]	[0.043]	[0.047]	[0.041]
edu_h345	0.107	0.097	0.096	0.098
	[0.055]	[0.052]	[0.052]	[0.053]
edu_m345	0.149**	0.138**	0.138**	0.140**
	[0.051]	[0.050]	[0.051]	[0.049]
time2	0.025	0.04	0.041	0.038
	[0.024]	[0.024]	[0.024]	[0.028]
time3	0.058	0.071	0.072	0.069
	[0.048]	[0.045]	[0.046]	[0.046]
rural	-0.046	-0.025	-0.024	-0.028
	[0.061]	[0.059]	[0.060]	[0.061]
time_hea	-0.087	-0.061	-0.061	-0.065
	[0.074]	[0.076]	[0.078]	[0.080]
time_hea2	-0.005	-0.017	-0.017	-0.015
	[0.014]	[0.015]	[0.016]	[0.017]
time_sch	-0.038	0.127	0.132	0.103
	[0.225]	[0.228]	[0.251]	[0.222]
time_sch2	0.139	-0.002	-0.006	0.019
	[0.246]	[0.224]	[0.241]	[0.221]
time_sch_mun	-3.733**	-3.097**	-3.077**	-3.191**
	[1.011]	[0.929]	[0.930]	[1.095]
time_sch_mun2	7.008**	5.118*	5.062*	5.398
	[2.360]	[2.457]	[2.470]	[2.927]
time_hea_sch	0.229**	0.272**	0.274**	0.266**
	[0.085]	[0.085]	[0.088]	[0.086]
hosp	0.142**	0.141**	0.141**	0.141**
	[0.045]	[0.042]	[0.043]	[0.043]
pipe	0.542*	0.419	0.415	0.437
	[0.226]	[0.224]	[0.229]	[0.244]
sewage	0.103	0.127	0.128	0.123
	[0.087]	[0.088]	[0.089]	[0.091]
region_2	0.392**	0.424**	0.425**	0.419**
	[0.106]	[0.103]	[0.104]	[0.108]
region_3	0.128	0.177*	0.178*	0.169
	[0.084]	[0.086]	[0.084]	[0.097]
region_4	0.213*	0.152*	0.15	0.161*
	[0.086]	[0.074]	[0.083]	[0.071]

altitud	0.076	0.171	0.174	0.157
	[0.132]	[0.122]	[0.128]	[0.137]
altitud2	-0.071	-0.096*	-0.097*	-0.092*
	[0.045]	[0.039]	[0.040]	[0.045]
insur_mun	-1.035	-1.145*	-1.149	-1.129*
	[0.602]	[0.573]	[0.595]	[0.557]
insur_mun2	0.798	0.802	0.802	0.801
	[0.518]	[0.493]	[0.500]	[0.498]
wage_fu	0.075	0.095	0.096	0.092
	[0.099]	[0.098]	[0.099]	[0.102]
wage_fr	-0.058	-0.075	-0.075	-0.072
	[0.093]	[0.090]	[0.091]	[0.094]
Constant	-8.714**	-8.553**	-8.548**	-8.577**
	[0.679]	[0.680]	[0.698]	[0.681]

* significant at 5%; ** significant at 1%

Table B5. Effect of Attendance on Child's Height

See Table 4.3 in the text

	OLS	t: Distance and F	Inst: Distance	Inst: Fee
asis_hc	-0.090*	0.590*	0.536	0.749
	[0.041]	[0.257]	[0.306]	[0.532]
female	0.146**	0.139**	0.140**	0.138**
	[0.034]	[0.033]	[0.034]	[0.032]
age_m	-0.026**	-0.042**	-0.041**	-0.046**
	[0.003]	[0.007]	[0.008]	[0.012]
age_m2	0.022**	0.041**	0.039**	0.045**
	[0.003]	[0.007]	[0.009]	[0.014]
ln_age_h	0.265**	0.280**	0.279**	0.284**
	[0.083]	[0.087]	[0.088]	[0.091]
ln_age_m	0.324**	0.360**	0.357**	0.368**
	[0.118]	[0.121]	[0.122]	[0.131]
height_mot	5.669**	5.637**	5.640**	5.630**
	[0.443]	[0.464]	[0.467]	[0.478]
ln_order	-0.282**	-0.303**	-0.301**	-0.308**
	[0.039]	[0.043]	[0.044]	[0.043]
edu_h345	0.106	0.094	0.095	0.091
	[0.056]	[0.056]	[0.056]	[0.058]
edu_m345	0.152**	0.160**	0.159**	0.161**
	[0.050]	[0.048]	[0.048]	[0.050]
time2	0.022	0.025	0.025	0.026
	[0.024]	[0.024]	[0.024]	[0.026]
time3	0.054	0.061	0.06	0.063
	[0.049]	[0.044]	[0.045]	[0.045]
rural	-0.046	-0.015	-0.017	-0.007
	[0.060]	[0.061]	[0.061]	[0.066]
time_hea	-0.096	-0.075	-0.077	-0.07
	[0.072]	[0.078]	[0.078]	[0.083]
time_hea2	0.002	-0.01	-0.009	-0.013
	[0.013]	[0.014]	[0.014]	[0.017]
time_sch	-0.067	0.138	0.122	0.186
	[0.229]	[0.246]	[0.259]	[0.259]
time_sch2	0.185	0.03	0.043	-0.006
	[0.253]	[0.247]	[0.257]	[0.246]
time_sch_mun	-3.878**	-2.870**	-2.950**	-2.635
	[1.031]	[1.009]	[1.017]	[1.341]
time_sch_mun2	7.419**	4.804	5.013	4.194
	[2.364]	[2.587]	[2.581]	[3.538]
time_hea_sch	0.199*	0.229*	0.226*	0.236*
	[0.085]	[0.094]	[0.094]	[0.100]
hosp	0.143**	0.144**	0.144**	0.144**
	[0.046]	[0.044]	[0.044]	[0.045]
pipe	0.542*	0.421	0.431	0.393
	[0.230]	[0.238]	[0.238]	[0.267]
sewage	0.088	0.127	0.124	0.136
	[0.088]	[0.091]	[0.092]	[0.102]
region_2	0.401**	0.403**	0.403**	0.403**
	[0.107]	[0.105]	[0.106]	[0.108]
region_3	0.138	0.153	0.152	0.157
	[0.086]	[0.091]	[0.091]	[0.100]
region_4	0.226*	0.142	0.149	0.123
	[0.090]	[0.077]	[0.085]	[0.084]

altitud	0.069	0.122	0.118	0.135
	[0.137]	[0.122]	[0.124]	[0.127]
altitud2	-0.068	-0.080*	-0.079	-0.083
	[0.047]	[0.041]	[0.041]	[0.042]
insur_mun	-0.949	-1.075	-1.065	-1.104
	[0.621]	[0.607]	[0.620]	[0.590]
insur_mun2	0.737	0.73	0.731	0.729
	[0.530]	[0.520]	[0.524]	[0.538]
wage_fu	0.063	0.078	0.076	0.081
	[0.102]	[0.097]	[0.098]	[0.102]
wage_fr	-0.055	-0.047	-0.047	-0.045
	[0.095]	[0.092]	[0.093]	[0.093]
Constant	-8.672**	-8.449**	-8.467**	-8.397**
	[0.669]	[0.719]	[0.726]	[0.740]
Observations	5921	5921	5921	5921

Robust standard errors in brackets
* significant at 5%; ** significant at 1%

Table B6. Effect of Attendance to HC on the mother's labour supply

See Table 4.4 in the Text

	Probit. Participation	Bivariate Probit (Participation in labour market)	Bivariate Probit (Attendance to HC)
asis_hc	0.327**	0.813**	
	[0.056]	[0.242]	
female	0.016	-0.002	0.106*
	[0.061]	[0.059]	[0.053]
age_m	0.005	-0.005	0.074**
	[0.005]	[0.007]	[0.007]
age_m2	0.002	0.014	-0.093**
	[0.006]	[0.009]	[0.007]
ln_age_h	0.019	0.032	-0.082
	[0.110]	[0.104]	[0.118]
ln_age_m	0.692**	0.746**	-0.462**
	[0.125]	[0.136]	[0.134]
height_mot	-0.825	-0.714	-0.754
	[0.474]	[0.444]	[0.484]
ln_order	0.130*	0.108	0.096
	[0.066]	[0.063]	[0.063]
edu_h345	-0.004	-0.016	0.052
	[0.056]	[0.061]	[0.069]
edu_m345	0.159**	0.161**	-0.037
	[0.061]	[0.062]	[0.063]
time2	-0.046	-0.045	-0.042
	[0.047]	[0.046]	[0.042]
time3	-0.104	-0.101	-0.068
	[0.084]	[0.081]	[0.075]
rural	-0.129	-0.111	0.03
	[0.088]	[0.085]	[0.086]
time_hea	-0.053	-0.027	0.013
	[0.146]	[0.149]	[0.112]
time_hea2	0.051*	0.039	0.032
	[0.025]	[0.025]	[0.021]
time_sch	-0.668	-0.457	-0.229
	[0.363]	[0.361]	[0.439]
time_sch2	0.459	0.297	0.298
	[0.414]	[0.412]	[0.678]
time_sch_mun	0.004	0.986	-3.522
	[1.652]	[1.791]	[2.111]
time_sch_mun2	0.48	-2.198	10.525
	[4.685]	[5.322]	[5.727]
time_hea_sch	-0.218	-0.181	-0.215
	[0.256]	[0.259]	[0.291]
hosp	0.05	0.051	-0.009
	[0.072]	[0.074]	[0.107]
pipe	0.45	0.368	-0.307
	[0.273]	[0.305]	[0.497]
sewage	0.384**	0.416**	-0.13
	[0.140]	[0.141]	[0.185]
region_2	0.078	0.076	0.094
	[0.151]	[0.154]	[0.229]

region_3	-0.268*	-0.257*	0.2
	[0.126]	[0.129]	[0.188]
region_4	0.351**	0.288	0.168
	[0.126]	[0.147]	[0.194]
altitud	-0.18	-0.109	-0.183
	[0.187]	[0.205]	[0.244]
altitud2	0.056	0.035	0.048
	[0.077]	[0.085]	[0.117]
insur_mun	-0.87	-1.041	0.958
	[0.830]	[0.801]	[1.221]
insur_mun2	0.562	0.626	-0.365
	[0.698]	[0.689]	[1.021]
wage_fu	-0.649	-0.585	-0.164
	[0.636]	[0.700]	[1.043]
wage_fr	-0.522	-0.608	0.403
	[0.543]	[0.581]	[0.829]
wage_fu2	0.129	0.114	0.138
	[0.310]	[0.344]	[0.518]
wage_fr2	0.322	0.369	-0.313
	[0.253]	[0.275]	[0.421]
time_hc			-1.728**
			[0.338]
time_hc2			0.483**
			[0.159]
time_hc_b			-0.863**
			[0.299]
time_hc_b2			0.306**
			[0.118]
hc_fee_med			-0.130**
			[0.050]
hc_fee_med2			0.005
			[0.003]
Constant	1.691	1.628	-0.333
	[0.919]	[0.891]	[0.771]
Observations	3681	3681	3681

* significant at 5%; ** significant at 1%

Table B7. OLS of distance from the house to the nearest HC centre
See Table 4.6 in the Text

	With other location variables	Without other location variables
time_hea	0.256**	
	[0.071]	
time_hea2	-0.051**	
	[0.014]	
time_sch	0.542**	
	[0.160]	
time_sch2	-0.456*	
	[0.203]	
time_sch_mun	0.95	
	[0.829]	
time_sch_mun2	-0.355	
	[2.744]	
time_hea_sch	0.344**	
	[0.119]	
female	0.012	0.013
	[0.010]	[0.011]
age_m	-0.002*	-0.002**
	[0.001]	[0.001]
age_m2	0.001*	0.002*
	[0.001]	[0.001]
ln_age_h	-0.003	0.024
	[0.024]	[0.029]
ln_age_m	0.011	-0.017
	[0.029]	[0.034]
height_mot	-0.028	-0.038
	[0.102]	[0.132]
ln_order	-0.013	-0.007
	[0.014]	[0.019]
edu_h345	-0.016	-0.021
	[0.014]	[0.018]
edu_m345	-0.009	-0.031*
	[0.010]	[0.012]
time2	-0.036**	-0.040**
	[0.012]	[0.011]
time3	-0.061**	-0.063*
	[0.018]	[0.025]
rural	0.097**	0.238**
	[0.016]	[0.036]
hosp	0.012	0.026
	[0.022]	[0.032]
pipe	-0.096	-0.08
	[0.079]	[0.119]
sewage	-0.005	-0.013
	[0.059]	[0.069]
region_2	0.120*	0.152
	[0.051]	[0.000]
region_3	0.077	0.151*
	[0.046]	[0.000]
region_4	0	0
	[0.000]	[0.000]

altitud	-0.019	0.098
	[0.083]	[0.101]
altitud2	0.009	-0.028
	[0.029]	[0.038]
insur_mun	-0.238	-0.086
	[0.486]	[0.671]
insur_mun2	0.095	-0.079
	[0.391]	[0.546]
wage_fr	0.002	-0.181**
	[0.071]	[0.061]
wage_fu	-0.003	0.188**
	[0.073]	[0.063]
region_2	0	0
	[0.000]	[0.096]
region_3	0	0
	[0.000]	[0.072]
region_4	-0.037	-0.082
	[0.048]	[0.071]
Constant	0.197	0.32
	[0.252]	[0.313]
Observations	5831	5831

* significant at 5%; ** significant at 1%

Table B8. Effect of HC on Child's Height. Municipality Fixed Effects

See Table 4.7 in the text

	Exposure. OLS	Exposure. Inst: Distance	Attendance. OLS	Inst: Distance
exposure	-0.086	0.619		
	[0.093]	[0.639]		
asis_hc			-0.125*	0.335
			[0.047]	[0.351]
female	0.159**	0.160**	0.159**	0.152**
	[0.033]	[0.032]	[0.033]	[0.034]
age_m	-0.028**	-0.034**	-0.025**	-0.036**
	[0.003]	[0.006]	[0.003]	[0.009]
age_m2	0.025**	0.029**	0.022**	0.034**
	[0.003]	[0.005]	[0.003]	[0.010]
ln_age_h	0.244**	0.268**	0.240**	0.249**
	[0.083]	[0.087]	[0.085]	[0.088]
ln_age_m	0.314*	0.323*	0.318*	0.334**
	[0.120]	[0.127]	[0.121]	[0.124]
height_mot	5.611**	5.677**	5.583**	5.620**
	[0.479]	[0.485]	[0.474]	[0.494]
ln_order	-0.273**	-0.291**	-0.275**	-0.283**
	[0.038]	[0.045]	[0.039]	[0.042]
edu_h345	0.120*	0.113*	0.119*	0.111
	[0.055]	[0.053]	[0.056]	[0.056]
edu_m345	0.137*	0.128*	0.139**	0.142**
	[0.052]	[0.053]	[0.051]	[0.050]
time2	0.012	0.026	0.01	0.015
	[0.023]	[0.025]	[0.023]	[0.023]
time3	0.086*	0.101*	0.081*	0.094*
	[0.041]	[0.042]	[0.040]	[0.043]
rural	-0.068	-0.053	-0.067	-0.055
	[0.066]	[0.065]	[0.064]	[0.065]
time_hea	-0.104	-0.086	-0.116	-0.101
	[0.069]	[0.071]	[0.066]	[0.069]
time_hea2	-0.005	-0.012	0.001	-0.005
	[0.013]	[0.015]	[0.013]	[0.013]
time_sch	-0.038	0.099	-0.051	0.087
	[0.214]	[0.258]	[0.215]	[0.254]
time_sch2	0.078	-0.033	0.1	0.012
	[0.242]	[0.244]	[0.249]	[0.248]
time_sch_mun	0.563	0.051	0.484	0.013
	[1.528]	[1.549]	[1.477]	[1.520]
time_sch_mun2	-0.981	-0.166	-0.724	0.208
	[3.643]	[3.821]	[3.572]	[3.512]
time_hea_sch	0.295**	0.324**	0.271**	0.284**
	[0.085]	[0.084]	[0.088]	[0.088]
Observations	5831	5831	5921	5921

* significant at 5%; ** significant at 1%

Table B9. Robustness Test: IV Estimates of HC on Birth Weight
See Table 4.8 in the Text

	Exposure	Attendance
exposure	0.818	
	[0.843]	
asis_hc		0.457
		[0.492]
female	-0.136**	-0.146**
	[0.045]	[0.046]
age_m	-0.003	-0.007
	[0.008]	[0.012]
age_m2	0.001	0.008
	[0.007]	[0.013]
ln_age_h	0.074	0.048
	[0.097]	[0.096]
ln_age_m	0.146	0.172
	[0.156]	[0.159]
height_mot	0.63	0.578
	[0.346]	[0.348]
ln_order	0.039	0.054
	[0.065]	[0.060]
edu_h345	0.05	0.04
	[0.048]	[0.048]
edu_m345	-0.067	-0.051
	[0.062]	[0.063]
time2	-0.135	-0.142
	[0.116]	[0.115]
time3	-0.295**	-0.343**
	[0.098]	[0.117]
rural	0.043	0.046
	[0.066]	[0.065]
time_hea	-0.15	-0.207
	[0.165]	[0.132]
time_hea2	0.131	0.158*
	[0.075]	[0.062]
time_sch	0.983*	0.972*
	[0.425]	[0.436]
time_sch2	-0.472	-0.479
	[0.361]	[0.376]
time_sch_mun	-0.945	-1.034
	[2.158]	[2.213]
time_sch_mun2	7.527	7.886
	[6.913]	[7.152]
time_hea_sch	-0.272	-0.276
	[0.223]	[0.246]
hosp	0.046	0.025
	[0.072]	[0.068]
pipe	-0.024	-0.003
	[0.350]	[0.336]
sewage	0.237*	0.226*
	[0.097]	[0.106]
region_2	-0.251	-0.284*
	[0.162]	[0.144]
region_3	0.157	0.135
	[0.144]	[0.121]

region_4	-0.263**	-0.245**
	[0.082]	[0.073]
altitud	-0.297	-0.360*
	[0.175]	[0.165]
altitud2	0.117*	0.136*
	[0.057]	[0.057]
insur_mun	-0.361	-0.55
	[0.672]	[0.578]
insur_mun2	0.381	0.593
	[0.662]	[0.551]
wage_fu	0.207	0.164
	[0.168]	[0.155]
wage_fr	0.015	0.067
	[0.173]	[0.154]
Constant	2.580**	2.752**
	[0.565]	[0.569]
Observations	1423	1433

Robust standard errors in brackets

* significant at 5%; ** significant at 1%

Table B10. Robustness Test: IV Estimates of HC on Mother's Height
See Table 4.8 in Text

	Exposure	Attendance
exposure	-0.031	
	[0.034]	
asis_hc		-0.011
		[0.014]
female	0.001	0.002
	[0.003]	[0.003]
age_m	0	0
	[0.001]	[0.001]
age_m2	0	0
	[0.000]	[0.001]
ln_age_h	-0.01	-0.01
	[0.006]	[0.006]
ln_age_m	-0.001	-0.003
	[0.008]	[0.009]
ln_order	0.004	0.003
	[0.004]	[0.003]
edu_h345	0.003	0.002
	[0.003]	[0.003]
edu_m345	0.014**	0.014**
	[0.003]	[0.003]
time2	0.009	0.009
	[0.005]	[0.005]
time3	0.011	0.014
	[0.007]	[0.008]
rural	-0.003	-0.003
	[0.005]	[0.005]
time_hea	-0.017	-0.016
	[0.009]	[0.009]
time_hea2	0.004*	0.004*
	[0.002]	[0.002]
time_sch	-0.012	-0.012
	[0.019]	[0.019]
time_sch2	0.003	0
	[0.020]	[0.020]
time_sch_mun	-0.199	-0.193
	[0.131]	[0.128]
time_sch_mun2	0.717*	0.689*
	[0.325]	[0.315]
time_hea_sch	0.006	0.008
	[0.009]	[0.008]
hosp	0.001	0.002
	[0.005]	[0.005]
pipe	0.051*	0.048*
	[0.023]	[0.022]
sewage	-0.002	-0.002
	[0.010]	[0.010]
region_2	-0.009	-0.009
	[0.010]	[0.010]
region_3	-0.009	-0.008
	[0.010]	[0.009]
region_4	-0.023*	-0.024*
	[0.010]	[0.010]

altitud	-0.026*	-0.023*
	[0.013]	[0.012]
altitud2	0.007	0.006
	[0.004]	[0.004]
insur_mun	-0.098	-0.095
	[0.085]	[0.087]
insur_mun2	0.045	0.043
	[0.067]	[0.068]
wage_fu	-0.012	-0.013
	[0.012]	[0.012]
wage_fr	0.015	0.015
	[0.012]	[0.012]
Constant	1.545**	1.546**
	[0.039]	[0.038]
Observations	1879	1894

* significant at 5%; ** significant at 1%

Table B11. FIRST STAGE REGRESSION for Female Labour Supply

Corresponds with Table 6.1 in the Text

	OLS for Mother's N hours	OLS for Mother's labor participation
time_hc	-0.052	-0.166*
	[0.113]	[0.073]
time_hc2	0.027	0.067
	[0.062]	[0.034]
time_hc_b	-0.323**	-0.171*
	[0.120]	[0.065]
time_hc_b2	0.138	0.084*
	[0.071]	[0.033]
hc_fee_med	-0.027	-0.033**
	[0.018]	[0.011]
hc_fee_med2	0.002*	0.003**
	[0.001]	[0.001]
female	-0.001	0.007
	[0.021]	[0.014]
age_m	0.003*	0.002*
	[0.001]	[0.001]
age_m2	-0.002	-0.001
	[0.002]	[0.001]
ln_age_h	0.112	0.029
	[0.071]	[0.041]
ln_age_m	0.292**	0.235**
	[0.078]	[0.043]
height_mot	-0.103	-0.351
	[0.280]	[0.180]
ln_order	0.073*	0.046
	[0.033]	[0.025]
edu_h345	0.058	-0.008
	[0.034]	[0.020]
edu_m345	0.096**	0.063**
	[0.035]	[0.019]
time2	-0.050*	-0.028
	[0.023]	[0.018]
time3	-0.029	-0.059
	[0.037]	[0.031]
rural	-0.04	-0.013
	[0.049]	[0.037]
time_hea	0.006	0.047
	[0.061]	[0.063]
time_hea2	0.018*	0.003
	[0.009]	[0.009]
time_sch	-0.108	-0.205
	[0.149]	[0.121]
time_sch2	0.13	0.245
	[0.137]	[0.131]
time_sch_mun	-0.861	-0.031
	[0.879]	[0.637]
time_sch_mun2	2.95	-0.1
	[2.157]	[1.575]
time_hea_sch	-0.172	-0.145
	[0.099]	[0.082]

hosp	-0.005	-0.027
	[0.033]	[0.025]
pipe	0.119	0.094
	[0.198]	[0.120]
sewage	0.217**	0.135**
	[0.067]	[0.047]
region_2	0.023	-0.021
	[0.092]	[0.057]
region_3	-0.067	-0.054
	[0.082]	[0.047]
region_4	0.179*	0.102
	[0.080]	[0.051]
altitud	0.122	0.015
	[0.116]	[0.075]
altitud2	-0.058	-0.017
	[0.043]	[0.026]
insur_mun	-0.715	-0.468
	[0.554]	[0.313]
insur_mun2	0.476	0.292
	[0.469]	[0.260]
wage_fu	-0.418	-0.256
	[0.354]	[0.227]
wage_fr	0.07	-0.121
	[0.267]	[0.169]
wage_fu2	0.139	0.08
	[0.176]	[0.111]
wage_fr2	0.043	0.055
	[0.134]	[0.081]
Constant	1.089*	1.462**
	[0.512]	[0.370]
Observations	5836	5876

* significant at 5%; ** significant at 1%

Table B12. Estimates using Production Function Approach
(Program and Labour Supply)
See Table 6.2 in Text

	Exposure and number of hours	Exposure and Any Work	Attendance and number of hours	Attendance and and Any Work
exposure	0.945*	0.981*		
	[0.410]	[0.428]		
work_hours_mot	0.032		0.168	
	[0.318]		[0.337]	
work_week_mot		-0.08		-0.008
		[0.267]		[0.283]
asis_hc			0.541*	0.605*
			[0.262]	[0.279]
female	0.147**	0.147**	0.137**	0.136**
	[0.033]	[0.034]	[0.031]	[0.033]
age_m	-0.037**	-0.037**	-0.042**	-0.043**
	[0.004]	[0.004]	[0.006]	[0.007]
age_m2	0.032**	0.032**	0.040**	0.041**
	[0.004]	[0.004]	[0.007]	[0.007]
ln_age_h	0.301**	0.296**	0.266*	0.275**
	[0.097]	[0.091]	[0.100]	[0.093]
ln_age_m	0.327*	0.360*	0.302*	0.363*
	[0.145]	[0.140]	[0.145]	[0.137]
height_mot	5.763**	5.696**	5.710**	5.654**
	[0.455]	[0.484]	[0.472]	[0.506]
ln_order	-0.317**	-0.308**	-0.316**	-0.301**
	[0.047]	[0.044]	[0.048]	[0.044]
edu_h345	0.106	0.099	0.095	0.096
	[0.054]	[0.053]	[0.058]	[0.057]
edu_m345	0.123*	0.134*	0.131*	0.153**
	[0.059]	[0.054]	[0.057]	[0.053]
time2	0.043	0.036	0.034	0.022
	[0.024]	[0.025]	[0.024]	[0.024]
time3	0.082	0.07	0.075	0.064
	[0.048]	[0.051]	[0.047]	[0.048]
rural	-0.02	-0.022	-0.005	-0.012
	[0.058]	[0.059]	[0.059]	[0.060]
time_hea	-0.051	-0.058	-0.066	-0.075
	[0.077]	[0.075]	[0.079]	[0.077]
time_hea2	-0.018	-0.017	-0.013	-0.01
	[0.018]	[0.015]	[0.017]	[0.014]
time_sch	0.197	0.134	0.226	0.164
	[0.233]	[0.238]	[0.250]	[0.255]
time_sch2	-0.04	-0.012	-0.014	0.011
	[0.216]	[0.223]	[0.240]	[0.243]
time_sch_mun	-3.032**	-2.925**	-2.738*	-2.713*
	[1.016]	[0.994]	[1.102]	[1.067]
time_sch_mun2	4.759	4.645	4.166	4.384
	[2.806]	[2.660]	[2.923]	[2.734]
time_hea_sch	0.266**	0.273**	0.235*	0.230*
	[0.093]	[0.088]	[0.099]	[0.097]
hosp	0.138**	0.138**	0.143**	0.143**
	[0.047]	[0.045]	[0.048]	[0.046]
pipe	0.474*	0.472*	0.457	0.461

	[0.228]	[0.233]	[0.236]	[0.243]
sewage	0.116	0.14	0.08	0.128
	[0.110]	[0.093]	[0.114]	[0.094]
region_2	0.443**	0.439**	0.415**	0.414**
	[0.111]	[0.109]	[0.112]	[0.109]
region_3	0.195*	0.176	0.184	0.156
	[0.092]	[0.089]	[0.099]	[0.095]
region_4	0.154	0.154	0.126	0.138
	[0.092]	[0.084]	[0.095]	[0.088]
altitud	0.169	0.164	0.107	0.117
	[0.129]	[0.128]	[0.128]	[0.129]
altitud2	-0.101*	-0.097*	-0.08	-0.083
	[0.043]	[0.043]	[0.044]	[0.044]
insur_mun	-1.055	-1.128	-0.894	-1.035
	[0.605]	[0.576]	[0.628]	[0.610]
insur_mun2	0.711	0.758	0.59	0.68
	[0.500]	[0.485]	[0.523]	[0.513]
wage_fu	0.476	0.429	0.44	0.351
	[0.488]	[0.478]	[0.510]	[0.480]
wage_fr	-0.332	-0.33	-0.269	-0.248
	[0.363]	[0.380]	[0.371]	[0.378]
wage_fu2	-0.192	-0.18	-0.17	-0.144
	[0.252]	[0.254]	[0.253]	[0.248]
wage_fr2	0.131	0.134	0.1	0.106
	[0.188]	[0.193]	[0.187]	[0.191]
Constant	-8.774**	-8.565**	-8.811**	-8.550**
	[0.809]	[0.865]	[0.834]	[0.906]
Observations	5744	5784	5834	5874

* significant at 5%; ** significant at 1%

Table B13. FIRST STAGE REGRESSION for Per Capita Ln of Total or Food Consumption

It corresponds with Table 6.1 in the Text

	OLS for Total	OLS for Food
female	-0.001	-0.002
	[0.015]	[0.015]
age_m	-0.001	-0.001
	[0.001]	[0.001]
age_m2	0	-0.001
	[0.001]	[0.001]
ln_age_h	-0.04	-0.117*
	[0.043]	[0.051]
ln_age_m	0.200**	0.183**
	[0.065]	[0.066]
height_mot	0.533**	0.388
	[0.172]	[0.197]
ln_order	-0.312**	-0.310**
	[0.028]	[0.030]
edu_h345	0.130**	0.070*
	[0.026]	[0.027]
edu_m345	0.156**	0.119**
	[0.025]	[0.026]
time2	-0.125**	-0.205**
	[0.025]	[0.032]
time3	-0.069*	-0.178**
	[0.033]	[0.047]
rural	-0.064	0.008
	[0.035]	[0.038]
time_hea	-0.097*	-0.063
	[0.047]	[0.048]
time_hea2	0.009	0.001
	[0.008]	[0.008]
time_sch	0.003	0.011
	[0.167]	[0.184]
time_sch2	0.14	0.152
	[0.180]	[0.204]
time_sch_mun	-0.019	0.015
	[0.726]	[0.739]
time_sch_mun2	0.426	0.409
	[1.924]	[1.860]
time_hea_sch	0.006	0.011
	[0.084]	[0.119]
hosp	0.072	0.046
	[0.040]	[0.033]
pipe	0.267	0.003
	[0.149]	[0.141]
sewage	-0.002	-0.008
	[0.080]	[0.074]
region_2	0.082	-0.007
	[0.074]	[0.064]
region_3	-0.02	-0.042
	[0.085]	[0.079]
region_4	0.066	0.048
	[0.091]	[0.081]
altitud	-0.129	-0.122

	[0.079]	[0.087]
altitud2	0.066*	0.072*
	[0.029]	[0.031]
insur_mun	-1.377**	-1.353*
	[0.472]	[0.534]
insur_mun2	0.995*	0.963*
	[0.384]	[0.417]
time_hc	0.007	0.077
	[0.083]	[0.106]
time_hc2	0.001	-0.037
	[0.036]	[0.049]
time_hc_b	-0.115	-0.093
	[0.106]	[0.111]
time_hc_b2	0.08	0.079
	[0.047]	[0.055]
hc_fee_med	-0.001	-0.025
	[0.015]	[0.016]
hc_fee_med2	0	0.001
	[0.001]	[0.001]
wage_m	0.562	0.791*
	[0.441]	[0.367]
wage_m2	-0.185	-0.277
	[0.231]	[0.184]
Constant	10.693**	10.540**
	[0.384]	[0.411]
Observations	6123	6109

* significant at 5%; ** significant at 1%

Table B14. Estimates using Production Function Approach
(Program, LN of per capita Food Consumption, and Labour Supply)
See Table 6.3 in the Text

	Exposure and number of hours	Exposure and Any Work	Attendance and number of hours	Attendance and and Any Work
exposure	0.836*	1.039*		
	[0.371]	[0.430]		
work_hours_mot	0.181		0.302	
	[0.288]		[0.302]	
food	0.491	0.39	0.537*	0.503*
	[0.247]	[0.236]	[0.263]	[0.242]
work_week_mot		-0.124		-0.027
		[0.289]		[0.303]
asis_hc			0.478*	0.632*
			[0.216]	[0.273]
female	0.142**	0.144**	0.135**	0.135**
	[0.032]	[0.033]	[0.032]	[0.034]
age_m	-0.036**	-0.037**	-0.040**	-0.043**
	[0.004]	[0.005]	[0.006]	[0.007]
age_m2	0.032**	0.033**	0.039**	0.043**
	[0.004]	[0.004]	[0.006]	[0.007]
ln_age_h	0.345**	0.355**	0.318**	0.346**
	[0.101]	[0.093]	[0.107]	[0.098]
ln_age_m	0.198	0.301	0.167	0.271
	[0.155]	[0.164]	[0.158]	[0.166]
height_mot	5.703**	5.633**	5.615**	5.542**
	[0.474]	[0.477]	[0.490]	[0.496]
ln_order	-0.183	-0.195*	-0.167	-0.153
	[0.095]	[0.088]	[0.097]	[0.087]
edu_h345	0.061	0.073	0.049	0.063
	[0.054]	[0.054]	[0.057]	[0.057]
edu_m345	0.036	0.073	0.038	0.078
	[0.063]	[0.063]	[0.064]	[0.063]
time2	0.172*	0.131*	0.173*	0.143*
	[0.071]	[0.065]	[0.076]	[0.071]
time3	0.179*	0.146	0.178*	0.160*
	[0.076]	[0.075]	[0.078]	[0.078]
rural	-0.023	-0.028	-0.01	-0.021
	[0.061]	[0.063]	[0.064]	[0.066]
time_hea	-0.012	-0.014	-0.022	-0.023
	[0.074]	[0.077]	[0.076]	[0.080]
time_hea2	-0.012	-0.011	-0.01	-0.006
	[0.017]	[0.016]	[0.015]	[0.015]
time_sch	0.232	0.134	0.234	0.15
	[0.241]	[0.242]	[0.255]	[0.263]
time_sch2	-0.071	-0.023	-0.055	-0.028
	[0.233]	[0.244]	[0.238]	[0.249]
time_sch_mun	-2.352*	-2.529*	-2.013	-2.300*
	[1.116]	[1.054]	[1.179]	[1.110]
time_sch_mun2	2.652	3.258	1.868	2.687
	[2.884]	[2.867]	[2.999]	[2.992]
time_hea_sch	0.152	0.156	0.142	0.132
	[0.109]	[0.099]	[0.103]	[0.090]
hosp	0.127*	0.136**	0.130*	0.139**

	[0.050]	[0.049]	[0.053]	[0.050]
pipe	0.327	0.34	0.32	0.33
	[0.237]	[0.249]	[0.242]	[0.258]
sewage	0.085	0.161	0.049	0.137
	[0.106]	[0.102]	[0.108]	[0.102]
region_2	0.453**	0.430**	0.440**	0.426**
	[0.104]	[0.105]	[0.106]	[0.106]
region_3	0.224*	0.168	0.224	0.169
	[0.104]	[0.109]	[0.112]	[0.117]
region_4	0.128	0.142	0.103	0.129
	[0.089]	[0.090]	[0.090]	[0.092]
altitud	0.297*	0.299*	0.248	0.265
	[0.134]	[0.138]	[0.129]	[0.138]
altitud2	-0.165**	-0.157**	-0.152**	-0.151**
	[0.044]	[0.047]	[0.044]	[0.049]
insur_mun	-0.369	-0.772	-0.138	-0.473
	[0.821]	[0.840]	[0.869]	[0.885]
insur_mun2	0.245	0.519	0.068	0.283
	[0.662]	[0.672]	[0.699]	[0.709]
Constant	-14.301**	-12.765**	-14.804**	-14.013**
	[2.646]	[2.809]	[2.842]	[2.872]
Observations	5926	5966	6018	6058

* significant at 5%; ** significant at 1%

Table B15. Estimates using Production Function Approach
(Program, LN of per capita Total Consumption, and Labour Supply)
See Table 6.3 in the Text

	Exposure and number of hours	Exposure and Any Work	Attendance and number of hours	Attendance and and Any Work
exposure	1.467*	1.230**		
	[0.662]	[0.456]		
work_hours_mot	-0.362		-0.1	
	[0.495]		[0.434]	
cons	0.718	0.529	0.626	0.547
	[0.475]	[0.290]	[0.436]	[0.304]
work_week_mot		-0.256		-0.209
		[0.296]		[0.301]
asis_hc			0.772*	0.762**
			[0.331]	[0.281]
female	0.145**	0.147**	0.134**	0.137**
	[0.038]	[0.035]	[0.034]	[0.035]
age_m	-0.040**	-0.039**	-0.046**	-0.045**
	[0.005]	[0.005]	[0.007]	[0.006]
age_m2	0.035**	0.034**	0.046**	0.046**
	[0.005]	[0.004]	[0.008]	[0.007]
ln_age_h	0.413**	0.349**	0.345**	0.324**
	[0.130]	[0.092]	[0.119]	[0.094]
ln_age_m	0.298	0.294	0.258	0.3
	[0.168]	[0.164]	[0.156]	[0.166]
height_mot	5.482**	5.479**	5.450**	5.388**
	[0.548]	[0.493]	[0.550]	[0.512]
ln_order	-0.084	-0.147	-0.11	-0.128
	[0.173]	[0.103]	[0.160]	[0.106]
edu_h345	0.029	0.028	0.025	0.024
	[0.070]	[0.066]	[0.070]	[0.067]
edu_m345	0.027	0.041	0.046	0.063
	[0.077]	[0.071]	[0.070]	[0.070]
time2	0.141*	0.116*	0.116	0.099*
	[0.068]	[0.049]	[0.060]	[0.048]
time3	0.149*	0.113	0.123	0.1
	[0.072]	[0.058]	[0.066]	[0.057]
rural	0.018	0.02	0.028	0.028
	[0.078]	[0.075]	[0.079]	[0.078]
time_hea	0.067	0.031	0.033	0.019
	[0.098]	[0.085]	[0.091]	[0.089]
time_hea2	-0.019	-0.018	-0.015	-0.013
	[0.019]	[0.017]	[0.016]	[0.016]
time_sch	0.189	0.131	0.208	0.131
	[0.273]	[0.259]	[0.280]	[0.279]
time_sch2	-0.092	-0.023	-0.052	0.003
	[0.258]	[0.253]	[0.259]	[0.267]
time_sch_mun	-2.988*	-2.459*	-2.459	-2.271*
	[1.421]	[1.069]	[1.300]	[1.114]
time_sch_mun2	4.148	2.988	3.022	2.672
	[3.523]	[2.804]	[3.246]	[2.891]
time_hea_sch	0.102	0.141	0.1	0.112
	[0.122]	[0.101]	[0.107]	[0.093]
hosp	0.096	0.102	0.108	0.109

	[0.069]	[0.064]	[0.067]	[0.066]
pipe	0.199	0.242	0.255	0.265
	[0.317]	[0.268]	[0.291]	[0.274]
sewage	0.202	0.175	0.132	0.159
	[0.163]	[0.122]	[0.139]	[0.122]
region_2	0.380**	0.368**	0.361**	0.344**
	[0.106]	[0.104]	[0.104]	[0.106]
region_3	0.161	0.14	0.151	0.116
	[0.109]	[0.104]	[0.106]	[0.107]
region_4	0.179	0.138	0.135	0.123
	[0.133]	[0.100]	[0.112]	[0.100]
altitud	0.413*	0.324*	0.299	0.262
	[0.186]	[0.143]	[0.150]	[0.142]
altitud2	-0.201**	-0.169**	-0.167**	-0.151**
	[0.060]	[0.046]	[0.050]	[0.047]
insur_mun	-0.523	-0.636	-0.322	-0.498
	[0.895]	[0.793]	[0.870]	[0.832]
insur_mun2	0.312	0.407	0.146	0.278
	[0.718]	[0.645]	[0.709]	[0.680]
Constant	-16.332**	-14.223**	-15.466**	-14.355**
	[4.857]	[3.233]	[4.475]	[3.343]
Observations	5940	5980	6032	6072

* significant at 5%; ** significant at 1%