Complementarities in the Production of Child Health

IFS Working Paper W19/15

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10th June 2019

Abstract

This paper estimates flexible child health production functions to investigate whether better water, sanitation and hygiene (WASH) practices make nutrition intake more productive for children aged 6-24 months. Using cohort data, with detailed information on nutrition intake and WASH investments, and a control function approach to account for endogeneity of inputs, we show that better WASH increases the productivity of protein and calories in the formation of child health using as proxies child height and weight. We also uncover heterogeneity in the productivity of these inputs by child gender: nutritional intake is found to be more productive for boys, and WASH investments more productive for girls. Further analysis indicates that this is not driven by differential parental investments by child gender. Although the study sample are children born in the early 1980s they faced similar nutritional and WASH conditions as those faced by children currently living in poor households in low-income settings.

JEL Codes: I12, I15, O15, O18, Q53

Keywords: child health; sanitation; nutrition; complementarities; health production function.

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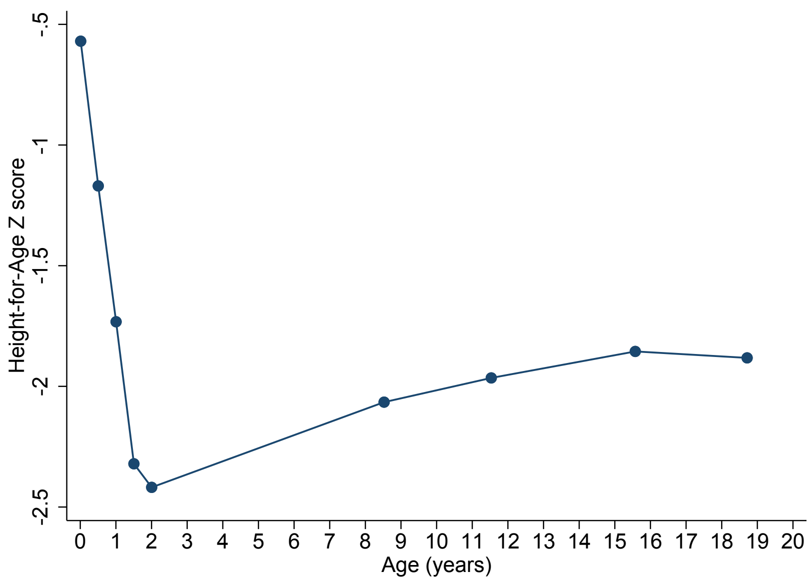
1 Introduction

Linear growth faltering, where the growth trajectory of children diverges from the healthy growth norm, is pervasive among children in developing countries. Emerging in the first two years of life, growth faltering is not recouped in later years (see Figure 1 for height-for-age Z-scores (HAZ) for children in the Cebu Longitudinal Health and Nutrition Survey), with long lasting implications for health, cognitive development and productivity (Hoddinott et al. (2008) and Hoddinott et al. (2013), Maluccio et al. (2009), Victora et al. (2010), Almond and Currie (2011)); affecting the ability of poor households to break free from a cycle of disadvantage (Ghatak (2015)). Understanding the drivers of this deterioration and how it can be ameliorated is therefore vital for social welfare, economic growth and development.

Figure 1: Mean Height-for-Age Z-scores by age



Source: Cebu Longitudinal Health and Nutrition Survey

The determinants of growth faltering are not fully understood. While under-nutrition is a widely recognized key component (see for example Engle et al. (2007), Black et al. (2008), Behrman et al. (2009) and Puentes et al. (2016), among others), an emerging literature suggests that nutritional investments alone are insufficient to reduce the level of linear growth faltering seen in low-income countries (Humphrey (2009), Mbuya and Humphrey (2016)). In particular, it is conjectured that nutritional investments ought to be complemented with a hygienic and safe environment in order to be sufficiently effective. A hygienic environment would reduce exposure to pathogens that lead to diarrhoea and other infections, and also reduce the likelihood of developing sub-clinical conditions such as environmental enteropathy, an inflammation of the gut which reduces the ability of the small intestine to effectively absorb nutrients (Lunn, Northrop-Clewes and Downes (1991), Campbell, Elia and Lunn (2003), Lin et al. (2013), Prendergast et al. (2014), Gough et al. (2016), Mbuya and Humphrey (2016) and George et al. (2016)). Whether, and the degree to which, an improved hygienic environment makes nutritional intake more productive has however not been established. Identifying the determinants of growth faltering, and consequently policy interventions to alleviate these requires an understanding of not only which inputs are relevant, but also of how they interact with one another.

Two key approaches have been used to identify the determinants of growth faltering. Numerous studies have estimated child health production functions (Cebu 1992, Puentes et al. 2016, Cao 2015). However, existing approaches either focus on one input only or employ very restrictive functional forms, that impose strong restrictions on the nature of interaction between inputs (e.g. perfect substitution). Alternatively, an extensive literature evaluates the effects of policies altering either one or multiple inputs. These estimated effects are not necessarily comparable to estimates of production function parameters, since households might adjust other inputs in response to policy changes (Todd and Wolpin 2003).

Moreover, studies focusing on specific policy changes might not have sufficient power to detect small interaction effects, especially since policies evaluated through randomised controlled trials often take a cluster (e.g. a village) as the unit of randomisation. For example, the WASH Benefits trial, a multi-arm randomised controlled trial implemented in Kenya and Bangladesh with arms providing either nutrition or WASH interventions on their own or in combination was powered to detect interactions twice as large as each intervention itself (Arnold et al. (2013)). Furthermore, attaining behaviour change particularly in the case of WASH practices is notoriously challenging, so that adherence to treatment protocols tends to be low (Clasen et al. 2014, Null et al. 2018 among others).

In this paper, we estimate flexible production functions of child health using as proxies child height and weight between 6 and 24 months using rich panel data from the Cebu Longitudinal Health and Nutrition Survey (CLHNS) to assess whether WASH investments and nutrition complement with one another. The functional form we employ, the translog, allows us to explicitly model the interaction without imposing strict restrictions on the nature of this interaction, as would be the case if we estimated linear, Cobb-Douglas or Constant Elasticity of Substitution (CES) production functions, as done in, for example, Puentes et al. (2016), Cebu (1992) and De Cao (2015). Our estimation approach allows for the inputs to be endogenous, either because parents choose them in response to unobserved shocks or in line with their unobserved preferences, and corrects for this endogeneity using a control function approach. As exclusion restrictions, we use variables which, conditional on a rich set of individual, household and community controls, meet the condition of affecting child height and weight primarily through directly influencing either nutrition or WASH investments. The effects of nutrition and WASH, including their interaction, could be heterogeneous. Thus, in further analysis, we consider heterogeneity along the margin of child gender, and explore whether these are driven by differential investments by parents.

The CLHNS is an especially well-suited data source for our analysis. It follows a cohort of around 2,800 children born between 1983 - 1984 from the third trimester of pregnancy to age 27 years, with measurements for each child every two months over the first 24 months of life. The surveys in the first two years of life collected detailed information on child-level feeding practices, and child- and household-level WASH practices, along with detailed information on community-level prices (food, sanitation and average wages) and geological characteristics which provide exclusion restrictions for the control function approach. Our focus on the 6-24 month age period is motivated by the fact that this developmental window covers the age range over which most of the linear growth faltering occurs.[1] The specific measures of nutrition intake we consider are protein and calorie intake, both of which are crucial for healthy child growth. We combine the numerous indicators of WASH practices into a parsimonious representation of WASH using exploratory factor analysis. This has the advantage of reducing the number of instruments needed, while also allowing us to deal with linear measurement error.

To make the estimation tractable, we estimate value-added translog production functions. These assume that parents make input decisions based on children's height and weight in the last period, so that conditional on past height and weight, past inputs will not independently affect current height and weight. The key advantage of this approach is that it dramatically reduces the number of endogenous inputs we need to account for in the estimation, while also accounting for endogeneity from unobserved endowments. Our detailed, high-frequency data allows us to relax some of the strong assumptions of the value-added production function, which we incorporate into our estimation.

The value-added approach does not resolve endogeneity emerging from parents making input choices in response to unobserved shocks or to unobserved preferences. Therefore, we tackle this endogeneity using a control function approach together with the value added model. As instruments, we use community-level prices of food and sanitation, community-level geological features, and community-level average wages, which conditional on a rich set of individual, household and community controls, meet the condition of affecting child height and weight primarily through directly influencing either nutrition or WASH investments. We discuss in detail the issue of instrument validity.

Our findings show that both nutrition intake - particularly protein - and WASH are important inputs into child height. We detect significant impacts of each input on children's growth separately, as well as a robust, positive and statistically significant, though quantitatively small, interaction between nutrition intake and WASH, indicating that WASH investments

[1] Breastfeeding also reduces gradually from this age. Children past the age of 6 months are in an age range where semi-solid and solid food intake becomes increasingly important, and breastfeeding becomes increasingly rare. The medical literature has established that breast milk can insulate children from infectious diseases by transmitting maternal antibodies to breastfed children (see, for example Sadeharju et al. (2007) and Victora et al. (1987)).

does indeed make nutrition investments more productive. In terms of magnitude, estimates indicate that the cumulative effect of a 20% increase in protein over the 6-24 month age range - equivalent to an additional egg a day - for a child at the 10th percentile of the WASH distribution would increase height by 2.57cm. For a child at the 90th percentile of the WASH distribution this gain would be around 0.16cm larger.

Our estimates similarly suggest a robust, positive interaction between nutrition intake and WASH for child weight, though the coefficients on the direct effects of nutrition and WASH are not statistically significantly different from 0. Increasing a child's intake of protein by an egg a day from the age of 6 months to 24 months increases the average child's weight at 24 months by 1.03kg, with a smaller effect for children in the 10th percentile of the WASH score distribution (0.74kg), than in the 90th percentile (1.19kg). This is a non-negligible difference, particularly given significant gaps in weight by wealth quintile in this context.

Estimating the production function separately for boys and girls uncovers interesting heterogeneity. We estimate a larger, positive marginal effect for nutrition intake, particularly protein intake, for boys. By contrast, WASH investments are more productive for girls. Moreover, the complementarities between WASH and nutrition intake are stronger for girls. This difference prevails despite the fact that our analysis rules out that this heterogeneity is driven by parents making differential investments by child gender.

This paper contributes to two main strands of literature in economics and child health more generally. First, it contributes to the established literature on the importance of nutrition for child health using child height and weight as proxies. Adair and Guilkey (1997) study age-specific determinants of stunting in Filipino children and highlights the importance of breastfeeding, preventive healthcare and maternal height to decrease the likelihood of stunting, while the review by Black et al. (2008) highlight effective nutritional interventions for child height formation. Contributions such as Puentes et al. (2016), Cao (2015) and Team et al. (1992) estimate linear child health production functions using the CLHNS data, showing respectively that protein intake is important for child height and weight gain in Guatemala and Philippines, and that nutritional inputs have different productivities for males and females. Liu, Mroz and Adair (2009) use the CLHNS data to estimate child health input demand functions and dynamic linear child health production functions for the first two years of a child's life, as this paper does, finding evidence of compensatory behaviour by parents. None of these studies considers the contribution of WASH, either directly or in interaction with nutritional inputs. Few studies of child health production functions allow for interactions between inputs. One exception is Rosenzweig and Schulz (1983), who estimate both Cobb-Douglas and translog production functions for child birth weight.

Second, our paper contributes to a more recent and growing literature exploring the importance of WASH on health outcomes in low-income setting.[2] These studies find mixed evidence

[2]A separate literature studies the importance of water and sewerage infrastructure on infant health in

of the effectiveness of separate WASH and combined WASH interventions on child health (Gera, Shah and Sachdev 2018, Dangour et al. 2013). Hammer and Spears (2016), Gertler et al. (2014), Pickering et al. 2015 and Augsburg and Rodrıguez-Lesmes (2018) find negative effects of poor sanitation on child height. However, studies by Clasen et al. 2014 among others find no effects of improved sanitation on child health. This is in line with the findings from the WASH Benefits and SHINE trials, which find no effect of WASH interventions on child height in the first two years of life, either on their own or when combined with other interventions (Null et al. (2018), Luby et al. (2018), Humphrey et al. 2019). However, systematic reviews remain positive about WASH interventions and support the scale-up of WASH in low and middle-income countries (Darvesh et al. 2017). Potential explanations that have been put forward for the lack of health impacts include low adherence to the trial interventions (Kenya WASH Benefits), intervening in an area with unexpectedly low prevalence of diarrhoea (Bangladesh WASH Benefits trial) or intervening during a period when children were mostly still breastfeeding (SHINE trial), hence providing adequate protection against infections though antibodies in breastmilk. In contrast to the WASH Benefits and SHINE trials, our paper focuses on a mostly urban sample (75%), who live in more densely populated areas which leave greater potential for negative externalities of poor WASH (Hathi et al. 2017 settings). Moreover, the sample children stop breastfeeding much earlier than for example children in the SHINE trial, where over 95% of children not exposed to HIV were being breastfed at age 18 months.

The remainder of the paper is structured as follows. Section 2 discusses the CHLNS data and the input measures, section 3 lays out the theoretical framework and estimation strategy and section 4 lays out our results before we conclude in section 6.

2 Context, Data and Measures

We use data from the Cebu Longitudinal Health and Nutrition Survey (CLHNS), an ongoing study of a cohort of Filipino children born between May 1, 1983 and April 30, 1984. Originally designed to study infant feeding patterns and their role in shaping child physical health, this data contains exceptionally detailed information on infant feeding, child health indicators, and measures of sanitation, water and hygiene practices, collected regularly over the first two years of the child's life. These features make the data particularly suitable for testing our hypothesis of whether better WASH makes nutritional investments more productive in the formation of child height and weight once complementary feeding starts. In addition, the surveys collected detailed background health and socio-economic information on the mother, and the household, as well as a range of community variables, including bi-monthly price surveys between 1983 and 1986 that collected prices of key foods including infant formula,

developed economies using historical data. Contributions include Cutler (2006) and Alsan and Goldin (2019) among others.

and on kerosene.

All mothers of children born between May 1, 1983 and April 30, 1984 living in 33 neighbourhoods, 17 urban and 16 rural, (hereinafter referred to as *communities*) were surveyed at the start of the third trimester of pregnancy (March 1983 - April 1984), and then at multiple points in time during the first two years of their child's life (a few days after birth, thereafter once every two months). Further follow-up surveys were conducted at older ages. For testing our hypothesis, we will focus on the data relating to children aged 6-24 months.

Participation rates in the survey were high. At baseline (during the third trimester of pregnancy), 3,327 women were successfully interviewed. Around 90% were surveyed at least once after their child's birth and 65% were surveyed in every follow up survey until the child turned two years of age.[3]

Table 1 shows dropouts by reason. 13.4% left the survey area during the study period, 6.2% of women dropped out due to miscarriage, stillbirth or death of their child, 0.8% were dropped due to the pregnancy resulting in multiple births, and the remaining women either refused to participate in the surveys, or were dropped due to erroneous information.[4]

Table 1: Dropout Reason

	No.	%
Sample woman with complete survey records	2,184.00	65.6
Sample woman left the survey area during the survey period	446	13.4
One or more missing longitudinal surveys, but confirmed that child is alive	377	11.3
Refused interview	66	2
Sample baby died	155	4.7
Stillbirth	38	1.1
Miscarriage	13	0.4
Twin birth, dropped from sample	26	0.8
Dropped because of erroneous information	22	0.7
Total	3,327	100

Though this data was collected over 30 years ago, conditions faced by the study sample are similar in many dimensions (e.g. education level, household composition and size, water and sanitation access) to those faced by poor households living in low-income settings today.

Table 2 provides descriptive statistics on characteristics of the community, households, children, and their mothers. A significant majority of study children -around three quarters- live in urban neighbourhoods, despite the equal number of urban and rural communities sampled, reflecting the higher population density in urban areas. Averaging over all communities, households need to travel on average 6km to the nearest public hospital. Before the birth of

[3]Of these 90%, 14.83% migrated out of the study area and were lost to follow-up.

[4]In Online Appendix A.1, we compare characteristics of attrited (not present in all bi-monthly surveys) and non-attrited households/mothers/children in table 16. Attrition is broadly balanced across a rich set of observed variable, with the exception of home ownership and number of children under the age of 5 in the household.

the study child, the typically male (95%) household head is just over 35 years of age, employed (95%), and has just over 7 years of education, implying that he would have on average completed (compulsory) elementary school plus one additional year. Households typically consist of 5-6 members, live in dwellings they own (71%), which are mostly constructed from poor materials (only 18% made of concrete) and have fewer than three rooms on average. Asset ownership is low, with only 6% owning a refrigerator, 70% owning benches or chairs and about 48% having electric lighting in their house. Conducting a rough back-of-the-envelope calculation, members living in our study households are below the official International Poverty Line of less than 1.90 USD per person per day, averaging approximately 1.77 USD in 2017 USD.

Table 2: Sample Characteristics

Variable	Mean	Sd	N
Household and Community Characteristics			
Household in urban community	0.74	0.44	2,302
Distance to nearest public hospital (km)	6.03	4.94	2,302
Age of household head (years)	35.51	12.21	2,302
Household head is female (%)	0.05	0.21	2,302
Household head is in employment (%)	0.95	0.21	2,302
Household head's years of education	7.21	4.04	2,302
Number of household members	5.72	2.79	2,302
Household owns dwelling (%)	0.71	0.46	2,302
Home made of concrete (%)	0.18	0.38	2,302
Households own a refrigerator (%)	0.06	0.24	2,302
Households own benches/chairs (%)	0.70	0.46	2,302
Households have electric lighting (%)	0.48	0.50	2,302
Number of Rooms (excluding bathrooms)	2.60	1.31	2,302
Household Income per capita (USD 2017)	1.77	1.67	2,302
Anthropometrics from 6 months			
Average height of child (all rounds, cm)	72.40	2.95	2,302
Average weight of child (all rounds, kg)	8.33	1.01	2,302
Stunted at 6 Months	0.21	0.41	2,274
Stunted at 24 Months	0.63	0.48	2,174
Mothers Characteristics			
Highest level of education of mother	7.39	3.69	2,302
Mother is spouse of/is household head	0.78	0.41	2,302
Mother age, years	27.05	5.94	2,302
No. of children under 5	1.27	1.00	2,302
Mother working during pregnancy	0.38	0.49	2,302
Child Birth Characteristics			
Childs gender (1=Male)	0.52	0.50	2,302
Birthweight (kg))	3.05	0.44	2,302
Birth Height (cm)	49.27	2.10	2,299

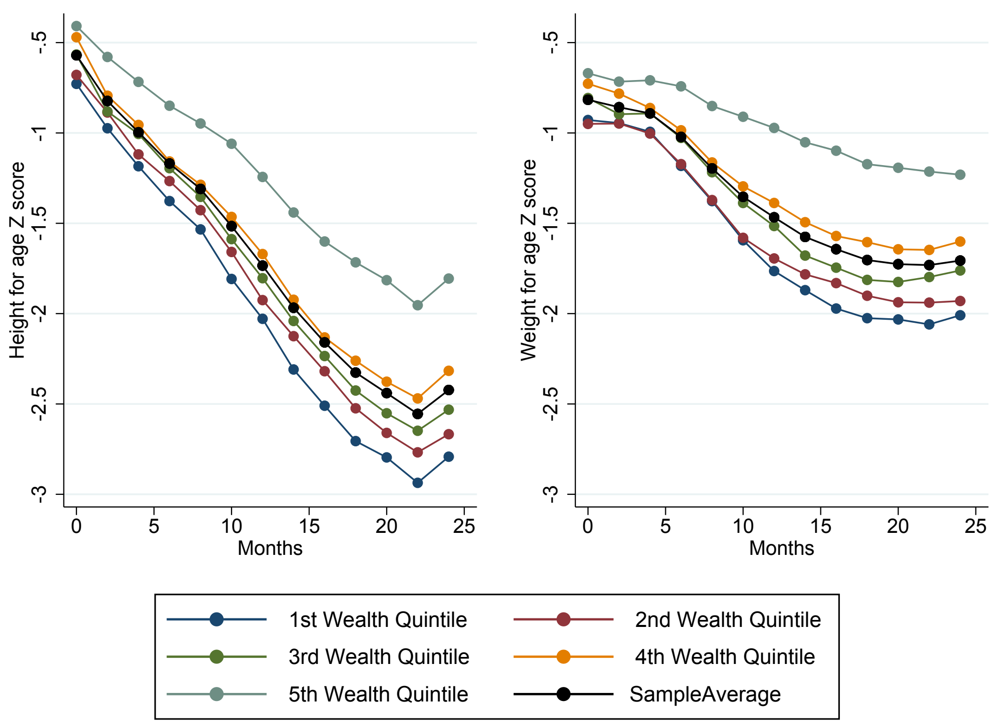
Notes: Averages calculated using children who are present at any point in the analysis period. Lower samples for height measurements are due to missing observations in selected rounds.

Mothers are on average 27 years of age, and have around 7.4 years of education. Most are the spouse of the household head or the head themselves (78%) and just over one third of the sample of mothers was working prior to the birth of the study child. The study child is typically their first child, with -on average- only every fifth child having a sibling at the time the baseline survey was conducted.

The CLHNS includes also anthropometric measurements collected at birth, and during the bi-monthly follow-up surveys. Table 2 also shows some characteristics of our sample children themselves. Just above half (52%) are girls and the average child weighed 3.05 kg at birth with a length of 49.27 cm. At the age of 6 months, the average child weighed 8.3 kg with a height of 72.4 cm. The proportion of stunted children is 21% at this age, but rises rapidly to 63% by 24 months.

Useful benchmarks for child anthropometrics are height-for-age and weight-for-age Z scores (WAZ), standardised relative to the median for children of the same age and gender in the WHO reference population. A child is considered stunted (underweight) if their HAZ (WAZ) falls below -2 standard deviations from the norm. Figure 2 displays the evolution of these scores with the child's age by wealth quintile for our sample.[5]

Figure 2: The evolution of HAZ and WAZ scores by child age in months



Note: Wealth quintiles generated from a principle component analysis of assets.

The left panel of Figure 2 indicates that the average child in our sample is shorter than the WHO reference population at birth (as indicated by the HAZ of about -0.5), and experiences

[5]The construction of the wealth index and wealth quintiles is detailed in Section A.2 in the Online Appendix.

a growth trajectory that diverges away from the healthy growth trajectory as the child gets older. Moreover, it also indicates substantial differences across wealth quintiles. At birth, the gap between the top and bottom quintiles is around 0.3 standard deviations. This increases to around 1 standard deviation by 20 months of age. Remarkably, it is only the top quntile that does significantly better, the gap opens already between the top and the fourth wealth quintile. By age 1 year the average child is stunted, which corresponds with being over 6 cm shorter than children from the healthy reference population. Stunting rates in this sample are high (62.4% by age 2 years), and comparable to those experienced in many developing countries today.

Child weight follows a similar, if less dramatic, pattern, as shown in the right panel of Figure 2. We find that the average study child starts out with low weight for age compared to the reference population and that about 10% of our sample are underweight at birth. While there is no dramatic deterioration in the first 5-6 months of life, it diverges significantly from the WHO reference population thereafter before stabilizing around 15 months of age. This deterioration coincides with the introduction of complementary feeding. Similarly to height for age, the difference between the top and bottom quintiles at birth grows from around 0.3 standard deviations at birth to around 0.7 standard deviations by the time the children reach 24 months. The difference between the 5th (top) and 4th quintile is again surprisingly large, with a 0.4 standard deviation gap opening up by the time the child reaches two years of age.

2.1 Inputs

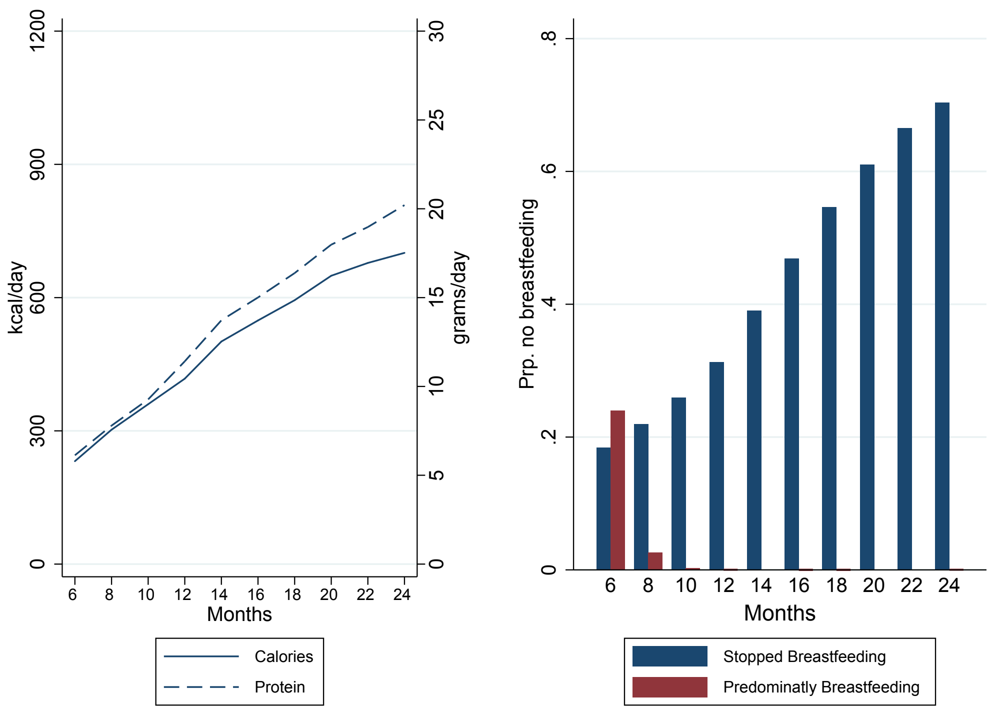
The main interest of this study is the role of different inputs, and the interaction between these, in the production of child health. The first key input we consider is nutrition.

2.1.1 Nutrition

The CLHNS data contains exceptionally detailed information on food intake over the first two years of the infant's life. Data was collected on the commencement, frequency and discontinuation of breastfeeding, and the intake of all liquids, solids and semi-solids in the 24 hours prior to the bi-monthly survey. Questions were asked about all the meals consumed by the child. Particular attention was paid to measuring quantities consumed: the survey enumerators were equipped with measuring aids, which allowed for accurate measurement (in common units). Quantities of nutrients were then calculated using food composition tables published by the Filipino Food and Nutrition Research Institute, which were supplemented with nutrient composition information obtained directly from manufacturers for foods such as infant formula (Bisgrove, Popkin and Barba (1989), Bisgrove, Popkin and Barba (1991), Perlas, Gibson and Adair (2004) provide more details).

The children in our sample consume on average 14.0 grams of protein and 510 kcal per day. The left panel of Figure 3 shows the breakdown of these averages in the cross-section at different ages. Unsurprisingly, calorie and protein intake increase with age. For instance, sampled children consume an average of 6.1 g of protein and 231 kcal per day at age 6 months, 11.4 g of protein and 417 kcals per day on average at age 12 months, and 20.2 grams of protein and 700 kcals on average at two years of age.

Figure 3: Nutritional inputs over time



Note: Predominant breastfeeding is defined along WHO guidelines (i.e. no semi-solid food yet introduced). Stopped breastfeeding is defined as having no intake of breast milk at all.

These values are lower bounds on nutrition intake. Proteins and calories consumed through breastmilk are not included in the calculations, as both the amount consumed of breastmilk as well as its protein component and/or caloric contents are notoriously difficult to measure. And indeed, the right panel of Figure 3, which displays the proportion of weaned children at different ages, reveals that breast-milk remains a component of the child's diet long beyond the introduction of solid foods and other liquids, with 69% of children still receiving breast-milk at one year of age and 46% at age 18 months. Predominant breastfeeding however falls from 24% at 6 months to 0.2% 2 months later. In our analysis, we will control for whether or not the child is being breastfed.

2.1.2 Water, Sanitation and Hygiene

The second input into child height and weight production considered is the child's environment, with a specific focus on water, sanitation and hygiene. While the relative effectiveness and importance of each of these components is of interest in itself, we face methodological constraints in assessing their individual contributions. In particular, including an independent variable for each of the three WASH dimensions would require a sufficiently strong instrument for each variable, which can be challenging to find. We therefore consider a composite indicator. By using this one indicator score instead of a full collection of hygiene- and sanitation-related variables, we require only one instrument and include WASH as a single term in a production function. Another advantage of this approach is that it eases the interpretation of the relationship between WASH and nutrition. Finally, it allows us to account for linear measurement error.

The data contains a number of measures of the child's household's practices around water, sanitation and hygiene. Some of these are measured in each survey round, others are only observed once. We combine all information into a single WASH score using polychoric exploratory factor analysis, estimated separately for each survey round. We retain the first factor as the WASH score.[6] In all cases, the eigenvalue associated with the first factor was always greater than 1.[7] The WASH score used in our analysis includes at least one variable related to each component of water, sanitation and hygiene practices.

To capture the *water* dimension, we use an indicator for whether or not drinking water given to the child was treated (collected in each of the longitudinal survey rounds). We construct an indicator which equals one if the child was not given untreated water (i.e treated water or nothing), or zero otherwise.[8] In our sample, only 45% of children were given treated water, as can be seen from the first row of Table 3.

[6] The WASH score is estimated separately by round, i.e. child age. However, we find little difference in the factor loadings across rounds.

[7] We explore the use of a second WASH score, which includes, in addition to these child- and household-level variables, a community-level average (excluding the household itself) of the same variables. The rationale behind doing so is the externality effect of WASH. Safe WASH is postulated to have not only private benefits, but also affect neighbours. Possibly because we do not have information on the whole community, but only on our specific sample, these community averages do not influence the results. We therefore present estimations without these averages. Those including the expanded WASH variable are available upon request.

[8] Notice that this indicator takes a value of 1 if the child was not given any water – which is especially relevant for predominantly breastfed children.

Table 3: Water, Sanitation and Hygiene Variables

	Descriptives			Factor
	mean	sd	N	loading
No water/treated water given to child (by round)	0.45	0.50	21,969	0.455
Safe toilet in household (dummy)	0.65	0.48	21,969	0.875
Child's feces is disposed of safely (i.e. toilet)	0.16	0.37	21,969	0.632
Weekly household soap expenditure (Pesos)	205.57	167.21	21,969	0.412

Note: Sample size for treated water variable is defined in each round. Safe toilet, feces disposal and soap expenditures are observed once.

For the *sanitation* dimension, we make use of information on the type of toilet facility owned by the household (collected at baseline), and how mothers dispose of their child's feces (collected when the child was around 18 months old). We construct indicators for whether or not a household owns a safe toilet - defined, following the Joint Monitoring Program (JMP) definition, as either a flush, water sealed or antipolo toilet - and whether a child's feces are safely disposed of - defined as disposal, either of waste water or of feces, directly into a toilet.[9] We see in Table 3 that around 65% of households own a safe toilet, but only 16% use that toilet to safely dispose of child excreta.

Finally, the *hygiene* dimension is captured through information on soap expenditures (collected at baseline), on which households spend on average 206 pesos (approx. USD 6.64).

The last column of Table 3 provides the factor loadings for our constructed WASH score. Results indicate that safe toilet ownership has the highest factor loading among the household-level variables, a point we will return to when discussing exclusion restrictions.[10,11]

We analyse how these variables vary with household's wealth quintile, shown in Table 4. Interesting, and sensible, patterns emerge. First, the percentage of households reporting to have given untreated water to their child decreases by wealth quintile from 94% in the first to 12% in the fifth quintile. Second, we find that no household in the lowest quintile owns a safe toilet, compared with universal safe toilet ownership among the highest wealth quintile. Ownership rates increase dramatically from 27% to 96% as we go from the second to the

[9] A significant proportion of households (27%) report disposing feces in the garbage. This need not correspond to safe disposal of feces, according to the UNICEF-WHO joint monitoring program.

[10] The surveys also collect information on the household's main source of drinking water, whether children are given leftovers, and if so, how food given to the child is stored; and interviewer observations of the cleanliness of the cooking area, and of the general area around the household. Factor loadings associated with these variables were very low in the exploratory factor analysis, indicating that they did not provide much more information or variation beyond that captured by other variables included in the factor analysis. These variables were therefore dropped in the construction of our WASH indicator.

[11] In robustness checks, we estimate WASH scores using either only time invariant variables (e.g. safe toilet ownership, soap expenditures and child feces disposal; or only safe toilet ownership) and time varying variables (e.g. treated water intake, cleanliness of the cooking area, and safe storage of food given to the child). The resulting WASH scores, and estimates of the production functions using these scores can be found in Online Appendix B.1.

third quintile. Third, safe disposal of child feces is basically non-existent in the three lowest quintiles (<5%), increasing to 15% in the 4th and 58% in the fifth. Finally, soap expenditures increase with wealth quintile.

Table 4: WASH inputs by Wealth Quintile

	1st	2nd	3rd	4th	5th
Safe toilet in household (dummy)	0.00	0.27	0.96	0.99	1.00
Child's feces is disposed of safely (i.e. toilet)	0.00	0.04	0.04	0.15	0.58
Log household soap expenditure	4.37	4.96	5.04	5.23	5.71
No water/treated water given to child (by round)	0.06	0.40	0.18	0.69	0.88
Log WASH	-1.10	-0.69	-0.33	-0.22	-0.07

Note: Each number represents the mean value of the WASH inputs by WASH quintile.

We assess how the resulting WASH score correlates with various child-, household- and community-level variables in Table 17 in Online Appendix B. We observe an increasing and concave relationship between the estimated WASH score and the child's age but no systematic correlation with the child's gender, as indicated by the small and statistically insignificant coefficient on the female dummy. There is an important positive wealth gradient, with children in wealthier households having a significantly larger WASH score. The WASH score is also larger where the household head has more education, particularly high school or greater. Households in larger, urban communities also have a larger WASH score, reflecting that safe water and sanitation facilities are much more widely available in urban than in rural communities.

3 Theoretical Framework and Estimation Strategy

In this section, we outline the theoretical framework and our estimation strategy. Starting from a very general production function, we lay out the assumptions that we make in order to obtain an empirically estimable specification. We start from the most general process of height, H, and weight W formation for child i at age t, which can be defined as:

$$H_{it} = H_t\left[\{N_{is}\}_{s=1}^{t-1}, \{S_{is}\}_{s=1}^{t-1}, \mu_i; X, \{\varepsilon_{is}\}_{s=1}^{t-1}\right] \tag{1}$$

$$W_{it} = W_t\left[\{N_{is}\}_{s=1}^{t-1}, \{S_{is}\}_{s=1}^{t-1}, \mu_i; X, \{\varepsilon_{is}\}_{s=1}^{t-1}\right] \tag{2}$$

Where $\{N_{is}\}_{s=1}^{t-1}$ and $\{S_{is}\}_{s=1}^{t-1}$ are the history of nutritional and WASH inputs given to the child from birth ($s = 1$) to age $s = t - 1$. $\{\varepsilon_{is}\}_{s=1}^{t-1}$ is a vector containing both the history of shocks experienced by the child from birth up to age $t - 1$ and parental preferences.μ_i is the child's health endowment. X is a vector of other variables which also effect the formation of height and weight, such as mother's height.

Estimation of such a production function poses several challenge related to its functional form and potential endogeneity of inputs.

It is not, *a priori* obvious what functional form the child health production should take. Common choices in the literature (such as Constant Elasticity of Substitution production function or linear production function) impose fairly strict assumptions on the process. For instance, linear production functions impose a strict separability of inputs, implying perfect substitutability, and force complete independence between the marginal products of inputs. This would imply for instance that households can compensate for poor hygiene by giving their child more food. This strikes us as too strong an assumption to make, given the biological and medical understanding of the process of child physical growth. Other popular functional forms such as the Cobb Douglas or Constant Elasticity of Substitution impose the restriction of homotheticity of inputs. The acknowledged unknowns in the medical science literature about the process of child height and weight formation suggest the need for a more flexible functional form to model this process.

We estimate a translog functional form, which is remarkably flexible and avoids imposing any of the substitutability or complementarity assumptions discussed above. Furthermore, we reduce the number of past inputs we need to consider by using the widely-used value added model. This makes the estimation more tractable, since it requires considering only the inputs made in the contemporaneous period.

Following Todd and Wolpin (2007) and Puentes et al. (2016), we lay out the assumptions under which the value added approach gives consistent estimates. We consider the joint production of child height and weight. We start with the full translog production functions for height and weight at period t, which can be expressed as follows:

$$H_{it} = \left[\alpha_0^h \prod_s^{t-1} N_{is}^{\alpha_{is}^h} \prod_s^{t-1} S_{is}^{\beta_{is}^h} \prod_s^{t-1} N_{is}^{Y_1} \prod_s^{t-1} S_{is}^{Y_2}\right] e^{(\delta_t^h \mathbf{X} + \sigma_t^h \mu_{i0} + \varepsilon_{it})} \tag{3}$$

$$W_{it} = \left[\alpha_0^w \prod_s^{t-1} N_{is}^{\alpha_{is}^w} \prod_s^{t-1} S_{is}^{\beta_{is}^w} \prod_s^{t-1} N_{is}^{Y_3} \prod_s^{t-1} S_{is}^{Y_4}\right] e^{(\delta_t^w \mathbf{X} + \sigma_t^w \mu_{i0} + \varepsilon_{it})} \tag{4}$$

Where $Y_1 = \frac{1}{2}(\sum_j^{t-1} \gamma_{Njs}^{h'} \ln N_{is} + \sum_j^{t-1} \gamma_{Njs}^{h} \ln S_{is})$, $Y_2 = \frac{1}{2}(\sum_j^{t-1} \gamma_{Sjs}^{h} \ln N_{is} + \sum_j^{t-1} \gamma_{Sjs}^{h'} \ln S_{is})$, $Y_3 = \frac{1}{2}(\sum_j^{t-1} \gamma_{Njs}^{w'} \ln N_{is} + \sum_j^{t-1} \gamma_{Njs}^{w} \ln S_{is})$ and $Y_4 = \frac{1}{2}(\sum_j^{t-1} \gamma_{Sjs}^{w} \ln N_{is} + \sum_j^{t-1} \gamma_{Sjs}^{w'} \ln S_{is})$.

These equations contain the entire history of nutrition and WASH inputs, as well as their interactions and quadratic terms. Broadly, our parameters of interest are both the α_i's and γ_i's in these equations, which jointly capture the marginal effect of each input, as well as their complementarities/substitutabilities. Considering the full translog specifications to the data will be infeasible. To make the model more tractable, we make several simplifying assumptions used in our estimation, detailed below.

Assumption 1. *$\gamma^{h'}_{Njs} = \gamma^{h'}_{Sjs} = 0$ and $\gamma^{h}_{Njs} = \gamma^{h}_{Sjs} = \gamma^{h}_{js}$ for all s.*

We assume first that the quadratic terms of each input have no additional impacts on height or weight. Given that we are modelling all of the interactions between inputs, this assumption does not place too much additional structure on the growth process. After taking logs and applying assumption 1, equations 16 and 17 simplify to the following:

$$\ln H_t = \alpha_0^h + \sum_s^{t-1} \alpha_s^h \ln N_s + \sum_s^{t-1} \beta_s^h \ln S_s + \sum_s^{t-1}\sum_j^{t-1} \gamma_{js}^h \ln N_s \ln S_j + \sigma_t^h \mu_0 + \delta_t^h \mathbf{X} + \varepsilon_t \tag{5}$$

$$\ln W_t = \alpha_0^w + \sum_s^{t-1} \alpha_s^w \ln N_s + \sum_s^{t-1} \beta_s^w \ln S_s + \sum_s^{t-1}\sum_j^{t-1} \gamma_{js}^w \ln N_s \ln S_j + \sigma_t^w \mu_0 + \delta_t^h \mathbf{X} + \varepsilon_t \tag{6}$$

These equations are more tractable than equations 16 and 17, but still pose serious problems in estimation. They still include the whole history of inputs of nutrition and sanitation, as well as all of their interactions. Furthermore, there is still the confounding influence of unobserved health endowment μ_0. To deal with this we add assumptions 2-4.

Assumption 2. *$\gamma^{i}_{js} = 0 \; \forall s, j \;\; s \neq j$*

This assumption imposes that only contemporaneous interactions between WASH and nutrition matter for height and weight formation (i.e. WASH at 6 months does not interact with protein at 8 months). This does not preclude correlations between lagged inputs and outputs at t, but implies that these interactions must work through height or weight in a previous period.

Assumption 3. *For $i \in \{h, w\}$: $\alpha^i_s = \lambda\alpha^i_{s-1}$, $\beta^i_s = \lambda\beta^i_{s-1}$, $\gamma^i_s = \lambda\gamma^i_{s-1}, \sigma^i_s = \lambda\sigma^i_{s-1}$*

This assumption is standard in the value added framework, that states the impact of past inputs follows a rate of decay λ, which is common across all inputs.

Assumption 4. *$\alpha^h_s = a\alpha^w_s$,$\beta^h_s = a\beta^w_s$,$\gamma^h_s = a\gamma^w_s$, $\sigma^h_s = a\sigma^w_s$ for some scalar constant a*

The final assumption, which is similar to that in Behrman et al. (2009), imposes that the coefficients on height and weight are the same up to a scalar constant. This assumption imposes that the effect of the unobserved endowment on height is linear in the effect on weight.

Taking the first difference of height and weight, and then taking the difference between the height and weight equations and applying assumption 2-4, leads to the following equation for height

$$\begin{aligned}\ln H_t = k^h + \alpha^h_{t-1} \ln N_{t-1} + \beta^h_{t-1} \ln S_{t-1} + \gamma^h_{t-1} \ln N_{t-1} \ln S_{t-1} \\ + \frac{a+\lambda-2}{a-1} \ln H_{t-1} - \frac{\lambda-1}{a-1} \ln W_{t-1} + b^h\mathbf{X} + \pi^{\Delta h}_t\end{aligned} \tag{7}$$

where, $k^h = \frac{\alpha^h_0 - \alpha^w_0}{1-a}$, $b^h = \delta^h_t - \delta^h_{t-1}\frac{a}{a-1} + \frac{\delta^w_{t-1}}{a-1}$ and $\pi^{\Delta h}_t = \varepsilon^h_t - \varepsilon^h_{t-1} + \frac{\varepsilon^h_{t-1} - \varepsilon^w_{t-1}}{1-a}$. A similar expression can be derived for weight and is given in Appendix A.1, which also contains the full derivation.

Abstracting from the endogeneity resulting from the unobserved shocks and unobserved parental preferences for the moment (which we will discuss next), we note that these assumptions would allow us to obtain consistent estimates of the parameters of interest. Unobserved endowments, captured in the μ_0 term, could still generate endogeneity in inputs if parents choose inputs in response to the child's endowment. Assumption 3, combined with the differencing of equations for height and weight allows us to remove μ from each equation. However, assumption 3 can be considered to be fairly restrictive. In the final estimation, we relax it by including interactions between nutrition and WASH inputs and lagged values of the variable of interest.

Putting this altogether yields our final estimation equations for height and weight respectively:

$$\begin{aligned}\ln H_{it} = \alpha^h_0 + \alpha^h_1 \ln N_{it-1} + \beta^h_1 \ln S_{it-1} + \alpha^h_2 \ln H_{it-1} + \gamma^h_{SN} \ln S_{it-1} \ln N_{it-1} \\ + \gamma_{SH} \ln S_{it-1} \ln H_{it-1} + \gamma_{NH} \ln H_{it-1} \ln N_{it-1} + \tau^h \ln W_{it_1} + \delta^h_t\mathbf{X} + \varepsilon^h_{it}\end{aligned} \tag{8}$$

$$\begin{aligned}\ln W_{it} = \alpha^w_0 + \alpha^w_1 \ln N_{it-1} + \beta^w_1 \ln S_{it-1} + \alpha^w_2 \ln W_{it-1} + \gamma^w_{SN} \ln S_{it-1} \ln N_{it-1} \\ + \gamma_{SW} \ln S_{it-1} \ln W_{it-1} + \gamma_{NW} \ln W_{it-1} \ln N_{it-1} + \tau^w \ln H_{it_1} + \delta^w_t\mathbf{X} + \varepsilon^w_{it}\end{aligned} \tag{9}$$

In the estimation, $\mathbf{X}$ will include a set of individual, community and child level controls. At the household level, to capture other unobserved inputs and preferences we control for wealth quintile, birth order, household head and mother age (quadratically), maternal education, dummies for if the household head is female, if the father is present in the household, total number of household members, number of children under 5 in the household, household income per capita, and the ratio of male and female household members. At the community level, we control for log population density, an index for health services available in the community, a dummy for whether the community is urban and municipality level fixed effects. At the child level, we control for birth-weight, gender, age (cubic), a dummy for any breastfeeding and mother's height.

In these equations, the marginal product of each input is given by the combined effect of the α, β and γ. Considering child height, differentiating with respect to $\ln N_{it-1}$ and $\ln N_{it-1}$ yields the following

$$\frac{\partial H_{it}}{\partial \ln N_{it-1}} = \alpha_1^h + \gamma_{SN}^h \ln S_{it-1} + \gamma_{NH} \ln H_{it-1} \tag{10}$$

$$\frac{\partial H_{it}}{\partial \ln S_{it-1}} = \beta_1^h + \gamma_{SN}^h \ln N_{it-1} + \gamma_{SH} \ln H_{it-1} \tag{11}$$

The γ_{SN}^h and γ_{SN}^w measure the complementarity between nutrition and WASH - if positive, nutrition will be more productive in the presence of a higher level of WASH (i.e. the inputs are complements); if negative, WASH and nutrition are substitutes for each other. A similar argument applies to γ_{SH} and γ_{NH} but here the sign of the coefficient reflects diminishing/increasing returns to inputs - a positive coefficient reflects taller children having higher returns to inputs, a negative coefficient indicates diminishing returns.

Whilst this procedure deals with endogeneity problem arising from the unobserved health endowment, the second challenge in estimating the production function stems from the fact that ε_{it}, shocks to child health and parental preferences, and some components of the child's health endowment, μ_i, will usually be unobserved. If these are correlated with observed inputs -which is plausible- they generate an endogeneity problem that must be dealt with in the estimation. If for example parents compensate (reinforce) for unobserved shocks, then ordinary last squares estimates of the input coefficients will be biased downwards (upwards). Importantly, the entire history of inputs might be correlated with the unobserved shocks or parental preferences. In such a case, our estimates for the effect of each input on child growth would be biased if parents changed their investment behaviour in response to unobserved child health shocks in previous periods. To address this we use a control function approach.

3.1 Control Function

To deal with the endogeneity of our inputs we implement a two stage control function approach. In the first stage, we estimate two control functions for $\ln N_{it-1}$ and $\ln S_{it-1}$ using the following equations:

$$\ln N_{it-1} = \beta_1 + \sigma_1 \boldsymbol{X} + \pi_1 \boldsymbol{Z} + upro \tag{12}$$

$$\ln S_{it-1} = \beta_2 + \sigma_2 \boldsymbol{X} + \pi_2 \boldsymbol{Z} + uwash \tag{13}$$

where $\boldsymbol{Z}$ is a set of excluded instrumental variables, and $upro$ and $uwash$ are the residuals from the first stage. We then include these control functions, along with a quadratic term and their interaction, $upro * uwash$ to the main, second stage, estimation equations, Equation 8 and 9. This approach collapses to the more familiar 2-stage least squares estimation with linear inputs. In non-linear settings such as ours Terza and Rathouz (2008) demonstrate that a control function provides significantly more efficiency. Non-parametric identification requires that, as with instrumental variables, $\boldsymbol{Z}$ satisfy two conditions, namely that (i) the excluded variables are predictive of the endogenous input variable and that (ii) the excluded variables affect $\ln H_{it}$ ($\ln W_{it}$) only through the input (*exclusion restriction*).

In particular, the reduced form of endogenous variables, that is, the linear projection of N and S onto the exogenous variables $\boldsymbol{X}$ and $\boldsymbol{Z}$ as shown in equations 12 and 13 plays a critical role. More concretely, we are explicitly modelling the errors in the second stage as functions of those in the first. When controlling for linear errors only, we model $E(\varepsilon_{it}|upro, uwash)$ as a linear function of the errors in the first stage. We relax this by including the square terms and interactions between residuals, but the control function approach still imposes significantly more structure than is the case in the simple instrument variable approach.

For both our input variables of interest, nutrition and WASH investments, we use input prices at the community level, and community-level wages as excluded instruments. For WASH inputs, we furthermore rely on a geological feature, soil depth as a further instrument.

Using prices as an exclusion restriction is a common approach when estimating health production functions (Todd and Wolpin (2003), Attanasio et al. (2015), Liu, Mroz and Adair (2009)), as they are understood to affect investment choices without entering the production function in a direct manner (Heckman and Macurdy (1986)). Following this strategy, we implicitly compare health of children whose parents are willing to invest in the given input but are restricted to do so by the level of prices in their communities, to those children whose parents are not restricted. Given the low wealth level of our households, we believe this to be a sensible approach. Further, several studies have shown the importance of price and budget constraints in decisions related to health and food investments in developing countries (Brinkman et al. (2010), Dupas (2011), Ben Yishay et al. (2017), Cohen and Dupas (2010), Spears (2012), Ashraf, Berry and Shapiro (2010)).

The most common difficulty researchers face when using prices as instruments is limited variation in observed prices along relevant dimensions, in our case, across children and over time. The unique data collection design and setting allows us to rely on meaningful spatial as well as temporal variation in the price variables considered.

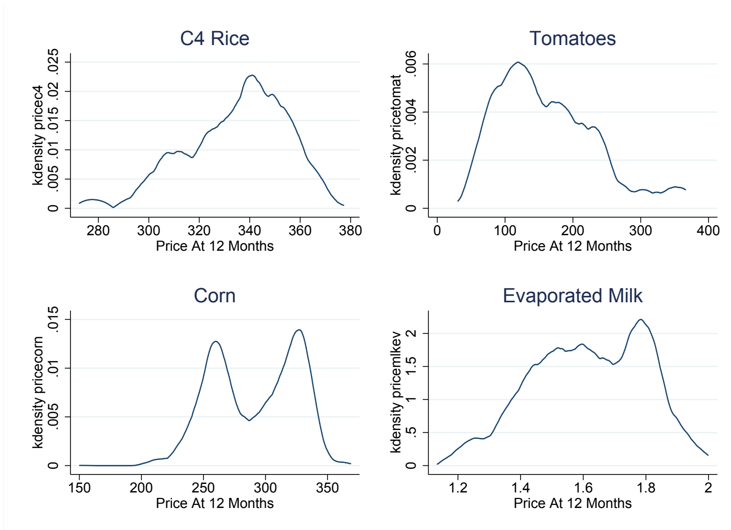
For food items, community-level prices were collected by enumerators on a bi-monthly basis from two stores in each community. While the set of food items for which prices were collected is extensive, not all items were available for purchase at each store and visit.[12] Our choice of price instruments therefore relies on a careful balance between availability at a high frequency, providing useful temporal variation, and an emphasis on prices for food items that have a high protein content and/or are important to (the preparation of) the local diet. An additional important source of variation our analysis benefits from is a large inflationary spike partway during the study period, which was caused by political turmoil and the consequent large devaluations of the Filipino peso (Solon and Floro (1993)). The spike affected prices

[12]Furthermore, rounds of price data collection do not necessarily coincide with dates of child measurements. We impute prices for months where data collection does not take place and match child level observations to the closest observed price (by days).

of tradeable goods such as evaporated milk more than those of non-traded goods such as tomatoes, as shown in Figure 5. Moreover, it affected children in our sample differently depending on their age: children born in May 1983 were older than those born in April 1984 when the spike hit, and their families experienced higher prices of foods for a shorter fraction of the first 2 years of the child's life.

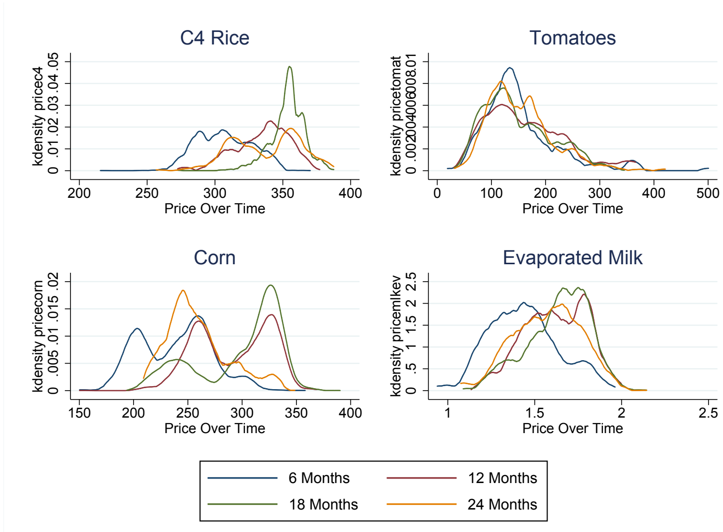
The set of prices used as excluded instruments in the first stage is that of rice, dried fish, corn, tomatoes, oil, condensed and evaporated milk, kerosene and formula milk.[13] We show the spatial and temporal variation in the prices of four goods (rice, tomatoes, corn, evaporated milk) in Figures 4 and 5 respectively.

Figure 4: Price variation across space



[13]Several of these prices are therefore in line with those used by Puentes et al. (2016), who rely on prices of dried fish, eggs, corn and tomatoes as their instruments.

Figure 5: Price variation across time



To account for the endogeneity of the WASH score, we rely on the community leader reported cost of installing an antipolo toilet at baseline. This is similar to Augsburg and Rodríguez-Lesmes (2018), who also use community level sanitation construction costs to correct for the endogeneity of toilet coverage on child height for age. Antipolo toilets are a type of sealed toilet introduced to the Philippines by the American colonial government in the early 20th century. They were designed as a cheap and easy alternative to traditional flushing toilets. They are still popular in poorer parts of the Philippines to this day as they are considered to be relatively easily and cheaply constructed. We only have information at the time of the baseline survey and hence rely on geographical variation for identification. Despite the lack of time variation they prove to be an important predictor of WASH investments.

The geographical variation we observe seems to be largely driven by accessibility. We show in Table 5 the results of regressing antipolo toilet costs on a number of access related variables. Similar to results for the Indian context analysed by Augsburg and Rodríguez-Lesmes (2018), we find that costs are associated negatively with availability of electricity, higher population and urban locations as well as availability of asphalt roads. The estimated coefficients are not statistically significant, but the power to detect effects is severely limited by the sample size of 33. The fact that toilet costs are lower in areas with easier access is likely driven by lower transportation costs of construction materials.

Having established that our price variables display meaningful and econometrically helpful variation, we next turn to discussing the exclusion restriction.

Whether the price information we use satisfies the exclusion restrictions depends on the competitive nature of the input market that our study households are operating in, as well as their preference structure. In other words, we need to establish that the observed price variation

Table 5: Exclusion Restrictions: Toilet Costs

	(1) Log Antipolo Cost	(2) Log Antipolo Cost	(3) Log Antipolo Cost	(4) Log Antipolo Cost	(5) Log Antipolo Cost
Has electricity	-0.181				0.000322
	(0.254)				(0.342)
Log 1980 Census population		-0.0304			0.269
		(0.111)			(0.171)
Urban			-0.367		-0.749
			(0.211)		(0.411)
Has asphalt roads				-0.293	-0.0401
				(0.216)	(0.362)
Constant	6.309***	6.407***	6.361***	6.341***	4.505***
	(0.221)	(0.860)	(0.151)	(0.164)	(1.168)
Observations	33	33	33	33	33

Notes: Outcome in each regression is log average (indoor and outdoor) antipolo toilet costs.

is not driven by (parental) demand.

While it is possible that households could influence certain food prices (such as those of infant formula), we are confident that at least part of the variation in prices we rely on could not be influenced by the household itself. In particular, the price increases among tradeable goods, triggered by the political turmoil in the country, is unlikely to be a result of our study household's behaviour. To counteract any additional concerns, we control for municipality fixed effects and have extensive community-level controls in our estimation, making us confident that any remaining price variation is (exogenously) driven by supply side factors.

The argument that toilet cost prices are uncorrelated with the error term in our production function follows closely Augsburg and Rodríguez-Lesmes (2018). In particular, construction material markets (which make up an important part of the costs of installing a toilet) are typically well developed and hence competitive in nature. In addition, we believe it reasonable to assume that, even if our study households have correlated WASH investment preferences, they are likely to remain price takers, given that the construction of toilets would only be a small fraction of the overall construction market.[14]

The finding that geographical price variation in WASH is driven by access, raises the concern that WASH prices might be reflecting access to other child health determinants. For example, if toilet costs proxy for access to health centers, this might impact on our study children's health through better care and bias our results if not accounted for in the analysis. To alleviate this concern we rely on the same strategy as discussed above, namely the inclusion of relevant community-level controls in our analysis. In particular, we account for the variables shown in Table 5.

While these price variables meet important criteria to serve as valid instruments, they, on their own, do not provide sufficient power to explain variation in endogenous inputs of interest and

[14]One caveat of the WASH price instrument is that the cost of the toilet conflates both material and labour cost. This is problematic if labour prices hide worker quality that, in turn, can affect the quality of the WASH investments. Augsburg and Rodríguez-Lesmes (2018) show that the inclusion of labour costs in their instrumental variable approach does not affect their results.

hence to satisfactorily account for the endogeneity in child health production inputs. We therefore make use of two further instruments in our analysis.

Specific to the WASH input, we use the average soil depth in the community. The rationale for its use is that soil depth influences the type of toilet that can be built in the area. In areas with low soil depth, the water table may be relatively shallow, and soils wet so that relatively cheap pit toilets cannot be built.

Relevant for both nutritional and WASH inputs, the final instruments we use are average wages of the largest employers of men and women in community as reported in the community survey. The argument for using aggregate wages as instruments follow closely those of food prices in that they induce changes in the budget constraint of households in a similar manner. The variation in these prices is largely driven by the type of industry available in community, in this setting farming and shipbuilding. We show in Tables 18 and 19 in Online Appendix A.2 the correlation of wages with other relevant access variables discussed in the context of prices and used in Table 5.

The joint F-stat of excluded instruments for our different input variables of interest are shown in Table 6. We see that the instruments are strongest for protein (25.82) but the commonly used rule of thumb threshold of 10 is satisfied for all inputs considered in our analysis.

Table 6: Joint F-test of Excluded Instruments

Log Protein	Log Calories	Log WASH
25.82	10.68	19.26

Thus, we are confident that our instruments will allow us to address the endogeneity of our input measures. In the next section, which discusses results, we will show how their inclusion affects our conclusion of whether better WASH makes nutrition investments more productive in forming child height and weight.

4 Results

We now display our findings, starting with specifications where our measure for nutrition is protein intake; before turning to estimates when the nutrition measure is calorie intake.

4.1 Protein

Table 7 presents the estimates for specifications 8 and 9 for height and weight respectively when we take protein intake as our measure of nutrition. Columns 1 and 2 present the ordinary least squares (OLS) and control function estimates for child height, columns 3 and 4 columns present the OLS and control function estimates for child weight. [15,16]

Height Column 1 of Table 7 shows the OLS estimates of the translog production for child height. Higher protein intake, and better WASH practices 2 months prior to the height measurement lead to an increase in child height. We further find a positive and statistically significant estimate on the interaction term between log protein intake and log WASH, thereby indicating a complementarity between these inputs. However, these estimates are correlations and might be biased as a result of endogeneity of the inputs. When we correct for this endogeneity using the control functions (Column 2), the coefficients on log protein intake, log WASH and the interaction term remain positive, and become larger in magnitude compared to the OLS coefficients. Moreover, the coefficients on the control functions are negative, though not always statistically significantly different from 0. These two patterns are consistent with parents compensating for (unobserved) bad shocks, in line with findings in (Liu, Mroz and Adair 2009).

The results thus confirm the general understanding that higher protein intake leads to an increase in the child's height, and further reveal that better WASH conditions makes higher protein intake more productive. Interestingly, we also obtain a positive interaction between log protein intake and log previous height - indicating that higher protein intake is more productive for those who are taller at age $t-1$ -, and a negative interaction between log previous height and log WASH, so that better WASH is more productive for those who are shorter (and presumably in worse health) at age $t-1$.

We further find that height at age t is highly correlated with height at age $t-1$, with a coefficient of around 0.77 in the control function approach estimation. This is not a surprise, since we study the formation of height over a relatively short time frame – 2 months. Moreover, the coefficient is statistically significantly different from 1, which confirms that we are studying height formation over a period when it can be impacted by parental investments and the general home environment.

To interpret the coefficients, we consider a simple thought exercise where we increase a child's protein intake by an egg a day (which corresponds with a 20% increase in the average child's daily protein intake) from the age of 6 months to 24 months, and consider how this changes

[15] In Online Appendix B.3 we build up the estimation, starting with estimating production functions for each input on their own, before combining the two inputs for a Cobb-Douglas production function, and finally estimating the full translog production function. These tables show how the marginal productivities of nutrition (and WASH) change as we add the other input, and interactions between the two inputs.

[16] In terms of inference, the main tables report standard errors clustered at the community level. These could be misleading since the WASH score is estimated. To assess how sensitive our results are to this, we also estimate standard errors using a block bootstrap (with the block defined as the community) and find that our inference does not change. The model estimated for the block bootstrapped standard errors omits the municipality fixed effects, since a number of resampling draws, in which no community from some small municipalities is drawn, need to be otherwise discarded.

Table 7: Effects of Protein Intake and WASH on Height and Weight

	Height (1) OLS	(2) CF	Weight (3) OLS	(4) CF
$\ln P_{it-1}$	0.000740***	0.00377*	0.00123***	0.0153
	(0.000151)	(0.00219)	(0.000426)	(0.00983)
upro		-0.00307		-0.0134
		(0.00218)		(0.00988)
$upro^2$		-0.0000112		0.000504**
		(0.0000731)		(0.000215)
$\ln S_{it-1}$	0.00126***	0.0197**	0.00494***	-0.00683
	(0.000416)	(0.00801)	(0.000920)	(0.0237)
uwash		-0.0183**		0.0119
		(0.00793)		(0.0239)
$uwash^2$		0.00105		0.000540
		(0.00144)		(0.00355)
$\ln P_{it-1} * \ln S_{it-1}$	0.000757**	0.00119***	0.00192**	0.00345***
	(0.000316)	(0.000334)	(0.000839)	(0.00115)
*upro*uwash*		-0.00109		-0.00390**
		(0.000664)		(0.00189)
$\ln P_{it-1} * \ln H_{it-1}$	0.00413***	0.00398***		
	(0.00116)	(0.00142)		
$\ln S_{it-1} * \ln H_{it-1}$	-0.0107**	-0.0131**		
	(0.00473)	(0.00487)		
$\ln P_{it-1} * \ln W_{it-1}$			-0.00114	-0.00282
			(0.00182)	(0.00231)
$\ln W_{it-1} * \ln S_{it-1}$			-0.0189**	-0.0206**
			(0.00893)	(0.00951)
$\ln H_{it-1}$	0.781***	0.774***	0.189***	0.191***
	(0.00668)	(0.00797)	(0.0163)	(0.0165)
$\ln W_{it-1}$	0.0541***	0.0549***	0.853***	0.852***
	(0.00157)	(0.00158)	(0.00877)	(0.00870)
Observations	21864	21864	21878	21878
Adjusted R^2	0.951	0.951	0.921	0.921
F-stat Protein		25.82		23.79
F-stat WASH		19.26		20.29

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered at community level.

Notes: Additional controls present in all columns include municipality dummies, interview month dummies, census population, an urban/rural dummy, wealth quintile, household income per capita, age of household head and their education, mother age and education as well controls for the distribution of ages within the household

the child's height in cm at age 24 months for different quintiles in the WASH distribution. For a child in the 90th percentile of the WASH score distribution, the additional egg per day results in an increase in height of 2.73cm by the age of 24 months. By contrast, the increase in height for a child in the 10th percentile of the WASH score distribution would have been 2.57cm. Thus, better WASH complements protein intake by a modest, but still important, amount.

Weight Next, we turn to the results on child weight. Unlike height, weight is more sensitive to contemporaneous inputs; though with the bi-monthly frequency of our data, we still expect that nutritional and WASH inputs will take some time before they affect child weight. Columns 3 and 4 of Table 7 displays the OLS and control function estimates for the production function for weight. The OLS coefficients indicate a positive and statistically significant, effect of protein intake on weight. Higher WASH investments are also associated with higher weight, and there is also a positive and statistically significant coefficient on the interaction term, suggesting that nutritional investments are more productive for children who are exposed to better WASH practices.

When we correct for endogeneity of the investments using the control functions, we obtain coefficients that are larger in magnitude for protein intake and the interaction between log WASH and log previous protein intake, though only the latter is statistically significantly different from 0. By contrast, the coefficient for log WASH becomes negative and is no longer statistically significantly different from 0. The quadratic of the control function, and the interaction between the two control functions are statistically significantly different from 0, indicating that protein intake and the interaction were endogenous. The sign of the coefficient on the control function for protein is negative, while that on the quadratic term is positive indicating that parents compensate for adverse shocks.[17] As with child height, we also see that child weight at age t is positively associated with child weight at age $t-1$, and better WASH practices are less productive for children with higher weight.

Increasing a child's intake of protein by an egg a day from the age of 6 months to 24 months increases the average child's weight at 24 months by 1.03kg. Moreover, the additional egg a day increases the child's weight by 0.74kg for children in the 10th percentile of the WASH score distribution, compared with 1.19kg for children in the 90th percentile of the WASH score distribution.

4.2 Calorie Intake

Next, we present the results for calorie intake as our measure of nutrition in Table 8.

[17] That for log WASH is positive, but not statistically significantly different from 0, though the excluded instruments have sufficient power, as can be seen by the value of the F-statistics.

Table 8: Effects of Calorie Intake and WASH on Height and Weight

	Height (1) OLS	(2) CF	Weight (3) OLS	(4) CF
$\ln C_{it-1}$	0.000676***	0.00231	0.00160***	0.0167
	(0.000145)	(0.00265)	(0.000478)	(0.0106)
ucal		-0.00168		-0.0144
		(0.00266)		(0.0108)
ucal^2		-0.0000502		0.000925**
		(0.000113)		(0.000391)
$\ln S_{it-1}$	0.00132***	0.0222***	0.00491***	0.00434
	(0.000405)	(0.00733)	(0.000911)	(0.0176)
uwash		-0.0208***		0.000575
		(0.00727)		(0.0178)
uwash^2		0.00122		0.000244
		(0.00138)		(0.00346)
$\ln C_{it-1} * \ln S_{it-1}$	0.000843**	0.00156***	0.00253**	0.00406***
	(0.000341)	(0.000371)	(0.00113)	(0.00129)
*ucal***uwash*		-0.00193**		-0.00422*
		(0.000728)		(0.00212)
$\ln C_{it-1} * \ln H_{it-1}$	0.00438***	0.00438***		
	(0.00138)	(0.00149)		
$\ln S_{it-1} * \ln H_{it-1}$	-0.0106**	-0.0147***		
	(0.00486)	(0.00493)		
$\ln H_{it-1}$	0.780***	0.772***	0.186***	0.184***
	(0.00668)	(0.00770)	(0.0169)	(0.0163)
$\ln W_{it-1}$	0.0546***	0.0554***	0.854***	0.855***
	(0.00154)	(0.00150)	(0.00922)	(0.00903)
$\ln C_{it-1} * \ln W_{it-1}$			0.000279	-0.000754
			(0.00226)	(0.00244)
$\ln W_{it-1} * \ln S_{it-1}$			-0.0210**	-0.0234**
			(0.00962)	(0.0102)
Observations	22082	22082	22096	22096
Adjusted R^2	0.951	0.951	0.922	0.922
F-stat Calories		10.68		10.20
F-stat WASH		21.66		22.59

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered at community level.

Notes: Additional controls present in all columns include municipality dummies, interview month dummies, census population, an urban/rural dummy, wealth quintile, household income per capita, age of household head and their education, mother age and education as well controls for the distribution of ages within the household

Height As with protein intake, the OLS coefficients in Column 1 indicate that both calories and WASH are associated with increased height. Moreover, there is also a positive and statistically significant interaction term, suggesting that calorie intake is more productive for children exposed to better WASH practices. Once we account for endogeneity of the inputs using the control functions (Column 2), we observe that the coefficients on log calorie intake, log WASH and the interaction between calories and WASH increase in magnitude. Moreover, the coefficients on the control functions are negative, though that for calories is not statistically significantly different from 0. This is in line with parents compensating children for adverse shocks unobserved by the econometrician. Importantly, the F-statistic of the excluded instruments is greater than 10, suggesting that the excluded instruments have sufficient power.

Weight Similarly to protein intake, the OLS coefficients, presented in Column 3, indicate that higher calorie consumption and exposure to better WASH practices is associated with higher height. Moreover, the two inputs interact positively. When we account for endogeneity in inputs (Column 4), the coefficients for calorie intake and the interaction term increase in magnitude (and remain positive), with the latter coefficient statistically significantly different from 0. The coefficient on log WASH remains similar in magnitude, but loses precision and is hence not statistically significantly different from 0. Interestingly, as with protein intake, the coefficients associated with the control functions are mostly statistically insignificantly different from 0 (other than that on the quadratic of the control function for calories).

Overall, the results for both protein and calorie intake indicate that better WASH makes nutritional investments more productive for children aged 6-24 months, though the magnitude of the complementarity is relatively small.

4.3 Robustness Checks

We conduct a number of robustness checks to assess the sensitivity of our findings to alternative formulations of the WASH score, and extending the control function.

4.3.1 Alternative Formulations of the WASH Score

In a first robustness check we alter the definition of the WASH score. The current score includes a mix of variables that are measured at one point in time only (household toilet ownership, child feces disposal, soap expenditures), and at multiple times over the course of data collection (child consumption of treated water, or no water). This mixture of stock and time varying variables may pose problems for interpretation and identification. In terms of interpretation, one cannot disentangle the effect of building a toilet from the effect of using clean water. For identification, one might worry that our instruments do not vary with either the time variant or time invariant components of the score.[18]

We experiment with two alternative definitions: one that includes only variables measured at one point in time, which could be thought of as measuring the household's WASH stock; and another definition that is based only on variables that we observe in each of the bi-monthly surveys, which can be thought of as measuring household WASH practices.

Tables 20 and 21 in Online Appendix B.1 present the findings for protein and calories respectively when we use the 'stock' formulation of WASH, while Tables 22 and 23 present findings for protein and calorie intake respectively when we use the 'variable WASH' formulation.

We see that when we use the 'stock' definition of WASH, the excluded instruments for log WASH are not as powerful, with F-statistics less than 10, while the excluded instruments for protein and calorie intake remain sufficiently strong. Probably as a consequence of the weaker excluded instruments, we do not find a consistent positive, statistically significant effect of log WASH on height and weight. However, reassuringly, the coefficient on the interaction term remains positive and statistically significantly different from 0. With 'variable' WASH, all effects of WASH on height and weight operate through the interaction term, which remains positive and statistically significant (though smaller in magnitude) throughout.

Overall, there remains a robust complementarity between nutrition and WASH even when we alter the definition of WASH from capturing both stock and flows, to capturing only one of these components.

4.3.2 Extending the Control Function

The key requirement of the control function approach is that, conditional on covariates and predicted errors in the first stage, the remaining error in the second stage is mean independent of height/weight. Whilst this is never directly testable, we can extend our approach further by interacting all explanatory variables with the predicted residuals from the first stage (i.e. dramatically increase the set of conditioning variables). The results from this are shown in Online Appendix B.2. Adding the additional controls does not substantially change the coefficients of interest, and consequently our conclusions hold.

Thus, our findings of positive and statistically significant effects of protein intake and WASH, and calorie intake on height and weight; and the positive interaction between nutrition intake and WASH remain remarkably robust.

[18] Note though that this problem is mitigated since we have both time invariant and time variant instruments.

5 Heterogeneity by Gender

We consider whether there is any heterogeneity in the effects of nutrition and WASH on child physical growth by the child's gender. There are three reasons why we might expect to find a difference: First, parental investments might vary by child gender if parents prefer children of one gender over the other. Second, male and female infants might engage in varied activities, leading to differential exposure to pathogens, and therefore differential needs and productivities for nutritional and WASH investments. Third, biological differences between boys and girls might result in different growth patterns in response to the same inputs (Tanner and Karlberg 1990). Barham, Macours and Maluccio (2013), for example, find that boys exposed to a conditional cash transfer in utero had improvements in cognition; similar improvements were not achieved for girls.

We first study whether there is any heterogeneity by gender in the effects of nutrition and WASH investments on child height and weight. Thereafter, we explore the channels through which any differences emerge.

Our findings, displayed in Tables 9 and 10 for height and weight respectively, yield positive coefficients for WASH and protein intake, and their interaction for boys once we correct for endogeneity. Importantly for us, the F-statistics for the excluded instruments are above 10 for both protein intake and WASH, indicating that they have sufficiently strong explanatory power. Interestingly, while the coefficient on the interaction term is now statistically significantly different from 0, indicating that better WASH makes nutritional intake more productive for boys; that for log WASH is not statistically significantly different from 0, as a result of larger standard errors. The negative signs on the control functions coupled with the larger coefficients in the specification including the control functions relative to the OLS specification is consistent with parents compensating boys for adverse unobserved shocks.

For girls, the coefficient on protein intake is negative, but statistically insignificant from 0, while those on log WASH and the interaction term increase in magnitude relative to the OLS estimates once we include the control functions and remain statistically significantly different from 0. Despite the excluded instruments having strong predictive power for protein intake for girls, as evidenced by the F-statistic of 13.21, the control function for protein is not statistically significantly different from 0. Moreover, it is positive, suggesting that for girls, parents choose to reinforce adverse shocks through nutritional investments (at least). By contrast, the control function for WASH has a negative coefficient and is statistically significantly different from 0. The positive and statistically significant coefficient on the interaction term indicates that higher protein intake is only productive for girls living in environments with better WASH.

Interestingly, the coefficients on log WASH and the interaction term between log WASH and log protein intake are larger in magnitude for girls than for boys, while that on protein intake is much larger in magnitude for boys than girls.

Turning to Table 10, we obtain somewhat weaker results, with positive though statistically significant control function estimates for the coefficients on log calories and log WASH. The point estimates are non-negligible, but are accompanied by larger standard errors, making it challenging to make conclusions about these effects. However, the coefficients associated with the interaction terms are positive and statistically significantly different from 0 for both boys and girls.

We also find some evidence of heterogeneity by gender in the formation of weight. When we consider protein intake as the measure of nutrition (Table 11), we find that higher protein intake and better WASH both result in increased height for boys. Moreover, the interaction term is statistically significantly different from 0, indicating that better WASH makes protein intake more effective. For girls, however, we find positive but statistically insignificant coefficients for protein intake and log WASH. We do uncover a positive and statistically significant interaction term, suggesting that for girls' weight formation, protein intake and better WASH are particularly effective when both are available. The results on calorie intake on weight follow a similar pattern, though they are more imprecise as shown in Table 12.

5.1 Drivers of the Heterogeneity

A number of other studies investigating the impacts of health inputs such as nutrition and infections have documented differences in impacts by child gender.

We are limited in our ability to explore all three of our proposed drivers by data availability. However, we are able to rule out the first explanation that parents might favour a specific gender when making health input decisions. We provide two sets of analyses, that exploit the rich data available to assess whether parents in this context favour male or female children when making health investments. To do so, we first consider whether investment choices vary with child gender for three investments that can be considered to be either private goods or public goods within the household.

Specifically, we consider whether WASH investments, the likelihood of being immunized, and the likelihood of consulting a doctor vary by gender of the child.[19] Table 13 presents these results. It shows no differences in these investments by gender of the child, for both private goods such as immunizations and doctor consultations; and public goods like many of the WASH investments. In fact, a couple of the coefficients are negative, though not statistically significantly different from 0.

The rich data further allows us to also construct a novel test for gender bias in parental health investments. Our test draws on data collected from mothers pre-birth – when child gender

[19] We also consider whether there are differences in nutritional intake by gender. Boys consume more calories and have a higher protein intake. However, this is likely driven by boys expending more energy, and thus have a higher biological requirement of nutrients. Indeed a report from a Joint FAO/WHO/UNU Expert Consultation on energy and protein requirements calculates the calorie requirement for a 9-10 month old boys to be 925 kcal/day, compared to 865 kcal/day for girls. The calorie requirements by gender diverge further by child age.

Table 9: Height by Gender (Protein)

	Male		Female	
	(1)	(2)	(3)	(4)
	OLS	CF	OLS	CF
$\ln P_{it-1}$	0.000805***	0.00670***	0.000666***	-0.00162
	(0.000174)	(0.00202)	(0.000227)	(0.00219)
uproh		-0.00595***		0.00228
		(0.00206)		(0.00212)
uproh2		-0.0000198		-0.00000195
		(0.000103)		(0.0000941)
$\ln S_{it-1}$	0.00112**	0.00858	0.00136**	0.0283***
	(0.000520)	(0.00929)	(0.000607)	(0.00790)
uwashhpro		-0.00750		-0.0269***
		(0.00917)		(0.00781)
uwashhpro2		-0.000571		0.00212
		(0.00184)		(0.00169)
$\ln P_{it-1} * \ln S_{it-1}$	0.000536	0.000914**	0.00102**	0.00156***
	(0.000342)	(0.000376)	(0.000464)	(0.000535)
uintph		-0.000991		-0.00132
		(0.000820)		(0.000964)
$\ln P_{it-1} * \ln H_{it-1}$	0.00315*	0.00311	0.00532**	0.00513**
	(0.00162)	(0.00203)	(0.00195)	(0.00222)
$\ln S_{it-1} * \ln H_{it-1}$	-0.00736	-0.00909	-0.0143**	-0.0177***
	(0.00763)	(0.00797)	(0.00642)	(0.00560)
$\ln H_{it-1}$	0.785***	0.781***	0.770***	0.762***
	(0.00993)	(0.0114)	(0.00759)	(0.00853)
$\ln W_{it-1}$	0.0534***	0.0538***	0.0560***	0.0579***
	(0.00260)	(0.00257)	(0.00205)	(0.00211)
Observations	11525	11525	10339	10339
Adjusted R^2	0.952	0.952	0.949	0.949
F-stat Protein		13.95		13.21
F-stat WASH		12.34		14.72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered at community level.

Notes: Additional controls present in all columns include municipality dummies, interview month dummies, census population, an urban/rural dummy, wealth quintile, household income per capita, age of household head and their education, mother age and education as well controls for the distribution of ages within the household

Table 10: Height by Gender (Calories)

	Male		Female	
	(1)	(2)	(3)	(4)
	OLS	CF	OLS	CF
$\ln C_{it-1}$	0.000627***	0.00382	0.000774***	0.00210
	(0.000186)	(0.00272)	(0.000212)	(0.00208)
ucal		-0.00325		-0.00136
		(0.00273)		(0.00203)
$ucal^2$		-0.0000701		-0.0000253
		(0.000154)		(0.000146)
$\ln S_{it-1}$	0.00129**	0.0143	0.00130**	0.0239***
	(0.000503)	(0.00984)	(0.000604)	(0.00679)
uwash		-0.0129		-0.0225***
		(0.00969)		(0.00676)
$uwash^2$		-0.000364		0.00249
		(0.00176)		(0.00168)
$\ln C_{it-1} * \ln S_{it-1}$	0.000725	0.00137**	0.000992*	0.00189***
	(0.000459)	(0.000508)	(0.000491)	(0.000610)
uint		-0.00182*		-0.00235*
		(0.00100)		(0.00116)
$\ln C_{it-1} * \ln H_{it-1}$	0.00509***	0.00526***	0.00487*	0.00467*
	(0.00166)	(0.00182)	(0.00248)	(0.00272)
$\ln S_{it-1} * \ln H_{it-1}$	-0.00863	-0.0122	-0.0138**	-0.0191***
	(0.00734)	(0.00751)	(0.00653)	(0.00612)
$\ln H_{it-1}$	0.785***	0.779***	0.768***	0.760***
	(0.00972)	(0.0108)	(0.00794)	(0.00883)
$\ln W_{it-1}$	0.0532***	0.0536***	0.0572***	0.0585***
	(0.00257)	(0.00241)	(0.00206)	(0.00212)
Observations	11641	11641	10447	10447
Adjusted R^2	0.952	0.952	0.949	0.949
F-stat Calories		7.962		16.42
F-stat WASH		14.20		17.77

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered at community level.

Notes: Additional controls present in all columns include municipality dummies, interview month dummies, census population, an urban/rural dummy, wealth quintile, household income per capita, age of household head and their education, mother age and education as well controls for the distribution of ages within the household

Table 11: Weight by Gender (Protein)

	Male		Female	
	(1)	(2)	(3)	(4)
	OLS	CF	OLS	CF
$\ln P_{it-1}$	0.00146**	0.0185**	0.000921	0.00291
	(0.000605)	(0.00847)	(0.000624)	(0.00904)
upro		-0.0162*		-0.00169
		(0.00856)		(0.00902)
$upro^2$		0.000708**		0.000268
		(0.000337)		(0.000167)
$\ln S_{it-1}$	0.00580***	-0.0106	0.00475***	0.00559
	(0.00146)	(0.0249)	(0.00134)	(0.0235)
uwash		0.0174		-0.00165
		(0.0254)		(0.0240)
$uwash^2$		0.00749**		-0.00893
		(0.00356)		(0.00672)
$\ln P_{it-1} * \ln S_{it-1}$	0.00218**	0.00404***	0.00175	0.00288**
	(0.000962)	(0.00129)	(0.00119)	(0.00134)
*uwash*upro*		-0.00523**		-0.00282
		(0.00255)		(0.00221)
$\ln P_{it-1} * \ln W_{it-1}$	-0.00118	-0.00361	-0.00108	-0.00202
	(0.00328)	(0.00392)	(0.00234)	(0.00265)
$\ln W_{it-1} * \ln S_{it-1}$	-0.0330**	-0.0344**	-0.00837	-0.00977
	(0.0126)	(0.0129)	(0.0115)	(0.0114)
$\ln H_{it-1}$	0.206***	0.209***	0.176***	0.176***
	(0.0221)	(0.0239)	(0.0239)	(0.0238)
$\ln W_{it-1}$	0.847***	0.848***	0.855***	0.855***
	(0.0118)	(0.0118)	(0.0109)	(0.0104)
Observations	11531	11531	10347	10347
Adjusted R^2	0.916	0.916	0.919	0.919
F-stat Protein		13.65		13.66
F-stat WASH		13.53		13.26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered at community level.

Notes: Additional controls present in all columns include municipality dummies, interview month dummies, census population, an urban/rural dummy, wealth quintile, household income per capita, age of household head and their education, mother age and education as well controls for the distribution of ages within the household

Table 12: Weight by Gender (Calories)

	Male		Female	
	(1)	(2)	(3)	(4)
	OLS	CF	OLS	CF
$\ln C\_it-1$	0.00171**	0.0236*	0.00131**	0.00854
	(0.000649)	(0.0135)	(0.000631)	(0.00898)
		-0.0208		-0.00688
		(0.0140)		(0.00888)
ucalw2		0.00135**		0.000490
		(0.000649)		(0.000301)
$\ln S\_it-1$	0.00548***	0.00711	0.00424***	0.00533
	(0.00133)	(0.0236)	(0.00126)	(0.0182)
uwashwcal		-0.00102		-0.00189
		(0.0242)		(0.0185)
uwashwcal2		0.00571*		-0.00847
		(0.00330)		(0.00634)
$\ln C\_it-1 * \ln S\_it-1$	0.00269**	0.00451***	0.00262*	0.00384**
	(0.00114)	(0.00128)	(0.00151)	(0.00164)
uintcw		-0.00560*		-0.00328
		(0.00297)		(0.00267)
$\ln C\_it-1 * \ln H\_it-1$				
$\ln S\_it-1 * \ln H\_it-1$				
$\ln H\_it-1$	0.197***	0.193***	0.174***	0.173***
	(0.0231)	(0.0238)	(0.0230)	(0.0228)
$\ln W\_it-1$	0.849***	0.852***	0.855***	0.855***
	(0.0121)	(0.0117)	(0.0109)	(0.0104)
Observations	11647	11647	10455	10455
Adjusted R^2	0.914	0.914	0.919	0.919
F-stat Calories		8.784		16.41
F-stat WASH		14.37		15.76

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered at community level.

Notes: Additional controls present in all columns include municipality dummies, interview month dummies, census population, an urban/rural dummy, wealth quintile, household income per capita, age of household head and their education, mother age and education as well controls for the distribution of ages within the household

Table 13: Differential Investment by Gender

	(1) Log WASH	(2) Immunizations	(3) Consulting Doctor
Childs gender (1=Male)	-0.0164	-0.0747	0.00103
	(0.0106)	(0.0877)	(0.00543)
Community Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Child Characteristics	Yes	Yes	Yes
Observations	20539	2406	20165
Adjusted R^2	0.522	0.165	0.011

Note: Additional controls present in all columns include municipality dummies, interview month dummies, census population, an urban/rural dummy, wealth quintile, household income per capita, age of household head and their education, mother age and education as well controls for the distribution of ages within the household. Immunizations is defined as the count of immunizations given to the child over the course of the first two years of life. Consulting doctor is a dummy equal to 1 if the mother went to see the doctor about their chikd's health in the past two months.

would not have been known – on their beliefs and expectations about various nutrition and child care practices, that we can match to actual practices once the child was born and child gender was known.[20] If mothers have a strong preference for one gender, we would expect them to update their expectations differentially by the child's gender. In particular, if they had a preference for male children, we would expect them to be more likely to update their behaviour with regards to feeding colostrum or delaying solid food introduction in the first 6 months of life if the child is a boy. However, as shown in Table 14, there is no evidence of mothers changing their behaviour differentially after child gender is revealed, thereby confirming that the differences observed in the productivities of inputs by child gender are not driven by parents favouring children of one gender over another.

Thus, it is unlikely that these differences can be explained by sex-biased parental investments. And indeed, unlike other countries in South-East Asia, the Philippines is not considered to be a country where households have a strong son preference. This is borne out in the balanced sex-ratio at birth (of roughly 1.05 boy to girl births) and other ages. Our findings are hence in line with this more general observation.

Instead, the differences we find by child gender therefore point to either differences in infant activities by gender or some inherent biological difference in the growth processes for male and

[20]Sex-determination ultrasound technology was not widely available in the study area in the early 1980s. Though the uptake of (general) ultrasound technology increased from the late seventies, it was concentrated around Metro Manila. See http://ultrasoundsocietyofthephilippines.org.ph/about.php (accessed 6 December 2018).

Table 14: Beliefs and realized choices by gender

	(1) Difference Colostrum	(2) Difference Solid Food Introduction
Childs gender (1=Male)	0.00464	-0.0967
	(0.0122)	(0.0690)
Community Controls	Yes	Yes
Household Controls	Yes	Yes
Child Characteristics	Yes	Yes
Observations	1954	2344
Adjusted R^2	0.008	0.024

Note: Difference Colostrum is a dummy variable equal to 1 if a mother fed her baby colostrum but had indicated in the pregnancy survey that she did not wish to feed her child colostrum in the first two days of life. Difference Solid Food introduction is a variable equal to the numbers of months positive difference between the month she expected to introduce solid food into her child's diet in the prenatal survey and the actual month solid/semi-solid food was actually introduced.

female infants.[21] Identifying the source of this heterogeneity is thus left to future research.

6 Conclusion

It is well established that development in early childhood can increase wellbeing on various dimensions throughout the life course and across generations (Cunha et al. 2006, Currie and Almond 2011). Yet, a staggering 250 million children under age five living in low- and middle-income countries are at risk of suboptimal development and not achieving their potential. Recent discussions in policy circles in particular have argued that an important driver of this gap is the failure of developing and delivering integrated approaches to child development (Britto et al. 2017). Especially the integration of environmental factors, in particular hygiene and sanitary conditions, has received increasing attention.

However, very limited evidence exists on the importance of interactions of different components. We consider in this paper nutrition and WASH investments. It is widely acknowledged that both components play an important and nuanced role in early childhood development. Whilst much evidence exists that both are separately important, our results are among the first to show that the interaction between them plays ad additional significant role. Our findings therefore provide clear evidence for the postulation that better WASH environments make nutrition inputs more productive in the formation of child health using as proxies child

[21]Unfortunately, our data do not contain much information on infant activities beyond the age when the child starts crawling, and whether or not the child is exposed to the sun. Across both of these margins, we find no evidence of any differences by child sex

height and weight.

In particular, we find that among children aged 6-24 months, both nutrition intake – particularly protein intake – and WASH investments are important determinants of child height. Moreover, we obtain is a statistically significant positive coefficient on the interaction between WASH investments and calorie and protein intake, indicating that each input is more productive when parents also invest in the other input. Interestingly, the productivity of the inputs varies with the child's gender, with boys benefiting more from nutritional inputs and girls from WASH investments, in line with Augsburg and Rodríguez-Lesmes (2018). The findings thus provide motivation for interventions targeting both nutrition and WASH investments. The exact mechanims behind these differential impacts by gender are left for future research.

Overall, our findings suggest that contamination of a child's environment, including solid food, plays a major role in transmitting illnesses in the home; once children are weaned they are more exposed to the consequences of poor sanitary conditions in their environment. When this happens WASH investment becomes a necessary complement to nutrition investment. This result is in line with the existing medical literature on the value of nutrition in child development, which places increasing emphasis on the impact of poor sanitary conditions on stunting and other poor health outcomes. The result goes some way to explaining the puzzle of stubbornly high stunting rates in some countries, even in the face of significant income growth.

References

Adair, Linda S, and David K Guilkey. 1997. 'Age-specific determinants of stunting in Filipino children'. *The Journal of nutrition* 127 (2): 314–320.

Almond, D., and J. Currie. 2011. *Human Capital Development Before Age 5*. Vol. pp.1315-1486. Elsevier.

Alsan, Marcella, and Claudia Goldin. 2019. 'Watersheds in Child Mortality: The Role of Effective Water and Sewerage Infrastructure, 1880–1920'. *Journal of Political Economy* 127 (2): 586–638.

Arnold, Benjamin F, et al. 2013. 'Cluster-randomised controlled trials of individual and combined water, sanitation, hygiene and nutritional interventions in rural Bangladesh and Kenya: the WASH Benefits study design and rationale'. *BMJ Open*, no. 3. doi:doi:10.1136/bmjopen-2013-003476.

Ashraf, Nava, James Berry and Jesse M. Shapiro. 2010. 'Can Higher Prices Stimulate Product Use? Evidence from a Field Experiment in Zambia'. *American Economic Review* 100 (5): 2383–2413. doi:10.1257/aer.100.5.2383. http://www.aeaweb.org/articles.php?doi=10.1257/aer.100.5.2383.

Attanasio, O., et al. 2015. 'Estimating the Production Function for Human Capital: Results from a Randomized Control Trial in Colombia'. NBER Working Paper No. 20965.

Augsburg, B., and P.A. Rodríguez-Lesmes. 2018. 'Sanitation and child health in India'. *World Development* 107:22–39.

Augsburg, Britta, and Paul Andrés Rodrıguez-Lesmes. 2018. 'Sanitation and child health in India'. *World Development* 107:22–39.

Barham, Tania, Karen Macours and John A Maluccio. 2013. 'Boys' cognitive skill formation and physical growth: Long-term experimental evidence on critical ages for early childhood interventions'. *American Economic Review* 103 (3): 467–71.

Behrman, J., et al. 2009. 'Nutritional Supplementation of Girls Influences the Growth of Their Children: Prospective Study in Guatemala'. *American Journal of Clinical Nutrition* 90 (5): 1372–9.

Ben Yishay, A, et al. 2017. 'Microcredit and willingness to pay for environmental quality: Evidence from a randomized-controlled trial of finance for sanitation in rural Cambodia.' *J Environ Econ Manage* Nov 86:121–140. doi:doi:10.1016/j.jeem.2016.11.004..

Bisgrove, Eilene Z, Barry M Popkin and Corazon Barba. 1989. 'Infant feeding in the Philippines: a cluster analysis approach'. *Ecology of food and nutrition* 23 (2): 75–90.

Bisgrove, Eilene, Barry M Popkin and Corazon Barba. 1991. 'Profiling infant feeding patterns in Cebu, Philippines'. *Ecology of food and nutrition* 26 (4): 291–302.

Black, R. E., et al. 2008. 'Maternal And Child Undernutrition: Global And Regional Exposures And Health Consequences'. *The Lancet* 371 (9608): 243–60.

Brinkman, Henk-Jan, et al. 2010. 'High Food Prices and the Global Financial Crisis Have Reduced Access to Nutritious Food and Worsened Nutritional Status and Health'. *The Journal of Nutrition* 140 (1): 153S?161S. doi:`https://doi.org/10.3945/jn.109.110767`.

Britto, PR., et al. 2017. 'Nurturing care: promoting early childhood development.' *The Lancet* 389 (10064): 91–102.

Campbell, DI, M Elia and PG Lunn. 2003. 'Growth faltering in rural Gambian infants is associated with impaired small intestinal barrier function, leading to endotoxemia and systemic inflammation'. *The Journal of nutrition* 133 (5): 1332–1338.

Cao, Elisabetta De. 2015. 'The Height Production Function from Birth to Age Two'. *Journal of Human Capital* 9 (3): 329–363. doi:`10.1086/682356`. eprint: `https://doi.org/10.1086/682356`. `https://doi.org/10.1086/682356`.

Cebu, Study Team. 1992. 'Achild health production funct estimated from longitudinal data'. *Journal of Development Economics* 38:323–351.

Clasen, Thomas, et al. 2014. 'Effectiveness of a rural sanitation programme on diarrhoea, soil-transmitted helminth infection, and child malnutrition in Odisha, India: a cluster-randomised trial'. *The Lancet Global Health*.

Cohen, Jessica, and Pascaline Dupas. 2010. 'Free distribution or cost-sharing? Evidence from a randomized malaria prevention experiment'. *Quarterly journal of Economics* 125 (1): 1.

Cunha, F., et al. 2006. 'Handbook of the Economics of Education'. Chap. Interpreting the evidence on life cycle skill formation. 1:697–812. Elsevier.

Currie, J., and D. Almond. 2011. 'Handbook of labor economics'. Chap. Human capital development before age five, 4:1315–1486. Elsevier.

Cutler, G., D.M.and Miller. 2006. 'Corruption and Reform: Lessons from America's Economic History'. Chap. Water, Water Everywhere: Municipal Finance and Water Supply in American Cities. 153–83. University of Chicago Press.

Dangour, AD., et al. 2013. 'Interventions to improve water quality and supply, sanitation and hygiene practices, and their effects on the nutritional status of children.' *The Cochrane Database of Systematic Reviews* 8.

Darvesh, N., et al. 2017. 'Water, sanitation and hygiene interventions for acute childhood diarrhea: a systematic review to provide estimates for the Lives Saved Tool.' *BMC Public Health* 17 (4): 776.

De Cao, Elisabetta. 2015. 'The height production function from birth to age two'. *Journal of Human Capital* 9 (3): 329–363.

Dupas, Pascaline. 2011. 'Health behavior in developing countries'. *Annu. Rev. Econ.* 3 (1): 425–449.

Engle, Patrice L, et al. 2007. 'Strategies to avoid the loss of developmental potential in more than 200 million children in the developing world'. *The lancet* 369 (9557): 229–242.

George, Christine Marie, et al. 2016. 'Unsafe child feces disposal is associated with environmental enteropathy and impaired growth'. *The Journal of pediatrics* 176:43–49.

Gera, T, D Shah and HS Sachdev. 2018. 'Impact of Water, Sanitation and Hygiene Interventions on Growth, Non-diarrheal Morbidity and Mortality in Children Residing in Low- and Middle-income Countries: A Systematic Review.' *Indian* 55 (5): 381–393.

Gertler, P., et al. 2014. 'How does health promotion work? Evidence from the dirty business of eliminatingopen defecation'.

Ghatak, Maitreesh. 2015. 'Theories of Poverty Traps and Anti-Poverty Policies'. *World Bank Economic Review* 29 ($suppl_1$): 77–105. `https://ideas.repec.org/a/oup/wbecrv/v29y2015isuppl_1ps77-s105..html`.

Gough, EK, et al. 2016. 'Linear growth faltering in infants is associated with Acidaminococcus sp. and community-level changes in gut microbiota'. *World review of nutrition and dietetics* 114:125–126.

Hammer, Jeffrey, and Dean Spears. 2016. 'Village sanitation and child health: Effects and external validity in a randomized field experiment in rural India'. *Journal of Health Economics* 48 (C): 135–148. doi:`10.1016/j.jhealeco.2016.0`. `https://ideas.repec.org/a/eee/jhecon/v48y2016icp135-148.html`.

Hathi, P., et al. 2017. 'Place and Child Health: The Interaction of Population Density and Sanitation in Developing Countries'. *Demography* 54 (1): 337–360.

Heckman, J. J., and T. E. Macurdy. 1986. 'Labor Econometrics'. Chap. 32 in *Handbook of Econometrics*, ed. by M. Griliches Z. Intriligator, 1917–1977. Elsevier.

Hoddinott, J. F., et al. 2008. 'Effect of a Nutrition Intervention During Early Childhood on Economic Productivity in Guatemalan Adults'. *The Lancet* 371 (9610): 411–6.

Hoddinott, J., et al. 2013. 'Adult Consequences of Growth Failure in Early Childhood'. *The American Journal of Clinical Nutrition* 98 (5): 1170–78.

Humphrey, Jean H. 2009. 'Child undernutrition, tropical enteropathy, toilets, and handwashing'. *The Lancet* 374 (9694): 1032–1035.

Humphrey, Jean H, et al. 2019. 'Independent and combined effects of improved water, sanitation, and hygiene, and improved complementary feeding, on child stunting and anaemia in rural Zimbabwe: a cluster-randomised trial'. *The Lancet Global Health* 7 (1): e132–e147. ISSN: 2214-109X. doi:`https://doi.org/10.1016/S2214-109X(18)30374-7`. `http://www.sciencedirect.com/science/article/pii/S2214109X18303747`.

Kolenikov, Stanislav, and Gustavo Angeles. 2009. 'Socioeconomic status measurement with discrete proxy variables: Is principal component analysis a reliable answer?' *Review of Income and Wealth* 55 (1): 128–165.

Lin, Audrie, et al. 2013. 'Household environmental conditions are associated with enteropathy and impaired growth in rural Bangladesh'. *The American journal of tropical medicine and hygiene* 89 (1): 130–137.

Liu, Haiyong, Thomas Mroz and Linda Adair. 2009. 'Parental compensatory behaviors and early child health outcomes in Cebu, Philippines'. *Journal of development economics* 90 (2): 209–230.

Luby, Stephen P, et al. 2018. 'Effects of water quality, sanitation, handwashing, and nutritional interventions on diarrhoea and child growth in rural Bangladesh: a cluster randomised controlled trial'. *The Lancet Global Health* 6 (3): e302–e315.

Lunn, PG, CA Northrop-Clewes and RM Downes. 1991. 'Intestinal permeability, mucosal injury, and growth faltering in Gambian infants'. *The Lancet* 338 (8772): 907–910.

Maluccio, J. A., et al. 2009. 'The Impact of Nutrition During Early Childhood on Education among Guatemalan Adults.' *Economic Journal* 119 (537): 734–63.

Mbuya, Mduduzi NN, and Jean H Humphrey. 2016. 'Preventing environmental enteric dysfunction through improved water, sanitation and hygiene: an opportunity for stunting reduction in developing countries'. *Maternal & child nutrition* 12 (S1): 106–120.

Null, Clair, et al. 2018. 'Effects of water quality, sanitation, handwashing, and nutritional interventions on diarrhoea and child growth in rural Kenya: a cluster-randomised controlled trial'. *The Lancet Global Health* 6 (3): e316–e329.

Perlas, Leah A, Rosalind S Gibson and Linda S Adair. 2004. 'Macronutrient and selected vitamin intakes from complementary foods of infants and toddlers from Cebu, Philippines'. *International journal of food sciences and nutrition* 55 (1): 1–15.

Pickering, A.J., et al. 2015. 'Effect of a community-led sanitation intervention on child diarrhoea and child growth in rural Mali: a cluster-randomised controlled trial'. *The Lancet* 3 (11): 701–711.

Prendergast, Andrew, et al. 2014. 'Stunting is characterized by chronic inflammation in Zimbabwean infants (620.4)'. *The FASEB Journal* 28 (1 Supplement): 620–4.

Puentes, Esteban, et al. 2016. 'Early life height and weight production functions with endogenous energy and protein inputs'. *Economics & Human Biology* 22:65–81.

Rosenzweig, M.R., and T.P. Schulz. 1983. 'Estimating a household production function: Heterogeneity, the demand for health input, and their effects on birthweight'. *Journal of Political Economy* 92:723–746.

Sadeharju, Karita, et al. 2007. 'Maternal antibodies in breast milk protect the child from enterovirus infections'. *Pediatrics* 119 (5): 941–946.

Solon, Orville, and Maria Floro. 1993. *The Philippines in the 1980s: A review of national and urban level economic reforms.* World Bank.

Spears, Dean. 2012. *Effects of rural sanitation on infant mortality and human capital: Evidence from india's total sanitation campaign.* Princeton.

Tanner, JM, and Johan Karlberg. 1990. 'Principles of growth standards'. *Acta Pædiatrica* 79 (10): 963–967.

Team, Cebu Study, et al. 1992. 'A child health production function estimated from longitudinal data'. *Journal of development Economics* 38 (2): 323–351.

Terza, A. Basu, J.V., and P.J. Rathouz. 2008. 'Two-Stage Residual Inclusion Estimation: Addressing Endogeneity in Health Econometric Modeling'. *Journal of Health Economics* 27(3):531–143.

Todd, P.E., and K.I. Wolpin. 2003. 'On The Specification And Estimation Of The Production Function For Cognitive Achievement'. *The Economic Journal* 113 (485): F3–F33.

Todd, Petra E, and Kenneth I Wolpin. 2007. 'The production of cognitive achievement in children: Home, school, and racial test score gaps'. *Journal of Human capital* 1 (1): 91–136.

Victora, CesarG, et al. 1987. 'Evidence for protection by breast-feeding against infant deaths from infectious diseases in Brazil'. *The Lancet* 330 (8554): 319–322.

Victora, C.G., et al. 2010. 'Worldwide Timing of Growth Faltering: Revisiting Implications for Interventions'. *Pediatrics* 125 (3): e473–e480.

A Appendix

A.1 Proofs

We start from the most general process of height, H, and weight W formation for child i at age t, which can be defined as:

$$H_{it} = H_t\left[\{N_{is}\}_{s=1}^{t-1}, \{S_{is}\}_{s=1}^{t-1}, \mu_i; X, \{\varepsilon_{is}\}_{s=1}^{t-1}\right] \tag{14}$$

$$W_{it} = W_t\left[\{N_{is}\}_{s=1}^{t-1}, \{S_{is}\}_{s=1}^{t-1}, \mu_i; X, \{\varepsilon_{is}\}_{s=1}^{t-1}\right] \tag{15}$$

Where $\{N_{is}\}_{s=1}^{t-1}$ and $\{S_{is}\}_{s=1}^{t-1}$ are the history of nutritional and WASH inputs given to the child from birth ($s = 1$) to age $s = t-1$. $\{\varepsilon_{is}\}_{s=1}^{t-1}$ is a vector containing both the history of shocks experienced by the child from birth up to age $t-1$ and parental preferences. μ_i is the child's health endowment. X is a vector of other variables which also effect the formation of height and weight, such as mother's height.

We approximate this production function using a translog functional form. To do this we are assuming that this function is separable in its arguments, smooth, doubly differentiable and continuous. In exponential form, this implies the following

$$H_{it} = \left[\alpha_0^h \prod_s^{t-1} N_{is}^{\alpha_{is}^h} \prod_s^{t-1} S_{is}^{\beta_{is}^h} \prod_s^{t-1} N_{is}^{Y_1} \prod_s^{t-1} S_{is}^{Y_2}\right] e^{(\delta_t^h \mathbf{X} + \sigma_t^h \mu_{i0} + \varepsilon_{it}^h)} \tag{16}$$

$$W_{it} = \left[\alpha_0^w \prod_s^{t-1} N_{is}^{\alpha_{is}^w} \prod_s^{t-1} S_{is}^{\beta_{is}^w} \prod_s^{t-1} N_{is}^{Y_3} \prod_s^{t-1} S_{is}^{Y_4}\right] e^{(\delta_t^w \mathbf{X} + \sigma_t^w \mu_{i0} + \varepsilon_{it}^w)} \tag{17}$$

Where $Y_1 = \frac{1}{2}(\sum_j^{t-1} \gamma_{Njs}^{h'} \ln N_{is} + \sum_j^{t-1} \gamma_{Njs}^{h} \ln S_{is})$, $Y_2 = \frac{1}{2}(\sum_j^{t-1} \gamma_{Sjs}^{h} \ln N_{is} + \sum_j^{t-1} \gamma_{Sjs}^{h'} \ln S_{is})$, $Y_3 = \frac{1}{2}(\sum_j^{t-1} \gamma_{Njs}^{w'} \ln N_{is} + \sum_j^{t-1} \gamma_{Njs}^{w} \ln S_{is})$ and $Y_4 = \frac{1}{2}(\sum_j^{t-1} \gamma_{Sjs}^{w} \ln N_{is} + \sum_j^{t-1} \gamma_{Sjs}^{w'} \ln S_{is})$.

These equations contain the entire history of nutrition and WASH inputs, as well as their interactions and quadratic terms. Taking logs and letting $\alpha_{it}^h = \alpha_t^h$ for all i yields the following expression for height

$$\begin{aligned}
\ln H_{it} &= \alpha_0^h + \sigma_t^h \mu_{i0} + \varepsilon_t + \delta_t^h \mathbf{X} + \alpha_1^h \ln N_{i1} + ... + \alpha_{t-1}^h \ln N_{it-1} + \beta_1^h \ln S_{i1} + ... + \beta_{t-1}^h \ln S_{t-1} \\
&+ \frac{1}{2}(\sum_j^{t-1} \gamma_{Nj1}^{h'} \ln N_{ij} + \sum_j^{t-1} \gamma_{Nj1}^{h} \ln S_{ij}) \ln N_{i1} + ... + \frac{1}{2}(\sum_j^{t-1} \gamma_{Njt-1}^{h'} \ln N_{ij} + \sum_s^{t-1} \gamma_{Njt-1}^{h} \ln S_{ij}) \ln N_{it-1} \\
&+ \frac{1}{2}(\sum_j^{t-1} \gamma_{Sj1}^{h} \ln N_{ij} + \sum_j^{t-1} \gamma_{Sj1}^{h'} \ln S_{ij}) \ln S_{i1} + ... + \frac{1}{2}(\sum_s^{t-1} \gamma_{Sjt-1}^{h} \ln N_{ij} + \sum_j^{t-1} \gamma_{Sjt-1}^{h'} \ln S_j) \ln S_{it-1} + \varepsilon_{it}^h
\end{aligned}$$

This is clearly not feasible to estimate given that it includes inputs in all periods, all of which are endogenous. We make several further assumptions

Assumption 1. *Let* $\gamma^{h'}_{Njs} = \gamma^{h'}_{Sjs} = 0$ *and* $\gamma^{h}_{Njs} = \gamma^{h}_{Sjs} = \gamma^{h}_{js}$ *for all* s*.*

In practical terms this means we are assuming the effect of the squared logarithmic in each period for each input is zero. The second statement clears up the nomenclature (γ^{h}_{Njs} and γ^{h}_{Sjs} cannot be separately identified).

$$\ln H_{it} = \alpha^h_0 + \sum_s^{t-1} \alpha^h_s \ln N_{is} + \sum_s^{t-1} \beta^h_s \ln S_{is} + \sum_s^{t-1}\sum_j^{t-1} \gamma^h_{sj} \ln N_{is} \ln S_{ij} + \sigma^h_t \mu_0 + \delta^h_t \mathbf{X} + \varepsilon^h_{it} \quad (18)$$

Following the same procedure for weight yields the following

$$\ln W_{it} = \alpha^w_0 + \sum_s^{t-1} \alpha^w_s \ln N_{is} + \sum_s^{t-1} \beta^w_s \ln S_{is} + \sum_s^{t-1}\sum_j^{t-1} \gamma^w_{sj} \ln N_{is} \ln S_{ij} + \sigma^w_t \mu_0 + \delta^w_t \mathbf{X} + \varepsilon^w_{it} \quad (19)$$

Assumption 2. *Only contemporaneous interactions between sanitation and nutrition matter. That is:* $\gamma^i_{sj} = 0 \ \forall s, j$ *where* $s \neq j$

Assumption 3. *For* $i \in \{h, w\}$*:* $\alpha^i_s = \lambda\alpha^i_{s-1}$ *,* $\beta^i_s = \lambda\beta^i_{s-1}$ *,* $\gamma^i_s = \lambda\gamma^i_{s-1}, \sigma_s = \lambda\sigma_{s-1}$*. The impact of past inputs follow a monotonic rate of change,* λ*, which is common across both weight and height.*

Applying assumption 1 and taking the first differences yields the following for height and weight

$$\Delta \ln H_{it} = \alpha^h_{t-1} \ln N_{it-1} + \beta^h_{t-1} \ln S_{t-1} + \gamma^h_{t-1} \ln N_{it-1} \ln S_{it-1} + \sum_s^{t-2} (\alpha^h_s - \alpha^h_{s-1}) \ln N_{is}$$
$$+ \sum_s^{t-2} (\beta^h_s - \beta^h_{s-1}) \ln S_{is} + \sum_s^{t-2} (\gamma^h_s - \gamma^h_{s-1}) \ln N_{is} \ln S_{is} + (\sigma^h_t - \sigma^h_{t-1})\mu_0 + (\delta^h_t - \delta^h_{t-1})\mathbf{X} + \varepsilon^h_{it} - \varepsilon^h_{it-1}$$

$$\Delta \ln W_{it} = \alpha^w_{t-1} \ln N_{it-1} + \beta^w_{t-1} \ln S_{t-1} + \gamma^w_{t-1} \ln N_{it-1} \ln S_{it-1} + \sum_s^{t-2} (\alpha^w_s - \alpha^w_{s-1}) \ln N_{is}$$
$$+ \sum_s^{t-2} (\beta^w_s - \beta^w_{s-1}) \ln S_{is} + \sum_s^{t-2} (\gamma^w_s - \gamma^w_{s-1}) \ln N_{is} \ln S_{is} + (\sigma^w_t - \sigma^w_{t-1})\mu_0 + (\delta^w_t - \delta^w_{t-1})\mathbf{X} + \varepsilon^w_{it} - \varepsilon^w_{it-1}$$

We can then apply assumption 2

$$\Delta \ln H_t = \alpha^h_{t-1} \ln N_{it-1} + \beta^h_{t-1} \ln S_{t-1} + \gamma^h_{t-1} \ln N_{it-1} \ln S_{it-1} + (\lambda - 1) \sum_s^{t-2} \alpha_{s-1} \ln N_{is}$$

$$+(\lambda-1) \sum_s^{t-2} \beta_{s-1} \ln S_{is} + (\lambda-1) \sum_s^{t-2} \gamma_{s-1} \ln N_{is} \ln S_{is} + (\lambda-1)\sigma^h_{t-1}\mu_0 + (\delta^h_t - \delta^h_{t-1})\mathbf{X} + \varepsilon^h_{it} - \varepsilon^h_{it-1} \tag{20}$$

$$\Delta \ln W_{it} = \alpha^w_{t-1} \ln N_{it-1} + \beta^w_{it-1} \ln S_{t-1} + \gamma^w_{t-1} \ln N_{it-1} \ln S_{it-1} + (\lambda - 1) \sum_s^{t-2} \alpha_{s-1} \ln N_{is}$$

$$+(\lambda-1) \sum_s^{t-2} \beta_{s-1} \ln S_{is} + (\lambda-1) \sum_s^{t-2} \gamma_{s-1} \ln N_{is} \ln S_{is} + (\lambda-1)\sigma^w_{t-1}\mu_{i0} + (\delta^w_t - \delta^w_{t-1})\mathbf{X} + \varepsilon^w_t - \varepsilon^w_{t-1} \tag{21}$$

We then follow Behrman et al. 2009 and make the following assumption on the relative impact of inputs on height and weight

Assumption 4. *The coefficients of inputs on height are the same as those on weight up to a constant, which is true for all inputs.* $\alpha^h_s = a\alpha^w_s$ *,*$\beta^h_s = a\beta^w_s$*,* $\gamma^h_s = a\gamma^w_s$*,* $\sigma^h_s = a\sigma^w_s$ *where* a *is some scalar constant.*

Taking the difference between (18) and (19) gives us

$$\ln H_{it-1} - \ln W_{it-1} = \alpha^h_0 - \alpha^w_0 + \sum_s^{t-2} (\alpha^h_s - \alpha^w_s) \ln N_{is} + \sum_s^{t-2} (\beta^h_s - \beta^w_s) \ln S_{is}$$

$$+ \sum_s^{t-2} (\gamma^h_s - \gamma^w_s) \ln N_{is} \ln S_{is} + (\sigma^h_{t-1} - \sigma^w_{t-1})\mu_{i0} + (\delta^h_{t-1} - \delta^w_{t-1})\mathbf{X} + \varepsilon^h_{it-1} - \varepsilon^w_{it-1}$$

Applying assumption 3 to this expression simplifies it to

$$\ln H_{t-1} - \ln W_{t-1} - \alpha^h_0 + \alpha^w_0 - \varepsilon^h_{it-1} + \varepsilon^w_{it-1} - (\delta^h_{t-1} - \delta^w_{t-1})\mathbf{X} =$$

$$(a-1)\left[\sum_s^{t-2} \alpha_{s-1} \ln N_{is} + \sum_s^{t-2} \beta_{s-1} \ln S_{is} + \sum_s^{t-2} \gamma_{s-1} \ln N_{is} \ln S_{is} + \sigma^h_{t-1}\mu_{i0} \right]$$

We can then substitute the term in the square brackets into equation (20) to get to

$$\Delta \ln H_{it} = k^h + \alpha^h_{t-1} \ln N_{it-1} + \beta^h_{t-1} \ln S_{it-1} + \gamma^h_{t-1} \ln N_{it-1} \ln S_{it-1} + \frac{\lambda - 1}{a - 1} \ln H_{it-1} - \frac{\lambda - 1}{a - 1} \ln W_{it-1} + b^h \mathbf{X} + \pi^{\Delta h}_{it} \tag{22}$$

where
$k^h = \frac{\alpha^h_0 - \alpha^w_0}{1-a}$
$b^h = \delta^h_t - \delta^h_{t-1} \frac{a}{a-1} + \frac{\delta^w_{t-1}}{a-1}$
$\pi^{\Delta h}_t = \varepsilon^h_t - \varepsilon^h_{t-1} + \frac{\varepsilon^h_{t-1} - \varepsilon^w_{t-1}}{1-a}$

The exact same logic can be applied for the weight equation, substituting the same term into equation (21).

A.2 Instruments

Table 15: First Stages

	(1) Protein	(2) Calories	(3) WASH
L.Log Price C4 Rice	0.682***	0.580**	0.0732
	(3.82)	(3.39)	(1.34)
L2.Log Price C4 Rice	0.216	0.0593	-0.0245
	(1.29)	(0.40)	(-0.43)
L.Log Price Corn	-0.226**	-0.0767	-0.00245
	(-3.06)	(-1.29)	(-0.12)
L2.Log Price Corn	-0.0403	0.0147	-0.0541*
	(-0.49)	(0.20)	(-2.22)
L.Log Price Capitol Oil	0.0859*	0.0678	-0.0109
	(2.32)	(1.97)	(-0.70)
L2.Log Price Capitol Oil	-0.0215	-0.0571	0.0210
	(-0.36)	(-1.00)	(1.27)
L.Log Price Dried Fish	0.0406	0.0351	0.00892
	(1.28)	(1.45)	(0.80)
L2.Log Price Dried Fish	0.0441	0.0161	0.00249
	(1.69)	(0.74)	(0.30)
L.Log Price Condensed Milk	-0.0580	-0.0363	-0.0108
	(-1.10)	(-0.80)	(-0.38)
L2.Log Price Condensed Milk	-0.0273	-0.0203	-0.0440
	(-0.36)	(-0.29)	(-1.44)
L.Log Price Evaporated Milk	-0.00250	0.00604	-0.00311
	(-0.04)	(0.13)	(-0.09)
L2.Log Price Evaporated Milk	0.0832	0.0538	-0.00730
	(1.29)	(0.89)	(-0.18)
L.Log Price Tomatoes	0.0539*	0.0471**	-0.0215*
	(2.60)	(2.76)	(-2.19)
L2.Log Price Tomatoes	0.0455*	0.0431**	-0.00825
	(2.56)	(2.74)	(-1.10)
L.Log Price Wag Wag Rice	-0.272	-0.186	-0.109*
	(-1.62)	(-1.21)	(-2.64)
L2.Log Price Wag Wag Rice	-0.250	-0.0825	-0.0238
	(-1.79)	(-0.69)	(-0.44)
L.Log Price Formula Milk	0.0262	-0.0143	-0.116
	(0.22)	(-0.13)	(-1.79)
L2.Log Price Formula Milk	0.0310	-0.0293	-0.0430
	(0.35)	(-0.32)	(-0.76)
L.Log Price Kerosene	0.0332	0.0527	-0.00649
	(0.66)	(1.14)	(-0.31)
L2.Log Price Kerosene	0.0259	0.0121	-0.0391
	(0.43)	(0.22)	(-1.88)
Log Antipolo toilet price (inside)	0.0668	0.0924*	0.0688
	(1.42)	(2.14)	(1.58)
Log Antipolo toilet price (outside)	-0.0642*	-0.0650*	-0.0242
	(-2.26)	(-2.40)	(-1.01)
Average Soil Depth	-0.0975**	-0.0572*	0.00123
	(-2.79)	(-2.11)	(0.04)
Average Male Wages	0.00338*	0.00282	0.00267
	(2.11)	(1.81)	(1.60)
Average Female Wages	0.000856	-0.000500	-0.00204
	(0.43)	(-0.27)	(-1.00)
Constant	-5.233**	-4.843**	1.226
	(-3.29)	(-3.01)	(1.13)
Observations	20319	20439	20539
F-stat	12.01	18.74	27.79

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors clustered at community level.

Additional controls present in all columns include municipality dummies, interview month dummies, census population, an urban/rural dummy, wealth quintile, household income per capita, age of household head and their education, mother age and education as well controls for the distribution of ages within the household