Complementarities in the Production of Child Health*

Laura Abramovsky, Britta Augsburg, Pamela Jervis

Bansi Malde, and Angus Phimister

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Abstract

We estimate 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 Filipino cohort data and a control function approach, we show that WASH and nutrition are complements in the formation of child height and weight. The productivities of these inputs vary with child gender: nutritional intake is more productive for boys, while WASH investments are more productive for girls. Nutritional and WASH conditions faced by sample children are similar to those currently encountered by poor children in low-income settings.

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

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*Laura Abramovsky is a Research Associate at the Institute for Fiscal Studies (IFS). Britta Augsburg is Deputy Director of the development sector of the IFS. Pamela Jervis is a Research Economist at the IFS. Bansi Malde (b.k.malde@kent.ac.uk) is a Lecturer in Economics at the University of Kent and affiliated with the IFS. Angus Phimister is a Research Economist at the IFS. We thank Linda Adair, Orazio Attanasio, Jere Behrman, Prashant Bharadwaj, Melanie Luehrmann, Dhanushka Thamarapani, and participants at the CEPR–LSE Stunting Conference, RES Junior Symposium, Essen Health Conference, Ce2 workshop, EEA-ESEM conference, IFS seminar, and RES conference for useful discussions and suggestions. Many thanks also to Nanette Lee for sharing the nutrition data aggregates. Funding from the ESRC Centre for Microeconomic Analysis of Public Policy at the IFS and the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 695300 - HKADeC - ERC-2015-AdG/ERC-2015-AdG) is gratefully acknowledged. All errors are our own.

I. Introduction

Early-life growth faltering, where the growth trajectory diverges from the healthy norm, is pervasive among children in developing countries. Significant deficits in height- and weight-for-age are often not recouped in later years (Shrimpton et al. 2001). This has long-lasting implications for health, cognitive development, and productivity (Hoddinott et al. 2008, 2013; Maluccio et al. 2009; Victora et al. 2010; Currie and Almond 2011), thereby undermining 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.

Children's vulnerability to poor diets and infections, particularly in the first two years of life, has been well documented (see Engle et al. 2007; Black et al. 2008; Behrman et al. 2009; Puentes et al. 2016, among others). Much less is known about the importance of environmental factors, particularly water, sanitation, and hygiene (WASH), which influence growth by reducing exposure to pathogens. Pathogens cause infections, and also increase the likelihood of developing environmental enteropathy—a subclinical condition that leads to permeability, malabsorption, and systemic and gut inflammation—which not only weakens the gut's ability to absorb nutrients, but also reduces the effectiveness of vaccines (Lunn, Northrop-Clewes, and Downes 1991; Campbell, Elia, and Lunn 2003; Levine 2010; Lin et al. 2013; Prendergast et al. 2014; George et al. 2016; Gough et al. 2016; Mbuya and Humphrey 2016). Strikingly, the knowledge gap is not just in terms of the impacts of specific factors, or inputs on child growth, but also in terms of how they interact with one another (Alderman and Headey 2018).

In this paper, we estimate the relative importance of nutritional intake and reduced pathogen exposure through WASH investments, and the interactions between these, in shaping children's height and weight in a low-income setting—the Philippines in the early 1980s. We estimate flexible child health production functions using rich panel data from the Cebu Longitudinal Health and Nutrition Survey (CLHNS), which yields among the first evidence that a hygienic environment can make nutritional investments more effective.[1]

Whether, and the degree to which, an improved hygienic environment reduces exposure to pathogens and thereby makes nutritional intake more productive has yet to be definitively established. Doing so is empirically challenging. Previous estimations of production functions either focus on one input only, or impose strong restrictions on the nature of interactions between inputs, such as perfect substitutes (Cebu Study Team 1992; De Cao 2015; Puentes et al. 2016, among others). However, randomized controlled trials (RCTs) of WASH and nutrition interventions have, to date, been unsuccessful in establishing the nature of the interaction between these inputs, partly because of insufficient power to detect interaction effects,[2] low adherence to the trial interventions (Clasen et al. 2014; Null et al. 2018), intervention in an area with an unexpectedly low prevalence of diarrhoea (Luby et al. 2018), implementation of insufficiently intensive interventions (Pickering et al. 2019), or intervention during a period when children were mostly still breastfeeding so that antibodies in breast milk provided (some) protection against pathogens (Humphrey et al. 2019).

Our estimation approach overcomes these shortcomings by estimating flexible production functions that do not impose especially restrictive assumptions on the interaction between inputs. At the same time, the 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 it corrects for this endogeneity using a control function approach. As instruments we use variables that, conditional on a rich set of individual, household, and community controls, are plausibly exogenous, meeting the condition of

[1] This is postulated in an emerging literature (Humphrey 2009; Dewey and Mayers 2011; Mbuya and Humphrey 2016).

[2] For example, the WASH Benefits trial, a multi-arm randomized 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), despite previous evidence that interaction effects can potentially be small (Kielmann et al. 1978; Taylor et al. 1978).

affecting child height and weight primarily through either nutrition or WASH investments. In particular, we use as instruments community-level prices of food and sanitation, community-level geological features, and community-level average wages. We discuss in detail the issue of instrument validity.

We use the CLHNS, which contains rich information that not only yields sufficient exogenous variation for the control function approach, but also contains detailed, high-frequency measures of child nutritional intake, child- and household-level WASH practices, and child height and weight. The survey follows a cohort of around 2,800 children born between 1983 and 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. A particular advantage of this data source is that it includes children living in urban areas— 75% of the sample—that are more densely populated areas, and hence are more vulnerable to negative externalities of poor WASH (Hathi et al. 2017).[3]

Our analysis focuses on children aged between six months and two years, who are in the developmental window where the bulk of linear growth faltering occurs, thus providing most scope for corrective action (Headey 2016).[4] It also exploits information available up to age 2, making it likely that we capture the full impact of WASH as a protective factor (Alderman and Headey 2018).

We find that both nutrition intake (particularly protein) and WASH are important investments to reduce growth faltering in the first two years of life. We detect significant and meaningful impacts of each input on children's growth, thereby contributing to two strands of the literature that establish nutrition and WASH as important drivers of child

[3]This is contrary to the well-known WASH Benefits and SHINE trials, which focus on rural areas.

[4]Though the data contain information on nutrition intake and WASH investments in the 0–6 month age range, we do not incorporate this range in our analysis for two reasons. First, the medical literature has established that breast milk can insulate children from infectious diseases by transmitting maternal antibodies to breastfed children (see, for example, Victora et al. 1987; Sadeharju et al. 2007). This implies that WASH investments during this developmental age are likely to be less important. Second, we do not have sufficiently strong sources of exogenous variation to account for endogeneity in breastfeeding, the most important nutritional input.

growth.[5] Further, we find a robust, positive, and statistically significant interaction between both inputs, indicating that nutrition is more productive in more hygienic environments. 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 2.57 cm. For a child at the 90th percentile of the WASH distribution, this gain would be around 2.73 cm.[6] This result is, to the best of our knowledge, the first rigorous evidence that WASH investments can indeed make nutrition investments more productive; hence, we find the existence of complementarities.

Further analysis indicates that the effects of nutrition and WASH, including their interaction, are heterogeneous by child gender. We estimate a larger, positive marginal effect for nutrition intake, particularly protein intake, for boys. By contrast, WASH investments are more productive for girls, a finding that is in line with De Cao (2015), which demonstrates that a girl's height is more sensitive to diarrhoea than that of boys. Moreover, we find a stronger interaction between WASH and nutrition for girls than boys, indicating that for girls at least, nutrition intake is more productive only in sufficiently hygienic environments. Interestingly, this heterogeneity is not driven by differences in parental investments by child gender. Instead, differences by gender in child activities, or in biological growth processes—which we cannot disentangle in the data—might drive the detected heterogeneity. Disentangling these is left to future research.

The remainder of the paper is structured as follows. In Section II, we discuss the CLHNS data

[5] For the relevance of nutrition, see Black et al. (2008), Puentes et al. (2016), and more specifically for our study context (i.e. the Philippines) Adair and Guilkey (1997), De Cao (2015), and Cebu Study Team (1992). Studies on the importance of WASH on health outcomes find more mixed evidence (Dangour et al. 2013; Gera, Shah, and Sachdev 2018), some reporting negative impacts of poor sanitation on child height for age (Gertler et al. 2014; Pickering et al. 2015; Hammer and Spears 2016; Augsburg and Rodríguez-Lesmes 2018), and others (including recent large-scale RCTs) detecting no impacts (Clasen et al. 2014; Patil et al. 2014; Briceño, Coville, and Martinez 2015; Luby et al. 2018; Null et al. 2018; Humphrey et al. 2019), with systematic reviews remaining positive about WASH interventions, and supporting their scale up in low- and middle-income countries (Darvesh et al. 2017).

[6] Our estimates similarly suggest a robust, positive interaction between nutrition intake and WASH for child weight.

and the input measures. In Section III, we lay out the theoretical framework and estimation strategy. In Section IV, we present the results. We conclude in Section V.

II. Context, Data, and Measures

We use data from the CLHNS, an ongoing study of a cohort of Filipino children born in the early 1980s. Originally designed to study infant feeding patterns and their role in shaping child physical health, these data contain 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. In addition, the surveys collected detailed background health and socioeconomic 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, and the main cooking fuel, kerosene.

All mothers of children born between May 1, 1983 and April 30, 1984 living in 33 neighborhoods, 17 urban and 16 rural (hereafter referred to as communities) were surveyed at the start of the third trimester of pregnancy. They were subsequently surveyed at multiple points in time during the first two years of their child's life (a few days after birth, and thereafter once every two months). Further follow-up surveys were conducted at older ages. For testing our hypothesis, we 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. Reasons for dropout (shown in Table A.1 in the Appendix) range from leaving the study area (13.4% of the baseline sample), to miscarriage, stillbirth, or death of child (6.2%), to being dropped from sample due to pregnancy resulting in multiple births (0.8%), and to either refusing participation in the surveys or having erroneous information (0.7%).[7]

Though these data were 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 1 provides descriptive statistics on characteristics of the communities, households, children, and mothers in our analysis sample. A significant majority of study children—around three-quarters—lived in urban neighborhoods, despite the equal number of urban and rural communities sampled, reflecting the higher population density in urban areas. Moreover, households needed to travel on average 6 km to reach the nearest public hospital. Before the birth of the study child, the typically male (95%) household head was aged just over 35 years, employed (95%), and had just over seven years of education, implying that, on average, he would have completed (compulsory) elementary school plus one additional year. Households typically consisted of five to six members and lived in dwellings they owned (71%). These were mostly constructed from poor materials (only 18% made of concrete) and had fewer than three rooms on average. Asset ownership was low, with only 6% owning a refrigerator, 70% owning benches or chairs, and about 48% having electric lighting in their house. Conducting a rough calculation, the average household had a per capita daily income of approximately US$1.77 in 2017 prices, which is below the official International Poverty Line of US$1.90 per person per day.

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

Just above half (52%) of the sample children were girls. The CLHNS collected anthropometric

[7] We compare the characteristics of attrited (not present in all bi-monthly surveys) and non-attrited households/mothers/children in Table A.2 in the Online Appendix. Attrition is broadly balanced across a rich set of observed variables, with the exception of home ownership and the number of children under the age of 5 in the household, which only show small differences in means though.

Table 1: Sample Characteristics

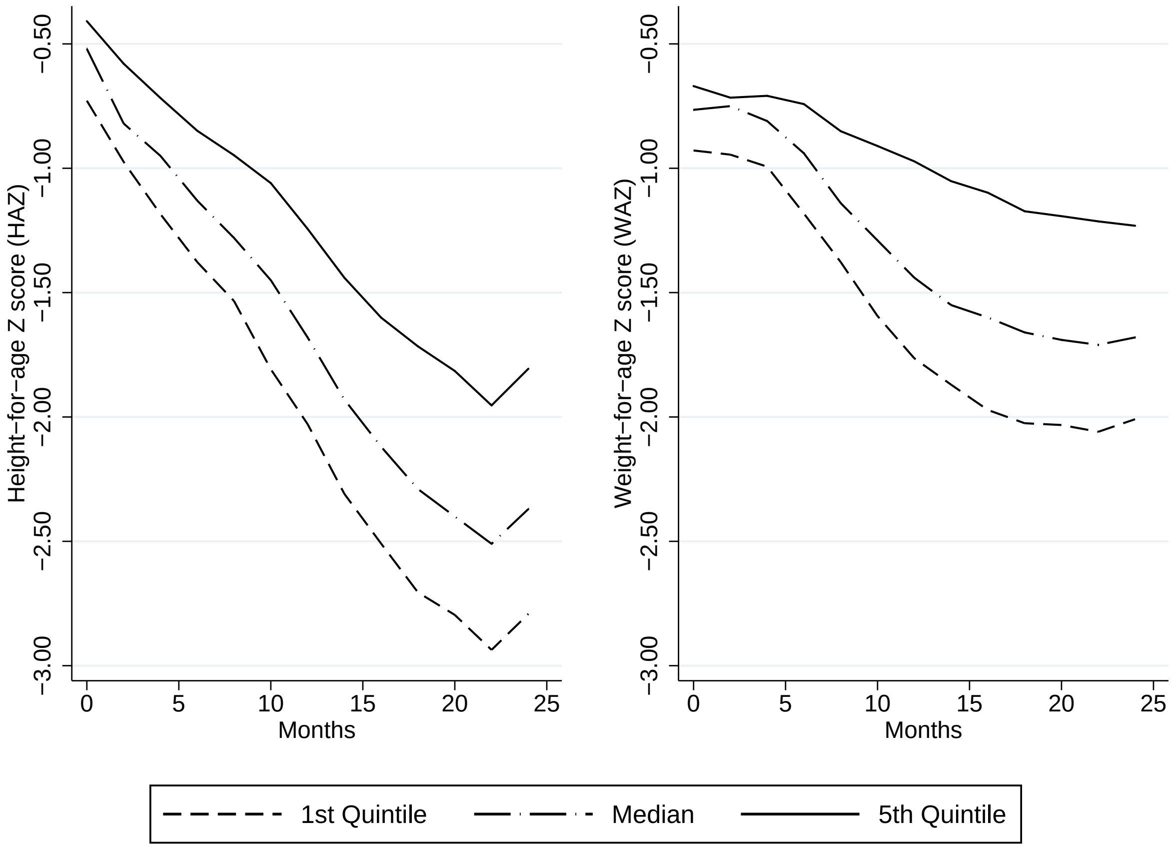
Variable	Mean	SD	N
Household and community characteristics			
Household in urban community	0.74	0.44	2,302
Distance to nearest public hospital (km)	6.03	4.94	2,302
Age of household head (years)	35.51	12.21	2,302
Household head is female (%)	0.05	0.21	2,302
Household head is in employment (%)	0.95	0.21	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
House made of concrete (%)	0.18	0.38	2,302
Household owns a refrigerator (%)	0.06	0.24	2,302
Household owns benches/chairs (%)	0.70	0.46	2,302
Household has electric lighting (%)	0.48	0.50	2,302
Number of rooms (excluding bathrooms)	2.60	1.31	2,302
Household income per capita (2017 US$)	1.77	1.67	2,302
Anthropometrics from six 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 six months	0.21	0.41	2,274
Stunted at 24 months	0.63	0.48	2,174
Mother's 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's age (years)	27.05	5.94	2,302
No. of children younger than 5	1.27	1.00	2,302
Mother working during pregnancy	0.38	0.49	2,302
Child's birth characteristics			
Child's gender (1 = male)	0.52	0.50	2,302
Birth weight (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.

measurements at birth, and during the bi-monthly follow-up surveys. The average child weighed 3.05 kg at birth, and had a length of 49.27 cm. This increased to a weight of 8.3 kg and a height of 72.4 cm at six months of age.

Useful benchmarks for child anthropometrics are height-for-age Z-score (HAZ) and weight-

Figure 1: The Evolution of HAZ and WAZ Scores by Child Age in Months



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

for-age Z-score (WAZ), standardized relative to the median for children of the same age and gender in the World Health Organization (WHO) reference population. A child is considered stunted (underweight) if their HAZ (WAZ) falls below −2 standard deviations from the norm. Figure 1 displays the evolution of these scores for our sample children by child's age for the first and fifth wealth quintile, along with the sample median.[8]

The left panel of Figure 1 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 a growth trajectory that diverges away from the healthy reference population as the child

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

gets older. This is apparent from stunting rates in the sample (reported in Table 1): at age 6 months, 21% of children were stunted; by age 24 months, 63% of children were stunted. Moreover, the figure 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. By age 15 months, the median 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 two years of age), and comparable with those experienced in many developing countries today.

Child weight follows a similar, if less dramatic, pattern, as shown in the right panel of Figure 1. The average child in our sample starts out with low WAZ compared with the reference population, and about 10% of our sample are underweight at birth. While there is no dramatic deterioration in the first five to six months of life, WAZ diverges significantly from the WHO reference population thereafter, before stabilizing around 15 months of age. The timing of deterioration coincides with the start of complementary feeding. Similarly to HAZ, the difference between the top and bottom quintiles grows from around 0.3 standard deviations at birth to around 0.7 standard deviations by the time the average child in the sample reaches 24 months of age.

A. Inputs

The main objective of this paper is to study how different inputs influence child growth, individually and in interaction. Having provided a picture of child growth in our study sample, we next outline the measures for the inputs we consider—nutrition and WASH.

1. Nutrition

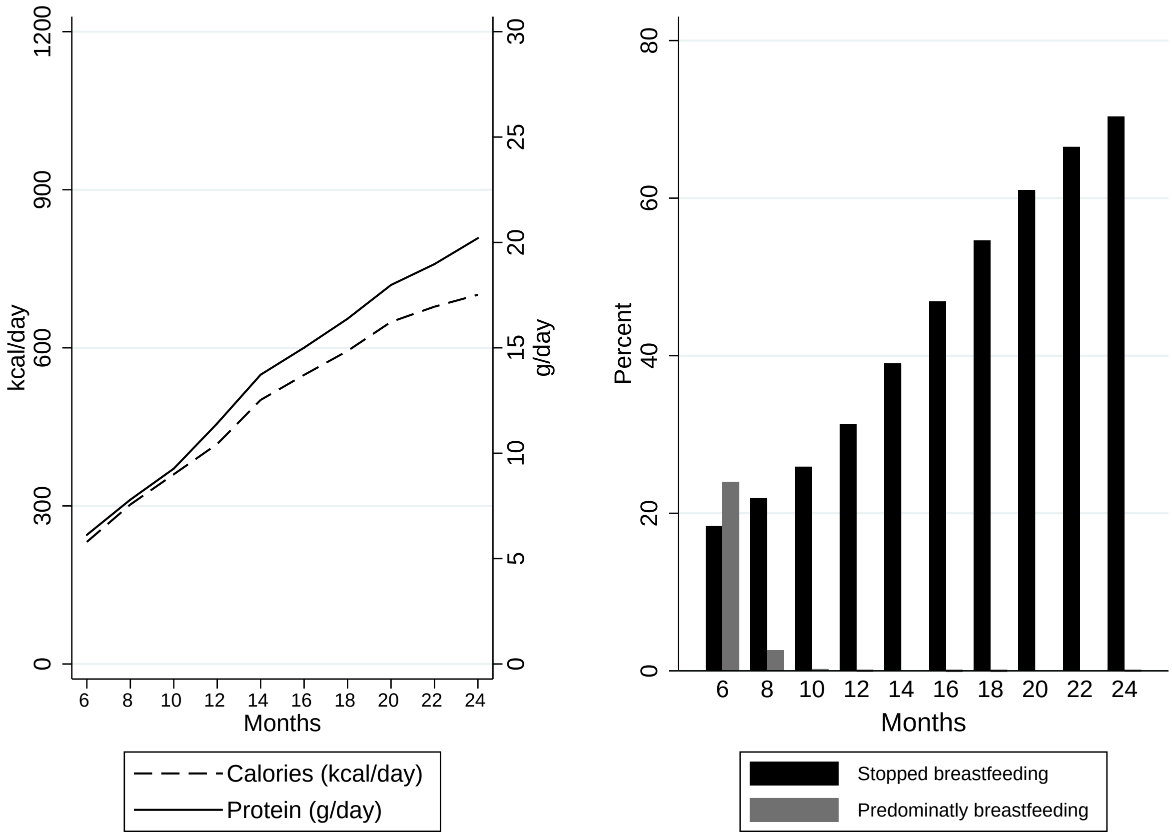
The CLHNS data contain exceptionally detailed information on food intake over the first two years of an infant's life. Data were collected on the commencement, frequency, and discontinuation of breastfeeding, and the intake of all liquids, solids, and semi-solids in the 24 hours prior to each bi-monthly recall 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 further supplemented with nutrient composition information obtained directly from manufacturers for foods such as infant formula; Bisgrove, Popkin, and Barba (1989, 1991) and Perlas, Gibson, and Adair (2004) provide more details.

As our key measure of nutrition, our analysis focuses on protein intake. Protein has been identified as crucial for healthy growth, as it is a component of every cell in the body and an essential ingredient for the repair of cells and the creation of new cells. Using a production function instrumental variables strategy, Puentes et al. (2016) demonstrate the importance of protein intake for the growth of children in our study context. As a robustness check, we also consider the total amount of calories consumed.

The children in our sample consume, on average, 14.0 grams of protein and 510 kcals per day. The left panel of Figure 2 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 kcals 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.

These values are lower bounds on nutrition intake. Proteins and calories consumed through breast milk are not included in the calculations, as the amount of breast milk consumed and its nutritional composition are difficult to measure. Indeed, the right panel of Figure 2, 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 semi-solid and solid foods and other liquids, with 69% of children still receiving breast milk at one year of age and 46%

Figure 2: Nutritional Inputs over Time



Notes: 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.

at age 18 months. Predominant breastfeeding, however, falls from 24% at six months of age to 0.2% two months later. In our analysis, we control for whether or not the child is being breastfed.

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 WASH. We use a composite measure that combines these three dimensions, and we include WASH as a single term in a production function. This provides a more informative and complete measure of the hygienic environment the child is exposed to, relative to including each input independently.

The data contain a number of measures of the household practices around WASH. Some of these are measured in each survey round, while others are only observed once. We combine all these variables into a single WASH score using polychoric exploratory factor analysis, which is estimated separately for each survey round. Variables with low factor loadings, which provided little additional information, were dropped from the construction of the WASH score.[9] We retain the first factor, which always had an associated eigenvalue greater than 1, as the WASH score.[10,11] The resulting WASH score used in our analysis includes at least one variable related to each component of WASH practices.

The *water* dimension is captured by an indicator for whether the child was not given untreated water (collected in each of the longitudinal survey rounds). Because some children might be predominantly breastfed at six months of age, the indicator is constructed to equal one if the child was *not* given untreated water (i.e. given treated water or nothing), or zero otherwise. Aggregating across rounds, we see that in 45% of instances children were given treated water, as shown in Table 2.

The *sanitation* dimension is captured by information on the type of toilet facility owned by the household (information collected at baseline), and how mothers dispose of their child's feces (information 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

[9] These include the household's main drinking water source, consumption of leftovers by the child, and, if so, how these were stored, and surveyor observations of the cleanliness of the cooking area and general area around the household.

[10] Though the WASH score is estimated separately by round, we find little difference in the factor loadings across rounds.

[11] We also explored 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 not only to have private benefits, but also to affect neighbors. 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. Therefore, we present estimations without these averages.

Table 2: 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 are 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

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

a child's feces are safely disposed of—defined as disposal, either of waste water or of feces, directly into a toilet.[12] We see in Table 2 that around 65% of households own a safe toilet, but only 16% use a toilet to safely dispose of child excreta.

Finally, the *hygiene* dimension is captured through information on weekly soap expenditures (collected at baseline), which amount to 206 pesos (approx. 2017 US$4.41) on average.

The last column of Table 2 provides the factor loadings for the constructed WASH score. Results indicate that safe toilet ownership has the highest factor loading among the household-level variables, a point we return to when discussing exclusion restrictions.[13]

We analyze how the WASH scores (in logs) vary with household wealth quintiles (Table 3). Interesting, and sensible, patterns emerge. First, the proportion of households reporting to have given untreated water to their child decreases by wealth quintile from 94% in the first quintile 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% in the second quintile to 96% in the third quintile. Third, safe disposal of child feces is basically non-existent in the three lowest

[12] 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.

[13] In robustness checks, we estimate WASH scores using either only time-invariant variables (e.g. safe toilet ownership, soap expenditures, and safe disposal of child feces; or only safe toilet ownership) or only 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 Section A.4 of the Online Appendix. Our results remain consistent.

Table 3: WASH Inputs by Wealth Quintile

	First	Second	Third	Fourth	Fifth
Safe toilet in household (dummy)	0.00	0.27	0.96	0.99	1.00
Child's feces are disposed of safely (i.e. in a 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

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

quintiles (<5%), increasing to 15% in the fourth and 58% in the fifth. Soap expenditures also increase with wealth quintile. In line with the increased values of the indicators, the resulting WASH score is also increasing with wealth.

We assess how the resulting WASH score correlates with various child-, household-, and community-level variables in Table A.3 in the Online Appendix. 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 a positive wealth gradient, with children in wealthier households having a significantly larger WASH score. The WASH score is also larger when 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 communities relative to rural communities.

III. Theoretical Framework and Estimation Strategy

We now outline the theoretical framework, and derive the empirical model before discussing the estimation strategy. Starting from the most general process of height and weight formation, we specify the assumptions needed to obtain an empirically tractable model that can be taken to the data. Thereafter, we discuss the estimation strategy, which allows us to deal with endogeneity of inputs, in more detail.

We define a general process of height H and weight W formation for child i at age t as

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

and

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

Here, $\{N_{is}\}_{s=1}^{t-1}$ 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 $t-1$, μ_i is the child's health endowment, and X is a vector of other variables that also affect the formation of height and weight, such as mother's height. In this general formulation, the production functions, H_t and W_t, are allowed to be age-specific.

Estimation of such a production function poses several challenges, namely: (1) functional form assumptions; (2) empirical tractability; and (3) endogeneity of inputs. We consider each of these in turn.

1. Functional Form

It is not *a priori* obvious what functional form the child health production should take. Common choices in the literature—such as the constant elasticity of substitution (CES) production function or the 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 means, for instance, that households can completely compensate for poor hygiene by giving their child more food—and, similarly, proper hygiene can compensate for lack of nutrition. Other popular functional forms such as the Cobb–Douglas or CES impose homotheticity of inputs, implying that the relative productivity of WASH and nutrition remains constant for a given ratio of inputs. In other words, a doubling of nutrition intake, as long as WASH input was doubled also, would not affect how productive nutrition was relative to WASH. The knowns, as well as 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 use a translog functional form, which does not impose any such substitutability or complementarity restrictions.

Imposing the translog functional form yields

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

and

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

where

$$\begin{aligned}
Y_1 &= \frac{1}{2}\left(\sum_r^{t-1} \gamma_{Nrs}^{\nu^h} \ln N_{ri} + \sum_r^{t-1} \gamma_{Nrs}^{h} \ln S_{ri} \right), \\
Y_2 &= \frac{1}{2}\left(\sum_r^{t-1} \gamma_{Srs}^{h} \ln N_{ri} + \sum_r^{t-1} \gamma_{Srs}^{\nu^h} \ln S_{rs} \right), \\
Y_3 &= \frac{1}{2}\left(\sum_r^{t-1} \gamma_{Nrs}^{\nu^w} \ln N_{ri} + \sum_r^{t-1} \gamma_{Nrs}^{w} \ln S_{ri} \right), \\
Y_4 &= \frac{1}{2}\left(\sum_r^{t-1} \gamma_{Srs}^{w} \ln N_{ri} + \sum_r^{t-1} \gamma_{Srs}^{\nu^w} \ln S_{ri} \right).
\end{aligned}$$

These equations contain the entire history of nutrition and WASH inputs, as well as their interactions and quadratic terms. The parameters of interest are α_s and β_s, which capture the marginal productivities of nutrition and WASH inputs at age s on height and weight at age t, and γ_s, which captures the interactions between nutrition and/or WASH inputs in contemporaneous and past periods with nutrition and/or WASH inputs in different periods on height and weight at age t.

2. Empirical Tractability

The inclusion of the entire history of past nutrition and WASH inputs imposes severe demands on the data, as is apparent from examining Equations 3 and 4, and this may make the estimation intractable. To make the estimation tractable, we use the widely used value-added model (Todd and Wolpin 2007; Puentes et al. 2016, among others), which, under the assumptions outlined below, allows us to use outcomes at age $t-1$ to capture the effects of past nutrition and WASH inputs on outcomes at age t. In order to implement this approach, it is only necessary to know the outcomes at ages t and $t-1$ and the inputs between these ages, thereby dramatically improving empirical tractability.

We lay out the assumptions under which the value-added approach gives consistent estimates, extending Puentes et al. (2016) to the translog functional form.

Assumption 1. *For* $m \in \{h, w\}$*:*

(a) $\gamma^{\nu^m}_{Nrs} = \gamma^{\nu^m}_{Srs} = 0$ *and* $\gamma^{m}_{Nrs} = \gamma^{m}_{Srs} = \gamma^{m}_{rs}$ *for all* s*;*

(b) $\gamma^{m}_{rs} = 0$ *for all* s, r $s \neq r$*.*

Assumption 1(a) rules out interactions between an input in period s and the same input in any other period. This imposes that the quadratic terms of each input have no additional effects on height or weight. Given that we are modeling all of the interactions between inputs, this assumption does not place too much additional structure on the growth process. This assumption is relaxed somewhat in the final estimation. The second statement in Assumption 1(a) is more innocuous, and simply imposes that the effect of the interaction between WASH and nutrition is the same as that of the interaction between nutrition and WASH.

Assumption 1(b) imposes that only contemporaneous interactions between WASH and nutrition matter for height and weight formation (i.e. WASH at six months of age does not interact with protein at eight 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. For convenience, we now denote $\gamma_{ss} = \gamma_s$.

After taking logs and applying Assumption 1, Equations 3 and 4 simplify to the following:

$$\ln H_{it} = \alpha_0^h + \sum_s^{t-1} \alpha_s^h \ln N_{is} + \sum_s^{t-1} \beta_s^h \ln S_{is} + \sum_s^{t-1} \gamma_s^h \ln N_{is} \ln S_{is} + \sigma_t^h \mu_0 + \delta_t^h \boldsymbol{X} + \varepsilon_t; \tag{5}$$

$$\ln W_{it} = \alpha_0^w + \sum_s^{t-1} \alpha_s^w \ln N_{is} + \sum_s^{t-1} \beta_s^w \ln S_{is} + \sum_s^{t-1} \gamma_s^w \ln N_{is} \ln S_{is} + \sigma_t^w \mu_0 + \delta_t^h \boldsymbol{X} + \varepsilon_t. \tag{6}$$

These equations are more tractable than Equations 3 and 4, but still pose serious problems in estimation. They include the confounding influence of unobserved health endowment μ_0. Furthermore, there remains the whole history of inputs of nutrition and sanitation, as well as all of their interactions. To further simplify, we require two further assumptions common to the value-added framework.

Assumption 2. *For* $m \in \{h, w\}$*:* $\alpha^m = \alpha_s^m = \lambda \alpha_{s-1}^m$*;* $\beta^m = \beta_s^m = \lambda \beta_{s-1}^m$*;* $\gamma_{SN} = \gamma_s^m = \lambda \gamma_{s-1}^m; \sigma^m = \sigma_s^m = \lambda \sigma_{s-1}^m$.

Assumption 3. $\alpha^h = a\alpha^w$, $\beta^h = a\beta^w$, $\gamma^h = a\gamma^w$, *and* $\sigma^h = a\sigma^w$ *for some scalar constant* a.

Assumption 2 states that the impact of past inputs follows a rate of decay λ, which is common across all inputs. Assumption 3, 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. It also imposes that the effect of the unobserved endowment on height is linear to the effect on weight. This is plausible, as height and weight are likely to be jointly determined in infancy, with inputs affecting each in similar ways.

Taking the first difference of height and weight, and then taking the difference between the height and weight equations and applying Assumptions 2 and 3, we find the following equation for height:

$$\ln H_{it} = \frac{\alpha^h - \alpha^w}{1-a} + \alpha^h \ln N_{it-1} + \beta^h \ln S_{it-1} + \gamma^h_{SN} \ln N_{it-1} \ln S_{it-1} + \frac{a+\lambda-2}{a-1} \ln H_{it-1}$$
$$-\frac{\lambda-1}{a-1} \ln W_{it-1} + \left(\delta^h_t - \delta^h_{t-1}\frac{a}{a-1} + \frac{\delta^w_{t-1}}{a-1}\right)\boldsymbol{X} + \varepsilon^h_t - \varepsilon^h_{t-1} + \frac{\varepsilon^h_{t-1} - \varepsilon^w_{t-1}}{1-a}. \quad (7)$$

In the absence of further endogeneity concerns, the model parameters can be consistently estimated. We extend the model from Equation 7 by including the interactions between past height and contemporaneous inputs. This allows the productivity to vary with accumulated height, as captured by γ_{SH} and γ_{NH}. Renaming the fractions in Equation 7 for parameters and grouping the error terms, we obtain our estimation equation:[14]

$$\ln H_{it} = \alpha_0 + \alpha^h \ln N_{it-1} + \beta^h \ln S_{it-1} + \gamma^h_{SN} \ln S_{it-1} \ln N_{it-1} + \gamma_{SH} \ln S_{it-1} \ln H_{it-1}$$
$$+\gamma_{NH} \ln H_{it-1} \ln N_{it-1} + \tau_h \ln H_{it-1} + \tau_w \ln W_{it_1} + b_h \boldsymbol{X} + \varepsilon^h_{it}. \quad (8)$$

In the estimation, $\boldsymbol{X}$ includes a set of household-, community-, and child-level controls. At the household level, to capture other unobserved inputs and preferences, we control for wealth quintile, household head, mother's age (quadratically), maternal education, dummies for whether the household head is female, whether the father is present in the household, total number of household members, number of children under 5 in the household, household per capita income, and the ratio of male and female household members. At the community level, we control for log population density, an index of 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, birth order, gender, age (cubic), a dummy for any breastfeeding, and mother's height.[15]

[14] For the sake of brevity, the full derivation and the estimation model for weight is given in the Appendix.

[15] In terms of inference, the main tables report standard errors clustered at the community level. These could be misleading because 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 we find that our inference does not change. The model estimated for the block bootstrapped standard errors omits the municipality fixed effects, because otherwise a number of re-sampling draws, in which no community from

Our parameters of interest are the marginal products for each input, and the interaction between the two inputs. The marginal product of each input is given by the combined effect of α, β, and γ. For child height, for instance, the marginal products for $\ln N_{it-1}$ and $\ln S_{it-1}$ are

$$\frac{\partial H_{it}}{\partial \ln N_{it-1}} = \alpha_1^h + \gamma_{SN}^h \ln S_{it-1} + \gamma_{NH} \ln H_{it-1}, \tag{9}$$

and

$$\frac{\partial H_{it}}{\partial \ln S_{it-1}} = \beta_1^h + \gamma_{SN}^h \ln N_{it-1} + \gamma_{SH} \ln H_{it-1}. \tag{10}$$

Here, γ_{SN}^h measures 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, while a negative coefficient indicates diminishing returns.

3. Endogeneity

The procedure explained under empirical tractability deals with the endogeneity arising from the child's unobserved health endowment, μ_0. However, there are other risks to identification, such as biases arising from unobserved shocks to child health and from unobserved parental preferences that might be correlated with observed contemporary or lagged inputs. The latter is relevant if parents compensate (reinforce) for contemporary or lagged unobserved health shocks. Not accounting for this source of endogeneity would result in ordinary least-squares (OLS) estimates of the input coefficients that are biased downwards (upwards) if parents compensate (reinforce). To deal with this source of endogeneity, and in light of our highly non-linear estimation equation, we use a control function approach.

To implement the control function approach, we start by estimating the following first-stage

some small municipalities is drawn, need to be discarded.

equations for $\ln N_{it-1}$ and $\ln S_{it-1}$:

$$\ln N_{it-1} = \beta_1 + \sigma_1 \boldsymbol{X} + \pi_1 \boldsymbol{Z} + upro; \tag{11}$$

$$\ln S_{it-1} = \beta_2 + \sigma_2 \boldsymbol{X} + \pi_2 \boldsymbol{Z} + uwash. \tag{12}$$

Here, $\boldsymbol{Z}$ is a set of excluded instrumental variables, and *upro* and *uwash* are the residuals, or control functions. In the second stage, we include these control functions, along with a quadratic term and their interaction, $upro * uwash$ as additional regressors in estimating Equations 8 and A.13. In non-linear specifications such as ours, Terza, Basu, and Rathouz (2008) demonstrate that a control function provides significantly more efficiency compared with instrumental variables.

Non-parametric identification requires that, as with instrumental variables, $\boldsymbol{Z}$ satisfy two conditions, namely: (i) the excluded variables are predictive of the endogenous input variable; and (ii) the excluded variables affect $\ln H_{it}$ ($\ln W_{it}$) only through the input (*exclusion restriction*).

For both our input variables of interest—nutrition and WASH investments—we use input prices at the community level, and community-level wages as instruments. For WASH inputs, we furthermore rely on a geological feature, soil depth. Using prices as an exclusion restriction is a common approach when estimating health production functions (Todd and Wolpin 2003; Liu, Mroz, and Adair 2009; Attanasio et al. 2015), 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 are implicitly comparing the health of children whose parents face different prices and hence choose different levels of the inputs. Furthermore, several studies have shown the importance of price and budget constraints in decisions related to health and food investments in developing countries (Ashraf, Berry, and Shapiro 2010; Brinkman et al. 2010; Cohen and Dupas 2010; Dupas 2011; Spears 2012; Ben Yishay et al. 2017).

The unique data collection design and setting allow us to rely on meaningful spatial as well as temporal variation in the price variables considered, which is not so commonly available in developing-country settings. For food items, community-level prices were collected 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.[16] 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 (calorie) content and/or are important to (the preparation of) the local diet. An additional important source of variation that benefits our analysis is a large inflationary spike partway during the study period, which was caused by political turmoil and the consequent large devaluation of the Filipino peso (Solon and Floro 1993). The spike affected prices of traded goods, such as evaporated milk, more than those of non-traded goods, such as tomatoes, as shown in Figure 4. 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 two years of the child's life.

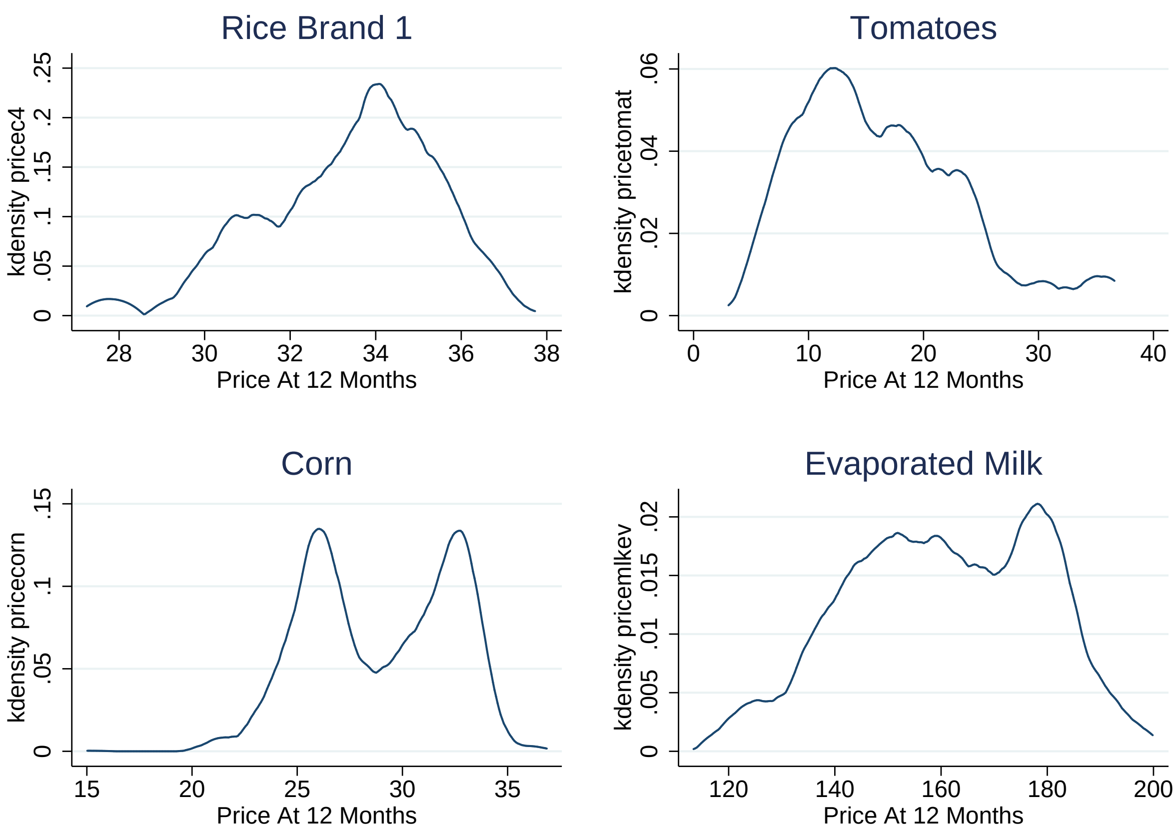
The set of prices used as excluded instruments in the first stage include those of rice, dried fish, corn, tomatoes, oil, condensed and evaporated milk, kerosene, and formula milk.[17] We show the spatial and temporal variations in the prices of four goods (rice, tomatoes, corn, evaporated milk) in Figures 3 and 4, respectively.

To account for the endogeneity of the WASH score, we rely on the cost of installing an antipolo toilet at baseline, as reported by a community leader. Thus, our strategy is similar to that of Augsburg and Rodríguez-Lesmes (2018), who also use community-level sanitation construction costs to correct for the endogeneity of toilet coverage. Antipolo toilets are a

[16]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 we match child-level observations to the closest observed price (by days) in their community.

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

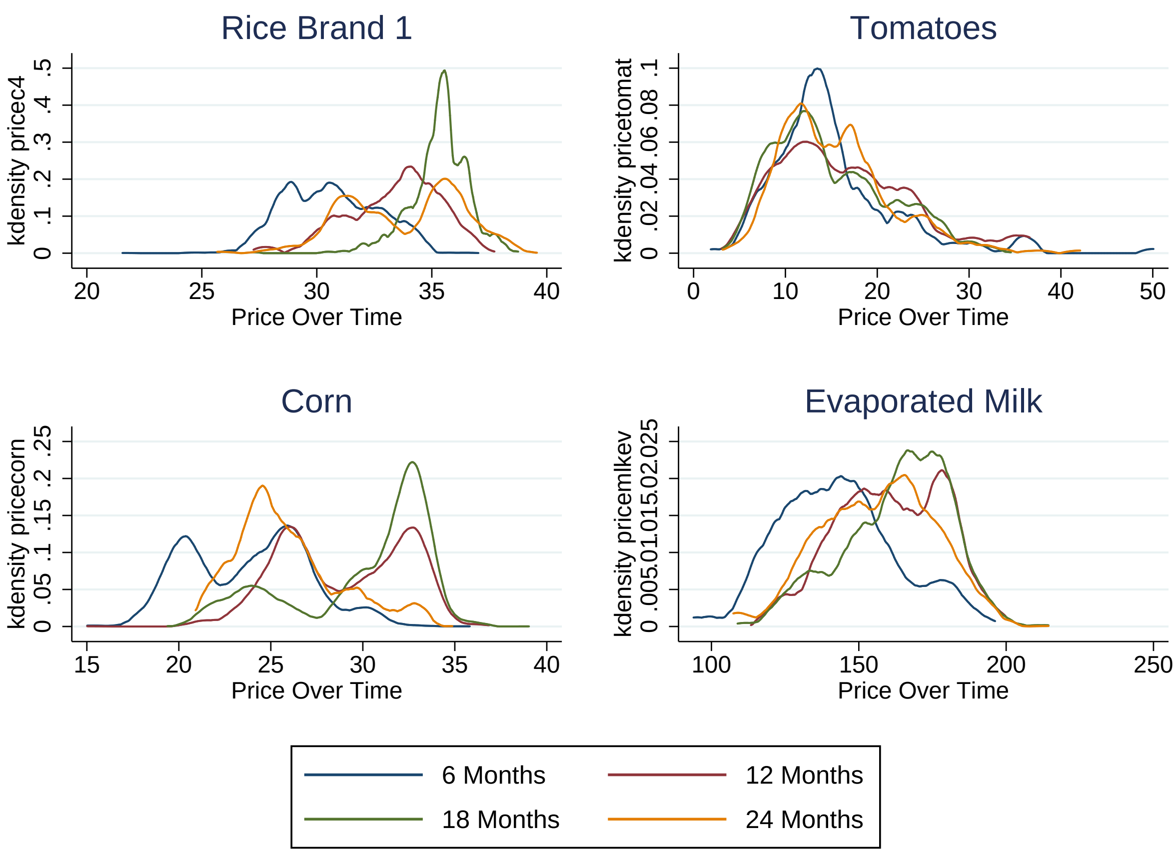
Figure 3: Spatial Price Variation



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. Table 4 shows the results of regressing the costs of antipolo toilets on a number of access-related variables. Similar to results for the Indian context analyzed by Augsburg and Rodríguez-Lesmes (2018), we find that costs are associated negatively with availability of electricity,

Figure 4: Temporal Price Variation



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 communities. The fact that toilet costs are lower in areas with easier access is likely driven by lower transportation costs for construction materials.

Having established that our price variables display meaningful and econometrically helpful variation, next we discuss the exclusion restrictions.

Whether the price information we use satisfies the exclusion restrictions depends on the competitive nature of the input market in which our study households are operating, as well as their preference structure. While it is possible that households could influence certain

Table 4: Exclusion Restrictions: Log Cost of Antipolo Toilets

	(1)	(2)	(3)	(4)	(5)
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 costs of (indoor and outdoor) antipolo toilets. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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, are unlikely to be a result of the behaviour of our study households. 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 costs are uncorrelated with the error term in our production function follows closely the one made by Augsburg and Rodríguez-Lesmes (2018). In particular, markets for construction materials (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 is 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.[18]

[18]One caveat of the WASH price instrument is that the cost of the toilet conflates both material and

The finding that geographical price variation in WASH is driven by access raises the concern that WASH prices might be reflecting access to other determinants of child health. For example, if toilet costs proxy for access to health centers, this might affect the health of our study children through better care, and might 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 4.

While the price variables meet important criteria to serve as valid instruments, they do not, on their own, provide sufficient power to explain variation in endogenous inputs of interest and hence to satisfactorily account for the endogeneity in child health production inputs. Therefore, we 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 the soil 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 the community as reported in the community survey. The argument for using aggregate wages as instruments follows closely that of food prices in that aggregate wages induce changes in the budget constraint of households in a similar manner. The variation in these wages is largely driven by the type of industry available in a community—in this setting, farming and shipbuilding. Tables A.4 and A.5 in the Online Appendix show the correlation of wages with other relevant access variables discussed in the context of prices and used in Table 4.

The first stage for both of our main inputs, log protein intake and log WASH, are shown in

labor cost. This is problematic if labor 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 labor costs in their instrumental variable approach does not affect their results.

Table 5: First Stages

	$\ln P_{it-1}$		$\ln S_{it-1}$	
First lag log price				
Rice brand 1	0.546***	(0.157)	0.0614	(0.0506)
Corn	−0.247**	(0.0923)	−0.00559	(0.0207)
Oil	0.0773*	(0.0393)	−0.0129	(0.0142)
Dried fish	0.0256	(0.0329)	0.00766	(0.0115)
Condensed milk	−0.109*	(0.0551)	−0.0301	(0.0300)
Evaporated milk	−0.126**	(0.0562)	0.00655	(0.0342)
Tomatoes	0.0507**	(0.0202)	−0.0214**	(0.00969)
Rice brand 2	−0.373**	(0.144)	−0.0933**	(0.0363)
Formula milk	−0.0205	(0.126)	−0.0855	(0.0605)
Kerosene	0.0680	(0.0542)	−0.00170	(0.0201)
Second lag log price				
Rice brand 1	0.231	(0.143)	−0.0126	(0.0625)
Corn	−0.0604	(0.0877)	−0.0647***	(0.0229)
Oil	0.00719	(0.0584)	0.0251*	(0.0145)
Dried fish	0.0301	(0.0334)	0.00210	(0.00847)
Condensed milk	0.0225	(0.0668)	−0.0407	(0.0317)
Evaporated milk	0.120**	(0.0532)	0.00687	(0.0411)
Tomatoes	0.0323*	(0.0181)	−0.00757	(0.00706)
Rice brand 2	−0.225	(0.159)	−0.0187	(0.0473)
Formula milk	−0.170*	(0.0992)	−0.0380	(0.0551)
Kerosene	0.00140	(0.0723)	−0.0283	(0.0219)
Log antipolo toilet price (inside)	0.0610	(0.0412)	0.0554*	(0.0326)
Log antipolo toilet price (outside)	−0.0410	(0.0322)	−0.0225	(0.0242)
Average soil depth	−0.101***	(0.0355)	0.00111	(0.0312)
Log average male wages	0.0979***	(0.0355)	0.0651*	(0.0337)
Log average female wages	0.0194	(0.0301)	−0.0278	(0.0375)
Observations	21,878		21,878	
Adjusted R^2	0.419		0.524	
F-statistics	23.79		20.29	

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's age and education, as well controls for the distribution of ages within household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

Table 5. Joint F-tests of significance demonstrate that our chosen instrument sets are more than strong enough to clear the commonly used rule-of-thumb value of 10, with values of 23.79 and 20.29, respectively.

IV. Results

A. Main Specification

We present our results for both outcomes (height and weight) as a function of protein intake and WASH.[19]

1. Height

Column 1 of Table 6 shows the OLS estimates of the translog production for child height. Higher protein intake and better WASH practices two months prior to the height measurement lead to an increase in child height. The coefficient on the interaction term between log protein intake and log WASH is positive and statistically significant, indicating a complementarity between these inputs. When we correct for endogeneity using the control function (CF) approach (Column 2), the coefficients on log protein intake, log WASH, and the interaction term remain positive and become larger in magnitude compared with 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).

[19] In Section A.6 of the Online Appendix., we build up the estimation, starting with estimating production functions for each input on its 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 another input, and interactions between the two inputs.

Table 6: Effects of Protein Intake and WASH on Height and Weight

	Height		Weight	
	OLS	CF	OLS	CF
	(1)	(2)	(3)	(4)
$\ln P_{it-1}$	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	21,864	21,864	21,878	21,878
Adjusted R^2	0.951	0.951	0.921	0.921
F-statistic Protein		25.82		23.79
F-statistic WASH		19.26		20.29

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

The results thus confirm the general understanding that higher protein intake leads to an increase in children's height, and further reveal that better WASH conditions make 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, as we study the formation of height over a relatively short time frame of two months. This high-frequency nature similarly explains the high R^2 in all specifications. Moreover, the coefficient is statistically significantly different from 1, which confirms that we are studying height formation over a period when it can be affected by parental investments and the general home environment.

To ease interpretation of the coefficients, we consider the effects on a child's height at the age of 24 months of increasing a child's protein intake by one egg a day, which corresponds to a 20% increase in the average child's daily protein intake from the age of six months to 24 months. For a child in the 90th percentile of the WASH score distribution, the additional egg per day results in an increased height of 2.73 cm by the age of 24 months. By contrast, the increase in height for a child in the 10th percentile of the WASH score distribution is lower, at 2.57 cm. Thus, better WASH complements protein intake by a modest, but still important, amount.

2. Weight

Unlike height, weight is more sensitive to contemporaneous inputs; although, with the bi-monthly frequency of our data, we still expect a time lag before nutritional and WASH inputs affect child weight. Columns 3 and 4 of Table 6 display the OLS and CF 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.[20] 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.

Conducting the same thought exercise as above, we find that increasing a child's intake of protein by one egg a day from the age of six months to 24 months increases the average child's weight at 24 months by 1.03 kg. Moreover, the additional egg a day increases the child's weight by 0.74 kg for children in the 10th percentile of the WASH score distribution, compared with 1.19 kg for children in the 90th percentile of the WASH score distribution.

B. Robustness Checks

We conduct a number of robustness checks to assess the sensitivity of our findings to alternative nutrition measures and alternative formulations of the WASH score, and to

[20] This is positive for log WASH, 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.

extending the control function.

1. Alternative Nutrition Measures

In a first robustness check, we alter the nutritional input used in the estimation from proteins to calories, carbohydrates, and fat. The results of these estimations are shown in Tables A.6–A.8 in the Online Appendix, and are all broadly consistent with the findings for protein. In the estimation using calories, we see that calories themselves have a statistically insignificant impact on height and weight, but there is a strong positive interaction between WASH and calorie intake in all specifications. Similarly for fat, the impact of the input itself is insignificant but the positive interaction between nutrition and WASH remains. Only for the estimation using carbohydrates do we see a statistically insignificant interaction between nutrition and WASH in the height estimation, and only a marginally significant interaction in the weight estimation. Despite this, it is clear that, for most choices of nutritional input, there is consistent evidence of complementarity between nutrition and WASH.

2. Alternative Formulations of the WASH Score

In a second 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, safe disposal of child feces, 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 (e.g. one cannot disentangle the effects of building a toilet from those of always using treated water) and identification (where a concern is that the instruments do not vary with either the time-varying or time-invariant components of the score).[21]

We experiment with two alternative definitions: one that includes only variables measured

[21] Note, though, that this problem is mitigated as we have both time-invariant and time-variant instruments.

at one point in time (akin to measuring the household's WASH stock); and another based on time-varying variables (akin to measuring household WASH practices).

Tables A.9 and A.10 in the Online Appendix present the findings when we use the 'stock WASH' and 'variable WASH' formulations, respectively. For the 'stock' definition of WASH, the excluded instruments for log WASH are not as powerful, with an F-statistic of less than 10. 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 the '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 stocks and flows, to capturing only one of these components.

3. Extending the Control Functions

A key condition of our estimation strategy is that, conditional on covariates and predicted errors in the first stage, the error terms in the second stage are exogenous. 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). We report these results in Section A.5 of the Online Appendix. The inclusion of additional controls does not substantially change the coefficients of interest, and consequently our conclusions hold.

In summary, the findings of positive and statistically significant effects of protein intake and WASH, and the positive interaction between nutrition intake and WASH, remain remarkably robust.

C. Heterogeneity by Gender

We consider whether there is any heterogeneity in the effects of nutrition and WASH on a child's physical growth by the child's gender. There are three reasons why we might expect to find a difference along this margin. 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).

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 Table 7 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, are 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 fact that the excluded instruments have 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 the coefficient on protein intake is much larger in magnitude for boys than girls.

We also find some evidence of heterogeneity by gender in the formation of weight (Table 8). Higher protein intake and better WASH both result in increased weight 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 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.

These results indicate heterogeneity by gender in the roles of nutritional and WASH investments in shaping child physical growth. An important question for policy is what drives these differences. Data availability limits the extent to which we can answer this question. Nonetheless, the available data allow us to rule out the explanation that parents might favor children of a specific gender when making decisions about health investment. First, in particular, we show that there are no differences by child gender in three investments: WASH investments, immunization, and doctor consultations.[22] The results

[22]We also consider whether there are differences in nutritional intake by gender. Boys consume more

Table 7: Height by Gender (Protein)

	Boys		Girls	
	OLS	CF	OLS	CF
	(1)	(2)	(3)	(4)
$\ln P_{it-1}$	0.000805***	0.00670***	0.000666***	−0.00162
	(0.000174)	(0.00202)	(0.000227)	(0.00219)
upro		−0.00595***		0.00228
		(0.00206)		(0.00212)
$upro^2$		−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)
uwash		−0.00750		−0.0269***
		(0.00917)		(0.00781)
$uwash^2$		−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)
*upro***uwash*		−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	11,525	11,525	10,339	10,339
Adjusted R^2	0.952	0.952	0.949	0.949
F-statistic Protein		13.95		13.21
F-statistic WASH		12.34		14.72

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

Table 8: Weight by Gender (Protein)

	Boys		Girls	
	OLS	CF	OLS	CF
	(1)	(2)	(3)	(4)
$\ln P_{it-1}$	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	11,531	11,531	10,347	10,347
Adjusted R^2	0.916	0.916	0.919	0.919
F-statistic Protein		13.65		13.66
F-statistic WASH		13.53		13.26

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

presented in Table 9 show no differences in these investments, which include both private goods (immunizations, doctor consultations) and public goods within the household (WASH investments).

Second, we also show that mothers do not update their nutrition and childcare practices (when child gender is known) from their pre-birth intentions (when child gender would not have been known) by child gender.[23] Such a novel test of gender bias in parental investments is only possible as a result of the rich data collected. If mothers have a strong preference for one gender (e.g. male), we would expect them to update their expectations and to alter their behavior differentially by the child's gender. However, as shown in Table 10, there is no evidence of mothers changing their behavior differentially after their child's gender is revealed, thereby confirming that the differences observed in the productivities of inputs by child gender are not driven by parents favoring children of one gender over another. Thus, it is unlikely that these differences can be explained by gender-biased parental investments.[24]

Instead, the heterogeneity by child gender therefore points to either differences in infant activities by gender or some inherent biological differences in the growth processes for male and female infants.[25] The latter has been documented for mortality, with female infants less likely to die during the neonatal period than male infants (Hill and Upchurch 1995), and

calories and have a higher protein intake. However, this is likely driven by boys expending more energy, and thus having 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 boys aged 9–10 months to be 925 kcal per day, compared to 865 kcal per day for girls. The calorie requirements by gender diverge further by the age of children.

[23]Ultrasound technology for the determination of gender was not widely available in the study area in the early 1980s. Though the uptake of (general) ultrasound technology increased from the late 1970s, it was concentrated around Metro Manila (see http://ultrasoundsocietyofthephilippines.org.ph/about.php; accessed December 6, 2018).

[24]Indeed, unlike other countries in South-East Asia, the Philippines is not considered to be a country where households have a strong preference for a son. This is borne out in the balanced gender ratio at birth (of roughly 1.05 male births to female births) and other ages. Our findings are hence in line with this more general observation.

[25]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 gender.

Table 9: Differential Investment by Gender

	Log WASH (1)	Immunizations (2)	Consulting doctor (3)
Child's 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	20,539	2,406	20,165
Adjusted R^2	0.522	0.165	0.011

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's 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 counted at 24 months. 'Consulting doctor' is a dummy equal to 1 if the mother has been to see the doctor about their child's health in the past two months.

Table 10: Beliefs and Realized Choices by Gender

	Difference colostrum (1)	Difference solid food introduction (2)
Child's gender (1 = male)	0.00464	−0.0967
	(0.0122)	(0.0690)
Community controls	Yes	Yes
Household controls	Yes	Yes
Child characteristics	Yes	Yes
Observations	1,954	2,344
Adjusted R^2	0.008	0.024

Notes: '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 positive difference in the number of months between the month the mother expected to introduce solid food into her child's diet in the prenatal survey and the actual month solid/semi-solid food was introduced.

for the susceptibility and immune responses to infectious diseases (Muenchhoff and Goulder 2014). Identifying the source of this heterogeneity is left to future research.

V. 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 Vogl 2013). Yet, a staggering 250 million children under five years of age living in low- and middle-income countries are at risk of suboptimal development and not achieving their potential (*The Lancet* 2016), with stunting and extreme poverty identified as the key mediators. Recent discussions in policy circles, in particular, have argued that an important driver of this gap is a failure in developing and delivering integrated approaches to child development (Britto et al. 2017), with the integration of interventions that improve hygiene and sanitary conditions receiving increasing attention.

However, very limited evidence exists on the nature or size of interactions between different components. In this paper, we consider the roles of nutrition and WASH investments, both of which are widely acknowledged to play important and nuanced roles in early childhood development. Whilst much evidence exists that both are separately important, our results are among the first to show that more hygienic environments, which reduce pathogen exposure, make nutrition investments more productive in the formation of child height and weight; hence, we find the existence of complementarities to exploit.

In particular, we find that among children aged between six and 24 months, both nutrition intake—particularly protein intake—and WASH investments are important determinants of child height. Moreover, we find that the inputs are complements: each input is more productive when parents also invest in the other. 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). Thus, our findings provide motivation for interventions targeting both nutrition and WASH investments. The exact mechanisms behind these differential impacts by gender are left for future research.

Overall, our findings suggest that contamination of a child's environment, including of 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 effects 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 and improved nutrition.

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Appendix: Derivations

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

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

and

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

Here, $\{N_{is}\}_{s=1}^{t-1}$ 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 $t-1$, μ_i is the child's health endowment, and X is a vector of other variables that also affect 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

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

and

$$W_{it} = \left[\alpha_0^w \prod_s^{t-1} N_{is}^{\alpha_s^w} \prod_s^{t-1} S_{is}^{\beta_s^w} \prod_s^{t-1} N_{is}^{Y_3} \prod_s^{t-1} S_{is}^{Y_4}\right] e^{(\delta_t^w \boldsymbol{X} + \sigma_t^w \mu_{i0} + \varepsilon_{it})}, \tag{A.4}$$

where

$$
\begin{aligned}
Y_1 &= \frac{1}{2}\Big(\sum_{r}^{t-1}\gamma_{Nrs}^{\nu^h}\ln N_{ri}+\sum_{r}^{t-1}\gamma_{Nrs}^{h}\ln S_{ri}\Big),\\
Y_2 &= \frac{1}{2}\Big(\sum_{r}^{t-1}\gamma_{Srs}^{h}\ln N_{ri}+\sum_{r}^{t-1}\gamma_{Srs}^{\nu^h}\ln S_{rs}\Big),\\
Y_3 &= \frac{1}{2}\Big(\sum_{r}^{t-1}\gamma_{Nrs}^{\nu^w}\ln N_{ri}+\sum_{r}^{t-1}\gamma_{Nrs}^{w}\ln S_{ri}\Big),\\
Y_4 &= \frac{1}{2}\Big(\sum_{r}^{t-1}\gamma_{Srs}^{w}\ln N_{ri}+\sum_{r}^{t-1}\gamma_{Srs}^{\nu^w}\ln S_{ri}\Big).
\end{aligned}
$$

These equations contain the entire history of nutrition and WASH inputs, as well as their interactions and quadratic terms. Taking logs, we obtain the following expression for height (and an almost identical equation for weight):

$$
\begin{aligned}
\ln H_{it} &= \alpha_0^h+\sigma_t^h\mu_{i0}+\varepsilon_t+\delta_t^h\boldsymbol{X}+\alpha_1^h\ln N_{i1}+\ldots+\alpha_{t-1}^h\ln N_{it-1}+\beta_1^h\ln S_{i1}\\
&\quad+\ldots+\beta_{t-1}^h\ln S_{t-1}+\frac{1}{2}\Big(\sum_{r}^{t-1}\gamma_{Nr1}^{\nu^h}\ln N_{ir}+\sum_{r}^{t-1}\gamma_{Nr1}^{h}\ln S_{ir}\Big)\ln N_{i1}\\
&\quad+\ldots+\frac{1}{2}\Big(\sum_{r}^{t-1}\gamma_{Nrt-1}^{\nu^h}\ln N_{ir}+\sum_{r}^{t-1}\gamma_{Nrt-1}^{h}\ln S_{ir}\Big)\ln N_{it-1}\\
&\quad+\frac{1}{2}\Big(\sum_{r}^{t-1}\gamma_{Sr1}^{h}\ln N_{ir}+\sum_{r}^{t-1}\gamma_{Sr1}^{\nu^h}\ln S_{ir}\Big)\ln S_{i1}\\
&\quad+\ldots+\frac{1}{2}\Big(\sum_{r}^{t-1}\gamma_{Srt-1}^{h}\ln N_{ir}+\sum_{r}^{t-1}\gamma_{Srt-1}^{\nu^h}\ln S_{ir}\Big)\ln S_{it-1}+\varepsilon_{it}^h.
\end{aligned}
$$

Assumption A.1. *For* $m \in \{h, w\}$*:*

(a) $\gamma_{Nrs}^{\nu^m}=\gamma_{Srs}^{\nu^m}=0$ *and* $\gamma_{Nrs}^{m}=\gamma_{Srs}^{m}=\gamma_{rs}^{m}$ *for all* s*;*

(b) $\gamma_{rs}^{m}=0$ *for all* s, r $s \neq r$*.*

Assumption A.1(a) rules out interactions between an input in period s and the same input in any other period. This imposes that the quadratic terms of each input have no additional effects on height or weight. The second statement in Assumption A.1(a) simply imposes that the effect of the interaction between WASH and nutrition is the same as that of the interaction between nutrition and WASH (γ^h_{Njs} and γ^h_{Sjs} cannot be separately identified). Applying Assumption A.1(a) implies the following for height (Equation A.5) and weight (Equation A.6):

$$\ln H_{it} = \alpha^h_0 + \sum_s^{t-1} \alpha^h_s \ln N_{is} + \sum_s^{t-1} \beta^h_s \ln S_{is} + \sum_s^{t-1} \sum_r^{t-1} \gamma^h_{sr} \ln N_{is} \ln S_{ir} + \sigma^h_t \mu_0 + \delta^h_t \boldsymbol{X} + \varepsilon^h_{it}; \quad \text{(A.5)}$$

$$\ln W_{it} = \alpha^w_0 + \sum_s^{t-1} \alpha^w_s \ln N_{is} + \sum_s^{t-1} \beta^w_s \ln S_{is} + \sum_s^{t-1} \sum_r^{t-1} \gamma^w_{sr} \ln N_{is} \ln S_{ir} + \sigma^w_t \mu_0 + \delta^w_t \boldsymbol{X} + \varepsilon^w_{it}. \quad \text{(A.6)}$$

Assumption A.1(b) imposes that only contemporaneous interactions between WASH and nutrition matter for height and weight formation. Now, denoting $\gamma_{ss} = \gamma_s$ and applying the assumption to the above equations, we obtain the following:

$$\ln H_{it} = \alpha^h_0 + \sum_s^{t-1} \alpha^h_s \ln N_{is} + \sum_s^{t-1} \beta^h_s \ln S_{is} + \sum_s^{t-1} \gamma^h_s \ln N_{is} \ln S_{is} + \sigma^h_t \mu_0 + \delta^h_t \boldsymbol{X} + \varepsilon_t; \quad \text{(A.7)}$$

$$\ln W_{it} = \alpha^w_0 + \sum_s^{t-1} \alpha^w_s \ln N_{is} + \sum_s^{t-1} \beta^w_s \ln S_{is} + \sum_s^{t-1} \gamma^w_s \ln N_{is} \ln S_{is} + \sigma^w_t \mu_0 + \delta^h_t \boldsymbol{X} + \varepsilon_t. \quad \text{(A.8)}$$

Assumption A.2. *For $m \in \{h, w\}$: $\alpha^m = \alpha^m_s = \lambda \alpha^m_{s-1}$; $\beta^m = \beta^m_s = \lambda \beta^m_{s-1}$; $\gamma_{SN} = \gamma^m_s = \lambda \gamma^m_{s-1}$; $\sigma^m = \sigma^m_s = \lambda \sigma^m_{s-1}$.*

Assumption A.2 is common to the value-added literature. First, taking the first difference between height in period t and $t-1$, we obtain the following:

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

We then apply Assumption A.2:

$$\begin{aligned}
\Delta \ln H_t &= \alpha^h_{t-1} \ln N_{it-1} + \beta^h_{t-1} \ln S_{t-1} + \gamma^h_{t-1} \ln N_{it-1} \ln S_{it-1} + (\lambda - 1) \sum_s^{t-2} \alpha^h_{s-1} \ln N_{is} \\
&\quad + (\lambda - 1) \sum_s^{t-2} \beta^h_{s-1} \ln S_{is} + (\lambda - 1) \sum_s^{t-2} \gamma^h_{s-1} \ln N_{is} \ln S_{is} + (\lambda - 1) \sigma^h_{t-1} \mu_0 \\
&\quad + (\delta^h_t - \delta^h_{t-1}) \boldsymbol{X} + \varepsilon^h_{it} - \varepsilon^h_{it-1}. \qquad \text{(A.9)}
\end{aligned}$$

The same procedure for weight yields the following:

$$\begin{aligned}
\Delta \ln W_{it} &= \alpha^w_{t-1} \ln N_{it-1} + \beta^w_{it-1} \ln S_{t-1} + \gamma^w_{t-1} \ln N_{it-1} \ln S_{it-1} + (\lambda - 1) \sum_s^{t-2} \alpha^w_{s-1} \ln N_{is} \\
&\quad + (\lambda - 1) \sum_s^{t-2} \beta^w_{s-1} \ln S_{is} + (\lambda - 1) \sum_s^{t-2} \gamma^w_{s-1} \ln N_{is} \ln S_{is} + (\lambda - 1) \sigma^w_{t-1} \mu_{i0} \\
&\quad + (\delta^w_t - \delta^w_{t-1}) \boldsymbol{X} + \varepsilon^w_t - \varepsilon^w_{t-1} \qquad \text{(A.10)}
\end{aligned}$$

To obtain our final estimation equation, we then follow Behrman et al. (2009) and make a final assumption on the relative impact of inputs on height and weight.

Assumption A.3. *$\alpha^h = a\alpha^w$, $\beta^h = a\beta^w$, $\gamma^h = a\gamma^w$, and $\sigma^h = a\sigma^w$ for some scalar constant a.*

These assumptions, together with some additional algebra, will yield the final estimation equations. First, taking the difference between Equations A.5 and A.6 gives us

$$\begin{aligned}
\ln H_{it-1} - \ln W_{it-1} &= \alpha^h_0 - \alpha^w_0 + \sum_s^{t-2} (\alpha^h_s - \alpha^w_s) \ln N_{is} + \sum_s^{t-2} (\beta^h_s - \beta^w_s) \ln S_{is} \\
&\quad + \sum_s^{t-2} (\gamma^h_s - \gamma^w_s) \ln N_{is} \ln S_{is} + (\sigma^h_{t-1} - \sigma^w_{t-1}) \mu_{i0} + (\delta^h_{t-1} - \delta^w_{t-1}) \boldsymbol{X} \\
&\quad + \varepsilon^h_{it-1} - \varepsilon^w_{it-1}
\end{aligned}$$

Applying Assumption A.3 to this expression simplifies it to

$$\ln H_{it-1} - \ln W_{it-1} - \alpha_0^h + \alpha_0^w - \varepsilon_{it-1}^h + \varepsilon_{it-1}^w - (\delta_{t-1}^h - \delta_{t-1}^w)\boldsymbol{X}$$
$$= (a-1)\Bigg[\sum_s^{t-2} \alpha_{s-1} \ln N_{is} + \sum_s^{t-2} \beta_{s-1} \ln S_{is} + \sum_s^{t-2} \gamma_{s-1} \ln N_{is} \ln S_{is} + \sigma_{t-1}^h \mu_{i0}\Bigg].$$

We can then substitute the term in the square brackets in the above equation into Equation A.9 to obtain the estimation equation:

$$\begin{aligned}\ln H_{it} \;=\; & \frac{\alpha^h - \alpha^w}{1-a} + \alpha^h \ln N_{it-1} + \beta^h \ln S_{it-1} + \gamma_{SN}^h \ln N_{it-1} \ln S_{it-1} + \frac{a+\lambda-2}{a-1} \ln H_{it-1} \\ & -\frac{\lambda-1}{a-1} \ln W_{it-1} + \left(\delta_t^h - \delta_{t-1}^h \frac{a}{a-1} + \frac{\delta_{t-1}^w}{a-1}\right)\boldsymbol{X} + \varepsilon_t^h - \varepsilon_{t-1}^h + \frac{\varepsilon_{t-1}^h - \varepsilon_{t-1}^w}{1-a}.\end{aligned} \tag{A.11}$$

The exact same logic can be applied for the weight equation. First, taking the difference between Equations A.6 and A.5, and applying Assumption A.3 gives us the following:

$$\ln W_{it-1} - \ln H_{it-1} - \alpha_0^w + \alpha_0^h - \varepsilon_{it-1}^w + \varepsilon_{it-1}^h - (\delta_{t-1}^w - \delta_{t-1}^h)\boldsymbol{X}$$
$$= (1-a)\Bigg[\sum_s^{t-2} \alpha_{s-1}^w \ln N_{is} + \sum_s^{t-2} \beta_{s-1}^w \ln S_{is} + \sum_s^{t-2} \gamma_{s-1}^w \ln N_{is} \ln S_{is} + \sigma_{t-1}^w \mu_{i0}\Bigg].$$

Substituting the square term into Equation A.10 gives us the equivalent equation for weight:

$$\begin{aligned}\ln W_{it} \;=\; & \frac{\alpha^w - \alpha^h}{1-a} + \alpha^h \ln N_{it-1} + \beta^h \ln S_{it-1} + \gamma_{SN}^h \ln N_{it-1} \ln S_{it-1} + \frac{\lambda-a}{1-a} \ln W_{it-1} \\ & -\frac{\lambda-1}{1-a} \ln W_{it-1} + \left(\delta_t^h - \delta_{t-1}^h \frac{a}{1-a} + \frac{\delta_{t-1}^w}{1-a}\right)\boldsymbol{X} + \varepsilon_t^h - \varepsilon_{t-1}^h + \frac{\varepsilon_{t-1}^w - \varepsilon_{t-1}^h}{1-a}.\end{aligned} \tag{A.12}$$

As in the case for height, we relax some of the earlier assumptions by including interactions between accumulated weight and current inputs, giving the final estimation equation:

$$\begin{aligned}\ln W_{it} &= \alpha_0^w + \alpha_1^w \ln N_{it-1} + \beta_1^w \ln S_{it-1} + \alpha_2^w \ln W_{it-1} + \gamma_{SN}^w \ln S_{it-1} \ln N_{it-1} \\ &+ \gamma_{SW} \ln S_{it-1} \ln W_{it-1} + \gamma_{NW} \ln W_{it-1} \ln N_{it-1} + \tau^w \ln H_{it_1} + \delta_t^w \boldsymbol{X} + \varepsilon_{it}^w. \quad \text{(A.13)}\end{aligned}$$

Online Appendix— NOT FOR PUBLICATION

A.1 Additional Tables

We document the extent of attrition over the sample period. Table A.2 displays the characteristics of those who attrited and those who stayed in the sample. Across almost all of the baseline characteristics described, attrited and non-attrited children are not statistically significantly different. There are however some notable exclusions to this rule, the most obvious being home ownership. Attrited mothers are less likely to own their own home, and are younger.

Table A.1: Attrition: Reasons for Dropout

	Number	%
Sample woman with complete survey records	2,184	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	2.0
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

Table A.2: Attrition: Attrited versus Non-Attrited Samples

Variable	Mean		
	Not attrited	Attrited	p-value
Household and community characteristics			
Percentage of households in urban community	0.75 (0.11)	0.81 (0.21)	0.81
Distance to nearest public hospital, km	5.92 (1.29)	5.39 (2.44)	0.85
Age of household head	35.52 (0.46)	34.74 (0.86)	0.43
Percentage of household heads in employment	0.95 (0.01)	0.93 (0.02)	0.51
Heads years of education	7.27 (0.47)	7.71 (0.89)	0.66
Proportion of households with safe toilets	0.65 (0.07)	0.75 (0.14)	0.52
Proportion of households with pumped/piped water	0.48 (0.07)	0.46 (0.14)	0.91
House made of concrete (1 = yes)	0.18 (0.03)	0.18 (0.05)	0.99
Household head is female	0.06 (0.01)	0.07 (0.02)	0.66
Number of household members	5.64 (0.10)	5.32 (0.19)	0.14
Home ownership	0.69 (0.05)	0.49 (0.10)	0.07
Household owns a refrigerator (1 = yes)	0.07 (0.01)	0.07 (0.02)	0.89
Household owns benches/chairs (1 = yes)	0.70 (0.02)	0.65 (0.03)	0.20
Household has electric lighting (1 = yes)	0.48 (0.07)	0.53 (0.09)	0.70
Mother's characteristics			
Years of education	7.48 (0.39)	7.87 (0.75)	0.65
Head/spouse of head	0.78 (0.02)	0.76 (0.03)	0.72
Age	26.83 (0.20)	26.50 (0.45)	0.51
Number of children under 5	1.23 (0.04)	1.07 (0.08)	0.08
Pregnancy at least part covered by insurance (1 = yes)	0.10 (0.01)	0.10 (0.02)	0.99
Percentage of mothers working during pregnancy	0.38 (0.03)	0.33 (0.05)	0.34
Child's birth characteristics			
Child gender (1 = male)	0.53 (0.016)	0.55 (0.04)	0.54
Child birth weight, g	3,045 (29.22)	2,957 (67.71)	0.24
Child birth height, cm	49.25 (0.09)	49.22 (0.21)	0.88

A.2 Wealth Index

Like most other surveys in developing countries, the CHLNS provides very detailed information on household assets, and it is necessary to reduce the dimensionality of the wealth information provided to create a wealth index that captures the underlying socioeconomic status of the household. To do this, we use a polychoric principle component analysis (PCA), following the approach laid out in Kolenikov and Angeles (2009). This allowed us to construct a wealth index combining continuous, categorical, and discrete variables to estimate the underlying wealth factor for each household without violating any assumptions of normality or the loss of information associated with a standard PCA approach.

Discrete variables on furniture ownership (cupboards, benches, tables, etc.), electrical appliances (electric fans, refrigerators, televisions, radios), and home ownership are used with categorical variables such as light source and cooking fuel type to construct the wealth index score. The first principle component in this analysis explains around 73% of the variation in these variables. This standardized wealth score is then broken into five evenly populated quintiles for use in later stages of the analysis.

Table A.3: Correlation between WASH Scores and Observed Variables

	$\ln S_{it-1}$	$\ln S_{it-1}$	$\ln S_{it-1}$
Childs gender (1=Male)	-0.00520	-0.0132	-0.0162
	(0.0111)	(0.00964)	(0.0106)
Childs age (months)	-0.0193	0.00910	0.0138
	(0.0122)	(0.0127)	(0.0118)
Childs age squared	0.000629	-0.000792	-0.00110
	(0.000856)	(0.000862)	(0.000800)
Childs age cubed	-0.00000866	0.0000174	0.0000238
	(0.0000180)	(0.0000183)	(0.0000170)
Wealth Quintile=2		0.0466	0.0549**
		(0.0292)	(0.0256)
Wealth Quintile=3		0.144***	0.125***
		(0.0224)	(0.0198)
Wealth Quintile=4		0.240***	0.213***
		(0.0213)	(0.0196)
Wealth Quintile=5		0.314***	0.275***
		(0.0278)	(0.0257)
Household Head Age (years)		0.617	0.626
		(1.180)	(1.087)
Household Head Age Squared		-0.808	-1.223
		(4.576)	(4.152)

Table A.3: Continued

	$\ln S\_it-1$	$\ln S\_it-1$	$\ln S\_it-1$
Mother age, years		0.0147**	0.0149**
		(0.00711)	(0.00681)
Mother age squared		-0.000191	-0.000189
		(0.000118)	(0.000114)
HH head has no education (dummy)		-0.199***	-0.120***
		(0.0314)	(0.0305)
HH head has some elementary schooling (dummy)		-0.141***	-0.0736***
		(0.0325)	(0.0263)
Whether household head is a farmer		-0.256***	-0.0907**
		(0.0529)	(0.0359)
HH head has elementary schooling (dummy)		-0.0907***	-0.0512*
		(0.0290)	(0.0253)
HH head has some high schooling (dummy)		-0.00717	0.0121
		(0.0184)	(0.0182)
HH head has completed high school (dummy)		0.0123	0.00995
		(0.0134)	(0.0166)
Mother has no education (dummy)		-0.265***	-0.261***
		(0.0726)	(0.0650)
Mother has some elementary schooling (dummy)		-0.185***	-0.148***
		(0.0262)	(0.0292)
Mother has elementary schooling (dummy)		-0.0582*	-0.0436
		(0.0296)	(0.0269)
Mother has some high schooling (dummy)		-0.0362	-0.0412*
		(0.0216)	(0.0203)
Mother has completed high school (dummy)		-0.0217	-0.0204
		(0.0257)	(0.0234)
Log population density			0.0362***
			(0.0115)
Household in urban community			0.150***
			(0.0512)
Log population density			0.0351**
			(0.0114)
Household in urban community			0.148**
			(0.0499)
Observations	20,539	20,539	20,539
Adjusted R^2	0.043	0.429	0.522

Notes: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A.4: Log Male Wages

	(1)	(2)	(3)	(4)	(5)
Urban	0.117				−0.0636
	(0.147)				(0.235)
Agriculture large employer		−0.388			−0.312
		(0.194)			(0.218)
Has electricity			0.283		0.229
			(0.165)		(0.216)
Log 1980 Census population				0.0751	0.00389
				(0.0733)	(0.118)
Constant	3.422***	3.541***	3.268***	2.903***	3.359***
	(0.105)	(0.0756)	(0.144)	(0.570)	(0.825)
Observations	33	33	33	33	33

Notes: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A.5: Log Female Wages

	(1)	(2)	(3)	(4)	(5)
Urban	0.226				−0.454
	(0.216)				(0.328)
Agriculture large employer		−0.161			0.174
		(0.303)			(0.305)
Has electricity			0.530*		0.482
			(0.236)		(0.302)
Log 1980 Census population				0.229*	0.308
				(0.102)	(0.165)
Constant	2.992***	3.132***	2.707***	1.339	0.576
	(0.154)	(0.118)	(0.205)	(0.791)	(1.151)
Observations	33	33	33	33	33

Notes: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

A.3 Other Nutritional Inputs

Table A.6: Effects of Calorie Intake and WASH on Height and Weight

	Height		Weight	
	OLS	CF	OLS	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	22,082	22,082	22,096	22,096
Adjusted R^2	0.951	0.951	0.922	0.922
F-statistic Calories		10.68		10.20
F-statistic WASH		21.66		22.59

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

Table A.7: Effects of Carbohydrate Intake and WASH on Height and Weight

	Height		Weight	
	OLS	CF	OLS	CF
$\ln Carb_{it-1}$	0.000359**	−0.00107	0.000814*	0.00876
	(0.000133)	(0.00315)	(0.000435)	(0.00976)
$ucarb$		0.00138		−0.00728
		(0.00315)		(0.0100)
$ucarb^2$		−0.0000652		0.000732
		(0.000131)		(0.000442)
$\ln S_{it-1}$	0.00132***	0.0251***	0.00493***	0.0119
	(0.000391)	(0.00723)	(0.000899)	(0.0161)
$uwash$		−0.0238***		−0.00703
		(0.00718)		(0.0163)
$uwash^2$		0.000948		0.000249
		(0.00142)		(0.00351)
$\ln Carb_{it-1} * \ln S_{it-1}$	0.000475	0.000723	0.00175	0.00282*
	(0.000392)	(0.000459)	(0.00121)	(0.00150)
$ucarb$*$uwash$		−0.000870		−0.00254
		(0.000715)		(0.00230)
$\ln Carb_{it-1} * \ln H_{it-1}$	0.00455***	0.00458**		
	(0.00159)	(0.00200)		
$\ln S_{it-1} * \ln H_{it-1}$	−0.00749	−0.00853		
	(0.00509)	(0.00522)		
$\ln Carb_{it-1} * \ln W_{it-1}$			−0.000668	−0.00302
			(0.00205)	(0.00254)
$\ln W_{it-1} * \ln S_{it-1}$			−0.0182*	−0.0190*
			(0.00949)	(0.00964)
$\ln H_{it-1}$	0.780***	0.773***	0.186***	0.191***
	(0.00663)	(0.00776)	(0.0173)	(0.0159)
$\ln W_{it-1}$	0.0548***	0.0552***	0.855***	0.852***
	(0.00156)	(0.00164)	(0.00943)	(0.00863)
Observations	22,039	21,602	22,052	21,615
Adjusted R^2	0.951	0.951	0.922	0.921
F-statistic Carbs		11.03		10.88
F-statistic WASH		14.23		18.22

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

Table A.8: Effects of Fat Intake and WASH on Height and Weight

	Height		Weight	
	OLS	CF	OLS	CF
$lnFat_{it-1}$	0.000441***	0.00181	0.00138***	0.0109*
	(0.0000985)	(0.00170)	(0.000258)	(0.00618)
$ufat$		−0.00135		−0.00931
		(0.00168)		(0.00614)
$ufat^2$		0.0000115		0.000280*
		(0.0000508)		(0.000143)
$\ln S_{it-1}$	0.00129***	0.0232***	0.00463***	0.000742
	(0.000444)	(0.00811)	(0.000965)	(0.0184)
$uwash$		−0.0220**		0.00410
		(0.00806)		(0.0186)
$uwash^2$		0.00108		0.000320
		(0.00147)		(0.00359)
$\ln Fat_{it-1} * \ln S_{it-1}$	0.000540**	0.000695***	0.00191***	0.00281***
	(0.000214)	(0.000233)	(0.000630)	(0.000729)
$ufat*uwash$		−0.000712		−0.00383**
		(0.000663)		(0.00159)
$\ln Fat_{it-1} * \ln H_{it-1}$	0.000691	0.000449		
	(0.000816)	(0.000887)		
$\ln S_{it-1} * \ln H_{it-1}$	−0.00606	−0.00625		
	(0.00501)	(0.00517)		
$\ln Fat_{it-1} * \ln W_{it-1}$			−0.00136	−0.00163
			(0.00166)	(0.00178)
$\ln W_{it-1} * \ln S_{it-1}$			−0.0189**	−0.0194**
			(0.00877)	(0.00894)
$\ln H_{it-1}$	0.780***	0.769***	0.187***	0.181***
	(0.00633)	(0.00730)	(0.0164)	(0.0159)
$\ln W_{it-1}$	0.0549***	0.0565***	0.853***	0.855***
	(0.00144)	(0.00139)	(0.00873)	(0.00847)
Observations	21,815	21,532	21,830	21,547
Adjusted R^2	0.951	0.951	0.921	0.921
F-statistic Fat		8.248		8.074
F-statistic WASH		10.91		11.33

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

A.4 Stock and Variable WASH

Table A.9: Stock WASH: Protein Height and Weight

	Height		Weight	
	OLS	CF	OLS	CF
$\ln P_{it-1}$	0.000749***	0.00500**	0.00106**	0.0194*
	(0.000150)	(0.00231)	(0.000429)	(0.00998)
upro		−0.00432*		−0.0178*
		(0.00230)		(0.0101)
upro^2		−0.0000245		0.000524**
		(0.0000747)		(0.000215)
$\ln S_i$	0.00264***	0.0192	0.00733***	−0.0425
	(0.000557)	(0.0117)	(0.00132)	(0.0311)
uwash		−0.0165		0.0498
		(0.0116)		(0.0315)
uwash^2		0.00164		−0.000567
		(0.00219)		(0.00610)
[3pt] $\ln P_{it-1} * \ln S_{it-1}$	0.00100***	0.00147***	0.00373***	0.00504***
	(0.000354)	(0.000423)	(0.00105)	(0.00139)
*upro*uwash*		−0.00127		−0.00369
		(0.000843)		(0.00261)
$\ln P_{it-1} * \ln H_{it-1}$	0.00420***	0.00418***		
	(0.00107)	(0.00135)		
$\ln P_{it-1} * \ln W_{it-1}$			−0.000762	−0.00238
			(0.00188)	(0.00238)
$\ln H_{it-1}$	0.779***	0.773***	0.181***	0.196***
	(0.00654)	(0.00855)	(0.0159)	(0.0166)
$\ln W_{it-1}$	0.0546***	0.0553***	0.854***	0.854***
	(0.00153)	(0.00157)	(0.00862)	(0.00860)
$\ln S_{it-1} * \ln H_{it-1}$	−0.0212***	−0.0241***		
	(0.00546)	(0.00562)		
$\ln S_{it-1} * \ln W_{it-1}$			−0.0335***	−0.0334***
			(0.0106)	(0.0110)
Observations	22,647	22,647	22,662	22,662
Adjusted R^2	0.952	0.952	0.921	0.921
F-statistic Protein		23.84		21.48
F-statistic WASH		6.556		5.298

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

Table A.10: Variable WASH: Protein Height and Weight

	Height		Weight	
	OLS	CF	OLS	CF
$\ln P_{it-1}$	0.000771***	0.00870***	0.000776*	0.0102
	(0.000150)	(0.00263)	(0.000387)	(0.00764)
upro		−0.00796***		−0.00887
		(0.00267)		(0.00778)
$upro^2$		−0.0000161		0.000493**
		(0.0000714)		(0.000223)
$\ln S_{it-1}$	0.0000369**	−0.000136	0.000200***	0.000578
	(0.0000169)	(0.000221)	(0.0000359)	(0.000722)
uwash		0.000174		−0.000394
		(0.000222)		(0.000724)
$uwash^2$		0.000000834		−0.00000695
		(0.00000145)		(0.00000414)
$\ln P_{it-1} * \ln S_{it-1}$	0.0000616***	0.0000959***	0.0000913***	0.000164***
	(0.00000854)	(0.0000185)	(0.0000233)	(0.0000474)
$upro * uwash$		−0.0000569**		−0.000142**
		(0.0000246)		(0.0000557)
$\ln P_{it-1} * \ln H_{it-1}$	0.00537***	0.00579***		
	(0.00122)	(0.00145)		
$\ln P_{it-1} * \ln W_{it-1}$			−0.000645	−0.00198
			(0.00163)	(0.00210)
$\ln H_{it-1}$	0.778***	0.780***	0.181***	0.173***
	(0.00643)	(0.00688)	(0.0158)	(0.0146)
$\ln W_{it-1}$	0.0547***	0.0545***	0.855***	0.855***
	(0.00150)	(0.00151)	(0.00850)	(0.00806)
$\ln S_{it-1} * \ln H_{it-1}$	−0.000857***	−0.00110***		
	(0.000158)	(0.000202)		
$\ln S_{it-1} * \ln W_{it-1}$			−0.00101***	−0.00107***
			(0.000264)	(0.000311)
Observations	22,647	22,647	22,661	22,661
Adjusted R^2	0.952	0.952	0.921	0.921
F-statistic Protein		23.84		21.36
F-statistic WASH		30.34		29.60

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

A.5 Extended Control Function

Table A.11: Protein Height and Weight

	Height		Weight	
	OLS	CF	OLS	CF
$\ln P_{it-1}$	0.000738***	0.00407*	0.00128***	0.0266**
	(0.000152)	(0.00227)	(0.000390)	(0.0112)
upro		0.000389		−0.0106
		(0.00977)		(0.0302)
$upro^2$		0.000802		−0.0167***
		(0.000803)		(0.00453)
$\ln S_{it-1}$	0.00126***	0.0203**	0.00459***	−0.0608**
	(0.000417)	(0.00809)	(0.000903)	(0.0281)
uwash		0.0107		0.127
		(0.0222)		(0.105)
$uwash^2$		0.0106		−0.0752*
		(0.00664)		(0.0416)
$\ln P_{it-1} * \ln S_{it-1}$	0.000757**	0.00542***	0.00201**	0.00569**
	(0.000317)	(0.000931)	(0.000797)	(0.00220)
*upro***uwash*		0.00158		0.0291
		(0.00356)		(0.0191)
$\ln P_{it-1} * \ln H_{it-1}$	0.00412***	0.0299***		
	(0.00117)	(0.00500)		
$\ln S_{it-1} * \ln H_{it-1}$	−0.0107**	−0.0873***		
	(0.00477)	(0.0125)		
$\ln P_{it-1} * \ln W_{it-1}$			−0.000852	0.00541
			(0.00188)	(0.00428)
$\ln W_{it-1} * \ln S_{it-1}$			−0.0202**	−0.0468***
			(0.00885)	(0.0157)
$\ln H_{it-1}$	0.781***	0.772***	0.187***	0.208***
	(0.00670)	(0.00822)	(0.0158)	(0.0159)
$\ln W_{it-1}$	0.0541***	0.0547***	0.852***	0.846***
	(0.00158)	(0.00159)	(0.00865)	(0.00775)
Observations	21,870	21,864	21,884	21,878
Adjusted R^2	0.951	0.952	0.920	0.920
F-statistic Protein		42.07		90.72
F-statistic WASH		42.41		65.05

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's age and education, as well controls for the distribution of ages within the household. F-statistics represent an F-test of all variables interacted with relevant control function. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

A.6 Input-by-Input Build-Up

Table A.12: Child Height and Protein Intake

	(1) OLS	(2) CF	(3) OLS	(4) CF	(5) OLS	(6) CF	(7) OLS	(8) CF	(9) OLS	(10) CF
$\ln P_{it-1}$	0.000554***	0.00726***			0.000512***	0.00366	0.000531***	0.00384*	0.000740***	0.00377*
	(0.000128)	(0.00234)			(0.000130)	(0.00220)	(0.000132)	(0.00219)	(0.000151)	(0.00219)
upro		−0.00669***				−0.00313		−0.00327		−0.00307
		(0.00237)				(0.00220)		(0.00219)		(0.00218)
$upro^2$		0.0000381				0.0000295		0.0000396		−0.0000112
		(0.0000609)				(0.0000609)		(0.0000625)		(0.0000731)
$\ln S_{it-1}$			0.00137***	0.0246***	0.00112***	0.0191**	0.00128***	0.0194**	0.00126***	0.0197**
			(0.000399)	(0.00749)	(0.000398)	(0.00815)	(0.000400)	(0.00816)	(0.000416)	(0.00801)
uwash				−0.0233***		−0.0181**		−0.0181**		−0.0183**
				(0.00742)		(0.00803)		(0.00806)		(0.00793)
$uwash^2$				0.000933		0.000828		0.00105		0.00105
				(0.00144)		(0.00145)		(0.00146)		(0.00144)
$\ln P_{it-1} * \ln S_{it-1}$							0.000537*	0.000824**	0.000757**	0.00119***
							(0.000291)	(0.000319)	(0.000316)	(0.000334)
*upro*uwash*								−0.000831		−0.00109
								(0.000632)		(0.000664)
$\ln P_{it-1} * \ln H_{it-1}$									0.00413***	0.00398***
									(0.00116)	(0.00142)
$\ln S_{it-1} * \ln H_{it-1}$									−0.0107**	−0.0131**
									(0.00473)	(0.00487)
Observations	21,864	21,864	21,864	21,864	21,864	21,864	21,864	21,864	21,864	21,864
Adjusted R^2	0.951	0.951	0.951	0.951	0.951	0.951	0.951	0.951	0.951	0.951
F-statistic Protein		25.82				25.82		25.82		25.82
F-statistic WASH				19.26		19.26		19.26		19.26

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.

Table A.13: Child Weight and Protein Intake

	(1) OLS	(2) CF	(3) OLS	(4) CF	(5) OLS	(6) CF	(7) OLS	(8) CF	(9) OLS	(10) CF
$\ln P_{it-1}$	0.00148***	0.0135*			0.00132***	0.0152	0.00135***	0.0156	0.00123***	0.0153
	(0.000410)	(0.00682)			(0.000398)	(0.00973)	(0.000409)	(0.00970)	(0.000426)	(0.00983)
upro		−0.0115				−0.0133		−0.0136		−0.0134
		(0.00693)				(0.00986)		(0.00980)		(0.00988)
$upro^2$		0.000447**				0.000411**		0.000432**		0.000504**
		(0.000169)				(0.000175)		(0.000177)		(0.000215)
$\ln S_{it-1}$			0.00491***	0.0136	0.00427***	−0.00892	0.00453***	−0.00829	0.00494***	−0.00683
			(0.000956)	(0.0148)	(0.000858)	(0.0238)	(0.000896)	(0.0238)	(0.000920)	(0.0237)
uwash				−0.00885		0.0127		0.0126		0.0119
				(0.0147)		(0.0239)		(0.0239)		(0.0239)
$uwash^2$				−0.000591		−0.00101		−0.000415		0.000540
				(0.00345)		(0.00353)		(0.00362)		(0.00355)
$\ln P_{it-1} * \ln S_{it-1}$							0.000857	0.00162**	0.00192**	0.00345***
							(0.000624)	(0.000764)	(0.000839)	(0.00115)
*upro*uwash*								−0.00200		−0.00390**
								(0.00165)		(0.00189)
$\ln P_{it-1} * \ln W_{it-1}$									−0.00114	−0.00282
									(0.00182)	(0.00231)
$\ln W_{it-1} * \ln S_{it-1}$									−0.0189**	−0.0206**
									(0.00893)	(0.00951)
Observations	21,878	21,878	21,878	21,878	21,878	21,878	21,878	21,878	21,878	21,878
Adjusted R^2	0.921	0.921	0.921	0.921	0.921	0.921	0.921	0.921	0.921	0.921
F-statistic Protein		23.79				23.79		23.79		23.79
F-statistic WASH				20.29		20.29		20.29		20.29

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's age and education, as well controls for the distribution of ages within the household. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors (in parentheses) are clustered at the community level.