Complementarities in the Production of Child Health

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We estimate flexible child health production functions to investigate whether more hygienic environments, characterized by better water, sanitation, and hygiene (WASH) practices, make nutrition intake more productive for the physical growth of children aged 6–24 months. Using 10 rounds of exceptionally rich longitudinal Filipino cohort data, we estimate value-added production functions with a control function approach. We show that WASH and nutrition are complements in the formation of child height and weight. Nutritional and WASH conditions faced by sample children are similar to those currently encountered by poor children in low-income settings with comparable stunting rates.

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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), which 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) and undermines 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.

Poor diets, inadequate care and feeding practices, as well as unhygienic living environments are all well known to affect children's development, particularly when encountered in the first 2 years of life (see, among others, Engle et al. 2007; Black et al. 2008; Behrman et al. 2009; Puentes et al. 2016). An emerging literature further postulates that these factors interact with one another, either as substitutes or complements. In particular, besides being a cause of diarrhea, unhygienic conditions also cause environmental enteric dysfunction (EED; Humphrey 2009; Dewey and Mayers 2011; Mbuya and Humphrey 2016; Spears 2020), an asymptomatic condition that leads to permeability, malabsorption, and systemic and gut inflammation. EED diminishes the ability to absorb nutrients and thus reduces the effectiveness of even the highest-quality nutrition in inducing child growth (Prendergast et al. 2014). It also interacts with infections and reduces the effectiveness of vaccines, leading to a vicious cycle that can propagate severe acute malnutrition (Lunn, Northrop-Clewes, and Downes 1991; Campbell, Elia, and Lunn 2003; Levine 2010; Lin et al. 2013; George et al. 2016; Gough et al. 2016; Mbuya and Humphrey 2016).

Strikingly, despite increasing recognition that the interaction between hygienic environments and nutrition might be considerable (Bekele, Rawstorne, and Rahman 2020), little is known about its size or sign. In this paper, we provide a quantitative estimate of the interaction between nutrition and a measure of a child's hygiene environment in shaping children's height and weight in a low-income setting—the Philippines in the early 1980s, providing among the first evidence that a hygienic environment can make nutritional investments more effective. In doing so, we bring together the literature on early-life growth faltering and the literature on the process of human capital accumulation over the first years of life. The latter literature has mostly focused on identifying complementarities between components of human capital such as health, education, and cognitive and socioemotional skills and investments in these, as studied by Spears and Lamba

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(2016), Attanasio et al. (2017), Villa (2017), and Attanasio, Meghir, and Nix (2020), among others.[1]

We estimate flexible early-childhood health production functions to model the effects of a vector of inputs on child physical growth by using rich panel data from the Cebu Longitudinal Health and Nutrition Survey (CLHNS). A translog functional form for the production function allows a more flexible interaction between inputs, and it is preferred relative to the constant elasticity of substitution (CES) specification because the latter imposes the same elasticity of substitution between any pair of inputs, which is a strong assumption for our study. Moreover, the translog production function allows for a nonlinear relationship between the inputs and the outcomes, which is another advantage in our context with respect to other commonly used functional forms such as the Cobb-Douglas, CES, and nested CES.

The survey, which follows a cohort of children born in 1983–84, includes detailed, high-frequency (every 2 months) measures of child nutritional intake, child- and household-level water, sanitation, and hygiene (WASH) environment, and child height and weight over the first 2 years of life. The data are unique in their details on relevant inputs and outcomes. They allow us to use two strategies to address endogeneity concerns arising from the fact that inputs are chosen on the basis of endowments, shocks, and preferences observed and known by parents but not by researchers. We account for the endogeneity of endowments by estimating value-added production functions (Todd and Wolpin 2007) allowing for the inclusion of the whole history of inputs and prior levels of health, and we address potential endogeneity of inputs by using a control function approach including appropriate instruments such as geologic features and prices of commonly consumed foods and of toilets, which reflect the budget constraint. The validity of the set of instruments is supported by the fact that their variability is due to exogenous variation (supply-side changes) and is unrelated to the shocks or unobserved inputs in the child health production functions, as discussed in detail in section III.C.

We build on previous contributions estimating production functions for children's height and weight (see, among others, Cebu Study Team 1992; De Cao 2015; Puentes et al. 2016) and contribute in two important ways. First, we flexibly allow for the inputs to interact with one another to produce future levels of child physical growth outcomes. This contrasts with previous studies that either consider one input only or specify production functions that are linear in inputs, thereby implicitly restricting them to be perfect substitutes. Second, we identify the effects of a child's hygiene environment, rather than infections and symptoms such as diarrhea, on child physical growth. This is an important distinction because it is well

[1] Our data do not have any information on cognitive or socioemotional skills or investments in these early years, so we are unable to study the nature of this important complementarity.

known that diarrhea is notoriously difficult to measure in large household surveys (Arnold et al. 2013a), and is not a symptom of EED and therefore likely to miss a key driver of growth faltering.[2] By considering a measure of a hygienic environment as an input, we capture not only an important cause of diarrhea (Wolf et al. 2014) but also the main cause of EED (Budge et al. 2019). Moreover, hygienic environments can be directly changed through policies. Diseases, by contrast, are a result of variation in inputs, unobserved endowments, and shocks, making them harder to shift. This distinction makes our findings more directly relevant to policy makers.

The data we use contain a wide array of measures relating to WASH behavior and infrastructure that capture the hygiene level of a child's environment. Rather than using the individual measures, we construct an index. This parsimonious measure of WASH has two advantages. First, each input into the production function is likely to be endogenous. Finding sources of exogenous variation for any single input, let alone numerous ones, is extremely difficult. Use of a composite index therefore greatly reduces the number of instruments needed for our analysis. Second, while one might rightly argue that disentangling the effects of different WASH factors on child growth is of interest, creating a hygienic environment is about reducing overall pathogen exposure, which can be achieved in many ways. In line, interventions targeting environmental improvements rarely focus on one factor only.[3] Moreover, the different factors could substitute for one another—for instance, Bennett (2012), who uses the same data as this study, finds that households substitute clean water and sanitation investments—so that focusing on the effects of one factor only would bias our results.

The data are also exceptionally detailed on food intake over the first 2 years of an infant's life, focusing on all meals consumed in the 24 hours prior to the survey, and quantifying these carefully. These data were then transformed into nutrient information by using food composition tables, enabling us to consider different nutritional inputs into the production function. In the main body of the paper, we focus on proteins, in line with other literature in the context (Puentes et al. 2016), but we also show consistent results when using total calories, carbohydrates, and fats as the nutritional input.

We find that both nutrition intake and WASH are important investments in shaping the formation of child height and weight in the first 2 years of life. We detect statistically significant and meaningful effects of each input on children's growth, thereby contributing to two strands

[2] A study on Gambian children found that dietary sufficiency and diarrhea were not associated with stunting, but measures of intestinal permeability (proxies for EED) explained 43% of linear growth (Lunn, Northrop-Clewes, and Downes 1991.

[3] For instance, the most commonly adopted national strategy in developing countries—community-led total sanitation—not only encourages households to build toilets but also delivers hygiene messages.

of the literature that establish nutrition and WASH as important drivers of child growth.[4] Further, we find a robust, positive, and statistically significant interaction between both inputs, indicating that nutrition is more productive in the formation of children's height and weight in more hygienic environments. In terms of magnitude, estimates indicate that the cumulative effect of a 20% increase in protein over the 6-to-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 2.43 cm and weight by 1.11 kg at the age of 2. For a child at the 90th percentile of the WASH distribution, these gains would be around 2.60 cm and 1.60 kg, respectively. This result is, to the best of our knowledge, the first rigorous quantification of the extent to which WASH investments can make nutrition investments more productive, thereby indicating the existence of complementarities.

Several recent randomized controlled trials (RCTs) have attempted to quantify the interaction of WASH and nutrition interventions. To date, these have been unsuccessful in establishing the nature of the interaction between these inputs for a range of reasons including insufficient power to detect interaction effects, low adherence to the trial interventions (Clasen et al. 2014; Null et al. 2018), intervening in an area with an unexpectedly low prevalence of diarrhea (Luby et al. 2018), implementation of insufficiently intensive interventions (Pickering et al. 2019), or intervening during a period when children were mostly breast-feeding (Humphrey et al. 2019).[5] Further analysis by Cumming et al. (2019) indicates that interventions that generate larger improvements in WASH may be required to improve child health.

Unlike these RCTs, we find significant effects of WASH and nutrition on child health. This difference may occur for several reasons. First, our WASH score captures much larger variation in WASH conditions than that generated in any of the treatments used. Second, 75% of children in our data reside in urban areas compared with the rural populations in each

[4] 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 effects of poor sanitation on child height for age (Gertler et al. 2015; Pickering et al. 2015; Hammer and Spears 2016; Augsburg and Rodríguez-Lesmes 2018), and others (including recent large-scale RCTs) detecting no effects (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).

[5] With respect to insufficient power to detect interaction effects, for example the WASH Benefits trial, a multi-arm RCT 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. 2013b), despite previous evidence that interaction effects can potentially be small (Kielmann et al. 1978; Taylor et al. 1978).

of these trials. Urban areas are more densely populated, raising exposure to negative externalities of poor WASH (Hathi et al. 2017), and have less livestock, a well-known vector for pathogens. Our estimates thus shed light on the effects of nutrition and WASH on a different type of sample.

The remainder of the paper is structured as follows. In section II, we discuss the CLHNS data and the input measures. In section III, we lay out the theoretical framework and estimation strategy. In section IV, we present the results, and section V concludes.

II. Context, Data, and Measures

We use data from the CLHNS, an ongoing longitudinal study of a cohort of Filipino children born in the early 1980s (Cebu Longitudinal Health and Nutrition Survey 2014). 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 including children's height and weight, and measures of sanitation, water, and hygiene practices, collected regularly over the first 2 years of the child's life. In addition, the data include detailed background health and socioeconomic information on the mother and the household, as well as a range of community variables, including bimonthly (i.e., every 2 months) price surveys between 1983 and 1986 that collected prices of key foods, including infant formula, and of 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 "communities"), were surveyed at the start of the third trimester of pregnancy. They were subsequently surveyed at multiple points in time during the first 2 years of their child's life (a few days after birth, and once every 2 months, or bimonthly, thereafter). Further follow-up surveys were conducted at older ages. To test our hypothesis, we focus on the data relating to children aged 6–24 months.[6]

Participation rates in the survey were high. At baseline (during the third trimester of pregnancy), 3,327 women were successfully interviewed. About 90% were surveyed at least once after their child's birth, and 65% were surveyed in every follow-up survey until the child turned 2 years of age.[7]

[6] Prior to age 6 months, most children are breast-fed. Existing literature suggests that breast milk protects children from the effects of less hygienic environments (VanDerslice, Popkin, and Briscoe 1994), suggesting a different production function for children aged 0–6 months. The data do not contain any sufficiently strong instruments for breast-feeding, so that we are unable to estimate the production function for children in this age range.

[7] Reasons for dropout (shown in table B.1; tables B.1–B.12 are available online) 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%). We compare the characteristics of attrited (not present in all bimonthly surveys) and nonattrited households/mothers/children in table B.2. Attrition is 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.

Though these data were collected more than 30 years ago, conditions faced by the study sample are similar in many dimensions 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. 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 7 years of education, implying that, on average, he would have completed (compulsory) elementary school plus one additional year. A significant majority of study children—around three-quarters—lived in urban neighborhoods. Households needed to travel on average 6 km to reach the nearest public hospital. 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,

TABLE 1
Sample Characteristics

Variable	Mean (1)	SD (2)	Observations (3)
Household and community characteristics:			
Household in urban community	.74	.44	2,333
Distance to nearest public hospital (km)	6.02	4.93	2,333
Age of household head (years)	35.51	12.22	2,333
Household head is female (%)	.05	.21	2,333
Household head is in employment (%)	.95	.21	2,333
Household head's years of education	7.20	4.04	2,333
Number of household members	5.72	2.79	2,333
Household owns dwelling (%)	.70	.46	2,333
Home made of concrete (%)	.18	.38	2,333
Households own a refrigerator (%)	.06	.24	2,333
Households own benches/chairs (%)	.70	.46	2,333
Households have electric lighting (%)	.48	.50	2,333
Number of rooms (excluding bathrooms)	2.60	1.31	2,333
Household income per capita (USD 2017)	1.76	1.67	2,333
Anthropometrics from 6 months:			
Average height of child (all rounds, cm)	72.42	2.96	2,333
Average weight of child (all rounds, kg)	8.33	1.01	2,333
Stunted at 6 months	.21	.41	2,293
Stunted at 24 months	.63	.48	2,204
Mothers' characteristics:			
Highest level of education of mother	7.39	3.68	2,333
Mother is spouse of/is household head	.78	.41	2,333
Mother age, years	27.01	5.94	2,333
Number of children under 5	1.27	1.00	2,333
Mother working during pregnancy	.38	.49	2,333
Child birth characteristics:			
Child's gender (1 = male)	.52	.50	2,333
Birth weight (kg)	3.05	.44	2,333
Birth height (cm)	49.26	2.10	2,330

Note.—Columns 1 and 2 report sample mean and SD, respectively; column 3 reports the number of observations for which the information is available. The sample represents all children who are present at any point in the analysis period.

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 was below the official International Poverty Line of US$1.90 per person per day established in 2015.

Mothers were on average 27 years of age and had about 7.4 years of education. Most mothers 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. This child was typically their first. On average, only every fifth study child had a sibling at the time of the baseline survey.

Just over half (52%) of the sample children were girls. The CLHNS collected anthropometric measurements at birth and every 2 months thereafter, until the child turned 2. The average child weighed 3.05 kg at birth and had a length of 49.26 cm. This increased to a weight of 8.33 kg and a height of 72.42 cm at 6 months of age.

A. *Outcomes*

Useful benchmarks for child anthropometrics are height-for-age *z*-score (HAZ) and weight-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 that child's HAZ (WAZ) falls below −2 SD from the norm. Figure 1 displays the evolution of these scores for our sample children by

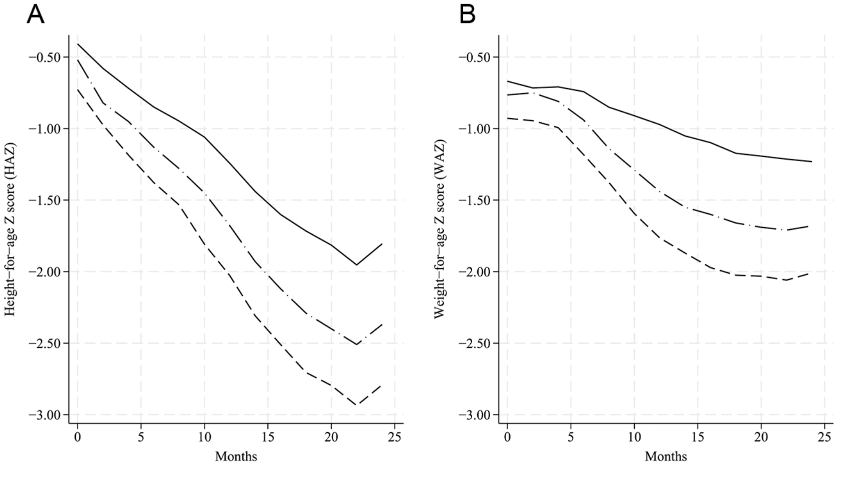

Figure 1.—Evolution of HAZ and WAZ by child age in months and wealth quintile. HAZ (*A*) and WAZ (*B*) for all children in the analysis sample, by age (in months) and wealth quintile. Wealth quintiles are generated from a principal component analysis of assets, as described in appendix B.2.

child's age for the 1st and 5th wealth quintiles, along with the sample median.[8]

Figure 1*A* 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 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 the wealth distribution. At birth, the gap between the top and bottom quintiles is about 0.3 SD. This increases to about 1 SD by 20 months of age. By age 15 months, the median child is stunted. Stunting rates in this sample are high (62.4% by 2 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 figure 1*B*. The average child in our sample starts out with low WAZ compared with the reference population, and about 10% of our sample is underweight at birth. While there is no dramatic deterioration in the first 5–6 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. Similar to HAZ, the difference between the top and bottom quintiles grows from about 0.3 SD at birth to about 0.7 SD by the time the average child in the sample reaches 24 months of age.[9]

B. Inputs

1. Nutrition

The CLHNS data contain exceptionally detailed information on food intake over the first 2 years of an infant's life. Data were collected on the commencement, frequency, and discontinuation of breast-feeding and on the intake of all liquids, solids, and semisolids in the 24 hours prior to each bimonthly 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

[8] The construction of the wealth index and wealth quintiles is detailed in app. B.2 (app. B is available online).

[9] In fig. B.1 (figs. B.1–B.4 are available online), we show that the evolution is very similar for girls and boys, which also holds for inputs over time (see fig. B.2) and is discussed in the next section. Because of these similarities and a lack of differential gender effect on the interaction term (see table B.3), we do not present a full analysis by gender.

from manufacturers for foods such as infant formula; Bisgrove, Popkin, and Barba (1989, 1991) and Perlas, Gibson, and Adair (2004) provide more details.

Healthy growth requires sufficient intakes of energy, protein, and fat. The main analysis focuses on protein intake, and results on total calories, carbohydrates, and fats—which yield similar conclusions—are presented in tables B.5–B.7. 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 (Millward 2017). Its importance for the growth of children in our study context has also been shown by Puentes et al. (2016).[10]

The children in our sample consume, on average, 14.0 g of protein and 510 kcal per day. Figure 2*A* shows the breakdown of these averages in the cross section at different ages. Unsurprisingly, calorie intake and protein intake increase with age. For instance, sampled children consume an average of 6.1 g of protein and 231 kcal per day at age 6 months, 11.4 g of protein and 417 kcal per day on average at age 12 months, and 20.2 g of protein and 700 kcal on average at 2 years of age. Similar figures for fats and carbohydrates are shown in figure B.4.

These values are lower bounds on nutrition intake. Proteins and calories consumed through breast milk are not included in the calculations, because the amount of breast milk consumed and its nutritional composition are difficult to measure. Indeed, figure 2*B*, 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 semisolid and solid foods and other liquids, with 69% of children still receiving breast milk at 1 year of age and 46% at age 18 months. Predominant breast-feeding, however, falls from 24% at 6 months of age to 0.2% two months later. In our analysis, we control for whether or not the child is being breast-fed.

2. Water, Sanitation, and Hygiene

The second input into the formation of child height and weight is the child's hygiene environment. The data contain a number of measures of household practices around WASH. Some of these are measured in each survey round, while others are observed only once. We combine all these variables into a single WASH score by using polychoric exploratory factor analysis (EFA) (Kolenikov and Angeles 2004), which is estimated separately for each survey round. We use this approach, rather than a standard EFA, because it uses a polychoric correlation matrix (rather than the Pearson correlation matrix), allowing us to conduct the EFA for binary and categorical variables. Variables with low factor loadings, which provided little additional information, were dropped from the construction of the WASH

[10] A key source of protein in this context is eggs, with more children consuming these than meat or fish.

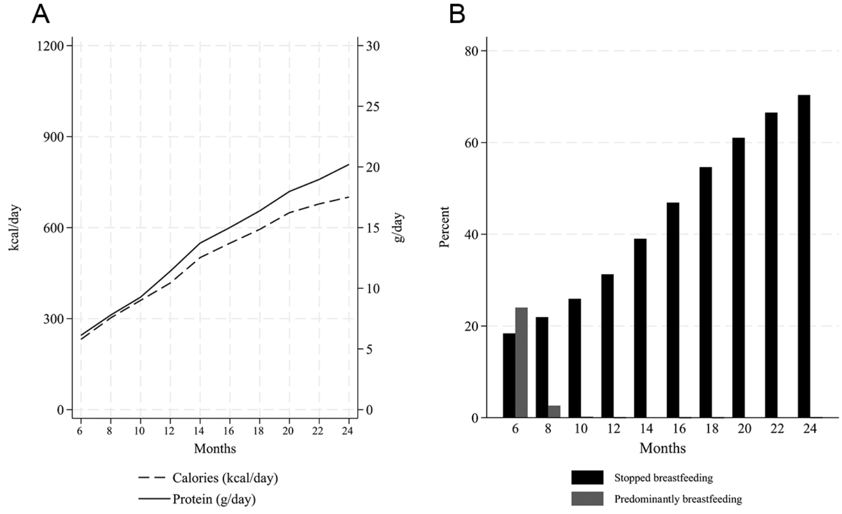

Figure 2.—Nutritional inputs over time. *A*, Calories (left *y*-axis) and grams of protein (right *y*-axis) consumed per day by analysis sample children at a given age (in months). *B*, Percentage of children who are predominantly (lighter bars) and not at all (dark bars) breast-fed by age of the child (in months). Predominant breast-feeding is defined along WHO guidelines (i.e., no semisolid food yet introduced).

score.[11] We retain the first factor, which has an associated eigenvalue greater than 1 across the estimates for all survey rounds, as the WASH score.[12] Finally, we transform the score to be strictly positive. Notably, the resulting WASH score includes at least one variable related to each component of WASH.

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 breast-fed at 6 months of age, the indicator is constructed to equal 1 if the child was given treated water or no water, and 0 otherwise. Aggregating across rounds, we see that in 45% of instances, children were given treated water or no water, as shown in table 2.

The sanitation dimension is captured by information on the type of toilet facility owned by the household (collected at baseline) and how

[11] 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.

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

	Descriptives			Factor
	Mean (1)	SD (2)	Observations (3)	Loading (4)
No water/treated water given to child (by round)	.45	.50	22,217	.455
Safe toilet in household (dummy)	.65	.48	22,218	.875
Child's feces are disposed of safely (i.e., toilet)	.17	.37	22,218	.632
Weekly household soap expenditure (pesos)	47.03	38.29	22,218	.412

Note.—Columns 1–3 report respectively sample mean, SD, and available sample size for variables feeding into the WASH score, S. Sample size for the variable "no water/treated water given to child" varies by round. Information on safe toilet ownership, safe disposal of child feces, and soap expenditures is observed once. Column 4 reports factor loadings for each variable, estimated separately by round.

mothers dispose of their child's feces (collected when the child was around 18 months old). We construct indicators for whether or not a household owns a safe toilet (defined, following the UNICEF-WHO Joint Monitoring Program [JMP] definition, as either a flush, water-sealed, or antipolo toilet) and whether a child's feces are safely disposed of (defined as disposal, either of wastewater or of feces, directly into a toilet).[13] We see in table 2 that about 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 (approximately US$4.41 in 2017) on average. Column 4 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.[14]

We analyze how individual WASH indicators as well as the composite score (in logs) vary with various household-, child-, and community-level variables. Table 3 shows correlates with household's wealth quintiles. 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 1st quintile to 12% in the 5th quintile. Second, we

[13] Twenty-seven percent of households report disposing of feces in the garbage, which need not correspond to safe disposal of feces according to the JMP because garbage is frequently disposed of in unregulated dumps or burned, leading to environmental contamination. Moreover, use of disposable diapers was not widespread in the study sample: only 1% of mothers reported that their child used a disposable diaper/panty.

[14] In robustness checks, discussed in sec. IV.C, we estimate WASH scores by 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). Our results remain consistent with these alternative definitions.

TABLE 3
WASH Inputs by Wealth Quintile

	1st (1)	2nd (2)	3rd (3)	4th (4)	5th (5)
No water/treated water given to child (by round)	.06	.39	.20	.70	.88
Safe toilet in household (dummy)	.00	.27	.96	1.00	1.00
Child's feces are disposed of safely (i.e., in a toilet)	.01	.04	.04	.15	.58
Log weekly household soap expenditure	4.34	4.97	5.04	5.23	5.71
Log WASH	−1.10	−.69	−.33	−.22	−.07

Note.—Columns 1–5 report the mean value of variables entering the WASH score, *S*, by wealth quintile. Log WASH is the log of the WASH score itself.

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 2nd quintile to 96% in the 3rd quintile. Third, safe disposal of child feces is basically nonexistent in the three lowest quintiles (<5%), increasing to 15% in the 4th quintile and 58% in the 5th quintile. Soap expenditures also increase with wealth quintile. In line with the increased values of the individual indicators, the resulting WASH score is also increasing with wealth.

We further observe an increasing and concave relationship between the estimated WASH score and the child's age (table B.4). The estimated WASH score is also increasing with the household head's education level. Finally, households in larger, urban communities have a larger WASH score, reflecting that safe water and sanitation facilities are much more widely available in urban communities relative to rural communities.[15]

III. Theoretical Framework and Estimation Strategy

This section outlines the theoretical framework and derives the empirical model before discussing the estimation strategy. Production functions are widely recognized in the child development literature as the gold standard framework to characterize the process of human capital accumulation over time. For a more realistic specification, we characterize the most general process of height and weight formation, which accounts for not only the dynamics of child physical growth, endowments, and investments but also for how these outcomes and inputs relate and evolve over time. Doing so raises several important challenges; therefore, we specify the assumptions needed to obtain an empirically tractable production function of child physical growth that can be taken to the data.

To achieve consistent estimates of the production function parameters, we explain how the assumptions are helpful to deal with the endogeneity

[15] Further, and reassuringly, in analysis available on request, we find that the number of episodes of diarrhea is negatively and statistically significantly correlated with the WASH scores (r = −0.03).

of endowments. Thereafter, we discuss in more detail the estimation strategy, which allows us to deal with endogeneity of investments.

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

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

and

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

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 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_{it} is a vector of other variables that also affect the formation of height and weight, such as mother's height. As outlined in section II, we focus on protein (P_{is}) as the main component of nutrition, N_{is}. In section IV.C.2, we consider alternative components of nutrition including calories (C_{is}), carbohydrates ($Carb_{is}$), and fats (F_{is}). In this general formulation, the production functions, H_{it} and W_{it}, are allowed to be age-specific.

We index the production function inputs by the child's age, s, to reflect the fact that the inputs can change with age. Similarly, the productivities of inputs can also change with age.

In this general formulation, inputs at age $s = 1 \ldots t - 1$ can influence height and weight of the child at age t through the following:

1. The direct effect of the input at age s.
2. Interactions between the same input N or S at different ages $r = 1 \ldots t - 1$ and s, where $r \neq s$.
3. Interactions between the inputs N and S at the same age $s = 1 \ldots t - 1$; and between ages $r = 1 \ldots t - 1$ and s, where $r \neq s$.
4. Interactions between the inputs N and S at different ages, and the child's endowment, μ_i, and various background variables, X_{it}.

Estimation of such a production function poses several challenges, namely (1) functional form assumptions; (2) empirical tractability; (3) endogeneity of endowments; and (4) endogeneity of investments. We consider each of these in turn.

A. *Functional Form*

The standard framework used in economics to model the dynamic process of human capital accumulation in early years is a production function approach (see, e.g., Cunha et al. 2006; Cunha and Heckman 2008; Cunha, Heckman, and Schennach 2010; Ehrlich and Yin 2013; Attanasio, Cunha, and Jervis 2019; Attanasio, Cattan, and Meghir 2022). However, it is not a priori obvious what functional form the child health production should take. Common choices in the literature—such as the 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 a 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, and of the WASH input, would not affect how productive nutrition is 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.

Although the translog function is a second-order Taylor polynomial approximation of the CES function, there are meaningful differences between the two. A translog functional form for the production function allows for more flexible interactions between inputs. It is preferred relative to the CES specification because the latter imposes that any pair of inputs has the same elasticity of substitution, which is a strong assumption for our study. Moreover, the translog production function allows for a nonlinear relationship between inputs and the outcome, which is another advantage in our context with respect to the CES, nested CES, or Cobb-Douglas specifications (for more references, see Pavelescu 2011; Attanasio, Cattan, and Meghir 2022). It also allows for both positive and negative contemporaneous complementarities between the marginal return to parental investments with respect to the current stock of child health—instead of weakly positive (see, e.g., Agostinelli and Wiswall 2016; Del Bono, Kinsler, and Pavan 2022). Therefore, with this approach we do not impose any such substitutability or complementarity restrictions or linearity.

Hence, imposing the translog functional form on equations (1) and (2) and taking logs yields the following:

$$\begin{aligned}\ln H_{it} = {} & \alpha_0^h + \sigma_t^h \mu_{i0} + \delta_t^h X_{it} + \sum_{s=1}^{t-1} \alpha_s^h \ln N_{is} + \sum_{s=1}^{t-1} \beta_s^h \ln S_{is} \\ & + \frac{1}{2} \sum_{s=1}^{t-1} \sum_{r=1}^{t-1} (\gamma_{Nrs}^{\nu^h} \ln N_{ir} \times \ln N_{is}) \\ & + \frac{1}{2} \sum_{s=1}^{t-1} \sum_{r=1}^{t-1} (\gamma_{Srs}^{\nu^h} \ln S_{ir} \times \ln S_{is}) \\ & + \frac{1}{2} \sum_{s=1}^{t-1} \sum_{r=1}^{t-1} (\gamma_{Nrs}^{h} + \gamma_{Srs}^{h}) \ln N_{ir} \times \ln S_{is} + \varepsilon_{it}^h \end{aligned} \tag{3}$$

and

$$
\begin{aligned}
\ln W_{it} = {} & \alpha_0^w + \sigma_t^w \mu_{i0} + \delta_t^w X_{it} + \sum_{s=1}^{t-1} \alpha_s^w \ln N_{is} + \sum_{s=1}^{t-1} \beta_s^w \ln S_{is} \\
& + \frac{1}{2} \sum_{s=1}^{t-1} \sum_{r=1}^{t-1} (\gamma_{Nrs}^{\nu^w} \ln N_{ir} \times \ln N_{is}) \\
& + \frac{1}{2} \sum_{s=1}^{t-1} \sum_{r=1}^{t-1} (\gamma_{Srs}^{\nu^w} \ln S_{ir} \times \ln S_{is}) \\
& + \frac{1}{2} \sum_{s=1}^{t-1} \sum_{r=1}^{t-1} (\gamma_{Nrs}^{w} + \gamma_{Srs}^{w}) \ln N_{ir} \times \ln S_{is} + \varepsilon_{it}^w.
\end{aligned} \tag{4}
$$

These equations contain the entire history of nutrition and WASH inputs, as well as the interactions between the same input at both the same and different ages (denoted s, r up to age $t - 1$), and between the nutrition and WASH inputs for each age s, r up to age $t - 1$. The parameters α_s^h (α_s^w) and β_s^h (β_s^w) capture the direct effects of nutrition and WASH inputs at age s on height (weight) at age t. The parameters $\gamma_{Nrs}^{\nu^h}$ ($\gamma_{Nrs}^{\nu^w}$) capture the interactions between the nutrition inputs at ages s and r on height (weight) at age t, while $\gamma_{Srs}^{\nu^h}$ ($\gamma_{Srs}^{\nu^w}$) do so for WASH inputs at ages s and r. Finally, γ_{Nrs}^{h} (γ_{Nrs}^{w}) and γ_{Srs}^{h} (γ_{Srs}^{w}) capture interactions between the nutrition and WASH inputs at the same age and at different ages, s and r.

B. Empirical Tractability and Endogeneity of Endowments

The inclusion of the entire history of past nutrition and WASH inputs imposes severe demands on the data, as is apparent from equations (3) and (4). To make the estimation tractable, we use the widely used value-added model (see, e.g., Todd and Wolpin 2007; Puentes et al. 2016; Keane, Krutikova, and Neal 2020), 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) $\gamma_{Nrs}^{\nu^m} = \gamma_{Srs}^{\nu^m} = 0$.
(b) $\gamma_{Nrs}^{m} = \gamma_{Srs}^{m} = \gamma_{rs}^{m}$ for all s, r.
(c) $\gamma_{rs}^{m} = 0$ for all s, r; $s \neq r$.

Assumption 1a rules out interactions between an input in period s and the same input in any other period r. Along with ruling out interactions between the same input across periods, 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. Assumption 1b is more innocuous and simply imposes that the interaction between WASH and nutrition is the same as that between nutrition and WASH at the same ages.

Assumption 1c imposes that only contemporaneous interactions between WASH and nutrition matter for height and weight formation (i.e., WASH at 6 months of age does not interact with protein at 8 months in the formation of child height at 10 months). While this may appear to be a strong constraint on the relationship between inputs and outputs, we relax this later by allowing interactions between inputs across periods to work through height or weight in a previous period. For convenience, we denote $\gamma_{ss} = \gamma_s$ in what follows.

After applying assumption 1, equations (3) and (4) simplify to the following:

$$\begin{aligned} \ln H_{it} = {} & \alpha_0^h + \sum_s^{t-1} \alpha_s^h \ln N_{is} + \sum_s^{t-1} \beta_s^h \ln S_{is} + \sum_s^{t-1} \gamma_s^h \ln N_{is} \ln S_{is} \\ & + \sigma_t^h \mu_{i0} + \delta_t^h X_{it} + \varepsilon_t; \end{aligned} \tag{5}$$

$$\begin{aligned} \ln W_{it} = {} & \alpha_0^w + \sum_s^{t-1} \alpha_s^w \ln N_{is} + \sum_s^{t-1} \beta_s^w \ln S_{is} + \sum_s^{t-1} \gamma_s^w \ln N_{is} \ln S_{is} \\ & + \sigma_t^w \mu_{i0} + \delta_t^h X_{it} + \varepsilon_t. \end{aligned} \tag{6}$$

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_{i0}. 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 additional assumptions common to the value-added framework.

Assumption 2. For $m \in \{h, w\}$: $\alpha^m = \alpha_s^m = \lambda\alpha_{s-1}^m$; $\beta^m = \beta_s^m = \lambda\beta_{s-1}^m$; $\gamma_{SN}^m = \gamma_s^m = \lambda\gamma_{s-1}^m$; $\sigma^m = \sigma_s^m = \lambda\sigma_{s-1}^m$ for $\lambda \in (0, 1)$.

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 effect of past inputs follows a rate of decay λ, which is common across all inputs. This monotonic rate of decay seems a natural assumption in context of height and weight formation—the most productive period for nutrition or WASH should be that when consumption of that input occurs.

Assumption 3, which is similar to that in Puentes et al. (2016), 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 linearly related to the effect on weight. This assumption is plausible because height and weight are likely to be jointly determined in infancy. For the sake of brevity, we focus now on the derivation of the height estimation equation.[16] Taking the first difference of height and weight equations, and then subtracting each differenced equation from the other and applying assumptions 2 and 3, we obtain the following equation for height:

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

These assumptions allow us to difference out the unobserved health endowment, thereby resolving the endogeneity concerns relating to this variable. In the absence of further endogeneity concerns, the model parameters can be consistently estimated.[17] We extend the model from equation (7) by including the interactions between past height and contemporaneous inputs. In doing so, we partially relax assumption 1c and allow past inputs to interact with current inputs, but through past height or weight. This allows the productivity to vary with accumulated height, as captured by γ^h_{SH} and γ^h_{NH}. Renaming the fractions in equation (7) for parameters and grouping the error terms, we obtain our estimation equation:

$$\begin{aligned}\ln H_{it} = {} & \alpha_0 + \alpha^h \ln N_{it-1} + \beta^h \ln S_{it-1} \\ & + \gamma^h_{SN} \ln S_{it-1} \ln N_{it-1} + \gamma^h_{SH} \ln S_{it-1} \ln H_{it-1} \\ & + \gamma^h_{NH} \ln H_{it-1} \ln N_{it-1} + \tau_h \ln H_{it-1} + \tau_w \ln W_{it-1} + b_h X_{it} + \varepsilon^h_{it},\end{aligned} \tag{8}$$

where

$$\alpha_0 = \frac{\alpha^h - \alpha^w}{1-a}, \tau_h = \frac{a+\lambda-2}{a-1}, \tau_w = \frac{\lambda-1}{a-1},$$

$$b_h = \delta^h_t - \delta^h_{t-1} \frac{a}{a-1} + \frac{\delta^w_{t-1}}{a-1},$$

$$\varepsilon^h_{it} = \varepsilon^h_t - \varepsilon^h_{t-1} + \frac{\varepsilon^h_{t-1} - \varepsilon^w_{t-1}}{1-a}.$$

[16] The full derivation and the estimation model for weight is given in app. A.

[17] If assumption 3 is violated, then the confounding influence of unobserved health endowment would create an endogeneity problem, with inputs correlated with the error term in eq. (8). Our control function strategy (sec. III.C) deals with this and other sources of endogeneity.

In the estimation, X_{it} 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's age, 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 breast-feeding, and mother's height.

The parameters of interest are the marginal products for each input and the interaction between the two inputs. The presence of the interactions between nutrition, sanitation, and past height/weight means that the marginal product will be a function of not just that input but also of the other input and past height/weight. For child height, for instance, the marginal products for $\ln N_{it-1}$ and $\ln S_{it-1}$ are

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

and

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

Here, γ_{SN}^h measures the degree of complementarity/substitutability 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}^h and γ_{NH}^h, 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.

C. *Endogeneity of Investments*

The assumptions made thus far account for the endogeneity arising from the child's unobserved health endowment, μ_0. However, there are other risks to identification, such as biases arising from shocks to child health that are unobserved by researchers and from unobserved parental preferences that might be correlated with observed contemporary or lagged inputs. The latter is relevant if parents compensate or reinforce for contemporary or lagged unobserved health shocks. If this source of endogeneity is not accounted for, ordinary least squares (OLS) estimates of the input coefficients would be biased downward (upward) if parents compensate (reinforce). To deal with this source of endogeneity, and in light of our highly nonlinear estimation equation, we use a control function approach (Gronau 1974; Heckman 1979; Wooldridge 2015). Specifically, we estimate "first-stage (or investment) equations," which include the set of exogenous regressors from the production function and a set of excluded instruments, and estimate the residual from these equations. Then, the estimated residual, which is the control function, is included as an additional regressor in the production function. Attanasio, Cattan, and Meghir (2022) review several studies that use either the control function or instrumental variables approach as a treatment of endogeneity.

1. Control Function Approach

To implement the control function approach, we start as mentioned previously by estimating the following first-stage equations for $\ln N_{it-1}$ and $\ln S_{it-1}$:

$$\ln N_{it-1} = \beta_1 + \sigma_1 X_{it} + \pi_1 Z_{it} + upro; \tag{11}$$

$$\ln S_{it-1} = \beta_2 + \sigma_2 X_{it} + \pi_2 Z_{it} + uwash. \tag{12}$$

Here, Z_{it} 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, $upro \times uwash$, as additional regressors in estimating equations (8) and (A13). This yields the following second-stage equation for height (eq. [A14] for weight):

$$\begin{aligned} \ln H_{it} = {} & \alpha_0 + \alpha^h \ln N_{it-1} + \beta^h \ln S_{it-1} + \gamma^h_{SN} \ln S_{it-1} \ln N_{it-1} \\ & + \gamma^h_{SH} \ln S_{it-1} \ln H_{it-1} \\ & + \gamma^h_{NH} \ln H_{it-1} \ln N_{it-1} + \tau_h \ln H_{it-1} + \tau_w \ln W_{it_1} \\ & + b_h X_{it} + upro + upro^2 \\ & + uwash + uwash^2 + upro \times uwash + \varepsilon^h_{it}. \end{aligned} \tag{13}$$

In terms of inference, we report standard errors from a stratified block bootstrap, with the community as the block and municipality as the stratum. This allows us to adjust for the fact that the control functions are estimated, and that we have only 33 communities in our sample. In nonlinear specifications such as ours, Terza, Basu, and Rathouz (2008) demonstrate that a control function is significantly more efficient than instrumental variables. Nonparametric 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 H_{it} ($\ln W_{it}$) only through the input.

For both our input variables of interest—nutrition and WASH investments—we use input prices at the community level. For WASH inputs, we furthermore rely on a geologic feature, soil depth. Use of 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), because 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 bimonthly 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.[18] 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 nontraded goods, such as tomatoes, as shown later 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 2 years of the child's life.

2. Instruments for N

The set of prices used as excluded instruments in the first stage includes prices of rice, dried fish, corn, tomatoes, oil, condensed and evaporated milk, kerosene, and formula milk.[19] We show the spatial and temporal variations in the prices of four goods (rice, tomatoes, corn, evaporated milk) in figures 3 and 4, respectively. Because responses of intakes to prices

[18] 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.

[19] 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.

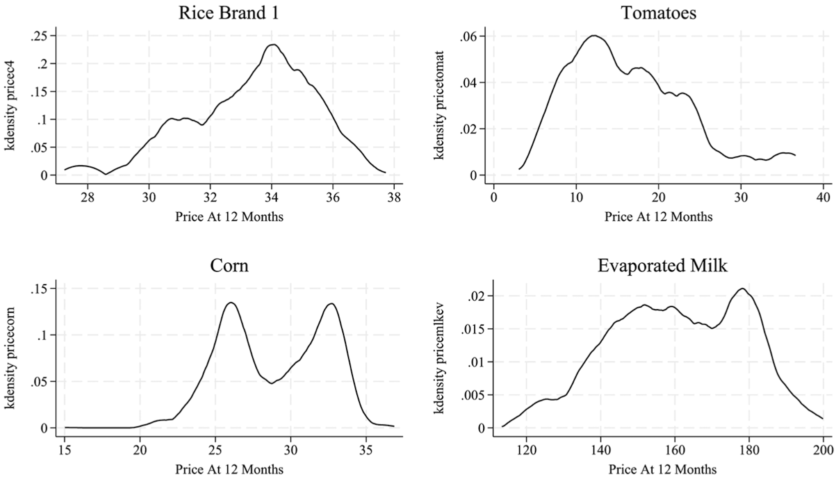

Figure 3.—Spatial price variation. Distribution of prices across study locations (barangays) when analysis children were 12 months of age. The top left panel focuses on rice of the most common brand, the top right panel on price of tomatoes, the bottom left panel on price of corn, and the bottom right panel on price of evaporated milk.

involve both an income and substitution effect, the signs on the coefficients of prices in the first-stage equation could be either positive or negative.

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

We argue that the price information we use satisfies the exclusion restrictions because food markets are competitive and households are not able to influence prices significantly. In particular, the price increases among tradable goods, triggered by the political turmoil in the country,

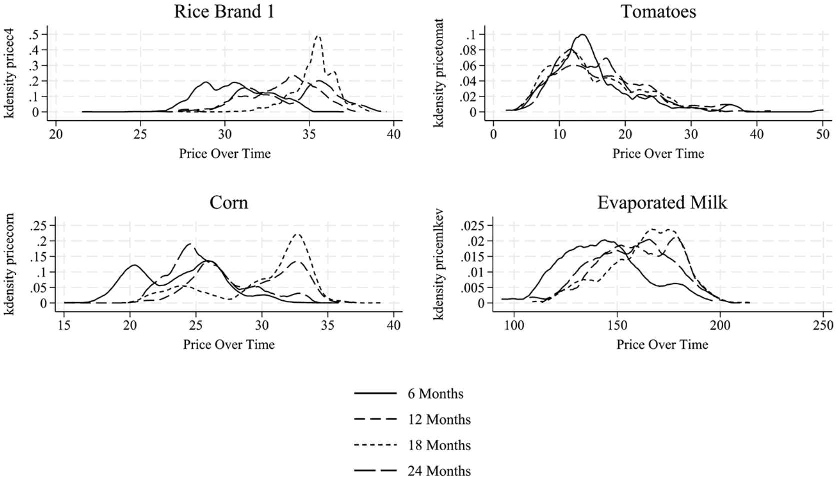

Figure 4.—Temporal price variation. Distribution of prices over time, for example, when analysis children were 6, 12, 18, and 24 months of age. Items are the same as in figure 3: rice, tomatoes, corn, and evaporated milk.

are unlikely to be a result of the behavior of our study households. To counteract any additional concerns, we control for municipality fixed effects and include extensive community-level controls in our estimation, making us confident that any remaining price variation used in the estimation is (exogenously) driven by supply-side factors.

3. Instruments for *S*

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.[20] Antipolo toilets are a type of sealed toilet introduced to the Philippines by the American colonial government in the early twentieth 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 because they are considered to be relatively easily and cheaply constructed. We have information only at the time of the baseline survey and hence rely on geographic variation for identification. Despite the lack of time variation, antipolo toilets prove to be an important predictor of WASH investments. The geographic 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, higher population, and urban locations, as well as availability of asphalt roads.[21] The estimated coefficients are mostly 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.

Turning to the exclusion restriction, our 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, it is reasonable to assume that, even if our study households have correlated WASH investment preferences, they are

[20] Other candidates for instrumental variables for the WASH score are soap prices at the community level and distance to water sources, both of which are available in the data. However, we are unable to use these because (i) the information on soap sizes is not sufficiently detailed or consistent across barangays to allow us to construct a comparable soap price across barangays, and (ii) the water component of the WASH score captures whether the child had treated or no water (compared with untreated water) and water is treated regardless of the source, hence distance to water sources will not be a good instrument.

[21] In fig. B.3, we display scatter plots of the log toilet costs with these variables. Reassuringly, none of the negative correlations is driven by a large outlier.

TABLE 4
Exclusion Restrictions: Log Cost of Antipolo Toilets

	(1)	(2)	(3)	(4)	(5)
Has electricity	−.181				.00490
	(.230)				(.375)
Log 1980 census population		−.0304			.259
		(.123)			(.174)
Urban			−.363		−.723*
			(.210)		(.329)
Has asphalt roads				−.293	−.0468
				(.217)	(.303)
Constant	6.309***	6.407***	6.359***	6.341***	4.566***
	(.189)	(.945)	(.151)	(.167)	(1.202)
Observations	33	33	33	33	33

Note.—Barangay-level regression of the log average costs of (indoor and outdoor) antipolo toilets on a number of access-related variables. Columns 1–4 show regression results with each access variable included separately; regression results in col. 5 include all variables at the same time. Standard errors (in parentheses) are clustered at the community level.
* $p < .10$.
*** $p < .01$.

likely to remain price takers, given that the construction of toilets would only be a small fraction of the overall construction market.[22]

The finding that geographic 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 variable meets important criteria to serve as a valid instrument for our WASH score, it does not, on its own, provide sufficient power to explain variation in endogenous inputs of interest and hence to satisfactorily account for the endogeneity in child health production WASH input. Therefore, we make use of one further instrument in our analysis, namely, 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.

4. First Stages

The first stage for both of our main inputs, log protein intake and log WASH, are shown in table 5. We note that we refrain from interpreting

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

coefficient estimates given the reduced-form nature of the regression. Only with a full demand model could we attempt to interpret the coefficients as structural parameters.[23] 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 21.59 and 15.51, respectively. Following Puentes et al. (2016), we also calculate the Hansen J-statistic overidentification test and fail to reject the joint null hypothesis that the instruments are valid and excluded instruments are correctly excluded from the estimated equation (p-value = .12) and calculate the Cragg-Donald F-statistic for underidentification (test statistic value = 3.041). We also calculate the Sanderson-Windmeijer partial F-statistic (Sanderson and Windmeijer 2016) to test whether a particular endogenous regressor is identified, obtaining F-statistic values of 16.84 and 10.38 for protein and WASH, respectively. In section IV.C.1, we assess the sensitivity of our findings to different sets of instruments, following a procedure similar to that of Puentes et al. (2016).

IV. Results

A. *Main Specification: Protein*

We present our results for both outcomes (height and weight) as a function of protein intake and WASH.[24]

Height.—Column 1 of table 6 shows the OLS estimates of the translog production for child height. Higher protein intake and better WASH environment 2 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 approach (col. 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 zero. These two patterns are consistent with parents compensating for (unobserved) bad shocks, in line with findings in Liu, Mroz, and Adair (2009).

The results thus confirm the general understanding that higher protein intake leads to an increase in children's height and further reveal

[23] For example, if a change in price involves a substitution and an income effect, then it could be possible to have positive effects on intakes despite higher prices if the income effect dominates.

[24] In app. B.9, 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. The tables in app. B.9 show how the marginal productivities of nutrition (and WASH) change as we add another input and show interactions between the two inputs. Further, we show results with other nutritional inputs (total calories, carbohydrates, and fats) in tables B.5–B.7.

TABLE 5
FIRST-STAGE REGRESSIONS FOR PROTEIN AND WASH

	$\ln P_{it-1}$ (1)	$\ln S_{it-1}$ (2)
First lag log price:		
Rice brand 1	.521***	.0560
	(.153)	(.0498)
Corn	−.235**	−.00974
	(.0896)	(.0218)
Oil	.0846*	−.00977
	(.0422)	(.0149)
Dried fish	.0164	.00473
	(.0334)	(.0112)
Condensed milk	−.113*	−.0306
	(.0589)	(.0337)
Evaporated milk	−.138**	−.000139
	(.0610)	(.0388)
Tomatoes	.0396*	−.0215**
	(.0209)	(.0104)
Brand 2 rice	−.429***	−.121***
	(.146)	(.0363)
Formula milk	−.117	−.0752
	(.128)	(.0527)
Kerosene	.0625	−.00454
	(.0550)	(.0187)
Second lag log price:		
Rice brand 1	.183	−.00452
	(.141)	(.0559)
Corn	−.0785	−.0597**
	(.0935)	(.0239)
Oil	.0256	.0350**
	(.0551)	(.0139)
Dried fish	.0238	.000575
	(.0335)	(.00935)
Condensed milk	.0115	−.0372
	(.0715)	(.0335)
Evaporated milk	.112**	.0121
	(.0546)	(.0464)
Tomatoes	.0285	−.00608
	(.0188)	(.00796)
Brand 2 rice	−.236	−.0344
	(.160)	(.0451)
Formula milk	−.248**	−.0365
	(.0998)	(.0483)
Kerosene	−.0175	−.0320
	(.0696)	(.0211)
Log antipolo toilet price (inside)	.0395	.0377
	(.0442)	(.0287)
Log antipolo toilet price (outside)	−.0181	−.0158
	(.0272)	(.0213)
Average soil depth	−.0950***	.00678
	(.0335)	(.0309)
Observations	21,870	21,870
Adjusted R^2	.418	.522
F-statistic	21.59	15.51

TABLE 5 (*Continued*)

	ln P_{it-1} (1)	ln S_{it-1} (2)
Sanderson-Windmeijer *F*-statistic	16.84	10.38
Cragg-Donald *F*-statistic	3.041	3.041
Hansen *J*-statistic *p*-value	.12	.12

Note.—First-stage regression for protein (ln P_{it-1}) and WASH (ln S_{it-1}), as displayed in eq. (11) and eq. (12), respectively. Instruments shown in the table. Additional controls included in all regressions are municipality dummies, interview month dummies, census population, an urban/rural dummy, child gender, cubic in child age, birth weight, whether child is breast-fed, mother's height, wealth quintile, household income per capita, age and education of the household head, mother's age and education, and controls for the distribution of ages within the household. Standard errors (in parentheses) are clustered at the community level.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

that better WASH conditions make higher protein intake more productive. Indeed, the overall marginal products for both inputs are positive and statistically significant when evaluated at the median of the distribution of the other input. Notably, 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 about 0.77 in the estimates accounting for endogeneity of inputs. This is not a surprise, because we study the formation of height over a relatively short time frame of 2 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 the 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 6 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 2.60 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 2.43 cm. Thus, better WASH complements protein intake by a modest, but still important, amount.

Weight.—Unlike height, weight is more sensitive to contemporaneous inputs; although, with the bimonthly 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 control function estimates for the production function for weight. The OLS coefficients indicate a

TABLE 6
Effects of Protein Intake and WASH on Height and Weight

	Height		Weight	
	OLS (1)	CF (2)	OLS (3)	CF (4)
$\ln P_{it-1}$	.000737***	.00252	.00128***	.0179*
	(.000142)	(.00245)	(.000360)	(.0106)
upro		−.00180		−.00160
		(.00245)		(.0107)
$upro^2$		−.00000621		.000506**
		(.0000657)		(.000198)
$\ln S_{it-1}$	.00127***	.0345***	.00460***	.00994
	(.000399)	(.00963)	(.000867)	(.0305)
uwash		−.0332***		−.00528
		(.00961)		(.0306)
$uwash^2$		.00118		.000185
		(.00110)		(.00331)
$\ln P_{it-1} \times \ln S_{it-1}$	.000761***	.00124***	.00201***	.00375***
	(.000289)	(.000309)	(.000755)	(.00104)
$upro \times uwash$		−.00119*		−.00440**
		(.000658)		(.00191)
$\ln P_{it-1} \times \ln H_{it-1}$	.00413***	.00401***		
	(.00106)	(.00129)		
$\ln S_{it-1} \times \ln H_{it-1}$	−.0107**	−.0131***		
	(.00431)	(.00440)		
$\ln P_{it-1} \times \ln W_{it-1}$			−.000843	−.00253
			(.00175)	(.00222)
$\ln W_{it-1} \times \ln S_{it-1}$			−.0202**	−.0223**
			(.00860)	(.00912)
$\ln H_{it-1}$	.781***	.768***	.187***	.182***
	(.00637)	(.00762)	(.0138)	(.0163)
$\ln W_{it-1}$	.0542***	.0554***	.852***	.853***
	(.00147)	(.00144)	(.00767)	(.00766)
Observations	21,870	21,870	21,884	21,884
Adjusted R^2	.951	.951	.920	.920
Marginal product protein		.0027*		.0184*
Marginal product WASH		.0346**		.0104
F-statistic protein		21.59		19.64
F-statistic WASH		15.51		17.01

Note.—Estimated based on child-level regression, col. 1 by using eq. (8), col. (2) by using eq. (A13), col. 3 by using eq. (13), and col. 4 by using eq. (A14). Instruments included are those shown in table 5. Additional controls included in all regressions are municipality dummies, interview month dummies, census population, an urban/rural dummy, child gender, cubic in child age, birth weight, whether child is breast-fed, mother's height, wealth quintile, household income per capita, age and education of the household head, mother's age and education, and controls for the distribution of ages within the household. Standard errors (in parentheses) are clustered at the community level. Marginal product for protein (WASH) calculated at the 50th percentile of the WASH (protein) distribution. CF = control function.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

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 a better WASH environment.

When we correct for endogeneity of the investments by using the control functions, we obtain coefficients that are larger in magnitude for protein intake, log WASH, and the interaction between log WASH and log previous protein intake, though that for log WASH is not statistically significantly different from zero while the other two are. The overall marginal product for WASH (and protein) is positive and statistically significant when evaluated at the median of the protein (WASH) distribution. The quadratic of the control function for protein and the interaction between the two control functions are statistically significantly different from zero, indicating that protein intake and the interaction were endogenous. Moreover, the negative coefficient on the control function for protein and the positive coefficient for the quadratic term indicate that parents compensate for adverse shocks. 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 environments 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 6 months to 24 months increases the average child's weight at 24 months by 1.44 kg. Moreover, the additional egg a day increases the child's weight by 1.11 kg for children in the 10th percentile of the WASH score distribution, compared with 1.60 kg for children in the 90th percentile of the WASH score distribution.

B. Main Specification: Alternative Nutrition Measures

We also study the effects of calories and of other macronutrients, specifically carbohydrates and fats. The results of these estimations are shown in tables B.5–B.7 and are all broadly consistent with the findings for protein. In the estimation using calories, we see that while the coefficient on calories itself is statistically insignificant in the specifications for both height and weight, there is a strong positive interaction between WASH and calorie intake in all specifications. Thus, the overall marginal products for both calories and WASH (evaluated at the median for the other input) are positive and statistically significant. For carbohydrates and fat, we find a positive and statistically significant interaction term between nutrition and WASH, leading to a positive and statistically significant marginal product for both fat and WASH inputs (when evaluated at the median for the other input). However, the exogenous instruments are not always very strong as evidenced from the F-statistics. Nonetheless, it is clear that, for most choices of nutritional input, there is consistent evidence of complementarity between nutrition and WASH.

C. Robustness Checks

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

1. Sensitivity of Findings to the Set of Exogenous Instruments

We assess the sensitivity of our control function estimates to the set of exogenous instruments we use in the first-stage estimation. To do so, we undertake an exercise similar in spirit to that of Puentes et al. (2016). In particular, we estimate control function estimates for all possible sets of exogenous instruments containing (1) the price of C4 rice and its lag; (2) the price of an antipolo toilet inside the house; and (3) for prices of food and kerosene, both the contemporaneous price and its lag. This leaves us with 2,048 sets of instruments. We then assess the distributions of the coefficients for $\ln P_{it-1}$, $\ln S_{it-1}$, and $\ln P_{it-1} \times \ln S_{it-1}$, focusing on sets for which the Hansen J p-value > .05 (i.e., the overidentification test is not rejected) and the Cragg-Donald (CD) statistic > 1, 3, and 5 (i.e., fewer concerns about weak identification).

Tables 7 and 8 display the 25th, 50th, and 75th percentiles of the coefficient distributions for the three coefficients of interest for the sets of instruments satisfying the Hansen J overidentification test and with CD > 1, 3, and 5. Reassuringly, we find that our main conclusions still hold: the medians of the coefficient distributions for protein, WASH, and the interaction term have the same sign and similar magnitudes as the coefficients reported in table 6. Thus our results are robust to varying the set of exogenous instruments.

2. Alternative Formulations of the WASH Score

We assess robustness of the findings to 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), though the latter problem is mitigated as we have both time-invariant and time-variant instruments.

We experiment with two alternative definitions: one that includes only variables measured 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 B.8 and B.9 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 weight. However, reassuringly, the coefficient on the interaction term remains positive and statistically significantly different

TABLE 7
VARYING SETS OF INSTRUMENTS: HEIGHT

Criterion	Observations (1)	25th Percentile (2)	50th Percentile (3)	75th Percentile (4)	Sig. < 0% (of No. < 0) (5)	Sig. > 0% (of No. > 0) (6)
Coefficient ln P_{it-1}:						
Hansen J $p>.05$	1,469	−.0047	.00009	.0047	11.5 (730)	16.78 (739)
Hansen J $p>.05$ and CD > 1	1,406	−.0044	.0005	.0048	10.1 (683)	17.01 (723)
Hansen J $p>.05$ and CD > 3	569	−.0011	.003	.0046	3.66 (164)	6.17 (405)
Hansen J $p>.05$ and CD > 5	20	.003	.0043	.0055	0 (4)	6.25 (16)
Coefficient ln S_{it-1}:						
Hansen J $p>.05$	1,469	.0366	.0492	.0613	0 (0)	99.86 (1,469)
Hansen J $p>.05$ and CD > 1	1,406	.0364	.0472	.0608	0 (0)	100 (1,406)
Hansen J $p>.05$ and CD > 3	569	.0366	.0403	.0566	0 (0)	100 (569)
Hansen J $p>.05$ and CD > 5	20	.0433	.0461	.0471	0 (0)	100 (20)
Coefficient ln $P_{it-1} \times \ln S_{it-1}$:						
Hansen J $p>.05$	1,469	.00119	.00121	.00122	0 (0)	100 (1,469)
Hansen J $p>.05$ and CD > 1	1,406	.0012	.00121	.00122	0 (0)	100 (1,406)
Hansen J $p>.05$ and CD > 3	569	.0012	.00122	.00123	0 (0)	100 (569)
Hansen J $p>.05$ and CD > 5	20	.00121	.00122	.00123	0 (0)	100 (20)

Note.—Columns 1–4 report respectively the sample size and 25th, 50th, and 75th percentiles of the coefficient distribution for control function estimates from all sets of instruments satisfying the criterion described in the "Criterion" column. Columns 5 and 6 report the proportion of coefficients that are statistically significant at the 5% level among those that are positive (col. 1) or negative (col. 2).

TABLE 8

VARYING SETS OF INSTRUMENTS: WEIGHT

Criterion	Observations (1)	25th Percentile (2)	50th Percentile (3)	75th Percentile (4)	Sig. < 0% (of No. < 0) (5)	Sig. > 0% (of No. > 0) (6)
Coefficient ln P_{it-1}:						
Hansen J $p > .05$	1,589	.0026	.0187	.0315	5.77 (364)	51.51 (1,225)
Hansen J $p > .05$ and CD > 1	1,509	.007	.0196	.0322	2.34 (2.99)	52.15 (1,210)
Hansen J $p > .05$ and CD > 3	572	.0098	.018	.0241	0 (93)	40.92 (479)
Hansen J $p > .05$ and CD > 5	9	−.0028	.0174	.0281	0 (3)	66.67 (6)
Coefficient ln S_{it-1}:						
Hansen J $p > .05$	1,589	−.0069	.0157	.0338	0 (523)	3.93 (1,066)
Hansen J $p > .05$ and CD > 1	1,509	−.0081	.0127	.031	0 (523)	2.63 (986)
Hansen J $p > .05$ and CD > 3	572	−.0017	.0159	.0299	0 (156)	.24 (416)
Hansen J $p > .05$ and CD > 5	9	.0155	.0217	.0298	0 (2)	0 (7)
Coefficient ln $P_{it-1} \times \ln S_{it-1}$:						
Hansen J $p > .05$	1,589	.0052	.00526	.0053	0 (0)	100 (1,589)
Hansen J $p > .05$ and CD > 1	1,509	.00522	.00526	.0053	0 (0)	100 (1,509)
Hansen J $p > .05$ and CD > 3	572	.00521	.00524	.00528	0 (0)	100 (572)
Hansen J $p > .05$ and CD > 5	9	.00522	.00524	.00526	0 (0)	100 (9)

Note.—Columns 1–4 report respectively the sample size and 25th, 50th, and 75th percentiles of the coefficient distribution for control function estimates from all sets of instruments satisfying the criterion described in the "Criterion" column. Columns 5 and 6 report the proportion of coefficients that are statistically significant at the 5% level among those that are positive (col. 1) or negative (col. 2).

from zero. 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. While 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 appendix B.8. The inclusion of additional controls reduces precision. However, we continue to detect a robust complementarity between protein intake and WASH, so our conclusions still hold.

In summary, the positive interaction between protein intake and WASH remains remarkably robust across the robustness checks conducted.

V. Conclusion

It is well established that development in early childhood can increase well-being 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 5 years of age living in low- and middle-income countries are at risk of suboptimal development and not achieving their potential (*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. While 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 6 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. Thus, our findings provide motivation for interventions targeting both nutrition and WASH investments.

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.

Appendix A

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

$$H_{it} = H_t\left[\{N_{is}\}_{s=1}^{t-1}, \{S_{is}\}_{s=1}^{t-1}, \mu_i; X, \{\varepsilon_{is}\}_{s=1}^{t-1}\right] \tag{A1}$$

and

$$W_{it} = W_t\left[\{N_{is}\}_{s=1}^{t-1}, \{S_{is}\}_{s=1}^{t-1}, \mu_i; X, \{\varepsilon_{is}\}_{s=1}^{t-1}\right]. \tag{A2}$$

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 by 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

$$H_{it} = \left[\alpha_0^h \prod_s^{t-1} N_{is}^{\alpha_s^h} \prod_s^{t-1} S_{is}^{\beta_s^h} \prod_s^{t-1} N_{is}^{Y_1} \prod_s^{t-1} S_{is}^{Y_2}\right] e^{(\delta_t^h \mathbf{X} + \sigma_t^h \mu_{i0} + \varepsilon_{it})} \tag{A3}$$

and

$$W_{it} = \left[\alpha_0^w \prod_s^{t-1} N_{is}^{\alpha_s^w} \prod_s^{t-1} S_{is}^{\beta_s^w} \prod_s^{t-1} N_{is}^{Y_3} \prod_s^{t-1} S_{is}^{Y_4}\right] e^{(\delta_t^w \mathbf{X} + \sigma_t^w \mu_{i0} + \varepsilon_{it})}, \tag{A4}$$

where

$$Y_1 = \frac{1}{2}\left(\sum_r^{t-1}\gamma_{Nrs}^{\nu^h}\ln N_{ri} + \sum_r^{t-1}\gamma_{Nrs}^{h}\ln S_{ri}\right),$$

$$Y_2 = \frac{1}{2}\left(\sum_r^{t-1}\gamma_{Srs}^{h}\ln N_{ri} + \sum_r^{t-1}\gamma_{Srs}^{\nu^h}\ln S_{ri}\right),$$

$$Y_3 = \frac{1}{2}\left(\sum_r^{t-1}\gamma_{Nrs}^{\nu^w}\ln N_{ri} + \sum_r^{t-1}\gamma_{Nrs}^{w}\ln S_{ri}\right),$$

$$Y_4 = \frac{1}{2}\left(\sum_r^{t-1}\gamma_{Srs}^{w}\ln N_{ri} + \sum_r^{t-1}\gamma_{Srs}^{\nu^w}\ln S_{ri}\right).$$

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):

$$\ln H_{it} = \alpha_0^h + \sigma_t^h\mu_{i0} + \delta_t^h X_{it} + \sum_{s=1}^{t-1}\alpha_s^h \ln N_{is} + \sum_{s=1}^{t-1}\beta_s^h \ln S_{is} + \frac{1}{2}\sum_{s=1}^{t-1}\sum_{r=1}^{t-1}(\gamma_{Nrs}^{\nu^h}\ln N_{ir}\times\ln N_{is})$$
$$+ \frac{1}{2}\sum_{s=1}^{t-1}\sum_{r=1}^{t-1}(\gamma_{Srs}^{\nu^h}\ln S_{ir}\times\ln S_{is}) + \frac{1}{2}\sum_{s=1}^{t-1}\sum_{r=1}^{t-1}(\gamma_{Nrs}^{h}+\gamma_{Srs}^{h})\ln N_{ir}\times\ln S_{is} + \varepsilon_{it}^h$$

and

$$\ln W_{it} = \alpha_0^w + \sigma_t^w\mu_{i0} + \delta_t^w X_{it} + \sum_{s=1}^{t-1}\alpha_s^w \ln N_{is} + \sum_{s=1}^{t-1}\beta_s^w \ln S_{is} + \frac{1}{2}\sum_{s=1}^{t-1}\sum_{r=1}^{t-1}(\gamma_{Nrs}^{\nu^w}\ln N_{ir}\times\ln N_{is})$$
$$+ \frac{1}{2}\sum_{s=1}^{t-1}\sum_{r=1}^{t-1}(\gamma_{Srs}^{\nu^w}\ln S_{ir}\times\ln S_{is}) + \frac{1}{2}\sum_{s=1}^{t-1}\sum_{r=1}^{t-1}(\gamma_{Nrs}^{w}+\gamma_{Srs}^{w})\ln N_{ir}\times\ln S_{is} + \varepsilon_{it}^w.$$

Assumption A1. 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 A1a 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 A1a 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_{Njs}^{h} and γ_{Sjs}^{h} cannot be separately identified). Applying Assumption A1a implies the following for height (eq. [A5]) and weight (eq. [A6]):

$$\ln H_{it} = \alpha_0^h + \sum_s^{t-1}\alpha_s^h\ln N_{is} + \sum_s^{t-1}\beta_s^h\ln S_{is} + \sum_s^{t-1}\sum_r^{t-1}\gamma_{sr}^h\ln N_{is}\ln S_{ir} + \sigma_t^h\mu_0 + \delta_t^h\boldsymbol{X} + \varepsilon_{it}^h; \tag{A5}$$

$$\ln W_{it} = \alpha_0^w + \sum_s^{t-1}\alpha_s^w\ln N_{is} + \sum_s^{t-1}\beta_s^w\ln S_{is} + \sum_s^{t-1}\sum_r^{t-1}\gamma_{sr}^w\ln N_{is}\ln S_{ir} + \sigma_t^w\mu_0 + \delta_t^w\boldsymbol{X} + \varepsilon_{it}^w. \tag{A6}$$

Assumption A1b 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:

$$\ln H_{it} = \alpha_0^h + \sum_s^{t-1} \alpha_s^h \ln N_{is} + \sum_s^{t-1} \beta_s^h \ln S_{is} + \sum_s^{t-1} \gamma_s^h \ln N_{is} \ln S_{is} + \sigma_t^h \mu_0 + \delta_t^h \boldsymbol{X} + \varepsilon_t; \quad \text{(A7)}$$

$$\ln W_{it} = \alpha_0^w + \sum_s^{t-1} \alpha_s^w \ln N_{is} + \sum_s^{t-1} \beta_s^w \ln S_{is} + \sum_s^{t-1} \gamma_s^w \ln N_{is} \ln S_{is} + \sigma_t^w \mu_0 + \delta_t^h \boldsymbol{X} + \varepsilon_t. \quad \text{(A8)}$$

Assumption A2. For $m \in \{h, w\}$: $\alpha^m = \alpha_s^m = \lambda \alpha_{s-1}^m$; $\beta^m = \beta_s^m = \lambda \beta_{s-1}^m$; $\gamma_{SN}^m = \gamma_s^m = \lambda \gamma_{s-1}^m$; $\sigma^m = \sigma_s^m = \lambda \sigma_{s-1}^m$.

Assumption A2 is common to the value-added literature. First, taking the first difference between height in period t and $t-1$, we obtain the following:

$$\begin{aligned}\Delta \ln H_{it} = {} & \alpha_{t-1}^h \ln N_{it-1} + \beta_{t-1}^h \ln S_{t-1} + \gamma_{t-1}^h \ln N_{it-1} \ln S_{it-1} + \sum_s^{t-2} (\alpha_s^h - \alpha_{s-1}^h) \ln N_{is} \\ & + \sum_s^{t-2} (\beta_s^h - \beta_{s-1}^h) \ln S_{is} + \sum_s^{t-2} (\gamma_s^h - \gamma_{s-1}^h) \ln N_{is} \ln S_{is} + (\sigma_t^h - \sigma_{t-1}^h) \mu_0 \\ & + (\delta_t^h - \delta_{t-1}^h) \boldsymbol{X} + \varepsilon_{it}^h - \varepsilon_{it-1}^h.\end{aligned}$$

We then apply assumption A2:

$$\begin{aligned}\Delta \ln H_t = {} & \alpha_{t-1}^h \ln N_{it-1} + \beta_{t-1}^h \ln S_{t-1} + \gamma_{t-1}^h \ln N_{it-1} \ln S_{it-1} + (\lambda - 1) \sum_s^{t-2} \alpha_{s-1}^h \ln N_{is} \\ & + (\lambda - 1) \sum_s^{t-2} \beta_{s-1}^h \ln S_{is} + (\lambda - 1) \sum_s^{t-2} \gamma_{s-1}^h \ln N_{is} \ln S_{is} + (\lambda - 1) \sigma_{t-1}^h \mu_0 \\ & + (\delta_t^h - \delta_{t-1}^h) \boldsymbol{X} + \varepsilon_{it}^h - \varepsilon_{it-1}^h. \end{aligned} \quad \text{(A9)}$$

The same procedure for weight yields the following:

$$\begin{aligned}\Delta \ln W_{it} = {} & \alpha_{t-1}^w \ln N_{it-1} + \beta_{it-1}^w \ln S_{t-1} + \gamma_{t-1}^w \ln N_{it-1} \ln S_{it-1} + (\lambda - 1) \sum_s^{t-2} \alpha_{s-1}^w \ln N_{is} \\ & + (\lambda - 1) \sum_s^{t-2} \beta_{s-1}^w \ln S_{is} + (\lambda - 1) \sum_s^{t-2} \gamma_{s-1}^w \ln N_{is} \ln S_{is} + (\lambda - 1) \sigma_{t-1}^w \mu_{i0} \\ & + (\delta_t^w - \delta_{t-1}^w) \boldsymbol{X} + \varepsilon_t^w - \varepsilon_{t-1}^w. \end{aligned} \quad \text{(A10)}$$

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

Assumption A3. $\alpha^h = a\alpha^w$, $\beta^h = a\beta^w$, $\gamma^h = a\gamma^w$, 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 (A5) and (A6) gives us

$$\begin{aligned}\ln H_{it-1} - \ln W_{it-1} = {} & \alpha_0^h - \alpha_0^w + \sum_s^{t-2} (\alpha_s^h - \alpha_s^w) \ln N_{is} + \sum_s^{t-2} (\beta_s^h - \beta_s^w) \ln S_{is} \\ & + \sum_s^{t-2} (\gamma_s^h - \gamma_s^w) \ln N_{is} \ln S_{is} + (\sigma_{t-1}^h - \sigma_{t-1}^w) \mu_{i0} + (\delta_{t-1}^h - \delta_{t-1}^w) \boldsymbol{X} \\ & + \varepsilon_{it-1}^h - \varepsilon_{it-1}^w.\end{aligned}$$

Applying assumption A3 to this expression simplifies it to

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

We can then substitute the term in the square brackets in the above equation into equation (A9) to obtain the estimation equation:

$$\begin{aligned}\ln H_{it} &= \frac{\alpha^h - \alpha^w}{1-a} + \alpha^h \ln N_{it-1} + \beta^h \ln S_{it-1} + \gamma_{SN}^h \ln N_{it-1}\ln S_{it-1} + \frac{a+\lambda-2}{a-1}\ln H_{it-1} \\ &\quad - \frac{\lambda-1}{a-1}\ln W_{it-1} + \left(\delta_t^h - \delta_{t-1}^h\frac{a}{a-1} + \frac{\delta_{t-1}^w}{a-1}\right)\boldsymbol{X} + \varepsilon_t^h - \varepsilon_{t-1}^h + \frac{\varepsilon_{t-1}^h - \varepsilon_{t-1}^w}{1-a}.\end{aligned} \tag{A11}$$

The exact same logic can be applied for the weight equation. First, taking the difference between equations (A6) and (A5) and applying assumption A3 gives us the following:

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

Substituting the square term into equation (A10) gives us the equivalent equation for weight:

$$\begin{aligned}\ln W_{it} &= \frac{\alpha^w - \alpha^h}{1-a} + \alpha^h \ln N_{it-1} + \beta^h \ln S_{it-1} + \gamma_{SN}^h \ln N_{it-1}\ln S_{it-1} + \frac{\lambda-a}{1-a}\ln W_{it-1} \\ &\quad - \frac{\lambda-1}{1-a}\ln W_{it-1} + \left(\delta_t^h - \delta_{t-1}^h\frac{a}{1-a} + \frac{\delta_{t-1}^w}{1-a}\right)\boldsymbol{X} + \varepsilon_t^h - \varepsilon_{t-1}^h + \frac{\varepsilon_{t-1}^w - \varepsilon_{t-1}^h}{1-a}.\end{aligned} \tag{A12}$$

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:

$$\begin{aligned}\ln W_{it} &= \alpha_0^w + \alpha_1^w \ln N_{it-1} + \beta_1^w \ln S_{it-1} + \alpha_2^w \ln W_{it-1} + \gamma_{SN}^w \ln S_{it-1}\ln N_{it-1} \\ &\quad + \gamma_{SW}\ln S_{it-1}\ln W_{it-1} + \gamma_{NW}\ln W_{it-1}\ln N_{it-1} + \tau^w \ln H_{it_1} + \delta_t^w\boldsymbol{X} + \varepsilon_{it}^w.\end{aligned} \tag{A13}$$

When we correct for endogeneity by using the control function method, we include the control functions *upro*, *uwash*, and the quadratic terms and *upro* × *uwash* as additional regressions in equation (A13). Our second-stage estimation equation for weight is thus

$$\begin{aligned}\ln W_{it} &= \alpha_0^w + \alpha_1^w \ln N_{it-1} + \beta_1^w \ln S_{it-1} + \alpha_2^w \ln W_{it-1} + \gamma_{SN}^w \ln S_{it-1}\ln N_{it-1} \\ &\quad + \gamma_{SW}\ln S_{it-1}\ln W_{it-1} + \gamma_{NW}\ln W_{it-1}\ln N_{it-1} + \tau^w \ln H_{it_1} + \delta_t^w\boldsymbol{X} + upro \\ &\quad + upro^2 + uwash + uwash^2 + upro \times uwash + \varepsilon_{it}^w.\end{aligned} \tag{A14}$$

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