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The Dynamics of Nutrition and Child Health Stocks

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Keywords: Child health, Health production, Height-for-Age, Weight-for-Age, Dynamic Panel Regression, GMM.

JEL: I12, O12, D91

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1 Introduction

The dynamic interaction between health stocks and nutrition flows is key to child health. Despite Grossman's seminal work (1972) who first modeled health and the demand for health dynamically, most of the empirical literature dealing with child nutrition in developing countries has been confined to static models. This is surprising, given that a child's long term health stock – usually measured by height-for-age Z-scores (HAZ)– is dynamically linked to short term nutritional status – usually measured as the weight-for-age Z-score (WAZ) – which is subject to substantial fluctuation in response to transitory shocks such as spells of illness.

While common sense leads parents and doctors to establish a connection between child weight and child height over time, the economics literature has so far only considered them independently. The basic purpose of this paper is to study the dynamics of the link between child weight and child height (and thus between WAZ and HAZ), as motivated by a simple household model of intertemporal optimization in terms of nutritional inputs. In order to test the model's predictions empirically we need to follow children over time. For most developing countries it is impossible to carry out this analysis given the dearth of child panel data.[1] We investigate this relationship using a unique Senegalese panel dataset that follows 305 children between age 0 and 5 biannually over a period of 2 years.

This paper ultimatley contributes to a deeper understanding of both WAZ and HAZ, which are among the most widely used measures of child and household welfare in development economics (e.g. Deaton, 2007 or Strauss and Thomas, 1998). In particular, these variables are used in the assessment of development programs, as they provide a precise metric that is seen as being common across geographic areas and time periods. Duflo (2003), for example, studies the impact of a cash transfer program in South Africa on children's WAZ and HAZ. Behrman and Hoddinott (2005) consider HAZ to analyze the impact of the Mexican PROGRESA program on child nutrition. Arcand and Bassole (2007) take both indicators and the dataset used in this paper to assess the impact of the Senegalese PNIR rural infrastructure program.

A resulting question is whether understanding the HAZ-WAZ link contributes anything to the manner in which policy interventions that are geared towards economic development and the improvement of child health should be viewed. Estimates in this paper point out that a single-period development intervention that aims at improving child health may have a relatively high snapshot impact but no sustainable effect. This view is supported

[1] For example, the widely-used DHS or MICS datasets, which include the most commonly used anthropometric indicators, are confined to repeated cross-sections and do not follow children over time.

by nutritionists who noted that randomized trials of the impact of, for instance, food complements on nutrition status and growth are mixed. Reviews of nutritional supplement programs in 14 countries (Allen and Gillespie, 2001 or Dewey, 2001) reveal that weight and height were only increased in three trials and in two others merely weight was increased. Most studies identify a critical period for children between 6 and 12 months, while program returns are substantially diminishing after the age of 1 year. Furthermore, long-term effects of infant malnutrition are persistent, so that no intervention helped children reach expected and healthy growth paths.

The remainder of the paper is structured as follows: in Section 2 we present an overlapping generations model of child health. Section 3 lays out the empirical model. We adopt difference GMM (Arellano and Bond, 1991) and system GMM (Arellano and Bover, 1995) estimators which control for time-invariant child-specific unobservables in order to estimate a dynamic child health production function. The dataset and the context are presented in Section 4. The data were collected in Senegal as part of a World Bank-funded rural infrastructure program. In Section 5 we present our results, which are robust to different GMM specifications. Section 6 discusses results with a simulation of the long run impact of a nutrition shock and concludes.

2 An overlapping generations model of child health

The overlapping generations model we present extends the skill formation technology discussed in Cunha and Heckman (2007) to child health. The two basic ideas are the following. First, the health production function displays *self-productivity*. A higher stock of child health in period $t-1$ raises the stock in period t. In other words, child health acquired in one period persists into future periods. The second feature is *dynamic complementarity*.[2] Child health produced in period $t-1$ increases the productivity of nutritional inputs in period t and all subsequent periods. The model allows one to establish an optimal relationship between nutritional inputs in early childhood and nutritional inputs in subsequent periods. For early investment in child health to be productive continuous re-investment is required.

Dynamic complementarity and self-productivity have consequences for the design of nutritional programs. First, they imply that investments in child health in early childhood increase the returns to child health programs in later years. Second, they explain why short term interventions, say nutritional supplements for newborns, have little lasting

[2]See Behrman (2000) for a discussion of synergies or complements in health production functions with respect to various inputs such as health stocks, nutrition and education.

impact. Continuous reinvestment in child health is needed to maintain their impact. Third, the model shows why a lack of nutritional inputs in early childhood cannot easily be offset in later periods of a child's life.

In what follows we solve a simple overlapping generations model that features dynamic complementarity and self-productivity in child health production. We assume that an individual lives for $2T$ periods. The first T years cover childhood, while years $T+1$ to $2T$ correspond to adulthood. At age $2T$ the individual dies. Thus, at each point in time two generations are alive. Cohorts across and within generations are equally sized. Each year $t \in \{1, 2, ..., 2T\}$ an equal number of individuals of each age is alive.

Parents have common preferences. Each household consists of one adult parent and one child. Parental labor is supplied inelastically. Parental investment in child nutrition is motivated by altruism. During childhood, children receive a nutritional input denoted by N_t. The nutritional input N_t is the investment in the stock of long term child health, denoted by H_t. This investment is fully controlled by the parent. Adults do not receive nutritional inputs as their growth process is assumed to be over and their level of physical and intellectual development is taken as given. In order to keep as flexible a dynamic process as possible while allowing for empirical tractability, we write the evolution of child health as a first-order difference equation in H, which is allowed to be a function of past health inputs:

$$H_{t+1} = H_{t+1}(X, H_t, N_{t+1}, N_t, N_{t-1,...}), \tag{1}$$

where X denotes time-fixed parental and child characteristics. We specify the model for a broad class of standard production functions that exhibit increasing returns to all their inputs, yet at a diminishing rate. Thus, the production technology of child health is a strictly increasing and concave function in N_{t+1}, and twice continuously differentiable in all arguments. It follows that contemporaneous dynamic complementarity is obtained when:

$$\frac{\partial^2 H_{t+1}(X, H_t, N_{t+1}, N_t, N_{t-1,...})}{\partial H_t \partial N_{t+1}} > 0;$$

the health stock accumulated at time t makes contemporaneous investments in health (at time $t+1$) more productive. In addition, self-productivity arises as

$$\frac{\partial H_{t+1}(X, H_t, N_{t+1}, N_t, N_{t-1,...})}{\partial H_t} > 0.$$

In other words, a higher stock of child health in period t leads to a higher stock in period $t+1$. The combined effect of self-productivity and dynamic complementarity implies that nutrition is more productive for disadvantaged babies at an early rather than at a later stage of their infancy.

Another feature of the production technology is that it can also account for particularly sensitive periods of early child development. For example, child health is more sensitive to nutritional inputs in period t^* than in period t if $\partial H_{t^*}/\partial N_{t^*} > \partial H_t/\partial N_t$.

In order to solve the model and to obtain a closed form solution, we assume that childhood takes three years and $T = 2$. Adult health stock is $H_2 = H_2(X, H_1, N_1, N_2)$. Further we assume for clarity a constant elasticity of substitution health production technology that is separable in X and H_0 on the one hand, and contemporaneous health inputs N_1 and N_2, on the other:

$$H_2 = H_2\left(X, H_1, \theta\left(N_1, N_2\right)\right), \tag{2}$$

where:

$$\theta\left(N_1, N_2\right) = \left[\gamma N_1^{\phi} + (1-\gamma) N_2^{\phi}\right]^{\frac{1}{\phi}}. \tag{3}$$

The parameter $\gamma \in [0, 1]$ represents the nutritional input multiplier that characterizes the direct and the indirect productivity effects of each period's nutritional input. The degree of complementarity between nutritional inputs in periods 1 and 2 is $\phi \leq 1$. Expressed in terms of the elasticity of substitution $\frac{1}{1-\phi}$, it captures the extent to which one can substitute between nutritional inputs in the two periods. When ϕ is small, substitutability is small.

The CES technology includes two special cases. First, if one assumes that $\phi = 1$ and $\gamma = \frac{1}{2}$, the timing of nutritional inputs is irrelevant. In the extreme case, a child could starve as a newborn (in period 1) but be overfed in later years (period 2). Conditional on X and H_0, such a child would have the same health stock H_2 as a child that would have been overfed in infancy and starved later on. In such a case, the timing of nutritional inputs is irrelevant. Second, one can consider the Leontieff case of perfect complementarity in which $H_2 = \widetilde{H}_2\left(X, H_2, \min[N_1, N_2]\right)$. This specification implies that nutritional inputs should be equally spaced over childhood: $N_1 = N_2$, and no compensation between periods is possible.

Having defined the production technology of child health, we can calculate the optimal investment scheme. The solution to the parent's maximization problem is the following:

$$\left(c_0^*, c_1^*, c_2^*, N_1^*, N_2^*, \tilde{b}^*\right) = \underset{\left\{c_0, c_1, c_2, N_1, N_2, \tilde{b}\right\}}{\arg\max} \left\{ \begin{array}{c} u(c_0) + \beta u(c_1) + \beta^2 u(c_2) \\ +\beta^3 \delta H_2\left(X, H_1, \theta\left(N_1, N_2\right)\right) \end{array} \right\} \tag{4}$$

$$\text{s.t.} \quad c_0 + \frac{c_1 + N_1}{(1+r)} + \frac{c_2 + N_2}{(1+r)^2} + \frac{\tilde{b}}{(1+r)^3} = y + \frac{y}{(1+r)} + \frac{y}{(1+r)^2} + b$$

and equation (2) and (3),

where $u(.)$ is the single-period parental utility function, β denotes the discount factor and δ represents parental altruism towards the child, c_i $(i = 0, 1, 2)$ is parental consumption in the first three periods of the life cycle, r denotes the interest rate, y parental income, $\tilde{b}$ is the bequest that parents leave to their children and b is the bequest that the parental generation received from *their* parents. For $-\infty < \phi < 1$ the FOCs imply that:

$$\frac{N_1^*}{N_2^*} = \left[\frac{\gamma}{(1-\gamma)(1+r)} \right]^{\frac{1}{(1-\phi)}}. \tag{5}$$

For $\phi \to -\infty$, $N_1^* = N_2^*$: high complementarity means that high investment in period 1 leads to similar investment in period 2. Low complementarity means that the importance of self-productivity increases and nutritional investment should be higher in the early years of the child's life cycle.

Note that with perfect credit markets, the optimal nutrition ratio is not affected by parental income. For the sake of brevity we do not derive results imposing credit constraints here. However, it can be easily shown that imposing the restriction that parents are not allowed to leave debts to their children, $\tilde{b} \geq 0$, results in lower investment in nutritional inputs in periods 1 and 2, relative to the unconstrained case. This implies that for children growing up in families that are credit-constrained malnutrition starts early on and remains throughout childhood.

In addition, the model can also be extended to a situation where parents cannot borrow future income to finance consumption and nutrition in the first period of childhood.[3] If both, bequest and saving constraints hold and we assume a CRRA utility function, it can be shown that the timing of income will matter for the optimal nutrition ratio $\frac{N_1^*}{N_2^*}$. Put differently, unless late nutrition is a perfect substitute for early nutrition, the level of parental income during early childhood affects long term health in credit constrained families.

3 Estimating Child Health Production

We now test for (i) self-productivity of the child health stock and (ii) dynamic complementarity empirically by estimating a linear version of the health production function

[3] A similar problem is solved by Cunha and Heckman (2007).

given by equation (1). We assume that the autoregressive lag of H enters linearly and therefore linearize production technology as:

$$H_2 = \alpha\ H_1 + \gamma\ N_1 + (1-\gamma)\ N_2 + X. \tag{6}$$

This translates into the following empirical panel specification:

$$y_{it} = \alpha\ y_{it-1} + \beta_1\ n_{it} + \beta_2\ n_{it-1} + \gamma_1\ x_{it} + \gamma_2\ x_{it-1} + \eta_i + \lambda_t + \nu_{it}, \tag{7}$$

where y_{it} is a proxy for long term child health defined as height-for-age Z-score. Nutritional inputs and their lag are represented by n_{it} and n_{it-1}. They are proxied by the child's weight-for-age Z-score. Contemporaneous control variables are collected in x_{it} and their lags in x_{it-1}. Amongst the control variables we include the age of the child and its squared term, household size, and total expenditures. The individual fixed effect is η_i. This also allows us to control for all time-fixed parental characteristics that influence child health. The period fixed effect controlling for common shocks to all individual children in the same period is represented by λ_t. To test the dynamic complementarity suggested by the theoretical model, we further introduce an interaction term between contemporaneous investment and lagged health stocks: $y_{it-1}n_{it}$. It is captured by the interaction between weight-for-age and lagged height-for-age.

Our model predicts that the coefficient on the lagged health stock α is positive due to self-productivity. Dynamic complementarity should result in a positive coefficient on the interaction term. The estimate of β_1 reflects the marginal effect of contemporaneous nutrition and is also expected to be positive. As is common in dynamic panel models we also control for the lag of nutrition.

So far we have presented and discussed the linearized empirical counterparts of the theoretical model. We now address some of the identification problems associated with the empirical model. Explanatory variables may be correlated with the error term introducing endogeneity. For instance, weight-for-age and height-for-age are likely to be correlated with unobservables such as the child's metabolism, immune system or genetics. This implies that applying Ordinary Least Squares to the empirical model will result in biased estimates. To control for time invariant unobservables such as the genotype we first difference equation (7).[4]

Although we control for time invariant effects at the child level and above, a number

[4]For panels with a small number of time periods T, the transformation into deviations with respect to individual-specific means induces correlation between the transformed lagged dependent variable and the transformed disturbance term. A consistent estimator is obtained by first differencing all variables, Δy_{it}.

of time-varying unobserveables may be correlated both with long and short-term child health. Furthermore, reverse causality between health stocks and nutritional investments cannot be ruled out. Therefore, in addition to first differencing the variables we use lagged levels of the endogenous variables as instruments for their own current differences under the assumption that the disturbance term ν_{it} is serially uncorrelated and uncorrelated with the excluded instruments. This boils down to the standard first-differenced GMM estimator proposed by Arellano and Bond (1991).

Furthermore, as we do have additional time series information for some children we also consider an orthogonal deviations specification (Arellano and Bover, 1995) for the GMM estimation. This allows us to exploit our dataset even further, as the difference estimator is vulnerable to gaps, whereas the orthogonal deviations estimator averages over all the available information.

There is one more concern we have to deal with. Both the difference and the orthogonal deviations specification perform poorly when child health stocks are highly persistent, and past levels of height-for-age contain little information about future changes in the variable as these changes are white noise. In terms of the econometric specification this means that the first differences instrumented with past levels will not identify the coefficients. To circumvent this problem levels are instrumented with differences in a system GMM model following Arellano and Bover (1995). This implies that *in addition to* the moment condition of the first differenced equation a moment condition in levels can be exploited.

In the following analysis we present results for all three GMM specifications for robustness reasons. Moreover, we carry out both, the one-step feasible and the two-step efficient GMM estimation using the asymptotically efficient variance-covariance matrix.

4 Data

We have data on child anthropometrics from 7 Senegalese regions,[5] 35 rural communities, and 60 villages. The regions are all located in the North and North-West of the country, with the exception of Tambacounda which is in the North-East of the country. The sample covers only 50 % of Senegal's regions. However, it covers those with the highest population density in the country. The survey was conducted between January 2004 and June 2005. Within that time-span surveys were repeated on a biannual basis. Data were collected as part of the impact evaluation of the *Programme national d'infrastructures*

[5] Djourbel, Fatick, Kaolack, Louga, St. Louis, Tambacounda, Thies.

rurales ("National Rural Infrastructures Program", henceforth PNIR[6]) which is a decentralized rural development program initiated by the World Bank and IFAD.

As a consequence of the relatively short time-span of six months between consecutive survey rounds, we were able to follow young children over multiple periods. Our sample consists of 305 children. For each child we have at least three consecutive observations of height-for-age and weight-for-age. Roughly half our sample covers observations between January 2004 and January 2005, the remaining 50 % are observed between June 2004 and June 2005. The panel is balanced in the sense that half the children were first surveyed in the baseline survey and followed in the second and third survey round, whereas the second half was first surveyed in the second survey round and followed upon until the last survey. Sources of attrition are very limited and negligible. In fact those few children that do drop out are older than 5 years old at which age their anthropometric information was no longer collected.

Descriptive statistics are presented in Table 1. Each observation corresponds to a child between 0 and 5 years of age. The mean age averaged over the lags is 1.9 years (22.7 months). The maximum age is 4.7 years (56.3 months). As the relatively high standard deviation of 9 months indicates, there is substantial variation in the sample in terms of the age structure. The sample is gender balanced. Half of the children are girls, half are boys. The summary statistics per lag structure show the expected pattern. Average age in periods dating back further is lower than average age in the current period. Median household size is roughly 13 people throughout the three periods and the period averages are slightly above the median and fluctuate to a small degree. It is noteworthy that we have households as small as four people and others consisting of 29 members in our sample. Average total expenditures are 143,306 CFA in the last six months. Total expenditure show substantial variation across households but relatively limited variation over time.

As this paper focuses on the link between long-term health and health inputs, we briefly recapitulate the construction of the two commonly-used child health measures. The indicators are expressed in terms of Z-scores. The calculation of these Z-scores can be thought of in the following simplified way:

$$Z = \frac{V - M_r}{sd_r}, \tag{8}$$

where V is the observed value of either child weight or height, M_r refers to the median value of either of the two measures in a reference population and sd_r is the value of the

[6]For further information about the PNIR, see Arcand and Bassole (2007)

standard deviation in this reference population. The reference population chosen here is US children. Replacing V with the observed child weight, the Z-score for weight-for-age (WAZ) can be calculated. WAZ is a short-term measure of underweight and proxies nutritional intake. As WAZ varies in the short-run it can be considered a flow variable of health which results from transitory income and health shocks. Thus, WAZ indicates short term malnutrition. The Z-scores for height-for-age (HAZ) are calculated in the same way. HAZ is a measure of the long-term health status of children; it reflects the cummulative impact of transitory shocks over time. It is also known as stunting and represents the health stock.

As should be clear from equation (8) the metric for Z-scores is standard deviations. A child with a Z-score of zero has no deviation of its health status with respect to the reference population. Positive Z-scores indicate that children are better off than children in the reference population. Children with an index less than -2 standard deviations from the median of the reference population are said to have global underweight (malnutrition) when considering WAZ (HAZ). Severe underweight (malnutrition) arises for -3 standard deviations or less of the WAZ (HAZ). The advantage of using Z-scores is that they are standardized by age and gender and are thus comparable across different cohorts and regions.

The mean WAZ in our sample is -1.07. Although children are on average underweight, they are not severely malnourished. However, as for the other variables in the sample, the variation among individuals is substantial. 16.0 % of the sampled children suffer from global underweight, 3.9 % even show signs of severe underweight. The descriptive statistics by lag structure show that the average for the latest observations is the highest, suggesting that, over time, child malnutrition becomes less severe. The difference in means test rejects the null hypothesis of equal means at conventional significance levels. The mean HAZ of -1.46 shows an even worse picture for the health stock than for health inputs. The lag structure shows that on average children are better off in later periods. Again, the difference is significant at conventional significance levels. Standard deviations are also large relative to the mean. Global malnutrition is found for 18.9 % of the children, severe malnutrition for 15.7 %. Thus, about a third of the children in the sample are 'globally' stunted.

5 Empirical Results

Results for the impact of nutritional inputs on long-term child health as estimated in equation (7) are presented in Table 2. The difference specification is shown in Column (1) and (2), the sytem GMM results are presented in Column (3) and (4) and the orthogonal deviations method is employed for the results in Columns (5) and (6). Across empirical specifications results suggest a strong role for the self-productivity of child health stocks. The coefficient on the lag of the height-for-age Z-score is always large, positive and significant and ranges between 0.424 and 0.628. The importance of these magnitudes is discussed at the end of this paper with a small numerical example.

Across specifications we fail to reject the simple theoretical prediction that *ceteris paribus* children with a high initial health stock will be healthier in the future. With a value of 0.628 in the one-step difference specification and 0.544 in the two-step difference specification the coefficient on lag HAZ is biggest compared to the other econometric specifications. Due to the nature of our panel data and the results from the overidentification tests the difference estimates are the preferred ones. Despite the sizable impact of the lagged height-for-age Z-scores the underlying time series does not have a panel unit root as can be seen from the statistical tests at the bottom of Table 2. This also implies that the difference specification is correctly identified as past levels are informative in predicting future changes in HAZ and in identifying the model.[7]

Although the self-productivity of child health stocks is noteworthy, our results also underline that a sustainable health stock requires regular nutritional updating. The impact of contemporaneous nutrition is positive and significant across specifications. Most interestingly, the coefficient on nutrition is statistically comparable in magnitude to the one associated with self-productivity. As such we fail to reject the null hypothesis that the coefficients on lagged HAZ and contemporaneous WAZ add up to one (see tests at the bottom of Table 2).

These findings illustrate that contemporaneous child health stocks are determined by the combined level of past health stocks and contemporaneous investment. This highlights the importance of constant nutritional updating for children to build up a healthy constitution. In contrast to physical capital health capital is quickly depleted and needs period-by-period reinvestment. Another noteworthy feature of our empirical specification is the fact that the marginal effect of lagged WAZ is negative and statistically the coefficients on WAZ and lagged WAZ add up to zero in the preferred difference GMM

[7]In the difference specification we fail to reject overidentification according to the Sargan and the Hansen test, suggesting that the model is properly identified. Conversely, the Hansen test statistic leads us to reject overidentification for the orthogonal deviations and system GMM models. In addition to the standard overidentification tests, the dynamic panel models also have two internal validation tests, the AR(1) and the AR(2) test in first differences. As the time series dimension in our dataset is limited, namely T=3, we can only test for the AR(1) in first differences. Reassuringly, we reject a unit root across all specifications. To check for the robustness of our results we also provide both one and two step estimation of the GMM models. The second column of each pair of results shows how the use of the efficient variance-covariance matrix affects coefficient size and significance relative to the feasible identity matrix. One and two step estimates are qualitatively similar in terms of size and significance levels.

specification. While this result is often found in dynamic panel applications, it can also be taken as evidence that parents smooth nutritional inputs around the steady state. This in turn indicates that excessive food supply in one period cannot be offset by subsequent malnourishment and vice versa.

In addition, there is evidence of dynamic complementarity, which is captured by the interaction term 'WAZ x Lag HAZ'. The positive and significant coefficient on the interaction term points to the reinforcing capacity of the lagged child health stock to utilize contemporaneous nutrition inputs. Indeed we fail to reject the theoretical prediction that a child that has been well fed in previous periods is likely to be in good health in later periods in our statistically preferred difference specification. Conversely, this implies that a child that was malnourished in previous periods drags on bad health into later periods regardless of contemporaneous nutrition. This impact of dynamic complementarity is not trivial, in our preferred difference specification presented in Columns (1) and (2) the lower bound of the coefficient is 0.128. Considering that our sample contains babies and infants between 0 and 5 years of age, the finding emphasizes the importance of accumulating a sufficient health stock during early infancy. Not only are contemporaneous nutritional investments more productive in previously well-nourished babies, but babies who had an adverse health shock in the past are in a bad position to assimilate nutrients.

In order to control for other observable characteristics that are not time-fixed we also included the child's age and its squared term, household size, total expenditure and period dummies. A child's age and the squared age have no significant impact in the difference GMM model. This is not surprising as HAZ and WAZ are already standardized by age. Neither do household size, nor total expenditure have any significant impact on child health as measured by HAZ and captured in this dynamic specification.

To address the sensitivity of our results we also tested for critical periods in child development as suggested by the theoretical model. However, in our sample we could not detect such periods in which nourishment has a greater impact than in others from a statistical point of view. For brevity results are not reported here.[8]

6 Discussion

This paper investigates the dynamics of child health using an overlapping generations model. The model highlights the role of (i) self-productivity of the health stock and (ii) the dynamic complementarity between the past health stock and contemporaneous nutri-

[8]Results are provided on request.

tion. Empirical tests of a linear version of the model's production technology on a panel of 305 Senegalese children fail to reject these two main predictions. Initially healthier children tend to be better off in the future in that existing health capital is carried on into the next period and impacts the effectiveness at which new nutritional inputs are transformed.

Using the estimates of this paper we can do a simple, but insightful simulation presented in Figure 1. The simulation underlines that only long-term nutrition or development programs can have a sustainable impact on child (and ultimately adult) health and create significant economic returns. Take for instance the impact of the rural development program PNIR in Senegal for which the data in this paper has been collected. The simulation is based on our coefficient estimates for WAZ and the lag of HAZ in Column (2) of Table 3 and the estimated treatment effects of PNIR are taken from Arcand and Bassole (2007).[9] Assume a 'hypothetical child' with initial HAZ and WAZ scores of zero. This hypothetical child's WAZ is boosted by 0.67 within a single six-month period due to PNIR projects in the village. Let us further assume that the program does no continue in subsequent periods and the child's WAZ score returns to zero after the one-time positive shock. Then, the effect of the program on the child's health stock (HAZ), although sizable initially, dies out after about 24 months. This admittedly rough calculation suggests that positive one-period nutrition shocks have no lasting impact on the long-run health stock of infants. Furthermore, these estimates also allow researchers to cross-check estimated treatment effects on HAZ and WAZ.[10]

Results in this paper also have important implications for the timing of nutrition programs in developing countries. In particular, long term returns to nutrition programs are higher if they reach babies early on and if they target children beyond the early months of infancy. Then, subsequent nutritional investments can reap dynamic complementarity effects.

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[9] For simplicity we fix all co-variates and insignificant variables to be zero.

[10] The simulation can be extended to take into account critical periods of child growth. Also dynamic complementarity can be illustrated with repeated WAZ shocks.

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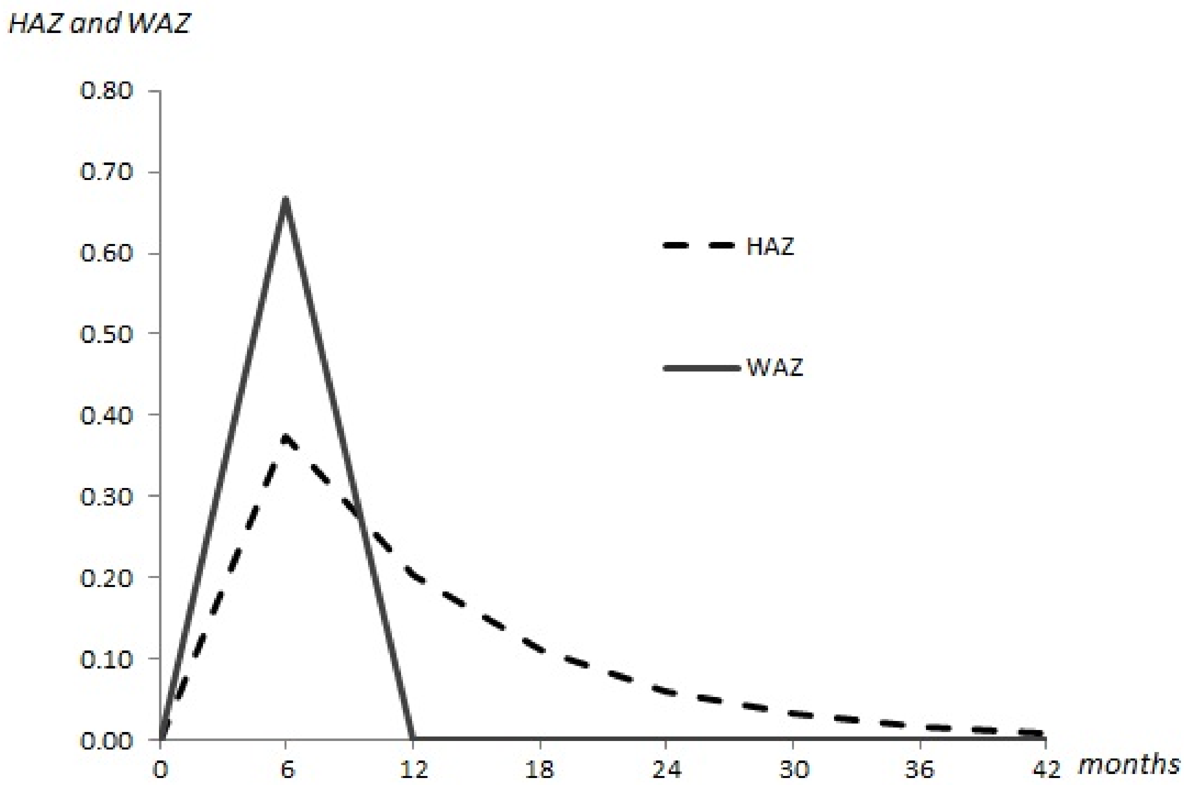

Figure 1: Simulation of the long term impact of the rural infrastructure program PNIR. The effect of PNIR's short term impact on nutrition (WAZ) on the child health stock (HAZ) is depicted. The average treatment effect on the treated of 0.67 on WAZ is taken from Arcand and Bassole (2007), coefficient estimates for the simulation are taken from Column (2) in Table 3.

Variable	Obs	Mean	Median	Std.	Min	Max
HAZ	305	-1.26	-1.36	1.37	-4.72	2.60
1st lag	305	-1.54	-1.52	1.44	-4.72	2.57
2nd lag	305	-1.58	-1.59	1.50	-4.75	2.73
WAZ	305	-0.95	-0.93	0.99	-3.31	1.88
1st lag	305	-1.16	-1.21	1.07	-4.15	2.22
2nd lag	305	-1.11	-1.19	1.29	-4.68	3.43
Age in months	305	28.26	27.76	9.16	11.60	56.34
1st lag	305	22.64	21.88	9.09	5.22	49.97
2nd lag	305	17.30	17.08	9.21	0.49	45.67
Gender dummy (Girl=1)	305	0.502				
1st period	305	0.502				
2nd period	305	0.498				
Household Size	305	13.574	13	5.679	4	29
1st period	305	13.413	13	5.577	4	29
2nd period	305	13.089	13	5.453	4	29
Total Expenditure in CFA	305	143,306.4	109,000	116,602.2	0	580,000
1st lag	304	133,826.4	95,505	118,633.8	1000	637,500
2nd lag	299	142,078.4	111,510.7	114,040.4	8	573,300

Table 1: Descriptive Statistics.

	(1)	(2)	(3)	(4)	(5)	(6)
	Difference GMM		System GMM		Orthogonal Deviations	
	1 step	2 step	1 step	2 step	1 step	2 step
Lag HAZ	0.628	0.544	0.427	0.485	0.424	0.488
	(0.166)	(0.146)	(0.123)	(0.132)	(0.123)	(0.137)
WAZ	0.438	0.562	0.759	0.778	0.759	0.786
	(0.245)	(0.225)	(0.142)	(0.153)	(0.140)	(0.154)
Lag WAZ	-0.409	-0.279	-0.190	-0.159	-0.182	-0.143
	(0.180)	(0.149)	(0.113)	(0.132)	(0.111)	(0.130)
WAZ*Lag HAZ	0.134	0.128	0.028	0.068	0.034	0.080
	(0.067)	(0.064)	(0.059)	(0.060)	(0.059)	(0.063)
Household Size	0.006	0.171	0.036	0.022	0.034	0.024
	(0.240)	(0.222)	(0.052)	(0.055)	(0.052)	(0.057)
Total Expenditure	-5.17e-7	-2.46e-6	-1.68e-6	-2.21e-6	-1.74e-6	-2.18e-6
	(2.22e-6)	(2.25e-6)	(1.37e-6)	(1.43e-6)	(1.38e-6)	(1.53e-6)
Age (in months)	-0.998	-0.665	0.034	0.039	0.037	0.042
	(0.985)	(0.895)	(0.017)	(0.018)	(0.017)	(0.018)
[Age (in months)]^2	0.001	0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Constant			-0.704	-0.395	-0.697	-0.467
			(0.693)	(0.712)	(0.687)	(0.729)
Observations	304	304	758	758	758	758
AR(1)-test in 1^{st} Δ	0.006	0.001	0.013	0.014	0.015	0.016
Hansen Test	0.575	0.575	0.000	0.000	0.000	0.000
Sargan Test	0.359	0.359	0.204	0.204	0.140	0.140
Tests						
Waz + Lag Waz = 0	0.930	0.306	0.007	0.009	0.005	0.006
Lag Haz = 1	0.026	0.002	0.000	0.000	0.000	0.000
Lag Haz + WAZ = 1	0.833	0.712	0.402	0.255	0.407	0.252

Table 2: GMM Results for Difference, System and Orthogonal Deviations GMM. For all specifications the one-step and the two-step estimators are presented. Robust standard errors are parentheses. All specifications include period dummies which are not shown here. For the tests at the bottom of the table p-values are presented.