PIER Working Paper
18-007

You Are What Your Parents Think: Height and Local Reference Points

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April 8, 2020
(First edition April 22, 2018)

https://ssrn.com/abstract=3167023
You are What Your Parents Think: Height and Local Reference Points

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Abstract

Recent estimates are that about 150 million children under five years of age are stunted, with significant long-run negative consequences on their schooling, cognitive skills, health and economic productivity. Understanding what determines such growth retardation, therefore, is very important. We build a structural model for nutritional choices and health with reference-dependent preferences. Parents care about the relative health of their child compared to some reference population. In our empirical model, we use height as the health outcome parents target, and reference height is an equilibrium object determined by parental nutritional choices for earlier cohorts in the same village. Taking advantage of a protein-supplementation experiment in Guatemala, we use exogenous variations in differential height growth paths between treated and control villages to estimate the model. We conduct a number of counterfactual policy simulations. First, we find that reference-point changes account for up to 60% of the 1.7cm in height difference between experimental and control villages at 24 months of age. Second, focusing on one-period effects, to obtain the same mean effects as an 1 cm increase in reference points would require a protein-price discount of 37 percent or an income increase of 60 percent. Third, endogenous reference-point changes lead to significant policy spillovers: under poor-targeted subsidy policies, richest households over time gain up to 50 percent of the height gains of poorest households; under an universal subsidy policy, poorest households’ height gains increase from an initially small change by up to 4.8 times across periods as richest households, who also receive subsidies, help push-up height reference points. JEL: I15, D8, D9, O15

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1 Introduction

Insufficient height and weight growth still affects many children around the globe. Estimates are that about 150 million (22 percent) of children under five years of age are stunted (FAO 2019). Studies suggest that these children are at risk of not developing their full potential in terms of schooling, cognitive skills, health, other dimensions of human capital and income (Behrman et al. 2009; Black et al. 2017; Hoddinott et al. 2008; Hoddinott, Behrman, et al. 2013; Hoddinott, Alderman, et al. 2013; Maluccio et al. 2009; Richter et al. 2017; Victora et al. 2008). Therefore, the long-run economic costs of early-life growth retardation appear considerable.

In general, anthropometric measures, such as height and weight, are partly determined by genes. But in many cases variability in anthropometrics due to race or ethnicity is negligible among children who are raised in favorable environments and born to mothers whose nutritional and health needs are met (see (Habicht et al. 1974) ). In contrast, environmental factors related to hygiene and sanitation, infections, maternal nutritional status, and protein intake are major determinants of growth in the first two years of life (Martorell and Zongrone 2012).

In this paper, we focus on another factor that could affect growth, which is parental perceptions. We write a model in which parents choose inputs of a health production function, but there are parental perceptions about what constitutes “normal” health outcomes, and these perceptions influence parental choices through reference-dependent utility. In our model, parents have adaptive expectations over uncertain reference-point distributions that shift dynamically given the health-input choices of parents for previous cohorts of children.

In our empirical application of the reference-point model for child health, we focus on how reference points might impact parental choices of a critical height determinant: the amount of protein in children’s diets. We focus on protein because it is an important input in the production of height (Victora et al. 2008; Puentes et al. 2016). Stunting rates are generally higher in locations in which families feed their young children with staple foods that have low protein density because of their availability or affordability (Dewey 2016). In these regions, policies

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1 Stunted children have height-for-age more than two standard deviations below the median for a well-nourished population. In 2018, 59 million (30 percent) of African children under five years of age were stunted and 82 million (23 percent) of Asian children (excluding Japan) were stunted (FAO 2019).

2 In the case of height, genes explain only 10% of the variability of adult height (Lango Allen et al. 2010; Berndt et al. 2013) for individuals of European ancestry in both cases.
that supplement food via lipid-based nutrient supplementation (e.g., Dewey (2016)) or that increase parental resources may improve infant outcomes (e.g., Groot et al. (2017)). However, it is important to recognize that stunting also occurs in locations in which animal-source foods are available and affordable (Penny et al. 2005). This finding suggests that factors other than family resources or prices of foods rich in protein play an important role in determining malnutrition in general and stunting in particular. Parental perceptions about what constitutes “normal” height could be one of the factors that influence parental feeding practices and thereby children’s growth.

Recent successful policies in the prevention of child stunting include actions to influence parental perceptions of normal growth. Marini, Rokx, and Gallagher (2017) provide a comprehensive description of how Peru successfully reduced stunting rates by 50 percent in the ten-year period between 2007 and 2016. In particular, it is important to emphasize two initiatives that may have contributed to shifting perceptions. First, the World Bank disseminated a video that communicated height standards that were easy to understand.3

Second, the government extended to the entire country the practices of the UNICEF “Good Start” Program.4 The government trained health professionals in local clinics so that they could assess, once a month, each child’s weight and height monthly and plot the information on growth charts.5,6 The health professionals used the visual information to inform parents about their children’s growth status and to inform parents about corrective actions if growth had not met targets. The Peruvian case, while illustrative of the forces studied in our paper, cannot be used to identify the importance of shifting parental and societal norms about “normal” growth because the country simultaneously implemented many different interventions.7

Evidence from Africa confirms the importance of parental perceptions in influencing feeding practices and reducing stunting rates. Fink et al. (2017) evaluate an intervention in which villages

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3 Video Link. Due to the perceived impact, the World Bank produced similar videos for other countries.

4 See Lechtig et al. (2009) for an evaluation of the UNICEF’s “Good Start” Program.

5 The UNICEF’s Good Start Program used a growth chart that was divided in two regions: red (indicating undernutrition) and green (indicating normal nutritional status). This simple visual chart contrasts with other growth charts that use percentile information that apparently are not easily understood by many parents (see evidence in Ben-Joseph, Steven A. Dowshen, and Izenberg (2009)) and use information on weights, not heights.

6 UNICEF and various ministries of health have advocated such growth monitoring for decades, but until recently there has been little systematic evidence of much if any effects of such efforts (e.g., Ruel and Habicht 1992).

7 See Marini, Rokx, and Gallagher (2017) and World Bank (2016) for a helpful summary of all of the programmatic actions that may have contributed to the reduction in stunting.
in rural Zambia were assigned to one of three mutually-exclusive groups: (1) a control group; (2) a community-meeting group; and (3) a growth-chart group. In the community meeting, children were measured for height and weight and parents received information about feeding practices that promoted healthy growth. Parents in the third group had a full-size growth chart installed in their home so that they could track children’s growth. The chart had a simple design (red if children were stunted for their ages, green if not)\(^8\) and contained information about how feeding practices could influence children’s healthy growth. The authors show that parents’ reports of protein intake increased in both intervention groups. However, stunting rates were reduced by 22 percentage points (from 94% to 72%) in the group of parents that received the growth charts, but not in the group with community meetings.

The evidence described above motivates the development of a model that incorporates parental perceptions of “normal” human capital whether health or skills. We write a model where parental preferences depend on the parents’ reference for health distribution in a way that is similar to Prospect Theory (Kahneman and Tversky 1979). We assume that parents believe that health in general, and height in particular, is normally distributed and that they estimate the mean and variance parameters by observing the heights of children from slightly older cohorts who reside in the same location. This assumption is consistent with evidence reported by research in medical and anthropological literatures that concludes that parents observe older siblings, other children in the family, or their friends’ children to infer what constitutes “normal” height and weight (see, e.g., Reifsnider, Allan, and Percy 2000; Lucas et al. 2007; Thompson, Adair, and Bentley 2014).\(^9\)

Reference-dependent preferences are consistent with data about parental behavior as documented in the health and anthropological literatures. Our parameterization of preferences introduces two distinct forces: asymmetry in responses and delay in action due to uncertainty about norms. Asymmetry in responses relates to the fact that parents who are concerned that their child may not reach the parents’ perceived height milestone by age 24 months will behave differently from parents of otherwise identical children who have lower perceptions about height milestones. This asymmetry is documented in the medical literature with respect to obesity and other dimensions of children’s health (May et al. 2007; Laraway et al. 2010; Mathieu, Drapeau, and

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\(^8\) See Marini, Rokx, and Gallagher (2017) for the design used in Peru and Fink et al. (2017) for the design used in Zambia. However, the Zambia chart also contained information about feeding practices.

\(^9\) Parents also report comparing children’s clothing to clothing recommended for their children’s ages.
Tremblay 2010; Moore, Harris, and Bradlyn 2012; Swyden et al. 2015; Almoosawi et al. 2016).

In our framework, parents are uncertain about health milestones at age 24 months. Because of uncertainty, parents may not seek help unless they perceive that their children are falling behind in many dimensions of development. Uncertainty coupled with biased reference means may lead parents to take too long to seek help (as reported, for example, in Ryan and Salisbury (2012) as well as Mulcahy and Savage (2016)). If there are critical or sensitive periods of development, delays in adjustment of parental behavior may cause permanent damages to children’s human-capital formation (Victora et al. 2008; Victora et al. 2010).

Parental uncertainty is captured by the reference health distribution that at each period \( y \) is an equilibrium object that is partially determined by the nutritional choices of parents of children born in period \( y - 1 \) in the same village (we assume each period to be 2 years). We assume that parents have adaptive expectations: parents of children born in period \( y \) observe the health of the children born in period \( y - 1 \) and estimate the reference health distribution parameters. Our adaptive expectation assumption is consistent with the results reported in Hansen et al. (2014) who showed that changes in development of children across cohorts affected parental perceptions of normal development as well as their reports about the developmental status of their own children.

We use data from The Institute of Central America and Panama (INCAP) nutritional trial to estimate the model described above for height. For this trial, there were four participant villages; two were randomly selected to receive a high-protein supplement, while the other two received a supplement devoid of proteins. In the data, we observe increasing height and nutritional input gaps between villages that experimentally received and did not receive protein-rich nutritional supplements. We estimate the model taking advantage of the exogenous variation in protein prices and reference points generated by the experimental design.

With our estimated model, we conduct three sets of counterfactuals. Our first counterfactual focuses on decomposing channels of impacts for the actual INCAP protein-supplementation experiment. Our second counterfactual focuses on the one-period effects of the model and what price and income changes would be required to have the same impact on child height as a given change in reference points. In our third set of counterfactuals, we exploit dynamic features of our model to distinguish among three possible effects of subsidy policies in an environment
with reference-dependent preferences for height: (1) the direct impact of subsidies on treated children; (2) the indirect effect of subsidies via shifting reference points on treated children; (3) the impact of shifting reference points on untreated children.

In our first set of counterfactuals, in a decomposition exercise to better understand what happened under the protein-supplementation experiment, we find that reference-point changes account for up to 60% of the nearly two centimeters in height difference between experimental and control villages at 24 months of age. We interpret the increasing gaps in heights and nutrition with children’s ages as substantially coming from changes in reference points in treatment villages.

In our second set of counterfactuals, we compare the **one-period** relative impacts of shifting household income, food price, and reference points in determining nutritional choices and heights. We find that the changes of 1 cm in reference points correspond to a discount of 37 percent in the price of protein or to an increase of 60 percent in income. If households could be convinced through an information campaign that they should consider a higher-height reference population in making nutritional choices, the information campaign could potentially be more cost-effective than reducing protein prices or increasing income.

For our third set of counterfactuals, we compare the effects of poor-targeted and universal subsidy policies. To be budget constant, we increase the subsidy to the poor when the program becomes more targeted. There is debate in the early childhood and development literature on the tradeoffs between targeted and universal policies.10 We contribute to this literature by evaluating policies taking into consideration endogenous shifts in reference points over time induced by transfer policies under the assumption that all local households with children in the same birth cohort share common local reference points. This introduces a channel for policy spillovers from the richest to the poorest households and vice-versa. We show that the effects of a universal policy on the change of the heights of the poor is initially small, but could increase by up to 4.8 times given subsequent endogenous upwards shifts in reference points as all village children—all of whom receive subsidies under the universal policy—increase nutritional intakes. We also show that, under a policy that targets only the poor, the children of the relatively-richest households, who do not receive subsidies, could experience up to 50 percent of the height gains experienced

10 See Besley and Kanbur (1990), Gelbach and Pritchett (1997), and Coady, Grosh, and Hoddinott (2004).
by the children of the poorest households.

Our work relies on the premise that parents compare their children to children who grow up in a similar geographic or socio-economic background. As a result, parents (or their children) form biased norms that, in turn, cause parents to over- or under-invest in their children. Our work is closest to the research by Kinsler, Pavan, et al. (2016) who study investments in the human capital of school-age children. Similar to our analysis, Kinsler, Pavan, et al. (2016) find that parents compare the abilities of their children with children from the same school. Because of school segregation, this comparison translates into low investment levels from parents (helping with homework or hiring a tutor) for children at the bottom of the skills distribution. An important difference between our work and theirs is that we take advantage of a randomized controlled trial that causes exogenous changes in parental norms. We use this exogenous variation to estimate the sensitivity of parental investment behavior to norms. Our work is also related to research by Liu and Zuppann (2016), who explore geographical moves to obtain exogenous variation in characteristics of peers. These authors show that children exposed to different sets of peers update norms about weights and behaviors that determine body mass.

In section 2, we present a model of reference points in a setting of a household deciding inputs for a child outcome, such as health. In Section 3 we describe the data we use to estimate the model. Section 4 describes the estimation method, shows parameter estimates and model fits. Section 5 discusses policy-relevant counterfactuals based on the estimated model. Section 6 concludes.

2 The Model

2.1 Model Description

In this section we develop a model in which parents have to choose a single input for one relevant child outcome. We focus on health outcomes and nutrition as the input, but the model can be applied to any skill or human-capital outcome developed during childhood.

In our model, household choices are functions of prices and incomes, as well as the reference-point distribution. Each household solves a static maximization problem after the birth of a child.

11 Similarly, Cunha, Elo, and Culhane (2013), Boneva and Rauh (2016), and Attanasio, Cunha, and Jervis (2019) find that parents might use wrong beliefs to decide investments, and if those beliefs were updated, children with parents near the bottom of the income distribution would benefit.
Individuals’ choices, however, have aggregate implications and determine the dynamic transition of health at the population level. We assume that households make a single decision about the total nutritional input for their new-born child from month 0 to month 24 and in the household utility function what matters in health at age 24 months. The nutritional input households choose could be grams of proteins if we were analyzing height or weight (see Moradi 2010; Puentes et al. 2016) Also, the input could be the frequency or the quality of the interactions with the child, if the outcome were socio-emotional skills.

Each household faces a reference-point distribution, about what a normal outcome is, by looking at their relevant comparison group. Parents that are choosing nutritional inputs for their new born use the heights of older children in their neighborhood or their village to help determine the reference-point distribution, and then decide the optimal nutritional level. If there is a policy that increases height for some children in a given village or neighborhood, the next generation will observe this new standard and update their reference-point distribution, impacting their nutritional decisions. Thus a one-time policy can have dynamic effects through the reference-point distribution. We describe this idea formally bellow.

2.1.1 Preferences

The utility for a household in village $v$ after the birth of a child in period $y$–each period is two calendar years–is determined by the health that this child will reach at 24 months of age $H_{24}$, and household expenditure $c$ other than on nutrition $N$ for the first 24 months for this child:

$$u_{yv} = c + \rho \cdot c^2 + \gamma \cdot H_{24} + \lambda \cdot (H_{24} - R_{yv}) \mathbb{1} (H_{24} > R_{yv})$$  

where $\mathbb{1}$ denotes the indicator function. Utility would be quasilinear in $c$ if $\rho$ were zero.

Preferences for $H_{24}$ represent the expected life-time values of children’s anthropometrics to households. Preferences for health are functions of the health of the children relative to $R_{yv}$–the reference health with which households compare their children’s health. $\gamma$ is positive, but, depending on the relative values of $\lambda$ and $\gamma$, preferences for health are flexible and could be linear, convex or concave. If $\lambda = 0$, preferences are linear in health $H_{24}$. If $\lambda > 0$, preferences are convex in health and parents invest more in health after health exceeds the reference point. If $\lambda = -\gamma$, households gain utility from increasing health up to the reference health $R_{yv}$, but

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12 The model considers 24 months as the relevant age for the production function. The first 1,000 days after conception is a critical period for nutrition and development (Victora et al. 2008; Victora et al. 2010).
there are no utility gains from increasing health beyond that point. If $\gamma < -\lambda$, preferences for health peak at the reference point, meaning that households want their children to be healthier (e.g. taller) below the reference point but not beyond it. The first and third cases are shown graphically in Panels (a) and (b) of Figure 1 respectively. In these panels, we show the health component of utility on the Y-axis and health deviation from $R_{yv}$ on the x-axis.

2.1.2 Budget

$Y$ is household income over the first 24 months of life after birth, which is spent on $c$ or $N^{13}$:

$$c = Y - p_{yv}^N \cdot N$$ (2)

$p_{yv}^N$ is the price for $N$ during the two calendar years that correspond to the first two years of life.

2.1.3 Production function

Health at month 24 is determined by:

$$H_{24}(N, X, \varepsilon) = \exp(A + X \cdot \alpha + \varepsilon) \cdot N^\beta$$ (3)

where covariate vector $X$ includes the initial conditions, such as length at birth and gender of the child, $\varepsilon$ represents the normally distributed i.i.d. health productivity shock for each child with standard deviation $\sigma_\varepsilon$. $A$ relates to the average level of productivity of $N$ in producing $H_{24}$, and $\alpha$ represents the impact of covariates on the marginal productivity of $N$. Initial conditions have positive impacts on month-24 height depending on the value of $\alpha$. The production function includes protein input $N$ in the first two years, with $\beta < 1$ determining the concavity of the production function with respect to nutritional inputs.

2.1.4 Information

We assume that households know the production function, and observe the i.i.d. productivity shocks at the time of making nutritional choices. This means nutritional choices are endogenous to productivity shocks that are unobserved by the econometrician.

Additionally, we assume that at the time of making nutritional choices in birth period $y$ in village $v$, households do not know the exact value of the reference health $R_{yv}$. However,

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13 The budget constraint implies that households can perfectly smooth incomes earned in the first 2 years after birth.
14 Given that the model only has one period, we do not need to distinguish between permanent unobserved heterogeneity and one-period shocks. With i.i.d shocks, we are assuming that productivity shocks are not specific to gender or different levels of initial conditions contained in $X$.
15 This is a more general specification than a model in which the difference in health between month 0 and month 24 is the production function output and initial health is not included in $X$. Compared to a model with difference in health as the output and that also includes initial health in $X$, the model here produces similar coefficients.
households know that the reference point follows a distribution $F(R_{yw})$, which is normal with mean $\mu_{R_{yw}}$ and $\sigma_{R_{yw}}$.

We assume that $\mu_{R_{yw}}$ and $\sigma_{R_{yw}}$ are the average and standard deviation of realized health from the cohort born in period $y - 1$, which means village households revise their previous expectation

\[ \begin{align*}
\text{(a) Reference Point Coefficient } & \lambda = 0 \\
\text{(b) } & \gamma = -\lambda \\
\text{(c) Shift } & \sigma_{R_{yw}} \ (\mu_{R_{yw}} = 77.75, \gamma = 0.03, \lambda = -0.045) \\
\text{(d) Shift } & \mu_{R_{yw}} \ (\sigma_{R_{yw}} = 3.5, \gamma = 0.03, \lambda = -0.045)
\end{align*} \]

\[ \begin{align*}
\text{Shift S.D. of Expected Ref. Point Dist.} \\
\text{Shift Mean of Expected Ref. Point Dist.}
\end{align*} \]

The assumption that parents learn from observing other children about reference points also relates to the assumption that parents know the production function parameters. In our empirical application, we assume that when parents of children born in 1972 see the health distribution of children born in 1970, they update their reference point, but they do not update production function parameters. This assumption is based on the literature described above and also that, for parents it is relatively easy to observe the height, weight or socio-emotional skills distribution of children born two years earlier, but is much more difficult to update production function parameters since this requires close experience with feeding or parent-child interaction and observing these practices for children born to other parents two years earlier. If we also were to model production function parameters updating, that could further amplify reference points effects.
of what is "normal" based on what is observed (Nerlove 1958; Greenwood and Hanson 2015). \( \sigma_{R_yv} \) could be interpreted as capturing village level uncertainty over the mean. But it also be interpreted as the expected utility from comparing the relative height of one’s child’s realized height to every other child in the perceived expected height distribution. Observing the health of children from earlier cohorts in the same village is plausible given the close proximity of households within these villages and the high level of economic and social interactions among households within villages. The assumption that the relevant comparison group corresponds to children from the same village is in line with the literature that has found that the relevant comparison groups are individuals who are closer. For instance, Card et al. (2012) finds that job satisfaction depends on the relative position among co-workers of the same pay unit and Kinsler, Pavan, et al. (2016) find that parents compare the abilities of their children with children in the same school.

Given that households only know the distribution of \( F(R_{yv}) \), in deciding nutritional choices, households integrate over \( F(R_{yv}) \) for the reference-health component of preferences:

\[
\gamma \cdot H_{24} + \lambda \cdot \int_{R_{yv}} (H_{24} - R_{yv}) I(H_{24} > R_{yv}) dF(R_{yv})
\]

The presence of uncertainty changes the shape of preferences with respect to height. Panels (c) and (d) of Figure 1 show this graphically. In those panels, we show the expected health component of utility on the Y-axis and individual health deviations from \( \mu_{R_{yv}} \) on the x-axis.

Panel (c) of Figure 1 presents four curves with \( \sigma_{R_{yv}} \) set at 0, 3, 3.5 and 4 health units, and with \( \mu_{R_{yv}} \) fixed at 77.75 health units \(^{18}\) and \( \gamma < -\lambda \). The curves show that preferences for health with \( \sigma_{R_{yv}} = 0 \) are piecewise linear with a kink at \( \mu_{R_{yv}} \); with \( \sigma_{R_{yv}} > 0 \), preferences for health are continuously differentiable and concave in health. Additionally, at low and high levels of health, the marginal gains and losses from additional units of health are identical across the four curves and are determined by the values of \( \gamma \) and \( \lambda \). Finally, with uncertainty over the reference point, marginal gains (loses) of additional units of health are larger (more negative) at health values further away from the reference point.

In panel (d) of Figure 1, we fix \( \sigma_{R_{yv}} \) at 3.5 health units and show health preference curves for

\(^{17}\) This also means that if a family moves to another village or location where the reference height distribution is different, they would adjust their nutritional choices given the updated reference distribution. Liu and Zuppann (2016) study, for example, shifts in reference weights for children who move in the US.

\(^{18}\) We are mimicking a height production function in this example so the health units match cm.
\( \mu_{\text{RY}} \) equal to 77, 77.75 and 78.5 health units, respectively. The curves show that peak health preferences shift with the mean reference point, and the gaps in preferences across different mean reference point curves widen significantly for higher health. This means that a higher mean reference point increases the region of health where marginal gains from additional health outcomes are positive, and also increases marginal gains in the region where marginal gain from additional health would be positive with a lower mean reference point.

We should note that \( \sigma_{\text{RY}} \) measures household uncertainty with respect to what the realized health gap between \( H_{24} \) and \( \mu_{\text{RY}} \) will be. In the above discussion, we have assumed that this uncertainty comes from uncertainty over reference points, but we can see from Equation 4 that uncertainty over \( H_{24} \)–in the form of an shock term that is unobserved by the household, but that will help determine realized height–will have equivalent effects. In our modeling framework, households do not distinguish between these two shocks, so they both have the same effect on household choices.

### 2.1.5 Maximization Problem

Given \( \mu_{\text{RY}} \), \( \sigma_{\text{RY}} \), and price \( p_{\text{NY}} \), each household solves the following maximization problem:

\[
\max_{c, N} \left\{ c + \rho \cdot c^2 + \left\{ \gamma \cdot H_{24} + \lambda \cdot \int_{R_{\text{RY}}} \mathbb{1} \{ H_{24} \geq R_{\text{RY}} \} dF(R_{\text{RY}}) \right\} \right\} \\
\begin{align} 
    c &= Y - p_{\text{NY}} \cdot N \\
    H_{24}(N, X, \epsilon) &= \exp(A + X \cdot \alpha + \epsilon) \cdot N^\beta
\end{align}
\]
The realized household utility $u_{yv}$ is a function of parameters and $Y, p^N_{yv}, X, F(R_{yv}), \varepsilon$. Households make choices given $\Omega = (Y, p^N_{yv}, X)$, the i.i.d. productivity shock $\varepsilon$, and $F(R_{yv})$. At the birth of a child, a household chooses the optimal amount of nutrition for the child over the next 24 months given the joint relative distribution of the reference health outcome and their own child’s health given that child’s productivity shock and nutritional intake. The parents choose knowing that more nutritional intake—at a decreasing rate of return—will increase the probability that their child will catch-up to or exceed the reference health.\(^{19}\)

In Figures 2 and 3, we show the consumption and health possibility frontier and indifference curves for an individual using estimated parameters from our empirical model. In Figure 2, for a particular reference point distribution, we show the household consumption possibility frontier and indifference curves for health and all consumption other than child nutrition.

In Figure 3, we show how increasing the reference point changes optimal household decisions. Specifically, as the reference-point distribution shifts higher with higher mean, consumption on other goods decreases, and the child’s health outcome increases. Importantly, at the lower-mean reference-point distribution shown in blue, the realized health outcome for the household shown on Figure 3 is higher than the initial mean reference point. If all households are identical, this would lead to an increase in the reference point. The opposite is true for the results shown in red on Figure 3, where starting at a higher mean reference point, the realized health outcome for a household is lower than the initial mean reference point. Driven by these opposing dynamics, if the heterogeneity in household conditions is fixed over periods, the mean reference point distribution converges towards a point where the health distribution is stationary. We define and discuss these dynamics in the following subsections.

### 2.1.6 Evolution of Reference Points and Month 24 Health

Let $\Gamma_{yv}$ be the probability measure of $H_{24}$ for children born in period $y$ and village $v$. $\Gamma_{yv}(\mathcal{H})$ reports the probability measure of individuals for whom $H_{24} \in \mathcal{H}.^{20}$ Under our assumptions described in the previous section, $\Gamma_{yv}$ is realized in period $y+1$ and observed by parents of new-

\(^{19}\) We assume that parents do not consider the nutritional choices of other parents for their own maximization in order to focus purely on the effect of the change in the reference point.

\(^{20}\) By definition, the CDF for $H_{24}$ is $F_{yv}(H) = \Gamma_{yv}([H_{\text{min}}, H])$.
where 1. This implies that the means and standard deviations of reference-point distributions are functions of \( \Gamma_{y} \): \( \mu_{R_{y+1},y} \) and \( \sigma_{R_{y+1},y} \). In this setting, static individual choices have dynamic aggregate effects: Month-24 health for the cohort born in period \( y \) are realized in period \( y + 1 \) and determine the reference-point distribution for the cohort born in \( y + 1 \); subsequently, health at month 24 for the cohort born in period \( y + 1 \) are realized in period \( y + 2 \) and determine the reference point for the cohort born in \( y + 2 \).

For village \( v \) child born in period \( y \), given \( p_{y,v}^{N} \), and \( \mu_{R_{y},v} \), \( \sigma_{R_{y},v} \), the decision rule is:

\[
N \left( Y, X, \varepsilon; p_{y,v}^{N}, \mu_{R_{y,v}}(\Gamma_{y-1,v}), \sigma_{R_{y,v}}(\Gamma_{y-1,v}) \right) = N \left( Y, X, \varepsilon; p_{y,v}^{N}, \Gamma_{y-1,v} \right)
\]

(7)

Given some joint distribution of \( F_{y,v}(Y, X, \varepsilon) \), we can write the following equation describing the transition from the health-at-month-24 distribution for the birth cohort born in period \( y - 1 \), \( \Gamma_{y-1,v} \), to the health-at-month-24 distribution for the birth cohort born in period \( y \), \( \Gamma_{y,v} \):

\[
\Gamma_{y,v}(\mathcal{H}) = \int_{Y \times X \times \varepsilon} 1 \left( H_{24} \left( N \left( Y, X, \varepsilon; p_{y,v}^{N}, \Gamma_{y-1,v} \right), X, \varepsilon \right) \in \mathcal{H} \right) dF_{y,v}(Y, X, \varepsilon)
\]

(8)

where 1 is again the indicator function. Given the optimal-nutrition decision rule, some initial distribution \( \Gamma_{initial,v} \) realized before period \( y_{min} \), and a sequence of price and income and covariate distributions \( \left( p_{y,v}^{N}, F_{y,v}(Y, X) \right)_{y=y_{min}}^{y_{max}} \) from year \( y_{min} \) to year \( y_{max} \), we can iteratively solve for a sequence of health-at-month-24 distributions across cohorts \( \left( \Gamma_{y} \right)_{y=y_{min}}^{y_{max}} \).

The implication of this process of updating the reference-point distribution is that if a policy subsidies \( p^{N} \) or provides transfers to increase \( Y \) starting in period \( y \), the distribution of health at month 24 for the cohort born in period \( y \) shifts just due to the change in budgets. In period \( y + 1 \) households also face a different reference-point distribution, which induces additional changes in choices and realized health at month 24 for successive cohorts.

### 2.1.7 Stationary Health Distribution

In a setting in which \( p^{N} \) and the distribution of \( F(Y, X, \varepsilon) \) are fixed, given the nutritional decision rule \( N(Y, X, \varepsilon; \Gamma) \) we can define a stationary distribution for health at month 24 \( \Gamma \):

\[
\Gamma(\mathcal{H}) = \int_{Y \times X \times \varepsilon} 1 \left( H_{24} \left( N \left( Y, X, \varepsilon; \Gamma \right), X, \varepsilon \right) \in \mathcal{H} \right) dF \left( Y, X, \varepsilon \right)
\]

(9)
Equation 9 describes the fixed point for $\Gamma$, which exists here given the concavity of the production function. As discussed earlier, households in our model do not distinguish between uncertainty with respect to reference points and with respect to own children’s realized $H_{24}$. This implies that even if mean village health is known, as might be the case if a stationary distribution is reached, it still is rational for households to consider $\sigma_R > 0$ that captures remaining uncertainty in the gap between own realized health and the average of village reference health.

3 Data

In this section, we describe the data we use to estimate the model presented in the previous section. It is challenging to estimate reference-point parameters. We present below specific data features that–in the context of the model–can be used to isolate the potential effects of reference-point changes. We use as the health outcome height of children at age 24 months. Height in early childhood is strongly associated with measures of cognitive and noncognitive development and insufficiency in height has been found to be a key risk factor that limits child development (Perkins et al. 2017). When other early childhood outcome measures are unavailable, height is often used as a proxy for overall health status.

3.1 Survey Design and Sample

The data we use in this paper come from an experimental intervention conducted by The Institute of Nutrition of Central America and Panama (INCAP), which started a nutritional-supplementation trial in 1969. Four villages from eastern Guatemala were selected, one pair of villages that were relatively populous (~900 residents each) and one pair that were less populous (~500 residents each). The villages were similar in child nutritional status, measured as height at three years of age (Habicht, Martorell, and Rivera 1995). Over 50% of children lacked proper nutrition and were severely stunted, measured as height-for-age z-scores less than -3.21 The intervention consisted of randomly assigning nutritional supplements. One large and one small village were selected to receive a high-protein drink called Atole, and the other two were selected to receive an alternative supplement called Fresco. Each serving of Atole (180 ml) contained 11.5 grams of protein and 163 kcal. Fresco had no proteins and each serving (180

21 Guatemala children continue to suffer from severe malnutrition. In 2015, among Guatemala households in the lowest quintile of wealth, approximately 70 percent of children younger than five were stunted. In middle-quintile Guatemala households, 45 percent of children younger than five were stunted (FAO 2019).
ml) had 59 kcal. The main hypothesis was that better nutrition would accelerate physical and mental development (Habicht, Martorell, and Rivera 1995). The intervention started in February 1969 in the larger villages and in May 1969 in the smaller villages, and lasted until the end of February 1977 with data collection taking place until September 1977 (Maluccio et al. 2009; Islam and Hoddinott 2009). The nutritional supplements were distributed in feeding centers located centrally in each village. The centers were open twice a day, two to three hours in the mid-morning and two to three hours in the mid-afternoon. All village members had access to the supplements at the feeding centers.

Information on supplement intake was collected daily for all children up to seven years old. Height and home dietary and supplement information was collected every 3 months for children between 0 and 24 months. All children reported positive levels of supplement intakes, which means the extensive margin of supplement usage was 100%. The home dietary data corresponds to 24-hour recall in the large villages and 72-hour recall in the small villages. From the home dietary data it is possible to calculate protein intakes, which we use in our estimations. Anthropometric measures were collected every three months for children 0 to 24 months-old.

Given the quarterly data collection for the INCAP dataset, in the first 24 months of life, a child was observed up to 9 times. There were 1155 individuals for whom we have at least 1 height observation between months 0 and 24, and 363 individuals for whom heights were observed 9 times. We focus on 503 individuals for whom we have heights at birth, heights at month 24, and at least 2 observations of nutritional inputs between months 15 and 24. For these 503 individuals, we have information on household income for one year in the period of analysis. We also have from the INCAP survey food price data measured at wholesalers’ purchasing cost per 10,000 grams of each type of food. The food prices are common for Atole and Fresco villages. Using these data, we estimate protein prices from a simple hedonic pricing equation system in which the price for each unit of food item is determined by the sum of the protein and non-protein caloric values for each unit of food item multiplied by the year-specific protein and non-protein-calorie prices up to a random error term. More information is available upon request.
Table 1: Summary Statistics for Various Variables

<table>
<thead>
<tr>
<th>Panel A: Gender Income Price (N=503, main sample)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Group Averages</td>
<td></td>
<td>p-Values Testing</td>
</tr>
<tr>
<td></td>
<td>mean (sd)</td>
<td>Fresco</td>
<td>Atole</td>
<td>Gap</td>
</tr>
<tr>
<td>Male</td>
<td>0.52 (0.50)</td>
<td>0.52 (0.50)</td>
<td>0.52 (0.50)</td>
<td>-0.00</td>
</tr>
<tr>
<td>Income (quetzale)</td>
<td>515.57 (460.9)</td>
<td>503.68 (464.4)</td>
<td>526.00 (458.4)</td>
<td>22.32</td>
</tr>
<tr>
<td>Mth 15-24 Protein Price (quetzale/10k grams)</td>
<td>52.58 (3.87)</td>
<td>52.47 (3.93)</td>
<td>52.68 (3.81)</td>
<td>0.21</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Gender Income (N=1115, height observed once in first 24 months)</th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Group Averages</td>
<td></td>
<td>p-Values Testing</td>
</tr>
<tr>
<td></td>
<td>mean (sd)</td>
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<td>Atole</td>
<td>Gap</td>
</tr>
<tr>
<td>Male</td>
<td>0.53 (0.50)</td>
<td>0.53 (0.50)</td>
<td>0.53 (0.50)</td>
<td>0.00</td>
</tr>
<tr>
<td>Income (quetzale)</td>
<td>449.49 (432.3)</td>
<td>444.63 (446.4)</td>
<td>454.06 (419.0)</td>
<td>9.43</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Height</th>
<th></th>
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<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Month 0 (cm) N=503</td>
<td>49.64 (2.29)</td>
<td>49.79 (2.29)</td>
<td>49.52 (2.29)</td>
<td>-0.27</td>
</tr>
<tr>
<td>Month 6 (cm) N=463</td>
<td>62.72 (2.46)</td>
<td>62.49 (2.50)</td>
<td>62.93 (2.42)</td>
<td>0.44</td>
</tr>
<tr>
<td>Month 12 (cm) N=475</td>
<td>68.81 (2.99)</td>
<td>68.45 (3.13)</td>
<td>69.13 (2.83)</td>
<td>0.68</td>
</tr>
<tr>
<td>Month 18 (cm) N=482</td>
<td>73.37 (3.23)</td>
<td>72.88 (3.26)</td>
<td>73.80 (3.15)</td>
<td>0.92</td>
</tr>
<tr>
<td>Month 24 (cm) N=503</td>
<td>77.66 (3.47)</td>
<td>76.94 (3.49)</td>
<td>78.29 (3.33)</td>
<td>1.36</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel D: Average Daily Nutritional Intake</th>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Month 15 (grams/day) N=464</td>
<td>17.43 (10.5)</td>
<td>14.29 (9.14)</td>
<td>20.07 (10.9)</td>
<td>5.78</td>
</tr>
<tr>
<td>Month 18 (grams/day) N=461</td>
<td>21.52 (11.4)</td>
<td>18.27 (9.61)</td>
<td>24.41 (12.0)</td>
<td>6.14</td>
</tr>
<tr>
<td>Month 21 (grams/day) N=475</td>
<td>24.45 (11.4)</td>
<td>20.17 (9.03)</td>
<td>27.99 (11.9)</td>
<td>7.82</td>
</tr>
<tr>
<td>Month 24 (grams/day) N=462</td>
<td>26.99 (12.0)</td>
<td>22.51 (9.02)</td>
<td>31.07 (13.0)</td>
<td>8.56</td>
</tr>
<tr>
<td>Avg Mth 15-24 (grams/day) N=503</td>
<td>22.54 (8.98)</td>
<td>18.81 (6.43)</td>
<td>25.80 (9.62)</td>
<td>6.99</td>
</tr>
<tr>
<td>Avg Mth 15-24 (kcal/day) N=503</td>
<td>691.78 (236.5)</td>
<td>681.78 (236.2)</td>
<td>700.55 (236.9)</td>
<td>18.77</td>
</tr>
</tbody>
</table>

### 3.2 Descriptive statistics

Table 1 presents summary statistics for key variables that we use from the survey. In Panels A and B, we show statistics on gender, income and prices for our main sample of 503 individuals (Panel A) and gender and income for the fuller sample of 1155 individuals (Panel B). In Panels C

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For 378 individuals, we observe nutritional intakes in months 15, 18, 21 and 24, for 100 individuals, we observe nutritional intakes 3 times, and for 25 individuals, we observe nutritional intakes 2 times.
and D, we show statistics on heights and nutritional intakes respectively. Table 1 has five columns. The first column presents the overall means and standard deviations in Atole and Fresco villages combined. The second and third columns present Atole and Fresco village-specific means and standard deviations. Column four shows the gaps in means between Atole and Fresco villages for each variable, and column five presents the p-value for the statistical significance of these gaps.

As mentioned before, the intervention took place in four villages, two of them are the Atole or treatment villages, and the other two are the Fresco or control villages. In the rest of the paper, when we refer to Atole and Fresco villages, we merge the information of the two villages that received the same supplement. The limited number of villages might impact the standard errors of the descriptive statistics, since villages can share common unobserved shocks. We follow the methods developed by (Donald and Lang 2007) and (Cameron and Miller 2015) to study how robust our results are to this clustering. The method proposed by (Donald and Lang 2007) consists first in estimating averages by clusters, controlling by individual variables, and using those averages in the regressions. This method greatly reduces the number of observations. We define cluster year-village pairs and half year-village pairs to implement this procedure. Following, (Cameron and Miller 2015) we also implement a pair cluster bootstrap, using the same cluster definition as in the (Donald and Lang 2007) method. In Table 1 and Figure 4 we report the results without using the clusters corrections, but the results are robust to those methods.

Panel A and B show that the survey is well-balanced for gender and income between Atole and Fresco villages. Panel A shows that male children account for 52 percent of our main sample in both Atole and Fresco villages. In Panel B, for the larger sample that includes any individuals for whom we observe height once in the first two years, the male share is 53 percent in both Atole and Fresco villages. These indicate that differences between Atole and Fresco villages in height outcomes and nutritional intakes are not driven by gender composition differences.

Panel A and B also show that household annual incomes\(^ {23}\) for Atole and Fresco villages are similarly distributed. In Panel A, for our main sample, average annual household incomes are 503

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\(^{23}\) The survey contains a wealth index constructed with data collected in 1967 and 1975 for all individuals. We also know the mean and the standard deviation of income for the year 1974 but only at the village level. Assuming that household annual income follows the same distribution as the household wealth distribution, and assuming also log-normality of the income distribution, we impute household annual income. We multiply annual income by 2 to calculate total resources available for each household in the first two years a child’s life.
quetzales$^{24}$ in Fresco villages, and 526 quetzales in Atole villages. The difference is statistically insignificant with the p-value equal to 0.59. Standard deviations for both villages are almost identical at ~460 quetzales, indicating high similarity in the distribution of incomes between Atole and Fresco villages. For the larger sample in Panel B, average incomes per year are almost identical at 454 quetzales in Atole villages and 444 quetzales in Fresco villages, a statistically insignificant difference of only 2 percent. The higher income in Panel A’s main sample compared to the income in Panel B’s larger sample indicates potential selection in terms of which children were observed more often and consistently, but both gender and income in both Panel A and B are almost exactly balanced, indicating high similarity between Atole and Fresco villages.

Panel A also presents summary statistics for the village averages of individual average protein prices between months 15 and 24 of age for each child. We calculate annual protein prices based on the average of annual food prices for rice, eggs, chicken, corn and beef weighted by their respective protein shares $^{25}$. By construction, food prices differ for each calendar year, but are identical for Atole and Fresco villages. For each child, we average over prices that the child faces in months 15, 18, 21, and 24 of age—the months over which we calculate average nutritional intakes shown in Panel D. Depending on the month and year of birth, the average price for each child differs. In Column one of Panel A, we show the overall averages of these individual averages, which is$^{26}$ 52.58 quetzales per 10k grams of protein. The standard deviation is 3.87 quetzales or 7.4 percent of the means, indicating significant price variations across individuals. The averages for Atole and Fresco villages are almost identical at 52.47 and 52.68 quetzales (p-value 0.54 for difference), indicating that the distribution of birthdates between Atole and Fresco villages are well-balanced.

Aggregating across cohorts, Panel C of Table 1 shows at birth, Atole village children, with average height at 49.52 cm, are in fact 0.27 cm shorter on average than Fresco village children whose average height is 49.79 cm. This difference is not statistically different (p-value 0.19). Moving from birth to month 24, heights for children in Atole villages increase faster than heights

$^{24}$ Real terms for 1975; exchange rate was 1 quetzal for 1 US dollar.

$^{25}$ We obtain protein shares from USDA Food Composition Database (United States Department of Agriculture 2016), which provides the protein values per 100 grams of various food items.

$^{26}$ The birth date distributions in Atole and Fresco villages are shown in Panels 1.1 and 2.1 of Figure 4 where the size of scatter plots indicate the relative sample sizes of birth in each half-calendar-year between 1970 and 1975.
for children from Fresco villages. At month 6, Atole children are on average 0.44 cm taller than Fresco children. This gap widens to 0.68 cm at 12 months and 0.92 cm at 18 months of age. At month 24, the average height in Atole villages is 78.28 cm, and the average height in Fresco villages is 76.94 cm—the Atole height premium is 1.36 cm (p-value $\leq 0.005$).

Panel D of Table 1 presents averages for nutritional intakes per day for children across birth cohorts between 1970 and 1975. We focus on nutritional intakes in the second year of life in months 15, 18, 21 and 24. For month 15 of age, Atole children average 20.07 grams of protein intake per day, 5.78 grams more than children in Fresco villages. In months 18, 21 and 24 of age, the average daily intake gap between Atole and Fresco villages widens to 6.14, 7.82 and 8.56 grams per day. Overall, averaging across the four quarters in the second year of life for each child, average protein intake in Atole villages at 25.80 grams is 6.99 grams (37 percent) higher than the average for Fresco villages (18.81 grams per day). The final row of Panel D shows the village averages of individual average kcal per day of caloric intakes from non-protein sources over months 15, 18, 21 and 24 of age, which is 700.55 kcal per day in Atole villages and 691.78 kcal per day in Fresco villages, a statistically insignificant gap of 2.7 percent.

### 3.3 Gaps Across Cohorts

We now present data on heights at 24 months of age and average protein intakes between months 15 and 24 of age across cohorts of children born between 1970 and 1975. As described earlier, the nutritional-supplementation experiments started in the first half of 1969. The 503 children in our main sample were born between 1970 and 1975. The children change across birth cohorts and the families into which they were born also change considerably. The percentage of parents in the 1971 cohort who were not parents in the 1970 cohort is 83%, the percentage of parents in the 1972 cohort who were not parents in the 1971 cohort is 87% (and, likewise, for the 1973 cohort 93%, for the 1974 cohort 92% and for the 1975 cohort 95%).

When we examine the heights at month 24 of children—as shown on the left Panels (1.1, 1.2)
of Figure 4—the height gaps are widening between Atole and Fresco village children across cohorts from 1970 to 1975. Corresponding to the increasing gaps in heights at month 24 are increasing gaps in protein intakes across cohorts shown in the right Panels (2.1, 2.2) of Figure 4. In Panels 1.1 and 2.1 of Figure 4, we show results for children in annual birth-cohort groups.\(^{29}\) Panels 1.2 and 2.2 show height and protein intake gaps for 1970, 1971, 1972-73 and 1974-75.\(^{30}\)

Figure 4: Increasing Protein and Height Gaps Across Cohorts

\(^{29}\) Results for aggregating children into 6-month birth groups show very similar patterns.

\(^{30}\) All results in Figure 4 are robust to the different cluster-correction methods discussed earlier.
3.3.1 Height Gaps Across Cohorts

Panel 1.1 presents results for cohorts aggregated over each birth year between 1970 and 1975. The average height at month 24 gaps between Atole and Fresco children are 0.2 cm (76.6-76.4) for the 1970 cohort, and 1.6 cm (78.8-77.1) for the 1975 birth cohort. Panel 1.1 also shows linear and local polynomial approximated height trends in Atole and Fresco Villages. They show a relatively flat pattern for height at month 24 across cohorts in Fresco villages and a significantly increasing pattern for height at month 24 across cohorts in Atole villages. Specifically, the linear trend indicates that each additional cohort year is associated with an increase of 0.34 cm (s.e. 0.13) in height at month 24 in Atole villages and a slightly positive but insignificant increase of 0.11 cm (s.e. 0.14) in height at month 24 in Fresco villages.

In Panel 1.2, we test whether the increasing height at month 24 gap across cohorts in Atole and Fresco villages could be explained by other variables. We regress height at month 24 on four birth cohort year groups--1970, 1971, 1972-73, and 1974-75--and the interaction of these birth cohort groups with the Atole dummy. We include here as covariates gender, protein prices, incomes and initial heights, the variables in the household state-space of our structural model (see Table 1). Panel 1.2 plots out the cohort-group and Atole interaction coefficients with confidence intervals. The diamond line shows regression results including the covariates, and the circle line shows raw cohort gaps. Across the cohort groups, the raw height gaps between Atole and Fresco villages are 0.21 cm (1970), 0.35 cm (1971), 1.28 cm (1972-73) and 1.46 cm (1974-75). Controlling for covariates, the height gaps are 0.62 cm, 1.06 cm, 1.54 cm and 1.32 cm. The results with and without covariates are similar, which is not surprising given that, as we saw in Table 1, there are no significant statistical differences between Atole and Fresco villages in gender ratios, incomes, protein prices, and initial heights. The 1970 and 1971 cohorts’ gaps are not statistically different from 0; the 1972-73 and 1974-75 cohorts’ gaps are statistically different from 0 at the 1 percent significance level.

3.3.2 Nutritional Gaps Across Cohorts

Panels 2.1 and 2.2 show protein intakes across cohorts. As mentioned before, we show village cohort averages aggregated over individual averages for 15, 18, 21 and 24 months of age. Children born in the first half of 1970 have approximately the same average height in Atole and Fresco villages at 24 months of age—both at approximately 76.4 cm. For those born in the second half of 1975, however, the average month-24 heights are 78.9 cm and 76.9 cm for Atole and Fresco village children, respectively.
age. We aggregate results to full-year cohorts in Panel 2.1, which shows that the average protein intake gap between Atole and Fresco villages in 1970 was 3.9 grams (21.3–17.4) and 7.9 grams (26.3–18.4) in 1975. Looking at percentage differences, for the annual cohorts, the average protein intakes in Atole villages are 22, 36, 37, 35, 40 and 43 percent higher in Atole villages than in Fresco villages for the six annual birth cohorts from 1970 to 1975.

Panel 2.1 shows trends from linear and local polynomial approximations of average protein intakes across cohorts that are similar to those for heights. Specifically, we find that each additional cohort year is associated with a 0.68 grams (s.e. 0.38) increase in intakes for Atole children, and an insignificant increase of 0.17 (s.e. 0.36) grams in intakes for Fresco children.

In Panel 2.2, we test for the significance of the average protein-intake gap between Atole and Fresco villages across cohorts. Similar to Panel 1.2, we include gender ratios, food prices, incomes and initial heights as covariates. Without controls, the average intake gaps are 3.85 (1970), 6.76 (1971), 6.70 (1972-73) and 8.02 (1974-75) grams per day between Atole and Fresco village cohorts. Including controls, the gap estimates are 4.31, 7.35, 6.88 and 7.88 grams per day, still showing a generally increasing trend.

Overall, the Panels in Figure 4 show that there are overall protein intake gaps between Atole and Fresco villages that correspond to the overall height gaps. Furthermore, for successive cohorts from 1970 to 1975, there are generally increasing protein intake gaps that correspond to increasing height gaps between Atole and Fresco villages. The overall Atole and Fresco protein-intake and height gaps have been observed before (see for example Puentes et. al. 2016), but not the increasing protein-input and height gaps across cohorts.

The empirical question that we face is what can explain these increasing gaps between Atole and Fresco villages. We discussed that gender shares, incomes, prices and initial heights do not differ significantly between Atole and Fresco villages and do not seem to be able to explain the increasing differences between Atole and Fresco villages across cohorts. There also were not any changes in the protein and non-protein supplementation policies carried out by local feeding centers over time that might have impacted cohorts differentially. Our structural model with

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32 Atole children born in the first half of 1970 have 21.1 grams of daily protein on average, and corresponding Fresco children have 17.4 grams on average (3.7 grams gap). For those born in the second half of 1975, the cohort-group average increased to 27.3 grams per day in Atole villages, and to 18.9 grams in Fresco villages (8.4 grams gap).
reference-dependent utility can help to explain these increasing protein-intake and height gaps between Atole and Fresco villages.

4 Estimation

4.1 Model Estimation, Maximum Likelihood and Identification

The data pattern described in the previous section offers the possibility of isolating the effects of reference points changes by exploiting the increasing gaps between Atole and Fresco villages. To estimate the model we modify the model to study the Atole intervention. We focus on height at age 24 months, $h_{24}$, and model the protein-supplementation policy in Atole villages as a $\delta^{33}$ discount on the price of protein in Atole villages.$^{34}$ The new budget constraint is:

$$c = Y - \left( p_{yv}^N \cdot (1 - \delta \cdot \mathbb{1}(v = atole)) \right) \cdot N \quad (10)$$

$p_{yv}^N$ is the price during the two calendar years that correspond to the first two years of life.

In the production function, we assume that only total protein intake in the first 24 months matters. Potentially, the timing of nutritional intakes within the first 24 months could be important. In the data, however, lagged inputs over the first 24 months of life are persistent, and it is difficult to distinguish relative productivity across subperiods (Puentes et al. 2016).

Related to the assumption that households know the production function, in the data we do not have survey information about households’ knowledge of anthropometrics production functions. The village feeding centers that distributed the supplements and also provided health checkups were potentially sources of health information but they attempted to provide the same health services and the same information for all Atole and Fresco villages. We do not include heterogeneity in the reference point update by socio-economic characteristics, since villages are relatively small, and we expect every household to observe the same height distribution.

$^{33}$ Modeling the supplementation policy as a price discount implies that if an Atole village child consumes $X$ grams of protein, the fraction $\delta$ comes from the feeding centers’ protein supplements. The share of proteins obtained from the feeding centers for each child is positive for all households, is on average 33 percent across cohorts, and is not significantly different across cohorts (F-test p-value 0.63).

$^{34}$ A potential alternative approach of modeling the protein supplementation policy would be to add a fixed cost to accessing the feeding centers and impose a quantity constraint on how much free protein could be obtained per trip, but that would lead to some households not obtaining protein supplements in contrast to the actual experience. Another alternative would be to model the protein supplements as fixed amounts of intake provided to households, but that would force all households to consume the same levels of protein supplements contrary to what actually was observed.
4.1.1 Measurement Error and Likelihood

We include in the model measurement errors that allow for maximum likelihood estimations. As described previously, households observe $\Omega = (Y, p_N^v, X)$, and the distributions of $R_{yv}$. The econometrician only observes $F^*$ and $N^*$, which differ from the true optimal nutritional choice $N$ by measurement error $\eta$ and true height outcome $h_{24}$ by $\iota$:

$$\log(N^*) = \log(N(Y, X, \varepsilon; p_N^v, \mu_{R_{yv}}, \sigma_{R_{yv}})) + \eta$$ (11)

$$\log(h_{24}^*) = \log(h_{24}(N(Y, X, \varepsilon; p_N^v, \mu_{R_{yv}}, \sigma_{R_{yv}}), X, \varepsilon)) + \iota$$ (12)

We assume that $\eta$ and $\iota$ are normally distributed, and that $\varepsilon$, $\eta$ and $\iota$ are independent. The standard deviation of $\eta$ is $\sigma_\eta$ and the mean is $\mu_\eta = -\frac{\sigma_\eta^2}{2}$. The standard deviation for $\iota$ is $\sigma_\iota$ with mean $\mu_\iota = -\frac{\sigma_\iota^2}{2}$. The likelihood is based on the model optimal and observed nutritional choices, as well as the model simulated and observed heights at 24 months of age:

$$\max_{\theta \in \Theta} \sum_{y=1970}^{1975} \sum_v \sum_{i=1}^{n_{yv}} \log \left( \int \phi_1(\ln h_{24,i}^* - \ln h_{24}(\theta, \mu_{R_{yv}}, \sigma_{R_{yv}})) \cdot \phi_\eta(\ln N_i^* - \ln N(\theta, \mu_{R_{yv}}, \sigma_{R_{yv}})) dF(\varepsilon_i) \right)$$

(13)

where, $\theta = \{ \rho, \gamma, \lambda, \delta, A, \alpha, \beta, \sigma_\varepsilon, \sigma_\eta, \sigma_\iota \}$ (14)

Equation 13 is determined by $\theta$ as well as a set of $(\mu_{R_{yv}}, \sigma_{R_{yv}})$ that are village- and time-specific. We do not impose assumptions about where the current height distribution is with respect to the stationary height distribution, and solve for optimal choices given the observed individual specific $\Omega_i$ and the observed $\mu_{R_{yv}}, \sigma_{R_{yv}}$ for each year $y$ in village $v$.

We solve the model using the solution method described in Appendix Section A.1. To find the $\theta$ that minimizes the likelihood, we search across parameter space using quasi-Newton methods, and initiate the likelihood with a range of parameter values to find the global maximum.\textsuperscript{35} We obtain standard errors from the approximated inverse Hessian.

\textsuperscript{35} Initial values of the parameters: for preference parameters, we investigate $\rho$ equals to or less than 0, and we test a range of $\gamma$ values, with corresponding $\lambda$ values that make preference in height linear, or have different degrees of concavity. For the Atole discount $\delta$ parameter, we test from 10 to 90 percent discounts at 10 percent intervals. We start production function parameters at the same values always, which are parameters estimated from a instrumental variable regression in which the Atole dummy is an instrument for protein intakes.
4.1.2 Identification of the Key Parameters

In Appendix Section A.2, we describe how we match the data described in Section 3.2 to model variables and values. In this section, we discuss aspects of the data that help identify key parameters. Parameter $\rho$ for the quadratic term of non-child-nutrition consumption $c$ determines the concavity of preferences with respect to $c$. If income does not matter, then the model is quasilinear in income with $\rho = 0$. Hence, $\rho$ is identified by the effect of income on choices.

For the linear height preference parameters, if $\gamma = 0$ (and $\lambda = 0$), that would lead to zero nutritional choices. Given positive nutritional choices, $\gamma > 0$. If average nutritional choices are high, $\gamma$ is higher to reflect higher preferences for height, and vice-versa.

In Figure 4, we show the nutritional-choice and height gaps between Atole and Fresco villages. The protein-supplementation policy experiment works through the $\delta$ parameter. We can adjust $\delta > 0$ to help match the overall nutritional gap between Atole and Fresco villages.

Crucial to our model is the reference-point parameter $\lambda$. If $\lambda = 0$, reference points have no impact on nutritional choices and heights. We discussed in Section 3.2 that there is no statistically significant differences in incomes, prices, gender and initial heights between Atole and Fresco villages. Therefore, if $\lambda = 0$, the nutritional choices and height gaps between Atole and Fresco villages across cohorts of children at 24 months of age should be constant. In Figure 4, however, as discussed in Section 3.2, we see increasing height and nutritional gaps between Atole and Fresco villages. $\lambda$ is identified by these increasing gaps.

Our production-function parameters are identified from the relationship between nutritional inputs, $X$ variables, and height outcomes. The productivity shocks impact both nutritional choices and height outcomes. $\sigma_e$ is identified by the positive covariance between the height at month 24 and nutritional choices that is not captured by income, price or components of $X$.36

Potentially, alternative theories could also be consistent with the observed height and protein gaps. If households slowly begin to trust the supplement, and that growing trust translates to increasing over time intakes of Atole and Fresco, we might observe the pattern of growing protein consumption and divergence in height between treatment and control villages. We do find that calories tend to increase over time in both villages, which is consistent with both the

---

36. The effect of $\epsilon$ on height is less than its effects on nutrition because households with more negative shocks choose higher levels of protein intakes, thus dampening the negative effects of negative shocks on height.
reference-point theory and the trust theory. However, for the trust theory to hold, households should build trust slowly, over a period of several years, which seems implausible. Possibly, households indeed do not decide to use the supplement immediately, but since the supplement is available daily, we would expect trust to be developed in a matter of weeks or months, not slowly over a decade. Additionally, the trust theory should lead to an increase in the extensive margin, but as discussed earlier, all children have positive supplement intakes.

Another theory that might be consistent with the gaps we find in the data is that the supplements allow households to learn about the production function. If parents have certain configurations of mean and variance beliefs about the impact of protein on height, then a learning model could generate similar dynamics. However, a learning model could also generate the exact opposite. This could arise if parents overestimate the impact of protein on height. It could also happen if parents face enough uncertainty about the impact of protein on height. In this case, parents may decide to experiment and give a lot more protein and, over time—and as they have more children—converge down to levels of protein intake that are consistent with updated process. In other words, the learning model does not definitely predict even the same qualitative path of adjustment of protein consumption and evolution of height over time (e.g., see Antonovics and Golan (2012)).

Additionally, consumption of protein takes place both in the centers as well as in the privacy of the home. In the data, over time, protein consumption at home and at the center grow at the same rates (so that the relative amounts are more or less constant over time). Even if other parents observed how much protein each village child consumes in the center, the community would have to know about the consumption that happens at home for the learning model to produce consistent paths of protein intake and height development over time. And most of the children’s consumption of nutrients (67% for proteins, 86% for total energy) occurs at home. Furthermore, as noted above, the new parents in one year were largely not new parents in the previous year (from 83% to 95% were not new parents in the previous year). Therefore private learning across cohorts is likely to be limited.

In spite of our strong beliefs that these explanations are unlikely to drive the dynamics we observe in this data, we recognize that these alternative theories cannot be directly rejected with the information we have in our data. A definite test of the different mechanisms implied by these models would require researchers to elicit parental trust about public programs, parental beliefs
about reference points and parental perceptions about height (or, more generally, human capital) production functions. To the best of our knowledge, no parenting program to date has collected simultaneously all of this information in surveys with participating parents.

4.2 Parameter Estimates

### Table 2: Estimated Model Parameters

<table>
<thead>
<tr>
<th>Parameter Estimates (s.e.)</th>
<th>Preference</th>
<th>Production Function</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Preference</strong></td>
<td>ρ</td>
<td>0.0725 (0.0038)</td>
</tr>
<tr>
<td></td>
<td>γ</td>
<td>0.0347 (0.0039)</td>
</tr>
<tr>
<td></td>
<td>λ</td>
<td>−0.041 (0.0065)</td>
</tr>
<tr>
<td><strong>Production Function</strong></td>
<td>A</td>
<td>4.1036 (0.020)</td>
</tr>
<tr>
<td></td>
<td>α_{H0}</td>
<td>0.0344 (0.016)</td>
</tr>
<tr>
<td></td>
<td>α_{male}</td>
<td>0.0074 (0.0026)</td>
</tr>
<tr>
<td></td>
<td>β</td>
<td>0.0753 (0.016)</td>
</tr>
<tr>
<td></td>
<td>σ_{ε}</td>
<td>0.0100 (0.0011)</td>
</tr>
</tbody>
</table>

| Price Discount             | δ          | 0.3756 (0.026)      |
|                           | σ_{η}      | 0.3830 (0.013)      |
|                           | σ_{i}      | 0.0425 (0.0013)     |

We present estimated parameters in Table 2, with standard errors shown in brackets. For preferences, ρ is estimated to be -0.0725, indicating concavity in preferences for c. γ is estimated to be 0.0347, and λ is −0.041. Given these parameters, we show the consumption- and height-possibility frontier along with indifference curves for an individual in Figures 2 and 3. Given these parameters, parents prefer taller children, but do not wish for their child to be taller than the reference comparison height. The price discount parameter δ is 0.3756, representing a 38% discount in protein prices in Atole villages. The production-function parameters are β = 0.075, α_{H0} = 0.034, α_{male} = 0.0074, A = 4.10, and σ_{ε} = 0.010. The measurement-error estimates are σ_{η} = 0.38 and σ_{i} = 0.04.

4.3 Model Fit

Given estimated parameters, we solve for optimal protein choices for each household. Table 3 compares simulated and actual average protein choices in Fresco and Atole villages, and average height outcomes at month 24 in Fresco and Atole villages. From Panel A, overall, the observed average Fresco village protein choice is 18.78 grams per day and the model simulated average is 19.29 grams. The observed average Atole protein choice is 25.84 grams per day, and the simulated Atole choice is 25.47 grams. For heights, the observed average heights in Fresco
and Atole villages are 76.97 cm and 78.30 cm at 24 months of age; the corresponding simulated values are 76.77 cm and 78.39 cm.

Panel B of Table 3 compares simulated and actual averages across gender. In the model, reference points for girls and boys differ by a constant, and there is also a gender–specific coefficient in the production function. With these two gender-related coefficients, we are able to match fairly well the gender gaps in nutritional choices and height outcomes. In Atole villages, observed average proteins for boys and girls are 26.43 grams and 25.19 grams and the simulated results are 26.60 grams and 24.24 grams. In Fresco villages, observed average proteins for boys and girls are 20.12 grams and 17.31 grams and the simulated results are 20.30 grams and 18.15 grams.

Table 3: The Fit of the Estimated Model’s Simulated Choices with Data

<table>
<thead>
<tr>
<th></th>
<th>Average Protein Choices</th>
<th>Average Height Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fresco</td>
<td>Atole</td>
</tr>
<tr>
<td></td>
<td>simu.</td>
<td>observed</td>
</tr>
<tr>
<td>Panel A: Average</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>19.29</td>
<td>18.78</td>
</tr>
<tr>
<td></td>
<td>76.77</td>
<td>76.97</td>
</tr>
<tr>
<td>Panel B: Averages Across Genders</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>18.15</td>
<td>17.31</td>
</tr>
<tr>
<td></td>
<td>76.11</td>
<td>76.19</td>
</tr>
<tr>
<td>Male</td>
<td>20.30</td>
<td>20.10</td>
</tr>
<tr>
<td></td>
<td>77.35</td>
<td>77.67</td>
</tr>
<tr>
<td>Panel C: Averages Across Years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1970-71</td>
<td>18.61</td>
<td>18.17</td>
</tr>
<tr>
<td></td>
<td>76.57</td>
<td>76.83</td>
</tr>
<tr>
<td>1972-73</td>
<td>19.25</td>
<td>18.97</td>
</tr>
<tr>
<td></td>
<td>76.79</td>
<td>76.73</td>
</tr>
<tr>
<td>1974-75</td>
<td>19.69</td>
<td>18.96</td>
</tr>
<tr>
<td></td>
<td>76.85</td>
<td>77.24</td>
</tr>
</tbody>
</table>

Panel C of Table 3 compares simulated and actual averages across calendar-year birth cohorts. Income, price, and initial height variations over the years impact the average height and protein choices in each year; however, only the differentially trended reference point sequence can explain the differential nutritional trends. Average protein choices increased rapidly in Atole villages, from 24.19 in 1970 to 1971 to 25.68 grams in 1972-1973, and then to 27.15 grams in 1974-1975. The corresponding simulated averages are 23.46, 24.92 and 27.46. In comparison, protein choices in Fresco villages increased from 18.17 grams in 1970-1971 to 18.97 grams in 1972-1973, and then to 18.96 in 1974-1975. The corresponding simulated results are 18.61, 19.25 and 19.69 grams, which are increasing at a slightly faster pace than the observed outcomes.
For the height outcomes across the years, the match is very close as can be seen from columns 4 through 8 in Panel C of Table 3. Average heights in Atole villages for 1970-71, 72-73, and 74-75 are 77.18 cm, 78.57 cm, and 78.77 cm respectively. Corresponding simulated heights in Atole villages are 77.88 cm, 78.27 cm and 78.87 cm. Average heights in Fresco villages for 1970-71, 72-73, and 74-75 are 76.83 cm, 76.73 cm, and 77.24 cm respectively. Corresponding simulated heights in Fresco villages are 76.57 cm, 76.79 cm and 76.85 cm.

5 Counterfactual Policy Experiments

Using the estimated model, we conduct three sets of counterfactual exercises. First, we decompose the relative contributions of prices and reference points to the height differences between Atole and Fresco villages. Second, we evaluate the impacts of changing reference heights exogenously in comparison with the effects of changes in income and price.

In our third sets of counterfactuals, we exploit dynamic features of our model with reference points to distinguish among three possible effects of protein-price-subsidy policies: 1, the direct impact of subsidies on the treated children; 2, the indirect effect of subsidies via shifting reference points on the treated children; 3, the indirect impact of shifting reference points on the untreated children. For the third set of counterfactual policy experiments, we compare poor-targeted and universal policy experiments.

5.1 Decomposition

In the model, the initial height gap between Atole and Fresco villages is driven by the protein input price reduction in Atole villages, which has a direct and immediate impact on household budgets. Additionally, the initial price reduction induces changes in reference heights in the following periods that lead to further increases in nutritional intakes and height. We show in Table 4 and Figures 5 and 6 counterfactual simulations that close the protein and height gaps between Atole and Fresco villages.

In the first column of the first panel on Table 4, we summarize, for households in Fresco villages, the simulated average height outcomes and protein choices. In column five, we show these for households in Atole villages. Comparing these two columns, the height gaps between Atole and Fresco villages for 1970-71, 1972-73 and 1974-75 are 1.31 cm, 1.48 cm and 2.02 cm, respectively. In the second column, Fresco households receive the 38% Atole protein price
Table 4: Decompose Protein Gaps between Atole and Fresco Villages

<table>
<thead>
<tr>
<th></th>
<th>Fresco</th>
<th>Fresco Counterfactuals</th>
<th>Atole</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>simulated no counterfactuals</td>
<td>Fresco with Atole Price Discount</td>
<td>Fresco with Atole Ref. Point</td>
</tr>
<tr>
<td><strong>Panel A: Height Across Birth Cohorts</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1970-71</td>
<td>76.57</td>
<td>77.29</td>
<td>77.09</td>
</tr>
<tr>
<td>1972-73</td>
<td>76.79</td>
<td>77.54</td>
<td>77.47</td>
</tr>
<tr>
<td>1974-75</td>
<td>76.85</td>
<td>77.69</td>
<td>77.70</td>
</tr>
<tr>
<td>Observations</td>
<td>7050</td>
<td>7050</td>
<td>7050</td>
</tr>
<tr>
<td><strong>Panel B: Protein Across Birth Cohorts</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1970-71</td>
<td>18.61</td>
<td>20.96</td>
<td>20.37</td>
</tr>
<tr>
<td>1974-75</td>
<td>19.69</td>
<td>22.63</td>
<td>22.85</td>
</tr>
<tr>
<td>Observations</td>
<td>7050</td>
<td>7050</td>
<td>7050</td>
</tr>
</tbody>
</table>

discount. This reduces the Atole–Fresco height gaps, by 72mm (55%) in 1970-71, 75mm (51%) in 1972-73 and 84mm (42%) in 1974-75. In column three, we replace the reference points in Fresco villages by the Atole reference points but do not change prices. Under these counterfactuals, height gaps decrease by 52mm (40%) in 1970-71, 68mm (46%) in 1972-73 and 85mm (42%) in 1974-75.

In column four of Table 4, Fresco households face both the effects of price discounts as well as the Atole schedule of reference heights. In Figure 6, we decompose this overall difference into the effects of the price discounts only (column two and one differences), and the additional effects from also imposing the reference points shifts (column four and two differences). The price discount’s impact is stable at around 79mm to 92mm over time. From 1970 to 1975, the contribution of the price discount to the overall effects decreases from 62% to 43%, and the additional reference-point effects increase from 48mm to 1.03cm.

37 The resulting outcomes closely approximate the simulated results from Atole villages shown in column five. This is not surprising given that other state variables do not vary significantly between Atole and Fresco villages as seen in Table 1.

38 The changes in this impact over time are due to price and income fluctuations.

30
5.2 Exogenously Shifting Reference Points

In this section, we focus only on the immediate one-period effects of the change. We compare the effects of exogenous one-period reference-point shifts to the one-period effects of protein price discounts and income subsidies. We find that a 1 cm increase in reference points corresponds to about 0.7 cm increase in height. We also find that a price discount of 37 percent and income increase of 60 percent would induce similar increases in mean heights as the 1 cm
### Table 5: One-Period Exogenous Reference Point Change vs Price and Income Changes

<table>
<thead>
<tr>
<th>Total Increase in Mean Reference Points</th>
<th>Cumulative Total Hgt Increase</th>
<th>Additional 0.5 cm Ref. Inc</th>
<th>Equivalent Price Discount</th>
<th>Additional perc. points</th>
<th>Equivalent Income Increase</th>
<th>Additional perc. points</th>
<th>% of Income Spent on Proteins</th>
</tr>
</thead>
<tbody>
<tr>
<td>+0.5 cm</td>
<td>+0.36</td>
<td>+0.357</td>
<td>20%</td>
<td>-20 pp</td>
<td>+32%</td>
<td>+32 pp</td>
<td>11.9%</td>
</tr>
<tr>
<td>+1.0 cm</td>
<td>+0.71</td>
<td>+0.349</td>
<td>37%</td>
<td>-17 pp</td>
<td>+60%</td>
<td>+28 pp</td>
<td>10.0%</td>
</tr>
<tr>
<td>+1.5 cm</td>
<td>+1.05</td>
<td>+0.346</td>
<td>51%</td>
<td>-14 pp</td>
<td>+86%</td>
<td>+26 pp</td>
<td>9.5%</td>
</tr>
<tr>
<td>+2.0 cm</td>
<td>+1.39</td>
<td>+0.338</td>
<td>64%</td>
<td>-13 pp</td>
<td>+107%</td>
<td>+20 pp</td>
<td>9.1%</td>
</tr>
</tbody>
</table>

An exogenous one-period shift in reference points also has real economic implications: this would happen if individuals moved to a different locality where the reference population is distributed differently (Bottan and Perez-Truglia 2017; Liu and Zuppann 2016). In our model, we assume that reference points could shift when households observe actual changes in heights within the village. Without relocation or observing real within-village changes, it might be difficult to convince households that they should make choices based on reference populations that they do not reside within. There is, however, recent experimental evidence that growth charts based on external populations could be effective in promoting height growth (Fink et al. 2017).³⁹

We simulate based on the distribution of Atole-village children, starting from 1970 reference points. Our results are shown in Table 5 where each of the four row corresponds to 0.5 cm increments in reference-point shifts. In the second and third columns of Table 5, average heights increase by 0.36, 0.71, 1.05, and 1.39 cm when the reference-point distribution shifts up by 0.5, 1.0, 1.5 and 2.0 cm. The incremental mean height gains, for each additional 0.5 cm increase in mean reference points, are 0.36, 0.35, 0.35 and 0.34 cm, so that each additional cm of reference-point increase induces about 0.70 cm increase in mean realized heights at month 24. The marginal rate of change decreases slightly with rising reference points.

From columns four to six of Table 5, we find that, in terms of inducing equivalent changes in mean heights, increasing mean reference points by 0.5, 1.0, 1.5 and 2.0 cm is equivalent

³⁹ As discussed earlier, Marini, Rokx, and Gallagher (2017) and Fink et al. (2017) find that growth charts could promote height growth. Earlier literature on growth charts, however, showed that parents often could not easily understand the possible relevance of growth charts for their children (Ben-Joseph, Steven A Dowshen, and Izenberg 2007).
to discounting prices by 20, 37, 51 and 64 percent.\footnote{Here we are considering a universal price discount that all children receive.} We determine the costs of these price-discount policies by multiplying the discount fraction by the amount of protein purchased: 4.1, 8.4, 12.5 and 16.7 grams per child per day respectively as shown in Column 6 of Panel A.

From columns seven to nine of Table 5, we find that, again in terms of inducing equivalent changes in mean heights, increasing mean reference points by 0.5, 1.0, 1.5 and 2.0 cm is equivalent to increasing incomes by 32, 60, 86 and 107 percent. The large income increase required here is due to Engel curve type patterns (Deaton and Muellbauer 1980) in which higher-income households spend smaller fractions of income on food. Specifically, in column 6 of Panel B, we present the shares of income spent on protein: 11.9, 10.0, 9.5 and 9.1 percent of income under each of the four sets of mean-preserving policies. As we double income, for each additional queztal, only about 9 centavos go to protein purchases.

### 5.3 Targeted vs Universal Policy Experiments

We evaluate the impacts of counterfactual policy experiments that target protein-price discounts towards poorest children and a universal policy that provides common price discounts for all, given a fixed budget.\footnote{See Appendix Section A.3 for details on how we compute budget-balancing policies.} Our outcome of interest remains height reached at 24 months of age. There has been a long debate in the both the development and early childhood literature about the trade-offs between targeted vs universal subsidy policies (Besley and Kanbur 1990; Gelbach and Pritchett 1997; Coady, Grosh, and Hoddinott 2004). Under universal subsidy policies, the entire population benefits, and under targeted policies, subsidies are generally given to those who are deemed (mean-tested for) the most in need.

Our first key result here is that the universal policy—which is generally considered to be insufficiently beneficial for the poor—is much better for poorest children in later cohorts whose heights increase substantially due to aggregate increases in reference points. The gaps between targeted and universal policies on the poor are smaller once we consider the endogenous evolution of reference points. Our second key result is that, after an initial period in which only targeted individuals benefit, the targeted policy—which would normally only benefit the poor—has substantial positive effects on the non-targeted richest children as well through the externality of reference point changes.
Both results show that reference points amplify the effects of targeted and universal subsidy policies on all children within the same village. We analyze the height distributions induced by budget-equivalent policies that gradually increase the proportion of children receiving price subsides. Overall, we find that within our context, all policies induce similar mean heights. The policies, however, generate substantial differences in height variances: the most-targeted as well as the most-universal policies both increase variances. Within the set of budget-balancing policies we consider, we find that variance in height is minimized when the 70 percent poorest children receive 18 percent price discounts.

5.3.1 Targeted Policies on Bottom Quintile ("Poorest") and Top Quintile ("Richest")

We discuss in this section the impact of policies with different degrees of targeting/price-discounts on children from the bottom 20 "poorest" and top 20 percent "richest" of the income distribution. We compare targeting 20, 40, 60, 80 percent of the poorest children along with universal policy. Price discounts at 55, 30, 21, 16 and 13 percent for each of the five policies are calculated to preserve budget balance. Poorest children receive subsidies under all five policies, but richest children only receive subsidies under the universal policy.

We start the simulation with the 1970 reference points and observable distributions. Figure 7 presents results for the cohort born in 1970. Figure 9 presents the differences in heights for poorest children from the 1970, 1972, 1974 and 1976 cohorts. Figure 8 presents results for the 1976 cohort. In all Figures, the orange solid (green dashed) line shows median heights for poorest (richest) children. The flat horizontal lines show that in the absence of the price discount policy, median heights at month 24 for poorest and richest children in the 1970 cohort were 76.7 and 77.4 cm respectively (0.7 cm gap).^42

Figure 7 shows that under targeted subsidies, poorest children from the 1970 cohort experience a significant increase in heights, with median heights increasing by 1.3, 0.6, 0.4, and 0.3 cm when poorest children receive 55, 30, 21, and 16 percent targeted discounts. With a 55 percent price discount, poorest children’ median height reaches 77.9 cm and is 0.5 cm higher than the median height for richest children. When both richest and poorest children receive 13 percent price discounts under the universal policy, median height increases more for the poorest (+0.25 cm) than the richest (+0.17 cm).

^42 These correspond to median daily protein intakes of 19.0 and 22.1 grams for the poorest and richest children.
Figure 9 shows that with 55 percent price discounts under the most-targeted policy, due to endogenous shifts in reference-point distributions, median heights increase significantly by 1.3, 1.9, 2.4, and 2.7 cm for 1970, 1972, 1974, and 1976 cohorts of poorest children. On the other hand, the universal policy provides small height increases to the poorest initially, but effects amplify significantly across cohorts. Specifically, for the 1970 cohort of poorest children, the median protein intake increases by 23, 38, 50 and 58 percent for these cohorts.

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43 Correspondingly, median protein intake increases by 23, 38, 50 and 58 percent for these cohorts.
most-targeted policy (55 percent discount) increases the median height by 1.3 cm, which is 4.8 times larger than the 0.26 cm median height increase induced by the universal policy (13 percent price discount). For the 1976 cohort of poorest children, however, the effect of the most-targeted policy is only 1.8 times greater than the effect of the universal policy, each of which increases median heights by 2.7 and 1.5 cm respectively.44

Figure 8 presents results for the 1976 cohort. Here we compare heights for the 1976 cohort to the heights at month 24 for the 1970 poorest and richest cohorts without subsidies. Across the five policies from most-targeted to universal, heights for the richest children increase by 1.3, 1.3, 1.3, 1.3 and 1.6 cm, equivalent to 48, 65, 76, 81 and 103 percent of the increases in heights for poorest children, which are 2.7, 2.0, 1.7, 1.6, and 1.5 cm. The 1.3 cm median height increases for the richest children under the four targeted policies are only due to the reference-point externality of the treatments on non-targeted individuals. The poorest children reach a higher median height (79.4 cm) than richest non-targeted children (78.8 cm) only under the 55 percent price discount policy.

44 Comparing poorest children across cohorts, the increase in median height is 5.8 times larger for the 1976 cohort compared to the 1970 cohort (1.5 vs 0.26 cm). The increase in median height for richest children across cohorts is 2.2 times (2.7 vs 1.25 cm). Additionally, for the 1970 cohort of poorest children, 100 percent of the increases in height are due to first-period price-discount effects, but for the 1976 cohort of poorest children, under 55, 30, 21, 15 and 13 percent price discounts, first-period price-discount effects only account for 46, 31, 24, 19, and 16 percent of the total effect of each policy.
5.3.2 Distributional Effects of Different Levels of Targeted Policies

This section focuses on the distributional effects of targeting. Given our sample of individuals, mean heights are relatively constant across targeting levels, and variance is minimized when 70 percent of the poorest children are targeted to receive subsidies. Specifically, we analyze the effects of targeting from 20 to 90 percent of the poorest children at 10 percent intervals along with a universal policy. Price discounts at 55, 39, 30, 25, 21, 18, 16, 14 and 13 percent for each of the nine policies are calculated to be approximately budget constant. Figure 10 plots various percentile levels of overall—including both targeted and non-targeted children—heights of month 24 distributions under each policy experiment.

The dashed black line in Figure 10 shows that the mean heights across policies differ by at most only 0.054 cm. Our policy experiments shift a fixed amount of subsidies from one subset of individuals to another in the form of price discounts. Similar mean heights across policies indicate that given the distribution of state-space values and model parameters, shifts in protein intakes across policies have approximately linear effects.

Who receives the transfers and how

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45 The highest mean, 78.58 cm, is achieved under targeting 20 percent of the poorest households, and the lowest mean, 78.52 cm, is achieved under the universal policy.

46 One might suspect that the variations in means across policies would be large given the concavity of the production function: all else equal, 1 gram of protein transferred from those with high intake to those with lower intake should lead to a net gain in overall height. Here, however, given that households re-optimize with new subsidies, the increases in protein intakes are less than the amounts of protein transferred to the poor.
much they receive change the relative heights among individuals, but not the overall average height significantly.

As policies shift price-discount intensity and recipients, there are significant variations in height distributions across policies. One measure of variation is the difference between the 10th and 90th percentiles of heights across policies. This is the difference between the dashed blue lines at the top and bottom of Figure 10. Showing a decreasing pattern, these gaps are 1.5, 1.1, 0.9 and 0.75 cm when 20, 30, 40, and 50 percent of the poorest children receive price discounts; the gaps are the tightest at 0.69, 0.66 and 0.66 cm under policies that provide 60, 70, and 80 percent of poorest children with price discounts;\(^47\) the gaps widen again to 0.8 and 0.9 cm under the two most universal policies.

The minimization of height variation when 70 percent of the poorest children are targeted is driven by a tightening of both the higher and lower percentiles of the heights at month 24 distributions. First, under the most-targeted policies, children from the poorest households receive very large discounts and become the tallest children, driving the 90th percentile of height at month 24 distribution up.\(^48\) Concurrently many children with below-median income do not receive subsidies under the most-targeted policies, and they push down the 10th and 20th percentiles of the height distribution. Second, under the most-universal policies, children from the richest households receive price discounts, and they drive the 90th percentile height distribution up.\(^49\) Concurrently, because subsidies for the poorest households are much lower than under more-targeted policies, they push the 10th and 20th percentiles of the height distribution lower. Consequently, we observe the wider distributions of heights under the most-universal and most-targeted policies, but tighter distribution in the middle of Figure 7.

\(^{47}\) The s.d. of heights, at 0.40 cm, is also the smallest for the policy that targets 70 percent of poorest children.

\(^{48}\) For the most-targeted policy that provides 55 percent price discounts to the children in the lowest quintile of income, these poorest children’s heights increase significantly and they move to the highest quintile of the realized height at month 24 distribution. As shown in Figure 7, the median heights of these poorest children under the 55 percent discount policy exceed the median heights of children from the richest quintile of income, hence this pushes the 80 and 90th percentile of the overall height distribution up under the most-targeted policies.

\(^{49}\) As shown in Figure 7, the smaller discount (13 percent discount under the universal policy) given to the richest children allows them to achieve higher heights at month 24 than a larger discount (16 to 21 percent under slightly more-targeted policies) given to children in the lower portions of the income distribution.
6 Conclusion

Despite progress in recent years, approximately 22 percent (150 million) of children below age five were stunted globally in 2018. Significant policy initiatives are required in order to reach the the UN and WHO’s Sustainable Development Goals of lowering the number of stunted children to 100 million by 2025 and end all forms of malnutrition by 2030 (FAO 2019). Given resource limitations of the global aid community, it is important to consider non-budgetary means of improving the child-height outcomes.

In this paper, we build and estimate a child-nutrition investment model. The model considers reference-dependent preferences, where the reference is with respect to the heights of the previous cohort of children who live in the same village. Reference points can shift endogenously as households observe the heights of children around them from earlier birth cohorts changing.

For researchers interested in the impact of price subsidies and income transfers, we have introduced a long-term secondary channel—endogenous changes in reference points—that might affect the impacts of these policies. For the protein-supplement experiment implemented in Guatemala, which we interpret as a price-discount policy, by 1975–6 years after the start of the policy—60% of the impact of the policy came through its impact on shifting reference points.

Our paper also shows the significant height increase that could be realized from shifting reference points for highly-stunted populations. It is an open question how to exogenously shift these reference points in the short run, although the Peruvian experience mentioned in the introduction indicates that educational campaigns could be effective on a large scale over time. The cost of an educational campaign to inform households about alternative reference heights could be lower compared to income transfers and price subsidies with similar effects on heights.

Reference points create channels of amplifying spillover effects so that the effects of targeted and universal policies are more similar than if reference points did not matter. We showed that targeted policies on the poorest children lead also to significant gains for children from the richest households over time. We also showed that policies that provide universal subsidies initially benefit the poorest little but these gains increase significantly over time as subsidies induce both the richest and poorest children to jointly consume more and push-up reference heights. In practice, our results mean that policy makers, in deciding between targeted and universal policies, should consider the size of the communities that the policy impacts and how
likely it is that these communities share reference-points mechanisms as channels of policy spillovers. If the richest and the poorest in a community are segregated, as in some urban contexts, there might be no spillovers between the richest and the poorest through reference-point changes. In the context of village economies, the probability for spillovers is likely greater. Thus incorporating local reference points leads to substantial amplification of policy effects and to a number of significant nuances in expected distributional effects of alternative policies.
References


Thompson, Amanda L., Linda Adair, and Margaret E. Bentley. 2014. “‘Whatever Average Is’: Understanding African American Mothers’ Perceptions of Infant Weight, Growth, and Health.” *Current Anthropology* 55, no. 3 (June 1): 348–355.


Appendices (for Online Publication)

A.1 Model Solution

Given the model, we solve for optimal choices using an iterative grid search routine that integrates over the two shocks facing the household: $R_{yv}$ and $\varepsilon$. First, for each household, given $\Omega = (Y, P_{yv}^N, X)$, we construct a grid with $Q_1$ points of household-specific nutritional choices from the minimum of zero up to the maximum that each household could purchase. Second, assuming that $R_{yv}$ and $\varepsilon$ are both normally distributed and are independent from each other, we draw $M$ productivity shocks $\varepsilon$ for each household, where $\varepsilon \sim N(0, \sigma^2_{\varepsilon})$. Third, for each household and each $\varepsilon$ shock drawn, we integrate $R_{yv}$ in the reference point component of the utility function analytically as a truncated normal function:

$$\int_{R_{yv}} (h_{24} - R_{yv}) 1 \{h_{24} \geq R_{yv}\} dF(R_{yv}) = (h_{24} - \mu_{R_{yv}}) \cdot \left( \Phi \left( \frac{h_{24} - \mu_{R_{yv}}}{\sigma_{R_{yv}}} \right) \right) + \sigma_{R_{yv}} \phi \left( \frac{h_{24} - \mu_{R_{yv}}}{\sigma_{R_{yv}}} \right) \tag{15}$$

Now each point on the choice grid has an expected utility value associated with it.

Fourth, we find the grid point that has the largest expected utility value. Fifth, we construct a new finer household-specific choice grid with $Q_2$ points around the optimal nutritional choice from the initial $Q_1$ point grid. We repeat steps one through four to evaluate utility and find the maximum as before. The process is iterated for $Z$ iterations until the total difference in optimal nutritional choices between iterations meets a convergence criteria. This solution provides the exact optimal choices for each household. Given our estimation problem, the speed of obtaining the likelihood function given each set of parameters is determined by $M$, the number of productivity shocks that we draw. For $M$ less than 50, each likelihood is obtained within seconds.

A.2 Data for Estimation

We include in the estimation sample children who were born between 1970 and 1975. We showed summary statistics for these children in Sections 3.2 and 3.3. As discussed earlier, we do not observe both initial heights and heights at month 24 information for children born before or after these years.

We use the months 15 to 24 average protein intakes, heights at month 24, protein prices, incomes, gender, and initial height variables shown in Table 1 and described in Section 3.2 as
For nutritional intakes, we use protein because Puentes et al. (2016) show that proteins rather than non-protein components of calories matter for height growth in these INCAP data. Ideally, our intake variable should be averaged from month 0 to month 24. However, we do not observe protein values from month 0 to month 12 for close to half of our sample due to the difficulty of calculating the protein component of breast–milk for children who rely on breast feeding in the first year of life.

In terms of reference points, controlling for gender, we use the predicted value of the linear trends across cohorts between 1970 to 1975—the trends and coefficients are shown in Figure 4 and described in Section 3.3—as the reference points for Atole and Fresco villages. Specifically, we use the linear trends from Panels 1.2 and 2.2 of Figure 4 along with a gender adjustment. The trend for Atole villages could also be approximated with a quadratic trend, but switching to quadratic trends has minimal effects on estimated parameters. Potentially, we could also use the local polynomial approximated nonlinear trends as reference points, but the linear trends as shown in Figure 4 closely approximate the local polynomial trends, which further could be fluctuating due to sample variation for each birth cohort group. This provides us with a set of village, cohort calendar year and gender-specific predictions of height at 24 months of age: \[ E(H_{24}|\text{year, gender, atole}) = \phi_0 + \phi_1 \cdot \text{year} + \phi_2 \cdot \text{atole} \cdot \text{year} + \phi_3 \cdot \text{gender}. \]

We use the 24 months of age height predictions to obtain \( \mu_{R_{\text{year, gender, atole}}} \). For example, the predicted linear trend value that corresponds to the height at month 24 of those born in 1970 is the mean reference point for the cohort born in 1972: \( \mu_{R_{1972, \text{gender,v}}} = E(H_{24}|1970, \text{gender, v}) \). By construction, if simulated results from our estimated model match the average 24 months of age heights for different cohorts, we will have matched also the mean reference points values. We fix \( \sigma_{R_{\text{year, gender, atole}}} = 3.5 \) for Atole and Fresco villages in all years. We do this because height variances across cohorts and villages do not seem to vary systematically. The standard deviations of heights in Fresco villages are 3.33, 3.34, 3.24 cm for 1970-71, 1972-73, and 1974-75 cohorts. The standard deviation of height in Atole villages are 3.13, 3.73, 3.53 cm for 1970-71, 1972-73, 1974-75 cohorts.

### A.3 Simulation Design–Budget Balancing Targeted to Universal Policies

In Section 5.3, we compare policies in which increasingly larger fractions of individuals in a village are targeted as subsidy recipients. To keep subsidy costs the same across policies, we reduce the subsidies provided to targeted children as the fraction of children targeted increases.
We conduct policy counterfactuals that target children by household annual income.

To simulate the policies, we draw 500 individuals based on the empirical joint distribution of incomes, gender and initial heights of all children from Atole villages. Then we start at the reference point from Atole villages in year 1970 and simulate our model forward. Each model period is 2 years, and we simulate the model 4 times to obtain results for the 1970, 1972, 1974 and 1976 cohorts. The state-space distribution and protein prices facing households are the same across cohorts, but each cohort faces different endogenously evolving reference points, which lead to variations in nutritional choices and heights.\(^{50}\)

Following the model interpretation of the protein supplementation policy as a price discount, our counterfactuals here involve changing that discount.\(^{51}\) Under the universal policies, all families receive subsidies through a common price discount. Under the policies that target the poor, we transfer the subsidies that rich children received under the universal policy to the poor by increasing the price discount that the poor receive. Specifically, let \(\tau\) be the fraction of poorest children receiving price discounts and \(\delta\) be the percentage price discount that children receive. \(Z(\tau, \delta)\) is the total cost of a subsidy in grams of protein for 1970, 1972, 1974 and 1976 cohorts, given reference point distribution \(\Gamma\) for each cohort:

\[
Z(\tau, \delta) = \sum_{\text{cohort} \in \{70, 72, 74, 76\}} \left\{ \delta \cdot \int_{\varepsilon} \int_{Y_{\text{min}}}^{F_Y^{-1}(\tau)} \int_{X} N\left(\frac{Y, X, \varepsilon}{\delta, \Gamma_{\text{cohort}}}\right) f(Y | X) f(\varepsilon | X, Y) f(\varepsilon) dX dY d\varepsilon \right\}
\]  

(16)

As described earlier, we fix the joint distribution of the state space variables across cohorts, and so only the reference point distribution \(\Gamma\) is cohort-specific in Equation 16. We start \(\Gamma_{1970}\) as mentioned using the actual reference points in year 1970 from Atole villages, and solve for subsequent reference point distributions following Equation 8.

We first solve for \(Z(\tau = 0.1, \delta = 0.9)\), when 10 percent of the poorest simulated households are provided with a 90 percent protein price discount.\(^{52}\) Then, for \(\tau \in (0.2, 0.3, ..., 0.9, 1.0)\), we

\(^{50}\) The goal is to isolate the effects of price subsidy and reference point changes, and abstract away from other potential observed differences in initial heights, non-protein prices and incomes. If the price discount policy were 38 percent and provided to all individuals, the height path would be similar to the observed height path, but it would not be identical because all of our simulated cohorts are identical except for their reference points.

\(^{51}\) Alternatively, we could provide households with different levels of protein transfers, but that involves forcing households to consume a fixed level of subsidy proteins (see footnote 33).

\(^{52}\) with 90 percent, we increase the fraction of children targeted, the price discounts will not fall below 10 percent.
solve for the $\delta$ that minimizes the difference between $Z(0.1, 0.9)$ and $Z(\tau, \delta)$:

$$
\delta (\tau, Z(0.1, 0.9)) = \arg \min_{\delta \in [0.01, \ldots, 1.00]} |Z(\delta, \tau) - Z(0.1, 0.9)|
$$

(17)

Solving for the $\delta$ values following Equation 17, we find that policies that provide 55, 50, 39, 30, 25, 21, 18, 16, 14 and 13 percent price discounts for 20, 30, 40, 50, 60, 70, 80, 90, and 100 percent of children, ranked from the poorest to the richest, cost approximately the same as $Z(0.1, 0.9)$. 