ESSAYS ON NUTRITION AND COGNITIVE PRODUCTION IN DEVELOPING COUNTRIES: EVIDENCE FROM ETHIOPIA & NEPAL

Mohammad Ali

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ESSAYS ON NUTRITION AND COGNITIVE PRODUCTION IN DEVELOPING COUNTRIES: EVIDENCE FROM ETHIOPIA & NEPAL

BY

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DISSERTATION

Submitted in Partial Fulfillment of the Requirements for the Degree of

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Albuquerque, New Mexico

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DEDICATION

For Madiha who never gave up on me.
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To my life-coach, my grandfather S. M. Younis: because I owe it all to you. Many Thanks!

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ABSTRACT

This dissertation is comprised of five chapters. The first chapter provides an outline of the three separate research papers that are combined in this dissertation. It highlights the goals of each paper, discusses their importance to the field of economics, and outlines their contributions to the existing literature. The final chapter summarizes the main conclusions from the three research articles and points to how my future research trajectory is shaped by my dissertation research.

The second chapter explores the effect of current health (denoted by BMI for age scores) on cognitive test scores directly and indirectly, through time allocated to studying, for a sample of Ethiopian children during childhood (5-8 years) and mid-childhood (8-12 years). Using a
novel method for using instrumental variables to conduct causal mediation analysis, I find that not only does current health improve cognitive test scores, but that this effect operates almost entirely through an indirect time allocation channel. Moreover, I also find that as the child approaches adolescence and the opportunity costs to study time increase, improved current health can lead to reduced study time and increased work time. My results point to time allocation as an important channel in the influence of current health on cognitive production during childhood. Finally, policies that improve returns to education and reduce returns to child labor are likely to improve cognitive outcomes during mid-childhood.

The third chapter explores patterns of persistence and catch-up growth in cognition (denoted by standardized mathematics scores) for a sample of Ethiopian children during childhood (5-8 years), middle childhood (8-12 years), early adolescence (12-15 years), and middle adolescence (15-19 years). I also examine whether perfect complementarity in cognition formation exists for this sample. The results suggest that persistence in cognition scores increases throughout the lifecycle of cognitive production. They also point towards early childhood (before age 5) as a “sensitive period” where the chances of catch-up growth in cognition are the highest, especially for children at the lower end of the cognition distribution. Finally, I also find evidence for the case of perfect complementarity in cognitive production, where investments in cognition seem necessary for the process of self-productivity in cognitive production to start.

The fourth chapter comes up with a set of adult-equivalent scales based on the specific daily intake requirement for macro- and micronutrients. I also attempt to find whether on average there are differences between the individual-level nutrient availability estimates when they are calculated through nutrient-specific and other (calorie-based, per capita, or OECD) adult-
equivalence scales. The results suggest that on average there are significant differences between the individual-level nutrient availability estimates depending on which adult-equivalent scale is used. Moreover, the nutrient-specific adult-equivalent scales derived in this paper have the potential to reduce measurement error in future studies relying on nutrient availability estimates obtained through household survey data.
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CHAPTER 1
Introduction

Economists have tended to agree on the importance of natural resources such as water, soil, and fossil fuels etc. in the economic development of a country. But to extract the maximum surplus from these scarce natural resources, they must be allocated efficiently within the economy. This efficient allocation relies on the capabilities of the human population in charge of resource allocation. These multi-dimensional capabilities are generally referred to as human capital by economists and range from cognitive skills, training, and health acquired through education, work experience, nutrition, and psychological well-being. Thus, human capital is one of the cornerstones of economic development, as improvements in it generally lead to higher productivity and technological progress.

Since the endowment of abilities which form human capital can be increased through investments in education and health, which are costly in themselves, disparities in human capital have naturally occurred between developed and developing countries. In fact, one of the biggest differences between developed and developing countries is the growth rate in human capital. Thus, it becomes important to explore the different ways through which human capital can be enhanced in developing countries. Moreover, since health, nutrition, and cognitive outcomes are so inseparably interrelated, while also dependent on household-level decision-making, it is imperative to explore these dynamics in the context of a developing country context. Thus, my dissertation attempts to explore the patterns of growth in cognitive outcomes for an Ethiopian dataset, while also looking at how household-level decisions can impact the interplay between different dimensions of human capital formation such as nutrition and cognitive ability.
Ethiopia is a suitable country to explore these dynamics as it suffers from a host of problems related to human capital formation found in a typical developing country. Ethiopia is part of sub-Saharan Africa, which is an area known for its high rates of malnutrition. But even within this area, Ethiopia has the second highest rate of malnutrition (OU, 2019). According to the 2016 Demographic Health Survey, 38% of the children were found to be stunted (measure of height for age), 10% were found to be wasted (measure of weight for height), while 24% were found to be underweight (measure of BMI for age) (USAID, 2018). These numbers show severe levels of malnutrition for children in Ethiopia.

Combined with this problem of malnutrition is the problem of child labor in Ethiopia. In the 2015 National Child Labor Survey, it was found that 41.7% of the children aged between 5 and 11 were involved in child labor of some sort, while 45.3% of them were engaged in hazardous work (ILO, 2018). Engagement in hazardous work was occurring in both the urban as well as rural areas. In the urban centers, hazardous work mostly comprised of children working in close proximity to heavy machinery in the weaving industry. On the other hand, hazardous work in rural areas mostly comprised of working for long hours on family farms.

Further exacerbating the potential for children’s human capital formation in Ethiopia is the fact that a large number of children do not finish primary schooling. As of 2015, the primary school completion rate was only 54% relative to the sub-Saharan average of 69% (The World Bank, 2018). Thus, a background of high rates of malnutrition and child labor, and low rates of primary school completion, provide an ideal opportunity to explore the patterns of cognitive formation in such a setting. Moreover, we can also examine how household-level
decision-making can affect the interplay between different dimensions of human capital such as nutrition and cognition.

Ample evidence demonstrates the importance of early childhood (including gestation) to long-term human capital formation. This period is commonly referred to as a “sensitive period” of development because investments during this time tend hold more influence than in later developmental stages. Consequently, the events of early childhood can influence future human capital outcomes such as adult height, health, and cognition (Cunha & Heckman, 2008; Cunha, Heckman, & Schennach, 2010; Almond & Currie, 2011; Lynch & Gibbs, 2017). Thus, early investments in children’s human capital are arguably both efficient and equitable (Cunha & Heckman, 2007; Alderman, 2010). But although there is a growing literature which suggests the existence of a second “sensitive period” during adolescence where catch-up growth can occur (Case & Paxson, 2008; Aguero & Deolalikar, 2012), there is still not a lot of literature which deals with the relationship between nutrition and cognitive outcomes during later stages of childhood. By focusing on this research area, I add to the existing literature which focuses on the “sensitive periods” during early stages of childhood.

This research area becomes even more important as currently we know very little about the importance of health and nutrition to cognitive achievement during later stages of childhood with early childhood health outcomes already realized. Furthermore, these later stages of childhood also coincide with Piaget’s preoperational (5 to 8 years), concrete operational (8 to 12 years), and formal (12 to 19 years) stages of cognitive development. The preoperational stage is marked with the use of words and pictures to denote objects, while the concrete operational and formal stages of cognitive development are marked by the start of use of inductive and deductive logic by children respectively (Piaget, 1964). There is also a limited
understanding of the mechanisms and channels that might explain the influence of health on cognition, especially during the middle and later childhood stages. Thus, the second chapter of my dissertation research examines the role of health and nutrition in cognitive production during middle and later stages of childhood which works through the time allocation channel for a sample of children in Ethiopia. Therefore, I explore whether during these later stages of childhood (beyond age 5), the external channels, such as parental decision-making outcomes, become more important than the biological processes that underlie cognitive production.

In this chapter, I examine the relationship between current health and cognitive production. Most evidence on the effect of health on cognition focus on measures of health stocks (or chronic health) such as height. However, conditional on health stock, variations in current health flows (i.e., acute health) such as those due to sickness or acute undernutrition can also influence cognitive production. For example, current health can directly influence brain function, energy, and school attendance. Additionally, current health may indirectly affect cognitive production through its effect on the opportunity cost of time devoted to school and study. For example, improvements in health may also increase the returns to entering the labor market earlier or working on the family farm. If this is the case, healthier children may devote less time to studying thus reducing the positive influence of health on cognition.

Specifically, I estimate the effects of Body Mass Index (BMI) for age z-scores on Peabody Picture Vocabulary Test (PPVT) and Mathematics test scores for a sample of Ethiopian children at age 8 and 12, using the Young Lives (YL) dataset. These ages in childhood and mid-childhood represent important stages of cognitive development and are called the Piaget’s preoperational and concrete operational stages of cognitive development (Piaget, 1964).
In addition to estimating BMI for age’s direct effects, I also examine the extent that current health affects cognitive scores through the channel of time devoted to studying by the children in the sample. I call this channel the study time allocation channel. In other words, I examine the relationship between children’s health and its effect on their time allocated to studying which in turn can affect their cognition (test scores). As the first step, I establish a causal relationship between BMI for age scores and test scores. I then explore the causal effect of BMI for age scores on time devoted to studying.

Finally, I measure the direct and indirect (through the study time allocation channel) causal effects of BMI for age on test scores using an innovative method proposed by Dippel et al. (2017) to perform mediation analysis with endogenous treatment and endogenous mediators. To my knowledge no existing research investigates the indirect effects of health on cognitive outcomes through the study time allocation channel. The results indicate that current health does indeed improve cognition test scores directly and indirectly (through the study time allocation channel) during childhood (5 to 8 years) even after controlling for early life health, where the indirect effect makes up most of the total effect. Thus, while many emphasize the first few years of life as the window for health/nutrition interventions, these results indicate that interventions aimed at improving health status can still improve child human capital outcomes even outside of “sensitive periods”. However, as children enter the pre-adolescence age (8 to 12), increases in current health (BMI for age) result in a higher allocation of work hours while a lower allocation of study hours. This alludes to the idea that during these ages the short run returns from the child joining the labor force become more than the long run returns to education. Therefore, policies that both improve returns to education as well as
reduce returns to child labor are likely to improve cognitive outcomes during later childhood stages.

The second chapter of my dissertation points to the existence of external channels like the time allocation channel being important in influencing the relationship between health and cognition during later stages of childhood. This points to the notion that such channels might play a much bigger role in cognitive production than the biological processes which shape cognition during the early stages of childhood. But this still begs the question whether human biology can still play a role in determining cognitive production during the later stages of childhood and adolescence. This question becomes even more important to explore as the patterns of persistence and chances of catch-up, based on previous cognition, might change during the lifecycle of cognitive production. Thus, self-productivity and complementarity might still combine to affect cognitive production even after the early stages of childhood have concluded. Knowing the importance of early investments in cognition, it also becomes important to investigate the case of perfect complementarity where later investments cannot overcome the lack of earlier investments.

The third chapter of my dissertation explores this idea in detail by measuring the extent that persistence or catch-up is possible in Mathematics test scores for the YL sample of Ethiopian children during childhood (5-8 years), middle childhood (8-12 years), early adolescence (12-15 years), and middle adolescence (15-19 years). Evidence from previous research shows that “sensitive periods” during early childhood are an important period for growth and that it is difficult to achieve catch-up from deficits in growth after this period (Fedorov & Sahn, 2005; Mani, 2008). However, we have little evidence on the extent that catch-up in cognitive deficits is possible after this period. Thus, I contribute to the existing literature on cognitive
catch-up by utilizing panel data from three rounds of the younger and older cohorts of the YL dataset, and investigate the relationship between past and current Mathematics scores during childhood, mid-childhood and adolescence stages to examine the patterns of catch-up or persistence in cognition throughout the lifecycle of cognitive production. Moreover, I look at the existence of perfect complementarity where later investments in cognition cannot overcome the lack of earlier investments.

To achieve this, I estimate a dynamic model of cognitive ability in which the coefficient of lagged Mathematics scores determines the scope for catch-up in cognitive production. This is similar to the approach taken by others to examine catch up growth in child height (e.g., Outes & Porter, 2013). My results show that the persistence in Mathematics scores increases as children move from childhood to adolescence. Furthermore, I find evidence for the case of perfect complementarity because children with no early investments in cognition never recover completely even with the existence of investments during later stages of childhood and adolescence. Therefore, policies for improving cognition should be targeted during early childhood which is commonly cited as the most important “sensitive period” in cognition formation (Cunha, Heckman, & Schennach, 2010; Victoria et al., 2010; Almond & Currie, 2011; Currie, 2011; Lynch & Gibbs, 2017).

The second and third chapters of my dissertation establish that during later stages of childhood, external channels affect cognitive production more than biological factors. One such channel which might be of importance is nutritional supplementation (Martorell, Khan, & Schroeder, 1994; Alderman, Hoddinott, & Kinsey, 2006). Thus, it would be interesting to look at how the consumption of different nutrients affect cognitive production during the earlier and later stages of childhood and adolescence. Ideally, data regarding nutrient intake
should be gathered through food frequency questionnaires which record every food eaten by individuals during the day for a long period of time. However, the collection of such data is usually expensive. Therefore, researchers have often resorted to translating household food availability in the form of food expenditures to individual-level nutrient availability. This conversion is usually done using the calorie-based, OECD and per capita adult-equivalent scales. These scales assume all the macro- and micronutrients to have the same requirements based on the age and sex of the individual which can lead to inaccurate measures of nutrient availability. This is even important because micronutrient deficiency is a much bigger problem than calorie deficiency currently in developing countries (Hoddinott, Rosegrant, & Torero, 2012). Therefore, having the correct conversion factors is important to calculate accurate measures of micronutrient availability. Using these measures, the correct effect of the intake of different nutrients on cognition can be studied.

The fourth chapter of my dissertation expands on this idea and calculates the nutrient-specific adult-equivalent scales using the daily nutrient intake guidelines provided by the Institute of Medicine (Institute of Medicine, 2006). I also calculate the magnitude of the difference in daily nutrient availabilities when using the nutrient-specific in comparison to calorie-based, per capita, and OECD adult equivalent scales by using the data from the third round of the Nepal Living Standards Survey (NLSS III). I find that on average there are significant differences in the individual-level daily nutrient availability estimates when calculated through different adult-equivalent scales. Thus, my analysis provides a much more accurate benchmark for future studies using household survey data to calculate individual-level nutrient availability estimates.
The rest of my dissertation is organized as follows: chapter 2 examines the relationship between current health and cognitive production which works through the study time allocation channel; chapter 3 examines the patterns of catch-up and persistence during different stages of later childhood and adolescence; chapter 4 calculates nutrient-specific adult-equivalent scales which can be used to calculate accurate measures of nutrient availability; and chapter 5 will conclude the dissertation and outline areas of future research.
Chapter 2
Are Healthy Kids All Work and No Study? Unpacking the Effect of Current Health on Time Allocation and Cognitive Production in Ethiopia

Introduction

Evidence demonstrates that improved childhood health improves a range of educational and cognitive outcomes (Behrman & Hoddinott, 2000; Glewwe, Jacoby, & King, 2001; Case, Fertig, & Paxson, 2003; Cunha & Heckman, 2008; Smith, 2009; Cunha, Heckman, & Schennach, 2010; Almond & Currie, 2011; Lynch & Gibbs, 2017; Villa, 2017). Most of this evidence focuses on the importance of health during the “sensitive periods” of childhood, namely in utero and the first few years of life (Almond, 2006; Chen & Zhou, 2007; Case & Paxson, 2008; Cunha & Heckman, 2007; Cunha & Heckman, 2008; Doyle et al., 2009; Smith, 2009; Alderman, 2010; Almond et al., 2010; Cunha, Heckman, & Schennach, 2010; Victoria et al., 2010; Almond & Currie, 2011; Currie, 2011; Lynch & Gibbs, 2017).¹ We know much less about the importance of health and nutrition to cognitive achievement during later childhood stages with early childhood health outcomes already realized. Moreover, there is currently limited understanding of the mechanisms that underlie the influence of health on cognition, particularly in the middle to later childhood stages.

Improved health can potentially improve cognitive ability through both direct and indirect channels. There is the direct biological effect through which health can affect cognitive outcomes (Fink & Rockers, 2014; Georgiadis, et al., 2017). An indirect effect of health on cognitive outcomes might operate through an effect on the returns to different activities (e.g.,

¹ A “sensitive period” refers to a stage in childhood during which investments or shocks have a greater effect on the development of a trait or skill than in other childhood stages.
studying and working) and thus influence decisions over time allocation (Becker & Tomes, 1976; Behrman, Pollack, & Taubman, 1982; Rosenzweig & Schultz, 1982). These indirect effects may become more pronounced as a child ages and returns to activities outside of studying increase. Thus, the potential positive influence of improved nutritional well-being may be mitigated if it also results in increased child labor and time away from school. A better understanding of these mechanisms can elucidate policies that can complement nutrition and health interventions in improving educational and cognitive outcomes.

In this article, we examine the effect of current health and nutritional status on cognitive achievement while conditioning on past investments in health during the periods of childhood (8 years) and mid-childhood (12 years). Specifically, controlling for height-for-age z-scores (HAZ), a proxy for previous health investments, we estimate the effect of body mass index (BMI) for age z-scores on child performance on two cognitive achievement tests for a sample of Ethiopian children. We further examine and test the extent that BMI’s influence over cognition occurs through direct channels or through the indirect channels of time devoted to studying by the children in our sample.

To address endogeneity in this relationship, we instrument BMI with previous growing season weather conditions. In our analysis of study time as a mediator in this relationship, we employ a novel method proposed in Dippel et al. (2017). This method allows us to instrument our endogenous treatment (BMI) and endogenous mediator (study time) with one set of instruments. In this way, we are able to disentangle these direct and indirect effects of BMI on cognition.
Like others, we find that improvements in current health result in improved cognitive test scores. However, in our mediation analysis we find that much of this effect is driven by the effect of current health on time allocation. In early school-age years, improved health increases time allocated to study. However, as the child approaches adolescence, improved health instead results in reduced study time. This is likely due to the increased opportunity cost of alternative uses of time for older children. Indeed, we also find that improved health in early adolescence substantially increases time allocated to work. This indicates that the positive effect of health on cognitive formation may be mitigated by improved health also causing child time to be allocated away from study and towards work during later childhood. This result seems to be largely driven by pre-adolescent boys.

We contribute to the existing literature on cognitive production by utilizing rich panel data from three rounds of the Ethiopian Young Lives (YL) project to ascertain the extent to which the relationship between contemporaneous health and cognitive scores operates through time allocated to studying. Previous evidence demonstrates an effect of early life health on cognitive production and thus highlights the direct biological implications of health and nutrition for cognitive production due to the rapid physical development that occurs during this period (Cunha, Heckman, & Schennach, 2010; Almond & Currie, 2011; Lynch & Gibbs, 2017; Villa, 2017). We, instead, examine the effect of current health and nutritional well-being on cognitive production in later childhood given past realizations in health. In this way, we show that due to the indirect effect on child time allocation, health and nutrition continue to significantly affect cognitive production throughout childhood beyond the periods where biological channels are most salient. This not only lengthens the potential window for intervention, but also, considering time allocation behaviors, expands the set of available
interventions. Thus, we add to the existing literature highlighting the importance of health investments early in a child’s life (Case & Paxson, 2008; Cunha & Heckman, 2008; Doyle et al., 2009; Smith, 2009; Cunha, Heckman, & Schennach, 2010; Victoria et al., 2010; Almond & Currie, 2011; Currie, 2011; Lynch & Gibbs, 2017) and make a case that interventions aimed at improving health status complemented with those that consider unintended time allocation effects, can still improve child human capital outcomes even outside of “sensitive periods”. Therefore, policies that both improve returns to education as well as reduce returns to child labor are likely to improve cognitive outcomes.

**Model of Current Health and Time Allocation in Cognitive Production**

Current health can impact cognitive production across different stages of a child’s life through multiple channels. Previous literature demonstrates that child health influences parents’ decisions to send their child to work or school (Becker & Tomes, 1976; Behrman, Pollack, & Taubman, 1982; Rosenzweig & Schultz, 1982). Given that time devoted to study is an input in cognitive production, it makes sense to explore whether current health may indirectly influence cognitive ability through a time allocation channel. While previous literature demonstrates that improvements in health can lead to improved cognitive outcomes (Fink & Rockers, 2014; Georgiadis, et al., 2017), none to our knowledge accounts for the indirect effect of current health through child time allocation on this process.

We present a simple model of cognitive production incorporating Todd & Wolpin’s (2003) model of cognitive achievement and the model of child time allocation laid out in Edmonds (2007). $C_0$ denotes the child’s cognitive outcome just before entering school. Adapting from Todd & Wolpin (2003), we denote $C_0$ as a function of family inputs before that time period,
$F_0$, and the child’s endowed ability, $\delta$. Adding to Todd and Wolpin (2003), we also include current health, $H_0$, as a determinant given the demonstrated relationship between health and skill formation (Fink & Rockers, 2014; Georgiadis, et al., 2017).

$$C_0 = g_0(F_0, H_0, \delta) \quad (1)$$

Similarly, cognitive ability at the start of the second year of schooling, $C_1$, depends on $C_0$, $F_1$, $H_1$, $\delta$ and $E_1$, where $E_1$ is time devoted to studying. For the purposes of this article, we include time devoted to study both inside and outside of school in this measure.

$$C_1 = g_1(C_0, F_1, H_1, E_1, \delta) \quad (2)$$

Substituting (1) into (2), we get equation (3):

$$C_1 = g_1(F_0, F_1, H_0, H_1, E_1, \delta) \quad (3)$$

Dynamically, this gives us a cumulative production function of cognition, defined in equation (4), where $F(a)$, $H(a)$, and $E(a)$ denote vectors comprising the cumulative history up to age $a$ of family, education and health inputs, respectively, and $\epsilon_t$ is measurement error in cognition.

$$C_a = g_a(F(a), E(a), H(a), \delta_0, \epsilon_a) \quad (4)$$

We assume that cognitive production follows a value-added process and that $C_{a-1}$ is a sufficient statistic for all previous family inputs ($F_0, F_1, \ldots, F_{a-1}$) and $H_{a-1}$ is a sufficient statistic for previous health realizations ($H_0, H_1, \ldots, H_{a-2}$). This allows us to rewrite equation (4) such that cognitive outcomes at age $a$ depend only on lagged cognition and health, and contemporaneous health and education and family inputs. We include age subscripts on the coefficients to allow for effects to vary across different stages of development.
\[ C_a = \gamma_{1,a}H_a + \gamma_{2,a}E_a + \gamma_{3,a}H_{a-1} + \gamma_{4,a}C_{a-1} + \gamma_{5,a}F_a + \epsilon_a \] (5)

where we assume \( \gamma_{1,a} > 0 \), \( \gamma_{2,a} > 0 \), \( \gamma_{3,a} > 0 \) and \( \gamma_{4,a} > 0 \).

However, health also influences study time such that \( E_a = e_a(H_a) \). But whether \( H_a \) increases or decreases the net time devoted to studying remains an empirical question. To see this, we incorporate a household model of child time allocation and labor as discussed in Edmonds (2007). We assume that parents receive utility from their current standard of living, \( S \), and the child’s future well-being over \( k \) time periods, \( V_k \), such that the marginal effect of \( S \) and \( V_k \) on utility is greater than zero. Thus, parents maximize their utility over the variables \( S \) and \( V_k \). The child’s total available time is divided between study, \( E \), leisure/play, \( L \), and work outside and inside the household, \( W \), such that:

\[ E + L + W = 1 \] (6)

Household’s standard of living, \( S \), is an increasing function of consumption, \( c \), and the child’s future well-being is an increasing function of time devoted to study and leisure such that:

\[ S = s(c) \] (7)
\[ V_k = v(E, L) \] (8)

Consumption is constrained by adult income, \( Y \), which is assumed to be exogenous, child earnings through work and the direct cost of schooling as follows:

\[ c = Y + wW - rE \] (9)

\(^2\) Edmonds (2007) distinguishes between child work inside and outside of the household. We combine them here for simplicity.
where $w^3$ denotes child wage rate and $r$ is the direct cost of an additional unit of time devoted to study. Thus, the parents have the following maximization problem:

$$\max_{E_{ta}, L_{ta}, W_{ta}, W_{1a}} u(s(Y + wW - rE), v(E, L))$$

subject to $E + L + W = 1$, $E \geq 0$, $L \geq 0$, $W \geq 0$

First order conditions give us the result that parents will choose a level of studying such that the marginal utility gained from improved future child well-being due to an additional hour of study is equal to its marginal opportunity cost to current consumption:

$$\frac{\partial u}{\partial V_k} \frac{\partial v}{\partial E} = \frac{\partial u}{\partial S} \frac{\partial s}{\partial c} (w + r)$$

where the left-hand-side (LHS) represents the household’s marginal utility from future returns to education while the right-hand-side (RHS) represents the household’s forfeited consumption due to the direct costs of schooling as well as the opportunity cost of child wage income.

However, health enters in to both the LHS and the RHS of equation (11). Evidence demonstrates that returns to education increase with health (Behrman & Hoddinott, 2000; Glewwe, Jacoby, & King, 2001; Case, Fertig, & Paxson, 2003). On the other hand, improved health also improves economic productivity and the corresponding wage rate (Strauss & Thomas, 2008). Taking derivatives of both sides of equation (11) with respect to health gives us:

\[\text{Because we don’t distinguish between labor outside and inside the household, we assume the economic value of both being equal to the child wage rate. This assumption is made for simplicity but can be relaxed without changing the implications of the model.}\]
Thus, improved health operating through the LHS of equation (12) (returns to studying) increases time devoted to studying, while health operating through the RHS of equation (12) (opportunity cost of studying) reduces time devoted to studying. Whether health, on net, increases or decreases time devoted to studying then remains an empirical question.

Turning back to equation (5) and incorporating the time allocation channel of health’s influence on cognitive production gives us:

\[ C_a = \gamma_{1,a}H_a + \gamma_{2,a}E_a(H_a) + \gamma_{3,a}H_{a-1} + \gamma_{4,a}C_{a-1} + \gamma_{5,a}F_a + \epsilon_a \]  (13)

Taking the derivative of (13) with respect to health gives us:

\[ \frac{\partial C_a}{\partial H_a} = \gamma_{1,a} + \gamma_{2,a} \frac{\partial E_a}{\partial H_a} \]  (14)

Thus, while health may improve cognition production, these effects may be mitigated or enhanced by the time allocation channel. If this is the case then policies that improve returns to studying and reduce returns to child labor will complement those that aim to improve cognitive outcomes through improved health. We incorporate the above model of cognitive achievement and study time allocation into an empirical model in section 5 of this article.

**Data**

To investigate the direct and indirect effects of health on cognitive production we use unique longitudinal data from the Young Lives Project (YL) in Ethiopia collected by University of
Oxford Department of International Development (ODID). The YL project surveys a sample of 3000 children (2000 from a younger cohort and 1000 from an older cohort) across four rounds covering the years 2002, 2006, 2009, and 2013. The approximate ages of the two cohorts at the time of the first round in 2002 were one and eight years (ODID, 2017). The data come from the five major regions of Ethiopia, namely Addis Ababa, Amhara, Oromia, SNNP and Tigray which comprise 96% of the total Ethiopian population (Wilson & Huttly, 2004). The YL project seeks to better understand the causes and consequences of childhood poverty. Thus, it contains rich data on economic, social and environmental characteristics at the child, household and community level. YL emphasizes child human capital and skill formation for children living in poverty and thus includes measures of cognition and health at multiple stages of childhood. Anthropometric measures were taken in each survey round and sample children were asked to take cognitive achievement tests once they were aged 5 years and above.

Our goal is to examine how nutritional status influences cognitive production during childhood (ages 5-8) and mid-childhood (ages 8-12). These stages coincide with Piaget’s preoperational and concrete operational stages of cognitive development. Typically, the preoperational stage is marked by a beginning of the use of language and pictures to represent words while the concrete operational stage usually marks the start of logical thinking (Piaget, 1964). We therefore focus on the younger cohort and use data from the second, third, and fourth survey rounds when the sample children were aged 5, 8, and 12, respectively. While there is sample attrition, the rate of attrition in the YL sample is comparatively lower than other longitudinal datasets reducing concerns about systematic changes occurring in the sample over time. However, there is sample loss due to missing
information, especially in the fourth round of data collection. Therefore, our final sample sizes at age 8 to examine the direct and indirect effect of BMI for age on PPVT and Math scores are 1,654 and 1,594, respectively. Similarly, the respective sample sizes at age 12 are 1,467 and 1,286. For more information on YL’s methodology and data collection procedures see Outes & Sanchez (2008) and Morow (2009).

In rounds two, three, and four, children were assessed on verbal and quantitative skills using the PPVT and Mathematics test. Both these tests are widely used as measures of receptive vocabulary and mathematical ability (Rosenzweig & Wolpin, 1994; Paxson & Schady, 2007). For the purposes of comparing across childhood stages, we standardize the PPVT and Mathematics scores using the data’s sample moments in each round.

We use measures of height-for-age z-scores (HAZ) and body mass index for age z-scores (BMI) to measure long-term and current health, respectively. HAZ is a good measure of previous investments in nutrition and health as it is a cumulative measure, which is primarily gained in the first few years of childhood. It is also sensitive to health shocks and changes in investments in the first few years of life but does not respond as quickly to current fluctuations in health and/or nutrient intake. We thus use HAZ as a proxy for previous investments in nutrition and health up to the current round of data collection. On the other hand, weight is sensitive to current health and health inputs as it can fluctuate with short-term changes in health and nutrient intake. Thus, BMI for age is a good proxy of current health and nutritional well-being as it captures the risk of being under- and overweight at a particular point in time. Since the Ethiopian sample used in this study consists of mainly poor

\[4\] In the second round, the quantitative test is the Cognitive Development Assessment-Quantity Test while in rounds three and four the quantitative test is the Mathematics Achievement Test.
households with high rates of undernourished children, improvements in BMI for age generally indicate improvements in health for this sample. BMI has been found to affect cognitive function in the existing medical literature (Suemoto et al., 2015; Kim, Kim, & Park, 2016). Thus, we use current BMI for age rather than HAZ as the measure of current health as the latter is a better measure of the health stock while the former better captures health flow.

Finally, the YL surveys include detailed time allocation modules in which parents were asked about the number of hours a child spends on a variety of activities in a typical day. From this information, we constructed two variables indicating the number of hours in a day the child typically devotes to study and work. We calculated study time by adding the number of hours spent at school and the number of hours spent studying outside of school time (e.g., at home, extra tuition) during a typical day. We calculated work time by adding the number of hours spent on the following activities: activities for pay/sale outside of household or for someone not in the household; the number of hours spent doing tasks on family farm, cattle herding, and other family business; and the number of hours spent on domestic activities (fetching water, fetching firewood, cleaning, cooking, washing and shopping etc.) in a typical day.

To obtain exogenous variation in current health status, we exploit information on temperature and precipitation for the growing season prior to the interview. The primary growing season in Ethiopia is meher and occurs during the months of June through October. During the meher season 90-95% of Ethiopia’s cereal output is produced (USDA, 2008). Consequently, growing season conditions (proxied by temperature and precipitation) during this season affects food security as well as disease environment. Robust evidence demonstrates the
influence of climate on health (Ebi & Paulson, 2007; McCartney, 2007; Ebi & Paulson, 2010; Bernstein & Myers, 2011; Seal & Vasudevan, 2011).

Our data on temperature and precipitation come from the University of Delaware Air Temperature and Precipitation (UDATP) available at Earth System Research Laboratory (ESRL) (ESRL, 2017). The UDATP provide data on monthly total rainfall and monthly average temperature for grids that are approximately 35 miles across at the equator (ESRL, 2017). The YL data do not provide geo-coordinates for sample communities, however, we do know which region households live in. We therefore calculate region-specific growing season conditions as follows. For each of the five regions in each year, we observe growing season total precipitation and average temperature for the region’s center grid and the grids farthest from the center to the east, west, north and south within that region. We then take the average across those grids to create a region- and year-specific measure of meher season temperature and rainfall. We do this for every year from 1965 to 2014. To purge these measures of systematic differences across regions we standardize them as follows:

\[
\tilde{Z}_{rt} = \frac{Z_{rt} - \bar{Z}_r}{\sigma_r},
\]

where \(Z_{rt} \in \{temperature_{rt}, precipitation_{rt}\}\) is the region-specific temperature and precipitation of the most recent growing season in region \(r\) and year \(t\). \(\bar{Z}_r\) and \(\sigma_r\) are mean and standard deviation of growing season temperature and precipitation in region \(r\) over the period 1965 to 2014.

Table 2.1 presents the summary statistics of the main variables in our model for all three rounds used in the study. The sample is restricted to children with non-missing data on PPVT and Mathematics scores in each round. The mean BMI for age and HAZ scores are over one standard deviation below zero in both the rounds and worsen between rounds three and four.
According to the World Health Organization (WHO) a mean z-score (HAZ or BMI for age) significantly below zero, the expected value of the mean for the reference distribution, indicates that most of the sample is at the risk of malnutrition (WHO, 2017). Indeed, 22% and 33% of our sample is stunted at ages 8 and 12, respectively. At age 8, 22% of our sample is underweight. This proportion increases to almost 50% at age 12. Average hours devoted to study in a typical day increases from 5.88 at age 8 to 7.16 at age 12. Average hours devoted to work, on the other hand, remains approximately the same from round three to four.

[Insert Table 2.1]

Using non-parametric fractional-polynomial plots with 95% confidence intervals, figure 2.1 depicts the relationship between BMI and standardized PPVT and Mathematics scores at ages 8 and 12. The relationship between BMI for age and cognitive test scores is generally positive across the BMI for age distribution. This positive relationship appears more prevalent in the mid- to upper-ranges of observed BMI in our sample. Additionally, at age 8, the test scores of truly underweight children (BMI z-score < -2) do not appear to response to improved nutrition. This may indicate that cognitive production may not improve with health status until a certain level of health is achieved.

[Insert Figure 2.1]

**Methodology**

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5 A child is considered stunted (underweight) if their HAZ (BMI) is two standard deviations or more less than zero.

6 We did all the parametric estimations in this article for the reduced sample of BMI for age between the values of -5 and 5 and HAZ between -6 and 6 following the WHO guidelines (WHO, 2017).
Most previous research conducting mediation analysis utilizes the procedure highlighted by Baron & Kenny (1986) for interpreting a mediation model. Their method establishes mediation if statistically significant relationships are found between the independent variable and the mediator, the independent variable and the dependent variable, and the mediator and the dependent variable. This procedure was later simplified by Zhao, Lynch Jr., & Chen (2010) which tests for the existence of mediation through a single bootstrap test of the indirect effect commonly known as the Preacher and Hayes test. However, none of these methods allow the use of an identification strategy employing instrumental variables (IV) if both the treatment variable and the mediator is endogenous, as in our case. Dippel et al. (2017) address this problem by expanding the mediation model to allow for the presence of an endogenous confounder and an unobserved mediator. They propose a simple solution that allows for the use of one set of instruments for both the treatment and mediator. They do this by utilizing the exogenous variation provided by the instruments to estimate the causal effect of the intermediate variable on the final outcome. We employ their method to disentangle current health’s direct effect on cognition as well as its indirect influence through time allocation.

Dippel et al. (2017) build on the mediation models which imply causality found in the previous literature (e.g., Imai, Keele, & Tingley, 2010; Pearl, 2014; Heckman & Pinto, 2015). Their model consists of three main variables: an endogenous treatment variable (current health), an intermediate variable (time allocation) and a final outcome (cognitive achievement). In this article, these variables are denoted by BMI for age, study time, and PPVT and Mathematics test scores, respectively. This allows us to test if the treatment variable causes the mediator variable and, in turn, impacts the final outcome variable.
The model adapted from Dippel et al. (2017) is a three-step model. In our case, the first step estimates the effect of current health on cognition (equation (15) below). The second step estimates the effect of current health on child time allocated to study (equation (16) below). The third step estimates the effect of current health on cognition while also controlling for time allocated to study (equation (17) below).

Using the methodology proposed in Dippel et al. (2017), we use equations (15), (16), and (17) to explore whether current health affects cognitive outcomes through a study time allocation channel:

\[ C_{it} = \alpha_{C-1}^C \cdot C_{it-1} + \alpha_{HAZ}^C \cdot HAZ_{it} + \alpha_{BMI}^C \cdot BMI_{it} + \alpha_X^C \cdot X_{it} + \epsilon_{it}^C \] \hspace{1cm} (15)

\[ T_{it} = \alpha_{C-1}^T \cdot C_{it-1} + \alpha_{HAZ}^T \cdot HAZ_{it} + \alpha_{BMI}^T \cdot BMI_{it} + \alpha_X^T \cdot X_{it} + \epsilon_{it}^T \] \hspace{1cm} (16)

\[ C_{it} = \alpha_{C-1}^{BMI} \cdot C_{it-1}^C + \alpha_{HAZ}^{BMI} \cdot HAZ_{it} + \alpha_{BMI}^{BMI} \cdot BMI_{it} + \alpha_T^{BMI} \cdot T_{it} + \alpha_X^{BMI} \cdot X_{it} + \epsilon_{it}^{BMI} \] \hspace{1cm} (17)

where \( C_{it} \) is the current cognitive ability, which we proxy with PPVT or Mathematics z-scores, for child \( i \) at time \( t \), \( C_{it-1} \) is the lagged cognitive test score, which in this value-added model we assume to be a sufficient statistic for previous investments in cognition. \( HAZ_{it} \) is current HAZ and reflects previous investments in health and nutrition. \( BMI_{it} \) is current BMI for age which proxies for current health status. \( T_{it} \) denotes hours devoted to study and is a potential channel through which BMI for age affects cognition. Finally, \( X_{it} \) is a set of control variables and includes sex, mother’s and father’s education, log of monthly expenditure per adult, wealth quartile of the household, urban/rural status and cluster fixed effects. Equations (15) to (17) are estimated separately for children when they were at ages 8 and 12 to allow
effects to differ between childhood and mid-childhood. We estimate equations (15) to (17) separately for PPVT and Mathematics scores as well.

Equations (15) through (17), when estimated together, provide the total, direct and indirect effects of BMI for age on cognitive test scores. From equation (15), $\alpha_{BM}^{C}$ gives the total effect of BMI for age on cognition scores. From equations (16) and (17), $\alpha_{BM}^{C|BM}$ gives the direct effect while the product of $\alpha_{T}^{C|BM}$ and $\alpha_{BM}^{T}$ provides the indirect effect of BMI for age on cognitive scores through study time. For more details on the derivation of the mediation model and the specification test used in this article, please refer to Dippel et al., (2017). Thus, the assumptions of the model estimated through equations (15) to (17) can be tested using the following specification test:

$$H_0: \alpha_{BM}^{C} = \alpha_{BM}^{C|BM} + \alpha_{T}^{C|BM} \cdot \alpha_{BM}^{T}$$

A rejection of the above hypothesis indicates that the model’s assumptions do not hold. A rejection may result from BMI for age not affecting cognitive outcomes through the study time allocation channel or from the total effect comprising of more than just the specified mediator.

Disentangling health’s direct and indirect effects presents a few empirical challenges. First, BMI for age is endogenous. In particular, omitted variable bias is a cause for concern as observed characteristics cannot completely control for parental preferences over child’s health and cognition, or household non-child health expenditure (Georgiadis, 2017). This can confound estimates on both the direct influence of BMI for age on cognitive scores as well as through the study time allocation channel.

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7 The specification test is essentially a Chi-squared test testing the null hypothesis of the total effect being equal to the sum of the direct and indirect effects.
Based on the theoretical model described in Section 2, our mediation model with a
*confounder* and *unobserved mediator* is described in the Directed Acyclic Graph (DAG) in
figure 2.2. The *confounder* refers to unmeasured individual and household characteristics
which affect current health, the allocation of child time, and cognitive outcomes. On the
other hand, the *unobserved mediator* is caused by the treatment variable and causes the
mediator and outcome variables. This *unobserved mediator* refers to unobserved study time
allocation and cognition variables affected by current health. The problem with this
mediation model is that it is underidentified. This underidentification results from selection
bias, arising from the unobserved variables, which affects the treatment, meditor and
outcome variables.

[Insert Figure 2.2]

Ordinary least squares (OLS) estimations of equations (15) to (17) will not yield consistent
estimates of the coefficients used in (18) as BMI for age in each period is endogenous.
Therefore, our use of the mediation model highlighted by Dippel et al., (2017) allows us to
use the same set of IV for equations (15) to (17). They show that it is possible to use the
same IVs for two endogenous variables if one of the endogenous variables is on the path
between the treatment and the outcome variable. This is important because of the difficulty in
obtaining instruments which pass the exclusion restriction from observational data. Hence, in
the above model when the treatment (BMI for age) and the mediator (study time allocation)
are both endogenous, a single set of instruments will suffice to derive causality after allowing
for the presence of *confounders* and *unobserved mediators* that might bias the estimates. The
crucial assumption here is that there are separate *confounders* which affect the treatment and
intermediate variables and those that affect the intermediate and outcome variables. We aim
to take advantage of this identification strategy to obtain a causal estimate of the relationship between current health and cognitive outcomes working through the study time allocation channel.

We instrument for BMI using standardized measures of growing season precipitation and temperature based on region-specific means and standard deviations for the most recent growing season. Precipitation and temperature shocks in the last growing season can result in crop failure, lower food production and food shortages in the vulnerable segments of the population (Lobell, Schlenker, & Costa-Roberts, 2011; Hagos et al., 2014). Therefore, climate has a direct relationship with household food availability (Haile, 2005) which in turn affects human health (Campbell-Lendrum & Woodruff, 2006). The relationship between climate and health can be especially strong in countries like Ethiopia which rely heavily on rain-fed agriculture (Parry et al., 2004; Hagos et al., 2014). Moreover, previous medical research shows that children’s health is also susceptible to changes in climate including rainfall and temperature (Ebi & Paulson, 2007; McCartney, 2007; Ebi & Paulson, 2010; Bernstein & Myers, 2011; Seal & Vasudevan, 2011).

Although we surmise that precipitation and temperature only affect cognitive outcomes through current child health, a possible concern to the validity of these measures as an instrument is that they might affect cognitive outcomes through the income channel. This is a bigger concern in rural areas as precipitation and temperature shocks can lead to reduced agricultural production and income which in turn can affect cognition (Dell, Jones, & Olken, 2014). We address this concern in two ways. First, we control for household income denoted by log of monthly expenditure per adult. Second, we measure precipitation and temperature
on the intensive margin rather than as extreme deviations from normal levels of rainfall and
temperature in the growing season.

Thus, using IV regression introduced by Dippel et al., (2017), the first stage equations for
equations (15) and (16) is equation (19) while equation (17)’s first stage equation is given by
(20) below:

\[
BMl_{it} = \alpha_{Z}^{BMl} \cdot Z_{it} + \alpha_{C}^{BMl} \cdot C_{it-1} + \alpha_{HAZ}^{BMl} \cdot HAZ_{it-1} + \alpha_{X}^{BMl} \cdot X_{it} + \epsilon_{it}^{BMl}
\]  
\[
T_{it} = \alpha_{Z}^{T|BMl} \cdot Z_{it} + \alpha_{C}^{T|BMl} \cdot C_{it-1} + \alpha_{HAZ}^{T|BMl} \cdot HAZ_{it-1} + \alpha_{BMl}^{T|BMl} \cdot BMl_{it} + \alpha_{X}^{T|BMl} \cdot X_{it} + \epsilon_{it}^{T|BMl}
\]

where \(Z_{it}\) is standardized precipitation and temperature which serve as the instruments in our
model.

**Results**

Table 2.2 reports the total and decomposed direct and indirect effects on BMI for age on
cognitive production for this Ethiopian sample. All effects are estimated with errors clustered
at the sampling unit level. Table 2.2 panel A reports the total estimated effect of instrumented
BMI for age on cognitive production estimated from equation (15). Columns 1 and 2 report
these effects estimated at age 8 while columns 3 and 4 report them at age 12. The instruments
are strong predictors at age 8 with first-stage F-stats of almost 200. The instruments appear to
be less strong when the cohort children are aged 12 with first-stage F-stats of 6.54 and 8.28
in the equations predicting PPVT and Math scores, respectively. According to table 2.2 panel
A, BMI for age exerts substantial influence over cognitive test scores with statistically
significant effects for each test at every age. Estimates of the marginal effect of BMI for age on PPVT scores is 0.452 (column 1) and 0.670 (column 3) at ages 8 and 12, respectively. This indicates that increasing BMI for age by one standard deviation will improve PPVT scores by approximately half a standard deviation or more. BMI for age appears to have an even larger influence over math scores with estimated marginal effects of 0.770 at age 8 (column 2) and 1.480 at age 12 (column 4). The results in table 2.2 panel A indicate that current health does indeed improve cognitive test scores even after controlling for early life health. Thus, while many emphasize the first few years of life as the window for health/nutrition interventions, these results indicate that interventions aimed at improving health status can continue to improve child human capital outcomes even outside of the “sensitive periods” typically focused on.

From table 2.2 panel A, we can summarize a few important points. Current health has a higher positive effect on Mathematics than on PPVT scores during both childhood and mid-childhood. This effect also increases from childhood to mid-childhood for both PPVT and Mathematics scores. This result is surprising since investments occurring earlier in childhood are typically viewed as being more productive in skill formation (e.g., Cuhna and Heckman, 2008). The enhanced productivity of early childhood is largely due to the rapid physical development that occurs during that developmental stage. If the effect of BMI on cognitive production is predominately due to direct biological effects, then we would expect its impact to decrease as a child ages. Therefore, the increasing magnitude of the estimated effects with

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8 The effect is significant at the 10% level for PPVT scores at age 12 and is significant at the one percent level in every other case reported in table 2.2 panel A.
child age may indicate the importance of indirect channels of BMI's influence on cognitive achievement. Therefore, we now turn to decomposing the total effects reported in table 2.2 panel A into their direct and indirect effects through the study time channel.

Table 2.2 panel B reports the effect of instrumented BMI on child study time estimated from equation (16). Because we estimate equation (15) separately for PPVT and Mathematics test scores, we also estimate equation (16) separately when controlling for lagged PPVT and Mathematics test scores. For example, column 1 of table 2.2 panel B reports the estimated effect of instrumented BMI on time devoted to study at age 8 while controlling for lagged PPVT scores. Column 2, on the other hand, estimates this same effect but controlling for lagged Mathematics scores rather than lagged PPVT scores. Regardless, the choice of which lagged test score we include as a control does not substantively affect the magnitude or significance of our estimates.

According to the results reported in table 2.2 panel B, child health and nutritional status significantly affects child study time at age 8 with estimated effects that are statistically significant at the one percent level. Improved BMI exerts a substantial effect on time devoted to study. Specifically, a one standard deviation increase in BMI for age increases time devoted study by over two hours in a typical day (columns 1 and 2).

Turning to child time allocation at age 12 (columns 3 to 4 of table 2.2 panel B) we see a slightly different story. At this age, improved BMI reduces time devoted to study. A one standard deviation increase in BMI reduces study time in a typical day by approximately 2.5 hours (column 3). The point estimate of this effect reduces to -1.17 when we control for
lagged Mathematics scores rather than lagged PPVT, however, it is unclear if this represents a true difference in magnitude or simply lost precision (column 4).

Finally, table 2.2 panel C reports the decomposed effects of BMI on cognitive test scores estimated from equation (17). In equation (17) we instrument for study time, different from equations (15) and (16), where we instead instrument for BMI for age. The dependent variable in the regressions reported in table 2.2 panel C is either PPVT (columns 1 and 3) or Mathematics (columns 2 and 4) test scores during childhood and mid-childhood.

At age 8, we see that increased study time increases cognitive test scores (columns 1 and 2) with statistically significant effects at the one percent level. Specifically, one extra hour of studying in a typical day increases PPVT and Mathematics scores by 0.203 and 0.33 of a standard deviation, respectively. At age 12, during mid-childhood, we see a slightly different story. Increased study time at this age only significantly affects PPVT scores and not Mathematics scores. Increasing study time by one hour at age 12, increases PPVT scores by approximately 0.35 standard deviations.

The results of table 2.2 panels A-C combined form the basis of our mediation model which examines whether BMI for age affects cognitive outcomes by working through the study time allocation channel. To check if the assumptions of the model hold and the total causal effect of current health on cognition is equal to the sum of direct causal effect and the indirect causal effect through study time, we test the hypothesis postulated in equation (18). A failure to reject the null is evidence that the assumptions of the model hold. Moreover, following Baron & Kenny (1986) rejecting the null hypothesis requires that the coefficients used to calculate the direct and indirect effects in equation (18) are significant.
Table 2.2 panel D summarizes the total, direct and indirect (through study time) effects of BMI for age on PPVT and Mathematics scores based on our estimates reported in table 2.2 panels A-C. Failing to reject the null in equation (18) is more likely when the total effect is approximately equal to the sum of direct and indirect effects. In columns 1 and 2 in table 2.2 panel D, the direct effect of BMI for age on cognition scores is not significant (estimated from equation 17). However, the indirect effect is significant for the study time channel as the two coefficients which make up this indirect effect are significant. At age 8, we fail to find statistically significant differences in the estimated total effects and the sum of the estimated direct and indirect effects (columns 1 and 2). This implies that the mediation model depicting BMI’s direct and indirect effects through child study time is a valid model in this production process. Moreover, the direct effect of BMI on test scores is not a statistically significant predictor of test scores (columns 1 and 2 of table 2.2 panels C and D). This implies not only that BMI exerts an indirect causal effect on cognitive test scores through the study time allocation channel at age 8, but also based on our point estimates, this channel represents the primary channel of influence. In fact, this appears to represent what is referred to as an indirect-only mediation which is also termed as full mediation as it lacks a significant direct effect (Baron & Kenny, 1986; Zhao, Lynch Jr., & Chen, 2010).

Turning to mid-childhood at age 12, we reject the hypothesis postulated in equation (18) that the total effect reported in table 2.2 panel A is equal to the sum of the direct and indirect effects based on estimates reported in table 2.2 panels B and C. This implies that the assumptions required for the mediation model we propose for BMI’s effect on cognitive test scores directly and through the study time do not hold at age 12. It may be that as a child ages, health affects cognitive production though an increasing number of mediators that are
not accounted for in our model. This would cause us not only to reject the hypothesis in equation (18) but also likely confound our results estimated for age 12.

Regardless, our results indicate that current health does indeed influence child study time. We additionally show that current child health has the potential to affect cognitive production during childhood through the indirect effect of parents allocating increased study time for healthier children. This implies that a healthier child is more likely to go to school or study at home during childhood. Moreover, our findings imply that the effect of BMI on cognitive test scores during this age is almost entirely driven by this indirect channel rather than through the direct biological impact.

We also find that increases in current health reduce the number of study hours allocated during mid-childhood. Given this result, it would be interesting to see whether at this age, this reduction in the allocation of study hours is also accompanied by a higher allocation of work hours as the returns to labor increase as the child approaches adolescence. Table 2.3 reports the effect of instrumented BMI on child work time. We find that BMI positively affects child time devoted to work during childhood (columns 1 and 2). However, the effect on work time is substantially smaller than on study time at this age. Increasing BMI by one standard deviation increases time devoted to work by approximately a third of an hour in a typical day at age 8. Thus, healthier children are likely to both study and work more than unhealthier children at age 8. This is likely due to the positive returns of health to both activities (e.g., Behrman, Pollack, & Taubman, 1982; Rosenzweig & Schultz, 1982; Strauss and Thomas, 2008). At age 12, BMI not only exerts a positive effect on child time devoted to work (columns 3 and 4), but this effect is substantially larger than at age 8 with a point estimate over 4.5. At age 12, increasing BMI by one standard deviation increases hours of
work time in a day by 4.6 to 4.9 hours. At age 12, children are close to entering adolescence when their returns to time devoted to work substantially increase. Thus, the negative effects of BMI on study time and the much larger effects on work time at this age likely reflects the increasing opportunity cost of time devoted to activities other than work.

[Insert Table 2.3]

Since we find that current health substantially increases work time while reducing study time during mid-childhood (age 12), it would be interesting to look at whether this effect is driven by children who were in school at 8 years of age and then dropped out of school by age 12, possibly to devote more time to work either outside or inside the home. Table A.1 in the appendix reports the effect of instrumented BMI on study and work time for children who were still enrolled in school at age 12. We find that the positive effect of current health on work time remains for this sub-sample and thus is not driven by children dropping out of school.

We further examine the effect of instrumented BMI on cognitive test scores and child time allocation at age 12 for children who reported no study time at age 5 separately from those who reported having any study time at age 5. The estimated effects on cognitive test scores are reported in table A.2 and those on time allocation are reported in table A.3. According to table A.2, BMI appears to only significantly affect the test scores of the group who were reported to have at least some study time at age 5. It did not have a statistically significant effect on the scores of the group who reported no study time at age 5. Similarly, in table A.3 we see that the instrumented BMI only has a statistically significant effect on the time allocation of children who had at least some study time at age 5. It’s effect on children with
no study time at age 5 is not statistically significant. The results reported in tables A.2 and A.3 further support the idea that the effect of BMI on child test scores primarily operates through child time allocation.

Although we control for sex, there might still be systematic differences in parent’s preferences in how they invest in healthier boys versus healthier girls. This can especially be true in the case of Ethiopia and developing countries in general, where there are differences by sex in the type and spatial distribution of the work being assigned. In Ethiopia, both boys and girls participate in on-farm work. However, girls are typically preferred over boys for domestic work, while boys are generally preferred for non-farm income generating work (Woldehanna et al., 2005). This can create a difference in the time allocation response between the current health of boys and that of girls.

We therefore estimate equations (15) through (17) separately for boys and girls. These results are presented in tables A.4 and A.5 in the appendix. Here we find that our main results are primarily driven by the boys in that our estimates from the boy subsample largely mirror those reported in our main results. Thus, similar to our combined sample, we find that current health affects cognitive outcomes positively through the study time channel during childhood for boys. Our findings for girls differ, however. In table A.5 panel A, column 3, we find that BMI actually reduces PPVT tests scores at age 12 for girls with an effect that is significant at the 10% level. We further find that increase in BMI significantly reduces study time for girls at this age (column 3 of table A.5 panel B). However, we find that we reject the hypothesis postulated in equation (18) for girls during both childhood and mid-childhood.

**Conclusion**
Previous literature related to early childhood development deals with the idea of investment during “sensitive periods”, namely in utero and the first few years of life, which can have long-lasting consequences as far as health, cognition and labor market outcomes are concerned (Cunha & Heckman, 2008; Cunha, Heckman, & Schennach, 2010; Almond & Currie, 2011; Currie, 2011; Lynch & Gibbs, 2017). Shocks in these periods can lead to unfavorable human capital outcomes in the future (Almond, 2006; Chen & Zhou, 2007; Almond et al., 2010). We add to this existing body of literature by exploring whether a relationship between current health and cognition exists directly and indirectly (through a time allocation channel) during later childhood stages, with early childhood health outcomes already realized. We employ a novel mediation model proposed in Dippel et al., (2017) to address endogeneity concerns in this relationship. This new approach in mediation analysis allows us to use the same set of instruments for the endogenous treatment (current health) and mediator (study time) variables.

We find that improvements in current health can improve cognition test scores during childhood (5-8 years) and mid-childhood (8-12 years). Thus, we add to the existing literature highlighting the importance of health investments early on in a child’s life (Case & Paxson, 2008; Cunha & Heckman, 2008; Doyle et al., 2009; Smith, 2009; Cunha, Heckman, & Schennach, 2010; Victoria et al., 2010; Almond & Currie, 2011; Currie, 2011; Lynch & Gibbs, 2017) and make a case that interventions aimed at improving health status can still improve child human capital outcomes even outside of “sensitive periods”. However, in our mediation analysis we find that much of this effect is driven by the effect of health on child time allocation. We also find that during mid-childhood, improved current health results in reduced study time and greater work time. This result seems to be largely driven by the boys...
in the sample. Thus, we highlight the role of the study time allocation channel as one of the underlying mechanisms in the relationship between health and cognitive production.

The prevalence of child labor during mid-childhood points to the short-term incentives which exist for parents in involving healthier children in work-related activities. As long as these incentives exist, the child labor market will exist. Therefore, policies that both improve returns to education as well as reduce returns to child labor are likely to improve cognitive outcomes during later childhood stages.
### Table 2.1: Summary Statistics for Main Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Round 3 (Age 8)</th>
<th>Round 4 (Age 12)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N=1,654</td>
<td>N=1,467</td>
</tr>
<tr>
<td>PPVT Score</td>
<td>-.014 (.991)</td>
<td>-.046 (1.003)</td>
</tr>
<tr>
<td>Mathematics Score</td>
<td>-.019 (.983)</td>
<td>.032 (.996)</td>
</tr>
<tr>
<td>BMI for Age</td>
<td>-1.30 (.949)</td>
<td>-1.81 (.988)</td>
</tr>
<tr>
<td>HAZ</td>
<td>-1.21 (1.05)</td>
<td>-1.43 (.969)</td>
</tr>
<tr>
<td>Study Time (hours)</td>
<td>5.88 (3.05)</td>
<td>7.16 (2.27)</td>
</tr>
<tr>
<td>Work Time (hours)</td>
<td>3.21 (2.32)</td>
<td>3.43 (2.20)</td>
</tr>
<tr>
<td>Precipitation Z-score</td>
<td>.122 (.122)</td>
<td>-.392 (.88)</td>
</tr>
<tr>
<td>Temperature Z-score</td>
<td>1.17 (.343)</td>
<td>.623 (.263)</td>
</tr>
<tr>
<td>Proportion Stunted</td>
<td>.22 (.629)</td>
<td>.33 (.483)</td>
</tr>
<tr>
<td>Proportion Wasted</td>
<td>.22 (.505)</td>
<td>.49 (.566)</td>
</tr>
</tbody>
</table>

Figures are mean with standard deviations in parenthesis. The PPVT and Mathematics scores are standardized.
Table 2.2: Estimated Direct and Indirect Effects of BMI on Cognitive Test Scores

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age 8</td>
<td>PPVT</td>
<td>Math</td>
<td>Age 12</td>
</tr>
<tr>
<td>BMI for Age ($\alpha_{BMI}^C$)</td>
<td>0.452***</td>
<td>0.770***</td>
<td>0.670*</td>
<td>1.480***</td>
</tr>
<tr>
<td></td>
<td>(0.0780)</td>
<td>(0.0839)</td>
<td>(0.371)</td>
<td>(0.438)</td>
</tr>
<tr>
<td>Panel A: Total Effect of Instrumented BMI on Cognition</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BMI for Age ($\alpha_{BMI}^T$)</td>
<td>2.236***</td>
<td>2.275***</td>
<td>-2.508**</td>
<td>-1.174</td>
</tr>
<tr>
<td></td>
<td>(0.213)</td>
<td>(0.189)</td>
<td>(1.081)</td>
<td>(1.302)</td>
</tr>
<tr>
<td>Included Lagged Cognition Scores</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV F-Stat (Panel A and B)</td>
<td>171.7***</td>
<td>196.21***</td>
<td>6.54***</td>
<td>8.38***</td>
</tr>
<tr>
<td>Panel B: Effect of Instrumented BMI on Study Time</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Study Time ($\alpha_{BMI}^C$)</td>
<td>0.203***</td>
<td>0.330***</td>
<td>0.350***</td>
<td>-0.0868</td>
</tr>
<tr>
<td></td>
<td>(0.0265)</td>
<td>(0.0276)</td>
<td>(0.106)</td>
<td>(0.225)</td>
</tr>
<tr>
<td>BMI for Age ($\alpha_{BMI}^T$)</td>
<td>-0.000929</td>
<td>0.0196</td>
<td>0.0274</td>
<td>-0.0131</td>
</tr>
<tr>
<td></td>
<td>(0.0253)</td>
<td>(0.0286)</td>
<td>(0.0205)</td>
<td>(0.0288)</td>
</tr>
<tr>
<td>IV F-Stat</td>
<td>138.82***</td>
<td>176.65***</td>
<td>27.19***</td>
<td>12.41***</td>
</tr>
<tr>
<td>Panel C: Effects of BMI and Instrumented Study Time on Cognition</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Effect</td>
<td>0.452</td>
<td>0.77</td>
<td>0.67</td>
<td>1.48</td>
</tr>
<tr>
<td>Direct Effect</td>
<td>-0.00093</td>
<td>0.0196</td>
<td>0.0274</td>
<td>-0.0131</td>
</tr>
<tr>
<td>Indirect Effect</td>
<td>0.454</td>
<td>0.751</td>
<td>-0.878</td>
<td>0.102</td>
</tr>
<tr>
<td>Direct + Indirect Effect</td>
<td>0.453</td>
<td>0.770</td>
<td>-0.850</td>
<td>0.089</td>
</tr>
<tr>
<td>Observations</td>
<td>1,654</td>
<td>1,594</td>
<td>1,467</td>
<td>1,286</td>
</tr>
<tr>
<td>Individual and Household Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Community Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age 8</td>
<td>Age 12</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Work Time</td>
<td>Work Time</td>
<td>Work Time</td>
<td>Work Time</td>
</tr>
<tr>
<td>BMI for Age</td>
<td>0.330**</td>
<td>0.319**</td>
<td>4.626***</td>
<td>4.934***</td>
</tr>
<tr>
<td></td>
<td>(0.154)</td>
<td>(0.148)</td>
<td>(1.441)</td>
<td>(1.251)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,654</td>
<td>1,594</td>
<td>1,467</td>
<td>1,286</td>
</tr>
<tr>
<td>IV F-Stat</td>
<td>171.7***</td>
<td>196.21***</td>
<td>6.54***</td>
<td>8.38***</td>
</tr>
<tr>
<td>Lagged Cognition Scores</td>
<td>PPVT</td>
<td>Math</td>
<td>PPVT</td>
<td>Math</td>
</tr>
<tr>
<td>Individual and Household Level</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Community Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Figure 2.1: Non-Parametric Regressions for BMI for Age's Effect on PPVT and Mathematics Scores
Figure 2.2: Directed Acyclic Graph for the Mediation Mode
Chapter 3
Early or Bust? Persistence and Catch-Up in Cognition Scores for Ethiopian Children during Childhood and Adolescence

Introduction

Medical research shows that cognitive development mostly occurs during gestation and childhood. These time periods are commonly referred to as “sensitive periods” because investments during these have the potential to positively determine future human capital outcomes such as adult height, health, and cognition in the short and long run (Case & Paxson, 2008; Cunha & Heckman, 2008; Doyle et al., 2009; Smith, 2009; Cunha, Heckman, & Schennach, 2010; Victoria et al., 2010; Almond & Currie, 2011; Currie, 2011; Lynch & Gibbs, 2017). “Sensitive periods” also present an opportunity for catch-up growth which is signified by an upward movement in the percentile position in the distribution of human capital outcome for a child (Boersma & Wit, 1997). Indeed, previous literature reveals that catch-up growth can be possible through better investments such as improvements in the living conditions or nutritional supplementation (Martorell, Khan, & Schroeder, 1994; Deolalikar, 1996; Adair, 1999; Fedorov & Sahn, 2005; Alderman, Hoddinott, & Kinsey, 2006; Mani, 2008). Although the existing literature on cognitive skills indicates that it is hard to overcome the deficiencies in early investments the later the correction in investments occur (Beckett, et al., 2006), there is a growing literature which suggests the existence of a second “sensitive period” during adolescence where catch-up growth can occur (Case & Paxson, 2008; Aguero & Deolalikar, 2012).
Our paper attempts to add to this strand of literature. First, we explore the patterns of persistence and chances of cognitive catch-up for children during childhood (5-8 years), middle childhood (8-12 years), early adolescence (12-15 years), and middle adolescence (15-19 years). Second, we examine how self-productivity and complementarity combine to affect cognitive production. More specifically, we investigate the existence of perfect complementarity in the production of cognitive skills.

We employ non-parametric analysis as well as a parametric dynamic model to conduct this analysis and use mathematics test scores, as a proxy for cognition, for a sample of Ethiopian children where the coefficient of lagged cognition scores determines the scope for catch-up growth. Outes & Porter (2013) employ a similar method to explore catch-up growth in height for age scores. We further expand this model to examine the effect of lagged cognition scores on current cognition scores with the interaction effects of different levels of investment in cognitive production. To address endogeneity in this relationship, we instrument lagged cognition scores with precipitation and temperature deviations for the most recent growing seasons.

We contribute to the existing literature on cognitive catch-up by utilizing panel data from three rounds of the younger and older cohorts from the Young Lives (YL) dataset. To our knowledge none of the existing research on cognitive catch-up and production looks at the relationship between past and current cognition scores throughout the lifecycle (childhood to middle adolescence) of cognitive production.

Our results indicate that the persistence in cogniton scores increases as children move from childhood to adolescence. But, as established in the previous literature (Almond & Currie,
We also identify early childhood (before age 5) as a “sensitive period” where the chances of catch-up growth in cognition are the highest. This is especially true for children at the lower end of the cognition distribution. We also find that opportunities for catch-up growth in cognition decline as children grow older. This seems to be true for both children at the lower end of the cognition distribution as well as for those who did not receive early investments in cognitive production. Thus, we find evidence for the case of perfect complementarity because children with no early investments in cognition never recover completely even with the existence of investments during later stages of childhood and adolescence. We also find evidence that without investments in cognition, the process of self-productivity in cognitive production might never start. The results from this paper suggest that policies for increasing cognition may be targeted during early childhood which is most commonly cited as the most important “sensitive period” in cognition formation. Similarly, efforts should also be directed towards ensuring that children do not suffer shocks during early childhood, as the chances of faltering are also the highest at this stage of cognitive production.

**Data**

To investigate the patterns of persistence and catch-up in cognition, we use panel data from the YL Project in Ethiopia collected by Oxofrd Department of International Development (ODID) at University of Oxford. The YL dataset comprises of two samples: a younger cohort of 2000 children and an older cohort of 1000 children where the ages of the two cohorts at the time of the first round of data collection were approximately one and eight years, respectively. So far the YL project has released four rounds of data covering the years 2002, 2006, 2009, and 2013 (ODID, 2017). The YL data is collected from the five most populous
regions of Ethiopia, namely Addis Ababa, Amhara, Oromia, SNNP and Tigray which comprise about 96% of the total Ethiopian population, making it a highly representative sample of the total population (Wilson & Huttly, 2004). The YL data primarily comprises of poor households providing useful insight into how human capital outcomes are affected in such a setting. Thus, it contains unique and important data on anthropometric measures in each round as well as data on cognitive achievement tests which were conducted at the time of data collection. The latter makes it a unique data as actual measures of cognition are hard to find because of cost and time constraints during data collection.

Our aim in this paper is to examine the patterns of persistence and catch-up in cognition during stages of later childhood and adolescence. We define these stages as childhood (5-8 years), middle childhood (8-12 years), early adolescence (12-15 years), and middle adolescence (15-19 years). The first two stages coincide with Piaget’s preoperational and concrete operational stages of cognitive development, while the last two coincide with formal operational stage of cognitive development. All three of Piaget’s stages signify different landmarks in cognitive development: the preoperational stage marks the start of the use of language and pictures to represent objects, the concrete operational stage marks the beginning of using inductive logic about concrete events, while the formal operational stage usually overlaps with the initiation of deductive logic and abstract thinking (Piaget, 1964). Therefore, to capture the patterns of persistence and catch-up growth in cognition during all of the stages mentioned above, we use data from both the younger and the older cohort. Specifically, the data for childhood and middle childhood comes from the second, third and fourth rounds of the younger cohort, when the children were 5, 8, and 12 respectively. On the other hand, the data for early adolescence and middle adolescence comes from the second,
third and fourth rounds of the older cohort, when the children were 12, 15, and 19 respectively. Data from the first round of the younger cohort was not used because the children were 1 year old at that time and as a result no cognition test was conducted. We could also not use the data from the first round of data collection for the older cohort as no mathematics test was conducted when the children were 8 years of age. Despite the rate of attrition being relatively lower than other longitudinal datasets, there is a loss of observations especially in the fourth round for both cohorts. Thus, our sample sizes at ages 8, 12, 15, and 19 are 1632, 1413 862, and 792 respectively. For more information on YL’s methodology and data collection procedures see Outes & Sanchez (2008) and Morow (2009).

We use the standardized scores of the mathematics test conducted during the second, third, and fourth rounds of the younger and older cohort as a proxy for cognitive status for comparison across different stages of childhood and adolescence. In the second round of both cohorts, the mathematics test conducted is the Cognitive Development Assessment-Quantity Test while in rounds three and four of both cohorts the quantitative test is the Mathematics Achievement Test. We use study time before age 5 as the proxy for earlier investments in cognition in this paper. The study time variable represents a value of 1 if the child spent any number of hours studying in school and outside the school during a typical day in the last week before age 5, and a value of zero otherwise.

To get exogenous variation in previous time period’s cognitive status, we use precipitation and temperature data to obtain climatic deviations for the growing seasons for every year of the child’s life, and the growing seasons year before birth of the child. The major growing season in Ethiopia is meher (from June through October) which produces 90-95% of the yearly cereal output (USDA, 2008). Therefore, any climatic deviations during meher will
have consequences for the food security and income of the household as well as for the
general disease environment (Bernstein & Myers, 2011; Seal & Vasudevan, 2011; Roberts,
2011; Dell, Jones, & Olken, 2014; Hagos et al., 2014). We use the University of Delaware
Air Temperature and Precipitation (UDATP) dataset to calculate precipitation and
temperature deviations to be used as instruments (ESRL, 2017). Since we do not have access
to the geo-coordinates for the sample communities, we use the mothly total rainfall and
monthly average temperature data in UDATP to calculate the region-specific climatic
deviations. We do this by taking the regional average of the total precipitation and average
temperature from the center grid and the four grids farthest from the center to the east, west,
north and south. Thus, we end up with region specific meher total precipitation and average
temperature for every year from 1965 to 2014. We further standardize these measures using
the mean and standard deviation of meher total precipitation and average temperature in
every region from 1965 to 2014.

**Methodology**

There is a general consensus in the existing literature that early inputs in human capital can
impact cognitive ability in the short-run but also impact future cognition and earning
potential in the long-run (Case & Paxson, 2008; Cunha & Heckman, 2008; Doyle et al.,
2009; Smith, 2009; Cunha, Heckman, & Schennach, 2010; Victoria et al., 2010; Almond &
extensive summary of the previous literature highlighting the importance of early
investments in human capital. However, this does not mean that recovery or catch-up from
early chidhood deficiencies is not possible. Human capital formation is a lifecycle
phenomenon which displays the dual processes of self-productivity and complementarity
(Cunha et al., 2006). Self-productivity refers to the ability of generating cognitive ability in a later time period based on the existing cognitive ability in a previous time period. This can be thought of as the process through which natural or inherited ability manifests itself in cognitive production throughout the life-cycle. On the other hand, complementarity is the ability through which the productivity of early investments in human capital can be increased by investments in later time periods. This can be thought of as the role that “nurture” can play in cognitive production. Thus, early investments are important as they can combine with inherited ability to have a multiplier effect on cognitive production during later time periods. This importance increases if the inherited ability is not high to begin with.

If it is found that investments in human capital in later stages of childhood and adolescence can help achieve catch-up in cognition, it would be evidence against the extreme case of perfect complementarity where later investments cannot overcome the lack of earlier investments. Barring the notion that later investments can be more cost-ineffective as both self-productivity and complementarity have to be overcome, this would not only mean that remediation in later stages of childhood and adolescence can be effective in closing the achievement and wage gap (Almond & Currie, 2010), but an equity-efficiency trade-off may exist for such investments (Outes & Porter, 2013). Therefore, it would be interesting to examine the patterns of persistence and catch-up in cognition, after investments in earlier periods have realized, but skill formation can still manifest itself through self-productivity and complementarity. If an opportunity for catch-up exists after the completion of early childhood, it would point to a possible window for intervention, through parental investments, and government policy etc., and might allude to a later “sensitive period”.
We hypothesize that persistence or catch-up can occur for cognition scores at different stages of a child’s life. Thus, we explore, through a dynamic model, how catch-up growth denoted by the coefficient on lagged mathematics scores varies during childhood (5-8 years), middle childhood (8-12 years), early adolescence (12-15 years), and middle adolescence (15-19 years) periods, after investments in early childhood have been realized. Previous literature has looked at either catch-up in child nutrition (Deolalikar, 1996; Fedorov & Sahn, 2005; Alderman, Hoddinott, & Kinsey, 2006; Mani, 2008; Outes & Porter, 2013) or how catch-up in nutrition leads to cognitive outcomes later in life (Fink & Rockers, 2014; Georgiadis, et al., 2017) but to our knowledge no current research looks at whether persistence or catch-up exists in cognition scores themselves. Furthermore, we look at the patterns of persistence and catch-up in cognition from ages 5 to 19 which, excluding early childhood, comprises the total lifecycle of cognitive production, providing a rare unified look at the process of skill formation (Cunha et al., 2006).

Empirically, we use equation (1) to explore the patterns of persistence and catch-up, where $C_{it}$ is the current cognitive ability, which we proxy with mathematics z-scores, for child $i$ at time $t$, $C_{i,t-1}$ is the lagged mathematics z-scores, which in this value-added model we assume to be a sufficient statistic for previous investments in cognition, $X_{it}$ is a set of child and household control variables including sex, height for age z-scores, body mass index z-scores, whether the child is attending school, whether the test language is the same as the child’s native language, mother’s and father’s education, whether the child is first-born, household size, sex of the household head, log of monthly expenditure per adult, wealth quartile of the household, urban/rural status, ethnic group, religion, and cluster fixed effects. Current
cognitive ability will also be affected by unobserved child and household characteristics ($\mu_i$), as well as unobserved community characteristics ($\mu_c$).

$$C_{it} = \alpha C_{it-1} + \beta X_{it} + \mu_c + \mu_i + \epsilon_{it}$$  \hspace{1cm} (1)

When consistently estimated, the coefficient of $C_{it-1}$ obtained through the estimation of equation (1) will provide a measure of the degree of persistence in cognition scores between the current and previous time periods. If catch-up is perfect, $\alpha$ will be close to zero while a coefficient close to one would show perfect persistence.

Equation (1) will reveal whether opportunities for catch-up growth in cognition are a possibility during later stages of childhood and adolescence. We can also examine whether this opportunity for catch-up changes for children with and without early investments in early childhood. This will expose the interplay between self-productivity and complementarity during later stages of childhood and adolescence. More specifically, we can assess the possibility of perfect complementarity where lack of earlier investments can not be overcome through later investments. We can also evaluate if self-productivity can remain active during later stages of childhood without investments in earlier or later time periods. To assess the impact of early investments in cognition, we will estimate the following equation:

$$C_{it} = \delta C_{it-1} * Invest_t + \gamma X_{it} + \mu_c + \mu_i + \epsilon_{it}$$  \hspace{1cm} (2)

where $Invest_t$ shows the level of investment in the cognitive production through three categories: continuous investments, no early but current investment, and no investments.

Ordinary least squares (OLS) estimations of equations (1) to (3) will not yield consistent estimates as cognitive status in two time periods is likely to suffer from endogeneity concerns. This endogeneity arises mainly from unobserved
individual and household characteristics might affect cognitive status in all time periods. Thus, in order to get exogenous variation of previous time period’s cognitive status on current time period’s cognitive status, we instrument lagged mathematics scores with standard deviations in precipitation and temperature from the region-specific means for the most recent yearly growing seasons going back to the previous round of data collection. For age 5 we use deviations for the yearly growing seasons starting at when the children were 4 years old and going back to a year before their birth.

Climatic deviations such as precipitation and temperature deviations during childhood can impact cognitive outcomes in the current and later stages of childhood and adolescence (Glewwe & King, 2001; Leight, Glewwe, & Park, 2015). This can especially be the case in a typical agrarian household scenario found in developing countries like Ethiopia where precipitation and temperature deviations can lead to lower food production and a decrease in household food availability (Haile, 2005; Lobell, Schlenker, & Costa-Roberts, 2011; Hagos et al., 2014). Apart from working through the household food availability channel, precipitation and temperature deviations can impact cognitive outcomes by working through the income channel. This is a bigger concern in rural areas as climatic deviations can result in lower agricultural output and decreased income impacting the ability to purchase food from the market (Dercon, 2002; Dell, Jones, & Olken, 2014). A third possible channel highlighted in the previous medical research is the impact of climatic deviations on the disease environment, through water contamination and a higher prevalence of water-borne diseases, which can impair cognitive production of children (Ebi & Paulson, 2007; McCartney, 2007; Ebi & Paulson, 2010; Bernstein & Myers, 2011; Seal & Vasudevan, 2011). A possible concern to the validity of our instruments is the impact of climatic shocks before the previous
round of data collection on the current cognitive outcome. But previous literature points to the decaying effects of climatic shocks during later stages of childhood and adolescence (Leight, Glewwe, & Park, 2015) which makes us confident that there are no major threats to the exclusion restriction of our chosen instruments.

**Descriptive Statistics and Non-Parametric Regressions**

Figure 3.1 represents the transition matrix for cognitive status using standardized mathematics scores during childhood (5-8 years), middle childhood (8-12 years), early adolescence (12-15 years), and middle adolescence (15-19 years) periods. The sample is restricted to children with non-missing observations for mathematics scores in the younger and older cohort respectively. As mentioned above, the number of total observations from the older cohort is half of those from the younger cohort, thus, we will rely on the transition percentages in each round, shown in Figure 3.1, to determine the movement from one cognitive status to the other. Figure 3.1 shows that the percentage of children who had a cognitive deficit in the previous round and remained with a deficit in the current round increases as we move up the ages from 3.92% at ages 5-8 to 8.96% at ages 15-19. Similarly, the percentage of children who were without a deficit in the previous and remained without a deficit in the current round generally increases as we move up the ages. These numbers point to a general trend of higher persistence as children transition from childhood to adolescence. Thus, once a child’s cognitive status is set early on, it has a huge role in determining their cognitive status in the future, pointing to the crystallization of mathematics skills as children grow. If persistence is the general trend in cognitive production, we would expect to see a decrease in the “Deficit to No Deficit” and “No Deficit to Deficit” categories as we move up the ages as any transition to a different cognitive status should become difficult as children
leave childhood and enter adolescence. Figure 3.1 shows the movement from having a deficit to not having one becomes difficult as the child ages, apart from at ages 12-15 when the percentage of this movement increases. On the other hand, we find that the movement from not having a deficit to having one becomes easier as children age, apart from at ages 12-15 when this movement becomes more difficult from the previous round. Thus, we don’t see a clear pattern of higher persistence as children grow older as transition becomes easier or more difficult at different ages. Both the “Deficit to No Deficit” and “No Deficit to Deficit” categories point to ages 12-15 as an age where catch-up growth in cognition is happening as the movement from “deficit to no deficit” becomes more prevalent while the movement from “no deficit to deficit” becomes less prevalent when compared to the previous round. While this might not allude to a possible “sensitive period” at ages 12-15 where both catch-up and Faltering can happen, it could suggest that at this age parents of kids with early promise undertake reinforcing investments while those with early deficits undertake compensating investment, thereby increasing the possibility of catch-up in cognition.

[Insert Figure 3.1]

Using non-parametric fractional-polynomial plots with 95% confidence intervals of the lagged standardized mathematics scores on current standardized mathematics scores at ages 8 through 19, Figure 3.2 depicts the relationship between lagged cognition and current cognition. If cognition in previous period is the same as the current period, the relationship will simply look like an upward-sloping 45 degree straight line with a slope of 1. This would signify complete/perfect persistence as current cognition is perfectly determined by lagged cognition. However, if the slope is less than 1 and closer to 0, it implies less persistence and a higher degree of catch-up or faltering. At age 8, we find a higher degree of catch-up at the
lower end of lagged mathematics scores, which decreases in magnitude as we move towards the upper end of the distribution, as shown by an increase in the slope. However, for most of the values of lagged mathematics scores at age 12, the relationship is linear at the lower end of the distribution implying higher levels of persistence. The situation once again changes at age 15 where we again find a higher degree of catch-up in cognition at the lower end of the lagged mathematics scores. Finally, we again find higher levels of persistence for lower lagged mathematics score at ages 15-19. This everchanging pattern of catch-up and persistence throughout the life-cycle of cognitive production, as shown by the fractional-polynomial plots, points to two major windows of opportunities at ages 5-8 and 12-15 where higher levels of catch-up can be achieved making it possible to transition from a cognitive deficit to not having one. The importance of the initial stage of childhood has already been well documented in the previous literature (Almond & Currie, 2010). But Figures 3.1 and 3.2 provide evidence for a possible second stage during early adolescence (12-15 years) where catch-up growth may be possible as children enter puberty which is usually accompanied by a growth spurt.

[Insert Figure 3.2]

Results from Parametric Analysis

In this section, we use econometric methods to verify the findings from the previous section and also look at the role that self-productivity and complementarity can play in cognitive production at different ages. All the results are estimated with errors clustered at the sampling unit level.
Table 3.1 reports the results obtained from the estimation of equation (1) for the total sample as well as for the upper and lower half of the cognitive distribution. Columns (1) and (2) report the results from the younger cohort while columns (3) and (4) report the results from the older cohort. If persistence in mathematics cores is perfect, we would expect a coefficient that is close to one. On the other hand, a coefficient close to zero will imply a higher chance of catch-up growth or faltering in cognition scores happening. At first glance, we find that the persistence of mathematics scores for the total sample is increasing when children move across childhood, middle childhood, and early adolescence as revealed by the increasing magnitude of the coefficients of lagged mathematics scores from columns (1) to (3). This points to the crystallization of mathematics skills as children grow older with previous levels of cognition determining later levels more and more. Thus, it becomes extremely important to ensure that a child’s early level of cognition is maximized as cognitive status later in life will be dependent on it. The coefficient in column (4) for the total sample is insignificant showing that previous cognition does not affect current cognition at age 19. The reason for this lack of significance in this relationship at this age might be the end of the lifecycle of cognitive production. Around this age, children cross puberty and enter into adulthood, signaling the end of self-productivity in cognitive production as their physical and mental growth has reached its full potential.

Table 3.1 also reveals the pattern of persistence as it varies across ages for the bottom and top halves of the cognition distribution. The coefficient (0.151) in column (1) for the bottom half of the cognition distribution shows that catch-up or faltering is a high possibility at this stage of cognitive production. Thus, the ages 5 to 8 can be considered an important period, especially for children with lower levels of mathematics skills, where timely investments
might result in catch-up growth in cognition. The coefficients in columns (2) to (4) for the bottom half of the cognition distribution are insignificant showing that lagged cognition does not affect current cognition at ages 12, 15, and 19. Thus, while Figures 3.1 and 3.2 alluded to the possibility of catch-up growth existing for children during ages 12 to 15 at the lower end of the cognition distribution, an insignificant coefficient (0.119) suggests that this possibility might not exist after all at this age. On the other hand, the coefficients in columns (1) to (4) for the top half of the cognition distribution show a general increase in persistence in cognition scores as children move from childhood to adolescence.

[Insert Table 3.1]

The results from Table 3.1 reveal two important findings. First, persistence in cognitive outcomes increases throughout the lifecycle of cognitive production. This is especially true for children at the upper end of the cognition distribution. Second, there is greater chance of catch-up growth or faltering happening in the early stages of childhood (Almond & Currie, 2010) for children at the lower end of the cognition distribution, making it an extremely important “sensitive period” for them.

Table 3.2 tries to look at how early investments in cognition affect the persistence and chances of catch-up in mathematics test scores during childhood and middle childhood. We define early investments in cognition as having any study time (either schooling or study time at home) before data collection in round two when the children were roughly five years old. Study time has been used in the previous studies as a measure of investment in cognitive

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9 Because of the insignificance, the coefficients in columns (2) to (4) might be true zeros or just imprecise estimates (due to large confidence bands). Thus, they might not be true zeros but noisy non-zeros. Due to this uncertainty, we think that no relationship exists between current and previous cognition scores at these ages for the bottom half of cognition distribution.
production (Cooper, Robinson, & Patall, 2006; Stinebrickner & Stinebrickner, 2008; Eren & Henderson, 2011; Kalenkoski & Pabilonia, 2014). Since we do not have data for study time before five years of age for the older cohort, we limit the analysis in Table 3.2 to just the younger cohort. We divide our sample at both ages 8 and 12 into three parts: children who had early investments in cognition along with having current investments in the form of schooling, children who did not have early investments in cognition but have current investments, and children who neither had early investments nor have current investments.

For children with continuous investments, we find that mathematics scores in the previous round have a significant relationship with current mathematics scores with persistence increasing to almost perfect persistence at age 12, as shown by the increase in coefficient from 0.439 to 0.954. This shows that even with continuous investments in cognitive production, the chances of catch-up decline as the child transitions from childhood to middle childhood. These group of children are benefitting from both self-productivity (shown by the significant coefficients) and complementarity (shown by the presence of early investments) in cognitive production. Furthermore, it can be seen from the means shown in columns (3) and (4) of Table 3.2 for this group that higher persistence is leading them towards crystallization of higher mathematics skills. When we look at children who did not have early investments in cognition but have access to current investment, we find that the relationship between lagged mathematics scores and current mathematics scores is insignificant at age 8 but positive and significant at age 12 with a coefficient of 0.717. This shows that although self-productivity is not actively contributing towards cognitive production from ages 5 to 8, investments later in the childhood affect cognitive production in such a way that self-productivity becomes evident by age 12 as persistence sets in. Thus, it seems that early
investments are necessary stimuli for the process of self-productivity in cognitive production to start. Furthermore, this higher level of persistence at age 12 is geared towards a lower level of cognition level as seen by the means mathematics scores in columns (3) and (4) which are lower than those for children with continuous investments. Therefore, current investments do not make up for the lack of early investments before age 5. The third sub-sample of children with neither early investments in cognition nor current investments shows an insignificant relationship between lagged mathematics scores and current mathematics scores for both ages 8 and 12. This implies that without early and later investments in cognitive production, self-productivity never becomes evident (shown by the insignificant coefficients) and the children on average end up with lower cognition levels than the children in the other two categories. The results from Table 3.2 provide evidence for the case of perfect complementarity where lack of early investments in cognition are never overcome even when investments in later periods is present.

[Insert Table 3.2]

Since Table 3.2 suggests that the effect of lack of early investments might last throughout the lifecycle of cognitive production, it will be interesting to see the distribution of cognition at different ages for the three categories of investments: continuous, no early but current investments, and no investments. Figure 3.3 provides this information through kernel density plots of mathematics scores for the different categories of investments at ages 5, 8, and 12. At age 5, there are only two possible categories as either children had study time before age 5 or they did not. At this early age we see that although children with continuous investments have better mathematics scores on average than those without study time, there is considerable overlap between the two distributions. This shows that although the kids have
started to differentiate themselves in terms of their investment status, the difference is not that vast, implying the existence of chances for catch-up growth. The difference in mathematics scores start to widen for the three investment categories when we move to ages 8 and 12. Here we see that children with no investments lag behind both children with “continuous” and “no early but current investments”. Furthermore, their distribution of mathematics scores is also narrow compared to children in other investment categories, implying less chances for catch-up growth. There is some overlap in the distributions of mathematics scores for children with “continuous” and “no early but current investments” at ages 8 and 12 but not as much as age 5. This shows that without early investments chances of catch-up growth in cognition dwindle as children grow older. Moreover, children with no early but current investments lag far behind on average when compared to children with continuous investments in terms of their mathematics scores at ages 8 and 12.

[Insert Figure 3.3]

The above results point to a general trend of persistence in cognition scores as children transition from childhood to adolescence. Moreover, we add to existing literature highlighting the importance of investments in cognition during the “sensitive period” of early childhood (Almond & Currie, 2010). It is in this time period that children are most vulnerable to shocks and therefore both faltering and catch-up growth become a greater possibility depending on the inputs that children receive. However, these opportunities of catch-up growth decline for the total sample as well as for the lower half of the cognition distribution and children without early investments. Thus, we find evidence for the case of perfect complementarity where the lack of early investments in cognitive production are never overcome even with the presence of later investments.
Conclusion

Previous literature suggests that early investments in cognition can impact cognitive outcomes during childhood as well as in later periods of adolescence and middle adolescence (Cunha & Heckman, 2008; Doyle et al., 2009; Smith, 2009; Cunha, Heckman, & Schennach, 2010; Victoria et al., 2010; Almond & Currie, 2011; Currie, 2011; Lynch & Gibbs, 2017). It has also been established that catch-up growth in cognition is also most likely during the early stages of childhood characterized as “sensitive periods” (Fedorov & Sahn, 2005; Alderman, Hoddinott, & Kinsey, 2006; Mani, 2008). We add to this literature by exploring patterns of persistence and catch-up growth throughout the life-cycle of cognitive production for children in Ethiopia. We also look at how self-productivity and complementarity combine to affect cognitive production at different stages. Our empirical analysis employs a dynamic model in which we find the effect of lagged cognition scores on current cognition scores where the coefficient of lagged cognition scores determines the scope for catch-up growth.

We find that persistence in cognition scores generally increases throughout the lifecycle of cognitive production. Our results also point to early childhood as the stage where chances for catch-up growth are the highest, especially for children at the lower end of the cognition distribution. The results from the empirical model also point towards the presence of perfect complementarity in cognitive production, thus, implying that children can never fully recover from a lack of early investments during later stages of childhood, even if investments are available during the later stages. It also seems that investments in cognition are necessary stimuli for the process of self-productivity in cognitive production to start. Therefore,
policymakers may focus on providing cognitive investments during the early stages of childhood as these can have implications for the lifecycle of cognitive production.
### Table 3.1: Persistence or Catch-Up of Mathematics Scores

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged Cognition Scores</td>
<td>0.562***</td>
<td>0.602***</td>
<td>0.632**</td>
<td>0.390</td>
</tr>
<tr>
<td></td>
<td>(0.128)</td>
<td>(0.173)</td>
<td>(0.319)</td>
<td>(0.271)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,632</td>
<td>1,413</td>
<td>862</td>
<td>792</td>
</tr>
<tr>
<td>R Squared</td>
<td>0.377</td>
<td>0.552</td>
<td>0.418</td>
<td>0.543</td>
</tr>
<tr>
<td>IV F-Stat</td>
<td>48.21***</td>
<td>11.10***</td>
<td>6.84***</td>
<td>2.79**</td>
</tr>
<tr>
<td>Lagged Cognition Scores for Bottom Half</td>
<td>0.151**</td>
<td>-0.227</td>
<td>0.119</td>
<td>0.159</td>
</tr>
<tr>
<td></td>
<td>(0.0740)</td>
<td>(0.197)</td>
<td>(0.176)</td>
<td>(0.350)</td>
</tr>
<tr>
<td>Observations</td>
<td>990</td>
<td>757</td>
<td>540</td>
<td>383</td>
</tr>
<tr>
<td>R Squared</td>
<td>0.102</td>
<td>0.006</td>
<td>0.341</td>
<td>0.274</td>
</tr>
<tr>
<td>Lagged Cognition Scores for Top Half</td>
<td>0.386**</td>
<td>0.482**</td>
<td>0.362</td>
<td>0.520***</td>
</tr>
<tr>
<td></td>
<td>(0.179)</td>
<td>(0.198)</td>
<td>(0.274)</td>
<td>(0.150)</td>
</tr>
<tr>
<td>Observations</td>
<td>642</td>
<td>656</td>
<td>322</td>
<td>409</td>
</tr>
<tr>
<td>R Squared</td>
<td>0.258</td>
<td>0.347</td>
<td>0.315</td>
<td>0.220</td>
</tr>
<tr>
<td>Individual and Household Level Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Community Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

---

10 The coefficients in column (4) were estimated without controlling for height for age z-scores and body mass index z-scores because of missing observations amounting to close to half of the total sample when these were included.
Table 3.2: Marginal Effects of Lagged Mathematics Scores at Different Levels of Investment in Cognition

<table>
<thead>
<tr>
<th>Variables</th>
<th>Marginal Effects</th>
<th>Means and SD\textsuperscript{11} for Cognition Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Mathematics Age 8</td>
<td>0.439***</td>
<td>0.954***</td>
</tr>
<tr>
<td>(0.153)</td>
<td>(0.146)</td>
<td>(1.00)</td>
</tr>
<tr>
<td>Mathematics Age 12</td>
<td>0.173</td>
<td>0.717***</td>
</tr>
<tr>
<td>(0.215)</td>
<td>(0.239)</td>
<td>(0.808)</td>
</tr>
<tr>
<td>No Early Investment with Current Investment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Investments</td>
<td>0.242</td>
<td>0.052</td>
</tr>
<tr>
<td>(0.209)</td>
<td>(0.410)</td>
<td>(0.328)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,133\textsuperscript{13}</td>
<td>990</td>
</tr>
<tr>
<td>R Squared</td>
<td>0.5462</td>
<td>0.5397</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

\textsuperscript{11} Standard deviations are listed in parenthesis in columns (3) and (4).

\textsuperscript{12} A fourth investment category of investment status exists where the child has early investments but no later investments. But, the number of children in this category were only 3 and 6 at ages 8 and 12 respectively. Given this small number of observations, we combined these children with the “no investments” category.

\textsuperscript{13} The number of observations in Table 3.2 is reduced from Table 3.1 as the data for early investments (study time before age 5) had more missing observations.
Figure 3.1: Visual Representation of the Transition Matrix
Figure 3.2: Non-Parametric Regressions for Lagged Cognition’s Effect on Current Cognition
Figure 3.3: Kernel Density Plots of Mathematics Scores at Different Levels of Cognitive Investments
Chapter 4
We are how much we Eat: Nutrient-Specific versus Calorie-Based Adult-Equivalent Scales

Introduction

Household-level surveys usually contain food modules which detail the household food availability in the form of food expenditures (Naska, Vaskedis, & Trichopoulou, 2001). Although not as precise as food frequency questionnaires (FFQs), these food modules are a cheaper and useful way of calculating individual food consumption (Trichopoulou & Naska, 2003; Engle-Stone & Brown, 2015). Individual food consumption has also been used to further extract information regarding individual-specific nutrient availability in previous studies (Abdulai & Aubert, 2004; Fiedler et al., 2008; Salois, Tiffin, & Balcombe, 2012; Ogundari & Abdulai, 2013; Ali, Villa, & Joshi, 2018). Initial studies which calculated per capita estimates of nutrient availability did not take into account household composition discounting the specific macro- and micronutrient requirements for each individual within the household (Blaylock, 1991). This gave rise to the development of adult-equivalent scales which assign a number value to each individual based on what proportion of an adult’s nutrient requirements they have. This allows the comparison of household nutrient availability between households with different compositions (Tedford, Capps, & Havlicek Jr., 1986; Deaton & Muellbauer, 1986).

However, the current adult-equivalent scales used by nutritionists are mostly based on the calorie requirements of different age groups and sex. Although calorie-based adult-equivalent scales are an improvement from per capita measures and are perfect for calculating
individual-level calorie availability, they still lead to unreliable estimates of availability for other nutrients such as macro- (fats, carbohydrates, and proteins) and micronutrients (vitamins and minerals). This becomes an even important issue keeping in mind that micronutrient deficiency is a much bigger problem than calorie deficiency now in developing countries (Hoddinott, Rosegrant, & Torero, 2012). Thus, any adult-equivalent scale based on caloric requirements by sex and age will not correctly calculate the individual-level micronutrient availability within a household. Therefore, having accurate conversion factors for these nutrients is important to better understand disparities in nutrient availability and food security in developing countries. Other commonly used equivalence scales, such as the Organization for Economic Co-operation and Development (OECD) scale, are generally developed for overall household consumption or expenditure (not just household nutrient availability). They also typically assume the existence of economies of scale. For example, the OECD scale assumes that additional adults are equivalent to 0.5 of the first adult. While, this is a reasonable assumption for expenditure measures, economics of scale does not exist for nutrient availability. Moving from a one adult to a two adult household (each with the same nutrient requirements) requires that the household’s nutrient availability must double (not increase by 0.5). Thus, the use of proper nutrient-specific adult-equivalent scales will allow the comparison of macro- and micronutrient availability across households with varying demographic makeup as children, adults, and elderly people have different nutrient requirements.

In this paper, we calculate nutrient-specific adult-equivalent scales using the daily nutrient intake guidelines provided by the Institute of Medicine (Institute of Medicine, 2006). We also calculate the magnitude of the difference in daily nutrient availabilities when using the
nutrient-specific in comparison to calorie-based, per capita, and OECD adult equivalent scales by using the data from the third round of the Nepal Living Standards Survey (NLSS III). Furthermore, we examine if these differences are statistically significant on average. Thus, our contribution is two-fold. First, the calculation of nutrient-specific adult-equivalent scales will enable researchers to accurately translate food availability data from household surveys to their respective macro- and micronutrient availabilities. Second, this paper also provides an estimate of the difference in the calculation of daily individual-level nutrient availabilities if the commonly used calorie-based, per capita, and OECD adult equivalent scales are used instead of those that are nutrient-specific.

We find that on average there are significant differences in the individual-level daily nutrient availability estimates when they are calculated using the nutrient-specific adult-equivalent scale designed in this paper compared to the other commonly used (calorie-based, per capita, and OECD) adult equivalent scales. The average difference is also not just in one direction, as in the use of calorie-based, per capita, and OECD adult equivalent scales overcalculates or undercalculates the mean nutrient availability depending on each specific nutrient. Thus, our study provides a much more accurate benchmark for future studies using household survey data to calculate nutrient availability estimates.

**Data**

We use data from NLSS III collected in 2010-2011 to ascertain if there are any differences in the individual nutrient availability estimates when they are calculated using the adult-equivalent scales devised in this paper in comparison to the calorie-based, per capita, and OECD adult-equivalent scales. NLSS III consists of a total of 5,988 observations at the
household level but because of missing observations our analysis is restricted to a sample of 5,372. NLSS III includes a food module containing information related to weekly household food availability based on foods obtained through home production, market purchases, and in-kind receipts. We use this food availability data to calculate daily household-level nutrient availability using the reference tables provided by the United States Department of Agriculture (USDA) National Nutrient Database for Standard Reference (USDA, 2018). The nutrients for which we calculate the daily household nutrient availability are proteins, carbohydrates, fats, vitamins A, C, B1, B2, B3, B6, B9, B12, calcium, iron, and zinc. We select these macro- and micronutrients as they form the most important protective and growth nutrients needed to maintain healthy bodily functions such as bone growth and brain activity (USFDA, 2018).

After calculating the daily household-level nutrient availability, we use the calorie-based (calculated by Claro et al. (2010)), per capita, and OECD adult-equivalent scales, as well as the nutrient-specific adult-equivalent scale constructed in this paper to create four sets of individual-level daily nutrient availabilities. Using these, we construct three variables equal to the difference between individual-level daily nutrient availability obtained through nutrient-specific adult-equivalent scale and individual-level daily nutrient availability obtained through calorie-based, per capita, and OECD adult-equivalent scales respectively. Further explanation of how these difference variables are used is provided in the next sections of this paper.

**Nutrient-Specific Adult-Equivalent Scales**
We construct nutrient-specific adult-equivalent scales using the daily nutrient intake guidelines provided by the Institute of Medicine (Institute of Medicine, 2006). These guidelines provide the exact daily intake requirements for all the macro- and micronutrients analyzed in this paper, accounting for age and sex differences. According to the Institute of Medicine (2006), the age groups which have different daily nutrient intake requirements are 1-3, 4-8, 9-13, 14-18, 19-30, 31-50, and above 50. Apart from the age group 1-3, the daily intake requirements for the rest of the groups also differ by sex.

To estimate the nutrient-specific adult-equivalent scales, we use the daily nutrient requirement for males in the 19-30 age group for each nutrient as the reference value to which the daily requirement for all other age and sex groups is compared. Thus, the adult-equivalent fractions for every nutrient were computed by dividing the daily requirement for each age and sex group with the reference value for that specific nutrient. Since, according to the Institute of Medicine’s guidelines, the fats and carbohydrates requirements do not change with age and sex, we do not include these macronutrients in Table 4.1 as all their adult-equivalent fractions would have been equal to 1.

Table 4.1 details the nutrient-specific adult-equivalent scales calculated using the above methodology. A close look at Table 4.1 suggests that the adult-equivalent fractions for every age group vary considerably across the nutrient distribution. This implies that the use of nutrient-specific versus calorie-based adult-equivalent scales can over- or undercalculate individual-level nutrient availability obtained from household surveys. We further explore this idea in the subsection below. As a point of reference, Table 4.2 provides the calorie-based and OECD adult-equivalent scales for different ages. It is important to keep in mind that these two scales do not differentiate between different macro- and micronutrients.
Differences between Nutrient-Specific and Calorie-Based Scales

Our hypothesis in this paper is that the estimates of nutrient availability measures obtained through nutrient-specific adult-equivalent scale are different from those obtained through calorie-based, per capita, and OECD adult-equivalent scales. To examine this, we construct three sets of variables equal to the difference between individual-level daily nutrient availability measures obtained through nutrient-specific adult-equivalent scale and individual-level daily nutrient availability obtained through calorie-based, per capita, and OECD adult-equivalent scales respectively, for each nutrient and test whether the means of these difference variables is equal to zero. We do this using a single sample t-test where the null hypotheses are that the difference variables are equal to zero. Thus, our hypotheses can be defined as:

\[ H_0: \text{Diff}_\text{Nutrient}_{hi} = 0 \] (1)

where \( \text{Diff}_\text{Nutrient} \) is the difference obtained by subtracting measures of daily individual-level nutrient availability calculated through calorie-based, per capita, and OECD adult equivalent scales from daily individual-level nutrient availability calculated through the nutrient-specific adult-equivalent scale for each nutrient \( i \) in household \( h \). The t-statistics obtained from the testing of these hypotheses will reveal whether the difference between the individual-level nutrient availabilities calculated through the nutrient-specific adult-equivalent scale are on average significantly different from those calculated through other (calorie-based, per capita, or OECD) adult-equivalent scales. Thus, if the null hypotheses are
rejected, it would imply that nutrient availability estimates obtained from the above-mentioned adult-equivalent scales are on average different from each other.

Results

Table 4.3 shows the summary statistics of the individual-level daily nutrient availability measures calculated through the use of nutrient-specific, calorie-based, per capita, and OECD adult-equivalent scales. The measures for fats, carbohydrates, and proteins are in grams, vitamins C, B1, B2, B3, B6, calcium, iron, and zinc are in milligrams, while those for vitamins A, D, B9, and B12 are in micrograms. When comparing the means of individual-level nutrient availabilities obtained through nutrient-specific and calorie-based scales, we find that on average the availability is greater for proteins, vitamins A, C, B1, B2, B3, B9, B12, and zinc when calculated using the former scale. For the rest of the nutrients, the average availability is greater when using the latter adult-equivalent scale. However, when the comparison is made between measures calculated using nutrient-specific and per capita scales, it is evident that on average nutrient-specific measures are higher than per capita ones with the only exceptions being calcium and iron. Finally, when the comparison is made between nutrient-specific and OECD measures, it is clear that on average the OECD scale overestimates individual-level nutrient-availability.

[Insert Table 4.3]

Table 4.4 further this analysis by using a single sample t-test where the null hypotheses are that the difference between nutrient-specific and calorie-based, per capita, and OECD

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14 Table 4.3 shows missing means for the difference between availabilities calculated through per capita and nutrient-specific adult-equivalent scales for fats, carbohydrates, and vitamin D. This is because according to the Institute of Medicine’s guidelines, the requirements for these nutrients do not change with age and sex.
measures of individual daily nutrient availabilities variables are equal to zero. The table reports the means of differences between the adult-equivalence scales mentioned above in three different columns. All the reported differences of means are significant at 1 percent level of significance showing that indeed the individual-level daily nutrient availabilities calculated through the calorie-based, per capita, and OECD adult-equivalent scales are on average statistically different from those obtained through the nutrient-specific adult-equivalent scale.

[Insert Table 4.4]

To further illustrate this point, we take the example of a representative household from the NLSS III dataset, comprising of two males, aged 48 and 15 years old, and four females aged 67, 43, 12, and 4 years old. These specific ages chosen above are the means of the ages of husbands, wives, sons, daughters, and elderly individuals in the NLSS III dataset.

Furthermore, we add the 4 year old female in the representative household to see the effect of children on the calculated individual-level nutrient availability. We also calculate the average nutrient availability per household for every nutrient in the dataset while assuming that if these amounts of every nutrient were available to the representative household described above, how the use of calorie-based, per capita, and OECD scales will compare with the use of nutrient-specific scale. Table 4.5 shows these results where a negative number means that the scale in question overestimates the individual-level availability for that specific nutrient while a positive number suggests underestimation of the same. For example, the calorie-based scale underestimates the individual-level availability of proteins while overestimating the individual-level availability of calcium for the representative household in comparison with the nutrient-specific scale.
The results in Table 4.5 clearly show that the use of a calorie-based, per capita, or OECD adult-equivalence scale for all macro- and micronutrients will either underestimate or overestimate the true nutrient availabilities for the representative household in the sample. Therefore, the nutrient-specific adult-equivalent scales developed in this paper provide a better way of converting the food purchases or consumption data from household surveys into reliable measures of individual-level nutrient availabilities, potentially reducing the measurement error in future studies.

[Insert Table 4.5]

**Nutrient-Income Elasticities from Different Scales**

As a robustness check for the finding that individual-level nutrient availabilities obtained from different adult-equivalence scales are significantly different from each other, we calculated the nutrient-income elasticities for all macro- and micronutrients using the Instrumental Variables (IV) regression model where the income is instrumented with wealth and the control variables include educational dummy variables for the household head, the number of male and female children (less than 17 years old) in the household, the number of male and female adults in the household, and dummy variables indicating whether the household is Brahmin caste (upper caste), lives in an urban center, and whether the household head is male. Community controls consist of spatial features including distance to market and regional dummies. We also control for community fixed effects. Table 4.6 shows these results.

[Insert Table 4.6]

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15 For further discussion on this model and the variables used, refer to Ali, Villa, & Joshi (2018).
Table 4.6 shows that using a nutrient-specific in comparison to calorie-based, per-capita, or OECD adult-equivalence scale results in very small changes in estimated nutrient-income elasticities. Therefore, we can conclude that the choice of adult-equivalence scale in the calculation of individual-level nutrient availability might not matter a lot. But to be sure whether this is indeed the case, further analysis is needed to see if the choice of adult-equivalence scale in the calculation of nutrient-income elasticities makes a difference when household composition is taken into account.

**Conclusion**

Household surveys usually contain data on food purchases or food consumption which have been used extensively in previous studies to arrive at measures of calorie and nutrient availability. The problem with this method is that household-level nutrient availability is easy to calculate but individual-level nutrient availability requires researchers to consider household composition which can be tricky when computing availability for a number of distinct macro- and micronutrients. The prevalent method has been to divide household-level nutrient availability by adult-equivalents, which are calculated using calorie-based, per capita, and OECD etc. adult-equivalent scales. While these are appropriate methods in certain situations, for example, when individual-level calorie availability is being calculated using a calorie-based adult-equivalent scale, it might confound the estimates when availability for other nutrients are being calculated.

In this paper we attempt to come up with a set of adult-equivalent scales for macro- (fats, carbohydrates, and proteins) and micronutrients (vitamins and minerals) based on the specific daily intake requirement for each nutrient. These set of scales can be potentially useful in
future studies relying on household surveys to arrive at individual-level nutrient availability estimates. Furthermore, this might reduce the possibility of measurement error in such studies. Using single sample t-tests, we also look at on average how different are the daily individual-level nutrient-availability estimates calculated through nutrient-specific and other commonly used adult-equivalent scales and whether these differences are statistically significant or not. The results suggest that on average there are significant differences between the daily nutrient-availability estimates derived from different scales, where the calorie-based, per capita, and OECD scales can overestimate or underestimate availability depending on the specific nutrient.
Table 4.1: Nutrient-Specific Adult-Equivalent Scales

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<tr>
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<th></th>
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<th></th>
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<td>0.69</td>
<td>0.75</td>
<td>0.77</td>
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<td>0.75</td>
<td>1.3</td>
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<tr>
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<td>0.75</td>
<td>0.69</td>
<td>0.75</td>
<td>0.77</td>
<td>0.75</td>
<td>0.75</td>
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<td>0.83</td>
<td>0.77</td>
<td>0.875</td>
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<td>1.875</td>
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<td>0.92</td>
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<td>0.875</td>
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<td>1</td>
<td>1.3</td>
<td>2.25</td>
<td>0.73</td>
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<td>0.875</td>
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<td>0.73</td>
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Table 4.2: Calorie-Based and OECD Adult-Equivalent Scales

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<th>Ages</th>
<th>OECD</th>
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<td>Male (&gt;50)</td>
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<td>VARIABLES</td>
<td>Nutrient-Specific</td>
<td>Calorie-Based</td>
<td>Per Capita</td>
</tr>
<tr>
<td>--------------</td>
<td>-------------------</td>
<td>---------------</td>
<td>------------</td>
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<tr>
<td></td>
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<td>Mean</td>
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<tr>
<td>Fats</td>
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<td>20.39</td>
<td>35.25</td>
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<td>Carbohydrates</td>
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<td>160.1</td>
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<td>62.17</td>
<td>30.34</td>
<td>53.32</td>
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<tr>
<td>Vitamin A</td>
<td>133.5</td>
<td>138.9</td>
<td>117.7</td>
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<tr>
<td>Vitamin C</td>
<td>65.47</td>
<td>71.59</td>
<td>53.30</td>
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<td>Vitamin D</td>
<td>0.416</td>
<td>0.559</td>
<td>0.456</td>
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<td>Vitamin B1</td>
<td>2.229</td>
<td>1.045</td>
<td>2.113</td>
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<tr>
<td>Vitamin B2</td>
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<td>11.51</td>
<td>21.83</td>
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<td>Vitamin B9</td>
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<td>626.2</td>
<td>589.2</td>
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<td>0.994</td>
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<tr>
<td>Zinc</td>
<td>12.58</td>
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<td>10.85</td>
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Table 4.4: Difference in Means between Nutrient-Specific and Other Nutrient Availabilities

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<tr>
<th>VARIABLES</th>
<th>Calorie-Based</th>
<th>Per Capita</th>
<th>OECD</th>
</tr>
</thead>
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<td>-3.368***</td>
<td>-</td>
<td>-23.59***</td>
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<tr>
<td>Carbohydrates</td>
<td>-36.64***</td>
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<td>Proteins</td>
<td>8.853***</td>
<td>14.03***</td>
<td>-22.65***</td>
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<td>Vitamin A</td>
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<td>26.80***</td>
<td>-49.45***</td>
</tr>
<tr>
<td>Vitamin C</td>
<td>12.16***</td>
<td>16.85***</td>
<td>-18.06***</td>
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<td>-</td>
<td>-0.305***</td>
</tr>
<tr>
<td>Vitamin B1</td>
<td>0.117***</td>
<td>0.320***</td>
<td>-1.139***</td>
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<td>Vitamin B2</td>
<td>0.0757***</td>
<td>0.151***</td>
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<td>9.947***</td>
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</table>
Table 4.5: Over- and Underestimation of Individual-Level Nutrient Availability from Different Adult-Equivalent Scales for a Representative Household

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<tr>
<th>VARIABLES</th>
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<th>Per Capita</th>
<th>OECD</th>
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</thead>
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<td>(2) Calorie-Based</td>
<td>(3) Per Capita</td>
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<td>0.717***</td>
</tr>
<tr>
<td></td>
<td>(0.0978)</td>
<td>(0.101)</td>
<td>(0.0978)</td>
</tr>
<tr>
<td>Vitamin B1</td>
<td>0.328***</td>
<td>0.376***</td>
<td>0.348***</td>
</tr>
<tr>
<td></td>
<td>(0.0621)</td>
<td>(0.0619)</td>
<td>(0.0605)</td>
</tr>
<tr>
<td>Vitamin B2</td>
<td>0.613***</td>
<td>0.650***</td>
<td>0.618***</td>
</tr>
<tr>
<td></td>
<td>(0.0620)</td>
<td>(0.0636)</td>
<td>(0.0592)</td>
</tr>
<tr>
<td>Vitamin B3</td>
<td>0.330***</td>
<td>0.378***</td>
<td>0.349***</td>
</tr>
<tr>
<td></td>
<td>(0.0614)</td>
<td>(0.0625)</td>
<td>(0.0609)</td>
</tr>
<tr>
<td>Vitamin B6</td>
<td>0.177***</td>
<td>0.289***</td>
<td>0.261***</td>
</tr>
<tr>
<td></td>
<td>(0.0592)</td>
<td>(0.0659)</td>
<td>(0.0617)</td>
</tr>
<tr>
<td>Vitamin B9</td>
<td>0.750***</td>
<td>0.806***</td>
<td>0.777***</td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td>(0.114)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>Vitamin B12</td>
<td>1.005***</td>
<td>1.061***</td>
<td>1.021***</td>
</tr>
<tr>
<td></td>
<td>(0.110)</td>
<td>(0.114)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>Calcium</td>
<td>0.811***</td>
<td>0.850***</td>
<td>0.821***</td>
</tr>
<tr>
<td></td>
<td>(0.0999)</td>
<td>(0.105)</td>
<td>(0.0993)</td>
</tr>
<tr>
<td>Iron</td>
<td>0.512***</td>
<td>0.503***</td>
<td>0.474***</td>
</tr>
<tr>
<td></td>
<td>(0.0759)</td>
<td>(0.0767)</td>
<td>(0.0755)</td>
</tr>
<tr>
<td>Zinc</td>
<td>0.366***</td>
<td>0.405***</td>
<td>0.376***</td>
</tr>
<tr>
<td></td>
<td>(0.0687)</td>
<td>(0.0699)</td>
<td>(0.0665)</td>
</tr>
<tr>
<td>Observations</td>
<td>4,425</td>
<td>4,425</td>
<td>4,425</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
CHAPTER 5
Conclusion

My dissertation examines the process of cognitive production at later stages of childhood and adolescence. It also looks at the relationship between health and cognitive production which works through the indirect channel of time allocation with early childhood health outcomes already realized. The relationship between investments in health and cognition has been well established in the existing literature, but most of this literature looks at this relationship during the early stages of childhood (Cunha & Heckman, 2008; Cunha, Heckman, & Schennach, 2010; Almond & Currie, 2011; Lynch & Gibbs, 2017). Although there is some literature which points to the relationship between health and cognition existing after early childhood (Case & Paxson, 2008; Aguero & Deolalikar, 2012), the exact mechanisms and channels through which this relationship might work are not completely understood. Thus, my dissertation adds to the current literature on “sensitive periods” during early stages of childhood.

There are several contributions to this strand of existing literature emanating from my dissertation. First, as much as early childhood is important in determining the short- and long-run trajectories of cognitive production, the significance of later childhood and adolescence to cognitive production should not be understated. This is because during these stages of cognitive development, factors such as parental decision-making become more important than the biological determinants, which have mostly been the focus of previous research.
Second, a clear distinction needs to be made between the stock and the flow of health and how each of these affect cognitive production. While the stock of health might be a good measure for all the previous investments in a child’s health, parental decisions in the current time period are mostly based on the flow of health i.e. the current health status of the child. Whereas, the existing literature mostly employs just the stock of health as a determinant of cognition, my dissertation takes into account the difference between current health and all previous investments in health by utilizing both measures as inputs into the cognitive production function.

Third, the second chapter of my dissertation reveals that indirect channels such as time allocation channel which relies on parental decision-making become more important for cognitive production during later stages of childhood and adolescence. Most of the current literature studies cognitive production during early childhood where biological and genetic factors are the main contributors towards cognitive production. These factors such as the maternal health during pregnancy and the child’s health right after birth are more dependent on the direct household-level inputs into the cognitive production, for example, the availability of the appropriate quality and quantity of food, socioeconomic status, environmental quality, parental education, social connections, and the quality of early childhood education available etc. But my dissertation points to the existence of indirect channels through which cognitive production can be affected during the later stages of childhood when the biological channels do not remain salient.

Fourth, I employ a novel approach to mediation model, highlighted by Dippel et al. (2017), in the second chapter of my dissertation to explore whether the relationship between current health and cognitive outcomes works through the study time allocation channel during the
later stages of childhood. Dippel et al. (2017) propose a mediation model which allows the use of the same set of instruments for all three equations of the mediation model if one of the variables lies on the path between the treatment and outcome variable. In the second chapter of my dissertation, that variable is the mediator variable proxied by the number of hours allocated for studying. This makes the use of mediation model a lot easier for researchers as it is always difficult to find appropriate instruments when working with observational data. By employing this innovative and useful, yet not widely used, approach to mediation model in my dissertation, I am attempting to explore an empirical methodology which has the potential to simplify modeling in future researches based on household-level observational data.

Fifth, the third chapter of my dissertation examines the patterns of persistence and catch-up in cognition scores during later stages of childhood and adolescence, providing a rare glimpse into the process of cognitive production throughout its lifecycle. This is important as policymakers get a better understanding of the different stages of childhood where catch-up or faltering can occur. I also examine how self-productivity and complementarity combine to affect cognitive production after early childhood and find evidence for the case of perfect complementarity where later investments in cognition are not enough to overcome the lack of early investments. Thus, I add to the existing literature which highlights the importance of investments during the early stages of childhood (Case & Paxson, 2008; Cunha & Heckman, 2008; Doyle et al., 2009; Smith, 2009; Cunha, Heckman, & Schennach, 2010; Victoria et al., 2010; Almond & Currie, 2011; Currie, 2011; Lynch & Gibbs, 2017).

Finally, the fourth chapter of my dissertation alludes to how we measure an important measure of health, individual-level food availability, which then influences cognitive

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production. I find significant differences between individual-level nutrient availability estimates when they are calculated through the nutrient-specific adult-equivalent scale, calculated in my dissertation, and other commonly used scales in the previous literature. Thus, my dissertation provides a much more accurate benchmark to calculate individual-level nutrient availability estimates.

The second chapter of my dissertation explores the effect of current health (denoted by BMI for age scores) on cognitive test scores directly and indirectly, through time allocated to studying, for a sample of Ethiopian children during childhood (5-8 years) and mid-childhood (8-12 years). I employ a novel method, highlighted by Dippel et al. (2017), for using instrumental variables to conduct causal mediation analysis. I find that not only does current health improve cognitive test scores, but that this effect operates almost entirely through an indirect time allocation channel. Furthermore, I also find that as the child enters adolescence where the opportunity costs to study time increase, improved current health can lead to reduced study time and higher work time. Thus, I make a case that interventions aimed at improving health status complemented with those that consider unintended time allocation effects, can still improve child human capital outcomes even during the later stages of childhood. Therefore, policies that both improve returns to education while simultaneously reducing returns to child labor are likely to improve cognitive outcomes.

The third chapter of my dissertation explores the patterns of persistence and catch-up growth in cognition during childhood (5-8 years), middle childhood (8-12 years), early adolescence (12-15 years), and middle adolescence (15-19 years). I employ non-parametric analysis as well as a parametric dynamic model to conduct this analysis and use mathematics test scores, as a proxy for cognition, for a sample of Ethiopian children where the coefficient of lagged
cognition scores determines the scope for catch-up growth. The results indicate that the persistence in cognition scores increases as children move from childhood to adolescence. But, as established in the previous literature (Almond & Currie, 2010), we also identify early childhood (before age 5) as a “sensitive period” where the chances of catch-up growth in cognition are the highest. The results also provide evidence for the case of perfect complementarity as children with no early investments in cognition never recover completely even with the existence of investments during later stages of childhood and adolescence. Thus, policies for increasing cognition may be targeted during early childhood while efforts should also be directed towards ensuring that children do not suffer shocks during this period, as the chances of faltering are also the highest at this stage of cognitive production.

The fourth chapter of my dissertation proposes a new set of adult-equivalent scale based on the specific daily intake requirement for macro- and micronutrients. I also examine whether this nutrient-specific adult-equivalent scale compared to other (calorie-based, per capita, or OECD) adult-equivalence scales on average leads to differences in the individual-level nutrient availability estimates. I find that there are significant differences between the individual-level nutrient availability estimates depending on which adult-equivalent scale is used. Thus, this chapter provides a much more accurate benchmark for future studies using household survey data to calculate nutrient availability estimates.

My future research direction is guided by the conclusions drawn from my dissertation where I would like to keep working to better understand the cognitive production process during the different stages of childhood and adolescence. Moreover, my future research will try to discover the different indirect channels, such as nutritional supplementation, and how these can affect cognitive production after early childhood. Therefore, the first research
question that I will explore is the relationship between specific nutrient intake and/or nutrient availability with health and human capital outcomes (cognitive and non-cognitive) during childhood and adolescence in developing countries and how these outcomes are interconnected with future productivity. In this regard, the fourth chapter of my dissertation can contribute by providing a much more accurate benchmark to calculate individual-level nutrient availability estimates. Another related question that I will study is the role which dietary diversity plays in improving the cognitive and non-cognitive status of children.

The second research question that I will explore is how idiosyncratic shocks, including monetary and household composition shocks, and covariate shocks, including natural disasters and economic shocks, affect the nutritional, cognitive and non-cognitive status of children in the short and long run. This strand of research can further elucidate the different indirect channels which can impact human capital outcomes beyond the early stages of childhood. Idiosyncratic and covariate shocks can reduce the income of the households, directly impacting the human capital outcomes for children. Moreover, households may also resort to sub-optimal coping mechanisms such as reduced expenditure on health, and schooling leading to long-term implications for human capital outcomes. Currently, there is some research on the impacts of exogenous shocks on children’s health and cognitive outcomes, but I plan to add to this strand of literature by making use of the Young Lives dataset to explore the impact of such shocks on non-cognitive and psychosocial outcomes.

Finally, I will conduct research to understand the different economic incentives at play in a developing country setting wherein parents make decisions, with long-term consequences, for their children during their childhood. Specifically, the incentives which make parents engage in reinforcing or compensating decision-making for their children, and its
consequences on the children’s cognitive and non-cognitive outcomes can be examined in
greater detail. I would like to contribute to this strand of literature by examining culturally
dictated norms regarding the relative importance of children within the household, based on
characteristics such as gender, birth order, genetic ability etc., and how these impact parental
resource allocation among siblings.

I specifically want to continue using the Young Lives dataset to explore these issues by
delving into the data from other countries (Vietnam, India and Peru) that I have not used until
now. I also want to employ the Indonesian Family Life Survey (IFLS) dataset as it comprises
of multiple rounds of panel data with interesting questions related to different dimensions of
human capital, especially the ones measuring psychosocial metrics.
Appendix

A.1: Effect of BMI for Age on Study and Work Times with BMI for Age Instrumented for Children who Remained in School during Mid-Childhood

A.2: Effect of BMI for Age on PPVT and Math Scores during Mid-Childhood with BMI for Age Instrumented for Studying and Non-Studying Children at Age 5 Separately

A.3: Effect of BMI for Age on Study and Work Times during Mid-Childhood with BMI for Age Instrumented for Studying and Non-Studying Children at Age 5 Separately

A.4: Estimated Direct and Indirect Effects of BMI on Cognitive Test Scores for Boys

A.5: Estimated Direct and Indirect Effects of BMI on Cognitive Test Scores for Girls
<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Study Time</th>
<th>(2) Work Time</th>
<th>(3) Study Time</th>
<th>(4) Work Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMI for Age</td>
<td>-1.385 (1.655)</td>
<td>5.754*** (1.811)</td>
<td>-1.082 (1.595)</td>
<td>5.940*** (2.007)</td>
</tr>
<tr>
<td>Lagged Cognition Scores</td>
<td>PPVT Yes</td>
<td>PPVT Yes</td>
<td>Math Yes</td>
<td>Math Yes</td>
</tr>
<tr>
<td>Individual and Household Level Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Community Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Table A.2: Effect of BMI for Age on PPVT and Math Scores during Mid-Childhood with BMI for Age Instrumented for Studying and Non-Studying Children at Age 5 Separately

<table>
<thead>
<tr>
<th>Variables</th>
<th>Non-Studying</th>
<th>Studying</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>PPVT Age 12</td>
<td>-7.353</td>
<td>0.880</td>
</tr>
<tr>
<td>Math Age 12</td>
<td>(14.86)</td>
<td>(1.250)</td>
</tr>
<tr>
<td>BMI for Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>709</td>
<td>598</td>
</tr>
<tr>
<td>Individual and Household</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Level Controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Community Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Table A.3: Effect of BMI for Age on Study and Work Times during Mid-Childhood with BMI for Age Instrumented for Studying and Non-Studying Children at Age 5 Separately

<table>
<thead>
<tr>
<th>Variables</th>
<th>Non-Studying</th>
<th>Studying</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Work Time</td>
<td>(25.82)</td>
<td>(11.15)</td>
</tr>
<tr>
<td>BMI for Age</td>
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<td></td>
</tr>
<tr>
<td>Lagged Cognition Scores</td>
<td>PPVT</td>
<td>PPVT</td>
</tr>
<tr>
<td>Individual and Household Level</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Community Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Observations: 709 709 598 598 758 758 688 688

Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Table A.4: Estimated Direct and Indirect Effects of BMI on Cognitive Test Scores for Boys

<table>
<thead>
<tr>
<th></th>
<th>Age 8</th>
<th>Age 12</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PPVT (1)</td>
<td>Math (2)</td>
</tr>
<tr>
<td><strong>Panel A: Total Effect of Instrumented BMI on Cognition</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BMI for Age ($\alpha_{BMI}^C$)</td>
<td>0.465***</td>
<td>0.838***</td>
</tr>
<tr>
<td></td>
<td>(0.0968)</td>
<td>(0.0981)</td>
</tr>
<tr>
<td><strong>Panel B: Effect of Instrumented BMI on Study Time</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BMI for Age ($\alpha_{BMI}^T$)</td>
<td>2.142***</td>
<td>2.302***</td>
</tr>
<tr>
<td></td>
<td>(0.208)</td>
<td>(0.217)</td>
</tr>
<tr>
<td>Included Lagged Cognition Scores</td>
<td>PPVT</td>
<td>Math</td>
</tr>
<tr>
<td>IV F-Stat (Panel A and B)</td>
<td>139.56***</td>
<td>135.52***</td>
</tr>
<tr>
<td><strong>Panel C: Effects of BMI and Instrumented Study Time on Cognition</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Study Time ($\alpha_{T</td>
<td>BMI}^C$)</td>
<td>0.229***</td>
</tr>
<tr>
<td></td>
<td>(0.0436)</td>
<td>(0.0366)</td>
</tr>
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<td>BMI for Age ($\alpha_{BMI}^C$</td>
<td>-0.0245</td>
<td>0.0135</td>
</tr>
<tr>
<td></td>
<td>(0.0326)</td>
<td>(0.0327)</td>
</tr>
<tr>
<td>IV F-Stat</td>
<td>123.45***</td>
<td>169.56***</td>
</tr>
<tr>
<td><strong>Panel D: Direct and Indirect Effects of BMI on Cognition</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Effect</td>
<td>0.465</td>
<td>0.838</td>
</tr>
<tr>
<td>Direct Effect</td>
<td>-0.0245</td>
<td>0.0135</td>
</tr>
<tr>
<td>Indirect Effect</td>
<td>0.491</td>
<td>0.824</td>
</tr>
<tr>
<td>Direct + Indirect Effect</td>
<td>0.466</td>
<td>0.838</td>
</tr>
<tr>
<td>Observations</td>
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<td>837</td>
</tr>
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<td>Individual and Household Controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Community Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Table A.5: Estimated Direct and Indirect Effects of BMI on Cognitive Test Scores for Girls

<table>
<thead>
<tr>
<th>Panel A: Total Effect of Instrumented BMI on Cognition</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMI for Age ($\alpha_{BMI}^C$)</td>
<td>0.328</td>
<td>-0.167</td>
<td>-0.597*</td>
<td>-0.0472</td>
</tr>
<tr>
<td></td>
<td>(0.292)</td>
<td>(0.232)</td>
<td>(0.363)</td>
<td>(0.603)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Effect of Instrumented BMI on Study Time</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMI for Age ($\alpha_{BMI}^T$)</td>
<td>-0.132</td>
<td>-0.537</td>
<td>-2.422*</td>
<td>-2.355</td>
</tr>
<tr>
<td></td>
<td>(1.307)</td>
<td>(1.194)</td>
<td>(1.273)</td>
<td>(1.903)</td>
</tr>
<tr>
<td>Included Lagged Cognition Scores</td>
<td>PPVT</td>
<td>Math</td>
<td>PPVT</td>
<td>Math</td>
</tr>
<tr>
<td>IV F-Stat (Panel A and B)</td>
<td>4.47**</td>
<td>5.0**</td>
<td>2.83</td>
<td>1.85</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Effects of BMI and Instrumented Study Time on Cognition</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study Time ($\alpha_{T</td>
<td>BMI}^C$)</td>
<td>-4.134</td>
<td>0.345</td>
<td>0.255</td>
</tr>
<tr>
<td></td>
<td>(72.21)</td>
<td>(0.838)</td>
<td>(0.157)</td>
<td>(0.259)</td>
</tr>
<tr>
<td>BMI for Age ($\alpha_{BMI}^{C</td>
<td>BMI}$)</td>
<td>-0.218</td>
<td>0.0209</td>
<td>0.0214</td>
</tr>
<tr>
<td></td>
<td>(4.184)</td>
<td>(0.0421)</td>
<td>(0.0277)</td>
<td>(0.0318)</td>
</tr>
<tr>
<td>IV F-Stat</td>
<td>0.003</td>
<td>0.218</td>
<td>3.10*</td>
<td>2.11</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel D: Direct and Indirect Effects of BMI on Cognition</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Effect</td>
<td>0.328</td>
<td>-0.167</td>
<td>-0.597</td>
<td>-0.047</td>
</tr>
<tr>
<td>Direct Effect</td>
<td>-0.218</td>
<td>0.0209</td>
<td>0.0214</td>
<td>-0.0323</td>
</tr>
<tr>
<td>Indirect Effect</td>
<td>0.546</td>
<td>-0.185</td>
<td>-0.618</td>
<td>-0.015</td>
</tr>
<tr>
<td>Direct + Indirect Effect</td>
<td>0.328</td>
<td>-0.164</td>
<td>-0.596</td>
<td>-0.047</td>
</tr>
<tr>
<td>Observations</td>
<td>784</td>
<td>757</td>
<td>691</td>
<td>607</td>
</tr>
</tbody>
</table>

| Individual and Household Controls | Yes | Yes | Yes | Yes |
| Community Fixed Effects | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
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[Chapter 5]


