Urban-rural health and achievement gaps across childhood: development and mediating mechanisms in Peru and India

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In recent decades, poverty has become more urbanized in low- and middle-income countries (LMIC). Yet, the majority of poor families continue to live in rural settings. Evidence suggests that children growing up in rural areas fare worse than their urban counterparts in education and health. Previous evidence suggests that these differences could be due to lower economic and infrastructural resources in rural areas. However, these studies have limited their attention to singular elements of families or infrastructure while also examining outcomes at adolescence or adulthood. Thus, there is little knowledge of how health and achievement gaps develop from early childhood to adolescence and there is limited empirical assessment of the multiple infrastructural and behavioral mechanisms underlying urbanicity-related differences. Furthermore, researchers have not considered whether urban children are also at a disadvantage due to higher pollution and violence in cities. Drawing data from the Young Lives Study, a longitudinal investigation following economically disadvantaged children in India and Peru, this project addressed these limitations. First, we described the development of urban-rural health and achievement gaps from age five to age fifteen. Second, we examined whether age-specific community characteristics and child time-use explained the urban advantage at ages 5, 8, 12, and 15. Third, we explored whether cumulative experiences of community factors and child time-use explained differences in children's trajectories of development. Results showed that while in Peru the urban advantage was large at early childhood and remained stable over time, the urban advantage in India was small at early childhood and modestly closed over development. When considering cumulative experiences, urban children's advantage was partially due to more time studying and less time working. At early childhood, higher access to educational and utility services showed to be central in explaining the early urban advantage. Some findings differed by country. In India, urban children were more exposed to the detrimental effects of violent crime on achievement at adolescence. In Peru, across all ages, the urban advantage was partially due to increased access to utility services. These identified processes have important implications for improving contextual supports for disadvantaged children and target scarce public resources.

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Preface

I want to express my sincere gratitude to my family, friends, and partner for their intellectual and unfailing emotional support. Their presence in my life has been fundamental to the completion of my doctorate degree. I am also grateful to Elizabeth Votruba-Drzal for her mentoring and vital contributions towards development and completion of this dissertation. I am especially thankful for her constant and invaluable support over the years.

I also would like to acknowledge the involvement of Young Lives participants on whose experience this analysis is based. I also want to indicate that the views expressed in this dissertation are not necessarily those of, or endorsed by Young Lives, the University of Oxford, DFID or other funders of the study. Young Lives is an international study of childhood poverty, following the lives of 12,000 children in 4 countries over 15 years (www.younglives.org.uk). Young Lives is funded by UK aid from the UK Department for International Development (DFID) and co-funded by the Netherland Ministry of Foreign Affairs from 2012 to 2014 and by Irish Aid from 2014 to 2015.

1.0 Introduction

Over 560 million children under age five reside in low and middle-income countries (LMIC), and 219 million (39%) children younger than 5 years are at risk of not reaching their developmental potential because they face environmental conditions that threaten their health and cognitive development (Black et al., 2017; McCoy et al., 2016; Britto et al., 2017). Although ample evidence indicates that poverty is associated with children's academic achievement and health (Aber et al, 1997; Duncan & Magnuson, 2012), the processes that underlie such links in LMIC's are still unclear. In recent decades, poverty has become more urbanized in LMIC, due to the natural growth of cities and the increase of families migrating from rural areas (Sekkat, 2017). In turn, the share of the world's population living in urban areas increased from 30% in 1950 to 55% in 2018, and is expected to increase to 60% in 2030 (UN, 2018). Still, in many LMIC, the majority of children live in rural areas (61.1%), where poverty is over represented. Seventy six percent of poor people reside in rural areas (UNICEF & World Bank Group, 2016). Given the geographical distribution of poor children in both urban and rural areas, it is increasingly important to consider how poor children's community of residence relates to their development.

Evidence suggests that the relation between poverty and child functioning differs by urbanicity –whether an individual resides in an urban or rural environment. Evidence from LMIC suggests that children growing up in rural areas perform worse than their urban counterparts on academic achievement and health (Othman & Mujis, 2012; Smith et al, 2005; Tayyaba, 2012). Demographers have suggested that the urban advantage is driven by the greater economic growth of cities, which is related to more employment opportunities, higher wages, better living standards, and larger governmental and private investments in infrastructure

(Khan, 2001). However, these studies have limited their attention to singular elements of families and infrastructure while also examining urban-rural differences on labor market outcomes at late adolescence or adulthood. Thus, there is little knowledge of how health and achievement gaps develop from early childhood to adolescence and there is limited empirical assessment of the multiple mechanisms underlying urbanicity-related differences across development.

This study explored the development of the achievement and health urban-rural gaps by considering proximal environments that shape child development and that underlie the urbanicity-related differences: time use and community stressors and resources. We drew data from the Young Lives Study –a multi-method and longitudinal investigation following children from economically disadvantaged communities from age 1 to age 15 in two different countries: India (N=2,011) and Peru (N=2,052). We pursued three aims. First, we described the development of urban-rural gaps across time and estimated the extent to which these gaps were explained by child and family's demographic characteristics. Second, we examined whether age-specific experiences of community characteristics and of time-use explained the urban advantage on health and achievement at ages five, eight, twelve, and fifteen. Third, we explored whether the cumulative experiences of community factors and child time-use mediated the associations between urbanicity and trajectories of development.

1.1 Conceptual model of child development

This study is grounded in bioecological theory of child development, which describes child development as driven by proximal processes or reciprocal interactions between children and the people and materials in the multiple environments in which children are embedded (Bronfenbrenner & Morris, 1998). The most influential proximal processes transpire within the microsystems, which are the most proximal settings that children inhabit and include homes, schools, and communities. Microsystems are embedded in the macrosystem –the largest and most distant system to the children. The macrosystem includes cultural patterns, dominant beliefs as well as political and economic systems. For the purposes of the current study, we argue that urbanicity is a feature of the child's macro-system and interacts with the family's poverty to shape characteristics of the communities in which children and families are embedded. The micro- and macrosystems, in turn, affect the children's experiences that shape development. Figure 1 presents a graphical representation of the conceptual model that guides this research.

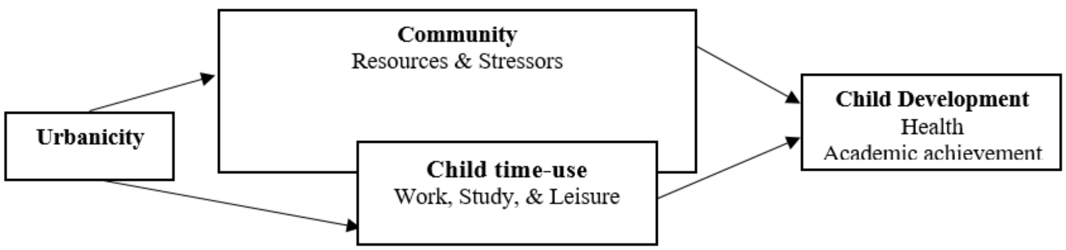

Figure 1. Conceptual model

Another factor of our conceptual model is time-use. Time-use reflects the activities that children do, which can be considered microsystems for child development. Time allocation is important in shaping children's development because the more time children are exposed to specific proximal processes, the stronger links tend to be with children's development. Interactions and contexts that children experience consistently for extended time tend to be more influential in shaping development than are those contexts that are more fleeting or episodic. Urbanicity could shape the microsystems in which children develop by influencing the activities made available by families, schools, and social circles to children and adolescents (Barnes et al. 2007; Wolf, Aber, & Morris, 2015). Thus, differences in how children spend their time may differ across urbanicity, which could have implications for children's development.

Children in low-income communities in more urbanized contexts may spend more time learning in school and outside of school, because they have greater access to schools and fewer demands to engage in work to support their family (Kurosaki, Ito, Fuwa, Kubo & Sawada, 2006). This may give rise to differences in academic achievement. Research on time use in LMIC shows that time spent at school and studying outside school is associated with higher cognitive and non-cognitive abilities, but it also indicates that child involvement in work activities leads to a reduction in academic skills (Borga, 2019). Previous research suggest that low-income children in rural contexts will are more likely to spend extended time engaged in labor (either paid or unpaid), to contribute to the provision of basic family needs and financial resources, and less time in school or studying (Ersado, 2005; Huisman & Smits, 2009; Khan, Khan & Rashid, 2010). Child labor can be directly harmful to child development because children's work often takes place outside the formal employment sector and under hazardous conditions. In addition, child labor can hinder child development indirectly through the reduction of time they invest in education (Akabayashi & Psacharopoulos, 1999; Borga, 2015) and in leisure activities, both important activities for child development (Rojas & Cussianovich, 2014).

Finally, another important feature in the bioecological model is the chronosystem (systems of time), which can be represented as the moment of life or developmental stage in which children experience their contexts. While urbanicity may shape the characteristics of the communities and patters of time use that children experience, the influence of those on child development may depend of the individual's biological and psychological capabilities to interpret those environmental contexts, which change with age (Bronfenbrenner & Morris, 1998). Associations between urbanicity and child development may be different at different ages, as prior research has suggested that children are differentially susceptible to environmental influences as a function of child age. For example, extant research has suggested that brain development is particularly sensitive to environmental inputs during the first years of life, which are considered a sensitive period of development (Fox, Levitt & Nelson, 2010). Similarly, evidence suggests that the prevalence of gangs and violence within communities may be particularly harmful during adolescence when youth have more direct access to the neighborhood social environment than younger children (Steinberg & Morris, 2001). However, we also recognize that cumulative characteristics of environments may be more robust predictors of developmental trajectories than characteristics at any one point in time. Studies have found that cumulative measures of neighborhood have larger associations with adolescents' educational attainment than neighborhood characteristics any single point (Crowder & South, 2011; South & Crowder, 2010; Wodtke, Harding, & Elwert, 2011). Thus, we also examined whether cumulative exposure to different urbanicity contexts is associated with trajectories of children's development. Importantly, neither the age-specific nor the cumulative associations of urbanicity contexts and child development have been examined in LMIC.

1.2 Urbanicity and child development: the elements of the conceptual model

1.2.1 Communities: microsystem of child poverty

To understand how urbanicity and communities shape the development of poor children, we rely two theoretical frameworks that explain how poverty influences child development — environmental stress theories and resource/investment theories.

Environmental stress theories argue that poverty increases stressors and elevates child and parent psychological distress, which compromise child development. Stress stemming from economic pressure, negative life events, and the environmental stress caused by chaos and overcrowding in the household, can affect both the family dynamics and children's development (Conger et al., 1994, 2002; Evans & Kim, 2013). Stress undermines children's cognitive, emotional, and behavioral development directly through heightened and prolonged activation of the stress response system, and indirectly through increased parental psychological distress and harsh parenting (Vernon-Feagans et al., 2012). The stressful environments that low-income families face extend beyond the family contexts into the communities in which economically disadvantaged families reside (Brooks-Gunn et al., 1997; Chetty, Hendren, & Katz, 2016). At the community level, stress processes play out in the forms of crime, violence, and pollution all of which threaten children's health and cognitive development (Coley et al., 2015; Conger et al., 2002; Evans & Kim, 2012; Vernon-Feagans et al., 2012). Living in disadvantaged neighborhoods can affect children directly because there may be damaging developmental consequences as a result of exposure to environmental hazards, such as lead in soil and paint or asthma-inducing air pollutants that are more prevalent among disadvantaged areas (Litt et al., 2002; Ash & Fetter, 2004). Greater levels of community stress can also indirectly affect child development by compromising parenting quality. When parents are exposed to greater community stress in the form of noise, pollution, crime, and disorder, it diminishes their mental and physical health (Hill, Ross, & Angel, 2005), which can result in neglective or harsher parenting practices as a response to perceived threats (Furstenberg et al., 1999). Here we hypothesize that urbanicity may give rise to differences in disadvantaged children's development because children and families in urban and rural setting may experience differential exposure to community stress.

The *resource/investment theory* indicates that income relates to the time and money invested in children, with poor children receiving fewer family, school, and community investments which give rise to less advanced skills development (Duncan & Brooks-Gunn, 2000; Foster, 2002; Guo & Harris, 2000; Leventhal & Brooks-Gunn, 2000). Poverty limits families' investments in materials and experiences that enhance children's development, such as stimulating materials, educational activities, adequate health services, and high-quality education (Becker, 1991). Children from economically disadvantaged families tend to have less access to resources at the community level as well, such as health facilities, educational services, and infrastructure (Dupere, Leventhal, Crosnoe, & Dion, 2010; Leventhal et al., 2015; Reardon & Bischoff, 2011), all of which are beneficial to children (Leventhal, Dupéré, & BrooksGunn, 2009). Additionally, research focused on neighborhood resources indicates that living in a resource-rich, organized, and stable neighborhood may enhance parental well-being and, in turn, parents' ability to provide learning activities in the home (Kohen, Leventhal, Dahinten, & McIntosh, 2008; Orr, Feins, Jacob et al., 2003). In the current investigation, we propose that urbanicity is associated with differences in low-income children's development because of differential access to community resources in urban and rural contexts.

Much of the evidence linking community stressors and resources to child development comes from the U.S. Unfortunately, very few studies have considered how community stressors and resources related to child development and more empirical evidence is needed. In LMIC, many public services are funded by the national or local government, which may make the distribution of resources more equitable across communities in comparison to the US.

1.2.2 Urbanicity as a macro-system of child development

The current study considers urbanicity as a macro-system that structures community characteristics, which, in turn, shape proximal experiences that drive child development. Specifically, urban and rural communities differ in the levels of resources and stressors and those are mechanisms that drive disparities in poor children's development as a function of urbanicity. For example, evidence from the U.S. suggests that while achievement of poor urban children related to higher access to cultural and recreational resources, it was also associated to higher levels of crime. Conversely, the lower levels of crime and disadvantage of rural poor children were positively associated with child development (Miller, Votruba-Drzal & Coley 2019). These results suggest that both community resource and stress processes are mechanisms linking urbanicity and child development, and that living in urban settings may confer advantages when considering when it comes to resource access while at the same time posing a risk for children's development.

In general, evidence from the U.S. has suggested that while cities are characterized by heightened levels of resources and stressors, rural areas show lower levels of both. In particular, poor families living in rural areas have less access to resources, such as center-based childcare, opportunities for educational activities (e.g. libraries, museums), health care, and community centers (Gordon & Chase-Lansdale, 2001). Furthermore, even if services are available, low-income families' in rural areas may have less access because of limited public transportation. Yet, rural families experience stronger social support networks and kinship ties than families in cities (Beggs, Haines, & Hurlbert, 1996; Duncan, Whitener, & Weber, 2002; Lee, Netzer, & Coward, 1994). Conversely, compared to rural areas, low-income families in urbanized communities face heighted stress from violent crime, pollution, and crowding. The multiple environmental stressors experienced in poor urban neighborhoods in the U.S. are negatively associated to the academic and behavioral development of low-income urban children in comparison rural children (Evans & Wachs, 2010; Shonkoff & Phillips, 2000; Supplee et al., 2007). They may also inhibit poor urban children's academic and behavioral functioning by increasing parental distress and, in turn, decreasing parenting quality (Evans & Saegert, 2000; Linares et al., 2001; Wachs & Camli, 1991).

When it comes to research from LMIC, several studies have identified an urban advantage in terms of health outcomes such as height-for-age (Smith, Ruel & Ndiaye, 2004), educational attainment (Lakin & Gasperini, 2003), and academic achievement (Tayyaba, 2012; Young, 1998). Nevertheless, the processes that give rise to these differences are not well understood.

When focusing on resources, many studies suggest that the urban advantage across all outcomes is driven by the larger economic growth of cities in comparison to rural areas, which is associated to factors such as more employment opportunities, higher wages, better living standards, and more governmental and private investments in infrastructure (Thu Le & Booth, 2014; World Bank, 2004; Young, 2013). Differences in expenditures have been associated to better cognitive skills (Thu Le & Boot, 2010) and better health outcomes (Smith, Ruel & Ndiaye, 2004) among children. Health researchers have pointed out that urban dwellers have access to more health facilities (Doctor, Nkhana-Salimu & Abdulsalam-Anibilowo, 2018) and better water and sanitation services (Cronk & Bartram, 2018). However, researchers reporting low resources in rural areas have not explicitly linked those to child health outcomes (for an exception see Nolan, 2018). When studying educational attainment, researchers have found that parents indicate that rural children often do not attend school because of low school availability, lack of grade-level availability, long travel time to school, and few transportation options (Lakin & Gasperini, 2003; Lewis & Lockheed, 2006; Lloyd, 2005). Regarding the educational performance gap, researchers have pointed out to lower teacher quality, lower teacher supply, and teacher absenteeism are common complaints among rural parents and teachers (Hanushek, 1997; Levira, 2000; Othman & Muijs, 2013; Vegas, 2007; Wodon, 2014). Researchers have found that school characteristics can explain up to 40% of the urban-rural differences in achievement (Castro & Rolleston, 2015). However, to our knowledge no research has considered whether multiple health and educational factors could simultaneously shape child development.

Furthermore, the mechanisms that drive the urban-rural gap are likely more complex because another literature suggests that environmental stressors are also more abundant in urban settings, which may threaten healthy child development (Gunther & Harttgen, 2012; UNICEF, 2012). In particular, rapid urbanization in LMIC has led to higher cost of living in cities and to the emergence of informal settlements (slums), with high levels of overcrowding, poverty concentration, crime, and pollution (Lall, Selod & Shalizi, 2006; Liu, 2013; Ooi & Phua, 2007; Zhang, 2016; Tacoli, 2012; World Bank, 2017). The rapid urbanization and industrialization have been linked to degradation of environmental quality especially the quality of water, air, and noise (McMichael, 2000; Uttara, Bhuvandas & Aggarwal, 2012). Additionally, air pollution in cities has increased with emissions from motor vehicles, industrial development and use of fuel sources that are harmful for the environment (Peña & Rollins, 2017). Research has shown that urban settings can be detrimental to health because of exposure to pollution and to overcrowded living arrangements, which increases disease transmission (Fink et al. 2014). Furthermore, urban dwellers are exposed to other urban stressors such as violence, crime, and noise pollution generated from the various human activities (Zhang, 2016). Heightened violence in urban settings in large cities in Latin America and Africa poses a threat to the well-being of children and families (Word Bank, 2010). For example, Cities such as Rio de Janeiro, São Paulo, Mexico City, Lima, and Caracas account for more than half the total of their national homicides (Briceño-León, 2002). Remarkably, differences in rural–urban violence levels are less salient in conflict or post-conflict countries, where rural violence could be higher than urban one (Imbusch, Misse & Carrión, 2011).

Differences in the resources and stressors related to urban and rural poverty in LMIC are well-documented, however, few studies consider whether these are mechanisms driving associations between urbanicity and low-income children's development. Among studies that have considered potential mechanisms (Doctor, Nkhana-Salimu & Abdulsalam-Anibilowo, 2018; Hirvonen, 2016; McEwan, 1999; Tayyaba, 2012), the tendency has been to focus on a single community characteristic, thereby disregarding a range of other possible mechanisms that may explain the urban advantage in children's development. This study intends to help fill this gap by exploring whether the characteristics of the communities in which children live and child time-use underlie disparities in children's development across urban and rural communities. A comprehensive characterization of the mechanisms that give rise to the rural–urban disparities in poor children's development in LMIC countries is crucial for informing efforts to support disadvantaged children.

1.3 Contexts of the countries of this study

1.3.1 Peru

Peru went through rapid urbanization during the second half of the 20th century, changing from a 46% of population living in cities in 1960 to 71% in 1995 and to 78% in 2019 (World Bank Data Bank, 2020a). Along with other Latin American countries, Peru has experienced an important economic improvement in the previous two decades (World Bank, 2017), but inequality remains high across urban and rural sectors. Although the rural poverty rates declined nearly 30% from 2000 to 2011 (83.4% to 56.5%), a rural disadvantage persists. According to 2016 data, the percentage of people living in extreme poverty in rural areas (37.1%) is more than seven times that of the population residing in urban areas (4.9%; World Bank, 2017). Poverty incidence is also appreciably higher in rural areas, where 56% of the population lives below the national poverty line, versus only 18% in urban areas (INEI, 2012).

There is a high contrast between health outcomes of urban and rural in Peru and this gap has been found to be the largest among Latin American Countries (Paciorek et al. 2013). Estimates indicate that between urban and rural children, there are differences between 0.6 and 1.0 standard deviation in height and weight (Paciorek et al. 2013). The rural-urban gap is also evidenced in the educational outcomes area despite near-universal access to primary schooling and a significant increase in secondary enrollments rates (from 68.8% in 2000 to 77.6% in 2011). While gross enrollment rates for both rural and urban regions are reasonably high, there is a noticeable rural-urban gap in the on-time school completion rate. In Peru, students attending rural schools demonstrate extremely poor learning outcomes and obtain results significantly below those of students in urban schools. Among rural second grade students, only 7% and 4% demonstrate ‘adequate’ reading and mathematical skills, respectively, as compared to 38% and 15% in urban areas (Guadalupe, León & Cueto, 2013).

There are important differences in the contexts that urban and rural children experience in Peru. Studies have shown that rural areas have fewer school hours, inadequate learning materials, and low teacher quality (Benavides, Carnoy, Cueto & Gove, 2007). Additionally, reports indicate that rural areas also suffer from lower access to utility services such as electricity. The rural electrification rate is 30% (vs. 91% for urban regions), one of the lowest in Latin America and among middle-income countries globally (World Bank, 2011a). In addition, studies have found lower access to health personnel. For example, less than half of rural women have reported having skilled attendants with them during a birth delivery, compared to nearly 90% of urban women (Borja, 2010).

1.3.2 India

While the economic growth of India during the 21st century has been well documented (Ahluwalia, 2019; Patnaik, 2016), the country also continues to suffer from widening economic and social disparities in educational attainment and health between the rural and urban population, between males and females, and among social groups and religions.

India has reached high levels of pre-primary school participation and nearly universal primary enrollment. However, around 29% of children drop out of school before completing the full cycle of elementary education (Unicef, 2020). Furthermore, learning assessments and surveys have consistently pointed to the poor learning levels of children even after eight years of elementary education (Unicef, 2020). Health data shows that health problems are common among children ages 0-14, with over 60% of children suffering from anemia, one in every 100 children suffering from acute respiratory infection, one in every five children suffers from diarrhea and more than 50% of children being malnourished (Partnership for Child Development, 2013). In fact, India is often categorized as an emerging economy but with the characteristic feature of the largest number of poor, illiterate and unemployed persons in the world (Deb, 2018).

While poverty rates in India have generally declined, the rural poverty fell at a slower rate than the urban poverty, which is worrisome considering that India’s population largely rural (65.5%; World Bank Data Bank, 2020b). About 25.7% of the rural population remained below the poverty line in comparison to 13.7% of the urban below poverty line population during 2011-12 (Deb, 2018). Important differences in educational attainment have been reported. The average number of years education is 94% higher for urban habitants in comparison to rural (Hnatkovskaa & Lahirib, 2013). Moreover, the illiterate population in urban areas is 17.15%, while in rural areas that amount is more than doubled at 38.34% (Agrawal, 2014).

There is limited knowledge of average differences in living standards of urban and rural habitats, as far more attention has been paid to the increase of urban poverty and slums in Indian cities, where about 26% of all urban population resides (World Bank, 2011b). Focus on slums has increased as their habitants are at high risk of health problems. The urban-rural differences haven been studied with regard to income and economic growth disparities (Azam, 2019), but studies assessing living standards and access to resources such as health services, education, and utilities are far more limited. Some studies show an urban advantage when it comes to family’s economic circumstances, school’s structural quality, teacher absenteeism, as well as children’s work (Kremer et al. 2005; Ramchandran, 2009; Tilak, 1996). A report by OECD (2019) has observed that deprivation in core public services is much higher in rural than urban areas, with a particularly marked rural-urban divide for electricity, sanitation, and trained health personnel.

When the Young Lives study started in 2001, the population of Andhra Pradesh, the specific Indian state in which this study is based, had almost 75.72 million habitants, which accounted for 7.37% of the India's population, making it the fifth largest of all the 35 states. Later, in 2014, the state's sub-region of Telangana became a separate state, changing the population of Andhra Pradesh to 49,634,314 and of Telangana to 35,193,978 residents. The region is largely rural with only 27% of the population living in urban areas (Mukherji, 2008). Literacy levels are 66.46% and 67.41% in Telangana and Andhra Pradesh, respectively. With over 80% of the population dependent on agriculture, the rural part of these states drive much of the economy. Importantly, the rural population growth due to new births decreased during the last three decades twice as fast (30.7%) as the national rural population rate (12.3%). Additionally, is very important to highlight that Andhra Pradesh has low rates of rural poverty (11.2%) compared to the national average (28.3%; Mukherji, 2008).

2.0 The present project

Research examining urbanicity's relation to child functioning is critical in light of the changing geography of poverty in LMIC. The present project used multi-level information that included data about children, families and communities and that is organized in a longitudinal manner in order to help to fill some gaps in the literature of child development in LMIC. While evidence suggests that low-income children's outcomes differ across urban and rural communities, no research has taken a developmental perspective in trying to understand the community pathways through which this occurs and the timing of those pathways.

Importantly, this project provides information to strengthen knowledge of *community effects* in LMIC. To our knowledge, this is the first study to explore whether community characteristics are associated with different developmental domains over the course of child development. Furthermore, no studies have explored associations of multiple community characteristics and child outcomes accounting for the longitudinal nature of child development. We considered a wide set of community characteristics and patterns of time-use to identify factors that explain differences in urban-rural development. We also assessed whether experiences of time-use and community characteristics have different effects as children age. Considering whether the patterns of time use at difference ages and timing of exposure to community stressors and resources is important for informing policy and practice.

Finally, drawing data from the *Young Lives Study,* which tracks the development of children across different countries, allowed us to consider whether urban-rural difference replicate across countries. This project aimed to strengthen our understanding of how urbanicity, time-use, community characteristics, and age interface to shape children's development in LMIC countries by addressing three aims:

(1) Describing the size of the gaps between children from low-income urban and rural communities when it comes to achievement and health, and estimating what proportion of these gaps are explained by child and family characteristics.

(2) Examining whether differences in time use and community resources and stressors are pathways through which urbanicity shapes child development at early childhood (age five), middle childhood (age eight), and adolescence (ages twelve and fifteen).

(3) Estimating whether cumulative experiences of communities and time-use mediate the associations between urbanicity and growth trajectories of health and cognitive skills from early childhood to adolescence (from age five to age fifteen).

3.0 Methods

3.1 Sample

Data for this study are drawn from Young Lives, a longitudinal study of childhood poverty that followed 12,000 children from Peru, Vietnam, Ethiopia, and India (only the states of Andhra Pradesh and Telangana) from 2002 to 2017. The study surveyed these children and their households in roughly 3 - 4 -year intervals starting in 2002, with five waves of data collection taking place in 2002, 2006, 2009, 2013, and 2017. For the purposes of this study you are only focused on the subsample of children from Peru and India.

Participant children were recruited from approximately 20 different low-income sentinel sites in each country, with equal proportions of girls and boys and diversity when it comes to ethnicity, religion, language, and urbanicity. The team, then, randomized households within the sentinel site locations and selected only one child per household. The concept of a sentinel site comes from health surveillance studies and is a form of purposive sampling where the site, or 'cluster', is deemed to represent a certain type of population, and is expected to show typical trends affecting those particular people or areas. In fact, while the Young Lives samples are not nationally representative, prior studies show they are appropriate for monitoring national-level indicators (Wilson & Huttly, 2004). Comparisons of the Young Lives study sample and nationally representative samples show that the Young Lives children in India and Peru were comparable (Barnett et al. 2012).

Children in the Young Lives study were divided in two age groups: 2,000 born around 1994 (the Older Cohort); and 4,000 born around 2001 (the Younger Cohort). The present project focused on the Younger Cohort because of its interest in examining associations between community characteristics at different ages and children's development. The Younger Cohort was selected because it has information from earlier ages (age 1) and because the measures used for assessing community characteristics and child outcomes were more consistent across time. Thus, information for the Younger Cohort is better suited for longitudinal analysis of community characteristics.

Young Lives includes rich information about children's development and important measures of family, school, and community contexts collected through several tools and respondents. The multilevel structure of the study allowed us to make linkages between child environments and children's development. Around 7% of children relocated from urbanicity during the course of the Young Lives Study. For the present study, only children that were stably urban or stably rural were included.

Children in Peru were clustered in 119 communities while children in India were clustered in 98 communities. The attrition rate is low compared to other longitudinal studies. Attrition between the first and last round was 4.1% in India and 9.8% in Peru. The main reasons for attrition are migration to places that were too difficult to track, marriage (some in-laws did not want participants to continue), and the feeling that the study has not brought any tangible benefits from government.

3.2 Measures

Although data from child, household, and communities is available at all waves, some of the methods, questionnaires, and measures changed over time. The multilevel, multimethod (i.e. direct assessments, child questionnaires, parent questionnaire, community leader's interviews), and longitudinal nature of Young Lives makes the study very unique in the context of LMIC, which explains the need for refinement and change during the waves of data collection. Modifications were necessary due to findings in the initial waves, children natural growth, country-level policy changes, and cultural adaptation that occurred over the waves of data collection.

3.2.1 Child outcomes

3.2.1.1 Height

Height was used as a measure of chronic nutritional status of the child. Height reflects past and present situations that affect health and it provides a cumulative picture of overall health status. The age-specific analysis were estimated using a standardized measure of height: height-for-age. This measure is a standardized score of child height relative to an international standard of healthy children. The use of a reference population makes possible the comparison of children's height across different ages and contexts. Contrastingly, the raw measure of high in centimeters was used for estimations that modeled physical growth (Aim 3). Linear growth modeling estimates the individual's rate of change over time. Thus, absolute values instead of population standardized scores are more meaningful.

3.2.1.2 BMI for age

BMI is considered an indicator of global health and nutrition. The measure of BMI-for-age was constructed using the World Health Organization (WHO, 2006) reference population, z-scores (HAZ). As with height-for-age, this measure is a standardized score of child height relative to an international standard of healthy children.

3.2.1.3 General health

General health status was obtained through a parent-report. The surveyed parent was asked to rate child's general health using a 5-point Likert scale: very poor, poor, average, good, and very good. The parent reported general health at ages 8-12, thus, the measure is not available at age five.

3.2.1.4 Receptive vocabulary

The Peabody Picture Vocabulary Test (PPVT) was used to measure receptive vocabulary but is also commonly used as a marker of general cognitive skills. The PPVT is a norm-referenced direct assessment of receptive vocabulary in people from 2.5 years old to adulthood. The scales differed by country. Researchers in Peru used the Spanish version of the PPVT-R (Dunn, Padilla, Lugo & Dunn, 1986), which consists of 125 items of increasing difficulty. Reliability was high with values above .90 and languages and all 125 items were used (Cueto & Leon, 2012; Cueto, Leon, Guerrero & Muñoz, 2009).The third version (PPVT III; Dunn & Dunn, 1997) was used in India, adapted from English into local languages. Although the English language version of the PPVT consists of 175 vocabulary items, data analysis of PPVT at rounds 2 and 3 indicated there was some disordering in the items due to the translation in India (Leon & Singh, 2017). Thus, in the final two rounds only a subset of 57 items was presented to children. The current study uses

PPVT scores based on only these 57 items across all waves (Leon & Singh, 2017). Thus, given differences in the language and the number of items that was retained in each country, the scores are not comparable across Peru and India.

3.2.1.5 Literacy

Literacy was measured only at ages 8-12 and the assessment method changed over time. At age eight, the Early Grade Reading Assessment (EGRA) was administered. The EGRA is an oral assessment that assesses basic literacy skills in the early grades using 14 items: recognizing letters of the alphabet, reading simple words, understanding sentences and paragraphs, and listening with comprehension. The EGRA items showed acceptable reliability in India (α=0.85) and Peru (α=0.75; Cueto & León 2012). At ages twelve and fifteen, a Reading Comprehension Test of 24 questions-long was given to children. Items were drawn from the International Student Assessment (PISA) and the UNESCO Literacy Assessment and Monitoring Programme. The test was adapted and piloted for each country (Dawes, 2020).

3.2.1.6 Mathematic abilities

Math skills were measured through three different tests depending on the age. At age five, the quantitative sub-scale of the Cognitive Development Assessment (CDA) was used. This fifteen item instrument asks children to select an image from a selection of three or four that best reflects the concept verbalized by the examiner (e.g. few, most, nothing, etc.). At age 8 years the Mathematics Achievement Test was administered, which was constructed with items from the Trends in International Mathematics and Science Study (TIMSS) that measured basic quantitative and number notions (nine items) as well as the performance on basic mathematics operations with numbers (20 items). The math test showed good reliability in India (α=0.93) and Peru (α=0.90;

Cueto & León 2012). The same test was used for testing 12- and 15-year-olds, with adaptation of items to adjust for differing levels of skill by age. Therefore, items are not comparable across ages (Tredoux & Dawes, 2018). These items examined children's performance on math operations as well as data interpretation, number problem solving, measurement, and basic knowledge of geometry.

3.2.2 Child time use

Participants reported on the number of hours a day, they spent in eight different activities: time at school, studying outside school, playing, sleeping, doing tasks, doing chores, working, and caring for others. Parents reported on these activities when children were 5 and 8 years old, and children reported on them when they were 12 and 15 year old. These activities were added into three categories of time use: work, studying, and playing (sleeping time was not included). Hours of work reflects the time that children spent on caring for others, doing household chores, doing activities at the family business or doing farm and paid activities outside home. Finally, hours studying is the total time spent at school and studying at home. Composites were created at each wave and were included in the age-specific models (Aim 2). For models predicting trajectories of growth across time (Aim 3), measures were aggregated across all rounds from age five to age fifteen in order to reflect average levels of time use across childhood.

3.2.3 Community characteristics

A field researcher interviewed key community members of the community in order to obtain information about the community Examples of suitable people include local mayors, community leaders, health, government officials, education or agricultural authorities, religious leaders, representatives of grass roots organizations, and caregivers of participant. Participants were invited to a meeting in which information was obtained and participants were surveyed.

Composites for each characteristic were created at each wave and were included in the age-specific models (Aim 2). For models predicting trajectories of growth across time (Aim 3), wave-specific measures were aggregated across all rounds from age five to age fifteen in order to reflect the accumulated value of community characteristics. Based on answers from participant community members, community data was created based on indicators that designated whether different resources or stressors were present in the community. Cumulative variables for each stressor and resource was created by averaging across waves from age five to age fifteen.

The measure of pollution was constructed as a sum of indicators of whether the following pollution problems are present in the community: industrial waste, air pollution, water pollution, garbage, sewage, and pesticides. The measure of violent crime was captured through a dichotomous indicator of whether people's day-to-day activities were seriously affected by violent crime. The total number of utility services was coded as the sum of indicators on whether the community leaders reported that following services were available in the community: public telephone, telephone network, public Internet cabin, electricity power supply, and drinking water.

In India, availability of health facilities was constructed as the sum of indicators on the community member's report of availability of the following in the community: public hospital, private hospital, public health center, private health center, and dispensary. In Peru, a measure of accessibility, and not only availability, was constructed given that data about travel time to each health facility was consistently available for this sample. To mark access to health facilities, an indicator of the availability of each facility was multiplied by the reverse travel time (in minutes) to each to these services from the community's downtown area, and then each of these values was aggregated into each wave's measure.

The measure of educational services reflected whether educational institutions at different levels and providers were available in the community. The Young Lives study team collected data about selected schools in the participant communities two times during the length of the study, in 2011 and 2016. Around 20% of participant children were enrolled in the surveyed schools (Guerrero et al., 2012; James, 2013). Although school-level data is more optimal than just availability of schools, this information was not used because it would have substantially reduced our sample and because the periodicity of data collection would have made it impossible to estimate age-specific effects. Instead, our measure of educational services reflected availability of educational services in each community. The measures differed by country, depending on the available services surveyed. For the Indian sample, the measure reflects a sum of indicators on the availability the following in the community: private preschool service, public preschool service, private elementary school, public elementary school, private secondary school, public secondary school, technical college, universities, and center for occupational education. Unfortunately, data about educational services were not obtained at wave 3 (when children were 8 years old) for the Indian sample. Thus, time specific models predicting age-8 outcomes used the educational measure variable obtained in the prior wave (when children were five). For the Peruvian sample, the measure reflects a sum of indicators on the availability the following in the community: private preschool service, public preschool service, preschool service of foundations or religious communities, private elementary school, public elementary school, elementary school of foundations or religious communities, private secondary school, public secondary school, and secondary school of foundations or religious communities, technical college, university, and center for occupational education.

3.2.4 Demographic characteristics

3.2.4.1 Child characteristics

Child sex is a dichotomous variable indicating whether the child is male or female (reference group), as reported at round 1 by the parent. Each wave parents reported parents or the children reported their age in months, with children reporting as they got older. Race/ethnicity was obtained from parent report at Round 1. Ethnicity/Caste groups in India were divided in five categories: Scheduled Castes, Scheduled Tribes, Backward Castes (reference group), Other non-Hindu, and Other Hindu. The first three categories reflect the groups that have historically faced more the deprivation and oppression, while the Other Hindu castes correspond to the traditionally upper castes. Race groups in Peru were divided in Mestizo (people of combined European and Indigenous descent who have strong European cultural inheritance and compose the majority of the population; reference group), White, and Other (composed by Black, Indigenous, and Asian).

3.2.4.2 Family characteristics

Per-capita monthly family expenditure is a continuous variable reported by caregivers in the local currency and reflects the per-capita household monthly expenses on food, transport, security, telephone, electricity, water supply, housing, clothes, and footwear. Expenditure is a more common measure of SES than monthly income in LMIC, due to monthly or seasonal fluctuations, rate of informal work, and reporting biases (Howe et al., 2012). Since expenditure changes over time, it was coded cumulatively up to the wave of each assessed outcomes in the age-specific models (Aim 2) and it was accumulative from age five to age fifteen for the trajectory models (Aim 3). In the Young Lives Study, expenditure was not collected at baseline (when children were 1). Thus, composite measures of expenditure only include reports when children were 5, 8, 12, and 15. Cumulative composites of expenditure were created by adjusting the expenditure measures to the 2016 currency, according to the price inflation rate of each country, and by averaging across waves. Additionally, to make expenditure coefficients more interpretable in the estimated results, raw expenditure values were divided by 1,000 for the Indian sample and by 100 for the Peruvian sample.

Mother's higher level of education was obtained from the caregiver report and was coded categorically at each wave. For Peru, education was classified as no education (reference group), elementary education (grades 1-5), some secondary education (grades 9-10), high school degree (grade 11), and postsecondary education. For India, categories were defined as follows: no education (reference group), lower primary (grades 1-4), upper primary (grades 5-8), secondary education (grades 9-12), and postsecondary education (reference group). Mother's education was surveyed across all fives waves of data, starting at age 1. A cumulative measure of education was created by indicating the educational level more often reported by the mother from the baseline wave up to the age of the child outcome predicted in the model. Mothers not having a majority of time in any of the levels were coded as the last education level reported. Marital status is a dichotomous variable indicating whether the mother (or main caregiver) was married at wave 1. Information about marital status was not surveyed in any other wave so the indicator obtained at wave 1. The number of adults, the number of adolescents, and the number of children living in the household was coded using the household roster obtained during the parent interview, in which the all people living in the household was listed. Cumulative measures of these variables were created by averaging them since children were one until they were fifteen up to the age of the child outcome predicted.

3.3 Analytical approach

This study explores whether community resources, community stressors, and child time-use are pathways through which urbanicity relates to children's development. For this, we examined these mediating associations at four different ages (5, 8, 12, and 15) and, also, how cumulative experiences and contexts change trajectories of development from early childhood to adolescence. These two approaches allow us to examine two different aspects of how communities and time-use patterns could influence child development. First, the age-specific models permit us examine whether the effects of community characteristics and time use depend on the timing of exposure. Through this approach, we examined whether specific community characteristics and patterns of time use has heterogeneous effects on child development during early childhood (age 5), middle childhood (age 8), or adolescence (ages 12 and 15). Second, models examining whether cumulative time-use and community characteristics predict trajectories of development (from age 5 to 15) allowed us to identify the factors that relate to development through continued exposure across childhood.

Multilevel structural equation modeling (MSEM) was used to address the three aims. Similar to a regression, MSEM decomposes the outcome variable into the sum additive parts: intercept, predictors, controls, and residuals. However, SEM allows for the specification of more than one predicted (endogenous) variable and to specify relationships among the predictor variables, making this method very suitable to estimate mediation. Furthermore, we used multilevel SEM it accounts for the nesting of the children (level one) within communities (level two) by incorporating random effects for communities. Given that our model contains a random effect, the traditional fit indices are not applicable and are not presented.

3.3.1 Aim 1: Size of the urban-rural gap

Our first aim was to describe the size of the urbanicity differences on child development (unadjusted gap) and to estimate how much of these gaps are explained by demographic characteristics (adjusted gap). First, to estimate the unadjusted urbanicity gaps, we predicted each child outcome with urbanicity. The comparison of the outcomes of urban and rural children requires a careful examination of the family's demographic characteristics because families select into urban and rural communities. It is important to examine how much of these gaps are accounted for by characteristics such as race/ethnicity, income, parental education, etc. Thus, as a second step, we estimated the size of the urbanicity-related differences on child outcomes that remains after controlling for all demographic covariates, using path analysis in multilevel structural equation modeling (SEM). Models predicting each child outcome at different ages were estimated separately in Stata 16 using full information maximum likelihood estimation, which handles missing data in an optimal fashion, minimizing bias and increasing statistical power (Allison, 2003). All models included a random intercept to adjust for the clustering of children within communities.

3.3.2 Aim 2: Assessment of age-specific mediating mechanisms of urbanicity and child development (or age-specific models)

Our second aim was to explore whether age-specific community resources and stressors, and child time-use are the mechanisms that underlie the relation between urbanicity and child development at four different ages: 5, 8, 12, and 15. For this, separate mediation models in a multilevel SEM frame were estimated for outcomes each age. The mediation models tested whether the observed relation between urbanicity and achievement at each age were explained by the effect of the age-specific mediators (non-cumulative measures of community characteristics and child time-use). For each separate model, child outcomes were modeled as a function of urbanicity, which operated through the mediating variables. See Figure 2 for a graphical representation of the model. All community and child time-use mediators were estimated in a single model, and the covariances among community characteristics and among child time-use were freely estimated. To help control for selection into communities and for individual differences in family characteristics and children's development, the set of child and family characteristics mentioned above were included as predictors for all endogenous variables in the models (community characteristics, child time-use, and child outcomes). Time-variant child and family characteristics were aggregated cross time up to the wave of the predicted outcome. Models were estimated in Stata 16 using full information maximum likelihood estimation, to handle missing data (Allison, 2003).

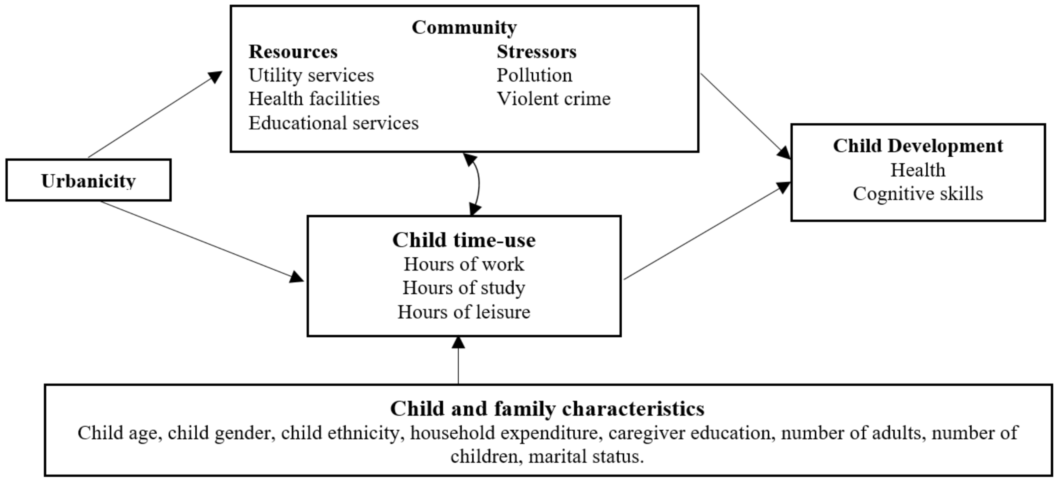

Figure 2. Graphic representation of time specific mediation model (Aim 2)

3.3.3 Aim 3: Assessment of cumulative mediating mechanisms of urbanicity and child development trajectories (or cumulative models)

Next, we examined which cumulative characteristics of child environments and experiences were robust predictors of child developmental trajectories from age five to age fifteen. For this, we examined how aggregate or cumulative characteristics of communities and child time-use mediated the relation between urbanicity and overall trajectories of development. Receptive vocabulary and height were the only child outcomes captured using comparable measures over time (PPVT and centimeters). Thus, only these two child outcomes were analyzed in Aim 3.

The linear latent growth model estimates the rate of change in height and vocabulary accounting for the individual variances around the average growth trajectory (Newsom, 2015). Independent analyses were estimated for receptive vocabulary and height by specifying latent variables for the intercept and the slope. The models included two levels, with community random effects that adjusted for the nesting of children within the communities in which children lived at age one (where they were recruited). Loadings for the slope factors were set to be equal to the number of months that passed since the first assessment (wave two or age five). This was done by subtracting child's age (in months) at baseline time from child age each wave time point. We follow this procedure because there could be large differences in the number of months that passed between each assessment. Because of this possibility, the TSCORES option in Mplus was used, which allows the slope for time to vary by person. This method is equivalent to using repeated measures in a long format to estimate growth while permitting estimations on the slope and the intercept in a wide format. In this way, the model generates a random slope for a random time variable and enables the residual variances to differ across the waves. We first estimated unconditional growth models to examine the average vocabulary and height levels at age five and the average growth until age fifteen of our sample. Second, growth model conditional to urbanicity were estimated. The goal of this step is to determine whether children in urban areas change at a faster (or slower) rate over time as compared to those in the rural areas. Third, we tested whether the mean differences in the growth trajectories between urban and rural children are mediated by the cumulative characteristics of communities and time-use. For this, cumulative mediators aggregated across all data collection periods were used to predict the height and vocabulary slopes. Figure 3 presents graphical representation of the model. In the figure, however, intercept and slope loadings are represented as wide in order to represent the model with more clarity.

Linear latent growth models with individually varying times of observation were estimated in Mplus 8 (Muthén & Muthén, 1998–2017). Multiple imputation was used to account for missing data. Formal tests of mediation were estimated with the MODEL

INDIRECT command, which measures the statistical significance of the proposed mediating pathways by using the delta method (used in the Sobel Test) in computing standard errors.

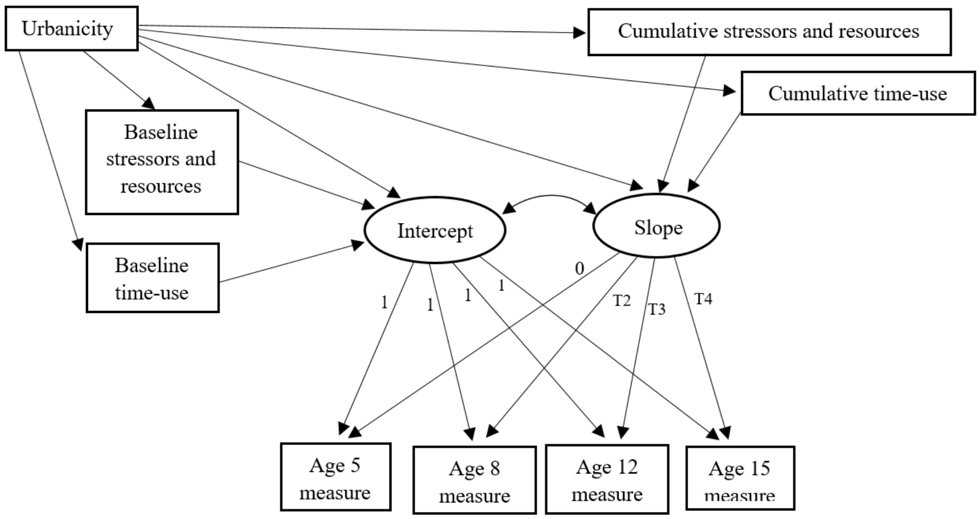

Figure 3. Graphic representation of cumulative mediation model (Aim 3)

4.0 Results

4.1 Descriptive statistics

Descriptive statistics on the full analytic sample by urbanicity are presented in Table 1 for Peru and Table 2 for India. It is important to note the diversity within each country in terms of expenditures, mother education, and other demographic characteristics. As expected, Peru is very urbanized, with 69.28% of the children living in cities, in comparison to India, where only a quarter of children resided in cities (25.54%).

4.1.1 Peru

Clear patterns emerged showing that urban children outscored rural ones. Urban children showed higher levels of academic achievement and health than their rural peers, with the only exception of BMI-for-age at age five. Formal tests of the urban-rural differences on child outcomes are presented in the section 4.2.1 (Aim 1).

Turning to differences by demographic composition, on average, a higher percentage rural habitants were from Black, Native, or Asian backgrounds (6.63%) in comparison to habitants in urban areas (1%). In fact, the urban sample was almost completely White or Mestizo (99%). Regarding household composition, rural families reported living in households with fewer adults (0.20-0.30 individuals), and more adolescents (0.20-0.30 individuals) and children (0.43-0.84 individuals). Families in rural areas showed a per capita expenditure of around half of the average expenditures that urban families reported, with differences between 93 and 135 soles (according to 2006 currency). In addition, rural mothers possessed lower levels of educational attainment, with around 70% of rural mothers reporting not completing elementary education at each wave in comparison to around 20% of mothers in urban areas.

Regarding time-use, children in urban areas spent more time studying, although differences decreased over time with urban children studying 1.61 more hours a day at age five and only 0.46 hours more at age fifteen than rural children. Urban children also spent around an hour less per day working (between 0.61-1.25 hours) than rural children, but time working increased over time for both groups. On average, urban children worked 0.61 hours a day at age five, which increased to 2.33 hours a day by age fifteen. In comparison, rural children worked 1.48 hours a day at age five and they increased their working time to 3.04 hours by age fifteen. Urban children also played between 20 and 30 minutes more than rural children did. The only exception to this pattern was the time playing at age five, which was around four hours a day for both groups of children. After age five, time playing more sharply reduced for rural children (from 4.11 hours at age five to 3.91, 3.28, and 3.20 at later ages) than for urban children (from 4.10 hours at age five to 4.29, 3.79, and 3.58 at later ages).

Turning to community factors, urban communities showed higher levels of resources while also presenting higher levels of violent crime and pollution problems. Specifically, habitants in urban communities reported availability of between 2.31 and 3.92 more utility services (out of the six utilities surveyed) than habitants in rural areas. While the number of utility services available remained stable for urban children (5.25-5.71 services), it increased for rural children, who increased their access from 2.07 services at age five to 3.24 services at age fifteen. Urban areas also offered more educational services, evidenced in the 1-3 more educational services accessible to the urban communities (out of the twelve services surveyed), in comparison to rural ones.

Notably, the number of education services increased over time across urban and rural areas. In urban communities, on average, 7.41 education services were reported at age five, which increased to 11.41 by age fifteen. In rural communities, an average of 4.40 education services were reported at age five and this resource almost doubled to 8.02 by age fifteen. Regarding health facilities, families in urban communities had higher proximity to health facilities, as indicated by the measure of reverse travel times to health facilities. Results showed that on average, health facilities are 2.13-2.85 minutes from downtown in urban areas and around 5.55-8.33 minutes from downtown in rural communities.

Turning to community stressors, although habitants in urban and rural areas reported suffering of 3-4 pollution problems (out of the six pollution problems surveyed), urban communities reported between 0.24 and 0.58 more pollution issues. The average number of pollution problems remained stable over time. Finally, when indicating if violent crime was a problem in the community, 42-50% of urban communities reported that violent crime was a problem, in comparison to only 11-17%% of rural communities.

Table 1. Descriptives statistics of the Peruvian sample

Variables	Age 5				Age 8				Age 12				Age 15			
	Urban		Rural		Urban		Rural		Urban		Rural		Urban		Rural	
	M or %	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*
Child health																
Height for age [a]	-1.25	1.09	-2.25	0.99	-0.93	1.02	-1.76	0.93	-0.75	2.64	-1.69	1.00	-0.95	0.83	-1.65	0.85
BMI for age [a]	0.70	1.10	0.66	0.90 [ns]	0.64	1.14	0.20	0.78	0.72	1.15	0.04	0.86	0.49	0.99	0.19	0.85
General health					3.75	0.65	3.62	0.66	3.72	0.59	3.65	0.58	3.82	0.62	3.68	0.64
Child cognitive skills																
Vocabulary	35.12	16.97	15.40	10.89	64.20	14.43	45.66	18.05	90.40	15.78	72.51	15.32	100.40	15.32	84.41	17.04
Math	8.81	1.99	7.37	2.21	15.61	5.31	10.71	5.55	17.23	5.07	13.10	5.49	12.01	4.91	8.90	4.25
Literacy					9.02	2.88	6.50	3.28	15.26	3.25	12.49	3.54	17.78	3.64	14.93	4.01
Time use																
Hours labor	0.61	0.95	1.48	1.74	1.28	1.29	2.40	1.65	2.27	1.64	3.52	1.96	2.33	2.02	3.04	2.36
Hours play	4.10	2.13	4.11	2.16 [ns]	4.29	1.67	3.91	1.80	3.79	1.43	3.28	1.40	3.58	1.58	3.20	1.57
Hours study	5.30	2.22	3.69	2.51	7.56	1.38	6.96	1.30	7.63	1.24	6.95	1.06	8.90	1.46	8.44	1.48
Child characteristics																
Gender (male)	51.03%		49.09%		50.65%		49.91%		50.75%		49.12%		50.76%		49.47%	
Age (months)	64.65	4.44	60.83	4.17	94.93	3.60	94.95	3.63 [ns]	142.88	3.72	143.35	3.78 [ns]	179.19	3.77	179.27	3.69 [ns]
White	7.35%		1.66%		7.12%		1.81%		7.04%		1.7%		6.57%		1.89%	
Mestizo	91.69%		91.71% [ns]		91.94%		90.96 [ns]		92.10%		90.37% [ns]		92.42%		90.74% [ns]	
Black/Native/Asian	0.95%		6.63%		0.93%		7.23%		0.86%		7.86%		1.01%		7.37%	
Household																
Married at age 1	86.56%		85.14% [ns]													
Mother education																
No elementary	21.57%		70.22%		21.53%		69.84%		21.17%		67.08%		18.96%		62.25%	
Less than HS	31.46%		22.72%		31.68%		22.76%		30.91%		23.96%		32.01%		27.15% [ns]	
High school	26.74%		5.51%		26.18%		6.03%		26.75%		6.88%		25.30%		7.95%	
Some post-HS	18.05%		1.55%		18.09%		1.36%		17.90%		2.08%		19.10%		2.65%	
Bachelor	2.17%		0.00%		2.52%		0.00%		3.27%		0.00%		4.63%		0.00%	
Expenditure per cap	215.72	173.82	122.86	75.74	229.23	165.62	150.59	85.71	342.52	355.33	207.17	149.82	346.90	971.53	217.03	142.99
Household size																
Adolescents	0.38	0.67	0.60	0.87	0.44	0.67	0.68	0.85	0.47	0.65	0.75	0.79	0.26	0.50	0.46	0.62
Adults	2.68	1.31	2.50	0.99	2.62	1.28	2.42	0.94	2.57	1.23	2.41	0.96	2.74	1.30	2.56	1.08
Children	1.17	1.08	2.01	1.31	1.13	1.04	1.88	1.29	1.03	0.97	1.52	1.28	1.12	1.06	1.55	1.37
Community																
Pollution problems	3.45	2.45	3.03	1.81	3.59	2.41	3.35	1.92	4.71	2.87	3.93	1.58	3.62	1.97	3.04	1.50
Violent crime	0.43	0.50	0.11	0.31	0.42	0.49	0.12	0.32	0.48	0.50	0.14	0.35	0.29	0.45	0.17	0.38
Utility services	5.25	1.33	2.07	1.27	5.62	0.77	2.71	1.14	5.71	0.99	3.10	1.31	5.55	0.88	3.24	1.28
Educational services	7.41	2.89	4.40	2.75	9.21	1.39	7.30	2.61	10.44	2.18	9.28	2.57	11.41	2.86	8.02	3.29
Health facilities	0.38	0.32	0.12	0.15	0.35	0.31	0.16	0.16	0.47	0.43	0.27	0.29	0.38	0.36	0.18	0.19

Note. All urban-rural comparison are significant except when "ns" is specified. [a] measure has been age-standardized.

4.1.2 India

Table 2 presents descriptive statistics for the Indian sample. Urban children had higher achievement and better health than rural children did in almost all instances Formal tests of the urban-rural differences on child outcomes are presented in the section 4.2.2 (Aim 1). Notably, both urban and rural children had negative means in the height-for-age and BMI-for-age measures, indicating that this sample of children was under the global expected average levels of BMI and height according to healthy global standards (WHO, 2006).

Regarding demographic differences by urbanicity, the urban sample had less tendency of being from a Scheduled Caste or Scheduled Tribe (lower level casts), but equal numbers of children from a Backward Caste. There were small differences on household composition. Rural households reported having slightly more adults, adolescents, and children (0.10-0.020 individuals) across time than urban households did, but differences were often non-significant. Families in rural areas showed a lower per capita expenditure (771-1,136 rupees) of that of their urban counterparts (932-1,539 rupees). In addition, while 61% of rural mothers in did not have any education, 23% of urban mothers had the same status; and while only 10% of rural mother had secondary education, 35% of urban mothers reached this level. Differences in time-use indicated that urban children spent one more hour studying at age five than rural children, but that reduced to half an hour or less afterwards. At age five, urban and rural children spent around a quarter of an hour working but after that, differences by urbanicity grew, with urban children spending one more hour working by age fifteen. Time playing did not differ by urbanicity.

Turning to community resources and stressors, urban areas generally had higher levels of resources and stressors in India but differences were less pronounced than in Peru. Furthermore, there were some unexpected differences by urbanicity in the Indian sample. Specifically, when indicating if violent crime was a problem in the community at age five, members in 8% of rural communities reported that violent crime was a problem, in comparison to no members in of urban communities reporting having this problem. After this age, reports of violent crime were higher in urban areas and descriptive information suggests violent crime grew over time in urban areas. While community members' reports indicated that on average 1-3% of rural communities had problems of violent crime, members of urban communities reported that 8% (age 8), 32% (age 12), and 30% (age 15) of urban communities had such problems. Another unexpected relation was found at age fifteen, as rural communities reported an average of 3.37 pollution problems while urban communities reported 2.51, out of the six surveyed. Notably, while urban areas showed higher number of pollution problems in comparison to rural areas at earlier waves (ages 5, 8, and 12), urban-rural differences reduced over time due to increase of pollution problems in rural areas. The number of pollution problems reported by rural participants increased from 2.18 pollution problems (out of the six surveyed) at age five to 3.37 problems at age fifteen. A third unexpected difference was found at age five, when rural community members indicated that their communities had an average of 8.65 health facilities, in comparison to the 8.40 average number of health facilities reported by urban members. At all other ages, differences in the number of health facilities continued to be small. Specifically, urban areas had one or less than one health facilities in comparison to rural ones. Turning to availability of utility services, the urbanicity differences were in the expected direction, with urban residents reporting an average of 1.5 more utilities (out of the six assessed) than rural residents. Finally, concerning educational services, urban residents reported between 0.79 and 1.42 more available services (out of the nine services surveyed) in comparison to the number of services available in rural areas.

Table 2. Descriptive statistics of the Indian sample

Variables	Age 5				Age 8				Age 12				Age 15			
	Urban		Rural		Urban		Rural		Urban		Rural		Urban		Rural	
	M or %	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*	*M or %*	*SD*
Child health																
Height for age[a]	-1.32	1.00	-1.76	1.13	-0.98	1.08	-1.58	1.18	-1.10	1.18	-1.60	1.04	-1.19	1.01	-2.69	40.43[ns]
BMI for age[a]	-1.11	1.02	-1.20	1.02[ns]	-1.16	1.33	-1.50	1.13	-0.81	1.52	-1.57	1.45	-0.71	1.46	-1.31	1.25
General health					4.03	0.71	3.90	0.66	3.86	0.72	3.71	0.72	3.86	0.61	3.93	0.67
Child cognitive skills																
Vocabulary	20.83	10.77	15.06	9.33	21.06	7.56	19.39	7.17	44.26	8.79	42.58	7.36	48.69	7.48	46.77	7.98
Math	10.09	2.54	9.16	2.58	12.94	6.00	11.69	6.54	14.11	6.72	12.22	6.48	11.56	5.48	9.74	4.87
Literacy					5.23	3.26	5.48	3.42	13.95	4.61	13.17	4.41	14.65	4.47	13.35	4.23
Time use																
Hours labor	0.13	0.45	0.27	0.68[ns]	0.40	0.70	0.63	1.00	0.88	1.14	1.33	1.72	1.46	1.99	2.51	3.33
Hours play	5.48	2.87	5.82	2.79[ns]	4.80	1.64	4.77	1.72[ns]	3.86	1.46	3.95	1.69[ns]	3.51	1.85	3.61	1.77[ns]
Hours study	7.53	2.67	6.53	2.57	9.30	1.22	9.16	1.24	9.98	1.29	9.34	1.44	10.98	1.54	10.15	1.62
Child characteristics																
Gender (male)	55%		53%		55%		53%		56%		53%		55%		53%	
Age (months)	63.97	4.13	64.35	3.80	95.54	3.73	95.35	3.87[ns]	144.01	3.71	143.72	3.85[ns]	180.10	3.80	179.93	3.77[ns]
Ethnicity																
Scheduled caste	12%		20%		11%		21%		13%		20%		12%		21%	
Scheduled tribe	5%		18%		6%		18%		6%		18%		5%		19%	
Backw caste	43%		48%[ns]		44%		48%[ns]		45%		47%[ns]		45%		47%[ns]	
Other Hindu	21%		12%		20%		12%		19%		12%		20%		11%	
Other non-Hindu	20%		2%		20%		2%		17%		2%		17%		2%	
Household																
Married at age 1	99%		99%[ns]													
Mother education																
No education	23.08%		61.02%		17.60%		52.57%		19.77%		52.82%		18.87%		54%	
Lower primary	17.61%		19.80%[ns]		20.30%		26.46%		21.47%		26.49%		22.14%		25%	
Upper primary	16.00%		8.44%		16.77%		9.56%		15.82%		9.32%		14.34%		9.14%	
Secondary	34.82%		10.11%		34.16%		10.56%		32.58%		10.52%		33.39%		11.33%	
Post-secondary	8.50%		0.63%		10.77%		0.86%		10.36%		0.86%		11.25%		0.86%	
Expenditure per capita	932	557	771	545	955	627	842	824	1,393	1,179	943	701	1,539	1,296	1,136	1,039
Household size																
Adolescents	0.11	0.36	0.18	0.48	0.27	0.55	0.35	0.63	0.58	0.72	0.58	0.67[ns]	0.52	0.61	0.44	0.58
Adults	2.75	1.37	3.01	1.64	2.71	1.33	2.92	1.61	2.54	1.22	2.64	1.22[ns]	2.70	1.15	2.82	1.30[ns]
Children	1.28	0.95	1.45	0.98	1.18	0.98	1.28	0.96[ns]	0.67	0.85	0.74	0.90[ns]	0.43	0.73	0.58	0.86
Community																
Pollution problems	3.29	1.66	2.18	1.24	3.17	2.25	2.65	2.66	3.84	2.13	3.40	2.28	2.51	2.41	3.37	2.22
Violent crime	0.00	0.00	0.08	0.27	0.08	0.27	0.03	0.18	0.32	0.47	0.01	0.10	0.30	0.46	0.01	0.10
Utility services	5.42	0.83	4.07	0.87	5.78	0.45	4.07	0.78	5.45	0.77	3.41	1.27	5.58	0.58	3.40	0.92
Educational services	7.59	0.59	6.80	0.86	7.59	0.59	6.80	0.86	6.43	2.25	5.54	2.47	6.21	3.84	4.79	2.72
Health facilities	8.40	1.63	8.65	0.93	7.48	3.03	1.28	1.33	8.60	2.17	8.26	2.88	9.67	0.84	8.08	2.99

Note. All urban-rural comparison are significant except when "ns" is specified. **[a]** measure has been age-standardized

4.2 Aim 1: Size of the urban-rural gap

Tables 3-6 present the results of multilevel models estimating the size of the unadjusted urban-rural gaps and adjusted by family and demographic characteristics. Outcome variables were standardized, thus, coefficients in the tables can be interpreted in number of standard deviations of the predicted outcome. Also, refer to Appendix A for a visual representation. Differently from descriptive statistics, these results include a random intercept to account for the clustering of children within communities. These results allow us to identify the size of the health and achievement urbanicity gaps and the extent to which this gap is explained by differences in demographic factors, while also accounting for inter-dependence of participants of the same community.

4.2.1 Peru

4.2.1.1 Achievement

Table 3 shows that the achievement urbanicity gaps in Peru were medium to large across all ages, ranging between 0.50 SD and 0.85 SD. The achievement gaps tended to grow over time, increasing from 0.50 at age five to 0.63 SD at age fifteen for math, from 0.75 SD at age five to 0.85 SD at age fifteen in vocabulary, and from 0.69 SD at age eight to 0.80 SD at age fifteen.

After accounting for demographic characteristics, the urbanicity gaps for all achievement outcomes remained significant and sizeable in Peru. The math achievement gaps were reduced by 0.20-0.30 SD (to 0.14-0.43 SD), the vocabulary gaps by 0.21-0.63 SD (to 0.39-0.58 SD), and literacy gaps by 0.24-0.37 SD (to 0.38-45 SD). While the math gaps were reduced by ~70% in age five and by ~50% at later ages, the vocabulary and literacy gaps were reduced between ~33% and ~48% at each of these times, respectively. All children and family demographic characteristics were significant predictors of achievement, with the exception of race/ethnic background. Notably, mother's education was the most salient predictor of achievement, surpassing the effect of urbanicity itself across the three achievement outcomes examined. In comparison to children with mothers with no education, children with mothers with elementary education (0.11-0.35 SD), some high school education (0.32-0.53 SD), high school degree (0.44-0.76 SD), and some post-secondary education (0.72-1.00 SD) had higher levels of math achievement. These associations increased over time, reaching a peak at age twelve and slightly decreasing again at age fifteen. Turning to vocabulary, in comparison to children with mothers with no education, children with mothers with elementary education (0.13-0.29 SD), some high school education (0.45-0.50 SD), high school degree (0.68-0.81 SD), and some post-secondary education (0.84-1.24 SD) had higher levels of vocabulary achievement. The strength of these associations did not show any consistent pattern of increments or decrements over time but, instead, was unstable over time. With regard to literacy, children with mothers with elementary education (0.32-0.33 SD), some high school education (0.43-0.49 SD), high school degree (0.60-0.76 SD), and some post-secondary education (0.80-1.14 SD) had higher literacy skills than children with mothers with no education. The strength of these associations was mostly stable over time.

4.2.1.2 Health

Table 4 shows that urban children had better health than rural children across outcomes and ages. The only two exceptions were BMI-for-age at age five general health at age twelve. The urbanicity gaps seem to be larger for the measure of height-for-age (0.59 SD- 1.00 SD), than for

BMI-for-age (0.30-0.56 SD), and general health (0.18-0.56 SD). The size of the gaps fluctuated across age, reaching a peak at age twelve for BMI- and height-for-age and decreasing at age fifteen.

After including all demographic characteristics in the models, the urbanicity gap for general health disappeared at all ages but at age fifteen (0.19 SD). The urban advantage on BMI-for-age at the later ages (0.37 at age 12; 0.26 SD at age 15) and all gaps of height-for-age (0.34-0.54 SD) remained significant. Similarly to results of achievement, child and demographic characteristics were associated to health outcomes, except for race and marital status. However, significant associations of demographic factors with health were scarce when examining BMI-for-age and general health. When considering height-for-age, more associations emerged, indicating that mother education was the most salient predictor of height. Specifically, results showed that children with mothers with elementary education (0.17-0.24 SD), some secondary education (0.21-0.54 SD), high school degree (0.23-0.55 SD), and some post-secondary education (0.44-52 SD) evidenced higher height-for-age than their peers with mothers with no education. The strength of these associations fluctuated over time.

Table 3. Unadjusted and adjusted achievment urban-rural gaps for the Peruvian sample

Predictors	Age 5		Age 8			Age 12			Age 15		
	Math	Vocab.	Math	Vocab.	Literacy	Math	Vocab.	Literacy	Math	Vocab.	Literacy
	Coeff.	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*
	(S.E)	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*
Unadjusted											
Urban	0.50***	0.75***	0.70***	0.79***	0.69***	0.76***	0.82***	0.75***	0.63***	0.85***	0.80***
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.091)	(0.08)	(0.08)	(0.09)	(0.08)
Intercept	-0.46***	-0.74***	-0.55***	-0.72***	-0.61***	-0.56***	-0.72***	-0.60***	-0.46***	-0.72***	-0.58***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)
Random interc.	0.14***	0.17***	0.10***	0.19***	0.12***	0.10***	0.15***	0.09***	0.06**	0.18***	0.05*
	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.04)	(0.02)
Random resid.	0.80***	0.55***	0.76***	0.62***	0.78***	0.79***	0.67***	0.79***	0.86***	0.70***	0.84***
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Adjusted											
Urban	0.14+	0.39***	0.32***	0.58***	0.45***	0.43***	0.55***	0.38***	0.33***	0.54***	0.45***
	(0.08)	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.09)	(0.07)
Age	0.06***	0.06***	0.06***	0.04***	0.03***	0.02***	0.02***	0.02***	-0.00	0.01*	0.02*
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Expenditure pc	0.04**	0.06***	0.08***	0.08***	0.07***	0.09***	0.12***	0.12***	0.03***	0.02**	0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)
Elementary	0.11+	0.13**	0.31***	0.29***	0.32***	0.35***	0.27***	0.33***	0.20**	0.28***	0.33***
	(0.06)	(0.03)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)
Less than HS	0.32***	0.45***	0.51***	0.45***	0.43***	0.53***	0.45***	0.49***	0.39***	0.50***	0.48***
	(0.07)	(0.05)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
High School	0.44***	0.79***	0.64***	0.68***	0.60***	0.76***	0.81***	0.76***	0.65***	0.69***	0.72***
	(0.08)	(0.06)	(0.08)	(0.07)	(0.08)	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)
Some post-HS	0.79***	1.24***	0.72***	0.95***	0.80***	1.00***	1.22***	0.99***	0.76***	0.84***	1.14***
	(0.18)	(0.13)	(0.18)	(0.17)	(0.19)	(0.17)	(0.16)	(0.17)	(0.18)	(0.17)	(0.18)
Minority	-0.21	0.12	-0.07	0.21	-0.01	-0.03	0.10	-0.13	-0.04	-0.09	-0.09
	(0.15)	(0.12)	(0.14)	(0.14)	(0.15)	(0.150)	(0.14)	(0.14)	(0.16)	(0.16)	(0.16)
White	-0.07	0.08	-0.05	0.00	-0.08	-0.09	-0.08	-0.03	0.02	-0.01	-0.11
	(0.09)	(0.07)	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)	(0.10)	(0.09)	(0.10)
Married at age 1	0.07	0.01	0.13*	0.09	-0.02	0.17*	0.07	0.07	0.14+	0.07	0.11
	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Adolescents	0.07*	-0.01	0.00	0.01	-0.01	0.09	-0.08	0.06	0.02	-0.07	-0.07
	(0.03)	(0.02)	(0.04)	(0.04)	(0.05)	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)
Adults	0.00	0.00	0.07***	0.05*	0.01	0.05*	0.07**	0.06*	0.07*	0.01	0.04
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Children	-0.06**	-0.05**	-0.13***	-0.08***	-0.09***	-0.08**	-0.10***	-0.09**	-0.08*	-0.11***	-0.08**
	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Intercept	-3.88***	-4.31***	-6.44***	-4.57***	-3.53***	-3.89***	-3.87***	-4.01***	-0.23	-3.05**	-3.56**
	(0.35)	(0.27)	(0.53)	(0.50)	(0.59)	(0.87)	(0.78)	(0.88)	(1.14)	(1.05)	(1.14)
Random interc.	0.07**	0.06***	0.05**	0.08***	0.05**	0.06**	0.04**	0.02	0.03*	0.09***	0.02
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)
Random resid.	0.73***	0.43***	0.63***	0.54***	0.71***	0.70***	0.57***	0.71***	0.81***	0.65***	0.77***
	(0.03)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)

Note. All dependent variables are standardized. *** p < .001. ** p < .01. * p < .05. + p < .10.

Table 4. Unadjusted and adjusted health urban-rural gaps for the Peruvian sample

Predictors	Age 5		Age 8			Age 12			Age 15		
	Height	BMI	Height	BMI	Health	Height	BMI	Health	Height	BMI	Health
	Coeff. (S.E)	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*
Unadjusted											
Urban	0.67***	0.01	0.67***	0.30***	0.18**	1.00***	0.56***	0.09	0.59***	0.32***	0.26***
	(0.09)	(0.07)	(0.08)	(0.08)	(0.06)	(0.15)	(0.08)	(0.06)	(0.07)	(0.07)	(0.06)
Intercept	-2.15***	0.67***	-1.73***	0.23***	-0.12*	-1.71***	0.07	-0.07	-1.62***	0.17**	-0.17**
	(0.07)	(0.05)	(0.06)	(0.06)	(0.05)	(0.12)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Random effect	0.14***	0.03**	0.11***	0.08***	0.01+	0.03	0.06***	0.01	0.05**	0.02*	0.01
	(0.03)	(0.01)	(0.03)	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Random residual	0.97***	1.04***	0.82***	1.00***	0.98***	5.81***	1.10***	0.99***	0.67***	0.90***	0.98***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.20)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)
Adjusted											
Urban	0.39***	-0.03	0.40***	0.12	0.07	0.54**	0.37***	0.03	0.34***	0.26**	0.19*
	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)	(0.18)	(0.09)	(0.07)	(0.07)	(0.08)	(0.08)
Age	0.02**	-0.01	-0.00	-0.01	-0.01	-0.05**	-0.00	-0.00	-0.01	-0.01	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Expenditure pc	0.06***	0.02	0.09***	0.08***	0.06**	0.10	0.08*	0.12***	0.02+	0.01	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
Elementary	0.24***	-0.07	0.17**	0.03	0.09	0.23	0.00	-0.08	0.17**	-0.02	0.07
	(0.06)	(0.07)	(0.06)	(0.08)	(0.07)	(0.18)	(0.08)	(0.07)	(0.06)	(0.07)	(0.07)
Less than HS	0.54***	0.12	0.45***	0.26***	0.12	0.75***	0.21*	0.04	0.39***	0.09	0.18*
	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.20)	(0.09)	(0.08)	(0.07)	(0.08)	(0.08)
High School	0.55***	0.23*	0.44***	0.38***	0.28**	0.49*	0.27**	0.07	0.34***	0.23*	0.09
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.24)	(0.10)	(0.10)	(0.08)	(0.09)	(0.09)
Some post-HS	0.51**	0.18	0.44*	0.44*	0.27	0.58	0.47*	0.40*	0.52**	0.21	0.36+
	(0.19)	(0.20)	(0.19)	(0.22)	(0.21)	(0.50)	(0.21)	(0.20)	(0.16)	(0.19)	(0.20)
Minority	0.00	-0.11	0.05	-0.26	0.23	0.21	-0.05	-0.13	0.03	-0.15	0.04
	(0.16)	(0.16)	(0.15)	(0.17)	(0.15)	(0.39)	(0.18)	(0.16)	(0.15)	(0.17)	(0.17)
White	0.02	0.01	0.19*	-0.09	0.09	-0.00	0.03	-0.05	0.03	-0.11	0.09
	(0.10)	(0.11)	(0.09)	(0.11)	(0.10)	(0.26)	(0.11)	(0.11)	(0.09)	(0.11)	(0.11)
Married at age 1	0.16*	-0.07	0.06	-0.05	0.14+	0.12	-0.05	0.08	0.00	-0.04	0.10
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.19)	(0.08)	(0.08)	(0.06)	(0.08)	(0.08)
Adolescents	-0.03	0.04	-0.02	0.02	-0.03	-0.02	0.10	-0.01	-0.04	0.11	0.14+
	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.16)	(0.07)	(0.06)	(0.06)	(0.07)	(0.08)
Adults	0.05*	0.00	0.06**	0.03	0.03	0.25***	-0.03	0.07*	0.03	-0.03	0.01
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.07)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Children	-0.11***	-0.01	-0.14***	-0.04	0.02	-0.08	-0.12**	0.04	-0.13***	-0.05	-0.06
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.09)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
Intercept	-3.34***	1.31***	-1.40*	0.86	0.04	4.10+	0.37	0.13	-0.14	1.21	2.23+
	(0.39)	(0.39)	(0.58)	(0.65)	(0.65)	(2.44)	(1.04)	(0.98)	(1.02)	(1.20)	(1.24)
Random interc.	0.05**	0.03**	0.04**	0.06***	0.01	0.01	0.05**	0.00	0.02+	0.02*	0.01
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Random resid.	0.90***	1.02***	0.75***	0.97***	0.97***	5.98***	1.07***	0.97***	0.64***	0.89***	0.96***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.22)	(0.04)	(0.0350)	(0.02)	(0.03)	(0.04)

Note. All dependent variables are standardized. *** p < .001. ** p < .01. * p < .05. + p < .10.

4.2.2 India

4.2.2.1 Achievement

Table 5 indicates that in India, the urban advantage with respect to achievement was more modest than in Peru (0.23 SD-0.49 SD) and non-significant for literacy at ages eight and twelve. The size of the urban-rural differences slightly fluctuated over time, but two patterns of change across time emerged. The math gap slightly increased over time from age five (0.37 SD) to age fifteen (0.45 SD), although they had a reduction from age five to age eight (0.28 SD). The vocabulary gaps slightly decreased from age five (0.41 SD) to age fifteen (0.26 SD), although there was a peak at age eight (0.49 SD).

Most of the urbanicity advantage on achievement was fully explained by the demographic characteristics, with the exceptions of math at age five (0.17 SD) and vocabulary at age eight (0.27 SD). Furthermore, the effect of urbanicity flipped to be negative after including demographic factors in the model predicting literacy at age eight, which may suggest a suppression effect. All child and family characteristics were associated with academic achievement. Child age was associated with higher achievement at age five (0.03-0.04 SD) and eight (0.02-0.04 SD), but not later. Expenditure consistently predicted higher achievement. An increase of 1,000 rupees was associated to increments of 0.12-0.25 SD math scores and 0.11-0.18 SD vocabulary scores. Expenditure associations with math and vocabulary did not change much over time. Contrastingly, the association of expenditure and literacy became stronger over time, first showing no associations at age eight, and then increasing to 0.15 SD (age 12) and 0.24 SD (age 15) by every 1,000 rupees.

Although children of mothers with lower elementary education were not significantly different from mother with no education, higher levels of education were important and consistent predictors of achievement. In comparison to children with mothers with no education, children with mothers with upper elementary education (0.28-0.25 SD), some secondary education (0.41-0.50 SD), and some post-secondary education (0.75-1.11 SD) had higher levels of math achievement. Associations between mother education and math achievement moderately increased in strength over time. Regarding vocabulary, in comparison to children with mothers with no education, children with mothers with upper elementary education (0.21-0.23 SD), some secondary education (0.24-0.44 SD), and some post-secondary education (0.48-1.41 SD) had higher levels of achievement. These associations decreased in strength over time. Finally, in comparison to children with mothers with no education, children with mothers with upper elementary education (0.18-0.21 SD), some secondary education (0.28-0.45 SD), and some post-secondary education (0.75-0.93 SD) had higher levels of achievement. Associations between expenditure and literacy skills moderately became moderately stronger over time for the most highly educated groups.

4.2.2.2 Health

Table 6 indicates that the urban advantage with regard to health was significant and sizeable, with differences ranging between 0.46-0.67 SD for height-for-age, between 0.42-0.84 SD for BMI-for-age, and between 0.21-0.22 for general health. The only exceptions were BMI-for-age at age five and general health at age fifteen, which were not significantly different across urbanicity. After including demographic characteristics, the urbanicity gap in general health was completely explained, while differences in BMI-for-age and height-for-age remained significant. After including demographic characteristics, height-for-age gaps and the BMI-for-age gaps were reduced by between 22% and 38% (to 0.27 SD- 0.68 SD).

Multiple child and family characteristics were associated to health, although associations were scarcer than in models predicting achievement. Coefficients in Table 6 represent associations in standard deviations units on the outcome variable. Every additional adult at home was associated with an increase of 0.05-0.06 SD in height-for-age. Contrastingly, every additional child at the home was associated with decreases of 0.09-0.10 SD in health.

Caste membership did not show consistent associations with health, but the associations that emerged where in the expected direction. In comparison to children from Backward Caste (one of the lower casts), children from the Other Hindi group (the upper casts) showed greater height-for-age (0.17-0.35 SD) and BMI-for-age (0.33-0.54 SD). Additionally, expenditure consistently predicted higher height-for-age, but no other health outcomes. An increase of 1,000 rupees was associated to increments of 0.18-0.26 SD on height. Mother education was also a significant predictor of health, although results were not consistent across all levels of mother education and across outcomes. An interesting pattern emerged with regard to the strength of associations between mothers with literacy education and health. Children of mothers with lower primary education showed saliently better health (0.37-0.45 SD) than children of mothers with no education. In contrast, these associations were smaller for children with mothers with upper elementary (0.15-0.20 SD) or secondary education (0.15-0.18 SD), when compared to mothers with no education.

Table 5. Unadjusted and adjusted achievement urban-rural gaps for the Indian sample

Predictors	Age 5		Age 8			Age 12			Age 15		
	Math	Vocab.	Math	Vocab.	Litera.	Math	Vocab.	Litera.	Math	Vocab.	Litera.
	Coeff. (S.E)	*Coeff.* (S.E)	*Coeff.* (S.E)	*Coeff.* (S.E)	*Coeff.* (S.E)	*Coeff.* (S.E)	*Coeff.* (S.E)	*Coeff.* (S.E)	*Coeff.* (S.E)	*Coeff.* (S.E)	*Coeff.* (S.E)
Unadjusted											
Urban	0.37***	0.41**	0.28*	0.49***	-0.04	0.35**	0.23+	0.16	0.45***	0.26*	0.37***
	(0.09)	(0.14)	(0.13)	(0.11)	(0.13)	(0.12)	(0.13)	(0.12)	(0.11)	(0.11)	(0.11)
Intercept	-0.13**	-0.13*	-0.10+	-0.16**	-0.01	-0.10*	-0.09	-0.06	-0.12*	-0.09+	-0.09*
	(0.04)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Random effect	0.08***	0.25***	0.21***	0.14***	0.20***	0.16***	0.19***	0.17***	0.13***	0.11***	0.12***
	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Random residual	0.89***	0.70***	0.76***	0.82***	0.77***	0.82***	0.79***	0.84***	0.83***	0.92***	0.86***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Adjusted											
Urban	0.17*	0.17	0.02	0.29**	-0.24*	-0.02	-0.02	-0.13	0.06	0.07	0.04
	(0.09)	(0.12)	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)	(0.11)	(0.09)	(0.10)	(0.10)
Age	0.04***	0.03***	0.04***	0.02***	0.03***	0.01	0.01*	0.01*	0.01*	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Expenditure pc	0.16***	0.13***	0.12**	0.17***	0.02	0.25***	0.18***	0.15**	0.19***	0.11*	0.24***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Lower primary	0.50***	0.30*	0.06	-0.01	-0.25+	-0.08	0.22	0.12	0.03	0.07	-0.05
	(0.15)	(0.14)	(0.14)	(0.15)	(0.15)	(0.15)	(0.15)	(0.16)	(0.16)	(0.17)	(0.17)
Upper primary	0.21***	0.21***	0.28***	0.10+	0.18**	0.25***	0.23***	0.21***	0.25***	0.06	0.20***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Secondary	0.41***	0.43***	0.47***	0.24***	0.28***	0.50***	0.42***	0.44***	0.49***	0.25***	0.45***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)
Post-secondary	0.75***	1.41***	0.78***	0.64***	0.75***	1.01***	0.73***	0.88***	1.11***	0.48**	0.93***
	(0.15)	(0.13)	(0.14)	(0.15)	(0.15)	(0.14)	(0.14)	(0.15)	(0.15)	(0.17)	(0.15)
Scheduled caste	-0.12*	-0.01	-0.03	0.08	0.09	-0.13*	0.00	-0.01	-0.12+	0.02	-0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)
Scheduled tribe	0.19*	0.28***	-0.22**	-0.06	-0.06	-0.10	-0.10	0.06	-0.02	-0.01	-0.02
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Other Hindi	0.07	-0.00	0.13*	0.19**	0.12+	0.14*	0.12	0.18*	0.27***	0.19*	0.13+
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)
Other non-Hindi	0.05	0.164+	-0.25**	0.01	-0.01	-0.19+	-0.40***	-0.19+	-0.08	-0.19	-0.23*
	(0.10)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
Married at age 1	0.17	-0.03	-0.18	-0.47+	-0.27	-0.14	0.16	-0.11	-0.05	0.10	-0.38
	(0.25)	(0.22)	(0.22)	(0.24)	(0.24)	(0.24)	(0.24)	(0.26)	(0.25)	(0.28)	(0.263)
Adolescents	-0.06	-0.16**	-0.18**	-0.10	-0.16*	-0.20**	-0.15*	-0.19*	-0.12	-0.15+	-0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Adults	0.05**	0.03*	0.07***	0.03	0.05**	0.11***	0.07***	0.07**	0.12***	0.08***	0.04+
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Children	-0.04	-0.05*	-0.03	-0.05+	-0.07*	-0.05	-0.11**	-0.05	-0.11**	-0.15***	-0.08+
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Intercept	-3.46***	-2.42***	-4.22***	-2.21***	-2.67***	-1.42	-2.50**	-2.15*	-2.75*	-1.53	-0.11
	(0.46)	(0.41)	(0.57)	(0.62)	(0.61)	(0.90)	(0.89)	(0.93)	(1.12)	(1.21)	(1.17)
Random intercept	0.06***	0.17***	0.13***	0.11***	0.15***	0.10***	0.12***	0.11***	0.06***	0.08***	0.07***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Random residual	0.81***	0.61***	0.66***	0.77***	0.73***	0.71***	0.71***	0.77***	0.74***	0.87***	0.79***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)

Note. All dependent variables are standardized. *** p < .001. ** p < .01. * p < .05. + p < .10.

Table 6. Unadjusted and adjusted health urban-rural gaps for the Indian sample

	Age 5		Age 8			Age 12			Age 15		
	Height	**BMI**	**Height**	**BMI**	**Health**	**Height**	**BMI**	**Health**	**Height**	**BMI**	**Health**
	Coeff. (S.E)	***Coeff. (S.E)***	***Coeff. (S.E)***	***Coeff. (S.E)***	***Coeff. (S.E)***	***Coeff. (S.E)***	***Coeff. (S.E)***	***Coeff. (S.E)***	***Coeff. (S.E)***	***Coeff. (S.E)***	***Coeff. (S.E)***
Unadjusted											
Urban	0.48***	0.12	0.67***	0.42***	0.22**	0.63***	0.84***	0.21**	0.46***	0.74***	-0.11
	(0.09)	(0.08)	(0.10)	(0.08)	(0.07)	(0.08)	(0.12)	(0.08)	(0.07)	(0.09)	(0.10)
Intercept	-1.76***	-1.20***	-1.59***	-1.51***	-0.05	-1.62***	-1.57***	-0.08*	-1.59***	-1.33***	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)
Random interc	0.06**	0.05**	0.07***	0.03*	0.03**	0.04**	0.08**	0.05**	0.03*	0.03+	0.08***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)
Random resid.	1.15***	0.99***	1.27***	1.35***	0.96***	1.13***	2.11***	0.96***	0.90***	1.66***	0.93***
	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.07)	(0.03)	(0.03)	(0.06)	(0.03)
Adjusted											
Urban	0.32***	0.10	0.48***	0.32***	0.09	0.39***	0.68***	0.09	0.27***	0.65***	-0.17+
	(0.09)	(0.08)	(0.10)	(0.08)	(0.08)	(0.08)	(0.11)	(0.09)	(0.07)	(0.09)	(0.10)
Age	-0.00	-0.03***	-0.00	-0.02**	-0.00	-0.01*	-0.02+	-0.00	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Expenditure pc	0.18***	0.04	0.20***	0.07	0.04	0.26***	0.27***	0.01	0.18***	0.22***	0.08
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.08)	(0.05)	(0.05)	(0.07)	(0.05)
Lower primary	0.26	0.29+	0.28	0.39*	0.14	0.37*	0.28	-0.02	0.42*	0.45*	-0.02
	(0.17)	(0.16)	(0.19)	(0.19)	(0.16)	(0.18)	(0.25)	(0.17)	(0.17)	(0.23)	(0.18)
Upper primary	0.11	-0.12+	0.15*	-0.08	-0.07	0.19**	0.02	-0.04	0.16*	0.20*	0.06
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.09)	(0.06)	(0.06)	(0.08)	(0.06)
Secondary	0.12+	-0.00	0.18*	0.15*	0.07	0.21**	0.19+	0.02	0.15*	0.11	0.02
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.10)	(0.07)	(0.07)	(0.09)	(0.07)
Post-secondary	0.35*	0.00	0.39*	0.38*	0.37*	0.43*	0.35	0.44**	0.14	0.22	0.31+
	(0.17)	(0.16)	(0.18)	(0.19)	(0.16)	(0.17)	(0.23)	(0.16)	(0.16)	(0.21)	(0.16)
Scheduled Caste	-0.03	0.00	-0.01	0.02	-0.02	-0.03	0.18+	0.02	-0.18**	0.10	-0.18*
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.10)	(0.07)	(0.07)	(0.09)	(0.07)
Scheduled Tribe	0.09	-0.04	-0.02	0.20*	-0.04	-0.07	0.34**	-0.06	-0.16*	0.30**	-0.08
	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.11)	(0.08)	(0.07)	(0.10)	(0.09)
Other Hindi	0.35***	0.09	0.21*	0.33***	0.12	0.17*	0.54***	0.12	0.13+	0.35***	-0.02
	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.12)	(0.08)	(0.08)	(0.10)	(0.08)
Other non-Hindi	0.08	-0.02	0.12	0.02	0.25*	0.07	0.08	0.23*	0.03	0.05	-0.12
	(0.11)	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.17)	(0.12)	(0.11)	(0.15)	(0.12)
Married at age 1	-0.05	0.09	-0.15	0.07	0.10	0.06	-0.01	0.03	0.18	0.28	0.74**
	(0.30)	(0.28)	(0.30)	(0.31)	(0.27)	(0.29)	(0.41)	(0.27)	(0.27)	(0.37)	(0.28)
Adolescents	0.01	-0.12+	-0.07	0.00	-0.03	-0.04	-0.23*	0.06	0.02	-0.42***	-0.02
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.12)	(0.08)	(0.08)	(0.11)	(0.09)
Adults	0.05**	0.01	0.04*	0.04*	0.05**	0.07**	0.02	0.01	0.06**	0.02	0.05*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
Children	-0.10**	0.03	-0.06	-0.09*	-0.05	-0.10*	-0.05	-0.01	-0.09*	0.05	0.04
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.04)	(0.04)	(0.06)	(0.05)
Intercept	-1.70**	0.55	-1.64*	0.43	0.18	0.06	0.49	0.27	-1.33	0.53	0.58
	(0.53)	(0.50)	(0.76)	(0.76)	(0.66)	(1.04)	(1.44)	(0.99)	(1.17)	(1.59)	(1.23)
Random interc	0.04**	0.04**	0.06**	0.01	0.03*	0.02	0.03	0.05**	0.01	0.01	0.07***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Random resid	1.10***	0.98***	1.23***	1.32***	0.95***	1.08***	2.07***	0.93***	0.87***	1.63***	0.91***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.07)	(0.03)	(0.03)	(0.06)	(0.03)

Note. All dependent variables are standardized. *** p < .001. ** p < .01. * p < .05. + p < .10.

4.3 Aim 2: Age-specific mediators of the urban advantage in achievement and health

Next, we examined whether community characteristics and time use predicted differences between urban and rural children on achievement and health at four different ages: 5, 8, 12, and 15. For this, we examined how age specific characteristics of communities and child time-use mediated the relation between urbanicity and child outcomes at each age. All achievement and health outcomes were included, but measures of literacy and math achievement changed over time. To make our results comparable across age, outcome variables were standardized.

4.3.1 Peru

4.3.1.1 Achievement

Table 7 shows the indirect effects of urbanicity on achievement that operated through the community and time-use factors measured at each separate age. Results reported here present standardized indirect effects. Findings indicated that the achievement advantage of urban children was partially due to patterns of time-use. Table 7 indicates that advantage that urban children showed when it came to achievement was partially due to their greater studying time. Furthermore, the strength of this pathway increased over time. While every urban children's additional hour a day of studying predicted increases on achievement between 0.01 and 0.03 SD, this same time studying significantly predicted higher achievement at ages twelve (0.02 SD for all outcomes) and fifteen (0.03-0.05 SD). Time spent playing and working did not mediate the relationship between urban residency and higher achievement, but both measures of time-use were directly associated to achievement (see Direct Effects section in Table 7).

Turning to the community mediators, results showed that living in urban areas was positively associated with achievement through resources and negatively associated with achievement through stressors. Urban residency was associated to higher access to utility services at all ages, which in turn predicted higher achievement (0.11-0.46 SD). Access to utility services showed to be the strongest and most consistent factor explaining the urban advantage in achievement, surpassing the effect size of any other factor. Living in cities was associated with higher availability of educational services, which in turn predicted greater vocabulary at age five (0.05 SD), vocabulary at age eight (0.06 SD), and literacy at age twelve (0.03 SD). The achievement advantage of urban children was partially explained by the higher access to health facilities that urban children experienced. Specifically, health facilities linked the positive association of urban living with literacy at age eight (0.04 SD) and with vocabulary at age twelve (0.03 SD). Contrastingly, there were also some negative links between urban residency and achievement that operated through pollution to predict urban children's decreased literacy at age fifteen (-0.02 SD) and lower math at age eight (-0.02 SD), twelve (-0.02 SD), and fifteen (-0.02 SD). Finally, an unexpected result was obtained with regard to violent crime. Urban residency predicted higher violent crime at the community, which was positively associated to vocabulary at age fifteen (0.06 SD).

4.3.1.2 Health

Table 8 presents the results of the age-specific mediating mechanisms of the relation between place of residency and health. Results showed that the significant explanatory variables of the urban advantage in health were scarce. The urban advantage with regard to height-for-age was partially explained through more time studying. Every hour studying a day at age five was associated with an increase of 0.02 SD in height-for-age. No other time-use patterns explained the differences in health markers between urban and rural children.

Results showed that several community characteristics were significant pathways that helped explaining why urban children had better health than rural ones. Greater access to utilities in urban communities partially accounted for urban advantages in height-for-age at age five (0.16 SD), general health at age eight (0.16 SD), BMI-for-age at age twelve (0.19 SD), and height-for-age at age fifteen (0.20 SD). Urban residents enjoyed of more access to health facilities, which helped explaining the advantage of urban children when it comes to height-for-age at ages five (0.07 SD or around 0.35 cm), eight (0.06 SD), and twelve (0.11 SD). Finally, greater access to health facilities also partially explained the advantage that urban children have with regard to BMI-for-age at age 15 (0.05 SD).

4.3.2 India

4.3.2.1 Achievement

Table 9 presents the results testing the mediating mechanisms that help explaining the advantage that Indian urban children had in achievement. Results reported here reflect standardized indirect effects. Every additional hour a day allocated to studying partially accounted for urban advantage in vocabulary at age five (0.06 SD), math at age five (0.06 SD), vocabulary at age fifteen (0.04 SD), math at age fifteen (0.06), and literacy at age fifteen (0.06 SD). At age twelve, every additional hour of studying a day marginally ($p<.10$) explained the urban children's advantage in math (0.04 SD), vocabulary (0.03 SD), and literacy (0.04 SD). Although results were not significative at the $p<.05$ cutoff, they indicate that more time studying was a consistent factor in explaining the urban children's advantage in achievement.

Turning to community factors, the greater access to utility services and to more educational services that urban residents enjoyed, partially explained the higher achievement scores of urban children in comparison to rural ones at age five. Specifically, urban access to an additional utility or educational service predicted an increase of 0.14 SD and of 0.18, respectively, in vocabulary skills at age five. Simultaneously, results indicated that several community mechanisms linked urban residency with decreased achievement. Specifically, an additional pollution problem in urban areas linked urban residency with lower levels of vocabulary at ages eight (-0.06 SD) and twelve (-0.03 SD). In addition, urban living was associated with higher rates of violent crime, which predicted lower math achievement at age twelve (-0.05 SD), vocabulary skills at age twelve (0.06 SD), literacy at age twelve (0.07 SD), and math skills at age fifteen (-0.05 SD).

4.3.2.2 Health

Table 10 indicates that in India, we found scarce significant paths that explained why urban children had better health than rural ones. Every additional hour spent studying by urban children partially explained their advantage with respect to height-for-age at age five (0.05 SD) and BMI-for-age at age fifteen (0.07 SD). Contrastingly, living in cities was associated with more pollution problems, each of which predicted worsening general health by -0.04 SD for urban habitants at age twelve. In addition, living in urban communities in which violent crime is problematic predicted worse height-for-age at age five (-0.02 SD), worse BMI-for-age at age five (-0.03 SD), and worse general health at age twelve (-0.04 SD) for urban residents in comparison to rural. Estimates also showed some unexpected results with respect of the number of health facilities available in the community. Specifically, the higher number of health facilities available in cities negatively linked urban residency and general health at age twelve (-0.13 SD) and BMI-for-age at age 15 (-0.12 SD).

Table 7. Age specific mediation models of achievement outcomes for the Peruvian sample

Predictors	Age 5		Age 8			Age 12			Age 15		
	Math	Vocab.	Math	Vocab.	Literacy	Math	Vocab.	Literacy	Math	Vocab.	Literacy
	Coeff. *(S.E)*	*Coeff.* *(S.E)*	*Coeff.* *(S.E)*	*Coeff.* *(S.E)*	*Coeff.* *(S.E)*	*Coeff.* *(S.E)*	*Coeff.* *(S.E)*	*Coeff.* *(S.E)*	*Coeff.* *(S.E)*	*Coeff.* *(S.E)*	*Coeff.* *(S.E)*
Direct effects											
Hs. labor	0.00	-0.01	0.04*	0.02	-0.00	0.00	0.00	0.03	-0.04*	-0.03*	-0.02
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Hs. play	0.01	0.02	0.03*	0.03+	0.03	-0.03+	-0.00	-0.00	-0.04*	-0.02	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Hs. study	0.08***	0.07***	0.11***	0.07***	0.06**	0.06**	0.07***	0.06**	0.07***	0.06***	0.10***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Pollution problems	-0.00	-0.03*	-0.04**	-0.01	0.00	-0.06**	-0.02	-0.03+	-0.05**	-0.04+	-0.04*
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Violent crime	-0.02	-0.05	0.11	0.01	0.08	0.02	0.09+	0.02	0.08	0.26*	0.02
	(0.08)	(0.05)	(0.08)	(0.08)	(0.08)	(0.10)	(0.05)	(0.08)	(0.11)	(0.11)	(0.10)
Utility services	0.05+	0.08***	0.08**	0.15***	0.08**	0.07*	0.14***	0.06*	0.08*	0.19***	0.04
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Educ. services	0.01	0.03***	0.01	0.03*	0.01	0.02	0.02	0.03+	0.01	-0.00	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Health facilities	-0.04	0.01	0.17	0.13	0.23*	0.03	0.16	0.03	0.01	0.18	0.03
	(0.11)	(0.08)	(0.11)	(0.11)	(0.11)	(0.12)	(0.10)	(0.10)	(0.12)	(0.12)	(0.10)
Urban	-0.01	0.16*	0.09	0.21*	0.23*	0.24*	0.14	0.18+	0.10	0.06	0.24*
	(0.09)	(0.07)	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)	(0.09)	(0.11)	(0.11)	(0.10)
Intercept	-3.68***	-4.38***	-7.96***	-6.25***	-4.71***	-4.24***	-4.68***	-4.67***	-1.11	-4.44***	-4.81***
	(0.37)	(0.28)	(0.59)	(0.57)	(0.67)	(0.92)	(0.82)	(0.92)	(1.19)	(1.08)	(1.20)
Random intercept	0.05*	0.02**	0.03*	0.04*	0.03*	0.03*	0.02*	0.00	0.01	0.04*	0.00
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)
Random residual	0.72***	0.40***	0.61***	0.53***	0.70***	0.68***	0.55***	0.70***	0.71***	0.56***	0.73***
	(0.03)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Indirect effects											
Urban → hs. labor	-0.00	0.01	-0.02+	-0.01	0.00	-0.00	-0.01	-0.02	0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	0.01	(0.01)	(0.01)	(0.00)
Urban → hs. play	0.00	0.01	0.01	0.01	0.01	-0.01+	-0.00	-0.00	-0.01+	-0.01	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	0.01	(0.01)	(0.00)	(0.01)	(0.01)
Urban → hs. study	0.03+	0.02+	0.02+	0.01+	0.01	0.02*	0.02**	0.02*	0.03*	0.03*	0.05**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Urban → Pollution prob.	-0.00	-0.01	-0.02*	0.00	0.00	-0.03*	-0.01	-0.01	-0.03*	-0.02+	-0.02*
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Urban → Violent crime	-0.01	-001	0.02	0.01	0.02	0.00	0.04+	0.01	0.02	0.06*	0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	0.02	(0.02)	(0.03)	(0.03)	(0.02)
Urban → Utility services	0.16*	0.19***	0.20***	0.39***	0.22**	0.17*	0.36***	0.16*	0.20*	0.46***	0.11
	(0.06)	(0.05)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)
Urban → Educ. services	0.01	0.05***	0.03	0.06*	0.00	0.03	0.01	0.03+	0.01	-0.01	0.03
	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	0.02	(0.01)	(0.03)	(0.03)	(0.03)
Urban → Health facility	-0.00	0.00	0.03	0.03	0.04*	0.01	0.03*	-0.00	0.00	0.04	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	0.02	(0.02)	(0.02)	(0.02)	(0.02)

Notes. All dependent variables are standardized. All models control for child age, gender, race/ethnicity, mother education, marital status, household composition, household expenditure.
*** p < .001. ** p < .01. * p < .05. + p < .10.

Table 8. Age specific mediation model of health outcomes for the Peruvian sample

Predictors	Age 5		Age 8			Age 12			Age 15		
	Height	BMI	Height	BMI	Health	Height	BMI	Health	Height	BMI	Health
	Coeff. (S.E)	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*	*Coeff. (S.E)*
Direct effects											
Hs. labor	0.00	-0.00	-0.00	0.02	0.00	-0.001	0.02	-0.02	-0.01	0.02	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Hs. play	-0.00	0.00	-0.01	-0.00	-0.01	0.04	-0.00	-0.00	-0.00	0.02	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Hs. study	0.05***	0.01	0.05*	0.06*	0.06**	-0.02	0.03	0.05*	0.00	0.02	-0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.06)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Pollution problems	0.03+	-0.02	0.01	-0.00	0.02	0.01	0.01	0.02	0.01	0.01	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Violent crime	-0.09	0.08	-0.07	0.21*	0.02	0.12	0.19+	0.07	-0.06	0.13	-0.06
	(0.07)	(0.08)	(0.08)	(0.10)	(0.07)	(0.24)	(0.12)	(0.09)	(0.10)	(0.12)	(0.12)
Utility services	0.06*	0.00	0.03	0.02	0.06*	0.07	0.08*	0.02	0.08**	0.06	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.08)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Educ. services	0.00	-0.01	0.01	0.00	0.01	-0.00	0.05*	-0.01	0.01	0.02	0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Health facilities	0.35**	0.07	0.28*	0.11	0.07	0.61*	0.20	0.12	0.17	0.26*	-0.15
	(0.12)	(0.12)	(0.11)	(0.14)	(0.12)	(0.30)	(0.14)	(0.11)	(0.11)	(0.13)	(0.12)
Urban	0.20*	-0.06	0.27**	0.00	0.19*	0.15	0.04	-0.11	0.03	-0.02	0.13
	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)	(0.27)	(0.12)	(0.11)	(0.10)	(0.12)	(0.12)
Intercept	-3.24***	1.54***	-1.86**	0.31	-0.25	3.12	-0.20	-0.54	-0.74	0.58	3.40*
	(0.41)	(0.42)	(0.65)	(0.73)	(0.72)	(2.76)	(1.14)	(1.07)	(1.10)	(1.29)	(1.34)
Random interc.	0.03*	0.03**	0.03*	0.06***	0.00	0.02	0.04*	0.00	0.01	0.02*	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Random resid.	0.90***	1.01***	0.75***	0.95***	0.95***	6.30***	1.05***	0.95***	0.60***	0.83***	0.91***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.24)	(0.04)	(0.04)	(0.02)	(0.03)	(0.04)
Indirect effects											
Urban → hs. labor	0.00	0.00	0.00	-0.01	-0.00	0.00	-0.01	0.01	0.00	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Urban → hs. play	-0.00	-0.00	-0.00	0.00	-0.00	0.01	-0.00	-0.00	0.00	0.01	0.00
	(0.00)	(0.00)	(0.00)	0.00	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Urban → hs. study	0.02*	0.01	0.01+	0.01+	0.01	-0.01	-0.01	0.01+	0.00	0.01	-0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Urban → Pollution prob.	0.01	-0.01	0.00	-0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.02+
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Urban → Violent crime	-0.01	0.02	-0.02	0.05*	-0.00	0.03	0.05	0.02	-0.01	0.03	-0.01
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.06)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
Urban → Utility services	0.16*	0.03	0.07	0.11	0.16*	0.18	0.19*	0.05	0.20**	0.15+	0.05
	(0.06)	(0.07)	(0.06)	(0.11)	(0.07)	(0.21)	(0.09)	(0.07)	(0.07)	(0.09)	(0.09)
Urban → Educ. services	0.01	-0.02	0.03	-0.01	0.02	0.00	0.07*	0.02	0.02	0.03	0.02
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.06)	0.03	(0.02)	(0.02)	(0.03)	(0.03)
Urban → Health facility	0.07**	0.01	0.06*	0.02	0.02	0.11*	0.04	0.00	0.02	0.05*	0.02
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.06)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)

Note. All dependent variables are standardized. All models control for child age, gender, race/ethnicity, mother education, marital status, household composition, household expenditure.
*** p < .001. ** p < .01. * p < .05. + p < .10.

Table 9. Age specific mediation model of achievement outcomes for the Indian sample

Predictors	Age 5		Age 8			Age 12			Age 15		
	Math	Vocab.	Math	Vocab.	Literacy	Math	Vocab.	Literacy	Math	Vocab.	Literacy
	Coeff.	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*
	(S.E)	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*
Direct effects											
Hs. labor	0.09*	0.00	0.10**	-0.00	0.10**	0.01	-0.02	0.04	-0.07*	-0.05	-0.01
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Hs. play	0.02	0.04**	0.08***	0.04+	0.03	0.01	-0.00	0.04+	-0.01	-0.01	0.01
	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Hs. study	0.07***	0.07***	0.20***	0.12***	0.13***	0.13***	0.09***	0.12***	0.09***	0.06**	0.10***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Pollution problems	-0.01	0.02	-0.04+	-0.07**	-0.05*	-0.05*	-0.06*	-0.03	-0.04*	-0.05*	-0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Violent crime	-0.10	-0.18	-0.31	-0.37	-0.38	-0.48*	-0.59*	-0.59*	-0.47*	-0.29	-0.22
	(0.13)	(0.15)	(0.22)	(0.23)	(0.24)	(0.22)	(0.24)	(0.24)	(0.19)	(0.23)	(0.21)
Utility services	0.07+	0.11**	-0.01	0.02	0.03	-0.02	0.04	0.025	-0.02	-0.02	-0.02
	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Educ. services	0.06	0.25***	0.12	-0.03	0.17	0.03	0.10+	0.07	0.03	0.01	0.02
	(0.05)	(0.05)	(0.10)	(0.10)	(0.11)	(0.05)	(0.06)	(0.06)	(0.02)	(0.03)	(0.02)
Health facilities	0.01	0.05	0.02	0.02	0.02	0.01	0.03	-0.02	-0.03	0.03	0.00
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Urban	0.03	-0.18	-0.10	0.26+	-0.43**	0.01	-0.15	-0.16	0.09	-0.00	0.00
	(0.11)	(0.13)	(0.14)	(0.14)	(0.15)	(0.13)	(0.13)	(0.14)	(0.12)	(0.15)	(0.13)
Intercept	-3.35***	-4.34***	-6.16***	-3.46***	-3.94***	-2.35*	-2.97**	-3.44***	-3.40**	-2.21+	-1.76
	(0.69)	(0.60)	(0.69)	(0.76)	(0.75)	(0.94)	(0.93)	(0.98)	(1.20)	(1.30)	(1.24)
Random interc.	0.00+	0.00+	0.06**	0.06**	0.06**	0.00	0.001	0.00	0.47**	0.47**	0.47**
	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.15)	(0.15)	(0.15)
Random resid.	0.78***	0.61***	0.63***	0.77***	0.72***	0.68***	0.66***	0.73***	0.69***	0.77***	0.72***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Indirect effects											
Urban → hs. labor	-0.01	-0.00	-0.02+	0.00	-0.02+	0-.00	0.00	-0.01	0.03	0.02	0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Urban → hs. play	-0.01	0.01	0.02	0.01	0.01	0.00	0.00	0.00	-0.00	-0.00	0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Urban → hs. study	0.06*	0.06**	0.03+	0.02+	-0.01	0.04+	0.03+	0.04+	0.06**	0.04*	0.06**
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Urban → Pollution prob.	-0.01	0.03	-0.04+	-0.06**	-0.04+	-0.03+	-0.03*	-0.02	-0.01	-0.01	-0.00
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Urban → Violent crime	0.01	0.01	-0.00	-0.00	-0.00	-0.05*	-0.06*	-0.07*	-0.05*	-0.03	-0.02
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	0.02	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Urban → Utility services	0.09+	0.14**	-0.02	0.03	0.03	-0.03	0.04	0.04	-0.04	-0.04	0.04
	(0.05)	(0.05)	(0.07)	(0.08)	(0.08)	(0.08)	(0.06)	(0.08)	(0.09)	(0.11)	(0.09)
Urban → Educ. services	0.04	0.18***	0.08	-0.02	0.12	0.02	0.04+	0.03	0.01	0.02	0.02
	(0.03)	(0.04)	(0.07)	(0.07)	(0.07)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Urban → Health facility	-0.01	-0.02	0.05	0.04	-0.04	-0.01	-0.02	-0.03	-0.05	0.06	0.00
	(0.01)	(0.02)	(0.07)	(0.07)	(0.08)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)

Note. All dependent variables are standardized. All models control for child age, gender, race/ethnicity, mother education, marital status, household composition, household expenditure.
*** p < .001. ** p < .01. * p < .05. + p < .10.

Table 10. Age specific mediation model of health outcomes for the Indian sample

Predictors	Age 5		Age 8			Age 12			Age 15		
	Height	BMI	Height	BMI	Health	Height	BMI	Health	Height	BMI	Health
	Coeff.	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*
	(S.E)	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*	*(S.E)*
Direct effects											
Hs. labor	-0.06	0.05	0.13**	-0.01	-0.01	0.07+	0.03	0.04	0.04	0.09+	0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)	(0.05)	(0.04)
Hs. play	-0.02	-0.01	0.07*	-0.01	-0.03	-0.04	0.00	0.10***	-0.00	0.02	-0.00
	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
Hs. study	0.06***	-0.00	0.11**	-0.03	0.03	0.05*	0.06+	0.08***	0.04*	0.11***	-0.01
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)
Pollution prob.	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03+	-0.04	-0.07***	-0.05**	-0.09***	0.05*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Violent crime	-0.31*	-0.37**	0.09	-0.42*	-0.19	0.20	-0.67**	-0.44*	0.11	-0.17	-0.05
	(0.13)	(0.12)	(0.24)	(0.19)	(0.18)	(0.19)	(0.26)	(0.19)	(0.17)	(0.23)	(0.24)
Utility services	0.01	-0.02	0.05	0.04	-0.04	-0.01	-0.01	0.04	-0.03	-0.01	0.01
	(0.04)	(0.04)	(0.06)	(0.05)	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)	(0.06)	(0.06)
Educ. services	0.06	0.06	0.02	0.00	0.07	0.03	0.01	0.06	-0.02	0.05+	-0.04
	(0.05)	(0.04)	(0.10)	(0.08)	(0.08)	(0.05)	(0.06)	(0.05)	(0.02)	(0.03)	(0.03)
Health facility	-0.02	0.04	-0.02	0.02	0.01	-0.00	-0.02	-0.07**	-0.03	-0.10**	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
Urban	0.28*	0.13	0.47**	0.271*	0.07	0.44***	0.78***	0.24*	0.39***	0.75***	-0.15
	(0.12)	(0.11)	(0.15)	(0.11)	(0.11)	(0.11)	(0.15)	(0.11)	(0.11)	(0.15)	(0.16)
Intercept	-0.93	0.09	-2.70**	0.27	0.38	0.26	1.23	-0.38	-1.33	1.35	-0.20
	(0.69)	(0.72)	(0.92)	(0.91)	(0.77)	(1.09)	(1.54)	(1.03)	(1.30)	(1.75)	(1.37)
Random interc.	0.00+	0.00+	0.059**	0.06**	0.06**	0.00	0.00	0.00	0.48**	0.47**	0.47**
	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.15)	(0.15)	(0.15)
Random resid.	1.09***	1.00***	1.24***	1.33***	0.90***	1.03***	2.07***	0.89***	0.85***	1.53***	0.88***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.03)	(0.04)	(0.08)	(0.03)	(0.03)	(0.06)	(0.03)
Indirect effects											
Urban → hs. labor	0.00	-0.00	-0.02+	0.00	0.00	-0.02	-0.01	-0.01	-0.02	-0.04	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)
Urban → hs. play	-0.01	-0.00	0.02	-0.00	-0.01	-0.00	0.00	0.01	0.00	0.00	-0.00
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)
Urban → hs. study	0.05*	-0.00	-0.01	0.00	0.00	0.02	0.02	0.03+	0.03+	0.07*	-0.01
	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.32)	(0.01)
Urban → Pollution prob.	-0.02	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02	-0.04**	-0.01+	-0.01	0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	0.01	(0.01)	(0.01)	(0.01)
Urban → Violent crime	-0.02*	-0.03**	0.00	-0.00	-0.00	0.02	0.02	-0.04*	0.01	-0.02	-0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Urban → Utility services	0.01	-0.02	0.08	0.06	-0.05	0.02	0.01	0.06	0.06	-0.01	0.02
	(0.05)	(0.04)	(0.08)	(0.07)	(0.06)	(0.07)	(0.08)	(0.07)	(0.09)	(0.11)	(0.11)
Urban → Educ. services	0.04	0.04	0.00	-0.01	0.05	0.01	0.01	0.01	-0.02	0.04+	0.04+
	(0.03)	(0.03)	(0.07)	(0.05)	(005)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Urban → Health facility	0.01	0.02	0.00	0.05	0.03	-0.01	-0.01	-0.13**	-0.05	-0.17*	0.01
	(0.01)	(0.01)	(0.08)	(0.07)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)

Notes. All dependent variables are standardized. All models control for child age, gender, race/ethnicity, mother education, marital status, household composition, household expenditure.
*** p < .001. ** p < .01. * p < .05. + p < .10.

4.4 Aim 3: Trajectories of achievement and health by urbanicity and their contributing factors

Next, we examined whether community characteristics and time use predicted differences in the developmental trajectories of urban and rural children from age five to age fifteen. For this, we examined how aggregated characteristics of communities and child time-use (from age five to age fifteen) mediated the relation between urbanicity and overall trajectories of development. Only receptive vocabulary and height were analyzed at this step given that these were the only child outcomes captured using comparable measures over time. It is important to note that the range of the receptive vocabulary measure differs in Peru and India. For the Indian sample, only 57 items shown to be valid were used. In the Peruvian sample, the full 125 items of the PPVT version adapted to Spanish was used.

4.4.1 Peru

Results of vocabulary and height growth models indicated that a linear pattern fitted the model well (figures 4 and 5). Estimates of growth models for vocabulary and health outcomes in the Peruvian sample are displayed in Table 11.

4.4.1.1 Vocabulary

The “Urbanicity” column of Table 11 presents estimates of the urban-rural differences at the intercept (age 5) and monthly slope. Results of the intercept indicated that by age five, urban children displayed 22.96 (1.29 SD) more points on receptive vocabulary in comparison to rural children. The gap at age five was large but did not change over time (see Figure 4), as both urban and rural children showed similar rates of gains by month (0.55-0.56 points or 0.03 SD). Even after adjusting for child and family demographics ("Demographics" column), urban-rural gaps remained large at age five (14.02 points, 0.79 SD) and remained stable as children progressed from early childhood through adolescence.

Cumulative measures of community factors and time-use were entered in the estimates presented in the "Full model" column. Results estimating variance at the intercept indicated that urban residency at age five was positively associated with vocabulary via time studying. Every additional hour a day of studying predicted an increase of 2.46 points (0.14 SD) for urban 5-year-old children. Results of examining community explanatory variables of the urban advantage at the intercept, indicated that the urban advantage on vocabulary skills was partially explained by the availability of utility services (3.27 points or 0.18 SD by each additional service) and more educational services (2.38 points or 0.18 SD by service). Although results of direct effects indicated that every additional pollution problem predicted a decrease of 0.43 (0.02 SD) points in vocabulary skills at age five, this association did not explain urbanicity differences in vocabulary.

Even though there was no significant difference between the urban and rural rate of growth (slope) in vocabulary, results indicated that urban children spent less time working and more time studying, which predicted higher, albeit small, monthly increase in vocabulary skills. Every fewer hour of time working predicted gains of 0.013 (0.001 SD) points for urban children in comparison to rural. Every additional hour of time studying was associated to more 0.008 points (0.001 SD) in receptive vocabulary for urban children in comparison to rural. Results examining community mediators indicated that no community factors were found to predict children's growth in achievement.

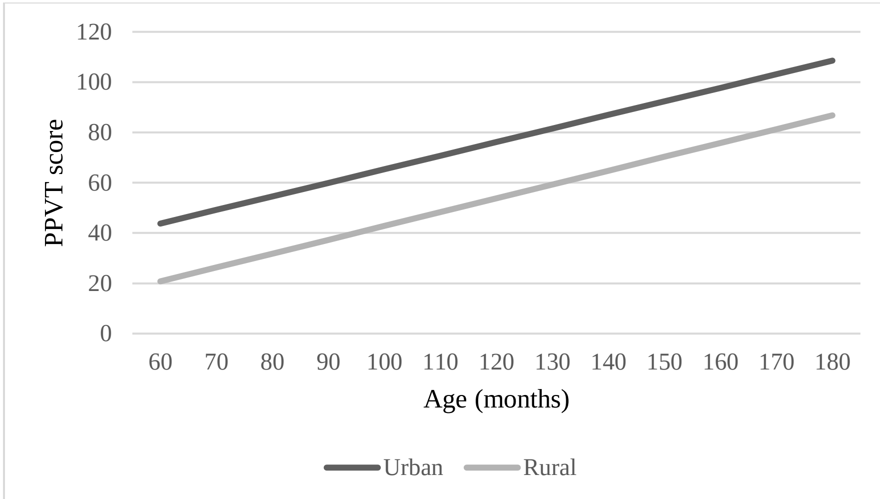

Figure 4. Trajectories of perceptive vocabulary by urbanicity in Peru

4.4.1.2 Height

The "Urbanicity" column of Table 11 presents estimates of the urban-rural differences at the intercept (age 5) and monthly slope. Results for height trajectories showed, as with achievement, that there was a large urbanicity gap at age five and it remained stable over time (see Figure 5). Results of the intercept showed that by age five there was already an urban advantage on height. While rural children had an average height of 99.85 cm, urban children had a very considerable difference of 7.19 more centimeters in height. The rate of growth (slope) by month (0.45 cm) was not significantly different for urban children in comparison to rural ones. After adjusting for child and family demographics ("Demographics" column), urban-rural gaps reduced by 64% but remained significant at the intercept (2.56 cm) and continued to be stable as children progressed from early childhood through adolescence.

Cumulative measures of community factors and time-use were entered in the estimates presented in the "Full model" column. Regarding factors that explained links between urbanicity and height at the intercept, we found time-use partially explained urban advantage on height. Every additional hour per day that urban children spent studying predicted an increase of 1.02cm at age five. Results also showed that higher availability of health facilities in cities partially explained the urban advantage with respect to height (0.73 cm). No community or time-use variables significantly predicted the slope of height.

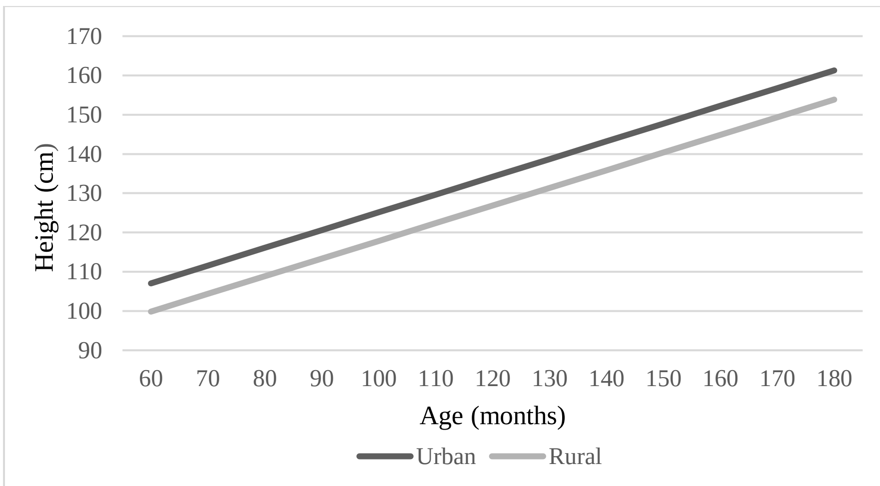

Figure 5. Trajectories of height by urbanicity in Peru

Table 11. Peru growth models: unconditional and conditional by urbanicity

Mediators	Vocabulary						Height					
	Urbanicity		Demographics		Full model		Urbanicity		Demographics		Full model	
	Coeff.	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*
Direct effects												
Intercept												
Urban	22.96***	1.96	14.02***	1.91	8.60***	1.69	7.19***	0.65	2.56***	0.72	2.47***	0.67
Pollution					-0.43*	0.21					0.12	0.10
Utility services					0.98**	0.37					0.26+	0.15
Education services					0.76***	0.16					0.11	0.10
Violent crime					-0.69	0.86					-0.39	0.48
Health facilities					1.52	1.67					2.70***	0.72
Hours labor					0.08	0.26					0.15	0.12
Hours Studying					1.37***	0.14					0.57***	0.07
Hours playing					0.13	0.14					-0.01	0.07
Intercept	20.79***	1.08	18.00***	1.51	24.71***	1.38	99.85***	0.32	97.27***	0.71	95.59***	0.85
Slope												
Urban	-0.01	0.02	-0.02	0.02	-0.030	0.020	0.002	0.003	0.004	0.005	0.003	0.005
Pollution					-0.004	0.002					-0.001	0.001
Utility services					0.009	0.006					0.001	0.002
Education services					-0.004*	0.002					0.000	0.001
Violent crime					-0.010	0.014					0.003	0.005
Health facilities					0.020	0.023					-0.011	0.008
Hours labor					-0.012***	0.004					-0.002	0.001
Hours studying					0.010***	0.003					-0.003+	0.001
Hours playing					0.002	0.004					0.000	0.001
Intercept	0.55***	0.01	0.55***	0.02	0.587***	0.022	0.45***	0.003	0.47***	0.01	0.49***	0.02
Random variances												
Intercept	125.08***	14.05	62.43***	9.36	50.78***	9.08	24.99***	1.97	19.52***	1.42	18.08***	1.23
Slope	0.000	0.002	0.001	0.002	0.001	0.002	0.000	0.000	0.000	0.000	0.000	0.000
Indirect effects												
Intercept												
Urban→ Pollution					-0.194	0.307					0.056	0.097
Urban→ Utility					3.268**	1.231					0.860+	0.509
Urban→ Education					2.380***	0.699					0.351	0.310
Urban→ Crime					-0.228	0.288					-0.128	0.157
Urban→ Health					0.414	0.485					0.732**	0.256
Urban→ Hs labor					-0.070	0.235					-0.137	0.112
Urban→ Hs study					2.458***	0.565					1.022***	0.270
Urban→ Hs play					-0.012	0.033					0.001	0.007
Slope												
Urban→ Pollution					-0.002	0.003					0.000	0.001
Urban→ Utility					0.026	0.018					0.001	0.005
Urban→ Education					0.001	0.005					-0.001	0.002
Urban→ Crime					-0.003	0.004					0.001	0.001
Urban→ Health					-0.005	0.006					-0.003	0.002
Urban→ Hs labor					0.013**	0.004					0.002	0.002
Urban→ Hs study					0.008**	0.003					-0.002	0.001
Urban→ Hs play					0.001	0.001					0.000	0.000

Note. Demographics and Full models control for child age, gender, race/ethnicity, mother education, marital status, household composition, household expenditure. *** p < .001. ** p < .01. * p < .05. + p < .10

4.4.2 India

Results of vocabulary and height growth models indicated that a linear pattern fitted the models well. Estimates of growth models in the Indian sample are displayed in Table 12.

4.4.2.1 Vocabulary

The "Urbanicity" column of Table 12 presents estimates of the urban-rural differences at the intercept (age 5) and monthly slope. Results showed that there was a urbanicity gap of 3.88 points (0.39 SD) at age five in vocabulary and that it closed over time as urban children made gains at a slightly lower monthly rate (0.28 points, 0.05 SD) than rural ones (0.30 points, 0.05 SD). See Figure 6. After adjusting for child and family demographics ("Demographics" column), urban-rural gaps were reduced by 43% but remained significant at age five with urban children displaying 2.20 more points (0.22 SD). Results for the slope indicated that the demographic characteristics fully explained the urban-rural differences on vocabulary monthly growth.

Estimates of the cumulative measures of community factors and time-use that explained differences in the vocabulary trajectories of urban and rural children are presented in the "Full model" column. The higher access to utility services and more time studying than urban children experienced at age five partially explained the urban advantage at the intercept. An additional hour a day that urban children spent studying was associated with an increase of 0.45 points in the vocabulary measure at the intercept. Every additional utility service experienced in cities predicted an increase of 1.31 (0.13 SD) in vocabulary scores at age five. Regarding the explanatory variables of the vocabulary slope, results indicated that urban children spent less time working and more time studying, which predicted slightly higher learning scores for urban children in comparison to rural. An additional hour a day that urban children spent studying was associated with a monthly increase of 0.008 points (0.001 SD) in the vocabulary measure. In addition, every fewer hours a day that urban children spent working, in comparison to rural ones, was associated with 0.013 (0.002 SD) more vocabulary scores by month. Surprisingly, higher access to utility services negatively predicted growth in vocabulary scores, which in turn translated into lower learning rates of urban children vs rural (-0.015 points, 0.002 SD).

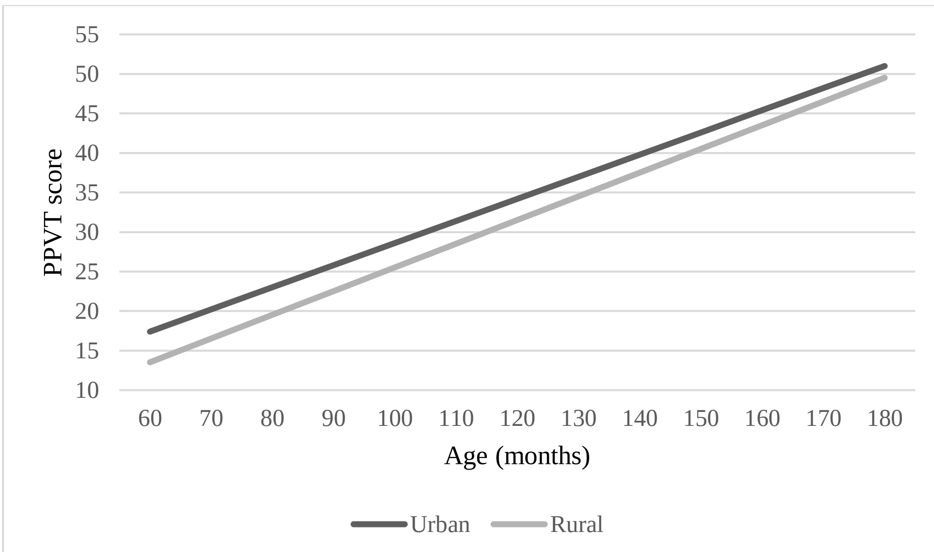

Figure 6. Trajectories of perceptive vocabulary by urbanicity in India

4.4.2.2 Height

Estimates of the urban-rural differences at the intercept (age 5) and monthly slope are presented in the "Urbanicity" column of Table 12. By age five, rural children had a height of 103.43 cm on averaged, being surpassed by 2.19 cm by their urban counterparts. The rate of growth by month was also higher for urban children (0.47 cm) in comparison to rural ones (0.45 cm), indicating that the urban-rural gap was not too large, but significant and that it slightly increased over time (see Figure 7). After adjusting for child and family demographics ("Demographics" column), urban-rural gaps reduced by 39% but remained significant at age five with urban children displaying 1.32 more centimeters in height. Similar to the vocabulary slope, results for the height slope indicated that the demographic characteristics fully explained the urban-rural differences on monthly growth.

Estimates of the cumulative measures of community factors and time-use that explained differences in the height trajectories of urban and rural children are presented in the "Full model" column. Results showed that no community factors mediated the associations between urbanicity and height trajectories. Contrastingly, time-use showed to be a significant predictor of both the intercept and the slope. Mediators of the urban-rural differences at the intercept were scarce. According to results for direct effects on the intercept, every hour a day more of working was directly and negatively associated with height, while every hour of time studying was positively associated with height. Urban children spent less time working and more time studying, which predicted increases of 0.061 cm and 0.232 in height, for urban children at age five, respectively, but only at a marginal level of significance. Surprisingly, results of direct effects for the slope showed every hour per day of more working (0.016) was directly associated with an increase of 0.016cm in physical growth. Thus, results of indirect effects showed that while more time studying in cities predicted higher growth for urban children, more time working in rural areas predicted higher growth for rural children. On the one hand, living in rural areas was associated with more time working, which in turn was positively associated with height. This translated into a negative pathway of urban residency and height (-0.008 cm per every hour of work a day). On the other hand, living in urban areas was associated with more time studying, which in turn predicted higher physical growth (0.009 cm per every hour of study a day).

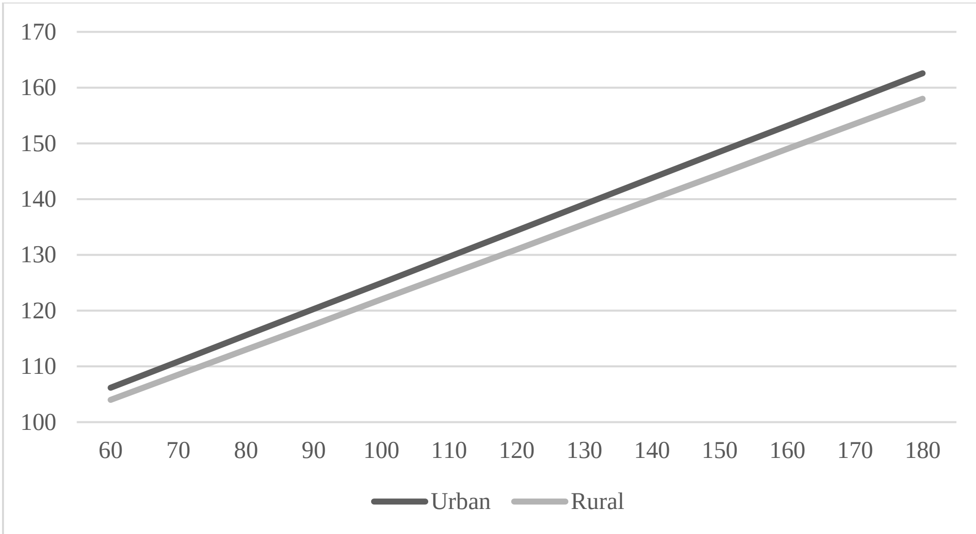

Figure 7. Trajectories of height by urbanicity in India

Table 12. India growth models: unconditional and conditional by urbanicity

	Vocabulary						Height					
	Urbanicity		Demographics		Full model		Urbanicity		Demographics		Full model	
	Coeff.	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*	*Coeff.*	*S.E*
Direct effects												
Intercept												
Urban	3.88***	1.12	2.20*	0.97	0.41	0.91	2.17***	0.39	1.32***	0.38	1.10+	0.58
Pollution					0.23+	0.13					-0.09	0.13
Utility services					0.97***	0.24					0.04	0.18
Education services					0.25	0.20					0.14	0.21
Violent crime					-0.85	0.46					1.33	0.82
Health facilities					-0.03	0.14					-0.16	0.14
Hours labor					0.30+	0.16					-0.41*	0.20
Hours studying					0.34***	0.09					0.18*	0.09
Hours playing					0.15*	0.08					-0.19*	0.09
Intercept	13.52**	0.38	12.29***	2.03	13.62***	2.00	104***	0.24	103***	1.18	104***	1.12
Slope												
Urban	-0.02**	0.01	-0.02+	0.012	-0.013	0.012	0.02***	0.01	0.014+	0.008	0.013	0.010
Pollution					-0.003*	0.001					-0.001	0.002
Utility services					-0.008*	0.004					0.002	0.003
Education services					0.001	0.002					0.003+	0.002
Violent crime					-0.027+	0.014					0.005	0.013
Health facilities					0.000	0.002					-0.002	0.002
Hours labor					-0.007**	0.003					0.016***	0.003
Hours studying					0.007**	0.002					0.010***	0.002
Hours playing					-0.002	0.002					0.004*	0.002
Intercept	0.30*	0.00	0.25***	0.03	0.28***	0.03	0.45***	0.00	0.43***	0.02	0.45***	0.020
Random variances												
Intercept	9.76**	3.01	6.07*	2.83	4.66+	2.74	22.51***	1.44	21.35***	1.50	20.50***	1.45
Slope	0.001	0.001	0.001	0.001	0.000	0.000	0.002***	0.001	0.002***	0.001	0.002***	0.001
Indirect effects												
Intercept												
Urban→ Pollution					0.247	0.196					-0.098	0.148
Urban→ Utility					1.31***	0.330					0.051	0.240
Urban→ Education					0.178	0.150					0.100	0.151
Urban→ Crime					0.048	0.044					-0.109	0.072
Urban→ Health					0.007	0.039					0.046	0.060
Urban→ Hs labor					-0.044	0.028					0.061+	0.032
Urban→ Hs study					0.452**	0.158					0.232+	0.131
Urban→ Hs play					-0.098	0.077					0.120	0.105
Slope												
Urban→ Pollution					-0.001	0.001					0.000	0.001
Urban→ Utility					-0.015*	0.007					0.004	0.006
Urban→ Education					0.001	0.002					0.003	0.002
Urban→ Crime					-0.002	0.002					0.000	0.001
Urban→ Health					0.001	0.004					-0.005	0.004
Urban→ Hs labor					0.004*	0.001					-0.008***	0.002
Urban→ Hs study					0.006*	0.003					0.009***	0.003
Urban→ Hs play					0.001	0.001					-0.001	0.001

Note. All models control for child age, gender, race/ethnicity, mother education, marital status, household composition, household expenditure. *** p < .001. ** p < .01. * p < .05. + p < .10

4.5 Sensitivity analysis of household expenditure and mother education as mediators

We estimated an additional step to test for the accuracy of our model specification. Our models showed that time-use and community characteristics significantly explained urban-rural differences on achievement and health, but the effect sizes of our main explanatory variables were occasionally surpassed by the direct effects of mother education and expenditure. It could be that mother education and family expenditures are mediators of the relation between urban residency and levels of achievement and health, instead of being merely control variables. In fact, researchers have shown that urban families have higher expenditures because urban residents have higher levels of industrialization and economic development, which relates to higher job availability and higher wages (Dobbs et al., 2012). Services and good in urban areas are also more expensive, thus families have to spend more money than families in rural sectors. Mother education may be higher in urban communities given that educating girls is perceived to be less important than educating boys, especially in rural areas. In fact, rural girls are twice as likely to be out of school as urban girls (United Nations, 2010). There are also cultural norms more prevalent in rural areas that are barriers for rural girls to attend school at the same rate than their urban counterparts. Rural women spend more time than urban women and men in reproductive and household work, including time spent obtaining water and fuel, caring for children and the sick, and preparing food (World Bank, 2012).

Although a strength of our models is the simultaneous inclusion of demographic variables as predictors of outcomes as well of as predictors of the mediating variables, we performed a sensitivity analysis to test whether expenditures and mother education were also mediators of the relation between urbanicity and child development and whether this model specification would modify our results. In order to test for mediation, mother education was entered as a continuous measure reflecting the years of education.

Results of these analyses indicated that mother education and household expenditures were strong paths of the link between urban residency and higher achievement and health. In Peru, urban residency was linked to additional 2.50-3.22 years of education for mothers in comparison to urban residency. This difference in education linked urban residency to 0.09-0.17 SD increased academic achievement. Urban households had monthly expenditures 2,850-4,242 (in soles) higher than rural households. This urban advantage on expenditures linked urban residency to 0.01-0.03 SD increased academic achievement in comparison to rural residency. In India, urban residency was linked to additional 4.10-4.40 years of mother education in comparison to rural residency did. The additional education or urban mothers linked urban residency with increments on academic achievement of 0.13-0.27 SD. Urban households' spent between 133,500 and 232,280 more rupees every month than rural households. The urban advantage on monthly expenditures translated into an indirect effect of 0.02-0.04 SD increased academic achievement for urban children in comparison to rural children.

As expected, findings indicate that markers of socioeconomic status are fundamental in linking urban residency with higher achievement scores and better health across age. However, the significance and strength of community and time-use findings we obtained in this study were not changed after including this new set of paths in the model. These results provide evidence to believe that the estimates obtained through our current model specification are not biased. Furthermore, we found evidence that the indirect effect of urbanicity that ran through these two socioeconomic factors did not always surpassed the indirect effect or urbanicity that ran through community and time-use mediators. As an example, we compared the strength of the indirect effects paths that link urbanicity with vocabulary scores in India. We found that at age five, the sum of indirect effects that ran through all community resources (0.32 SD, $p<.001$) were comparable to the sum of indirect effects that ran through expenditures and mother education (0.29 SD, $p<.001$). We also found that the indirect effects of urbanicity on vocabulary scores at age fifteen that ran through the sum of measures of time-use (0.08 SD, $p<0.001$) were larger that the indirect effects that ran through socioeconomic factors (0.06 SD $p<.01$). Assessments of indirect effect sizes at ages eight and twelve showed that socioeconomic factors were stronger links between urbanicity and vocabulary achievement (0.16 SD and 0.18 SD, $p<0.001$, respectively) than other measures. The sum of indirect effects of time-use (SD= 0.02, n.s. and 0.05 SD, $p<0.05$, respectively), of the sum of indirect effects of community stressors (-0.05 and -0.08, $p<0.05$, respectively), and the sum of indirect effect of community resources (0.05 SD, and 0.13 SD, n.s., respectively) were smaller than the indirect effect of socioeconomic markers. Similar patters emerged for other outcomes in India and in Peru. This suggests that urban residency is associated to child development through multiple mechanisms and that socioeconomic status, community resources, community stressors, and time-use patters all play a role.

5.0 Discussion

5.1 Urban-rural differences appeared early and their development differed by country

Aligned with previous scholarship, our findings showed that there is an urban advantage on achievement and health among children from low-income communities in India and Peru (Kremer et al. 2005; Ramchandran, 2009; Tilak, 2009; Castro & Rolleston, 2015). This study builds onto this literature to explore how these differences develop. We found that these differences already exist by age five; suggesting that well intended interventions aiming to close the achievement gaps in LMIC need to focus on the early years instead of start intervening when children are in elementary or secondary school.

Results also showed that the size and trajectories of the urban-rural gaps differed by country, evidencing that urban-rural differences largely diverge across LMIC and developmental stage. In Peru, the urban-rural achievement and health gaps were large at early childhood and remained stable over time. In India, the achievement and health gaps were modest at early childhood and while the vocabulary gap tended to close over time, the health gap modestly increased across childhood. Thus, the general view that rural children in LMIC always are at disadvantage needs to be reconsidered with respect of age and country. Furthermore, results indicated that child and family factors differentially explained the urban-rural gap in each country. While child and family characteristics explained around half of the urban-rural achievement gap in Peru, these same factors completely explained achievement gaps in India. This result suggest that compositional differences of urban and rural communities are at the heart of the Indian urban-rural gaps and that interventions focusing on improving parental education and home expenditure may be the most beneficial in closing the urban-rural inequality.

These results also suggested that factors that influence trajectories of development had a different temporal nature in Peru and India. In Peru, very early experiences seem to be the most influential for child development. Efforts to ameliorate the large urban-rural achievement and health gaps in Peru must start before the age of five. Furthermore, for the case of height, interventions could be done even before birth. In fact, previous findings have suggested that urban-rural differences in nutritional features, such as birth weight, are already present at birth and that mother’s health, nutritional status, and health care should be an initial target to improve child health in rural areas (Nolan, 2016). When analyzing explanatory variables, community and time-use factors were particularly salient at age five, confirming that early mechanisms seem to define trajectories of the urban-rural gap in Peru. The achievement advantage of urban residents was partially explained by the higher access to educational services and to utility services that urban habitants enjoyed at earlier ages. Similarly, the urban health advantage was partially explained by the higher access to health facilities and more time studying of urban five-year-olds. Interestingly, results also indicated that urban residents were exposed to higher levels of pollution than rural habitants, which negative predicted math achievement across age. Notably, the effect sizes of the mediation that ran through resources, largely surpasses the size of the mediation that ran through stressors. This indicates that the rural advantage in terms of lower stressors, translated into smaller returns to child development than those of resources. Thus, improving rural children’s development requires of investments on educational services and utility resources that benefit very young children and mothers. However, it is important to consider the possibility that the smaller effect sizes associated with community stressors in comparison to resources are due to a measurement issue. Our measure of stressors reflect whether the community suffers of a given problem and, thus, it did not capture the proximity –physical and temporal– that different participants could have had to each of those. Community members could potentially have equal access to the resources available to the community, if they seek them, because they are generally stable factors (hospitals, schools, etc.). Contrastingly, within community variability may be an important issue when referring to stressors. Instances of violent crime fluctuate over time and pollution issues can be more acute in an area of the community then another, thus, exposure may not be equal to all community members. Our measure, unfortunately, did not capture the intensity and proximity to those stressors.

Indian urban children gained height at a faster rate over time while also learning at a slower rate across years than their rural peers, suggesting that experiences across all stages of childhood seem to influence trajectories of development. This divergence between trajectories of health and achievement also suggests that the processes that influence development differ for the health and cognitive dimensions. Urban children had higher levels of vocabulary at age five, but the differences reduced over time due to a flatter urban slope in comparison to the rural one. Better access to utility services and more time studying predicted higher vocabulary scores of urban children at age five. Notably, when it came to processes over time that explained patters of development, there were offsetting forces. Specifically, while urban children showed higher learning scores partially due to less time working and more time studying, higher urban access to utility services and more violent crime predicted slower vocabulary scores over time. These patterns of results may explain why the Indian urban advantage on achievement disappeared as children aged. Turning to the developmental processes that explained the urban advantage in trajectories of growth, results showed that that time-use partially explained the larger growth of urban children. Time spent on studying and working positively related to growth trajectories. One the one hand, rural children spent more time working which in turn was positively associated with height growth (which translated into a negative link between urban residency and height). On the other hand, living in cities was associated with more time studying, which in turn predicted higher physical growth for urban children.

Overall, results suggested that although urban children spent more time studying, less time working, and had more access to community resources, they are also exposed to more disadvantages in the form of higher levels of pollution and violent crime. Time studying was the most consistent predictor of the urban advantage in achievement across all ages and for health at early childhood. These results suggest that policies aiming to improve the child development of low-income children in LMIC need to target different processes in urban and rural areas.

5.2 Child and family characteristics were strong predictors of the urban-rural gap but their contribution on explaining the gap differed by country

We found evidence that urban families were at advantage compared to rural ones when it came to socioeconomic status characteristics. Families living in rural areas had lower educational attainment, less expenditures, and were more likely to be from underrepresented racial or caste groups in comparison to urban families. In both countries, over 60% of rural mothers did not complete elementary school in comparison to around 20% of urban mothers. These demographic differences consistently explained the urban-rural gaps. Child and family factors explained around half or less of the urban-rural gaps in Peru and almost completely explained achievement gaps and around half of the health gas in India. Together, these results suggest that compositional differences in who lives in urban and rural settings largely contribute to explain differences between urban and rural habitants, in comparison to characteristics of urban and rural areas themselves. This comes with no surprise as prior studies in Latin America and Asia have shown that much of the urban advantage is due to the socioeconomic differences of urban and rural families (Ramos, Duque & Nieto, 2016; Saikia, Singh, Jasilionis & Ram, 2013; Van de Poel et al., 2007; Wang, Li & Wang, 2018).

Across both countries, mother education was the most salient predictor for all outcomes, surpassing any other predictor –including urbanicity itself. Results indicated that any additional level of education (e.g. a change from elementary to secondary educational attainment) was associated with additional benefits to children's development. Researchers and policy makers have often argued in favor of policies to achieve higher economic growth in rural areas (i.e. infrastructure for transportation, agricultural research, and development; Fan, Chan-Kang & Mukherjee, 2005; Imai & Malaeb, 2018). Our results suggest that investments that increase rural women's educational attainment could yield large returns to child development. For years, researchers from LMIC have argued in favor of increasing public investment in women's education. Gender inequality on educational attainment per se, continues to be a problem in LMIC, with the problem exacerbating in rural areas and for poor populations (Birdsall, Levine & Ibrahim, 2005; Filmer, 1999). Beyond the gender gap, there are other reasons to promote girls education. Frequently, the rate of private returns (earnings) to schooling for women is as large as or larger than for men (Deolalikar; 1993; Schultz; 1993). Also, there is a sizeable literature showing associations between women education and macro- and micro- economic growth, lower fertility rates, and decreased child mortality rates (Schultz, 2001; Strauss & Thomas, 1995). Our results suggest that investment in increasing rural women's educational attainment could also yield returns for child health, nutrition, and cognitive development larger than factors such as family composition, household expenditure, and place of residency. Interventions must start early in strengthening pathways to higher education for girls (Schultz, 2001) but increasing women's access to higher levels of education after they have become mothers may be important as well. Indeed, interventions from the US have shown that investments in maternal education relate to benefits when it comes to improved parenting practices, maternal expectations of child education, and social and cognitive skills (Chase-Lansdale & Brooks-Gunn, 2014; Kaushal, 2014). Evaluations of two-generation programs that combine education or job training for adults with early childhood education for their children have been successful in increasing mother education, helping families to achieving job stability, and have been associated with children's good academic performance (Chase-Lansdale & Brooks-Gunn, 2014).

Household expenditure and the number of children at home were also important predictors of all child outcomes across time. Helping families by increasing the expenditure per capita in the home can help to improve the developmental outcomes of rural children. In fact, data shows that while 20% of rural families with three children or more in comparison to only 5% of urban ones, suggesting that rural families tend to be bigger while also counting with less monetary resources to support childrearing (Bongaarts, 2001).

There are two surprising results with regard of how demographic characteristics contribute to the health and achievement urban-rural gaps. First, although in Peru almost all demographic characteristics significantly predicted achievement and health, race/ethnic background did not. This non-significant result of race/ethnicity is surprising, as results from previous research suggest that there are large differences in achievement and health between White/Mestizo children and children from minority groups, especially indigenous (Arteaga & Glewwe, 2014). It is possible that we were unable to capture these differences due to the small sample of children who were not White or Mestizo (2.63%) or the diversity of the group itself (Indigenous, Black, and Asian).

A second unexpected result is that in India while the achievement urban-rural gaps were fully explained by demographic factors, the health gaps remained sizeable after including demographic characteristics. It is startling to see that the health gaps were persistent after accounting by family characteristics, but achievement were not. A possible explanation for this result is that while mother education was highly associated with achievement, this association was not as strong for health outcomes, reducing much of the explanatory power of family characteristics. There is evidence to suggest that health disparities can be explained by better health systems and policies that favor urban cities and go beyond family socioeconomic characteristics. A study analyzing the health and educational services across the country found that the differences between the rural and urban areas with respect of health provision were wider than in the educational dimension (Deb, 2018). Furthermore, researchers have suggested that rural communities have both limited availability of health services as well as lower quality and less accessible health care (Das, Holla, Das, Mohanan, Tabak & Chan, 2012). For example, urban health services are often subsidized, so people living in rural communities often pay more than urban citizens (Deb, 2018).

5.3 Aspects of time-use that explained urban-rural differences on achievement and health, and their effect across age

The effects of time-use on the urban-rural gaps were similar across both countries, with time studying as the most consistent mediator of achievement across all childhood. According to our results, policies to increase rural children's dedication to studying can be an important measure to help closing the urban-rural gaps, beyond solely increase availability of educational services. More time studying is a promising target in order to improve rural children's achievement and early health, but this is not a simple task to and multiple paths to solve this issue could be proposed. Researchers have been concerned about disinterest and difficulties to keep children engaged in school, due to conflict with seasonal agricultural work, long distances to schools, and perceived lack of job opportunities that more commonly are found in rural areas (Deb, 2018). It seems, then, that increasing time studying requires of an integrated approach that improves access to schooling, provides accurate information about the returns to education, and adapts education to rural realities (WISE, 2019). Currently in Peru, there are pilot programs in place aiming to reduce school dropout at the secondary level in rural areas, which have tried to adapt the educational curriculum to rural needs (WISE, 2019) and to educate children and parents about the returns of secondary education (IPA, 2018). However, our results suggest that these efforts to increase dedication to schooling in rural areas should start from early childhood, as a gap in time-use is already evidenced at that age. Previously, researchers have reported on the reduced number of early educational services and types available to rural residents in comparison to urban ones (Woodhead et al., 2009), which could be widening the urban-rural gaps.

According to results of age-specific and cumulative models, time allocated to studying also partially explained the urban advantage with regard to health at early childhood (age five) in Peru and across development in India. This difference between the countries on when studying plays a role aligns with found patterns for trajectories, in which early childhood factors seem prominent for the Peruvian urban-rural gaps while cumulative factors predict Indian urban-rural differences across development. The relation of time studying and health is difficult to interpret. Given that our measure of time studying includes time at school plus time studying out-of-school, this result could be driven by the time that children spent at school, where health services and nutrition are generally provided. As a sensitivity analysis, we entered independent measures of time at school and time studying out of school into our models and found that both types of studying predicted better health. Notably, time studying out of school had a stronger effect than time at school, indicating that what children do after school may be a more refined measure to discern the daily processes that relate to health. There are several related possibilities to understand why time studying relates to health. First, school attendance could bring health benefits and children who study at home are most likely already are enrolled at school. At school children could be receiving the nutritional benefits (D'Onise, Lynch, Sawyer & McDermott, 2010; UNSCN, 2017). Also, there is evidence from India to suggest that everyday travel by walking and cycling to school (the most common ways of transportation to school) is associated with positive health benefits (Lubans, Boreham, Kelly & Foster, 2011), mostly for urban children (Tetali, Edwards & Roberts, 2016). A second possibility is that as more time studying occurs at the expense of other tasks (labor, chores, care provision, etc.), more studying time may reflect a general family's environment in which enriching activities are prioritized and work-related activities are reduced. The third possible explanation may be the more plausible. This result could be due to reverse causality as children who study more are more likely to have better nutritional status, which allow them to engage consistently in school and related activities. In fact, the relation between height and malnourishment with educational outcomes has been well stablished (Mani, 2008).

In the age-specific models, time working had some direct effects on child outcomes, but none of them mediated the links between urban residency and achievement. Surprisingly, across both countries, time working was positively associated with math achievement at early ages and negatively associated with math and vocabulary at age fifteen when considering its age-specific effects. It is unclear why time working related to better math skills at early and middle childhood, as previous studies have shown that child labor, mostly at early ages, can be harmful for children (Borga, 2019). Child labor almost always comes with a reduction to schooling and studying activities (Akabayashi & Psacharopoulos, 1999; Borga, 2019). Given that previously research has found child labor is only detrimental for achievement if it significantly reduces study time (Keane, Krutikova & Neal, 2018), it is possible that by including time studying in the models we were already controlling for this issue. Thus, we decided to estimate models for each country without including study time and found that the positive association between working time and achievement became non-significative for both countries. Then, there is a positive effect of working time on math only if time studying is already accounted for in the models. Still is unclear why, even if studying time stays the same for children, working would be beneficial for math achievement. It is possible that some of the activities learned while helping with a family business of paid job require some math skills (Banerjee, Bhattacharjee, Chattopadhyay & Ganimian, 2017). Alternatively, this result could be due to a selection issue. It is possible that children that do better academically or are perceived to be smarter are given more responsibilities of care, chores, and labor precisely because of those qualities.

Time working had mixed effects on children's development. Cumulative models for both countries showed that time working is negative in the long-term for academic achievement. These results suggest that time working has a more detrimental effect on achievement when it is experienced cumulatively across childhood and adolescence. It is important to consider that this effect is significant even after accounting for studying time, which suggest that working seems to be harmful for child development independently of its effect on displacing studying. However, researchers have suggested that laws against child labor have negative effects, as child labor decisions are more likely a response to poverty and subsistence requirements. Thus, income supplement programs, such as conditional cash transfers, have been proposed as possible mechanisms for alleviating child labor by supplementing family income and conditioning it to school attendance (Ersado, 2003). These programs succeed in decreasing child labor while increasing school enrollment (Bourguignon, Ferreira, & Leite, 2003; Ranzani & Rosati, 2014).

Simultaneously, our study provided evidence that work may be beneficial for the physical growth of children in India. It is possible that this result was due to reverse causality, indicating that children who are over time healthier are more often asked to work throughout childhood and adolescence. However, it is also possible that this is a true effect as some studies of child labor show that the relation between child labor and health may not be negative in all cases. This issue is difficult to disentangle as the endogeneity of child health and work present a major challenge to the field (Doorslaer & Rosati, 2002). One the one hand, strong evidence have shown that children's participation in jobs that are physically demanding or involve significant risks to health or safety, such as agriculture, construction, or mining jobs are hazardous to child health. However, children health may not necessarily be affected in the short term of if the child is not involved in an accident (Doorslaer & Rosati, 2002). Notably, a negative effect of work on health has not being found in other types of work such as helping in a family business of taking care of others (Agarwal & Kelly, 2004; Dachille, Guarcello & Lyon, 2015). These types of work, however, have been linked to reductions on time studying and school enrollment (Keane, Krutikova & Neal, 2018). On the other hand, child work may increase household resources, which could have a positive impact of living standards and health of children (Smith, 1999; O'Donnell, Doorslaer & Rosati, 2002). In fact, researchers have pointed out that often poor households in LMIC are dependent on the contributions of their children and are resistant to give up child work as it would hurt the household unit (Shafiq, 2005). This contribution may be more important for families in residency areas where children received better wages (Shafiq, 2005). Other research has found that a positive association between child work and health for girls. Specifically, the wages resulting from work increased the relative preference of girls in comparison to boys in the household, which resulted in healthier weight and height for the girls (Koolwal, 2007). Finally, an issue to consider is whether the pecuniary benefits of child work could be used to send the child to school, which in turn could relate to better health, as our results suggested. The evaluation of a cash transfer program that partially subsidized the cost of school attendance showed that children from the most vulnerable families increased both school attendance and child labor. Because school attendance represented a cost to the household, these children began working for pay to make up a substantial share of this cost (de Hoop, Friedman, Kandpal, & Rosati, 2016). Thus, there is evidence that earnings generated by children's work may benefit the working child. Overall, while there is a consensus in the field that children should be at school rather than working, evidence suggest the effects of work on health are mixed and the results of the present study are consistent with this broader literature.

5.4 Aspects of communities that explained urban-rural differences on child development and their effect across age

5.4.1 Resources

Results showed that urban children had higher levels of achievement and health in comparison to rural ones due, partially, to the increased access to utility services in cities. However, while evidence of this association was consistent across age for health and achievement in Peru, it only appeared for vocabulary at age five in India. Furthermore, results of our growth/cumulative models showed that higher urban access to utility services negatively predicted growth in vocabulary scores in India. Although the effect size was small, it is certainly unexpected. This result could be due to a spurious relation, such as a correlation of urban residency, availability of utilities, and residential overcrowding. Another factor to consider is that our measure of utility services captures the number of utility services available in the community but it does not measure which source the family uses to obtain their services, the number of hours a day that those services are available, and the quality of those services. Quality is a very important issue in India given their well-known problem with the treatment of waste water. In fact, only 2% of India's towns and cities have sewage systems and treatment facilities (Shah, 2016). As a result, even if there is running water in the community, sewage water is often not treated, findings its way to ponds, lakes, and rivers, and then becoming and open source of contamination for citizens and further polluting water sources in India (Chaturvedi, 2018). While the problem of inadequate access to water and sanitation exists in India's rural and urban areas, the problem is particularly pressing in cities. Rapid urbanization and rural-to-urban migration have led to an increasing proportion of the poor living in slums (Duflo, Galiani, & Mobarak, 2012). Therefore, it is possible that the inadequate access to safe water and exposure to pathogens through the poor treatment of solid waste will give rise to the negative association between availability of utilities and children's academic achievement. However, although this problem has been evidenced, no assessment has been done to evaluate its impact on children. More evidence is needed in order to understand whether negative associations between access to utilities and child health is due to a spurious relation or to poor quality of available services. Future studies in India would benefit from measures of quality of utility services. Identifying specific areas in which quality of services is low is a key factor in order to target policies to improve the living standards of citizens.

Access to utility services at the household has been associated to better educational outcomes for household members (Khandker, Barnes, & Samad, 2012). However, household-level services have been often examined as consequence of higher socioeconomic status of families who can pay for those services. Contrastingly, this study aimed to examine whether family access to utilities depends on the larger context in which the household is situated (Kulkarni & Barnes, 2017). A family of higher status may not have access to utilities if these are not available in the community. It is also possible that even if services are available, they are of poor quality. Contrastingly, a family of low status that may not have access at the house to potable water or internet, could benefit from public sources available in the community, such as well or a café-internet. Our results suggest that even after controlling for markers of family status such as expenditure, education, and race/ethnicity, availability of quality utility services in the community is influential for academic achievement and health. These results indicated that increasing community infrastructure such as electricity, running water, sanitation, modes of media, and communication in rural Peru could be beneficial in reducing the urban-rural achievement and health gap (Kulkarni & Barnes, 2017). They also suggest that it is possible that more evidence about the quality of utilities in urban India and its association to child development is needed.

Turning to educational services, results indicated that urban children's advantage with regard to receptive vocabulary at age five seemed to be partially due to more educational services in urban communities. Educational services were not a significant mediator for other outcomes or at other ages. The limited role of community availability educational services evidenced in both countries contrasts with studies showing that schools play an important role in explaining the urban-rural gap in Peru (Castro & Rolleston, 2015) and India (Kremer et al., 2005; Tilak, 2009). Importantly, those studies examined markers of school quality, which may be more important in shaping urban and rural children's achievement. Unfortunately, school quality was not included in this study because school information in the Young Lives study was only collected on two occasions, which were not aligned with child assessments. Furthermore, the surveyed schools were linked only to around 25% of participant children. Even if availability of educational resources did not play a role in explaining urbanicity-related gaps as expected, resources related to education may be vitally important in explaining urbanicity-related differences. Thus, future research with better measures of school quality are needed in combination with measures of other community resources and stressors.

Finally, proximity to health facilities was a significant mediator of urban living and height-for-age across time in Peru. Previous studies have not found such association when they have assessed with this same sample whether availability of hospitals is associated with height (Nolan, 2016). Differently from Nolan's study, our measure captured proximity to available hospitals. These divergent results could suggest that accounting for proximity may be a better measure of access than availability alone. Contrastingly and unexpectedly, the number of available health facilities was negatively linked to health outcomes in India when predicting two outcomes: General health at age twelve and BMI at age fifteen. Although this result was not found for other outcomes or ages, it is not clear why the higher number of health facilities that urban residents enjoy would translate into diminished health in comparison to rural adolescents. Previous studies analyzing this same sample have not found a positive or negative association with health (measured through height) when they have considered whether there is a hospital in the community (Nolan, 2016). As our measure of health facilities includes clinics and health centers as well, our measure can me reflecting remedial services available for minor and reoccurring health issues in cities.

5.4.2 Stressors

An important issue not examined much when referring to the urban-rural gaps in LMIC is whether urban children are partially at disadvantage via higher exposure to stressors. We found evidence to partially support that family stress models extend to the community level. Results of this study suggest that community resources and stressors play distinct roles, through different mechanisms, in the development of achievement and health. This further highlights the importance of accounting for various aspects of children's communities and the biases likely to underlie studies assessing the effect of one characteristic in isolation.

Unexpectedly, we found that pollution linked urbanicity with reduced achievement, but not with worse health. In Peru, higher pollution in urban areas was linked with lower levels of math achievement across all ages, but not with other achievement measures or health outcomes. In India, higher pollution in cities showed to be a significant mediator of the negative association between living in an urban area and vocabulary achievement. Although pollution did not explain the urban-rural achievement differences at age fifteen, pollution was still a significant direct predictor of achievement. Pollution ceased to be a significant mediator as children aged because the number of pollution problems in rural areas grew over the span of the study and it stopped being different across urbanicity in India. In fact, a recent study suggested that although health authorities have traditionally only focused on urban contamination, air pollution is responsible for more deaths in rural areas and urban (Karambelas et al., 2018). Certainly, it is startling to find that more pollution problems predicted decreased achievement but not health. In fact, decreased health can be possibly a mechanism of the link between health and pollution (Roth, 2018). It is possible that our health measures did not capture the major health problems that traditionally have been associated with pollution, such as chronical incidence of pulmonary problems, cancer, and mortality (WHO, 2014). Instead, our measures mostly captured nutritional status through BMI and height, which has a less chronical nature and more directly relates to quantity and quality of food intake. Furthermore, researchers that have linked pollution with achievement have suggested that contemporaneous mild health issues are a possible channel. Specifically, issues of irritation of the eyes, nose, and throat, as well as asthma attacks, headaches, dizziness, and fatigue could be more at culprit for reduced student achievement (Roth, 2018). Thus, our measures of health could have failed to capture either chronic health issues usually associated with pollution or more mild contemporaneous issues directly associated with increased daily pollution. Nevertheless, this result continues to be surprising considering that issues such as water pollution or problems with solid waste could have a direct impact on nutritional status. Future research may need to capture more refined measures of health and of type and proximity of pollution.

Turning to violent crime, results largely differed by country. In Peru, unexpectedly, we found that more violent crime in cities was positively associated with math at age fifteen and BMI-for-age at age eight. This result seems inconsistent across our results, as no patters by age or outcome was found, which may suggest that it is only a spurious relation of urban living.

In contrast, when predicting vocabulary in Peru, the negative effect of violent crime showed to be salient in adolescence. Higher exposure to violent crime at ages twelve and fifteen linked urban residency to lower vocabulary. Similarly, results of the Indian context suggested that violent crime is particularly important in adolescence. Results indicated that this stressor significantly mediated the negative association between urban residency and achievement at adolescence (ages twelve and fifteen). This aligns with previous evidence from LMIC that showed that recent exposure to gangs disputes in the neighborhood affects fifth graders performance on academic tests (Monterito & Rocha, 2017) and that homicides have a negative impact on academic performance fifth and nine grade (Cristancho, Harker & Molano, 2016). These results indicate that designing policies to maintain safety in urban communities and reduce the psychological effects of violent crime in the community are important to promote adolescents wellbeing. For example, evidence from the US have shown that safe schools can potentially buffer the negative effects of community violence on achievement (Laurito et al. 2019).

Worth mentioning, results showed that exposure to violence has a direct detrimental association with achievement at later ages and is harmful for health at earlier ages. Specifically, results showed that violent crime explained the negative association between urban living and health at earlier stages (ages five, eight and twelve). This temporal difference could due to the possibility that the mechanisms linking violence to child health and achievement differ by age. Unfortunately, no studies have considered both types of outcomes simultaneously, some research suggest that the prevalence of gangs and violence within communities may be particularly harmful during adolescence when youth have more direct access to the neighborhood social environment and more capabilities to interpret community safety than younger children (Steinberg & Morris, 2001). Instead, younger children may be indirectly affected by community violence via parental stress, as their direct contact with the neighborhood is dependent of parents. In addition, other research from the U.S. indicates that the link between violence and child health can be present since earlier ages by increasing the risk of adverse birth outcomes (Felker-Kantor, Wallace, Theall, 2017), problems sleeping (Lepore & Kliewer, 2013), and elevated risk of obesity during early to middle childhood (Nogueira, Ferrão, Gama et al, 2013). Thus, studies with samples from diverse countries examining the age-specific developmental consequences to violence exposure are still lacking.

5.4.3 Comment on the fit of resource and stress models for the context of LMIC

We found evidence to partially support that family resource and stress models extend to the community level. Results of this study suggest that community resources and stressors play distinct roles in linking economic disadvantage and urbanicity to child development. However, since these conceptual models emerged in industrialized countries, it is important to reflect on how these processes may differ in the context of LMIC. There are three main issues that may differ across contexts.

According to our results, community resources were associated with particularly large benefits for children's development. These benefits were generally larger than the harmful effects of community stressors. Furthermore, our results suggested that rural children may also experience high levels of certain stressors, such as pollution. Because some fundamental resources (clean running water, reliable electricity, sewage treatment, and health care) are often not present in LMIC, resources may play a more central role in explaining individual differences in children's development than stressors. In contrast, when it comes to industrialized countries, these basic resources are generally taken for granted. In fact, the salient role of resources over stressors helped explaining the urban advantage on achievement and health in the samples of this study. In contrast, research from the U.S. showed that average levels of academic skills across urban and rural children did not differ, but found that urbanicity operated through contrasting resource and stress processes to shape children's development (Miller et at., 2019). More evidence from LMIC examining the relative importance of resources over stressors is necessary to refine our understanding of how community resources and stressors operate.

Relatedly, the types of resources that seem to matter most are basic resources such as access to safe drinking water, reliable electricity, sanitation, modern cooking fuel, modes of media and communication, and basic health care (Barbier, 2012; Kulkarni & Barnes, 2017). This is in contrast to studies in the U.S. that have highlighted the importance of cognitively enriching resources such as libraries, museums, and parks (Miller et al., 2019). Instead, we found that access to more basic services is particularly salient for children. Thus, when considering resources in LMIC it is crucial to measure basic services alongside more enriching resources.

Additionally, there is some evidence to suggest that beyond the availability of resources the quality of basic resources may be crucial as well. Quality of basic resources may be a pathway through which poverty and urbanicity interact to shape child development in LMIC. For example, access to running water at the community seems to be related to an increase of water pollution in India due to the widespread lack of treatment plants for waste water (Chaturvedi, 2018). This issue seems to be of particular urgency in urban areas, where proliferation of habitants and slums have provoked rapid deterioration of water deposits that low income residents live close to and obtain water from (Chaturvedi, 2018). Thus, even when families have access to some resources, the quality of those is not granted for poor families. Instead, while there may be individual differences in the quality of resources in the US, with a few notable exceptions, basic utilities tend to be safe, reliable and secure. The low quality of basic resources has led urban families to purchase private services of water delivery and to pay for private health care instead of using public low quality services (Barik, & Thorat, 2015; Sengupta & Nundy, 2005; Venkatachalam, 2015). This situation is particularly worrisome for low-income families, which may have to use low-quality services or may have to deplete their scarce resources into buying private services. For example, research from India has indicated that the general population prefers private health services as public ones are low quality, have limited medicines and tests, and require extremely long waits in overcrowded health centers (Sengupta & Nundy, 2005). Unfortunately, the cost of private medicine leads low-income habitants to postpone receiving care until conditions are aggravated and to lend money or sell assets in order to pay for of private health services (World Bank, 2001). Turning to water utility services, evidence has shown that low income habitants in urban areas have no or interment access to piped water, which has led urban residents to buy private supplies from informal markets pay at high prices (McIntosh, 2003; Venkatachalam, 2015).

A final issue to consider is whether the psychological experience of stress and distress of parents and children are different in LMIC and industrialized countries. On the one hand, poverty is higher and material hardship is more widespread in LMIC, which could translate into deeper stress levels of the poor. The psychological distress of families who face challenges such as scarcity of food or seasonality of work could be larger than the challenges that poverty in industrialized countries present. On the other hand, it is possible that the psychological experience of poverty differs in industrialized countries and in LMIC because families' perception of socioeconomic stratification, inequality, and their relative position within the socioeconomic hierarchy may be more evident in countries such as the U.S. With more widespread poverty and income instability in LMIC, it is possible that people's perception of their own poverty is not as negatively assessed in LMIC as in industrialized countries. In fact, surveys on people's perceived income position showed that habitants from the US or Germany underestimated their income position whereas habitants from Brazil overestimated it (Bublitz, 2016). However, more research needs to be done to examine whether urban and rural residents in LMIC may have diverse perceptions of inequality and how these perceptions relate to parents and children feelings of stress.

Although we found some evidence that the resource and stress models can be used to understand the mechanisms that link poverty and urbanicity to child development, further evaluations of the model adaptations need to be made. Future research could benefit of including samples of children across the income spectrum, in order to study whether income inequalities and urbanicity interact to shape families' access and quality of community resources and stressors. For instance, income gaps may be attenuated in rural areas if community resources are equally unavailable to all families. In contrast, it could be that in urban areas, income gaps relate to larger differences in access and quality of resources for low- and high-income families.

Furthermore, the field of child poverty in LMIC would benefit from studying whether community and family stressors and resources relate to family dynamics (e.g. child physical maltreatment, interparental violence, cognitive stimulation, etc.) and to child outcomes more directly related to psychological distress (e.g., internalizing and externalizing behavioral problems). Further development of theoretically informed models are among the pressing next steps in research on how urbanicity and income relate to low children's development.

5.5 Limitations

First, these results are correlational and, hence, must be interpreted with caution. Although this study provides a rich description of the community and family contexts of poor children across urbanicity, it is possible that the observed associations between urbanicity, community characteristics, and achievement were caused by some unmeasured features of family, children, or communities children in our sample. For example, even if we accounted for ethnicity in all models, it is possible that underlying factors such as discrimination may affect certain groups' use of community resources. Notably, attempts were made to limit endogeneity bias by controlling for children and family characteristics at all instances, but future work in this area should try to leverage experimental and quasi-experimental designs to better address selection effects.

Second, the operationalization or urbanicity with a dichotomous indicator likely obscured differences that exist within groups. Instead of simply classifying communities as urban or rural, urbanicity may be better characterized by a continuum. Although the urban/rural division has traditionally been used by researchers and international organizations to assess urbanization across the globe (UN, 2018), it is certainly imperfect. In reality, there is a rural to urban continuum, ranging from sparsely populated isolated settlements to small towns to secondary cities to megacities. Thus within any given country there is heterogeneity within areas that are classified as rural or urban. However, these settlements change rapidly. Although nearly 10% of the urban population is found in megacities – each with more than 10 million people, most urban growth is taking place in smaller cities and towns, home to the majority of urban children and young people (Stephens, 2012). The classification we selected matched the classification done by the Young Lives Study and allowed for a more consistent comparison across countries and time, given that factors that define belonging into more refined categories (e.g. population density, city limits, economic growth, etc.) changed over the length of the study.

Third, despite the comprehensiveness of data used in this study, measurement weaknesses were also apparent. Mainly, the community characteristics variables were not directly measured but instead reported by community members, which could certainly lead to inaccurate estimates. Accordingly, measures of community factors may be biased by participants' own feelings of distress. For instance, participants could be unhappy and perceive their neighborhood as more dangerous and less resourceful. Instead, independent administrative data could useful in understanding the contexts of child development (Miller, Votruba-Drzal, & Coley, 2019). Unfortunately, few administrative data is available to measure resources in LMIC (for an exception of administrative police data, see Cristancho, Hacker & Molano, 2016). Also, community data were collected only every three-four years, which may obscure possible fluctuation in community resources and stressors that can affect child development and family processes like spikes in community violence or pollution. Finally, our data did not include measurements of quality of resources and severity of stressors, which without a doubt can provide a better understanding of the everyday experiences that families face.

The lack of information about school quality is a salient limitation. Although the Young Lives Study collected information about schools, this was not included because it would have severely reduced the sample and the data wave's availability. Our results based solely on information about availability of educational services were underwhelming. This is a significant limitation because prior studies show that school characteristics explain up to 40% of the urban-rural differences in achievement (Castro & Rolleston, 2015). The present research most probably failed to capture the characteristics of school that more directly relate to achievement and that differ across urban and rural areas. For example, previous research has found that lower teacher quality, lower teacher supply, and teacher absenteeism are common problems in rural areas (Hanushek, 1997; Levira, 2000; Othman & Muijs, 2013; Vegas, 2007; Wodon, 2014). However, it is important to indicate that previous studies did not account for other community-level characteristics, which could have also overstated the effect of schools. Future work should strive to simultaneously consider important features of schools and communities.

Measurement error in community characteristics may be related with the consistently small effect sizes obtained from our results. Although moderate to large indirect effects (0.16-0.46 SD) emerged when assessing the mediating nature of key community resources, most effect sizes were quite small. Measurement problems may help explain why the indirect effects that ran through the community stressors and resources were small. We argue that results still have practical importance. Although reports of community members are not an ideal measures of quality or proximity to community features, they are almost certainly reliable accounts of the presence of resources and stressors in the community. There reason to believe that representative members of the community were well informed of community services and problems. Additionally, it is important to note that even with these notable measurement limitations, the majority of our community measures showed reliable associations with academic achievement and health that were significant beyond and above measures of family characteristics.

Another limitation to consider for the present study is that gender differences were not examined. Numerous research from LMIC has shown that across LMIC there are marked gender preferences in favor of boys, which could play a role in exacerbating the role of low resources for girls. Previous evidence has shown that when family resources are scarce, families more often that girls drop out of school than decide that for boys (Cameron & Worswick, 2001). Also, when utility services lack at the household, girls are expected to help more in the household chores such as fetching water (Koolwal, 2007). Some evidence also suggest that boys are provided with more food and receive more caloric intake and health care than girls due to son preference (Arnold, 1992; Koolwal, 2007). Future research about family and community resources in LMIC would benefit of examining whether associations of resources and child development are moderated by gender.

Despite its limitations, this study provides important information regarding differences in the lives of children and families in low-income communities across urbanicity. Disadvantage displays differently urban and rural areas. This study demonstrates that it is necessary to understand the various resources and stressors at the community level in order to develop policies and programs tailored to the children and families in different urbanicities.

5.6 Conclusions

As the developing world continues to be drastically divided between urban and rural areas, it is important to understand the mechanisms that drive development across urban and rural communities. Yet, no research has taken a developmental perspective in trying to understand the community pathways through which these outcomes occur and the timing in which those pathways affect development. To our knowledge, this is the first study to explore whether various community characteristics and patterns of time-use are associated to different developmental domains over the course of child development.

Results from the three aims contained in this dissertation give us some insight into mechanisms that contribute to academic and health outcomes of urban and rural children as they age. While the pattern of urban advantage was apparent in both countries, the factors that explained these geographical differences varied by country and age. In India, urban-rural differentials became statistically insignificant when the socioeconomic status of the household and mother's education were taken into account, suggesting that populations in urban and rural sectors may be fundamentally different. Thus, policies targeting to improve child development in India should be aimed at improving the socioeconomic circumstances of families. In Peru, child and family characteristics only partially explained differentials but evidence suggested that differences are already stablished by age five. Thus, focusing on access to resources during the early childhood or even before birth may be a particular important path to achieve equitable trajectories of development.

The study of how urbanicity affects children is complex and varies across age and country. Some results reproduced across countries and developmental stages; more time studying surged as an important and beneficial factor across all ages, while more time working was detrimental only when considered under a cumulative light. Time working and studying could be thought as two related proximal processes as dedication to one generally comes with at expenses of the other (Putnick & Bornstein, 2015). Our results suggest that child labor policies should aim to for a shift from child and adolescent work to educational activities. As the decision of directing children to working is more likely a response to poverty and subsistence requirements, income supplement programs and programs that reward dedication to school are possible mechanisms for alleviating child labor improve child development.

Results analyzing the community effects showed that early childhood factors are important in defining trajectories of child development. These identified processes have important implications for efforts to improve contextual supports for disadvantaged children and target scarce public resources. Specifically, policies improving access to preschool services, promoting children attendance to those services, and improving rural availability of utility services during early childhood are important strategies to reduce the urban-rural gaps from early in life. Even though educational resources did not play a role in explaining urbanicity-related gaps beyond preschool age, it is most possible that school availability and quality are very important in explaining urbanicity-related differences in achievement and health during middle childhood and adolescence. Measures of community characteristics in combination with strong measures of school quality could provide a more precise assessment of the extent to which educational availability contributes to explain the urban-rural gap on achievement and health.

Beyond early childhood, other community factors showed to be important across age to improve the child development but those varied by country. Given that rural children showed to be lacking resources and urban children were more exposed to stressors, the processes by which urbanicity is associated with low-income children's development vary notably depending on place. Detrimental effects of violent crime on achievement were salient in adolescence. Thus, designing policies to maintain safety in urban communities –including school zones– are important to promote adolescents wellbeing. Also programs at school that help students coping with the psychological effect of violence or that promote safe schools can be important. In fact, evidence from the US have shown that safe schools can potentially buffer the negative effects of community violence on achievement (Laurito et al. 2019). Additionally, further investigation incorporating measures of proximity and length of exposure are of utmost importance to identify the children more at risk of suffer the stress as a result of violence in the community and of reduced academic achievement. In the context of Peru, results indicated that rural children of all ages would benefit from increased access to utility services. More utilities have the potential to improve health and academic achievement. In fact, previous evidence have shown that electrification in Peru has been associated with higher chances of school enrollment and increased reading or study time, specially when children are older and they academic task may need larger hours of work (Kulkarni & Barnes, 2017). Providing higher access to utility services for those in the most vulnerable rural areas is a way to promote equality on health and education and, thus the government should pay special attention to universalizing rural household electrification, sanitation, and communication.

Another lesson garnered from this study is less related is that multiple characteristics, that often act in contradictory ways, are related within communities. It is critical to understand these independent factors to understand the constellation of community factors that are most beneficial or most detrimental to human development. This evidence can give important information about where we should be focusing intervention and prevention efforts. Thus, studies examining one of these community factors without looking at related others may obtain biased estimates of the associations between the community factor and outcomes. Secondly, because some of the community factors operated in opposite fashion, it is important to examine numerous aspects of community before making assumptions regarding the differences by urbanicity. For example, researchers looking at differences in outcomes across urbanicity often deduce that there are associations via school availability only. Instead, researchers may want to look at several aspects affecting outcomes in opposite ways or playing additive effects. In addition, our study showed that researchers need to consider that community factors change over time and so does the associations of place and child outcomes. For example, pollution levels increased over time in rural areas of

India, which increased the number of detrimental factors that rural children had and increasing their exposure to risks.

Clearly, additional work is necessary to further expand the knowledge of the quality of services and the strength of risks that children at each urbanicity face. Furthermore, more studies that include community level data and from other countries are necessary to increase our knowledge regarding how urbanicity shapes the lives of children and thus, how can we alleviate the large urban-rural disparities.

Appendix A Size of the urban advantage

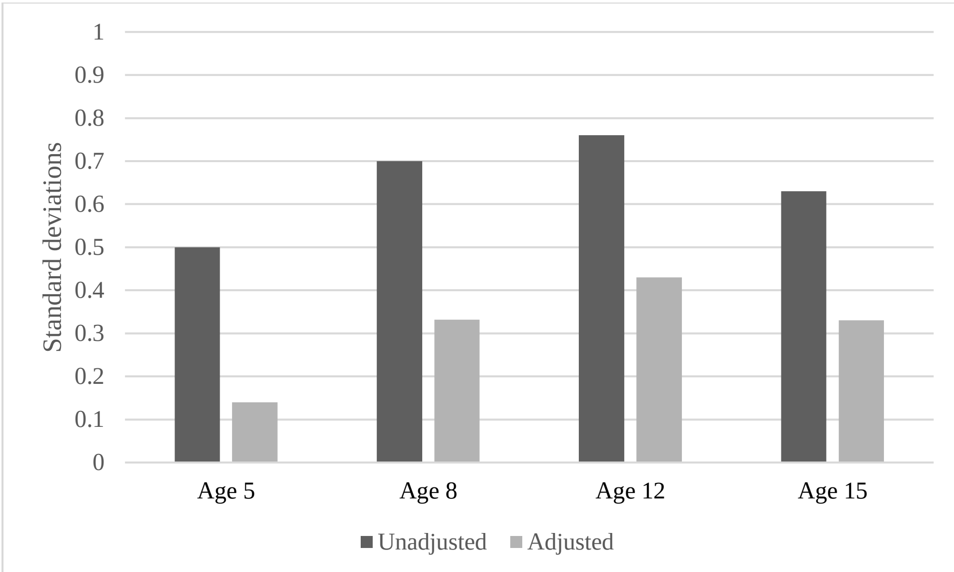

Figure 8. Size of the adjusted and unadjusted math urban advantage in Peru

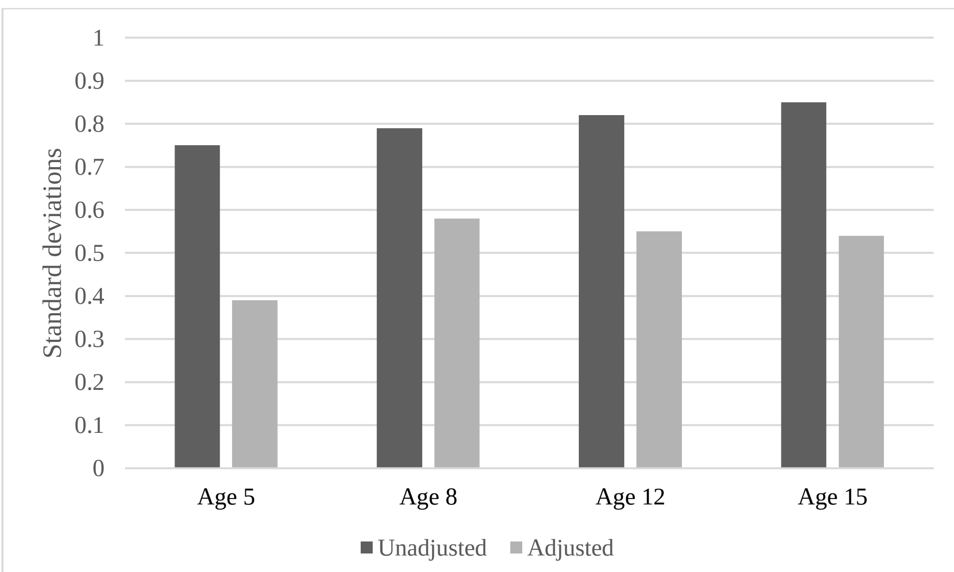

Figure 9. Size of the adjusted and unadjusted vocabulary urban advantage in Peru

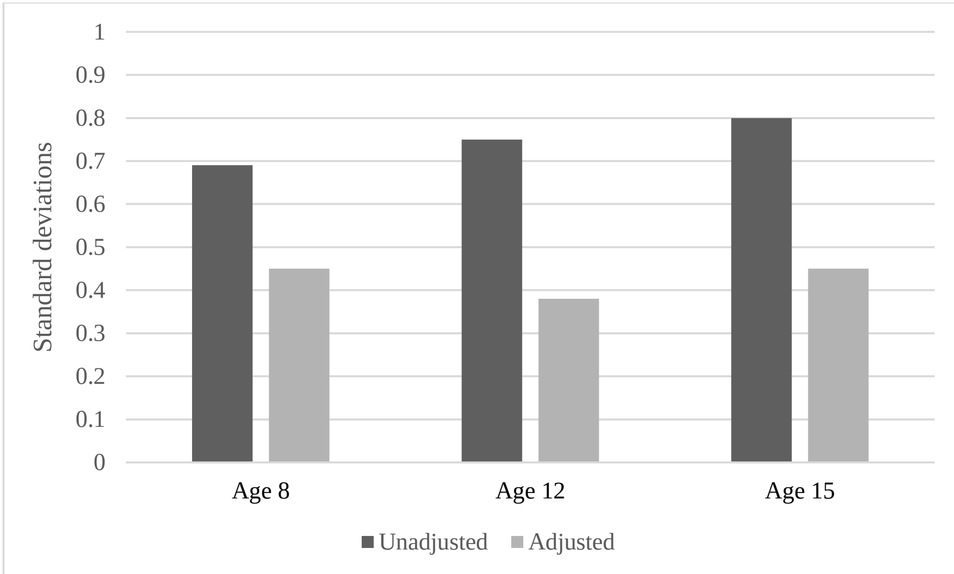

Figure 10. Size of the adjusted and unadjusted literacy urban advantage in Peru

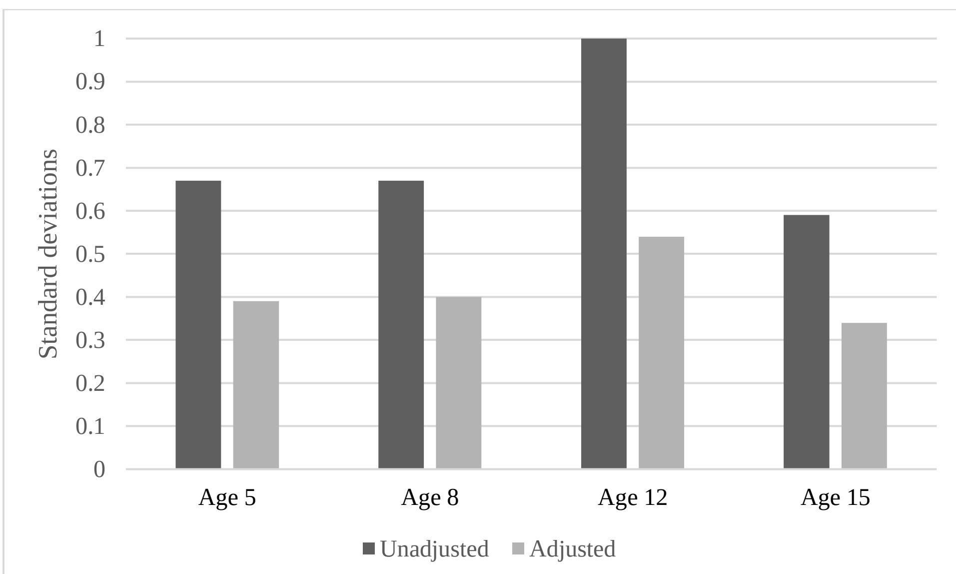

Figure 11. Size of the adjusted and unadjusted height-for-age urban advantage in Peru

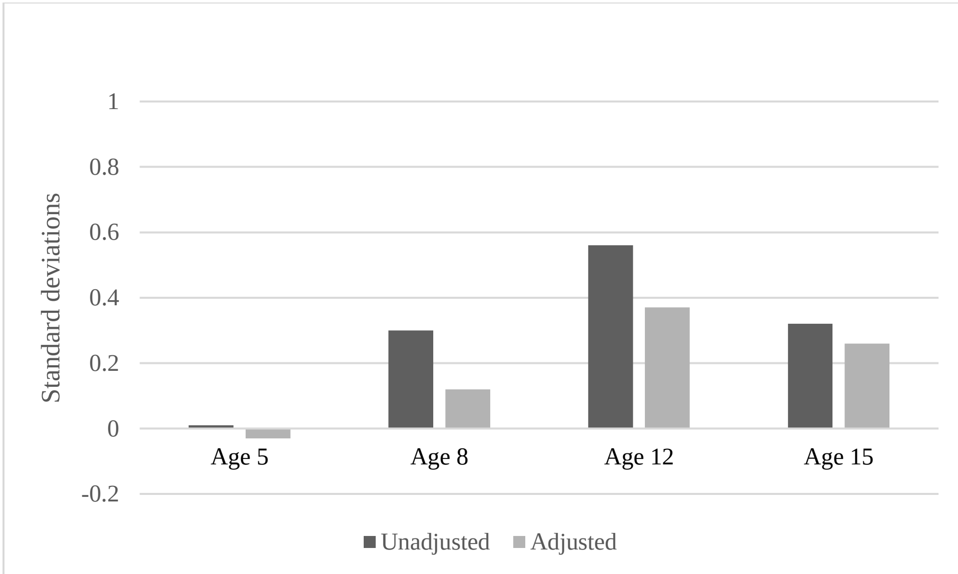

Figure 12. Size of the adjusted and unadjusted BMI-for-age urban advantage in Peru

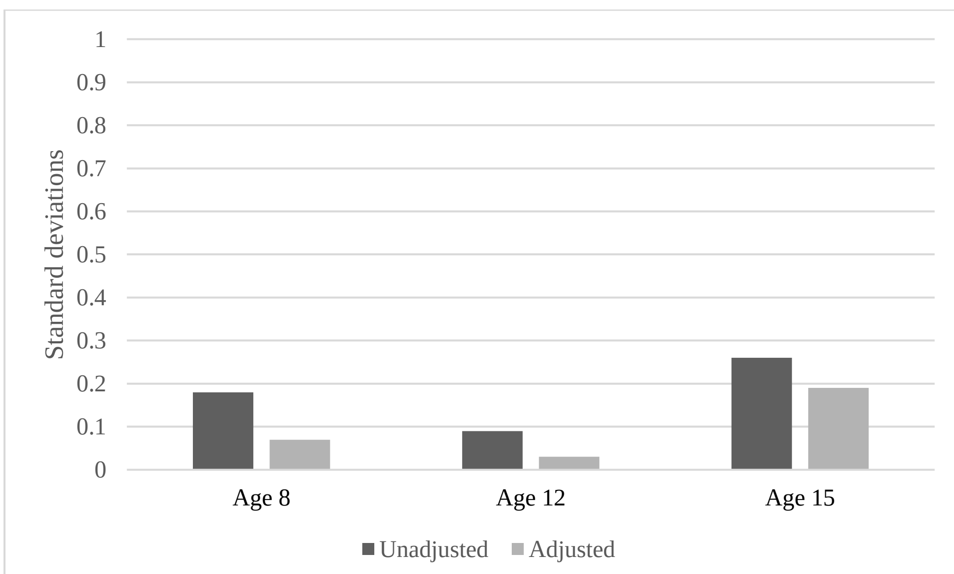

Figure 13. Size of the adjusted and unadjusted general health urban advantage in Peru

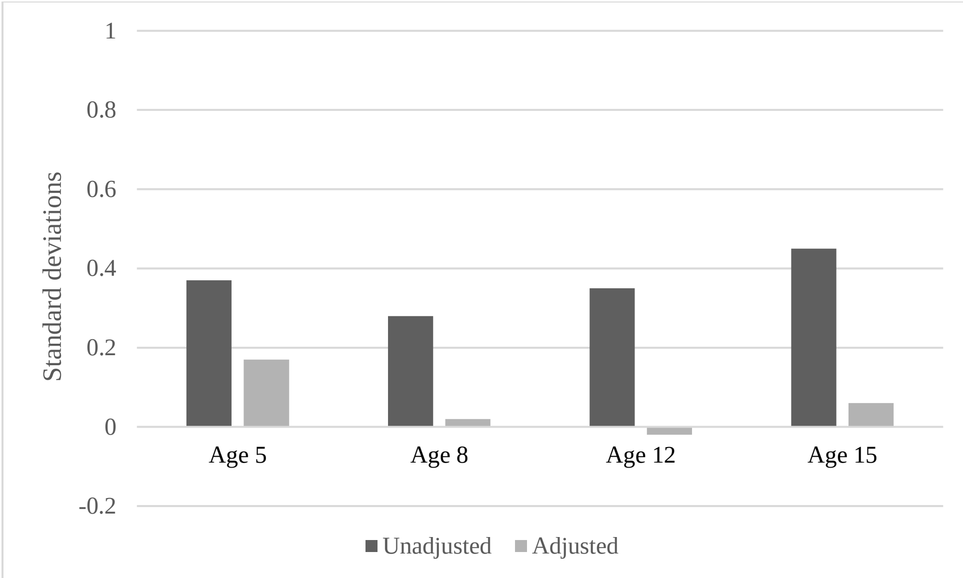

Figure 14. Size of the adjusted and unadjusted math urban advantage in India

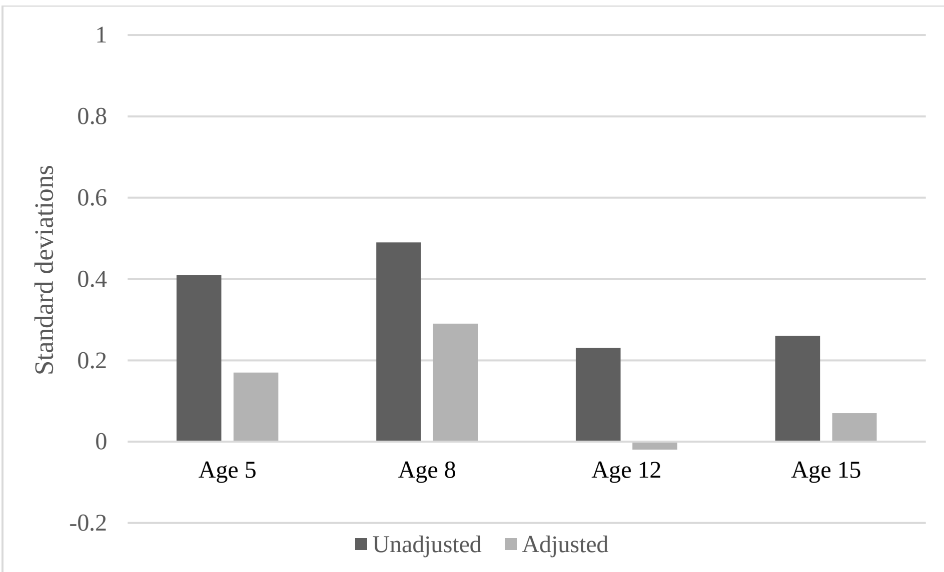

Figure 15. Size of the adjusted and unadjusted vocabulary urban advantage in India

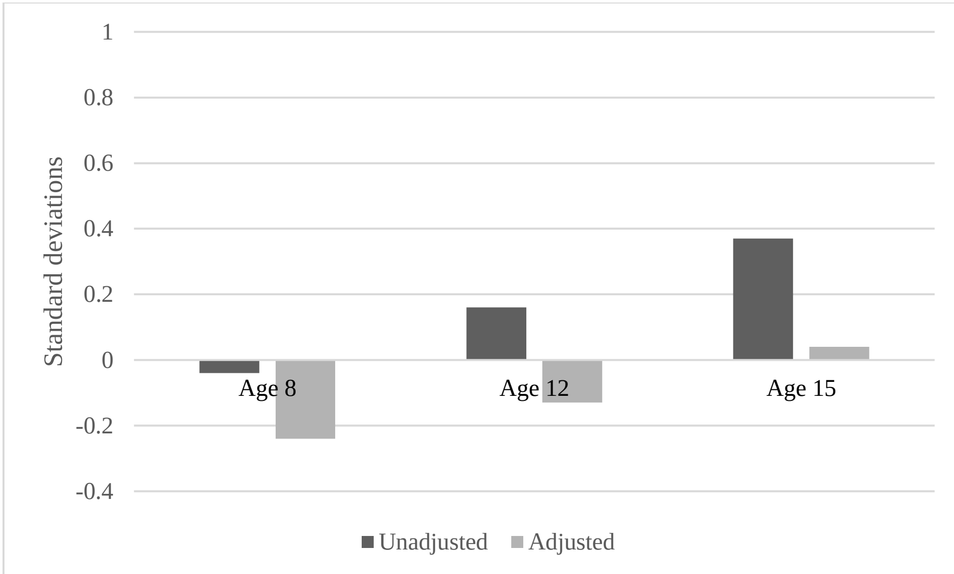

Figure 16. Size of the adjusted and unadjusted literacy urban advantage in India

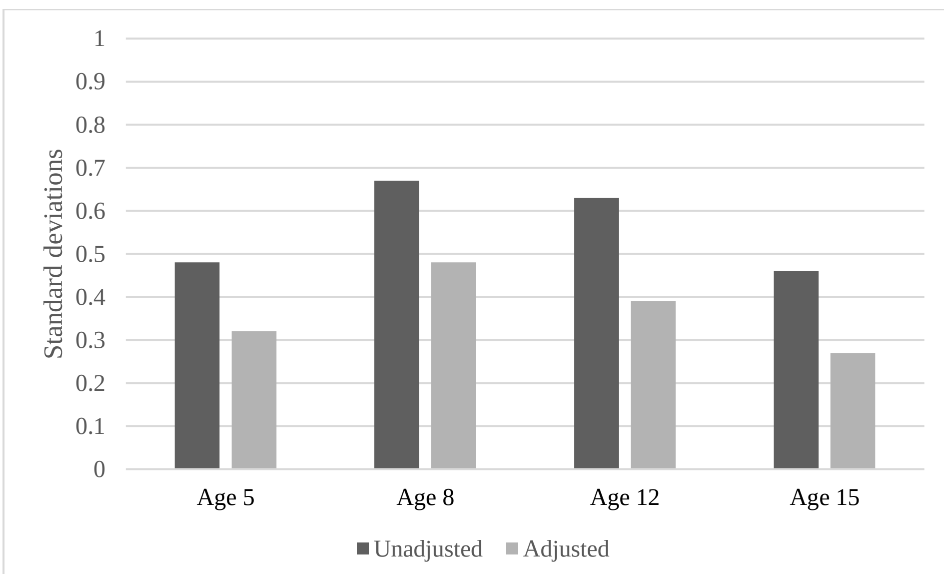

Figure 17. Size of the adjusted and unadjusted heigh-for-age urban advantage in India

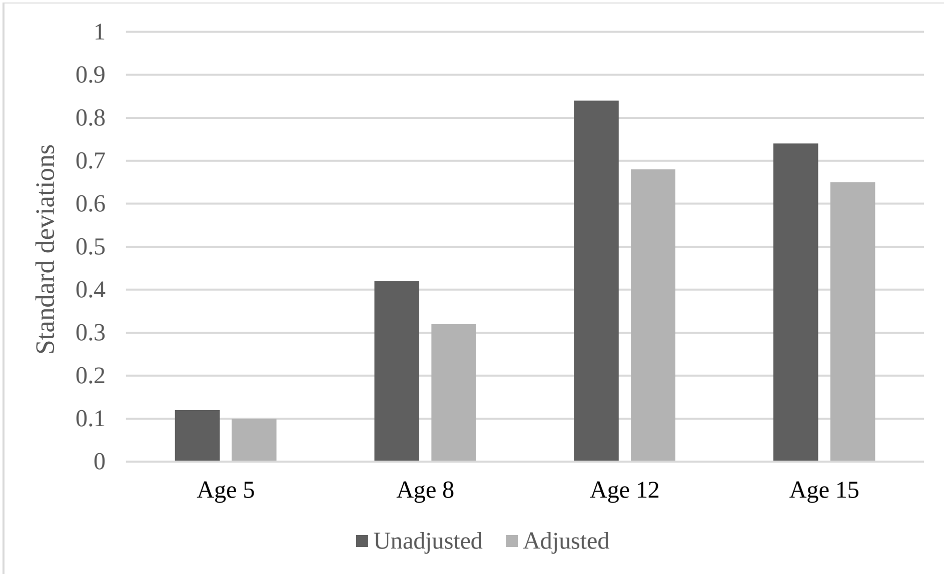

Figure 18. Size of the adjusted and unadjusted BMI-for-age urban advantage in India

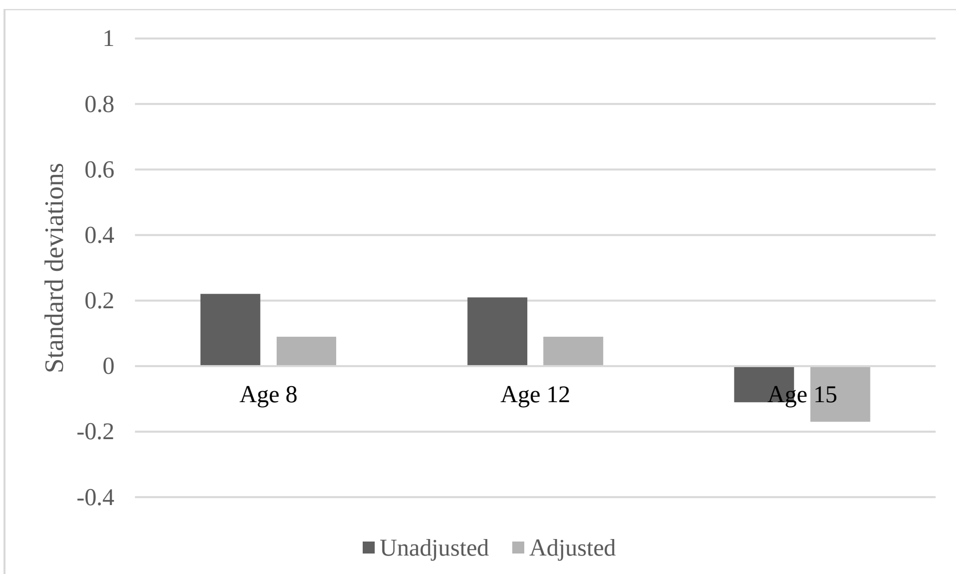

Figure 19. Size of the adjusted and unadjusted general health urban advantage in India

Bibliography

Aber, J. L., Bennett, N. G., Conley, D. C., & Li, J. (1997). The effects of poverty on child health and development. Annual review of public health, 18(1), 463-483.

Agrawal, T. (2014). Educational inequality in rural and urban India. *International Journal of Educational Development, 34, 11-19*. doi:10.1016/j.ijedudev.2013.05.002

Agarwal, M., & Kelly, L. (2004). Addressing challenges of globalization-an independent evaluation of the World Bank's approach to global programs-case study. Understanding Children's Work (UCW) Program, 32910, 1-69. The World Bank.

Ahluwalia, M. S. (2019). India's economic reforms: Achievements and next steps. *Asian Economic Policy Review, 14*(1), 46-62.

Akabayashi, H., & Psacharopoulos, G. (1999). The trade-off between child labour and human capital formation: A Tanzanian case study. *The Journal of Development Studies, 35*(5), 120-140.

Allison, P. D. (2003). Missing data techniques for structural equation modeling. *Journal of abnormal psychology, 112*(4), 545.

Arnold, F. (1992). Sex preference and its demographic and health implications. *International Family Planning Perspectives, 18*(3), 93-101

Ash, M., & Fetter, T. R. (2004). Who lives on the wrong side of the environmental tracks? Evidence from the EPA's risk-screening environmental indicators model. Social Science Quarterly, 85(2), 441-462.

Azam, M. (2019). Accounting for growing urban-rural welfare gaps in India. *World Development, 122*, 410-432

Banerjee, A. V., Bhattacharjee, S., Chattopadhyay, R., & Ganimian, A. J. (2017). The Untapped math skills of working children in India: Evidence, possible explanations, and implications. Unpublished manuscript. Available at https://iraparenting.com/wp-content/uploads/2017/10/Banerjee+et+al.+2017+-+2017-08-17.pdf

Barbier, E. B. (2012). *Natural capital, ecological scarcity and rural poverty*. The World Bank.

Barik, D., & Thorat, A. (2015). Issues of unequal access to public health in India. *Frontiers in Public Health, 3*(245), 1-3.

Barnes, G. M., Hoffman, J. H., Welte, J. W., Farrell, M. P., & Dintcheff, B. A. (2007). Adolescents' time use: Effects on substance use, delinquency and sexual activity. *Journal of Youth and Adolescence, 36*, 697

Barnett, I., Ariana, P., Petrou, S., Penny, M., Duc, L., Galab, S., Woldehanna, T., Escobal, J., Plugge, E., & Boyden, J. (2012). Cohort Profile: The Young Lives Study. *International Journal of Epidemiology,1,* 1-8.

Becker, G. S. (1991). *A Treatise on the Family*. Cambridge, MA: Harvard University Press.

Beggs, J. J., Haines, V. A., & Hurlbert, J. S. (1996). Revisiting the Rural-Urban Contrast: Personal Networks in Nonmetropolitan and Metropolitan Settings. *Rural Sociology, 61*(2), 306-325.

Benavides, Carnoy, Cueto & Gove. (2007). Evaluation of the World Bank's Assistance to Primary Education in Peru: A Country Case Study. The World Bank: Washington, D.C.

Birdsall, N., Levine, R., & Ibrahim, A. (2005). Towards universal primary education: investments, incentives, and institutions. *European Journal of Education, 40*(3), 337-349.

Black, M. M., Walker, S. P., Fernald, L. C. H., Andersen, C. T., Digirolamo, A. M., Lu, C., … Indies, W. (2017). Advancing Early Childhood Development : from Science to Series Early childhood development coming of age: science through the life course. The Lancet, 389(10064), 77-90. https://doi.org/10.1016/S0140-6736(16)31389-7

Bongaarts, J. (2001). Household size and composition in the developing world in the 1990s. *Population studies, 55*(3), 263-279.

Borja, A. (2010). Medical Pluralism in Peru--Traditional Medicine in Peruvian Society (Doctoral dissertation, Brandeis University).

Borga, L. G. (2019). Children's Own Time Use and its Effect on Skill Formation. *The Journal of Development Studies, 55*(5), 876-893.

Bourguignon, F., Ferreira, F. H., & Leite, P. G. (2003). Conditional cash transfers, schooling, and child labor: Micro-simulating Brazil's Bolsa Escola program. *The World Bank Economic Review, 17*(2), 229-254.

Briceño-León, R. (2002). La nueva violencia urbana de América Latina. *Sociologias, 4*(8), 34-51.

Britto, P. R., Lye, S. J., Proulx, K., Yousafzai, A. K., Matthews, S. G., Vaivada, T., … Bhutta, Z. A. (2017). Nurturing care: promoting early childhood development. The Lancet, 389(10064), 91–102. https://doi.org/10.1016/S0140-6736(16)31390-3

Bronfenbrenner, U., & Morris, P. A. (1998). The ecology of developmental processes. In W. Damon (Series Ed.) & R. M. Lerner (Vol. Ed.), Handbook of child psychology: Vol. 1. Theory (5th ed.). New York: Wiley

Brooks-Gunn, J., Duncan, G. J., Leventhal, T., & Aber, J. L. (1997). Lessons learned and future directions for research on the neighborhoods in which children live. In J. Brooks-Gunn, G. J. Duncan, & J. L. Aber (Eds.), *Neighborhood poverty: Context and consequences for children* (pp. 279 – 297). New York: Russell Sage Foundation.

Bublitz, E. (2016). *Perceptions of Inequality: Survey 2015/2016*. Bertelsmann Stiftung, GED Study.

Cameron, L. A., & Worswick, C. (2001). Education expenditure responses to crop loss in Indonesia: a gender bias. *Economic Development and Cultural Change, 49*(2), 351–363.

Castro, J., & Rolleston, C. (2015). Explaining the urban-rural gap in cognitive achievement in Peru: The Role of Early Childhood Environments and School Influences. *Young Lives, working paper 139*.

Chase-Lansdale, P. L., & Brooks-Gunn, J. (2014). Two-generation programs in the twenty-first century. *The Future of Children, 24*(1), 13-39.

Chaturvedi, A. (2018). Fixing India's Sewage Problem. *Spotlight on Sanitation: Stanford Social Innovation Review*. Available at https://ssir.org/pdf/Spring_2017_fixing_indias_sewage_problem.pdf

Chetty, R., Hendren, N., & Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment. American Economic Review, 106(4), 855-902.

Coley, R. L., Lynch, A. D., & Kull, M. (2015). Early exposure to environmental chaos and children's physical and mental health. *Early Childhood Research Quarterly, 32*, 94-104

Conger, R. D., Ge, X., Elder, G. H., Lorenz, F. O., & Simons, R. L. (1994). Economic stress, coercive family process, and developmental problems of adolescents. *Child Development, 65*(2), 541-561.

Conger, R. D., Wallace, L. E., Sun, Y., Simons, R. L., McLoyd, V. C., & Brody, G. H. (2002). Economic pressure in African American families: a replication and extension of the family stress model. *Developmental psychology, 38*(2), 179.

Cristancho, J. C., Harker, A., & Molano, A. E. (2016). Desarrollo humano en contextos hostiles: impacto de la violencia urbana sobre el desempeño académico. *Documentos CEDE, 33*. Universidad de Los Andes Available at https://repositorio.uniandes.edu.co/handle/1992/8700

Cronk, R., & Bartram, J. (2018). Environmental conditions in health care facilities in low-and middle-income countries: coverage and inequalities. *International journal of hygiene and environmental health, 221*(3), 409-422.

Crowder, K., & South, S. J. (2011). Spatial and temporal dimensions of neighborhood effects on high school graduation. *Social Science Research, 40*, 87–106.

Cueto, S., & Leon, J. (2012). Psychometric characteristics of cognitive development and achievement instruments in round 3 of Young Lives. *Young Lives Technical Note 25.*

Cueto, Leon, Guerrero, & Muñoz. (2009). Psychometric characteristics of cognitive development and achievement instruments in round 3 of Young Lives. *Young Lives Technical Note 15.*

Dachille, G., Guarcello, L., & Lyon, S. (2015). *Child and youth agricultural work in sub-Saharan Africa: perspectives from the World Bank Integrated Surveys on Agriculture Initiative*. Understanding Children's Work Programme Working Paper. International Labour Organization (ILO) and Centre for Economic and International Studies (CEIS): Rome.

Das, J., Holla, A., Das, V., Mohanan, M., Tabak, D., & Chan, B. (2012). In urban and rural India, a standardized patient study showed low levels of provider training and huge quality gaps. Health affairs, 31(12), 2774-2784.

Dawes, A. (2020). *Measuring the Development of Cognitive Skills across Time and Context: Reflections from Young Lives*. Young Lives Insight Reports, October 2020. Available at https://www.younglives.org.uk/sites/www.younglives.org.uk/files/YL-Dawes-MeasuringDevelopment-InsightReport-Oct20.pdf

De Hoop, J., Friedman, J., Kandpal, E., & Rosati, F. C. (2016). *Complementarities between schooling and child work in the presence of an education subsidy.* Understanding Children's Work Working Paper.

Deb, S. (2018). Globalization and the Rural-Urban Divide: An Inquiry on the Health, Education and Basic Amenities in India. *IARIW General Conference.* Copenhagen, Denmark, August 20-25, 2018.

Deolalikar, A. (1993). Gender Differences in the Returns to Schooling and School Enrollment Rates in Indonesia. *Journal of Human Resources*, *28*(4), 899–932.

Doctor, H. V., Nkhana-Salimu, S., & Abdulsalam-Anibilowo, M. (2018). Health facility delivery in sub-Saharan Africa: successes, challenges, and implications for the 2030 development agenda. *BMC public health*, *18*(1), 765.

Dobbs, R., Remes, J., Manyika, J. M., Roxburgh, C., Smit, S., & Schaer, F. (2012). *Urban world: Cities and the rise of the consuming class*. McKinsey Global Institute. Available at: https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Urbanization/Urban%20world%20Cities%20and%20the%20rise%20of%20the%20consuming%20class/MGI_Urban_world_Rise_of_the_consuming_class_Full_report.pdf

D'Onise, K., Lynch, J. W., Sawyer, M. G., & McDermott, R. A. (2010). Can preschool improve child health outcomes? A systematic review. *Social Science & Medicine*, *70*(9), 1423-1440.

Duflo, Galiani, & Mobarak, 2012. Improving Access to Urban Services for the Poor. Cambridge, MA J-PAL Urban Services Review Paper. Retrieved from http://econweb.umd.edu/~galiani/files/usi-review-paper.pdf

Duncan, G. J., & Brooks-Gunn, J. (2000). Family poverty, welfare reform, and child development. *Child Development*, *71*(1), 188-196.

Duncan, G. J., & Magnuson, K. (2012). Socioeconomic status and cognitive functioning: Moving from correlation to causation. *Wiley Interdisciplinary Reviews: Cognitive Science, 3,* 377–386. doi:10.1002/wcs.1176

Duncan, G., Whitener, L. A., & Weber, B. A. (2002). Welfare Reform and Food Assistance in Rural America. *Rural dimensions of welfare reform, 455*.

Dunn, L.M. & Dunn, L. M. (1997). Examiner's manual for the Peabody Picture Vocabulary Test-Third edition. Circle Pines, MN: American Guidance Service.

Dunn, L. M., Padilla, E. R., Lugo, D. E., & Dunn, L. M. (1986). Examiner's manual for the Test de Vocabulario en Images Peabody (Peabody Picture Vocabulary Test) Adaptacion Hispanoamericana (Hispanic American adaptation). Circle Pines, MN: American Guidance Service.

Dupere, V., Leventhal, T., Crosnoe, R., & Dion, E. (2010). Understanding the positive role of neighborhood socioeconomic advantage in achievement: The contribution of the home, child care, and school environments. *Developmental Psychology*, *46*(5), 1227.

Dakkak, A. (2020, April 5). Water Pollution Worries in Developing World. Retrieved from https://www.ecomena.org/water-pollution/

Ersado, L. (2003). Child labor and school decisions in urban and rural areas: Cross country evidence. FCND Discussion Paper 145. Available at https://ageconsearch.umn.edu/record/16392

Ersado, L. (2005). Child labor and schooling decisions in urban and rural areas: comparative evidence from Nepal, Peru, and Zimbabwe. World development, 33(3), 455-480.

Evans, G. W., & Wachs, T. D. (2010). Chaos and its influence on children's development. Washington, DC: American Psychological Association.

Evans, G. W., & Kim, P. (2013). Childhood poverty, chronic stress, self-regulation, and coping. *Child Development Perspectives*, *7*(1), 43-48.

Evans, G. W., & Saegert, S. (2000). Residential crowding in the context of inner city poverty. In *Theoretical perspectives in environment-behavior research* (pp. 247-267). Springer, Boston, MA.

Fan, S., Chan-Kang, C., & Mukherjee, A. (2005). Rural and urban dynamics and poverty: Evidence from China and India. *FCND Discussion Paper 196*. Available at https://ageconsearch.umn.edu/record/59598

Felker-Kantor, E., Wallace, M., & Theall, K. (2017). Living in violence: Neighborhood domestic violence and small for gestational age births. Health & Place, 46, 130-136.

Filmer,D. (1999) *The Structure of Social Disparities in Education: Gender and Wealth. Background paper World Bank, Engendering Development — Through Gender Equality* *in Rights, Resources, and Voice*. Policy Research Report on Gender and Development. Washington, D.C.: World Bank

Foster, E. M. (2002). How economists think about family resources and child development. Child Development, 73(6), 1904-1914.

Fox, S. E., Levitt, P., & Nelson, C. A. (2010). How the timing and quality of early experiences influence the development of brain architecture. Child development, 81(1), 28-40.

Glewwe, P., & Arteaga, I. (2014). Achievement gap between indigenous and non-indigenous children in Peru an analysis of Young Lives Survey Data. *Young Lives Working Paper 130*.

Gordon, R. A., & Chase-Lansdale, P. L. (2001). Availability of child care in the United States: A description and analysis of data sources. *Demography, 38*(2), 299-316.

Guerrero, G.; Leon, L.; Rosales, E.; Zapata, M.; Freire, S.; Saldarriaga, V., & Cueto, S. (2012). Young Lives School Survey in Peru: Design and Initial Findings. *Young Lives Working Paper, 92*.

Gunther, I. & Harttgen K. (2012). Deadly Cities. Spatial Inequalities in Mortality in sub-Saharan Africa. *Population and Development Review, 38*(3), 469-486.

Guo, G., & Harris, K. M. (2000). The mechanisms mediating the effects of poverty on children's intellectual development. *Demography, 37*(4), 431-447.

Fink, G., Günther, I., & Hill, K. (2014). Slum residence and child health in developing countries. *Demography, 51*(4), 1175-1197.

Furstenberg, F. F., Cook, T. D., Eccles, J., & Elder, G. H. (2000). *Managing to make it: Urban families and adolescent success*. University of Chicago Press.

Hanushek, E. A. (1997). Assessing the effects of school resources on student performance: An update. *Educational Evaluation and Policy Analysis, 19*(2), 141-164.

Hill, T. D., Ross, C. E., & Angel, R. J. (2005). Neighborhood disorder, psychophysiological distress, and health. *Journal of health and social behavior, 46*(2), 170-186.

Hnatkovska, V., & Lahiri, A. (2013). The rural-urban divide in India. International Growth Center, Working Paper. Retrieved from https://www.theigc.org/wp-content/uploads/2014/09/Hnatkovska-Lahiri-2012-Working-Paper-March.pdf

Hirvonen, K. (2016). Rural–urban differences in children's dietary diversity in Ethiopia: A Poisson decomposition analysis. *Economics Letters, 147*, 12-15.

Howe, L. D., Galobardes, B., Matijasevich, A., Gordon, D., Johnston, D., Onwujekwe, O., ... & Hargreaves, J. R. (2012). Measuring socio-economic position for epidemiological studies in low-and middle-income countries: a methods of measurement in epidemiology paper. *International journal of epidemiology, 41*(3), 871-886.

Huisman, J., & Smits, J. (2009). Effects of household-and district-level factors on primary school enrollment in 30 developing countries. World development, 37(1), 179-193.

Imai, K. S., & Malaeb, B. (2018). Asia's Rural-Urban Disparity in the Context of Growing Inequality. *IFAD Research Series, 27.* Available at https://ssrn.com/abstract=3285058

Imbusch, P., Misse, M., & Carrión, F. (2011). Violence research in Latin America and the Caribbean: A literature review. *International Journal of Conflict and Violence, 5*(1), 87-154.

IPA (2018). *Choosing a Better Future: Information to Reduce School Drop Out and Child Labor Rates in Peru. IPA Preliminary Results Team*. Available at https://www.poverty-action.org/sites/default/files/publications/Peru-Returns-to-Education-Brief-English-Sept-2018.pdf

James, Z. (2013). *Young Lives school survey, India 2010/2011. Data user guide.* Young Lives.

Karambelas, A., Holloway, T., Kinney, P. L., Fiore, A. M., DeFries, R., Kiesewetter, G., & Heyes, C. (2018). Urban versus rural health impacts attributable to PM2. 5 and O3 in northern India. *Environmental Research Letters, 13*(6), 064010.

Kaushal, N. (2014). Intergenerational payoffs of education. *The Future of Children, 24*(1), 61-78.

Keane, M. P., Krutikova, S., & Neal, T. (2018). The impact of child work on cognitive development: results from four Low to Middle Income countries. *IFS Working Papers W18/29*.

Khan, M.H. (2001). Rural Poverty in Developing Countries: Implications for Public Policy. *Economic Issues, 26*.

Khan, R. E, Khan, T. & Rashid, A. (2010). Comparative Analysis of Rural and Urban Child Labor in Pakistan. *European Journal of Economics, Finance and Administrative Sciences, 27*.

Khandker, S. R., Samad, H. A., Ali, R., & Barnes, D. F. (2012). Who benefits most from rural electrification. *World Bank policy research working paper, 6095*.

Kohen, D. E., Leventhal, T., Dahinten, V. S., & McIntosh, C. N. (2008). Neighborhood disadvantage: Pathways of effects for young children. *Child development, 79*(1), 156-169.

Koolwal, G. B. (2007). Son preference and child labor in Nepal: The household impact of sending girls to work. *World Development, 35*(5), 881-903.

Kremer, Michael, Karthik Muralidharan, Nazmul Chaudhury, Jeffrey Hammer, and F. Halsey Rogers. (2005). Teacher Absence in India: A Snapshot. *Journal of the European Economic Association, 3*(2-3), 658-667.

Kulkarni, V. S., & Barnes, D. F. (2017). Education in rural Peru: Exploring the role of household electrification in school enrollment. *Journal of Research in Rural Education, 32*(10), 1-19.

Kurosaki, T., Ito, S., Fuwa, N., Kubo, K., & Sawada, Y. (2006). Child labor and school enrollment in rural India: Whose education matters?. *The Developing Economies, 44*(4), 440-464.

Lakin, M. & Gasperini, L. (2003). Basic Education in Rural Areas: Status, Issues and Prospects. In: Atchoarena David, Gasperini Lavinia. (Ed.), *Education for Rural Development: Towards New Policy Responses*. FAO and UNESCO: Rome and Paris.

Lall, S. V., Selod, H., Shalizi, Z.. (2006). Rural–Urban Migration in Developing Countries: A Survey of Theoretical Predictions and Empirical Findings. *The World Bank Policy Research Working Paper Series, 3915*.

Laurito, A., Lacoe, J., Schwartz, A. E., Sharkey, P., & Ellen, I. G. (2019). School climate and the impact of neighborhood crime on test scores. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, *5*(2), 141-166.

Lee, G. R., Netzer, J. K., & Coward, R. T. (1994). Filial responsibility expectations and patterns of intergenerational assistance. *Journal of Marriage and the Family, 56*(3), 559-565.

Lepore, S. J., & Kliewer, W. (2013). Violence exposure, sleep disturbance, and poor academic performance in middle school. *Journal of Abnormal Child Psychology, 41*(8), 1179-1189.

Leventhal, T., & Brooks-Gunn, J. (2000). The neighborhoods they live in: the effects of neighborhood residence on child and adolescent outcomes. *Psychological bulletin, 126*(2), 309.

Leventhal, T., Dupéré, V., & A. Shuey, E. (2015). Children in neighborhoods. *Handbook of child psychology and developmental science*, 1-41.

Leventhal, T., Dupéré, V., & Brooks-Gunn, J. (2009). Neighborhood influences on adolescent development. *Handbook of Adolescent Psychology, 2*, 411-443.

Levira, M. A. (2000). *Instructional resources as a factor in educational performance: A case study in Tanzania*. Unpublished doctoral dissertation, Concordia University, Montreal

Leon, J., & Singh, A. (2017). Equating test scores for receptive vocabulary across rounds and cohorts in Ethiopia, India and Vietnam. *Young Lives Technical Note, 40.*

Lewis, M. A., & Lockheed, M. E. (2006). Inexcusable absence: why 60 million girls still aren't in school and what to do about it. Center for Global Development: Washington, DC.

Linares, L. O., Heeren, T., Bronfman, E., Zuckerman, B., Augustyn, M., & Tronick, E. (2001). A mediational model for the impact of exposure to community violence on early child behavior problems. *Child Development, 72*(2), 639-652.

Litt, J.S. Hynes, P. Carrol, P. Maxfield, R. McLaine, P. & Kawecki, C. (2002). Lead safe yards: a program for improving health in urban neighborhoods *Journal of Urban Technology*, *9*(2), 71-93.

Liu, Q. (2013). Urbanization and Urban Poverty in Southeast Asia. The International Poverty Reduction Center in China. Available at: http://www.iprcc.org/Index/down/id/3944.html

Lloyd, C. B. (2005). Schooling. In *Growing Up Global: The Changing Transitions to Adulthood in Developing Countries*, Lloyd, C. B. (Ed). Washington, DC: National Academies Press.

Lubans, D. R., Boreham, C. A., Kelly, P., & Foster, C. E. (2011). The relationship between active travel to school and health-related fitness in children and adolescents: a systematic review. *International Journal of Behavioral Nutrition and Physical Activity, 8*(1), 1-12.

Mani, S. (2008). Is there Complete, Partial, or No Recovery from Childhood Malnutrition? Empirical Evidence from Indonesia. *Oxford Bulletin of Economics and Statistics, 74*(5), 691–715.

McCoy, D. C., Peet, E. D., Ezzati, M., Danaei, G., Black, M. M., Sudfeld, C. R., … Fink, G. (2016). Early Childhood Developmental Status in Low- and Middle-Income Countries: National, Regional, and Global Prevalence Estimates Using Predictive Modeling. PLoS Medicine, 13(6), 1–18. https://doi.org/10.1371/journal.pmed.1002034

McEwan, P. J. (1999). Recruitment of rural teachers in developing countries: An economic analysis. *Teaching and Teacher Education, 15*(8), 849-859.

McMichael, A. J. (2000). The urban environment and health in a world of increasing globalization: issues for developing countries. *Bulletin of the World Health Organization, 78*(9), 1117-1126.

Miller, P., Votruba-Drzal, E., & Coley, R. L. (2019). Poverty and Academic Achievement Across the Urban to Rural Landscape: Associations with Community Resources and Stressors. *RSF: The Russell Sage Foundation Journal of the Social Sciences, 5*(2), 106-122.

Monteiro, J., & Rocha, R. (2017). Drug battles and school achievement: evidence from Rio de Janeiro's favelas. *Review of Economics and Statistics, 99*(2), 213-228.

Muthen, L. K., & Muthen, B. O. (2017). Mplus. Version 8. Los Angeles, CA: Muthen & Muthen.

Newsom, J. T. (2015). *Longitudinal structural equation modeling: A comprehensive introduction*. New York, NY: Routledge.

Nogueira, H., Ferrão, M., Gama, A., Mourão, I., Marques, V. R., & Padez, C. (2013). Perceptions of neighborhood environments and childhood obesity: evidence of harmful gender inequities among Portuguese children. *Health & Place, 19*, 69-73.

Nolan, L. B. (2016). Rural–Urban Child Height for Age Trajectories and Their Heterogeneous Determinants in Four Developing Countries. *Population Research and Policy Review*, *35*(5), 599-629.

O'Donnell, O., Van Doorslaer, E., & Rosati, F. C. (2002). *Child labour and health: Evidence and research issues.* Understanding Children's Work Programme Working Paper.

OECD. (2019). OECD Economic Surveys: India Economic Snapshot, 2019. http://www.oecd.org/economy/surveys/India-2019-OECD-economic-survey-overview.pdf

Ooi, G. and Phua, K. (2007). Urbanization and Slum Formation. *Journal of Urban Health, 84*(S1), 27-34. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1891640/

Orr, L., Feins, J., Jacob, R., Beecroft, E., Sanbonmatsu, L., Katz, L. F., ... & Kling, J. R. (2003). *Moving to opportunity: Interim impacts evaluation*.

Othman, M & Muijs, D. (2013) Educational quality differences in a middle-income country: the urban-rural gap in Malaysian primary schools. *School Effectiveness and School Improvement, 24*(1), 1-18.

Peña, M. S. B., & Rollins, A. (2017). Environmental exposures and cardiovascular disease: a challenge for health and development in low-and middle-income countries. *Cardiology clinics, 35*(1), 71-86.

Patnaik, P. (2016). Economic Liberalisation and the Working Poor. *Economic & Political Weekly, 51*(29), 47-51.

Putnick, D. L., & Bornstein, M. H. (2015). Is child labor a barrier to school enrollment in low-and middle-income countries?. International journal of educational development, 41, 112-120.

Ramachandran, V. (2009). Systemic barriers to equity in education. *Concerns, Conflicts and Cohesions: Universalisation of Elementary Education in India.* Oxford University Press, New Delhi.

Ramos, R., Duque, J. C., & Nieto, S. (2020). Decomposing the rural-urban differential in student achievement in Colombia using PISA microdata. *Studies of Applied Economics, 34*(2), 379-412.

Reardon, S. F., & Bischoff, K. (2011). Income inequality and income segregation. *American Journal of Sociology, 116*(4), 1092-1153.

Rojas, V., & Cussianovich, A. (2014). Creciendo en el Perú: una mirada longitudinal al uso del tiempo de los niños y las niñas en el campo y la ciudad. *Avances de Investigación, 14*. Lima: GRADE Group for the Analysis of Development. Retrieved from https://nbn-resolving.org/urn:nbn:de:0168-ssoar-56547-7

Ranzani, M., & Rosati, F. C. (2014). *The impact of Oportunidades on school participation and child labour*. Understanding Children’s Work Programme Working Paper Series. Unicef.

Roth, S. (2017). Air pollution, educational achievements, and human capital formation. *IZA World of Labor, 381.* doi: 10.15185/izawol.381

Saikia, N., Singh, A., Jasilionis, D., & Ram, F. (2013). Explaining the rural–urban gap in infant mortality in India. *Demographic Research, 29*(18), 473-506.

Sengupta, A., & Nundy, S. (2005). The private health sector in India. Is burgeoning, but at the cost of public health care. *BMJ, 331*(7526), 1157–1158.

Sekkat, K. (2017). Urban concentration and poverty in developing countries. Growth and Change, 48(3), 435-458.

Shafiq, M. N. (2007). Household schooling and child labor decisions in rural Bangladesh. *Journal of Asian Economics, 18*(6), 946-966.

Shah, M. (2016). Urban water systems in India: A way forward. *Indian Council for Research on International Economic Relations (ICRIER): New Delhi. Working Paper, No. 323*. Available at: http://hdl.handle.net/10419/176350

Shonkoff, J. P., & Phillips, D. A. (2000). *From neurons to neighborhoods: The science of early childhood development*. National Academy Press: Washington, DC.

Schultz, P. (1993). Investments in the Schooling and Health of Women and Men: Quantities and Returns. *Journal of Human Resources, 28*(4), 694–734.

Schultz, P. (2001). Why Governments Should Invest More to Educate Girls. *World Development, 30*(2), 207-25.

Smith, J. (1999). Healthy bodies and thick wallets: the dual relation between health and economic status. *Journal of Economic Perspectives, 13*(2): 145-166

Smith, L. C., Ruel, M. T., & Ndiaye, A. (2005). Why is child malnutrition lower in urban than in rural areas? Evidence from 36 developing countries. *World Development*, *33*(8), 1285-1305.

South, S. J., & Crowder, K. (2010). Neighborhood poverty and nonmarital fertility: Spatial and temporal dimensions. *Journal of Marriage and Family, 72,* 98–104.

Steinberg, L., & Morris, A. S. (2001). Adolescent development. *Annual Review of Psychology, 52*, 83–110.

Stephens, C. (2012). Urban Social and Environmental Inequities: Impacts on child rights, health and wellbeing in cities. *UNICEF Background Discussion Paper for State of the World's Children*.

Strauss, J. & Thomas, D. (1995). Human Resources: Empirical Modeling of Household and Family Decisions. In J. Behrman & T. N. Srinivasan (Eds.), *Handbook of Development Economics*, (vol. 3A, p. 1883–2023). Amsterdam: North Holland.

Supplee, L. H., Unikel, E. B., & Shaw, D. S. (2007). Physical environmental adversity and the protective role of maternal monitoring in relation to early child conduct problems. *Journal of applied developmental psychology, 28*(2), 166-183.

Tacoli, C. (2012). *Urbanization, gender and urban poverty: paid work and unpaid carework in the city*. Human Settlements Group, International Institute for Environment and Development

Tayyaba, S. (2012). Rural-urban gaps in academic achievement, schooling conditions, student, and teachers' characteristics in Pakistan. *International Journal of Educational Management, 26*(1), 6-26.

Tetali, S., Edwards, P., & Roberts, G. M. I. (2016). How do children travel to school in urban India? A cross-sectional study of 5,842 children in Hyderabad. *BMC Public Health, 16*(1099).

Thu Le, H., & Booth, A. L. (2010). Inequality in Vietnamese urban–rural living standards, 1993–2006. *IZA DP*, 4987. Retrieved from http://ftp.iza.org/dp4987.pdf

Thu Le, H., & Booth, A. L. (2014). Inequality in Vietnamese urban–rural living standards, 1993–2006. *Review of Income and Wealth, 60*(4), 862-886.

Tilak, J. B. (1996). How free is' free'primary education in India?. *Economic and Political weekly, 31*(6), 355-366.

UNICEF. (2012). Children in an increasingly urban world. In *The State of the World's Children*. New York: NY.

UNICEF. (2020). *Education: UNICEF is committed to ensuring all children in India have access to inclusive and equitable quality education.* Retrievened on October 15 of 2020 from https://www.unicef.org/india/what-we-do/education

UNICEF & World Bank Group (2016). *Ending Extreme Poverty: A Focus on Children.* Briefing Note.

United Nations. (2010). *Millennium Development Goals Report.* New York: United Nations.

United Nations. Department of Economic and Social Affairs, Population Division. (2018). *World Urbanization Prospects 2018: Highlights.* New York: NY.

United Nations System Standing Committee on Nutrition. (2017). *Schools as a System to Improve Nutrition: A new statement for school-based food and nutrition interventions*. Available at https://www.unscn.org/uploads/web/news/document/School-Paper-EN-WEB.pdf

Uttara, S., Bhuvandas, N., & Aggarwal, V. (2012). Impacts of urbanization on environment. *International Journal of Research in Engineering and Applied Sciences, 2*(2), 1637-1645.

Van de Poel, E., O'Donnell, O., & Van Doorslaer, E. (2007). Are urban children really healthier? Evidence from 47 developing countries. *Social science & medicine, 65*(10), 1986-2003.

Vegas, E. (2007). Teacher labor markets in developing countries. *Future of Children, 17*(1), 219-232.

Venkatachalam, L. (2015). Informal water markets and willingness to pay for water: a case study of the urban poor in Chennai City, India. *International Journal of Water Resources Development*, *31*(1), 134-145.

Vernon-Feagans, L., Garrett-Peters, P., Willoughby, M., Mills-Koonce, R., & Family Life Project Key Investigators. (2012). Chaos, poverty, and parenting: Predictors of early language development. *Early Childhood Research Quarterly*, *27*(3), 339-351.

Wang, J., Li, H., & Wang, D. (2018). Bridging the rural-urban literacy gap in China: a mediation analysis of family effects. *Journal of Research in Childhood Education, 32*(1), 119-134.

Wachs, T. D., & Camli, O. (1991). Do ecological or individual characteristics mediate the influence of the physical environment upon maternal behavior. *Journal of environmental psychology, 11*(3), 249-264

WISE. (2019). Alternate Education for Rural Development in Peru, April 24, 2019. Retrieved on October 12 of 2020 from https://www.wise-qatar.org/project/alternate-education-rural-development-peru-spain/

Wodtke,G., Harding, D. J.,& Elwert, F. (2011).Neighborhood Effects in Temporal Perspective. *American Sociological Review*, *76*(5), 713–736.

Wodon, Q. (2014). *Education in Sub-Saharan Africa: comparing faith-inspired, private secular, and public schools*. World Bank Publications.

Wolf, S., Aber, J. L., & Morris, P. A. (2015). Patterns of time use among low-income urban minority adolescents and associations with academic outcomes and problem behaviors. *Journal of youth and adolescence, 44*(6), 1208-1225.

Woodhead, M., Ames, P., Vennam, U., Abebe, W., & Streuli, N. (2009). Equity and quality? Challenges for early childhood and primary education in Ethiopia, India and Peru. *The Bernard van Leer Foundation Working Papers in Early Childhood Development, 55.*

World Bank. (2001). *Health, Nutrition, Population Sector Unit India South Asia Region. Raising the sights: better health systems for India's poor*. Washington: World Bank.

World Bank. (2004). *Issues and Dynamics: Urban Systems in Developing East Asia-Vietnam*. East Asia Infrastructure Department.

Word Bank (2010). *Violence in the City Understanding and Supporting Community Responses to Urban Violence*. Available at: https://www.unicef.org/protection/Violence_in_the_City.pdf

Word Bank (2011b). *Urbanization in India.* Retrieved on October 12 of 2020 from https://www.worldbank.org/en/news/feature/2011/09/22/india-urbanization

World Bank. (2011a). Peru: A second rural electrification project (Report No. 60154-PE). Retrieved from http://documents.worldbank.org/curated/en/550011468325218624/pdf/601540PAD0P117 1OFF ICIAL0USE0ONLY191.pdf

World Bank. (2012). *World Development Report 2012: Gender Equality and Development (WDR)*. Washington DC: World Bank

World Bank (2017). Philippines Urbanization Review: Fostering Competitive, Sustainable and Inclusive Cities. Available at: http://documents.worldbank.org/curated/en/963061495807736752/ pdf/114088-REVISED-PUBLIC-Philippines-Urbanization-Review-Full-Report.pdf

World Bank Data Bank. (2020a). Urban population –Peru. Estimated obtained retrieved from https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=PE

World Bank Data Bank. (2020b). Urban population –India. Estimated obtained retrieved from https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=IN

World Health Organization. (2006). *WHO Child Growth Standards: Length/height-for-age, weight-for-age, weight-for-length, weight-for-height and body mass index-for-age: Methods and development.* Geneva: World Health Organization.

World Health Organization. (2014). Ambient (outdoor) air quality and health. *Fact sheet, 313.* Available at https://www.who.int/en/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

Young, D.J. (1998). Rural and urban differences in student achievement in science and mathematics: a multilevel analysis. *School Effectiveness and School Improvement, 9*(4), 386-418.

Young, A. (2013). Inequality, the urban-rural gap, and migration. *The Quarterly Journal of* Economics, 128(4), 1727-1785.

Zhang, X. Q. (2016). The trends, promises and challenges of urbanisation in the world. Habitat International, 54, 241-252