Courant Research Centre
'Poverty, Equity and Growth in Developing and Transition Countries: Statistical Methods and Empirical Analysis'

Georg-August-Universität Göttingen
(founded in 1737)

Discussion Papers

No. 262

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July 2019

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April 2019

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Abstract

Early motherhood remains a widespread phenomenon in low- and middle-income countries (LMICs). While the consequences of early motherhood for the mother have been extensively investigated, the impact on their children is severely understudied, especially in LMICs, which host 95% of teen births globally (WHO, 2014). Using panel and sibling data from India, this paper investigates the effect of early maternal age on offspring human capital development in terms of health and cognition, and relies on mother fixed effects to allow for household and mother unobserved heterogeneity. Furthermore, this paper explores the evolution of these effects over time during childhood and early adolescence for the first time. Results indicate that early maternal age has an overall detrimental effect on offspring health and cognition. We show that children born to early mothers are shorter for their age and perform poorer in the math test. Interestingly, the effect on child's heath is observed at early ages and weakens over time, while the cognition effect surges only in early adolescence. The analysis on heterogeneous effects suggests that children and in particular girls born to very young mothers are worst off. The transmission channel analysis tentatively hints at some behavioral channels driving the relationships of interest and documents a positive (and modest) association between height-for-age and subsequent math performance. Overall, our results support both restorative policies assisting children born to early mothers and preventive policies tackling early pregnancy.

JEL: I15, I25, J13, J16, O15
Keywords: Adolescent Motherhood, Human Capital, Child Development, Cognition, Health, Nutrition, Gender, Parenting

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* Acknowledgments: We would like to thank Jere Behrman, Axel Dreher, Stephan Klasen, Krisztina Kis-Katos and Holger Strulik for their comments. We also thank Kristine Briones for her support with the Young Lives data and her insights on data-related issues, as well as conference participants at Oxford (Oxford Development Economics Workshop), Göttingen (Globalization and Development Conference) and Benin (Poverty Reduction, Equity and Growth Conference) for their valuable input. The paper was partially supported by the International Development Research Centre (IDRC) in Canada as part of the Young Marriage and Parenthood Study (YMAPS), a programme of comparative research (2017-2020) examining young marriage and parenthood in collaboration with Young Lives (www.younglives.org.uk).

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"The most valuable of all capital is that invested in human beings; and of that capital the most precious part is the result of the care and influence of the mother. "

(Marshall, *Principles of Economics*, 1890)

1. Introduction

Early motherhood remains a widespread phenomenon in low- and middle-income countries (LMICs), where 19 million teenage girls give birth every year (EWEC, 2015; UNFPA, 2015; Neal et al., 2012). In spite of this large number, research on the consequences of early motherhood for the offspring is strikingly scarce, particularly in the context of LMICs that host 95% of global teen births (WHO, 2014). This paper contributes to closing this gap by investigating the role of early motherhood on offspring human capital in the Indian states of Andhra Pradesh and Telangana, where teenage fertility rates amount to 12% and 11%, respectively (IIPS, 2017).

Our analysis has three main objectives. First, we test whether children born to adolescent mothers have poorer health and cognitive outcomes during childhood and early adolescence than children born to adult mothers. We hypothesize that adolescent mothers are biologically and behaviorally immature for childbearing and child rearing, ultimately having detrimental effects on the human capital production of their children. The assertion on biological immaturity relies on the medical literature linking adolescent pregnancy to labor complications and poor neonatal outcomes (Fall et al., 2015; Gibbs et al., 2012; Neal et al., 2012; Conde-Agudelo et al., 2005), while the assertion on behavioral immaturity is stimulated by the literature on intra-household resource allocation, which highlights the role of the mother in human capital investments for children (Doss, 2013; Duflo, 2003). In this context, we argue that adolescent mothers might have both lower knowledge and lower bargaining power over decisions affecting the human capital of their children. Second, we investigate how the effect of early maternal age on child human capital evolves over time, covering the transition from childhood into early adolescence. Third, we investigate heterogeneous effects by more detailed maternal age groups and gender, and tentatively explore potential transmission channels mediating the relationship between maternal age and offspring outcomes.

Previous research shows that early motherhood is correlated with poor offspring outcomes, including low birth weight, low cognitive test scores, behavioral outcomes, grade repetition and adult economic disadvantage (see Azevedo et al., 2012 for a comprehensive review). Nevertheless, there is a lack of consensus about the causal links between early parenting and subsequent outcomes. The main concern is the role played by unobservable mother and family characteristics. Because women living in poor socioeconomic settings are overrepresented among adolescent mothers (see IIPS, 2017 for Indian statistics), differences in child's outcomes by maternal ages may reflect differences in pre-childbearing characteristics rather than the effects of maternal age itself.

We attempt to recover the causal effect of being born to an adolescent mother by adopting a mother fixed effects approach (MFE). Since mother unobserved heterogeneity confounds the effect of interest, we circumvent this issue by comparing the offspring outcomes of children born to the same biological mother. That is, we exploit the maternal age at birth variation of children within the same family. Such siblings-difference models are established empirical tools widely used in studies on human capital production (Cunha and Heckman, 2008; Todd and Wolpin, 2007; Alderman et al., 2006; Glewwe et al., 2001). They are also favored by the literature on the consequences of maternal age on offspring outcomes using data from developed countries such as Sweden (Carslake et al., 2017), Norway (Aizer et al., 2018), the UK (Francesconi, 2008) and the US (Levine et al., 2007; López-Turley, 2003; Rosenzweig and Wolpin, 1995; Geronimus et al., 1994).

Evidence from such studies, using either sister-fixed effects or mother-fixed effects models, is mixed. For example, Geronimus et al. (1994) conclude that lower offspring cognitive skills are the result of unobserved pre-childbearing maternal characteristics. Similar implications are suggested by Rosenzweig and Wolpin (1995), who find no differences in birthweight by maternal age groups in a siblings-difference model. In the same vein, López-Turley (2003) and Levine et al. (2007) conclude that unobserved family background drives poorer cognitive skills and increased behavioral problems of children born to younger mothers, although the latter study reports detrimental effects in some children's behavioral outcomes. Levine et al. (2007) argue that the effect of maternal age on children's behaviors tend to emerge at older ages. Conversely, recent studies suggest that early motherhood is indeed detrimental to offspring development indicators in young adulthood such as height and cognitive scores (Aizer et al., 2018; Carslake et al., 2017), noncognitive skills (Carslake et al., 2017) and educational attainment and income (Aizer et al., 2018; Francesconi, 2008).

Somewhat unexpectedly, related studies on LMICs are remarkably scarce. To the best of our knowledge, only one paper looks at the effect of maternal age on offspring development (Branson et al., 2015), while two others look at the effect of marriage age (Chari et al., 2017; Delprato et al., 2017).[1] All three studies suggest that younger ages are detrimental to offspring development. More specifically, Branson et al. (2015) look at the effect of teenage fertility on offspring's height-for-age in Cape Town, South Africa, using propensity score matching. They find that children born to teen mothers are shorter and have lower birthweight. Chari et al. (2017) use nationally representative household data from India and rely on age at menarche as an instrumental variable for marriage age. Their findings suggest that delayed marriage results in larger birth length, higher weight-for-height and improvements in cognition outcomes. Finally, Delprato et al. (2017) use demographic and health surveys from 25–32 sub-Saharan Africa countries to find that being born to mothers who had married young reduces schooling outcomes, particularly for girls. They address the endogeneity of early marriage employing an instrumental variable approach, with the past prevalence of early marriage in the community as an instrument.

Our analysis contributes to the literature on the consequences of early motherhood in several ways. First, this paper is the first to address early motherhood endogeneity using a MFE framework in a LMIC context such as India. Second, we exploit the panel dimension of the dataset used to estimate the effect of early maternal age at birth on offspring outcomes at different ages and to investigate for the first time how the effect of interest evolves over time. Our analysis covers the offspring transition from childhood into adolescence, a period recently referred to as the missing middle, given the scarcity of studies on this key developmental stage (Almond et al., 2018). Finally, we explore biological and behavioral transmission channels, some of which have not been previously investigated.

[1] While closely interrelated, marriage age and maternal age at birth are not necessarily equivalent. In a sample of Indian states, for instance, only 33.7% of married women aged 15-19 have given birth (IIPS, 2017).

Our estimates suggest that early maternal age is detrimental to offspring development in terms of both health and cognition. Being born to an adolescent mother is associated with lower height-for-age during childhood. This effect weakens as children grow older, pointing to a partial catch-up over time. As physical growth is minimal after early adolescence, this finding implies that the detrimental effect is permanent in the lives of the offspring. Furthermore, the magnitude of the effect increases for children born to very young mothers and is even stronger for their female offspring. For cognition, we find a significant effect for children born to very young mothers. The effect seems to strengthen over time and to be stronger among girls. We find some evidence on the role of dietary diversity and parental involvement in education as two important transmission channels explaining the negative effect of early maternal age at birth on offspring human capital. Finally, our results on the health-cognition nexus, together with our main results, indicate that early health deficits are detrimental to subsequent cognitive skills, even in a context of partial catch-up growth in height-for-age.

The rest of the paper unfolds as follows. Section 2 describes the data used. Section 3 outlines the empirical strategy. Section 4 presents the main results, dynamics over time, heterogeneous effects and transmission channels. Section 5 concludes.

2. Data and descriptive statistics

We use household data from the Young Lives study for our analysis. Young Lives is a longitudinal study on childhood poverty following 12,000 children of two cohorts in Ethiopia, India (Andhra Pradesh and Telangana), Peru and Vietnam over 15 years. The older cohort consists of around 1,000 children per country who were born in 1994-1995 and tracked since ~ age 8, while the younger cohort of around 2,000 children per country was born in 2001-2002 and tracked since ~ age 1. We use the younger cohort data for our analysis given that sibling information is not available for the older cohort. The first study round was in 2002, when children were 1 year old. It was followed by four subsequent rounds in 2006 (age 5), 2009 (age 8), 2013 (age 12) and 2016 (age 15).[2] We restrict our analysis to the Indian dataset given the prevalence of early motherhood in the sample and the adequate number of sibling pairs observed for regression analysis.

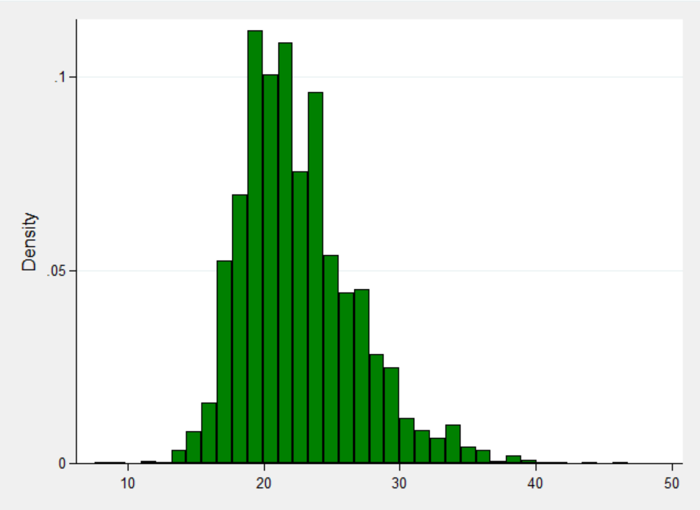
The sampling design consisted of two stages. In the first stage, 20 clusters (mandals) were sampled based on a set of economic, human development and infrastructure indicators with the purpose of oversampling poor households. Hence, the Young Lives household surveys do not constitute a nationally representative survey, although it does cover the diversity of children in the country (Young Lives, 2017; Kumra, 2008). In the second stage, approximately 100 households with a child born in 2001-02 were randomly selected from each cluster. The initial sample for the younger cohort in India consisted of 2,011 children living both in rural and urban communities and spread across seven districts in three regions.[3] These children are referred to as index children in this paper. The attrition rate across all five rounds is only 6%, a remarkably low value compared to other longitudinal studies.

[2] For more information on Young Lives visit www.younglives.org.uk.

[3] The districts are Srikakulam and West Godavari in Coastal Andhra, Anantapur and Kadapa in Rayalaseema, and Karimnagar, Mahbubnagar and Hyderabad in Telangana.

Since the third survey round in 2009, additional anthropometric (Rounds 3 to 5) and cognition (Rounds 4 and 5) data were collected on one sibling of each index child. Among available siblings, the next younger sibling of the index child was selected whenever present at the time of the interview. In their absence, the next older sibling was interviewed. For the current analysis, we restrict our sample to sibling pairs, composed of the index child and a younger or older sibling, with available data on height-for-age or math and the relevant child-level control variables used in the empirical analysis. We end up using observations from 1,692 households with sibling pairs, of which 916 contain a younger sibling and 776 an older one.[4] The age gap between panel siblings and index children is remarkably symmetric. Older siblings are on average 3 years older, while younger siblings are 3 years younger on average.[5] In our sample, all sibling pairs are reported to have the same biological parents. Note that the time period of our sample covers the transition of children from middle childhood to adolescence, a phase in child development that is understudied (Almond et al., 2018).

Figure 1. Distribution of maternal age at birth



Notes: Maternal ages at birth for all sibling pairs used in the main empirical analysis.

In this paper, maternal age at birth is constructed as the difference between the child's age and mother's age at the time of each interview. Figure 1 shows the distribution of maternal age at birth for the sibling pairs used in the main empirical analysis. The average maternal age is 23 years and the distribution is quite dispersed. For the empirical analysis, we use these values to compute binary indicators for children born to adolescent mothers (aged <18), to young mothers (16-17), to very young mothers (<16) and to adult mothers (>18).[6]

[4] The index children with available sibling data are based on household and offspring characteristics very similar to the overall sample of index children (see

Table A3).
[5] The number of sibling pairs across rounds is quite stable. See Table A1 for observations per round.
[6] The cut-off of 18 years old is based on the legal age of sexual consent in India, which considers the legal independence of individuals, whereas the 16 years old cut-off is motivated by the medical literature (Criminal Law Act, 2013; Neal et al., 2012).

Besides anthropometric and cognition data, we obtain information on the geographic location of the household (the state and mandals of residency and whether the household is in a rural/urban area) and on the socioeconomic background of the children as indicated by maternal education (highest grade completed), total expenditure of the household in real terms and a wealth index, which consists of a composite measure of living standards (see Briones, 2017 for details), and mother's height, as an indicator of potential intergenerational cycles of malnutrition and poverty. Moreover, we observe the ethnicity of children, as well as their gender, age and birth order. The latter is constructed by comparing the ages of all the siblings living in the same household during any of the survey rounds.

Table 1 shows the sample average characteristics of children born to very young mothers, to young mothers, to adolescent mothers and to adult mothers. As expected, children born to adolescent mothers come from families with a poorer socioeconomic background than children born to adult mothers. Their mothers have lower education, tend to be shorter, live in households that have lower total expenditures per capita and are less wealthy. While children born to adult mothers are virtually equally distributed across wealth tertiles, those born to adolescent mothers are overrepresented in the first two tertiles. Furthermore, children born to adolescent mothers are more likely to live in rural areas and more likely to be a member of a disadvantaged ethnicity/caste than those born to adult mothers. Among children born to adolescent mothers, children born to very young mothers appear to be the most disadvantaged.[7] These raw differences, suggesting socioeconomic disadvantages for children born to younger mothers, manifest the empirical challenge of disentangling the effects of maternal age and socioeconomic background on offspring development and highlight the importance of mother fixed effects. Finally, Table 1 shows that offspring born to adolescent mothers are more likely to be a firstborn than children born to adult mothers and therefore tend to be older. The share of females among adolescent mothers is also 4 percentage points lower than children born to adult mothers. Contrasting children born to very young mothers to those born to young mothers reveals similar differences. As age, gender and birth order are likely to influence height-for-age and cognition, it is important to control for these differences in the regression framework.

Young Lives collects child anthropometrics and various measures of cognition throughout rounds. We use height for age z-scores (henceforth HAZ) and math scores as our health and cognition outcomes, respectively.

HAZ is a universally comparable indicator of child growth standardized according to age- and gender-specific child growth references of a well-nourished population (WHO, 2007).[8] A deficit in a child's HAZ is an indicator for chronic malnutrition and cumulative deficient growth widely used in development economics (Alderman, 2000). Furthermore, it is less sensitive than other nutritional indicators, such as weight-for-age and weight-for-

[7] An additional variable that could systematically vary by maternal age groups is marital status. However, in Round 1 of data collection, when the index child was on average 1 year old, only eight mothers in total were identified as divorced, separated, single or widowed.
[8] We follow WHO guidelines (2006) and set values out of the -6:6 range to missing due to their biological implausibility. Additionally, we correct for measurement error in height-for-age by setting to missing 40 observations that implausibly suggest a decrease in absolute height over time.

height, to temporary shocks due to morbidity, illnesses or seasonal variations in food availability.

Table 1. Sample characteristics by maternal age groups

Born to:	Very young mothers (<16)		Young mothers (16-17)		Adolescent mothers (<18)		Adult mothers (>=18)	
	Mean	N	Mean	N	Mean	N	Mean	N
Household characteristics								
Maternal age at birth	14.68	175	17.11	778	16.66	953	23.20	8,141
Mother's education	3.34	173	3.78	773	3.70	946	4.20	8,080
Mother's height	149.87	51	150.03	385	150.01	436	151.57	4,072
Total expenditure	974.6	174	1,006.5	768	1,000.6	942	1,065.7	7,968
Wealth tertiles								
1st	0.41	175	0.35	778	0.36	953	0.34	8,139
2nd	0.37	175	0.39	778	0.38	953	0.34	8,139
3rd	0.23	175	0.26	778	0.26	953	0.33	8,139
Urban	0.14	175	0.24	777	0.22	952	0.29	8,100
Region								
Coastal Andrah	0.37	51	0.33	390	0.34	441	0.34	4,085
Rayalaseema	0.27	51	0.29	390	0.29	441	0.29	4,085
Telangana	0.35	51	0.38	390	0.37	441	0.37	4,085
Ethnicity/caste								
Scheduled Caste	0.18	175	0.22	778	0.21	953	0.18	8,141
Scheduled Tribe	0.22	175	0.16	778	0.17	953	0.15	8,141
Backward Class	0.53	175	0.48	778	0.49	953	0.47	8,141
Other	0.07	175	0.14	778	0.13	953	0.21	8,141
Offspring characteristics								
Age	14.75	175	12.83	778	13.19	953	11.21	8,141
Female	0.49	175	0.44	778	0.45	953	0.49	8,141
Birth order								
Firstborn	0.87	175	0.76	778	0.78	953	0.26	8,141
Second born	0.13	175	0.22	778	0.20	953	0.46	8,141
Third born	0.00	175	0.02	778	0.01	953	0.19	8,141

Notes: Statistics correspond to child-round-level observations from the pooled sample of households with available information on age, gender, birth order, maternal age and HAZ or math data for the sibling pairs participating in Rounds 3 (2009), 4 (2013) and 5 (2016). All time-variant variables (wealth tertiles, total expenditure, location-related variables, mother's education and age of the child) are measured in the three rounds. Maternal age is computed by averaging the differences between the child's age and mother's age across rounds. Mother's education consists of her highest completed grade. Mother's height is reported in cm. Total expenditure refers to household total monthly expenditure per capita in 2006 constant rupees. A composite wealth index was used for the estimation of the share of observations within each wealth tertile (see Briones 2017 for details). For the computation of birth order, the ages among siblings that lived in the Young Lives household during any of the five survey rounds were compared.

For the computation of math scores, the survey team developed a mathematics test, which was adapted for each survey round to ensure its appropriateness (Cueto and Leon, 2012; Cueto et al. 2009). The math test was administered to all children, regardless of whether or not they were attending school at the time of the interview. It was not designed for a specific school grade but rather to incorporate questions at widely differing levels of difficulty. At the basic level, the tests included questions assessing basic number identification and quantity discrimination; at the intermediate level, questions were based on calculation and measurement; and at the advanced level, questions related to problem-solving embedded in hypothetical contexts that simulate real-life situations (e.g. tables in newspapers). The tests scores used in this paper are constructed using Item

Response Theory (IRT) models, which are commonly used in international assessments such as Programme for International Student Assessment (PISA) and Trends in International Mathematics and Science Study (TIMSS). The main advantages of IRT models consist of acknowledging item difficulty and enhancing comparability over time and across ages (see Leon and Singh, 2017 for more details).[9]

Table 2 presents the mean values of the outcomes of interest by maternal age groups.[10] The mean values of HAZ across maternal age groups suggest a positive relationship between maternal age and offspring health. While all groups show negative mean values, indicating that all children on average present growth deficits, children born to adolescent mothers show larger deficits than children born to adult mothers. Moreover, children born to very young mothers do worse than children born to young mothers. These raw differences are all statistically significant, as suggested by the p-values from t-tests for differences in means reported in the table notes. Math scores show a different pattern. Children born to adolescent mothers do better than children born to adult mothers when comparing unadjusted means. However, children born to very young mothers again show worse values than those born to young mothers. The raw differences in math are all at least marginally statistically significant levels.

Table 2. Average outcomes by maternal age groups

Born to:	Very young mothers (<16)		Young mothers (16-17)		Adolescent mothers (<18)		Adult mothers (>=18)	
	Mean	N	Mean	N	Mean	N	Mean	N
HAZ	-1.94	147	-1.72	750	-1.76	897	-1.46	7,823
Math	444.72	118	484.56	497	476.91	615	465.05	5,257

Notes: Statistics correspond to child-round-level observations from the pooled sample of households with available information on age, gender, birth order, maternal age and the respective outcome variable for the sibling pairs participating in Rounds 3 (2009), 4 (2013) and 5 (2016). Ages in parenthesis refer to maternal ages at birth. HAZ is height-for-age in z-scores collected in the three rounds, while math consists of IRT scores collected in Rounds 4 and 5. HAZ values lower than -6 and larger than 6 are set to missing as they are considered biologically implausible (WHO, 2006). Mean differences between maternal age groups are statistically significant at the 1% level, except for the comparison of math ((1)-(4)), which has a p-value of 0.051).

While the patterns in Table 2 are informative, it is plausible that the gaps across maternal age groups are a reflection of differences in the socioeconomic background of children and/or their age, gender and birth order profile, among others. We follow a regression framework as described in the next section to adjust these raw differences in an attempt to isolate the main effect of interest.

3. Empirical strategy

Our estimates of the impact of maternal age at birth on the health and cognition of children are nested in a theoretical framework that models the human capital production of children (Attanasio, 2015; Cunha et al. 2006; Todd and Wolpin 2003).[11] In this section,

[9] The key results of the analysis are qualitatively similar when using raw scores instead of IRT.
[10] See Figure A1 for the means by rounds.
[11] Attanasio (2015), extending the model by Cunha et al. (2006), is the only model that explicitly considers the health dimension as a separate element of human capital and is therefore our preferred theoretical framework.

we describe the empirical approach used to overcome the main empirical challenges encountered in estimating the effect of early maternal age on offspring human capital. First, poorer outcomes of children born to adolescent mothers might be the result of unobserved disadvantaged socioeconomic background rather than the consequences of early motherhood itself. For instance, early school dropout, frequently observed among adolescent mothers, might both induce girls to get pregnant earlier and negatively affect the wellbeing of their offspring. In this case, the estimated parameter for maternal age would overestimate the effect of interest. Second, while adolescent mothers might come from a poorer socioeconomic background in comparison to their peers, they grew up in a more recent time period than older mothers. Assuming general socioeconomic progress over time, women who grew up in say the 1990s rather than the 1970s were exposed to a relatively improved prenatal, postnatal and childhood environment, for example, in terms of better health and education services. Somewhat surprisingly, this mother cohort issue has not been sufficiently emphasized in the literature. Neglecting these unobservables would downwardly bias the effect of maternal age on offspring outcomes.

To tackle these sources of endogeneity, we exploit the availability of siblings' data and rely on MFE. Since mother unobserved heterogeneity potentially biases OLS estimations, we account for mother's unobserved characteristics by looking at the outcomes of offspring born to the same mother. Specifically, we estimate the following regression model to investigate the relationship between adolescent motherhood and Y_{ijr} , which denotes a health or cognition outcome *Y* measured at round *r* for offspring *i* born to mother *j*.

$$Y_{ijr} = \alpha_i + \boldsymbol{\beta AM_{ij}} + \boldsymbol{\omega Z'_{ijr}} + \boldsymbol{\mu_j} + \boldsymbol{\theta_r} + \varepsilon_{ijr} \qquad (1)$$

AM_{ij} is a dummy variable indicating children born to adolescent mothers, defined as mothers under 18 years of age at childbirth. Hence, the coefficient of interest β shows the effect of being born to an adolescent mother on child's health or cognitive outcomes. Further, to investigate systematic differences among children born to adolescent mothers, we distinguish between children born to very young mothers (under 16 years old) and young mothers (16-17 years old) compared to children born to adult mothers (18 years old or over). $\boldsymbol{Z'_{ijr}}$ is a vector of child's characteristics such as age (in years), gender (a dummy equal to 1 if the child is a female), birth order dummies and, in addition, schooling starting age for cognition regressions only. $\boldsymbol{\mu_j}$ are the mother fixed effects, $\boldsymbol{\theta_r}$ are data round/time fixed effects and ε_{it} is an error term, clustered at the mother level to correct for within-family correlation. The two outcome variables are HAZ and math IRT scores, collected for the sibling pairs in Rounds 3, 4 and 5 and Rounds 4 and 5, respectively.

As discussed above, MFE offer a number of advantages compared to OLS estimates. However, for comparison purposes, we also present OLS regressions. For these estimates, we include additional pre-childbearing controls at the mother level, such as ethnicity/caste (dummies for Scheduled Caste, Scheduled Tribe, Backward Class; and other as the reference group), mother's height (in cm) and rural/urban location of the household residence in Round 1.[12] Mother's height is a good measure of maternal nutrition, reflecting accumulated investments she has been exposed to during her (pre-childbearing) lifetime and, to some extent, genetic predisposition (Subramanian et al., 2009; Duflo, 2000). Also, there is a certain degree of intergenerational persistence in nutritional status which suggests that maternal nutrition might indeed be an important factor to explain child' nutritional status (see, for example, Ramakrishnan et al., 1999). We abstain from including factors at the mother level that might be affected by childbearing in the OLS regressions, as they would constitute an endogenous control.

We further exploit the panel dimension of our data to investigate how the effect of maternal age on child's outcome evolves over time. To do so, we interact equation (1) with the round dummies, as specified in equation (2). Note that by interacting the round dummies with the vector of controls, we allow the influence of child-specific variables to vary over time. In equation (2), the coefficient $\boldsymbol{\beta}$ recovers the effect of being born to an adolescent mother in the earliest round in which the outcome variable is measured (Round 3 in the case of HAZ and Round 4 in the case of math), while the interactions with the round dummies indicate the change of this effect over time. The overall effect of maternal age in each specific round is the sum of the $\boldsymbol{\beta}$ coefficient and of the relevant round interactions.

$$Y_{ijr} = \alpha_i + \boldsymbol{\beta AM_{ij}} + \boldsymbol{\gamma AM_{ij}} * \boldsymbol{R'} + \boldsymbol{\omega Z'_{ijr}} + \boldsymbol{\omega Z'_{ijr}} * \boldsymbol{R'} + \boldsymbol{\mu_j} + \boldsymbol{\theta_r} + \varepsilon_{ijr} \quad (2)$$

It is worth emphasizing that controlling for birth order fixed effects is particularly relevant. We acknowledge that birth order might affect a child's development for a number of reasons and in a priori unknown direction (see De Haan et al., 2014 for a review of studies testing negative and positive birth order effects in developed and developing countries). For instance, children of higher birth order might either benefit from learning-by-doing parenting effects or be negatively affected by the relaxation of rearing practices over time (Lehmann et al., 2018). Another example of the importance and ambiguity of birth order effects relates to financial resources. While one could argue that first-born children might benefit from exclusive expenditure in the first years of life and even longer-term parental favoritism, they might also be – to the detriment of their development – more exposed to child labor in comparison to their siblings (Jayachandran and Pande, 2017; De Haan et al., 2014). The birth order dummies in our model absorb these effects.

The MFE estimates have the main advantage of accounting for all time-invariant mother and household-specific factors common to the index child and the panel sibling (including shared genetic factors and mother cohort effects) and unobserved context-specific factors that are constant among siblings (including access to health and education services).[13] Moreover, these estimates account for differences in family sizes, which can affect offspring human capital in several ways (Behrman and Taubman, 1986; Spears et

[12] Girls reach most of their adult height by the time of puberty, such that it is reasonable to assume that mother's height is predetermined to the offspring's birth (WHO, 2007). Similarly, the rural/urban location of residence of the household in Round 1 is in the vast majority of the cases the same at the time the mother conceived the index child.

[13] A disadvantage of this procedure relates to the fact that by dropping between-mother variation, we cancel important channels through which early motherhood might affect offspring development, such as lower mother's education due to pregnancy-induced school dropouts.

al., 2019). However, while much of the negative selection into early motherhood is shared by siblings, these models would be able to recover the causal effect of maternal age only in the absence of systematic child-specific unobserved heterogeneity (Aizer et al., 2018). In this respect, two concerns are worth discussing. First, while the model allows for child-specific idiosyncratic endowments, we are required to assume that there are no maternal responses to differences in these endowments, net of gender, age and birth order effects (Rosenzweig and Wolpin, 1995).[14] Second, time-varying household-level covariates that are not related to the mother's aging also represent a threat for identification. If, for instance, the household significantly improved its socioeconomic status between rounds independently from mother's age, the younger sibling would then be exposed to a better environment at earlier ages than his/her sibling would. To ease this concern, as robustness check, we control for the exposure of the child to household shocks during early childhood, household wealth and household consumption during the same period.[15] [16]

Furthermore, we apply the Oster method to investigate the role of child-specific unobservables in our estimates. The Oster method is a useful empirical tool, particularly powerful in a setting of siblings-difference models, as recognized by Aizer et al. (2018). The test draws on coefficient and R-squared movements to identify the delta statistic, which stands for the ratio of selection on unobservables to selection on observables which would make the coefficient of interest equal to zero. Oster (2017) generally indicates values larger than 1 as evidence for the presence of robust effects. Such values would indicate that for the effect to be zero, the role of what is unobserved in a specific dataset would have to be larger than the role of observables in explaining the association of interest. In our case, such a delta value would imply that child-specific factors within a household (and net of age, gender and birth order effects) would have to play a bigger role than household and mother-level factors for the coefficient of adolescent mothers to be zero. Values significantly below a unit on the other hand would represent a concrete threat to our estimates.[17]

Finally, although our MFE model gets close to isolating the net effect of maternal age, it shares an important limitation with other studies exploring these effects on children and adolescents. These results are likely affected by selection biases related to mortality rates among young mothers and their offspring, as health and cognition data on children who have died are naturally missing.[18] This is an important consideration given that the leading cause of death for 15-19-year-old girls is pregnancy (WHO, 2016). Moreover, the fetal, neonatal and infant mortality are likely not uniformly distributed. Children born to teen mothers are at higher risk of being born underweight and premature and ultimately face

[14] The related literature has found empirical evidence for both reinforcing and compensating behavior. Note that the former would tend to overestimate the effect, while the latter would underestimate it (see Almond et al. 2018 for a review, and Fan and Porter (2018) for an example of compensating behavior using Young Lives Ethiopian data).

[15] More concretely, we assign the values of these household-level covariates from Rounds 1, 2 and 3 to the older siblings, index children and younger siblings, respectively.

[16] Another concern of such family-fixed effects estimations is the exacerbation of attenuation bias stemming from classical measurement error in explanatory variables (Griliches, 1979). However, we conjecture that the role of classical measurement error is limited in the measurement of maternal age group indicators.

[17] We perform this test exclusively for the main specification, including the adolescent mother dummy (without gender or round interactions).

[18] In India, the maternal mortality rate was estimated at 174 deaths per 100,000 live births in 2015 (WHO et al., 2015), whereas perinatal mortality was 36 deaths per 1,000 pregnancies in 2015-16 (IIPS, 2017).

a higher risk of infant mortality (García-Hombrados, 2018). This survival selection would bias our estimates downward.

4. Results

4.1. Adolescent motherhood and offspring outcomes

The OLS and MFE estimated effect of being born to an adolescent mother on offspring outcomes are shown in Table 3. The first two columns report estimates for HAZ as a dependent variable, while the last two columns show estimates for math scores.

The OLS regression in column 1 suggests that being born to an adolescent mother is associated with 0.21 lower HAZ on average, compared to children born to adult mothers, the estimated coefficient being significant at the 1% level. Notably, controlling for mother fixed effects barely alters these results. The point estimate remains highly significant and slightly increases to 0.23. For the average offspring age in our sample of 11.2 years, this implies a penalty of 1.57 cm for boys and 1.54 cm for girls, according to WHO Child Growth Standards (2007).[19] While moderate, such differences might be quite relevant for the development of vulnerable children, as discussed later in this section.

Given the significant jump in the explanatory power of the model caused by the inclusion of mother fixed effects, the stability of the coefficient of interest is remarkable. We perform the Oster method to derive formal implications of these movements and report the delta statistic at the bottom of Table 3.[20] The test results suggest that for the true effect of adolescent mother to be zero, selection on child unobserved heterogeneity would have to be significantly larger than selection on observables, which in this case include all time-invariant mother and household characteristics. As the latter factors are established key determinants of child anthropometrics, we argue that such an assertion is rather implausible. Hence, this result reinforces the conclusion that adolescent motherhood is detrimental to HAZ.

Results in columns 3 and 4 show that the evidence for a detrimental effect of being born to an adolescent mother is weaker for cognition outcomes, as measured by math scores. The OLS estimates suggest that children born to adolescent mothers perform worse in the math test by 12.3% SD on average. However, this effect is not robust to the inclusion of mother fixed effects, suggesting that the detrimental effect is the result of selection into early motherhood rather than signaling a negative effect of early maternal age on children's cognition.

[19] To put this in perspective, Aizer et al. (2018) use sister fixed effects and Norwegian data to estimate a gain of 0.6 cm for boys born to non-teen mothers. Schroeder et al. (1995) report that in Guatemala, being randomly exposed to a protein-rich food supplement for three years starting from birth and on a twice-daily basis resulted in a positive treatment effect of 2.5 cm by the end of the exposure period, while the 0-12-year-old offspring of the treated children also benefited with average gains of 0.26 HAZ (Behrman et al., 2009). Miguel and Kremer (2014) find in their randomized control trial that after a year of deworming treatment for Kenyan pupils of grades 3-8, they gained 0.08 HAZ compared to children with no treatment. However, Baird et al. (2016) find no effect on height ten years later. Behrman and Hoddinott (2001) use child fixed effects to find that infant children participating in the Progresa program in Mexico, which combines conditional cash transfers, nutritional education and micronutrient-fortified supplements, gained an additional 1 cm per treated year. Similarly, boys exposed to Juntos program, a cash transfer program in Peru conditional upon health care visits for more than two years, gained 0.43 HAZ at ages 7-8 years (Andersen et al. 2015).

[20] For this exercise, we follow Oster's guidelines (2017) and set R_{max} to $1.3\tilde{R}$.

Given well-documented linkages between health and cognition, a reasonable prior would be to observe similar tendencies for both outcomes (Lo Bue, forthcoming; Sudfeld et al., 2015; Victora et al., 2008; Grantham-McGregor et al., 2007). However, we find evidence for a detrimental effect for HAZ but no effect for math. Possibly, these results might be due to measurement errors. If math skills are measured with more measurement error than HAZ, then it would be harder to detect significant estimates in math regressions. Andersen et al. (2015) speculate on the (in)sensitivity of cognitive test scores to explain a similar combination of results. In addition, we argue that health aspects are closer in the causal chain of interest than cognition aspects, making it easier to detect systematic relationships in the case of health outcomes.

Table 3. Regression results: adolescent motherhood and offspring outcomes

	HAZ		Math	
	(1) OLS	(2) MFE	(3) OLS	(4) MFE
Adolescent mother	-0.21***	-0.23***	-13.56**	-1.84
	(0.06)	(0.08)	(5.91)	(7.26)
Delta (Beta=0)	-	1.23	-	-
R-squared	0.13	0.59	0.21	0.69
Observations	8650	8720	5714	5761

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level, respectively. Clustered standard errors at mother level are in parenthesis. The sample includes sibling pairs for Rounds 3, 4 and 5 for HAZ regressions, and Rounds 4 and 5 for math regressions. Adolescent mother refers to children born to mothers under 18 years of age. The reference category is the maternal age group of mothers 18 years old and older at the time of childbirth. The dependent variables are HAZ (z-scores) and math (IRT scores). All regressions control for dummies for age, gender, birth order and round, and in addition for schooling starting age in math regressions. The OLS regressions include ethnicity, mother's height and rural/urban status in Round 1. The MFE regressions control for mother fixed effects. The statistic Delta is obtained through the STATA command *psacalc* (Oster, 2017).

4.2. Dynamics over time

We now attempt to shed light on the dynamics of the effect of adolescent motherhood over time, taking advantage of having repeated measures of the same developmental indicators. Considering the age range of our sample and the scarce evidence on the effects of childhood circumstances on middle childhood to adolescence outcomes, estimating the trajectories of these effects would be particularly informative. In contrast to studies focusing on a single cross-section, this allows us to get a wider perspective on the relationship at hand. It tells us in which of the childhood stages covered are effects observed and whether these effects tend to accumulate or diminish over time. For instance, there might be early factors that affect children during middle childhood but not in adolescence due to catching-up dynamics (see Jones et al., 2018 for catch-up estimates using Young Lives data). Conversely, associations that remain latent through middle childhood and become apparent only in early adolescence due to cumulative processes in child development are also possible (Cunha et al., 2006). The panel nature of our data and our study design let us identify these trajectories.

We present these results in Table 4, which adds a set of interactions between the dummy for being born to an adolescent mother and data rounds. The round used as base category is the earliest available for each outcome variable. Hence, the coefficient for adolescent mother (without interaction) relates to Round 3 for HAZ regressions and to Round 4 for math regressions. The sum of the coefficient for adolescent mother and the interaction coefficient gives the point estimate of the respective round. Corresponding p-values from t-tests are reported at the bottom of the table.

Table 4. Regression results: adolescent motherhood and offspring outcomes over time

	HAZ		Math	
	(1) OLS	(2) MFE	(1) OLS	(2) MFE
Adolescent mother	-0.28***	-0.30***	-9.58	5.28
	(0.07)	(0.09)	(6.66)	(7.70)
Adolescent mother # R4	0.11**	0.13**		
	(0.05)	(0.05)		
Adolescent mother # R5	0.14**	0.11	-7.23	-13.90*
	(0.07)	(0.07)	(7.13)	(7.97)
p(<18 (R4)=0)	0.01	0.05		
p(<18 (R5)=0)	0.04	0.05	0.02	0.331
R-squared	0.15	0.60	0.22	0.69
Observations	8610	8720	5687	5761

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level, respectively. Clustered standard errors at mother level are in parenthesis. The sample includes sibling pairs for Rounds 3, 4 and 5 for HAZ regressions, and for Rounds 4 and 5 for math regressions. Adolescent mother refers to children born to mothers under 18 years of age. The reference category is the maternal age group of mothers 18 years old and older at the time of childbirth. The dependent variables are HAZ (z-scores) and math (IRT scores). All regressions control for dummies for age, gender, birth order and round, and in addition for schooling starting age in math regressions. The OLS regressions include ethnicity, mother's height and rural/urban status in Round 1. The MFE regressions control for mother fixed effects. All regressions include round interactions with controls.

OLS and MFE of the HAZ regressions show very similar results. Both indicate that the detrimental effect of adolescent motherhood is largest in the earliest round, when children are on average 8 years old. In the model that controls for all time-invariant mother and household characteristics, the penalty associated with being born to an adolescent mother is of 0.3 HAZ (and significant at the 1% level) in Round 3, when children are on average 8 years old. Interestingly, the magnitude of the effect decreases over time and remains significant in both subsequent rounds, suggesting that a partial catch-up might have taken place during the transition between childhood and adolescence. In Round 5, children are on average 15 years old. Given that height growth is minimal after this age (WHO, 2007), this implies that the estimated negative association might be for life, and could therefore reverberate to labor productivity effects later in life (LaFave and Thomas, 2017).

Turning to the math results, OLS estimates suggest a strengthening of the effect over time, as the negative relationship is statistically significant in Round 5 but not in Round 4.

However, the effect on math is weaker when accounting for MFE. The MFE point estimate is not statistically significant in any of the rounds. The estimated coefficient for Round 4 is positive while the effect turns negative in Round 5, although evidently smaller in magnitude than its OLS counterpart and insignificant, as indicated by the corresponding p-value at the bottom of the table. Note that the two outcomes of interest show different trajectories, an issue that will be commented below.

As shown in

Table A4 and Table A5, these results are robust against controlling for time-varying family-level covariates that are contemporaneous to the early childhood of each child, including the number of shocks suffered by the household during the years before the survey, the family wealth index and (real per capita) total expenditure.[21] Point estimates are barely affected, which suggests that the role of such time-varying household-level covariates is unlikely to be driving the results.

4.3. Heterogeneous effects by maternal age categories and child gender

So far, we have compared children born to adolescent mothers and children born to adult mothers, ignoring that there might be important differences within the adolescent mothers' group. Since we hypothesize and find that early maternal ages are detrimental to offspring development, it is worth investigating whether the effect of early motherhood is stronger for those children born to the youngest mothers among adolescent mothers. To explore this, we distinguish between children born to *very young* mothers (<16 years old) and to *young* mothers (16-17 years old), previously combined into the adolescent mothers' group.[22] Moreover, we investigate heterogeneous effects by gender. Human capital investments in Indian children have been shown to be gender-skewed (Barcellos et al., 2014; Behrman, 1988), in particular for disadvantaged families (Asfaw et al., 2010).

Results for HAZ and for math are presented in Table 5 and 6, respectively. Each table shows OLS and MFE estimates, but for the sake of simplicity we will focus on the MFE estimates only. The first two columns report estimates that pool all data rounds. The third and fourth column show results with round interactions to identify dynamics over time. The last two columns report results with a triple interaction between maternal age groups, data rounds and gender in order to explore heterogeneous effects by gender.

[21] See Briones, 2018 for a detailed description of shocks and the wealth index.

[22] The 16 years old cut-off among adolescent mothers is guided by the medical literature, which suggests that girls under the age of 16 are at higher risk of eclampsia, anemia, postpartum hemorrhage, obstetric fistula, obstructed labor due to underdeveloped pelvic bones and worse neonatal outcomes than older adolescents (Neal et al., 2012).

Table 5. Regression results: disaggregated age groups, gender and health

	HAZ					
	(1) OLS	(2) MFE	(3) OLS	(4) MFE	(5) OLS	(6) MFE
Very young mother	-0.31***	-0.38**	-0.46***	-0.55***	-0.80***	-0.92***
	(0.11)	(0.19)	(0.15)	(0.21)	(0.24)	(0.28)
Very young mother # R4			0.23*	0.21	0.48**	0. 36*
			(0.14)	(0.14)	(0.21)	(0.21)
Very young mother # R5			0.26	0.24	0.19	0.15
			(0.16)	(0.17)	(0.24)	(0.28)
Very young mother # Boy					0.69**	0.79**
					(0.29)	(0.35)
Very young m. # Boy # R4					-0.50*	-0.31
					(0.27)	(0.26)
Very young m. # Boy # R5					0.04	0.11
					(0.30)	(0.34)
Young mother	-0.19***	-0.22**	-0.26***	-0.27***	-0.25**	-0.24*
	(0.06)	(0.09)	(0.07)	(0.09)	(0.10)	(0.14)
Young mother # R4			0.10*	0.11**	0.08	0.09
			(0.06)	(0.06)	(0.09)	(0.09)
Young mother # R5			0.13**	0.09	-0.01	-0.00
			(0.07)	(0.07)	(0.11)	(0.12)
Young mother # Boy					-0.03	-0.03
					(0.13)	(0.17)
Young mother # Boy # R4					0.03	0.03
					(0.11)	(0.11)
Young mother # Boy # R5					0.25*	0.16
					(0.14)	(0.14)
p(<16 (R4)=0)			0.07	0.08		
p(<16 (R5)=0)			0.14	0.17		
p(16-17 (R4)=0)			0.01	0.08		
p(16-17 (R5)=0)			0.06	0.06		
p(<16 (R4, G)=0)					0.05	0.01
p(<16 (R5, G)=0)					0.00	0.01
p(16-17 (R4, G)=0)					0.06	0.28
p(16-17 (R5, G)=0)					0.00	0.09
p(<16 (R3, B)=0)					0.46	0.61
p(<16 (R4, B)=0)					0.46	0.79
p(<16 (R5, B)=0)					0.53	0.66
p(16-17 (R3, B)=0)					0.00	0.01
p(16-17 (R4, B)=0)					0.06	0.15
p(16-17 (R5, B)=0)					0.70	0.33
R-squared	0.13	0.59	0.14	0.60	0.14	0.60
Observations	8650	8720	8650	8720	8650	8720

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level, respectively. Clustered standard errors at mother level are in parenthesis. The sample includes sibling pairs for Rounds 3, 4 and 5. Very young mothers and young mothers refer to children born to mothers under 16 years old and 16-17 years old, respectively. The reference category is the maternal age group of mothers 18 years old and older at the time of childbirth. The dependent variable is HAZ (z-scores). All regressions control for dummies for age, gender, birth order and round. The OLS regressions include ethnicity, mother's height and rural/urban status in Round 1. The MFE regressions control for mother fixed effects. Columns 3-6 include round interactions with controls. Columns 5 and 6 include full two-way and three-way interactions between rounds, maternal age groups and gender.

The p-values from t-tests of the overall effects in each round and for each gender are reported at the bottom of the tables.

HAZ regressions are shown in Table 5. Overall, there are three main messages from the analysis. First, children born to young and very young mothers tend to have lower HAZ than children born to adult mothers. The statistical significance of these associations varies depending on the round or gender, and slightly varies across maternal age groups. Second, detrimental effects are the strongest for very young mothers, in line with our hypothesis. Third, effects generally weaken over time. We now comment on the results in more detail.

Pooled estimates reported in column 2 indicate that children born to young and very young mothers have 0.22 and 0.38 lower HAZ than children born to adult mothers. Both coefficients are statistically significant. When we look at the dynamics over time in column 4, we observe the same pattern across maternal age groups. The strongest effects are observed in the earliest round, and the magnitude of the effects decrease over time. Remarkably, the HAZ penalty for children born to very young mothers in Round 3 is approximately twice as large as the penalty experienced by children born to young mothers (0.55 versus 0.27, respectively), a ratio that remains in Round 4 and slightly decreases in Round 5. All coefficients in column 4 remain significant at the 10% level in Rounds 4 and 5, with the exception of the coefficient for very young mothers in Round 5. Notably, although point estimates for very young mothers are always larger in magnitude, estimation for this variable is usually less precise.

In column 6 we report MFE results of a model that adds double and triple interactions between the maternal age groups, rounds and gender. For children born to very young mothers, girls are clearly worse off. In Round 3, they show HAZ values that are 0.92 SD lower than their counterparts born to adult mothers. What is more, these differences remain significant throughout rounds, while coefficients for boys are negative but statistically insignificant in all rounds. This implies that the negative effect found for children born to very young mothers (column 4) is driven by girls.

The gender-skewed effects observed among children born to very young mothers are in line with the literature documenting gender discrimination in India manifested in gender-biased parental investments such as childcare quality, healthcare financing and the provision of vitamin supplements (Barcellos et al., 2014; Asfaw et al., 2010; Behrman, 1988). However, given the reduced number of observations from which the gender-specific coefficients draw upon, some caution is suggested in interpreting the statistically insignificant results for boys as evidence for null effects.

We now turn to the MFE results for math, reported in Table 6. Overall, we identify two main messages. First, children born to very young mothers tend to perform worse in the math test than children born to adult mothers. This seems not to be the case for the offspring of young mothers. Second, detrimental effects associated to very young mothers strengthen over time, being statistically significant only in Round 5.[23]

[23] Results (available upon request) are robust against controlling for time-varying family-level covariates that are contemporaneous to the early childhood of each child, including the number of shocks suffered by the household during the years before the survey, the family wealth index and (real per capita) total expenditure.

Table 6. Regression results: disaggregated age groups, gender and cognition

	Math					
	(1) OLS	(2) MFE	(3) OLS	(4) MFE	(5) OLS	(6) MFE
Very young mother	-41.43***	-30.89*	-37.83***	-19.41	-48.53**	-25.16
	(14.24)	(15.84)	(14.60)	(16.72)	(23.57)	(22.85)
Very young mother # R5			-5.47	-22.21	-15.34	-32.29
			(15.98)	(18.55)	(25.05)	(29.61)
Very young mother # Boy					19.53	12.06
					(28.33)	(28.14)
Very young m. # Boy # R5					17.53	18.00
					(31.39)	(36.39)
Young mother	-7.82	1.79	-4.26	7.91	-11.87	6.27
	(5.87)	(7.24)	(6.72)	(7.83)	(9.28)	(10.57)
Young mother # R5			-7.54	-12.42	2.17	-5.48
			(7.31)	(8.23)	(11.25)	(13.17)
Young mother # Boy					13.46	3.43
					(12.18)	(13.86)
Young mother # Boy # R5					-17.28	-12.02
					(13.64)	(15.71)
p(<16 (R5)=0)			0.02	0.04		
p(16-17 (R5)=0)			0.10	0.61		
p(<16 (R5, G)=0)					0.01	0.04
p(16-17 (R5, G)=0)					0.36	0.95
p(<16 (R4, B)=0)					0.09	0.53
p(<16 (R5, B)=0)					0.26	0.29
p(16-17 (R4, B)=0)					0.86	0.34
p(16-17 (R5, B)=0)					0.11	0.46
R-squared	0.21	0.69	0.22	0.69	0.22	0.69
Observations	5714	5761	5714	5761	5714	5761

Note: ***, **, * denote statistical significance at the 1, 5 and 10% level, respectively. Clustered standard errors at mother level are in parenthesis. The sample includes sibling pairs for Rounds 4 and 5. Very young mothers and young mothers refer to children born to mothers under 16 years old and 16-17 years old, respectively. The reference category is the maternal age group of mothers 18 years old and older at the time of childbirth. The dependent variable is math (IRT scores). All regressions control for dummies for age, gender, birth order, schooling starting age and round. The OLS regressions include ethnicity, mother's height and rural/urban status in Round 1. The MFE regressions control for mother fixed effects. Columns 3-6 include round interactions with controls. Columns 5 and 6 include full two-way and three-way interactions between rounds, maternal age groups and gender.

Interpreting the estimates for children of very young mothers in more detail, estimates in column 2 show that being born to a very young mother is associated with a decrease in math scores of 0.28 SD compared to children born to adult mothers. Looking at the dynamics over time in column 4, we observe that the effect strengthens over time and turns statistically significant only in Round 5, when children born to very young mothers perform 0.38 SD worse.[24] The strengthening of these effects over time are consistent with the notion of skills self-productivity put forward by Cunha et al. (2006).

[24] The following references are guidelines for interpreting the magnitudes of these effects. Aizer et al. (2018) use Norwegian data and sister fixed effects to estimate that being born to a 15-17-year-old mother is associated with a decrease of 0.18 SD in an IQ test. The education literature using experimental methods to study cognitive test scores consider effects between 0.1 SD and 0.3 SD as medium effects (Dhaliwal et al., 2013). However, we advise caution in overemphasizing the comparison of these effects. As the

In column 6, we explore heterogeneous effects by gender over time. Similar to the results for HAZ, girls of very young mothers do worse than boys in the math test. The magnitude of the statistically significant coefficient in Round 5 is now larger than 0.5 SD. We again abstain from interpreting the insignificant effects for boys of very young mothers as null effects due to precision issues.

In summary, we find that early maternal age is detrimental to offspring health and cognition. Children born to adolescent mothers are shorter for their age, while children born to very young mothers perform poorer in math tests, compared with children born to adult mothers. Furthermore, we show that the negative effect on child's health is already observed at middle childhood and weakens as children grow older, pointing to a partial catch-up during the childhood-adolescence transition, whereas the cognition effect surges only in early adolescence. The fact that we observe a detrimental height effect in early adolescence suggests that consequences are likely to be permanent. Moreover, our estimates show that children, and in particular girls, born to very young mothers are worst off in both health and cognition.

4.4. Transmission channels

In this section, we explore some of the transmission channels possibly explaining the relationship found between early maternal age and the health and cognition of children. Building on a human capital theoretical framework (Attanasio, 2015; Cunha et al. 2006; Todd and Wolpin 2003), we hypothesize maternal age to enter the child's human capital production function via two main pathways: the "behavioral channel" and the "biological channel".

In relation to the behavioral channel and adopting Attanasio's (2015) terminology, child outcomes depend on "parental investments" and "parental background" variables, conditioned on initial conditions and shocks. Parental investments in human capital are themselves a function of parental characteristics, including maternal age, and observables and unobservable factors related to it, such as education and socioeconomic background, preferences, expectations and psychological maturity. These factors are likely to affect mothers' behaviors and practices, particularly in regard to prenatal care, childrearing practices and, more broadly, decisions around investments in child's human capital. We follow the literature on intra-household resource allocation highlighting the role of mothers in human capital investments for their children, and explore to what extent being an adolescent mother might imply having little knowledge and/or low bargaining power within the household, resulting in limited investments in children's human capital (Doss, 2013).

For the biological channel, we hypothesize that adolescent mothers are biologically immature for childbearing, which might negatively affect the initial human capital endowment of the child. These disadvantaged initial conditions that are of a biological nature negatively affect children's subsequent human capital outcomes (Attanasio, 2015). Indeed, children born to young mothers face poor neonatal outcomes such as an

distribution of scores are not constant across studies, similar SD movements might stand for very different cognition gains in absolute terms (see Ost et al. (2017) for an analysis of this issue).

increased risk of preterm birth and low birth weight, among others (Fall et al., 2015; Gibbs et al., 2012; Neal et al., 2012; Conde-Agudelo et al., 2005).

In this section, we investigate channels that are either biological or behavioral in nature. We employ regression analysis with the hypothesized channels for child's health and cognition as dependent variables in order to investigate whether maternal age groups are systematically related to them. Unfortunately, our ability to explore these channels is limited by the quantity and quality of the information available either for the index children only or for the sibling pairs. In the first case we can only report OLS results, otherwise, when data are available on the sibling pairs, we report both OLS and MFE estimates. While the results presented here should be cautiously interpreted and are not comprehensive in exploring the pathways through which maternal age affects child's human capital, they provide additional instructive insights.

To shed light on the mechanisms explaining the effect of maternal age on child's HAZ, we look at the variables of birthweight and dietary diversity. Children born to adolescent mothers have been found to be at higher risk of low birthweight, which in turn has been associated with negative impacts on children's anthropometrics (McGovern, 2018; Black et al., 2007; Behrman and Rosenzweig, 2004).[25] For dietary diversity, we follow the guidelines of Bilinsky and Swindale (2006) to construct the individual dietary diversity score, a measure of nutritional quality that reflects macro and micronutrient adequacy of children (FANTA, 2006; Mirmiran et al., 2004). The 0-7 score counts the number of nutritionally meaningful food groups consumed in the previous 24 hours by the child.[26] We hypothesize that mothers' knowledge of nutrition and cooking practices increases with age, as well as their bargaining power over the purchase and consumption of more adequate food items in the household. If this were the case, children born to adolescent mothers would achieve lower dietary diversity scores, which in turn would affect their nutrition.

In Table 7 we report the results for both birthweight and dietary diversity. OLS estimates for birth weight show that being born to a very young mother reduces child's birthweight by 169 grams, at the 10% level of significance. Controlling for mother fixed effects results in a stronger effect for children born to very young mothers. However, the point estimate is insignificant due to magnified standard errors. Aizer et al. (2018) and Rosenzweig and Wolpin (1995) find that point estimates decrease to biologically and statistically insignificant levels after controlling for family fixed effects and conclude that maternal family background, rather that maternal age, explains OLS results. It is worth acknowledging that birthweight data are missing for more than half of our sample, which contributes to the lack of estimation precision. Unlike the aforementioned studies, we do not interpret our results as evidence for null effects given the lack of precision due to the small sample size and the amount of missing data for this variable.

OLS estimates for dietary diversity shows that at the age of 8, children born to very young mothers achieve lower dietary diversity scores than those born to adult mothers. They

[25] Although we show this variable as a potential transmission channel for health outcomes, it also embodies a potential mechanism for cognition (Figlio et al., 2014).
[26] See

Table A2 for a detailed description of this and other variables.

consume 0.39 (0.46 SD) fewer food groups, which constitutes a modest but non-negligible difference considering that on average children in Round 3 consume 4.35 food groups daily. Interestingly, the correlation weakens over time, suggesting that as very young mothers' age, the diet quality of their children improves. Moreover, these results emulate the trajectory over time of our results for HAZ, as the effect of maternal age decreases as the child grows up. Hence, we interpret these estimates as suggestive evidence for dietary diversity as a mediation channel for children born to very young mothers.

We now look at the transmission channels for child's cognition. We focus on the children born to very young mothers only, as these children are the ones found to perform worse in the math test compared to children born to adult mothers. We investigate whether slow school grade progression (or being overage-for-grade), education expenditure and maternal involvement in child's education behave as mediating channels for the detrimental effects of early motherhood on cognition.

Table 7. Regression results: exploring the transmission channels for child's health

	Birthweight		Dietary diversity
	(1) OLS	(2) MFE	(3) OLS
Very young mother	-169.07*	-294.93	-0.39**
	(86.37)	(217.37)	(0.19)
Very young mother # R4			0.30
			(0.23)
Very young mother # R5			0.49
			(0.30)
Young mother	17.95	45.06	-0.06
	(51.90)	(99.76)	(0.07)
Young mother # R4			0.06
			(0.11)
Young mother # R5			0.03
			(0.11)
Sample	Sib. pairs	Sib. pairs	Index child
p(<16 (R4)=0)			0.670
p(<16 (R5)=0)			0.670
p(16-17 (R4)=0)			0.980
p(16-17 (R5)=0)			0.754
R-squared	0.035	0.600	0.049
Observations	1421	1434	5625

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level, respectively. Clustered standard errors at mother level are in parenthesis. The sample consists of the sibling pairs for birthweight regressions and of index children in Rounds 3, 4 and 5 for the dietary score regression. Very young mothers and young mothers refer to children born to mothers under 16 years old and 16-17 years old, respectively. The reference category is the maternal age group of mothers 18 years old and older at the time of childbirth. The dependent variables are birthweight (grams) and individual dietary diversity score (0-7 range). OLS regressions control for gender, birth order, ethnicity, rural/urban status in Round 1 and mother's height. The dietary score regression controls in addition for age and round dummies. The MFE regression controls for mother fixed effects.

Overage-for-grade is a dummy that indicates whether the child is overaged for the school grade she is enrolled in at the start of the school year, taking into account the official entrance age for each grade in the states of Andhra Pradesh and Telangana. The hypothesis is that if children born to adolescent mothers experience lower and inefficient investments in human capital, they would tend to fall behind in school, increasing their likelihood of being overaged. This in turn would flatten their learning curves, creating a vicious cycle in which overage would be both a cause and a consequence of poor cognition (see UNESCO, 2012 and Alexander et al., 2003 for suggestive evidence and conceptual discussions).

Table 8. Regression results: exploring the transmission channels for child's cognition

	Overage		Education expenditure.	Teacher's name
	(1) OLS	(2) MFE	(3) OLS	(4) OLS
Very young mother	0.14**	0.12	-0.01	0.03
	(0.06)	(0.10)	(0.02)	(0.11)
Very young m. # R4	-0.03	0.04	0.02	-0.24*
	(0.06)	(0.06)	(0.05)	(0.14)
Very young m. # R5	-0.08	0.02	0.01	-
	(0.10)	(0.10)	(0.08)	-
Young mother	0.08**	0.11***	0.02	0.01
	(0.03)	(0.04)	(0.02)	(0.04)
Young mother # R4	-0.02	-0.00	-0.03	-0.13**
	(0.03)	(0.03)	(0.02)	(0.06)
Young mother # R5	-0.02	0.00	-0.09***	-
	(0.04)	(0.03)	(0.03)	-
Sample	Sib. pairs	Sib. pairs	Index child	Index child
p(<16 (R4)=0)	0.039	0.066	0.860	0.021
p(<16 (R5)=0)	0.480	0.223	0.934	
p(16-17 (R4)=0)	0.029	0.001	0.655	0.007
p(16-17 (R5)=0)	0.074	0.001	0.006	
R-squared	0.166	0.578	0.165	0.143
Observations	5935	5981	4942	3511

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level, respectively. Clustered standard errors at mother level are in parenthesis. The sample consists of the sibling pairs for overage regressions and of index children in Rounds 3,4 and 5 for the remaining columns. All children considered are enrolled formally. Very young mothers and young mothers refer to children born to mothers under 16 years old and 16-17 years old, respectively. The reference category is the maternal age group of mothers 18 years old and older at the time of childbirth. The dependent variables are a dummy for overage for grade, the share of real education expenditure on the index child in total expenditure of the household, and a dummy indicating whether the mother knows the name of the child's teacher. OLS regressions control for dummies for age, gender, birth order, schooling starting age, ethnicity, rural/urban status in Round 1, and in addition for mother's height. The education expenditure regression includes total expenditure per capita in real terms. The MFE regression controls for dummies for age, gender, birth order, rounds and a schooling starting age, in addition to mother fixed effects.

Education expenditure and maternal involvement in child's education are our most direct proxies for parental investments in education. The former is defined as the share of total household expenditure per capita in real terms assigned to educational fees, including both school fees and private tuition fees. The latter is a dummy variable indicating whether the mother knows the name of the child's teacher. Presumably, this variable correlates with mother-teacher meetings, which reflect the value that mothers place on their child's education and has been linked to significant improvements of learning outcomes (Islam, 2019).

In Table 8, OLS estimates suggest that being born to a very young mother increases the likelihood of being overaged by 14 percentage points in the earliest round. The association weakens over time and turns statistically insignificant in Round 5. Including mother fixed effects changes the dynamics over time and significance by round. The association now tends to slightly increase over time and is marginally significant only in Round 4. At this round, the likelihood of being overage-for-grade increases by 16 percentage points for children born to very young mothers.

Turning to our proxies for parental investments, we do not find statistically significant effects for educational expenditures. However, we do find suggestive evidence for teacher's name estimates. The coefficient for very young mothers is tiny and insignificant in Round 3. However, the point estimate turns large in magnitude and significant at conventional levels when children are 12 years old on average (Round 4). At this round, very young mothers at birth are 21 percentage points less likely to know the name of the child's teacher. This suggests that the gap in these type of investments between adult mothers and very young mothers surges only during late-middle childhood.

Finally, we now explore the correlation between child's health and cognition, hypothesizing that health factors play a role as determinants of cognition.[27] Increasingly, the economic literature attempts to quantify the relationship between health outcomes and subsequent cognitive achievement (Lo Bue, forthcoming; Sánchez, 2017; Spears, 2012; Miguel and Kremer, 2004; Glewwe et al., 2001). Our results show that being born to an adolescent mother has negative consequences for HAZ. We also observe that the group of children with the largest effects on HAZ, that is, those children born to very young mothers, is the same group that perform the poorest in the math test. In light of these results, we investigate the health-cognition nexus by regressing math scores on HAZ using our preferred MFE specification.

Table 9 shows the MFE estimates for the health-cognition nexus. Estimates in column 1 suggest a positive and statistically significant relationship between HAZ and math scores. If the median child in our sample had the median HAZ of the well-nourished reference population, she would achieve 0.08 SD higher math scores, net of household and mother time-invariant characteristics. These results might be indicative of the mediating role of health on the maternal age-cognition nexus.

[27] As such, health outcomes might be the result of both behavioral and biological processes.

Table 9. MFE regression results: health as a predictor for cognition

	Math		
	(1) MFE	(2) MFE	(3) MFE
HAZ	5.63***		1.89
	(2.01)		(2.32)
HAZ (R3)		7.17***	6.35***
		(1.96)	(2.19)
p(b(HAZ)=b(HAZ(R3)))			0.25
R-squared	0.71	0.72	0.72
Observations	5529	5379	5379

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level, respectively. Clustered standard errors at mother level are in parenthesis. The sample includes sibling pairs for Rounds 4 and 5. The dependent variable is math (IRT scores). All regressions control for dummies for age, gender, birth order and round, and in addition a continuous measure for schooling starting age. All regressions include round interactions with controls and control for mother fixed effects.

However, the contemporaneous nature of the two indicators raise reverse causality concerns. To ease such concerns, we regress math performance in Rounds 4 and 5 on HAZ in Round 3 (column 2). Again, the association is found to be positive, statistically significant and larger. An increase of HAZ of the median child to median levels of a well-nourished population is now associated with a 0.1 SD increase in math scores. This is consistent with the idea of early health outcomes having a larger impact than contemporaneous ones and with the skills self-productivity rationale (Heckman 2006; Glewwe et al., 2001). To test this directly, we include both HAZ variables in column 3. Point estimates for HAZ in Round 3 remain highly statistically significant, while contemporaneous HAZ does not. Moreover, the differences in the size of point estimates are obvious, although they are not statistically different from each other.

Finally, these results can relate to our findings on the weakening over time of the effect of maternal age on HAZ and the surge of effects on cognition only in early adolescence, as discussed in previous sections. Results in Table 9, in combination with our main results, suggest that while physiological catch-up growth is to some extent possible and possibly cognitive-enhancing, disadvantages in health outcomes earlier on will still affect subsequent cognition. In other words, catch-up growth might have cognitive gains but it might not fully compensate for the effects of past health deficits on cognitive skills. Following the rationale of skills self-productivity, health-induced cognitive gaps would widen over time. We consider these conjectures to be fertile ground for future research.

5. Conclusion

This paper investigates the effect of early maternal age on offspring human capital development during childhood and early adolescence. We attempt to recover the causal effect of being born to an adolescent mother by comparing the offspring outcomes of children born to the same mother and exploiting within-mother variation of maternal age at birth.

Our results suggest that early maternal age is negatively associated with offspring health and cognition. In the earliest data round, when children are on average 8 years old, being born to an adolescent mother is associated to 0.3 lower HAZ compared to children born to adult mothers. This detrimental effect weakens over time but remains statistically significant until early adolescence, suggesting both a partial catch-up and permanent effects. Moreover, the negative effects for children born to very young mothers are significantly larger than the effects for children born to young mothers, particularly among girls.

In terms of cognition, children born to very young mothers perform worse than children born to adult mothers (0.28 SD). This effect strengthens over time, turning statistically significant in Round 5 (0.38 SD), when children are on average 15 years old. The trajectory of this effect is in line with the skills self-productivity argument, suggested by Cunha et al. (2006). Similar to the HAZ results, girls born to very young mothers perform particularly worse in the math test. This is consistent with previous evidence on gender discrimination in parental human capital investments in India (Barcellos et al., 2014; Asfaw et al., 2010; Behrman, 1988).

We hypothesize that early maternal age at birth might affect children's human capital development through two main channels: behavioral channels and biological channels. Although limited in its scope, our analysis provides suggestive evidence on the role of behavioral channels related to food diversity, school progression and maternal involvement in education as mediating factors behind the estimated detrimental effects of early childbearing. For biological channels, we fail to find an effect of early maternal age on children's birthweight.

Furthermore, we find a positive and modest association between HAZ and subsequent math performance. The latter implies that initial health outcomes might play a role in the poor math performance of children born to very young mothers. We observe that HAZ measured at the earliest ages is more strongly associated with subsequent math performance than contemporaneous HAZ. We argue that this result might suggest that the catch-up growth might not be able to fully compensate for the detrimental effects of past health deficits on cognitive skills. Following the notion of skills self-productivity, these health-induced cognitive gaps would widen over time and become more apparent in adult life. These conjectures would be a fruitful area for further research.

This paper has two main limitations. First, the sample size of our data is relatively small for the analysis of heterogeneous effects. Second, the transmission channel analysis is limited in scope due to data availability, for which we partly rely on OLS estimations. Further research into the broader investigation of potential transmission channels, and in particular into the relative importance of behavioral vis-à-vis biological channels is essential. The latter remains an open question in this paper and it is of great relevance for policymakers. In this context, the role of institutional and family safety nets in compensating for these detrimental effects in both LMICs and high-income countries should be explored.

This paper provides additional and powerful motivation to implement preventive measures that reduce early maternal age. We would stress that this instrumental motivation complements intrinsic concerns of early pregnancy related to human rights issues. Likewise, the paper results support restorative policy measures assisting early mothers and their offspring to lower the burden of early motherhood and foster the development of their offspring. Such policy measures might have the potential to enhance the human capital of children, ultimately driving economic development.

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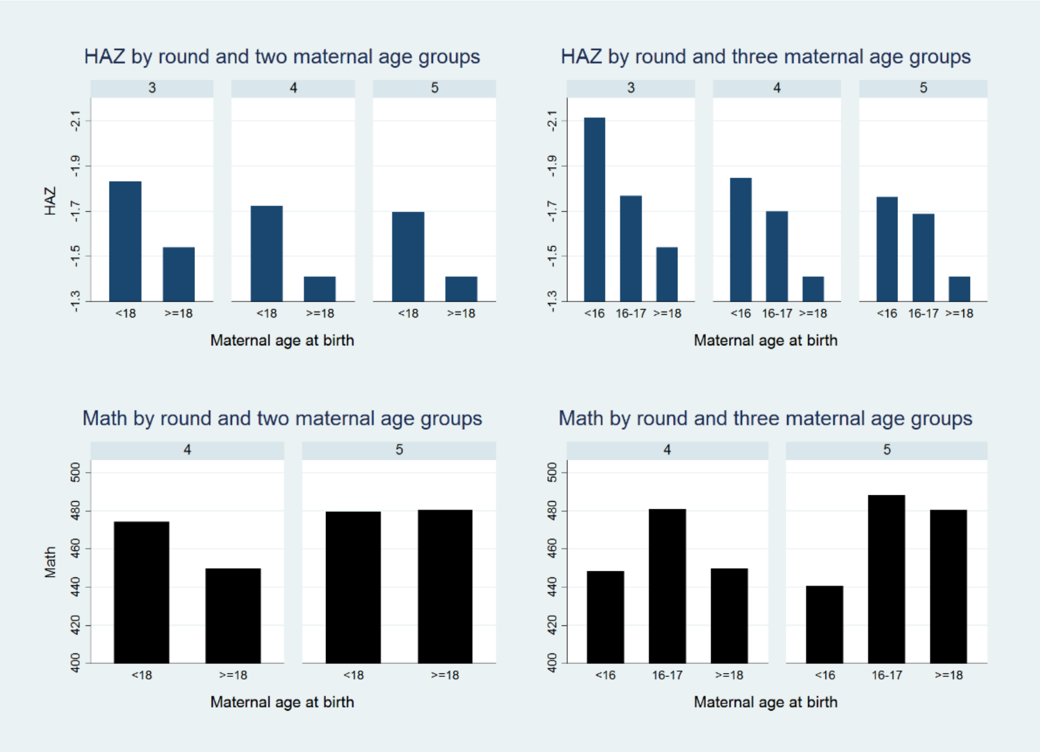
Appendix

Table A1. Age of index children and siblings by round

		Index children			Siblings		
		Mean	SD	N	Mean	SD	N
Child age	R3 (2009)	8.0	0.3	1,534	7.9	3.2	1,534
	R4 (2013)	12.0	0.3	1,607	11.7	3.5	1,607
	R5 (2016)	15.0	0.3	1,462	14.5	3.4	1,462

Notes: Sample per round is restricted to households with sibling pairs information on age, gender, birth order and height-for-age or math scores.

Figure A1. Mean of HAZ and math by round and maternal age group



Notes: Statistics correspond to child-round-level observations with available information on age, gender, birth order, maternal age and the respective outcome variable for the sibling pairs participating in Rounds 3 (2009), 4 (2013) and 5 (2016). The maternal age groups are shown on the x-axis. HAZ is height-for-age in z-scores collected in the three rounds, while math consists of IRT scores collected in Rounds 4 and 5. HAZ values lower than -6 and larger than 6 are set to missing as they are considered biologically implausible (WHO, 2006).

Table A2. Detailed description of variables

Variable	Description
Maternal age variables	
Maternal age at birth	Mother's age at the time of childbirth. This variable is constructed by taking the difference between the child's age (reported in months) and mother's age (reported in years) at the time of each data round.
Adolescent mother	Binary indicator taking the value of 1 for children born to mothers under the age of 18 at the time of childbirth and 0 otherwise.
Young mother	Binary indicator taking the value of 1 for children born to mothers that were 16-17 years old at the time of childbirth and 0 otherwise.
Very young mother	Binary indicator taking the value of 1 for children born to mothers under the age of 16 at the time of childbirth and 0 otherwise.
Outcome variables	
Height-for-age (HAZ)	Standardized height indicator (z-scores) according to age- and gender-specific child growth references of a universally comparable well-nourished population (WHO, 2007). Values outside the -6:6 range are considered biologically implausible and set to missing.
Math score	Scores computed using Item Response Theory (IRT) models, which enhance score comparability over time and across ages. This score derives from a mathematical test covering a wide range of difficulty, from basic number identification and quantity discrimination, to calculation, measurement and items related to problem solving of real-life math applications.
Transmission channels	
Birthweight	Birthweight in grams. Retrospectively collected, from birth documentation whenever possible.
Dietary diversity	Nutritional quality measure reflecting macro and micronutrient adequacy of children. The construction of this variable follows the guidelines by Bilinsky and Swindale (2006) which suggests a 0-8 score. The data for this paper however allow for a 0-7 score. The indicator counts the number of nutritionally meaningful food groups consumed by the child in the previous 24 hours. The food groups are: grains, roots or tubers; vitamin A-rich plant foods, fruits and vegetables; meat, poultry, fish and seafood; eggs; pulses, legumes and nuts; milk and milk products; food items cooked in oil/fat.
Overage	Binary indicator taking the value of 1 if the child is overaged for the school she is enrolled in at the beginning of the school year and 0 otherwise. The variable takes into account the official entrance age for each grade in the states of Andhra Pradesh and Telangana: age 3 for pre-primary education, 6 for primary education, 11 for upper primary education, 14 for high school, 16 for senior secondary and 18 for university. Only children in full-time enrolment are considered.
Education expenditure	Share of total household expenditure per capita in real terms assigned to educational fees, including school fees and private tuition fees. The consumer price index used as deflator to obtain real values (base year 2006) is built using information from the Young Lives community questionnaire. Only children in full-time enrolment are considered.
Teacher's name	Binary indicator taking the value of 1 if the mother knows the name of the offspring's teacher and 0 otherwise. Only children in full-time enrolment are considered.
Control variables	
Age	Age in rounded years (reported in months).
Gender	Binary indicator taking the value of 1 for female and 0 for males.
Birth order	Constructed by comparing the ages of all the siblings living in the same household during any of the five round interviews of the Young Lives study.
Mother's height	Mother's height in cm.
Ethnicity/caste	Ethnicity/caste indicator with the following categories: Scheduled Caste, Scheduled Tribe, Backward Class, and other.
Rural/urban	Binary indicator taking the value of 1 if the household is located in an urban area and 0 if located in a rural area.

Total expenditure	Total household expenditure in per capita and real terms. The consumer price index used as deflator to obtain real values (base year 2006) is built using information from the Young Lives community questionnaire.
Wealth index	A composite and continuous measure of living standards equally weighting subindices for housing quality, access to services and consumer durables (Briones, 2017).
Number of household shocks	Number of household shocks suffered by the household in Rounds 1, 2 and 3. For the first round, shocks in the past four years are considered. For the second and third round, the shocks experienced by the household between data rounds are considered (four and three years, respectively). The shocks include natural disasters, significant changes in the economy, significant changes in the state regulation, theft, significant house damages and significant changes in the family such as death or illness of parents, among others (Briones, 2018).

Table A3. Sample characteristics: all index children and index children with siblings

Sample:	All index children		Index children with siblings	
	Mean	N	Mean	N
Household characteristics				
Maternal age	22.62	6,015	22.37	4,603
Mother's education	4.08	5,634	4.12	4,569
Mother's height	151.43	5,742	151.41	4,563
Total expenditure	1,085.68	5,611	1,061.59	4,508
Wealth tertiles				
First wealth tertile	0.34	5,753	0.33	4,602
Second wealth tertile	0.33	5,753	0.33	4,602
Third wealth tertile	0.33	5,753	0.34	4,602
Urban	0.28	5,717	0.28	4,582
Region				
Coastal Andrah	0.35	5,706	0.34	4,582
Rayalaseema	0.29	5,706	0.29	4,582
Telangana	0.35	5,706	0.37	4,582
Ethnicity/caste				
Scheduled Caste	0.18	6,033	0.18	4,603
Scheduled Tribe	0.15	6,033	0.15	4,603
Backward Class	0.46	6,033	0.47	4,603
Other	0.21	6,033	0.20	4,603
Offspring characteristics				
Age	11.65	5,740	11.62	4,603
Female	0.46	6,033	0.45	4,603
Birthweight	2,763.65	2,604	2,770.74	2,031
Birth order				
Firstborn	0.38	6,033	0.35	4,603
Second born	0.38	6,033	0.40	4,603
Third born	0.15	6,033	0.16	4,603

Notes: Statistics correspond to child-round-level observations from Rounds 3 (2009), 4 (2013) and 5 (2016) for two samples. The first sample consists of all index children with available information on the corresponding variable. The second sample covers all index children with available information on age, gender, birth order, maternal age and HAZ or math data for him/her and the sibling. All time-variant variables (wealth tertiles, total expenditure, location-related variables, mother's education and age of the child) are measured in the three rounds. Maternal age is computed by averaging the differences between the child's age and mother's age across rounds. Mother's education consists of her highest completed grade. Mother's height is reported in cm and birthweight in grams. Total expenditure refers to household total monthly expenditure per capita in 2006 constant rupees. A composite wealth index was used for the estimation of the share of observations within each wealth tertile (see Briones 2017 for a detailed description). For the computation of birth order, the ages among siblings that lived in the Young Lives household during any of the five survey rounds were compared.

Table A4. Regressions results: adolescent motherhood and height-for-age

	(1) MFE	(2) MFE	(3) MFE	(4) MFE	(5) MFE
Adolescent mother	-0.30***	-0.30***	-0.30***	-0.30***	-0.30***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Adolescent mother # R4	0.13**	0.13**	0.12**	0.12**	0.12**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Adolescent mother # R5	0.11	0.12*	0.09	0.11*	0.10
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
p(<18 (R4)=0)	0.05	0.05	0.05	0.05	0.05
p(<18 (R5)=0)	0.05	0.06	0.03	0.06	0.04
R-squared	0.60	0.60	0.60	0.60	0.60
Observations	8720	8702	8702	8702	8702

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level, respectively. Clustered standard errors at mother level are in parenthesis. The sample includes sibling pairs for Rounds 3, 4 and 5. The reference category is the maternal age group of mothers 18 years old or older at the time of childbirth. The dependent variable is height for age (z-scores). All regressions control for mother fixed effects, age fixed effects, gender, birth order, a survey round indicator and its interaction with these controls. The second, third and fourth column control for child-specific shocks, wealth index and real total expenditure per capita during early childhood and their interactions with round dummies, respectively. The fifth column controls for all three robustness variables simultaneously.

Table A5. Regression results: adolescent motherhood and math

	(1) MFE	(2) MFE	(3) MFE	(4) MFE	(5) MFE
Adolescent mother	5.28	5.44	4.30	5.47	4.60
	(7.70)	(7.72)	(7.76)	(7.72)	(7.78)
Adolescent mother # R5	-13.88*	-13.99*	-12.44	-13.68*	-12.44
	(7.97)	(7.98)	(8.07)	(8.01)	(8.09)
p(<18 (R5)=0)	0.33	0.34	0.36	0.36	0.38
R-squared	0.69	0.69	0.69	0.69	0.69
Observations	5761	5749	5749	5749	5749

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level, respectively. Clustered standard errors at mother level are in parenthesis. The sample includes sibling pairs for Rounds 4 and 5. The reference category is the maternal age group of mothers 18 years old or older at the time of childbirth. The dependent variable is math scores. All regressions control for age fixed effects, gender, birth order, schooling starting age, a survey round indicator and its interaction with these controls and mother fixed effects. The second, third and fourth column control for child-specific shocks, wealth index and total expenditure per capita in real terms during early childhood, respectively. The fifth column controls for all three robustness variables simultaneously.