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Early Motherhood and Offspring Human Capital in India*

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Abstract

Using panel data from India, this paper investigates the effect of early maternal age on offspring human capital. The analysis relies on mother fixed effects to allow for mother unobserved heterogeneity and employs a variety of empirical strategies to address remaining concerns related to sibling-specific unobserved heterogeneity. Our results indicate that children born to early mothers are shorter for their age and perform poorer in math, with stronger effects for (female) offspring born to very young mothers. By exploring the evolution of effects over time for the first time in the literature, we find that the height effect weakens as children grow older, while the cognition effect surges in early adolescence. Further analysis suggests both biological and behavioral factors as transmission channels.

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

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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, amounting to 95% of global teen births (EWEC, 2015; UNFPA, 2015; WHO, 2014; Neal et al., 2012). Such scale of early motherhood might have important implications for offspring development in LMICs. For instance, the medical literature has linked early pregnancy to labor complications and poor neonatal outcomes (Neal et al., 2018; Fall et al., 2015; Gibbs et al., 2012; Neal et al., 2012; Conde-Agudelo et al., 2005). In the same vein, the important role that mothers play in human capital investments for children suggests that the mother's age and its associated knowledge and bargaining power might be crucial for child development (Doss, 2013; Duflo, 2003). Such medical and behavioral implications of early maternal ages gain further relevance in light of the long-term consequences of prenatal and early childhood circumstances (Almond et al., 2018; Rosales-Rueda, 2018; Carlson, 2015; Almond and Mazumder, 2011).

In this paper, we investigate the causal effect of early motherhood on offspring human capital in terms of health and cognition in the Indian states of Andhra Pradesh and Telangana, where teenage fertility rates amount to 12% and 11%, respectively (IIPS, 2017). In addition to testing whether children born to adolescent mothers systematically suffer from poorer human capital outcomes compared to children born to adult mothers, we investigate for the first time how the early motherhood effect evolves over time, covering the offspring transition from childhood into early adolescence. Furthermore, we investigate heterogeneous effects across different maternal age groups and offspring gender, and explore potential transmission channels.

The main empirical challenge for our purpose consists of unobserved mother and family characteristics. As women from poor socioeconomic backgrounds are more likely to experience early motherhood, differences in offspring outcomes by maternal ages may simply reflect differences in pre-childbearing characteristics.[1] Moreover, mother cohort effects might also confound the effect of interest. Using longitudinal data spanning 7 years on 1690 sibling pairs, we circumvent these issues by adopting a mother fixed effects approach (MFE). We thereby exploit the maternal age at birth variation within the same family and compare offspring outcomes of children born to the same biological mother.[2] To ease remaining concerns related to sibling unobserved heterogeneity, we i) control for child-specific and time-varying family-level covariates, ii) perform the Oster (2019) method and iii) run falsification tests with a higher maternal age cut-off.

Our estimates suggest that early maternal age is detrimental to offspring development in terms of both health and cognition. In our health analysis, we find that being born to an adolescent mother is associated with 0.23 lower height-for-age z-scores (HAZ). The effect is largest at early ages (0.33) and weakens as children enter adolescence (0.19), pointing to a partial catch-up over time. In spite of this trajectory, effects in early adolescence are more than 2.4 times larger than estimates from a developed country context (Aizer et al., 2018). What is more, as physical growth is minimal after early adolescence, this finding implies that the detrimental effect is permanent in the offspring lives. 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 negative effect of 0.35 SD in math scores for children in early adolescence born to very young mothers, which is more than 1.9 times larger

[1] Hence, while previous research has shown that early motherhood is correlated with poor offspring outcomes, there is a lack of consensus on the causality of this association. See Azevedo et al. (2012) for a review and Levine (2007) and Aizer (2018) for examples of contrasting conclusions.

[2] Such siblings-difference models are established empirical tools used in studies on human capital production (see for instance Kreiner and Sievertsen (2020); Autor et al. (2016); Black et al. (2016); Figlio et al. (2014); Lundborg et al. (2014); Glewwe et al. (2001)) and on the literature on the consequences of maternal age on offspring outcomes using data from high-income 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).

than those found for the Norwegian context (Aizer et al., 2018). Such effect sizes are considered large by the education literature on LMICs (Muralidharan et al., 2019).[3] The effect strengthens over time and is larger among girls.

We use a variety of empirical strategies to address remaining endogeneity concerns, in particular those related to child cohort and birth order effects. In addition to controlling for age and birth order fixed effects throughout our specifications, we observe supporting evidence from the Oster method, which indicates that sibling-specific factors net of age, gender and birth order effects, would have to play a bigger role than all household and mother-level factors in the development of HAZ and math skills for the early motherhood effect to be null. This suggests that the empirical relevance of omitted variables for our estimates is limited. What is more, alternative maternal age cut-offs produce coefficient movements that speak against alternative interpretations of our results. In line with the early motherhood narrative, a lower maternal age cut-off result in stronger negative effects of being born to an early mother, while falsification tests with a higher age cut-off fail to reproduce negative effects. As we have no reason to assume such coefficient behavior stemming from child cohort or birth order effects, we interpret this combination of results as strong evidence for early maternal age effects.

Turning to the transmission channel analysis, we find some evidence on the role of birthweight, dietary diversity and parental involvement in education as three important mechanisms explaining the negative relationship between early maternal age and child development. In an extension, we explore the health-cognition nexus and find that early health deficits are detrimental to subsequent cognitive skills, even in a context of partial catch-up growth in HAZ.

[3] We advise caution in overemphasizing the comparison of these cognition effects given the possibility of differing distributional properties of test scores (see Ost et al., 2017).

Our analysis contributes to the economic literature on the consequences of early motherhood in several ways.[4] First, this paper advances the literature significantly by using data from LMICs. Surprisingly, such studies are remarkably scarce despite the concentration of global teen births in LMICs. To the best of our knowledge, Branson et al. (2015) is the only existing study investigating the effect of maternal age on offspring development in a LMIC context (Branson et al., 2015).[5] Using propensity score matching to analyze data from Cape Town, South Africa, the authors find that children born to teen mothers are shorter for their age and have lower birthweight. Moreover, we make an important contribution by addressing endogeneity with a siblings-difference framework in a LMIC context for the first time, which is an established tool in the literature on human capital production and in particular among early motherhood studies using data from high-income countries.

Interestingly, the evidence from high-income countries is mixed. While earlier studies conclude that observed offspring differences in birthweight and cognitive skills, among others, are the result of unobserved pre-childbearing characteristics (Levine et al., 2007; López-Turley 2003, Rosenzweig and Wolpin, 1995; Geronimus et al., 1994), more recent ones 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).

Finally, we make a significant contribution to the literature by exploiting the panel dimension of the data and exploring for the first time the evolution of the early motherhood

[4] More broadly, we contribute to the literature on the long term consequences of prenatal and childhood environments on human development (Almond et al., 2018; Rosales-Rueda, 2018; Carlson, 2015; Almond and Mazumder, 2011).

[5] Two other studies look at the effect of marriage age instead and find that delaying marriage age is beneficial for offspring development (Chari et al., 2017; Delprato et al., 2017). While closely interrelated, marriage age and maternal age at birth are not equivalent. In a sample of Indian states, for instance, only 34% of married women aged 15-19 have given birth (IIPS, 2017).

effect over time, which allows us to obtain a wider perspective of the association of interest. Interestingly, 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 (see Almond et al. (2018) for a review).

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). 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.[6] 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 considering the time period covered by the study.

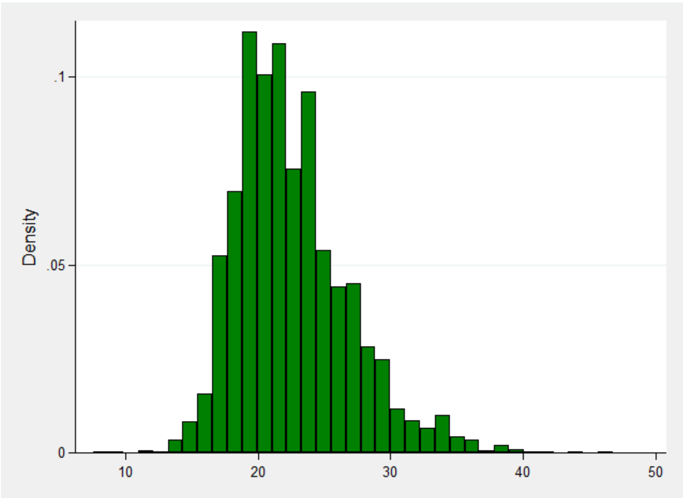
Since the third survey round in 2009, additional anthropometric (Rounds 3 to 5) and cognition (Rounds 4 and 5) data were collected on one sibling of each index child. Among available siblings, the next younger sibling of the index child was selected. If not available, the next older sibling was interviewed.[7] 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 (HAZ) or math performance and the relevant child-level control variables used in the empirical analysis.[8] We end up using observations from 1,690 households with sibling pairs, of which 910 contain a younger sibling and 754 an older one.[9] 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.[10] 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).

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

[6] The districts are Srikakulam and West Godavari in Coastal Andhra, Anantapur and Kadapa in Rayalaseema, and Karimnagar, Mahbubnagar and Hyderabad in Telangana.
[7] In 746 cases out of 754 for which a younger sibling was not available, the index child was the youngest child in the household.
[8] The index children with available sibling data are very similar to the overall sample of index children, based on household and offspring characteristics (see Table A3).
[9] The remaining 26 households are composed of same-aged siblings.
[10] The number of sibling pairs across rounds is stable. See Table A1 for observations per round.

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).[11]

Figure 1. Distribution of maternal age at birth



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

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.

[11] 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).

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.[12] 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 offspring of 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 HAZ and cognition, it is important to control for these differences in the regression framework.

[12] 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.

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	974.60	174	1,006.48	768	1,000.59	942	1,066.47	7,968
Wealth tertiles								
1st	0.39	175	0.34	778	0.35	953	0.33	8,139
2nd	0.38	175	0.39	778	0.39	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	14.78	175	12.82	778	13.18	953	11.18	8,141
Female	0.49	175	0.44	778	0.45	953	0.49	8,141
Birth order								
Firstborn	0.88	175	0.78	778	0.80	953	0.27	8,141
Second born	0.12	175	0.20	778	0.19	953	0.47	8,141
Third born	0.00	175	0.02	778	0.01	953	0.18	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.

Young Lives collects child anthropometrics and various measures of cognition throughout rounds. We use HAZ z-scores and math IRT 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).[13] 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-height, to temporary shocks due to morbidity, illnesses or seasonal variations in food availability.

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).[14]

Table 2 presents the mean values of the outcomes of interest by maternal age groups.[15] 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

[13] We follow WHO guidelines (2006) and set values out of the -6:6 range to missing due to their biological implausibility. We also correct for measurement error in height-for-age by dropping 53 observations that implausibly suggest a decrease in absolute height over time.
[14] The key results of the analysis are qualitatively similar when using raw scores instead of IRT.
[15] See Figure A1 for the means by rounds.

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 at the 1% level. 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.

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	749	-1.75	896	-1.45	7,802
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 across maternal age groups are statistically significant at the 5% 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).[16] In this section, 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 have 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 received less attention 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 sibling data to rely on mother fixed effects (MFE). Since mother unobserved heterogeneity potentially biases OLS estimations, we account for mother's unobserved characteristics by looking at the outcomes of offspring pairs born to the same mother. Specifically, we estimate regression model (1) 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. AM_{ij} is a dummy variable indicating children born to adolescent mothers, defined as mothers under 18 years of age at childbirth. The coefficient of interest β identifies the effect of being born to an adolescent

[16] 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 reference.

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).

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

$\boldsymbol{Z'_{ijr}}$ is a vector of child's characteristics such as age dummies, gender (a dummy equal to 1 if the child is a female), birth order dummies and, in addition, schooling starting age for cognition regressions. $\boldsymbol{\mu_j}$ 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 height-for-age z-scores (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 models offer a number of advantages compared to OLS estimates. We nevertheless also present OLS estimates for comparison purposes. 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.[17] 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

[17] 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.

nutrition might indeed be an important factor to explain child' nutritional status (see for an 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.[18]

We further exploit the panel dimension of our data to investigate how the early motherhood effect 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 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 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

[18] See for instance Lang and Weinstein (2015).

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). Moreover, these estimates account for differences in family sizes, which can affect offspring human capital in several ways (Spears et al., 2019; Behrman and Taubman, 1986).[19]

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).[20] Second, time-varying household-level covariates such as child cohort effects 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. As a robustness check, we therefore

[19] 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 (e.g. Grépin and Bharadwaj, 2015).

[20] 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 Bharadwaj et al. (2018) and Fan and Porter (2018) for examples of compensating behavior).

control for the exposure of the child to household shocks during early childhood, household wealth and household consumption during the same period.[21]

To further ease concerns associated with sibling-specific unobserved heterogeneity such as child cohort and birth order effects, we run falsification tests with a maternal age cut-off of 10 years older, at 28 years of age, thereby comparing siblings born to mothers under and above 28 years of age.[22] The purpose of these regressions is to shed light on the role of alternative factors in driving our results. If the estimates are similar to what we find in our main regressions, this would suggest that our results are driven by alternative factors rather than by early motherhood.

Furthermore, we apply the Oster (2019) 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 (2019) 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 all household and mother-level factors for the

[21] 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. 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 rather limited in the measurement of maternal age group indicators.

[22] This falsification cut-off allows us to compare sibling pairs with maternal ages that remain unchallenged by the medical literature (Kahveci et al., 2018; Neal et al., 2018; Fall et al., 2015; Gibbs et al., 2012; Neal et al., 2012; Conde-Agudelo et al., 2005). The vast majority of sibling pairs contributing to this estimate have maternal ages of 22-33 years of age, with an average maternal age of 28 years and a standard deviation of 3.5.

coefficient of adolescent mothers to be zero. Values significantly below a unit on the other hand would represent a threat to our estimates.[23]

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.[24] 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 a higher risk of infant mortality (Neal et al., 2018; Conde-Agudelo et al., 2005). This survival selection would bias our estimates towards zero.

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 height-for-age z-scores (HAZ) as a dependent variable, while the last two columns show estimates for math IRT scores.

The OLS regression in column 1 suggests that being born to an adolescent mother is associated with 0.22 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

[23] Note that while we do not observe all household and mother-level factors per se, we are able to account for them in the MFE models. Therefore, these factors act as observables in this exercise. By design, we are able to perform this test for uninteracted coefficients of interest.
[24] In India, the maternal mortality rate was estimated at 174 deaths per 100,000 live births in 2015 (WHO et al., 2015). Perinatal mortality amounted to 36 deaths per 1,000 pregnancies in 2015-16 (IIPS, 2017).

effects barely alters these results.[25] The point estimate remains highly significant and amounts 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).[26] While moderate, such differences might be quite relevant for the development of vulnerable children, as discussed later in this section.

Table 3. Regression results: adolescent motherhood and offspring outcomes

	HAZ		Math	
	(1) OLS	(2) MFE	(3) OLS	(4) MFE
Adolescent mother	-0.22***	-0.23***	-12.89**	-2.01
	(0.06)	(0.08)	(5.96)	(6.08)
Delta (Beta=0)		1.16		
R-squared	0.13	0.59	0.21	0.69
Observations	8630	8698	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, 2019).

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

[25] This can be the result of biases discussed in section 3 canceling each other out. Alternatively, selection mainly occurring on observables or slightly different sample sizes across models might be responsible for the similarity of these results.

[26] 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).

perform the Oster method to derive formal implications of these movements and report the delta statistic at the bottom of Table 3.[27] 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 controlled factors, 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 0.12 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 unobserved selection into early motherhood rather than signaling a negative effect of early maternal age on children's cognition.

Given well-documented linkages between health and cognition, a reasonable prior would be to observe similar tendencies for both outcomes (Lo Bue, 2019; 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.

[27] For this exercise, we follow Oster's guidelines (2019) and set R_{max} to $1.3\tilde{R}$.

Finally, Table A6 in the appendix reproduces Table 3 with a maternal age cut-off at 28 years of age instead of 18 years of age. If we were to find the same results as those reported in Table 3, this would raise concerns about the estimated early motherhood effect and unobserved factors systematically disfavoring the older sibling would gain in relevance. As shown in column 2 of Table A6, the maternal age coefficient is *positive* and statistically significant, indicating that for these offspring pairs born to adult mothers, older siblings are benefitted rather than disfavored. This suggests that if anything, results in Table 3 are lower bound estimates of the effect of being born to adolescent mothers.

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 (Levine et al., 2007; 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.

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 MFE model, the penalty associated with being born to an adolescent mother is of 0.33 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 at the 5% level in both subsequent rounds, suggesting that a partial catch-up have taken place during the transition between childhood and adolescence. In Round 5, when children are on average 15 years old, the point estimate amounts to 0.19, which implies a penalty of 1.48 cm and 1.31 cm for boys and girls, respectively.[28] 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 and turns negative in Round 5. While it remains insignificant as indicated by its p-value, the interaction itself shows a downward trajectory that is statistically significant. Note

[28] This effect is more than 2.4 times larger than those estimated for a developed country context such as Norway (Aizer et al., 2018). This differential could be for instance linked to a younger profile of adolescent mothers in LMICs or to compensation mechanisms available in developed countries, such as social safety nets.

that the two outcomes of interest show different trajectories, an issue that will be commented below.

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

	HAZ		Math	
	(1) OLS	(2) MFE	(1) OLS	(2) MFE
Adolescent mother	-0.30***	-0.33***	-8.00	6.21
	(0.07)	(0.08)	(6.69)	(6.43)
# R4	0.13**	0.14***		
	(0.05)	(0.05)		
# R5	0.15**	0.14**	-7.44	-14.07**
	(0.07)	(0.06)	(7.12)	(6.70)
p(<18 (R4)=0)	0.01	0.02		
p(<18 (R5)=0)	0.03	0.03	0.03	0.29
R-squared	0.14	0.59	0.22	0.69
Observations	8590	8698	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.

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.[29] Point estimates are barely affected, which suggests that the role of such time-varying household-level covariates is unlikely to be driving the results.[30]

[29] See Briones (2018) for a detailed description of shocks and the wealth index.

[30] We conduct falsification tests equivalent to those discussed in the previous section 4.1. The results shown in Table A7 show that estimates from Table 4 fail to reproduce, confirming again the maternal age narrative.

4.3. Heterogeneous effects by maternal age categories and 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.[31] Moreover, we investigate heterogeneous effects by gender. Human capital investments in Indian children have been shown to be gender-skewed (Barcellos et al., 2014). More closely related to our exercise, previous research suggests that Indian households facing adverse circumstances favor sons over daughters (Asfaw et al., 2010; Rose, 1999; Berhman, 1988).

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. 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.

[31] 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	-0.32***	-0.37**	-0.45***	-0.54***	-0.78***	-0.91***
	(0.11)	(0.17)	(0.15)	(0.18)	(0.24)	(0.24)
# R4			0.23*	0.21*	0.45**	0.36*
			(0.13)	(0.12)	(0.19)	(0.18)
# R5			0.22	0.24	0.17	0.18
			(0.16)	(0.15)	(0.24)	(0.26)
# Boy					0.66**	0.79**
					(0.28)	(0.32)
# Boy # R4					-0.45*	-0.30
					(0.26)	(0.23)
# Boy # R5					0.01	0.05
					(0.30)	(0.30)
Young mother	-0.20***	-0.21***	-0.29***	-0.30***	-0.27***	-0.28**
	(0.06)	(0.08)	(0.07)	(0.08)	(0.10)	(0.13)
# R4			0.12**	0.13**	0.11	0.12
			(0.06)	(0.05)	(0.09)	(0.08)
# R5			0.15**	0.12*	-0.00	0.02
			(0.07)	(0.06)	(0.11)	(0.11)
# Boy					-0.03	-0.02
					(0.13)	(0.15)
# Boy # R4					0.03	0.02
					(0.11)	(0.10)
# Boy # R5					0.26*	0.17
					(0.13)	(0.13)
Delta (Beta=0, <16)		1.56				
Delta (Beta=0, 16-17)		1.60				
p(<16 (R4)=0)			0.07	0.06		
p(<16 (R5)=0)			0.09	0.14		
p(16-17 (R4)=0)			0.01	0.04		
p(16-17 (R5)=0)			0.05	0.04		
p(<16 (R4, G)=0)					0.05	0.00
p(<16 (R5, G)=0)					0.00	0.01
p(16-17 (R4, G)=0)					0.07	0.19
p(16-17 (R5, G)=0)					0.00	0.05
p(<16 (R3, B)=0)					0.44	0.61
p(<16 (R4, B)=0)					0.51	0.80
p(<16 (R5, B)=0)					0.74	0.68
p(16-17 (R3, B)=0)					0.00	0.00
p(16-17 (R4, B)=0)					0.06	0.09
p(16-17 (R5, B)=0)					0.69	0.31
R-squared	0.13	0.59	0.14	0.59	0.14	0.60
Observations	8630	8698	8630	8698	8630	8698

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 statistics Delta are obtained through the STATA command *psacalc* (Oster, 2019).

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. Second, detrimental effects are the strongest for very young mothers, in line with our hypothesis. Third, effects generally weaken over time.

Estimates reported in column 2 indicate that children born to young and very young mothers have 0.21 and 0.37 lower HAZ than children born to adult mothers. Both coefficients are statistically significant. Moreover, they both show Delta statistics significantly higher than unity, supporting the conclusion that adolescent motherhood is detrimental to HAZ. 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 1.8 times larger than the penalty experienced by children born to young mothers (0.54 versus 0.30, respectively), a ratio that slightly increases 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 0.91 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. Moreover, negative effects for girls born to young mothers are statistically significant in rounds 3 and 5, while for boys they are significant in rounds 3 and 4, but turn insignificant in round 5.

The gender-skewed effects observed among children born to very young mothers are in line with the literature documenting parental responses favoring sons to adverse circumstances in India (Asfaw et al., 2010; Rose, 1999; Behrman, 1988) and Sub-Saharan Africa (Delprato et al., 2017). However, given the limited power we face for this gender analysis, some caution is suggested in interpreting the statistically insignificant results for boys born to very young mothers 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. Importantly, the Delta statistic for the very young mother coefficient is substantially higher than 1, strongly supporting the early maternal age narrative. Second, detrimental effects associated to very young mothers surge during early adolescence.

Interpreting these results in more detail, estimates in column 2 show that being born to a very young mother is associated with a statistically significant decrease in math scores of 0.27 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 0.35 SD worse.[32] The strengthening of these effects over time are consistent with the notion of skills self-productivity put forward by Cunha et al. (2006).

[32] 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. As an additional reference point, the effect size we estimate is considered as large in the education literature using experimental methods in LMICs (Muralidharan et al., 2019). However, we advise caution in overemphasizing the comparison of these effects. As the distribution of scores are not constant across studies, similar SD movements might stand for different cognition gains in absolute terms (see Ost et al. (2017) for an analysis of this issue).

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	-41.74***	-29.88**	-35.74**	-14.47	-48.45**	-19.72
	(14.20)	(13.37)	(14.95)	(14.14)	(23.72)	(19.19)
# R5			-8.98	-24.07	-19.85	-37.75
			(15.87)	(15.28)	(24.51)	(24.35)
# Boy					22.90	11.45
					(28.34)	(23.72)
# Boy # R5					20.00	24.77
					(30.64)	(29.57)
Young mother	-6.87	1.48	-2.72	8.27	-10.49	7.34
	(5.94)	(6.08)	(6.73)	(6.54)	(9.43)	(8.99)
# R5			-6.94	-12.11*	2.68	-4.88
			(7.32)	(6.97)	(11.38)	(11.17)
# Boy					13.78	2.30
					(12.22)	(11.51)
# Boy # R5					-17.09	-12.48
					(13.78)	(13.27)
Delta (Beta=0, <16)		6.93				
p(<16(R5)=0)			0.01	0.02		
p(16-17(R5)=0)			0.18	0.61		
p(<16(R5,G)=0)					0.01	0.02
p(16-17(R5,G)=0)					0.48	0.82
p(<16(R4,B)=0)					0.14	0.64
p(<16(R5, B)=0)					0.27	0.32
p(16-17(R4, B)=0)					0.71	0.25
p(16-17(R5, B)=0)					0.20	0.38
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. The statistics Delta are obtained through the STATA command *psacalc* (Oster, 2019).

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 0.52 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 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 in the dynamic model. 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. Importantly, we are able to ease concerns on unobserved factors at the child level within families. With help of the Oster method, we show that the detrimental HAZ and cognition effects that we observe are highly unlikely to be driven by unobserved factors. Furthermore, results are robust to controlling for the socioeconomic progress of households. Finally, falsification tests, together with the stronger negative effects identified for children born to very young mothers, strongly suggest that our results are driven by maternal age dynamics, as we have no reason to assume similar coefficient behavior from child cohort or birth order effects.

4.4. Transmission channels

In this section, we explore some of the transmission channels possibly explaining the estimated relationship between early maternal age and offspring health and cognition. Building on human capital theoretical frameworks such as those in Attanasio (2015), Cunha et al. (2006) and 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.[33] 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. Using Attanasio's (2015) terminology, these disadvantaged initial conditions of biological nature would then negatively affect children's subsequent human capital outcomes. Indeed, children born to young mothers face higher risks of poor neonatal outcomes such as preterm birth and low birthweight, among others (Neal et al., 2018; Fall et al., 2015; Gibbs et al., 2012; Neal et al., 2012; Conde-Agudelo et al., 2005). In turn, such poor neonatal outcomes have been associated with negative impacts on offspring anthropometrics, schooling and adult earnings (McGovern, 2018; Black et al., 2007; Behrman and Rosenzweig, 2004).

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

[33] Some of these factors, such as parental socioeconomic background, do not vary across siblings and hence speak only to OLS estimates. Others, such as preferences and psychological maturity, might change over time and hence vary across siblings' exposure to parenting. For instance, Icenogle et al. (2019) suggests that psychosocial maturity continuously increases with age, using data from individuals between 10 and 30 years in India and other 10 countries. This type of variation speaks to MFE estimates.

related to them. 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. 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 HAZ, we look at the variables of birthweight and dietary diversity.[34] 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 for 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.[35] 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 birthweight show that being born to a very young mother reduces birthweight by 176 grams, at the 5% level of significance. Controlling for mother fixed effects results in a stronger and statistically significant effect of 307 grams. The size of the effect might be relevant given that the average birthweight in the sample is of 2770 grams. That is, for the average child, the effect would imply falling below 2500 grams into a low birthweight category as defined by the WHO (2004). However, it is worth acknowledging that birthweight data are missing for

[34] Although we portray birthweight as a potential transmission channel for health outcomes, it also embodies a potential mechanism for cognition (Figlio et al., 2014).
[35] See Table A2 for a detailed description of this and other variables.

more than half of our sample, a limitation to be considered in the overall assessment of these results.

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

	Birthweight		Dietary diversity
	(1) OLS	(2) MFE	(3) OLS
Very young mother	-176.21**	-306.59**	-0.39**
	(86.17)	(152.87)	(0.18)
# R4			0.31
			(0.22)
# R5			0.49*
			(0.30)
Young mother	12.26	33.26	-0.06
	(52.02)	(70.45)	(0.07)
# R4			0.06
			(0.11)
# R5			0.03
			(0.11)
Sample	Sib. pairs	Sib. pairs	Index child
p(<16 (R4)=0)			0.70
p(<16 (R5)=0)			0.67
p(16-17 (R4)=0)			0.96
p(16-17 (R5)=0)			0.76
R-squared	0.03	0.60	0.05
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.

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 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 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.

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).

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 12 percentage points in the earliest round. The association weakens over time and turns statistically insignificant in Round 5. Including MFE changes the dynamics over time and significance by round. The association now tends to slightly increase over time and is also significant only in Round 4. At this round, the likelihood of being overage-for-grade increases by 17 percentage points for children born to very young mothers.

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

	Overage		Education expenditure	Teacher's name
	(1) OLS	(2) MFE	(3) OLS	(4) OLS
Very young mother	0.12**	0.13	-0.02	0.03
	(0.06)	(0.08)	(0.02)	(0.11)
# R4	-0.02	0.04	0.02	-0.23*
	(0.06)	(0.05)	(0.05)	(0.14)
# R5	-0.07	0.02	-0.00	
	(0.11)	(0.08)	(0.08)	
Young mother	0.08**	0.12***	0.02	0.02
	(0.03)	(0.03)	(0.02)	(0.04)
# R4	-0.03	-0.01	-0.03	-0.13**
	(0.03)	(0.02)	(0.03)	(0.06)
# R5	-0.03	-0.01	-0.09***	
	(0.04)	(0.03)	(0.03)	
Sample	Sib. pairs	Sib. pairs	Index child	Index child
p(<16 (R4)=0)	0.07	0.04	0.90	0.03
p(<16 (R5)=0)	0.54	0.14	0.81	
p(16-17 (R4)=0)	0.05	0.00	0.66	0.01
p(16-17 (R5)=0)	0.13	0.00	0.01	
R-squared	0.17	0.58	0.17	0.15
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.

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 small 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.[36] Increasingly, the economic literature attempts to quantify the relationship between health outcomes and subsequent cognitive achievement (Lo Bue, 2019; Bharadwaj et al., 2018; Sánchez, 2017; Spears, 2012; Miguel and Kremer, 2004; Glewwe et al., 2001). Our previous 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. According to this estimate, if the median child in our sample had the median HAZ of the well-nourished reference population, she would achieve 0.070 SD higher math scores, net of

[36] This is an additional analysis that aims at linking our two human capital indicators to shed some light on the cognitive implications of the maternal age effect on HAZ.

household and mother time-invariant characteristics. These results might be indicative of the mediating role of health on the maternal age-cognition nexus.

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 slightly larger. An increase of HAZ of the median child to median levels of a well-nourished population is now associated with a 0.084 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. The differences in the size of point estimates are obvious, although they are not statistically different from each other.

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

		Math	
	(1) MFE	(2) MFE	(3) MFE
HAZ	5.18***		1.94
	(1.67)		(1.92)
HAZ (R3)		6.27***	5.43***
		(1.57)	(1.75)
p(b(HAZ)=b(HAZ(R3)))			0.27
R-squared	0.71	0.72	0.72
Observations	5516	5369	5369

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.

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 estimate the effect of being born to an adolescent mother by comparing the offspring outcomes of children born to the same mother, thereby exploiting within-mother variation of maternal age at birth. We further ease remaining concerns on child-specific unobserved heterogeneity within households and net of age, gender and birth order effects with further specifications involving time-varying family-level covariates, the Oster method and falsification tests.

Overall, our results suggest that early maternal age is causally and 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 with 0.33 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 (0.27 SD). This effect strengthens over time, amounting to 0.35 SD in Round 5, 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 as a response to adverse circumstances (Asfaw et al., 2010; Rose, 1999; Behrman, 1988). Given that our estimates appear to be larger than those estimated for a developed country context (Aizer et al., 2018), the role of institutional and family safety nets in compensating for the detrimental effects of early motherhood in both LMICs and high-income countries should be explored.

We further investigate behavioral and biological transmission channels. Although limited in its scope, our analysis provides suggestive evidence on the role of birthweight, food diversity, school progression and maternal involvement in education as mediating factors behind the estimated detrimental effects. Further research should engage with a broader investigation of potential transmission channels and with the relative importance of behavioral vis-à-vis biological channels, which might have important policy implications.

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 suggests 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 salient in adult life. These conjectures would be a fruitful area for further research.

Finally, we provide instrumental motivation to implement preventive measures that reduce early maternal age, complementing intrinsic concerns of early pregnancy related to human rights issues. Likewise, our results support restorative policy measures assisting early mothers and their offspring to lower the burden of early motherhood and foster the human capital of children.

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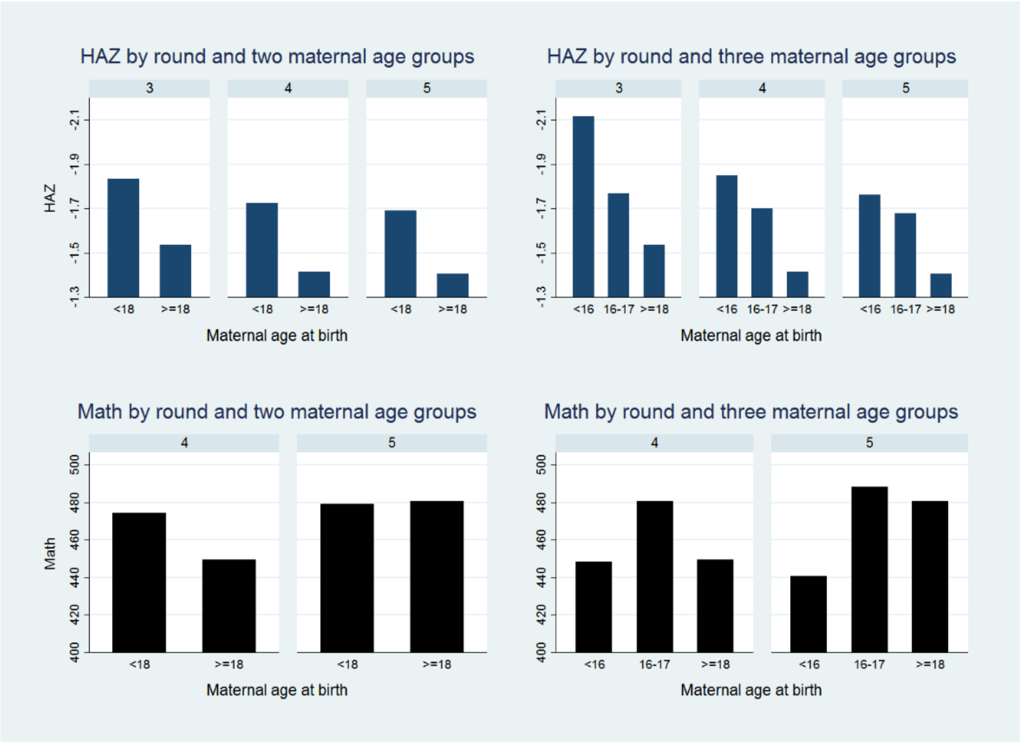
Appendix

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 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	1,535	7.9	3.2	1,535
	R4 (2013)	12.0	0.3	1,607	11.7	3.5	1,607
	R5 (2016)	15.0	0.3	1,462	14.5	3.6	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.

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.
Maternal age<28	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.
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 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	4,604
Mother's education	4.08	5,634	4.12	4,570
Mother's height	151.43	5,742	151.41	4,564
Total expenditure	1,085.68	5,611	1,061.49	4,509
Wealth tertiles				
First wealth tertile	0.34	5,753	0.33	4,603
Second wealth tertile	0.33	5,753	0.33	4,603
Third wealth tertile	0.33	5,753	0.34	4,603
Urban	0.28	5,717	0.28	4,583
Region				
Coastal Andrah	0.35	5,706	0.34	4,583
Rayalaseema	0.29	5,706	0.29	4,583
Telangana	0.35	5,706	0.37	4,583
Ethnicity/caste				
Scheduled Caste	0.18	6,033	0.18	4,604
Scheduled Tribe	0.15	6,033	0.15	4,604
Backward Class	0.46	6,033	0.47	4,604
Other	0.21	6,033	0.20	4,604
Offspring characteristics				
Age	11.62	5,740	11.59	4,604
Female	0.46	6,033	0.45	4,604
Birth order				
Firstborn	0.38	6,033	0.36	4,604
Second born	0.38	6,033	0.40	4,604
Third born	0.15	6,033	0.16	4,604

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	-0.33***	-0.33***	-0.33***	-0.33***	-0.33***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
# R4	0.14***	0.15***	0.14***	0.15***	0.14***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
# R5	0.14**	0.15**	0.12*	0.14**	0.12**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
p(<18 (R4)=0)	0.02	0.02	0.02	0.02	0.02
p(<18 (R5)=0)	0.03	0.03	0.02	0.03	0.02
R-squared	0.59	0.60	0.60	0.60	0.60
Observations	8698	8631	8631	8631	8631

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	6.21	6.07	5.04	6.07	5.20
	(6.43)	(6.43)	(6.47)	(6.44)	(6.49)
# R5	-14.07**	-13.75**	-12.35*	-13.46**	-12.34*
	(6.70)	(6.71)	(6.78)	(6.73)	(6.80)
p(<18 (R5)=0)	0.29	0.30	0.33	0.32	0.34
R-squared	0.69	0.69	0.69	0.69	0.69
Observations	5761	5717	5717	5717	5717

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.

Table A6. Regression results: adult motherhood and offspring outcomes

	HAZ		Math	
	(1) OLS	(2) MFE	(3) OLS	(4) MFE
Maternal Age<28	-0.06	0.26**	5.97	-14.20
	(0.07)	(0.11)	(6.65)	(8.68)
Delta (Beta=0)		-6.77		
R-squared	0.13	0.59	0.21	0.69
Observations	8630	8698	5714	5761

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. Clustered standard errors at mother level in parenthesis. The sample includes sibling pairs for rounds 3, 4 and 5 for height-for-age regressions and rounds 4 and 5 for math regressions. Maternal Age<28 refers to children born to mothers under 28 years of age. The reference category is the maternal age group of mothers 28 years old and older at the time of the childbirth. The dependent variables are height-for-age (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, 2019).

Table A7. Regression results: adult motherhood and offspring outcomes over time

	HAZ		Math	
	(1) OLS	(2) MFE	(3) OLS	(4) MFE
Maternal Age<28	-0.10	0.22*	3.53	-14.13
	(0.09)	(0.12)	(7.86)	(9.44)
# R4	0.08	0.08		
	(0.07)	(0.07)		
# R5	0.10	0.11	5.50	-0.78
	(0.09)	(0.09)	(7.83)	(7.48)
p(<18 (R4)=0)	0.820	0.009		
p(<18 (R5)=0)	0.991	0.002	0.238	0.126
R-squared	0.14	0.59	0.22	0.69
Observations	8590	8698	5687	5761

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. Clustered standard errors at mother level 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. Maternal Age<28 refers to children born to mothers under 28 years of age. The reference category is the maternal age group of mothers 28 years old and older at the time of the 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.