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ABSTRACT

Cycles of Malnutrition: Intergenerational Health Transmission in India*

We provide the first estimates of broad-based health transmission between parents and their young children in India. The correlations between maternal health and child health outcomes—such as anemia, stunting, and body mass index—are approximately 0.20. When aggregating these health measures into a general index of latent health, we estimate a correlation of 0.22, comparable to intergenerational persistence estimates in other countries. Absolute health mobility is lower for poorer households and for scheduled castes and scheduled tribes. We document significant geographic heterogeneity in health transmission, lower mobility in northern and central India, and higher mobility in the southern regions. Consistent with this pattern, states with higher poverty rates and higher anemia prevalence tend to exhibit lower upward mobility.

JEL Classification: I14, I15, O12

Keywords: intergenerational mobility, anemia, stunting, latent health, nutrition, India

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1 Introduction

The prevalence of the disease among women and young children is a significant public health challenge in developing countries. Micronutrient deficiencies affect approximately 50% of children under five years of age and two-thirds of women of reproductive age (Stevens et al., 2022). One such health condition is anemia, predominantly caused by iron deficiency, have far-reaching and lifelong consequences for human capital formation in developing countries (Chong et al., 2016). Anemia can lead to increased susceptibility to infections, higher mortality, impaired cognitive function, and decreased long-term earnings (WHO, 2023). This condition represents just one aspect of a broader health crisis in developing countries that includes widespread malnutrition, stunted childhood growth, respiratory infections, diarrheal diseases, measles, and malaria among children.

Understanding how these health conditions persist across generations is of particular concern to policymakers and researchers. The persistence of poor health across generations can create cycles of adverse health outcomes that can lead to perpetuation of poverty from one generation to next. Effective policies that reduce the severity of disease prevalence in early life would not only improve immediate health outcomes and human capital but also help reduce the transmission of poor health across generations.

Although there is extensive research on the intergenerational transmission of economic outcomes (e.g. education, labor market outcomes, occupation, and wealth) in developing countries (Azam and Bhatt, 2015; Mohammed, 2019; Asher et al., 2024), the intergenerational transmission of health remains largely under explored in poorer countries. While there is some new work that focuses on mental health transmission to young adults (Hervé et al., 2025), there is no work of which we are aware that focuses on the broader-based health of children under the age of five. This gap in the literature is notable, as there is growing evidence that early life health is an important predictor of an individual's cognitive development, educational attainment, and long-term economic prospects (Almond et al., 2018) and that health is an important component of welfare (Jones and Klenow, 2016).

In recent years, a growing literature has focused on the intergenerational transmission of broad-based measures of health in advanced economies (e.g. (Halliday et al., 2021; Andersen, 2021; Bencsik et al., 2023; Chang et al., 2024)). However, there is limited evidence on intergenerational (IG) health transmission from developing countries, particularly in contexts with significant health disparities like India (Lu and Vogl, 2023).[1] We begin to fill this important gap in the literature by providing the first estimates of broad-based IG health persistence from parents to young children in India. India provides a compelling context for investigating IG health transmission due to its socioeconomic diversity and persistent health inequalities. Despite progress in access to healthcare and rapid economic growth, nearly half of young children and their mothers suffer from various forms of malnutrition and nutritional deficiencies. These early health disadvantages can trigger a cycle of poor outcomes that extends across generations, ranging from impaired cognitive function and stunted growth in childhood to reduced earnings and productivity in adulthood. [2]

We use the National Family Health Survey (NFHS), a large and nationally representative survey. We measure correlations between parent and child health using several health outcomes: hemoglobin levels (Hb), anemia, height-for-age z-score (HAZ), stunting, body mass index z-score (BMI), and malnutrition. In addition, we construct a measure of what we refer to as "latent health" using the first principal component from the covariance matrix of our standardized health measures for each generation (Andersen, 2021; Chang et al., 2024).

We focus on two measures of intergenerational mobility. First, we estimate the inter-

[1]Exceptions include Bhalotra and Rawlings (2011) who examine the gradient between parent and child health across 38 developing countries and the macroeconomic factors that affect the gradient, and Venkataramani (2011) who examine the IG persistence in height in Vietnam.

[2]The NFHS-5 reports that more than half of women and under-five children are anemic, one-third of children are stunted, and about 20% of children are malnourished (IIPS and ICF, 2021).

generational health association (IHA) between parental and child health using our various health outcomes. The IHA is a measure of relative mobility that describes the degree of persistence between parents and children in health units. One minus the IHA can be viewed as an index of mobility. For a subset of outcomes that are continuous such as Hb, HAZ, BMI, and latent health, we also estimate a rank-rank correlation between parental and child outcomes. This provides a measure of persistence in *positions* in the distribution rather than in health units. We also estimate conditional expected ranks such as the expected rank of children at the 25th and 75 percentiles, which provide measures of absolute upward and downward mobility. These are most useful for assessing subgroup differences with respect to the national distribution. All of these mobility measures are descriptive and should not be interpreted causally.

Our estimates of the IHA tend to be on the order of 0.2 with a few exceptions (e.g. 0.087 for malnourishment and 0.407 for HAZ). Importantly, the IHA for our most comprehensive health measure, latent health, is 0.216. These magnitudes are similar to other estimates in the literature that look at associations between parents and their adult children (Halliday, 2023; Mazumder, 2024). However, it is possible that these magnitudes could change if children's health were measured in adulthood, as with other studies in the literature.

We also examine heterogeneity in health persistence and the factors that mediate it. We show that absolute health mobility is lower for poorer households and for scheduled castes and scheduled tribes. We also explore how these associations are mediated by poor health at birth (proxied by birth weight), the socioeconomic status of the household, iron supplementation, and dietary diversity. We find some evidence that dietary diversity contributes meaningfully to IG persistence.

Finally, we examine how intergenerational health persistence varies geographically across states. We find stark differences. Southern and northeastern states exhibit significantly higher upward mobility compared to poorer northern and central states. For instance, a child in a southern state like Kerala, whose parent ranks at the 25^{th} percentile of the national health distribution, can expect to reach the 52^{nd} percentile. In contrast, a similar child in a northern state like Bihar can expect to reach only the 43^{rd} percentile.

We contribute to the literature in several ways. First, we are among only a few studies to estimate health persistence in broad-based health measures in a developing country. Nearly all previous studies have investigated IG health mobility in high-income countries and there are only a few set in middle-income countries such as Indonesia (Kim et al., 2015) and Taiwan (Chang et al., 2024). Two recent studies explore health transmission in India but do not use *broad-based* health measures. Kumar and Nahlen (2023) estimate the relationship between maternal and childhood Hb and anemia and Hervé et al. (2025) estimate intergenerational persistence in mental health in India.[3] The latter study obtain IHA estimates of 0.61 for depression and 0.68 for anxiety which is indicative of low mobility in mental health in India. Second, we use objective measures of health, including anthropometrics and biomarker data such as Hb which may be preferable to using subjective measures (Bütikofer et al., 2023).[4] Third, our sample size—nearly 200,000 mother-child pairs—is substantially larger than most previous studies, enabling us to analyze heterogeneity and geographic differences in greater detail.

Finally, our study focuses on children under five years of age, a critical period in which childhood health strongly predicts long-term outcomes, including education and earnings (Case et al., 2005; Kumar et al., 2022). Interventions that improve health outcomes for children born to unhealthy parents can significantly enhance their future prospects. In our mediation analysis, we explore several potential mechanisms including: supplementary food programs, weekly iron and folic acid supplementation, and targeted interventions for

[3]While our study builds on Kumar and Nahlen (2023), it differs in several key respects: we also investigate paternal health; we explore additional outcomes such as stunting, BMI, and a broad-based measure of latent health; and we document important geographic variations as well as their correlates.

[4]Bütikofer et al. (2023) argue that self-reported subjective measures could lead to bias and complicate the interpretation of IHA coefficients, although Halliday et al. (2021) and Bencsik et al. (2023) find very similar results when using subjective or objective self-reported health measures.

iron-deficient pregnant women. Among these, our findings suggest that supplementary food programs show the most promise, while iron supplementation appears to have a relatively smaller impact.

Our paper is structured as follows. In Section 2, we describe the related literature. In Section 3, we describe the sampling frame, data, and variables used in the study. In Section 4, we describe the empirical strategy. In Section 5, we present the main findings and discuss the results of the heterogeneity analysis. In Section 6, we discuss geographical differences in health transmission by states and districts. Finally, in Section 7, we conclude with key findings and their implications for future research and policies.

2 Related Literature

There is a vast literature that has studied IG associations in lifespans. Black et al. (2024) examine this question using arguably the best genealogical data available for the United States. The authors find that the IG correlation in lifespan is about 0.09 for both sexes and is not affected by race, education groups, cohorts, and birth states. When both parents are pooled, the IG correlation is slightly higher at 0.14 for both males and females. Interestingly, these estimates are remarkably similar to older estimates of the IG correlation in lifespans from Beeton and Pearson (1901) published almost 125 years prior.

A related strand of the literature examines IG persistence in anthropometric measures such as birth weight, height, and BMI. Estimates of the intergenerational association in birth weight typically range from 0.1 to 0.2, with evidence from California (Currie and Moretti, 2007; Royer, 2009), Florida (Giuntella et al., 2023), and Norway (Black et al., 2007). Studies using height, weight, or BMI generally find much higher intergenerational persistence. For example, in the US, Akbulut-Yuksel and Kugler (2016) estimate intergenerational associations in these measures on the order of 0.4 or higher, although other studies have found somewhat lower estimates (Classen, 2010; Classen and Thompson, 2016). On the other hand, estimates of the intergenerational correlation in obesity between mothers and their children in the US are lower with estimates in the vicinity of 0.14 (Classen, 2010; Classen and Thompson, 2016). Turning to BMI, Dolton and Xiao (2017) estimate that the intergenerational elasticity in BMI is about 0.2 in the six countries studied (UK, USA, China, Indonesia, Mexico, and Spain). Finally, Venkataramani (2011) estimates that the intergenerational transmission between the height of parents and their young children is around 0.2.

In recent years, there have been a number of studies that have examined IG persistence in measures of latent adult health, either by using panel surveys with questions on self-reported health status, or administrative data from health records. We provide a brief summary of some of those studies here, but interested readers should see Halliday (2023) and Mazumder (2024) for more comprehensive reviews. Most of these studies are conducted in high-income countries.

A pair of recent studies using the Panel Study of Income Dynamics (PSID) shows that the IHA and rank-rank correlations in the US tend to be on the order of 0.2 to 0.3. Halliday et al. (2021) estimate an IHA of 0.23 when pooling sons and daughters and combining the health of both parents. The analogous rank-rank slope is estimated to be 0.26. Halliday et al. (2020) use Bayesian methods to estimate a latent variable model using the same PSID sample as Halliday et al. (2021); they obtain slightly higher estimates of the IHA but very similar estimates of the rank-rank correlation.

Bencsik et al. (2023) examine health persistence in the UK using a similar approach to Halliday et al. (2021). They convert the survey responses to the SF-12 questionnaire to a continuous measure of health and estimate an IHA of 0.19 and a rank-rank correlation of 0.17. One advantage of the UK study is that SF-12 allows researchers to separately study IG persistence in both physical health and mental health. They find quite similar estimates of intergenerational persistence.[5] However, in a "horse race" pitting mental

[5] Johnston et al. (2013) previously found similar estimates of the intergenerational association in mental

health against physical health, they show that parental mental health is far more predictive of child health than parental physical health.

Two studies have used population-wide administrative health records to estimate IG persistence in latent health. These studies use principal component analysis (PCA) to extract the first principal component of health from broad categories of diagnosis codes as well as information on general practitioner visits. Using Danish data, Andersen (2021) estimates intergenerational persistence in the range of 0.11 and 0.15. Chang et al. (2024) conduct a similar exercise in Taiwan and estimate an IHA of 0.28 when pooling sons and daughters and combining both parents' health and a rank-rank slope of 0.22.

While we are beginning to understand the magnitude of intergenerational transmission of health in various countries, our understanding of the underlying mechanisms is far from clear. One factor that comes to mind when thinking about health conditions is genetics. However, given the polygenic nature of most diseases, the intergenerational transmission rates of specific diseases are typically not nearly as large as one might initially suspect (Mukherjee, 2016). The early results from the literature also typically find that IG associations in health are lower than comparable associations in education and income which involve behavioral choices and might be less genetically determined. However, future work should continue to investigate this issue further.

3 Data

We use the fourth round of the NFHS data conducted in 2015-16. The NFHS is a large-scale multi-round survey that provides information on key outcomes, including fertility; infant and child mortality; family planning; maternal and child health; reproductive health; nutrition; and use and quality of health and family planning services (IIPS and ICF, 2021). The NFHS-4 is a nationally representative survey of more than 600,000

health using different data.

households drawn from 640 districts in 36 states. The survey interviewed 699,686 women aged 15 to 49 years and 112,122 men in the age groups 15 to 54. We used the NFHS-4 children's file and mapped it to the person file to create a sample of child-parent pairs where children are between the ages of 6 and 59 months.

3.1 Variable Definitions

The NFHS has nutritional and biomarker information for more than 200,000 of the children in the sample. Our main outcome variables are Hb measured in grams per deciliter (g/dL) and the anemic status of the children. Anemic status is classified as < 11.0 g/dL for children, < 12.0 g/dL for mothers, and < 13.0 g/dL for fathers. In addition, we also consider anthropometric indicators for both children and mothers such as HAZ, BMI, stunting, and malnourishment. HAZ measures height relative to a reference population set by the WHO. These reference populations refer to the median height of a "typical" population. Stunting is defined as binary indicator of HAZ < -2 SD from the WHO child growth standard median.[6] BMI is the ratio of weight in kilograms to the square of height in meters (kg/m^2). BMI is a commonly used indicator to determine whether an individual is underweight, healthy weight, overweight, or obese. We use a binary indicator of malnourishment defined as a BMI z-score less than -2 SD.[7]. We also used information on the age and gender of the child as well as the age of the mother. In some specifications, we include household caste information, birthweight and birth order of the child, mother's education, religion, wealth, and rural residence. We typically include these additional covariates so that we can investigate possible mechanisms.

[6] An anthropometry measure expressed in reference standard deviation units is also known as a z-score

[7] We used altitude-adjusted Hb levels to define anemia since altitude tends to increase Hb.

3.2 Sample Characteristics

In Table 1, we provide key descriptive statistics for our estimation sample consisting of 200,427 child-mother pairs and 31,161 child-father pairs, obtained after linking the children with their parents. Column (1) shows the mean, while standard deviations are reported in column 2. The mean Hb level is 10.59 and 11.52 g/dL among children and mothers, respectively. Fathers have slightly better Hb levels at 14.13 g/dL. Based on the WHO cut-off point, approximately 58% of children and 56% of mothers are anemic. Approximately one fifth of fathers suffer from anemia in the estimation sample. Stunting affects about 40% of children and 51% of mothers in the sample. The BMI z-scores (standardized measures of body mass index)show that both children and mothers are substantially below international norms. Children's average BMI z-score is -0.97 and mothers' average BMI z-score is -1.04, both about 1 standard deviation below normal. The standard deviations in column (2) indicate substantial variation in these measures across the population. For example, the standard deviation of 1.34 for child BMI z-scores shows there is considerable spread in nutritional status among children. About 20% of children and 19% of mothers are malnourished in our sample. The fact that more than half of mothers are stunted and similar levels of malnutrition affect mothers and children suggests that these nutritional deficits may persist over generations.

The average age of children is 2.24 years and almost half of the children are female (48%). On average, mothers have attained 6.12 years of schooling, whereas fathers have attained 7.63 years of schooling. Most of the sample is Hindu (73%) and approximately three-quarters of the sample resides in rural areas. Looking at caste, two-fifths of the sample belong to scheduled caste (SC) and scheduled tribe (ST), which tend to be socially disadvantaged. Finally, almost half of children live in a household that has access to an improved source of toilet.

The survey contains a household wealth index based on indicators for the ownership of various durable goods and housing characteristics including televisions; bicycles; cars; sources of drinking water; type of toilet facilities; and flooring materials (IIPS and ICF, 2021). The wealth index was derived using principal component analysis. Based on this wealth score, households were divided into five categories ranging from the poorest to the richest. Close to half of the population is in the bottom two wealth quintiles (50%). In contrast, a third (30%) of households are in the two highest wealth quintiles.

4 Methodology

4.1 Intergenerational Health Association

The IHA in a particular outcome is estimated by regressing the child's outcomes on the parent's outcomes. The model typically includes only a minimal set of controls, such as a quadratic function of the child's and parents' ages, along with a possible control for gender (Halliday et al., 2021). Researchers do this since the aim of this literature is to carefully estimate a descriptive association across generations that is *inclusive* of all factors correlated with parental health. The inclusion of other controls (e.g. caste or religion) may be informative of possible mechanisms for the transmission (Halliday, 2023). The variable, H_c, denotes the health outcome of the child c whereas $H_{p(c)}$ denotes the health of the parent p of the child c. We then estimate the simple linear model

$$H_c = \alpha + \beta H_{p(c)} + \theta X_c + \varphi Z_{p(c)} + \epsilon_c \tag{1}$$

where X_c includes the age and quadratic age of the child, $Z_{p(c)}$ includes the age and quadratic age of one or both parents, and ϵ_c is the error term. The health outcomes we consider in this study are Hb, anemia status, HAZ, stunting, BMI, and malnourishment. The parameter β shows intergenerational persistence in health outcomes. A large value of β indicates higher persistence (low mobility) while a smaller value of β indicates lower persistence (higher mobility). Robust standard errors are reported throughout.

Ideally, we would like to include both parents in our model however, incorporating the father's health significantly reduces the sample size.[8] Therefore, our preferred estimates use only the mother's health. We estimate β separately for sons and daughters to account for variations in intra-household inequalities in the allocation of food resources, healthcare use, or discrimination between sons and daughters as gender disparities in food consumption are quite prevalent in India. For example, prior studies have shown that parents allocate more nutritious foods to boys than to girls in India (Aurino, 2017). Following the literature, we do not control for geography in equation (1). However, to assess the importance of geography in our main findings, we incorporate district fixed effects in robustness checks in the appendix.

4.2 Rank Mobility Measures

To analyze health mobility differences across population subgroups - such as caste, wealth level, or region - we follow Halliday et al. (2021) and use rank-based measures based on national ranks.[9] Rank-based mobility measures can also be used to capture patterns of upward and downward absolute mobility (Chetty et al., 2014) and permit "apples-to-apples" comparisons across different health domains.

To estimate the rank-rank correlation, we first calculate the rank of age-adjusted health within the entire sample for each generation and then estimate equation (1) using ranks instead of health levels with the relevant subsample.[10] The slope coefficient from this regression is the rank-rank correlation. Following Halliday et al. (2021), we estimate the

[8]The NFHS-4 sampled only 15% of the couples/partners, thus the father sample is significantly reduced compared to the mother's sample.

[9]Since the IHA is only informative about persistence *within* groups it is less informative about how groups perform relative to the nation overall.

[10]We regress each health outcome on age and age squared and do this separately for children, mothers, and fathers. We then create ranks using the residuals.

following regression:

$$r^C_c = \gamma + \rho r^P_{p(c)} + \upsilon_c \tag{2}$$

where r^C_c and $r^P_{p(c)}$ denotes the percentile rank of health for children and parents, respectively. We run this for two outcomes, Hb and "latent health" which we discuss in greater detail in Section 4.3. The rank-rank correlation is ρ which is mathematically equivalent to the Spearman correlation.

The parameters, β and ρ, reflect different concepts of health mobility. ρ measures relative *positional mobility* only highlighting changes in the individual's relative ordering whereas β captures changes in the *magnitude of differences* in terms of health units.

We also use the rank-rank regression framework to estimate conditional expected ranks of children at different ranks of the parent (Chetty et al., 2014). A particular focus is on the 25^{th} percentile (P25). We also estimate P50 and P75 (the child's expected rank when the parent is at the 50^{th} or 75^{th} percentile). Conditional expected ranks are indicative of *absolute mobility* and highlight directional mobility (upward in the case of P25 or downward in the case of P75) by examining how children from families with varying health backgrounds perform relative to the overall national distribution. For example, if children from families at the 25^{th} percentile of health achieve the 65^{th} percentile in their generation, this indicates significant upward mobility of 40 percentile points.

To calculate measures of absolute mobility, we require both the constant and the slope coefficients from the rank-rank regression. For example, to compute P25, we multiply ρ by 25 and add it to γ so that we can calculate the expected rank of the child at the 25^{th} percentile of the parent health distribution. As mentioned previously, when assessing subgroup variations (e.g. by caste, religion, wealth level, etc.), we calculate ranks relative to the *national* distribution. This standardization ensures meaningful cross-group comparisons of mobility patterns within a unified framework.

4.3 Constructing Latent Health Measures

One of our preferred health outcomes is "latent health" which is an omnibus measure of health that uses information from several measures of health. Examples include Andersen (2021) and Chang et al. (2024) - both of whom construct measures of latent health from the international classification of disease (ICD) codes from single-payer claims data in Denmark and Taiwan, respectively. Other studies have estimated latent health using survey data (Halliday et al., 2021; Bencsik et al., 2023) by using longitudinal measures of self-reported health.

Since we have a single cross-section of households, our approach is more similar to Andersen (2021) and Chang et al. (2024) who use indicators constructed from broad ICD codes in claims data. Analogously, we use individual information on Hb, anemia status, HAZ, stunting, BMI, and malnourishment. We then generate latent health from a PCA of standardizations (when the variable is not already standardized) of these six variables. We conduct the PCA separately for each generation. Our measure of latent health is constructed from the first principal component.

5 Results

5.1 Intergenerational Health Mobility

5.1.1 Anemia

In Table 2, we present our estimates of IHA and rank-rank correlation in hemoglobin in panel A, as well as IHA estimates for anemia status in panel B. Each cell in the table corresponds to a separate regression estimate. We see that the IHA in Hb in the pooled sample is 0.181 for mothers and 0.096 for fathers. Both estimates are statistically significant at the 1% level of significance. Generally, the IHA estimates are higher for mother-child pairs than they are for father-child pairs. This is a common finding in the IG health literature (Halliday et al., 2021; Fletcher and Jajtner, 2021; Bencsik et al., 2023; Chang et al., 2024). In addition, the IHA is slightly higher at 0.216 when averaging both parents, compared to when only one parent is considered at a time. This is another common finding in the intergenerational literature and is typically attributed to the averaging that reduces the impact of measurement errors (Halliday et al., 2021; Chang et al., 2024).

The IHA estimates presented in this table have similar magnitudes to other estimates in the literature. For example, as a benchmark, the IHA in a measure of latent health based on self-reported health status measures in the United States is 0.172 when considering fathers paired with all children, 0.204 when considering mothers paired with all children, and 0.23 when using both parents and pooling all children (Halliday et al., 2021). Given that Hb is just one biomarker, our estimate of 0.22 is somewhat large when viewed in the context of the broader literature.

In columns (4)-(6) in Table 2, we report *rank-rank* estimates for Hb. These coefficients tell a similar story to the IHA estimates in Hb in the first three columns. The rank-rank estimates are 0.198 and 0.119 for mothers and fathers, respectively, and are only slightly larger than the IHA estimates. In panel B, we find that for anemia, the IHA is 0.132 using mothers, 0.102 using fathers, and 0.138 if both parents are anemic (Table 2). All estimates are significant at the 1% level of significance and economically meaningful. The estimates imply that the probability of being anemic is between 10 and 14 percentage points (PP) higher when a parent is also anemic. As with Hb, the transmission is higher for mothers.

In Table 2, we also estimate the IHA and the rank-rank correlation separately for sons and daughters. Columns (2)-(3) in panel A report the IHA for Hb by gender while columns (5)-(6) report rank-rank correlations for Hb by gender. Panel B estimates the IHA in anemia by gender. Overall, the estimates for sons and daughters are quite similar and not statistically different from each other suggesting that there are no systematic differences in health mobility by gender. This contrasts with Chang et al. (2024) who find stronger transmission of latent health to sons than to daughters.

Three key points emerge from Table 2. First, depending on the outcome, the IHA estimates range from 0.1 to 0.2, consistent with findings in the existing literature from high-income countries using adult children. Second, maternal health plays a more significant role than paternal health in shaping children's health outcomes. Third, there are no statistically significant differences in the estimates by child gender, indicating that sons and daughters are similarly influenced by their parental health.

5.1.2 Anthropometrics

In Table 3, we use a variety of anthropometric health measures including HAZ; stunting (HAZ less than -2 SD); the BMI z-score; and malnutrition (BMI less than -2 SD). In panel A, we report the IHA estimates and in panel B, we report the rank-rank correlations for the continuous variables (e.g. HAZ, BMI z-scores, and latent health). In each panel and for each outcome, we present three transmission estimates: mother to all children (pooling sons and daughters); mother to son; and mother to daughter.

We find a statistically significant transmission in both HAZ and its companion, stunting. In the first column of panel A, we estimate an IHA in HAZ of 0.41 for the pooled sample. We note that this is substantially higher than the IHA's that we report for Hb and anemia in Table 2 which are on the order of 0.10 to 0.20 with most tending towards the upper end of this range. However, the rank-rank correlation in HAZ reported in the first column of panel B is substantially higher at 0.256 and is also highly significant. Hence, there is substantially more persistence in height when measured in ranks or in levels and the high persistence in height is consistent with the estimates in the literature. Next, in the second column of panel A, we report that the IHA in stunting is 0.179 in the pooled sample indicating that children with a stunted mother have a risk of stunting that is 17.9 PP higher. There appears to be substantial IG transmission of both HAZ and stunting.

Next, we turn to BMI and malnourishment. In the third column of panel A, the IHA in the BMI z-score is 0.190. The corresponding rank-rank estimate in panel B is slightly smaller at 0.172. In the fourth column, we estimate an IHA in malnourishment of 0.087 indicating that children with malnourished mothers have a risk of malnourishment that is 8.7 PP higher. The estimates of IG transmission of BMI are similar to estimates across a wide array of countries including China (0.215), Indonesia (0.155), the United Kingdom (0.184 and 0.201), the United States (0.177), Spain (0.171), and Mexico (0.117) (see Table 3b of (Dolton and Xiao, 2017)).

Finally, Table 3 does not find evidence of gender disparities in IG transmission of anthropometric outcomes. Indeed, for all anthropometric outcomes in columns one through four, transmission from mothers to daughters is similar to transmission from mothers to sons. This is similar to Table 2 in which there were similar IG associations of Hb and anemia for both sons and daughters.

5.1.3 Latent Health

In the fifth column of Table 3, we report estimates of IG transmission of our latent health measure. Once again, in panel A, we report the IHA and in panel B, we report the rank-rank correlation. As with anthropometric results, all estimates of latent health transmission are significant at a 1% level of significance. When pooling children, we obtain an IHA of 0.216 and a rank-rank correlation of 0.225. These estimates remain similar when we consider transmission to either sons or to daughters. Overall, we find that estimates of IG transmission in latent health are just around 0.20 and are very stable when changing mobility measures (e.g., the IHA or the rank-rank correlation) and the gender of the child.

The IHA in latent health in India appears to align closely with estimates from a diverse range of countries. For instance, Andersen (2021) estimates the IHA in Denmark to be between 0.11 and 0.15. Similarly, Bencsik et al. (2023) finds an IHA of 0.19 in the

UK, Chang et al. (2024) reports a range of 0.11 to 0.20 in Taiwan, and Halliday et al. (2021) estimates values between 0.17 and 0.23 in the US. Together, these findings suggest a consistent pattern of IHA in latent health across various countries worldwide - even countries with significantly differing living standards.

5.2 Absolute Mobility

In Table 4, we present estimates of P25, P50, and P75 for Hb, BMI, and latent health across three mother-child pairings (mother to all children, mother to son, and mother to daughter). The P25 estimates consistently fall within the range of 44 to 45 across all measures and pairings, reflecting significant upward health mobility of approximately 20 rank points. Similarly, P75 estimates, ranging from 53 to 55, indicate a comparable level of downward mobility of roughly 20 rank points. These findings highlight substantial mean reversion in the three health outcomes analyzed.

While population-wide mean reversion in health outcomes is substantial, it conceals significant heterogeneity within the population. To explore this variation, we estimate rank-rank regressions for two continuous health outcomes: Hb, shown in Figure 1, and latent health, depicted in Figure 2. These figures illustrate positional mobility across the entire distribution of parent health status. Each figure further disaggregates mobility patterns by caste, residence, wealth level, child age, and religion.

In Figure 1, we observe lower absolute upward mobility (and consequently greater downward mobility) among children from scheduled castes and scheduled tribes (SCST), rural areas, poorer households, and those younger than 24 months. However, we do not find notable differences by religion (panel e).

Turning to latent health in Figure 2, we observe similar but more pronounced patterns. For instance, the wealth gradient in panel (c) is steeper for latent health than for Hb, highlighting stronger socioeconomic disparities in this broader measure of health. We also now observe differences between Hindus and non-Hindus, with Hindus exhibiting slightly greater upward mobility across all points in the distribution compared to non-Hindus.

5.3 Mechanisms and Robustness checks

Maternal and household socioeconomic factors are likely to affect child anemic status (Kumar and Nahlen, 2023; De Neve et al., 2024). In Table A1, we report a similar set of estimates as those in Table 2, but now we add a series of controls for district, socioeconomic status, birth weight, and a series of proxies for nutrition. In general and as previously discussed, researchers in this literature do not add a rich set of covariates to baseline estimates of the IHA (Halliday, 2023). The reason for this is that including only a parsimonious set of regressors such as a quadratic in age and a gender indicator allows the researcher to focus on the fundamental intergenerational correlation, while progressively adding controls elucidate potential mechanisms for the transmission.

In the first two columns of Table A1, we present the baseline estimates pooling all children from Table 2 in column (1) and then with district fixed effects in column (2). One interesting finding is that district fixed effects greatly attenuate the IHA in both Hb and in anemia. For example, maternal transmission of Hb is 0.181 without adjustment in column (1) and 0.144 with district fixed effects in column (2). Similarly, in panel B, maternal transmission of anemia is 0.132 in column (1) but 0.105 with district fixed effects in column (2). What this suggests is that there are powerful factors varying at somewhat granular geographical levels that are associated with IG transmission of anemia. Some of these factors might include socioeconomic status, birth weight, and nutrition.

5.3.1 Socioeconomic status

In column (3) of Table A1, we include a series of controls for socioeconomic status including birth order; maternal and paternal education; caste; religion; a wealth index; and an indicator of rural residence. Moving from the first to the third column (with SES controls), we see that maternal transmission Hb decreases from 0.181 to 0.171 and anemia transmission decreases from 0.132 to 0.124. This suggests that differences in SES between households explain some of the transmission of Hb and, in turn, anemia across generations.

5.3.2 Birthweight

Child health at birth, as determined by birth weight, may affect the child's physical and nutritional development. For example, children who have low birth weight are more likely to be stunted and wasted at five years old (Mertens et al., 2023). To better understand to what extent health conditions at birth can mediate the link between parent and child health, we include birth weight as an additional control in the base specification of equation (1) in the fourth column of Table A1. Maternal transmission of Hb is now 0.179 and transmission of anemia is 0.130. Both estimates are very close to the baseline estimates in the first column, suggesting that birth weight may not be a mediating channel.

5.3.3 Consumption of iron pills and diet diversity

Iron and folic acid supplementation is recommended to mitigate the risks of low birth weight, maternal anemia, and child anemia (WHO, 2018). In columns (5) and (6) of Table A1, we include additional controls for whether mother is currently taking iron pills, sprinkles, or syrup (col 5) and whether mothers received antenatal iron supplementation (through iron pills, or syrup) during pregnancy (col 6). binary indicator for the consumption of iron pills. About 25% of mothers reported using some form of iron supplementation, with fewer than 1% unaware of its availability. Nearly three-fourths of mothers reported having taken iron pills/syrups while pregnant. Both sets of estimates in columns (5) and (6) are quantitatively similar to the baseline estimates in the first column indicating that iron supplementation for mothers either during prenatal or postnatal period does not significantly affect the IHA coefficient for Hb or anemia.

We also explored whether dietary diversity and the consumption of iron-rich foods might weaken the association between maternal and child anemia. Food consumption data was collected for children aged 6 to 23 months, resulting in a significant reduction in the sample size. The food consumption module asked about the frequency of various food types consumed (daily, weekly, occasionally, or never). The food categories included eight groups: breast milk; grains, roots, and tubers; legumes and nuts; dairy products; meat, fish, and poultry; eggs; vitamin A-rich fruits and vegetables; and other fruits and vegetables.

Using this information, we constructed two indicators for dietary diversity. First, we constructed an indicator for consuming iron-rich foods (IRF), such as eggs, meat, liver, and fish. Next, following the WHO definition, we created a minimum diet diversity (MDD) score, which requires that at least five food groups be consumed daily. In our sample, approximately 20% of children achieved the minimum diet diversity. In column (7), we adjust for IRF and, in column (8), we adjust for MDD. In both columns, we see that the inclusion of this indicator does not impact the IHA in Hb but we see that the IHA in anemia moves from 0.132 at baseline to 0.115. Prima facie, this indicates that dietary diversity and maternal iron-rich food consumption might impact the transmission of anemia from mothers to their children.

Finally, in Table A2, we conduct a similar exercise as in Table A1 using stunting (panel A), malnourishment (panel B), and latent health (panel C) as outcomes. Our basic takeaway remains when using stunting as the outcome. We see that the inclusion of the SES variables in column (3) and dietary controls in columns (7) and (8) does the most to attenuate the IHA estimates relative to the baseline in the first column. This, however, is not the case in panel B where malnourishment is the outcome. However, when latent health is the outcome in panel C, we once again see that the inclusion of the SES and the dietary variables greatly attenuates the IHA estimates.

6 Geographical Variations in Health Transmission

We now examine regional variation in upward health mobility. To do so, we estimate P25 for Hb and latent health across broadly defined regions: east, northeast, north, central, west, and south.[11] These estimates are presented in Figure 3. The highest levels of upward mobility for both outcomes are observed in the northeast and the south. For Hb, the P25 estimates are 58.2 in the northeast and 50.9 in the south. For latent health, both regions have estimates of approximately 52, indicating a substantial degree of upward mobility. Conversely, the lowest P25 estimates for both outcomes are found in the north and central regions. For Hb, P25 is 42.3 in the north and 44.5 in the central region. Similarly, for latent health, P25 is 43.4 in the north and 44.4 in the central region, highlighting significantly lower upward mobility in these areas.

Figure 4 provides a more detailed examination of regional variation in upward health mobility. This figure presents state-level variations in P25 for Hb (Panel A) and latent health (Panel B). Lighter colors indicate higher absolute mobility, while darker colors represent lower absolute mobility. We observe substantial variation in upward mobility across states, with southern states exhibiting significantly higher mobility compared to northern states. This north-south disparity is even more pronounced for latent health, as shown in Panel B.

Why do southern states experience significantly higher rates of upward mobility compared to northern states? We examine this question by looking at state-level predictors of intergenerational mobility in Figure 5 where we plot the state-level correlations of P25. In particular, the figure examines how state characteristics such as GDP per capita, the Multidimensional Poverty Index (MDPI), adult education levels, and health infrastruc-

[11] South region includes Andaman & Nicobar Islands, Andhra Pradesh, Karnataka, Kerala, Lakshadweep, Puducherry, Tamil Nadu, Telangana; North: Chandigarh, Delhi, Haryana, Himachal Pradesh, Jammu & Kashmir, Ladakh, Punjab, Rajasthan, Uttarakhand; Northeast: Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura; Central: Chhattisgarh, Madhya Pradesh, Uttar Pradesh; East: Bihar, Jharkhand, Odisha, West Bengal; West: Dadar & Nagar Haveli, Daman & Diu, Goa, Gujarat, Maharashtra

tures are associated with P25. Panel A shows the results for Hb and panel B shows the results for latent health.

Health, poverty, and socioeconomic factors play crucial roles in shaping upward mobility. We find a negative correlation between adult anemia rates and upward mobility, indicating that a higher disease burden, as measured by anemia prevalence, hinders mobility. Conversely, the number of primary health centers per capita is positively correlated with upward mobility, although this relationship is not statistically significant. In addition, states with higher poverty levels, as measured by the MDPI and poverty intensity, tend to exhibit lower latent health mobility. GDP per capita, median wealth, the share of SCST, and adult education also show positive correlations with upward mobility, although these associations are also not statistically significant.

7 Conclusion

In this paper, we provide evidence of the persistence of health across generations in India with a particular focus on biomarkers including hemoglobin, anemia, and anthropometrics and on transmission to young children. Using a nationally representative sample, we document strong associations between parental and child health. We find that the IHA is 0.18 for hemoglobin and 0.13 for anemia. The latter indicates that being born to an anemic mother is associated with a 13 percentage point increase in anemia risk. When we derive a composite measure of overall health using principal components analysis on a range of health outcomes, we estimate an IHA of 0.22 which is on par with IHA estimates from richer countries such as the United States (Halliday et al., 2021), the United Kingdom (Bencsik et al., 2023), and Taiwan (Chang et al., 2024). However, we do offer the caveat that we focus on young children between the ages of zero and five and these other studies focus on adult children.

We document some heterogeneity in intergenerational transmission of health and explore potential mechanisms that drive this persistence. Specifically, we find that the persistence of health is strongest among the poorest households and is higher among scheduled castes and scheduled tribes. Examining potential mechanisms, we observe that adjusting for socioeconomic variables slightly attenuates health persistence, although the effects are modest. Furthermore, we did not find evidence that iron supplementation moderates health persistence; however, there are indications that more nutritious diets may play a role in reducing persistence.

Finally, our geographic analysis reveals stark regional differences in health mobility. Southern states like Kerala and Tamil Nadu show greater health mobility, while northern states like Bihar exhibit lower mobility. These regional disparities highlight the need for region-specific policy interventions. Although interventions such as iron supplementation and dietary diversity programs have been implemented, our analysis suggests that these measures alone may not be sufficient to break the cycle of intergenerational health disadvantage. Instead, more comprehensive policy interventions that focus on maternal and early childhood nutrition, access to healthcare care, and socioeconomic inequalities may be effective in reducing health persistence across generations.

8 Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Table 1: Descriptive statistics for analytical sample (N = 200,427)

Variables	Mean	Standard Deviation
	(1)	(2)
Outcomes		
Child Hb level	10.59	1.39
Mother Hb level	11.52	1.47
Father Hb level	14.13	1.59
Child is anemic (%)	0.58	0.49
Mother is anemic (%)	0.56	0.50
Father is anemic (%)	0.22	0.41
Child height for age z score	-1.29	5.60
Mother height for age z score	-2.00	0.98
Child is stunted (%)	0.40	0.49
Mother is stunted (%)	0.51	0.50
Child BMI z score	-0.97	1.34
Mother BMI z score	-1.04	1.13
Child is malnourished (%)	0.20	0.40
Mother is malnourished (%)	0.19	0.40
Child demographics		
Female (%)	0.48	0.50
Birth order	2.26	1.40
Age	2.24	1.30
Households' demographics		
Mother's education	6.12	5.12
Father's education	7.63	4.88
Access to improve toilet (%)	0.51	0.50
Religion (%)	0.73	0.44
Social group(SC–ST) (%)	0.39	0.49
Wealth groups		
Poorest	0.26	0.44
Poor	0.24	0.42
Middle	0.20	0.40
Rich	0.17	0.37
Richest	0.13	0.34
Rural (%)	0.76	0.43
Districts	640	

Notes: SC–ST: Scheduled caste and scheduled tribe; mother and father's education is in years of schooling

Table 2: IHA and Rank-Rank Correlation in Hb and Anemia

	Child's Hb Level					
	IHA			Rank-Rank correlation		
	Pooled (1)	Sons (2)	Daughters (3)	Pooled (4)	Sons (5)	Daughters (6)
Panel A: Hemoglobin levels						
Mother's Hb level	0.181***	0.177***	0.186***	0.198***	0.193***	0.203***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
N	200427	104320	96107	200427	104320	96107
Father's Hb level	0.096***	0.105***	0.086***	0.119***	0.131***	0.107***
	(0.007)	(0.010)	(0.011)	(0.009)	(0.012)	(0.013)
N	25654	13341	12313	25654	13341	12313
Parent average Hb	0.216***	0.219***	0.214***	0.192***	0.195***	0.190***
	(0.010)	(0.013)	(0.014)	(0.009)	(0.012)	(0.013)
N	25654	13341	12313	25654	13341	12313
Panel B: Anemia						
	Child is anemic					
	Pooled	Sons	Daughters			
Mother is anemic	0.132***	0.133***	0.131***			
	(0.003)	(0.004)	(0.005)			
N	200427	04320	96107			
Father is anemic	0.102***	0.094***	0.111***			
	(0.010)	(0.014)	(0.015)			
N	26140	13590	12550			
Both parents anemic	0.138***	0.140***	0.136***			
	(0.011)	(0.015)	(0.017)			
N	26140	13590	12550			
Controls	✓	✓	✓			

Notes: Hb—hemoglobin level in grams per deciliter (gm/dL). Robust standard errors are reported in parentheses. Each coefficient are from a separate regression model. All models include controls except for models in columns (4)-(6). Controls include age, and square of the age of the child, as well as the age and square of the age of the mother and father.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Intergenerational Transmission of Anthropometrics and Latent Health

	HAZ	Stunting	BMI z-score	Malnourishment	Latent health
	(1)	(2)	(3)	(4)	(5)
Panel A: IHA					
Mother-Pooled	0.407***	0.179***	0.190***	0.087***	0.216***
	(0.019)	(0.003)	(0.004)	(0.003)	(0.003)
N	192140	192140	190225	190225	190210
Mother-Son	0.410***	0.177***	0.194***	0.086***	0.212***
	(0.028)	(0.004)	(0.005)	(0.005)	(0.004)
N	99497	99497	98535	98535	98528
Mother-Daughter	0.403***	0.182***	0.186***	0.088***	0.219***
	(0.025)	(0.004)	(0.005)	(0.005)	(0.004)
N	92643	92643	91690	91690	91682
Controls	✓	✓	✓	✓	✓
Panel B: Rank-Rank correlation					
Mother-Pooled	0.256***		0.172***		0.225***
	(0.003)		(0.003)		(0.003)
N	192140		190225		190210
Mother-Son	0.253***		0.174***		0.222***
	(0.004)		(0.004)		(0.004)
N	99497		98535		98528
Mother-Daughter	0.258***		0.169***		0.229***
	(0.005)		(0.005)		(0.005)
N	92643		91690		91682

Notes: Robust standard errors are reported in parentheses. Panel A includes the baseline controls while Panel B does not include controls. Each coefficient is derived from a separate regression, and each row represents outcomes grouped by relation. Panel A controls for age, and square of the age of the child, as well as the age and square of the age of the mother. Stunting and malnourishment are binary variables. Stunting is defined as HAZ < -2 SD, while malnourishment is defined as BMI z-score < -2 SD. Latent health scores were generated using PCA method based on the following variables: Hb, anemia status, HAZ, BMI z-score, stunting, and malnourishment status. All variables were standardized to account for differences in scale (binary vs. continuous) before conducting PCA. Separate PCA models were run for child and mother health indicators.

Table 4: Expected ranks of children's health conditional on P25, P50 and P75

	Hb level			BMI			Latent Health		
	25th	50th	75th	25th	50th	75th	25th	50th	75th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mother-All Children	44.78	49.73	54.67	44.88	49.17	53.46	44.83	50.46	56.09
	(0.19)	(0.23)	(0.29)	(0.19)	(0.23)	(0.29)	(0.19)	(0.24)	(0.32)
N	200427	200427	200427	190225	190225	190225	190210	190210	190210
Mother-Son	45.02	49.84	54.65	44.84	49.19	53.55	44.92	50.51	56.04
	(0.27)	(0.33)	(0.41)	(0.26)	(0.32)	(0.41)	(0.27)	(0.33)	(0.41)
N	104320	104320	104320	98535	98535	98535	98528	98528	98528
Mother-Daughter	44.52	49.61	54.69	44.92	49.14	53.35	44.68	50.41	56.14
	(0.27)	(0.33)	(0.42)	(0.27)	(0.33)	(0.42)	(0.28)	(0.34)	(0.42)
N	96107	96107	96107	91690	91690	91690	91682	91682	91682

Notes: This table presents percentile estimates for different outcomes using the rank-rank regression model. Robust standard errors are in parenthesis.

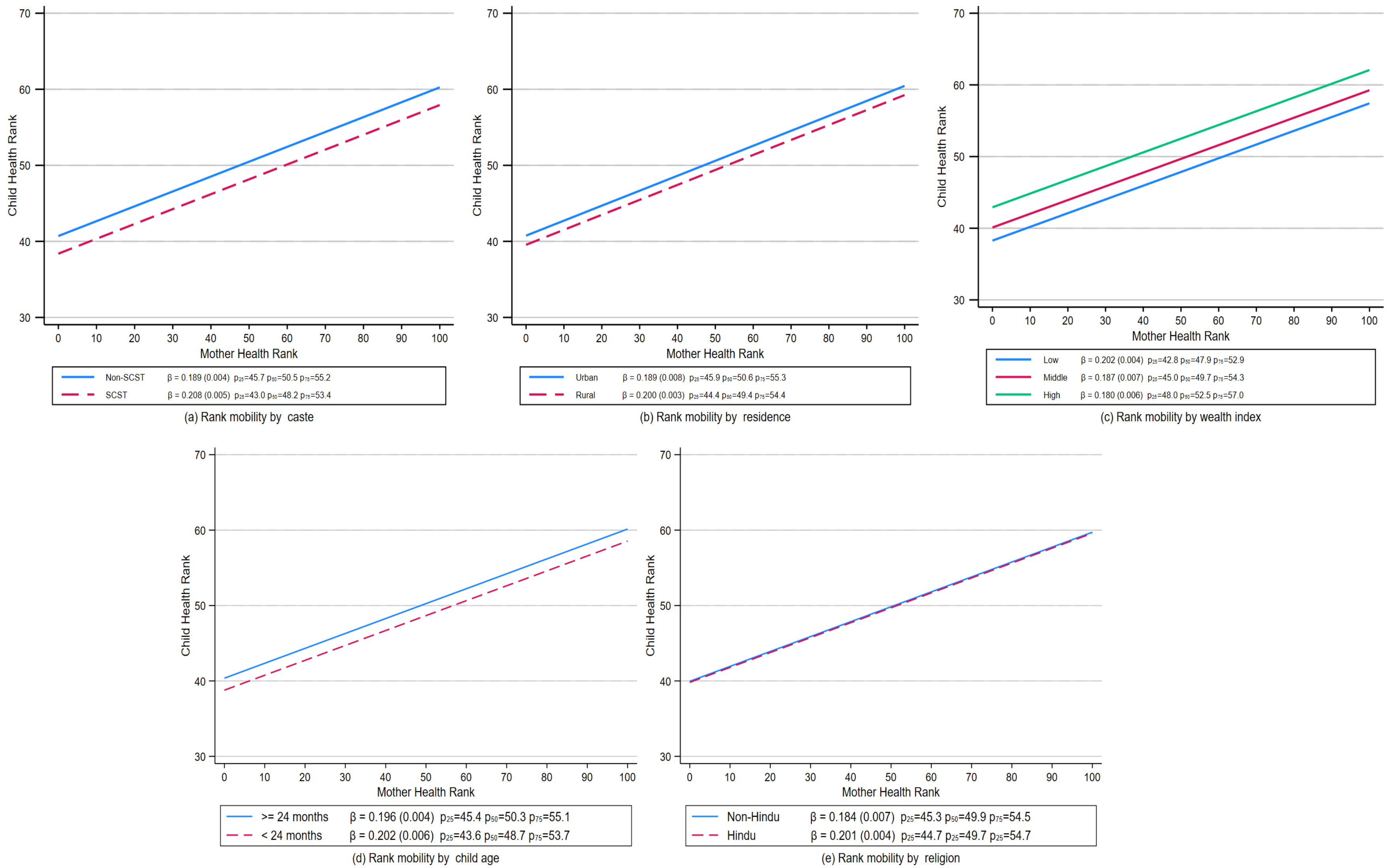

Figure 1: Hb rank mobility by caste, residence, wealth index, child's age, and religion

Notes: Figure 1 plots estimated regression lines from the regressions of child health rank on maternal health rank by caste, residence, wealth index, child's age, and religion. The rank-rank slope, denoted by ρ, is the coefficient on mother's health percentile. The expected rank at the 25th (p25) or 75th (p75) percentiles corresponds to the predicted rank for children whose mothers are at the 25th or 75th percentile of the maternal health rank distribution. The health percentile ranks are constructed from the age and gender adjusted baseline health measure and are ranked separately by generation. Robust standard errors for the regression coefficients are reported in parentheses.

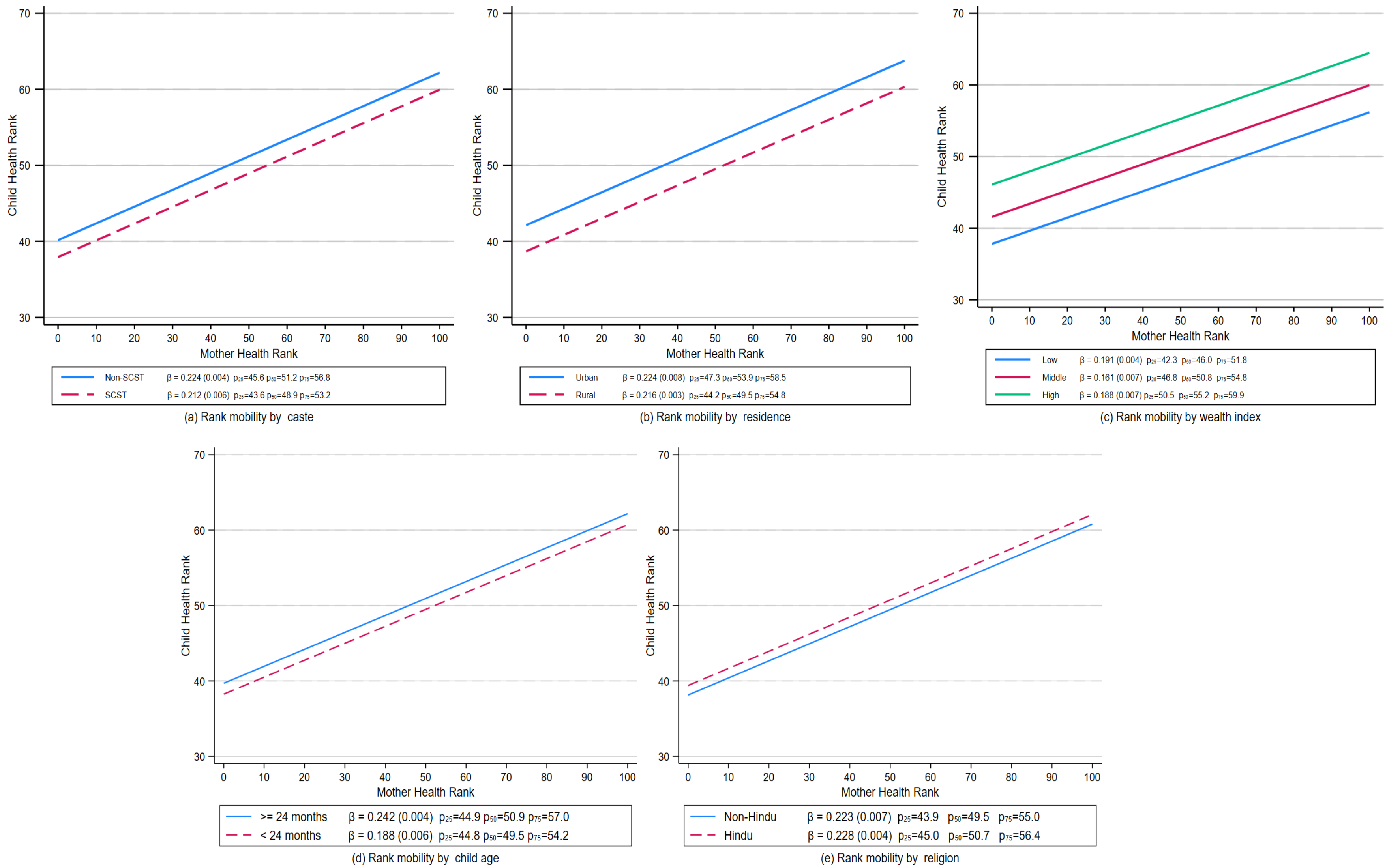

Figure 2: Latent health rank mobility by caste, residence, wealth index, child's age, and religion

Notes: Figure 2 plots estimated regression lines from the regressions of child health rank on maternal health rank by caste, residence, wealth index, child's age, and religion. The rank-rank slope, denoted by ρ, is the coefficient on mother's health percentile. The expected rank at the 25th (p25) or 75th (p75) percentiles corresponds to the predicted rank for children whose mothers are at the 25th or 75th percentile of the maternal health rank distribution. The health percentile ranks are constructed from the age and gender adjusted baseline health measure and are ranked separately by generation. Robust standard errors for the regression coefficients are reported in parentheses.

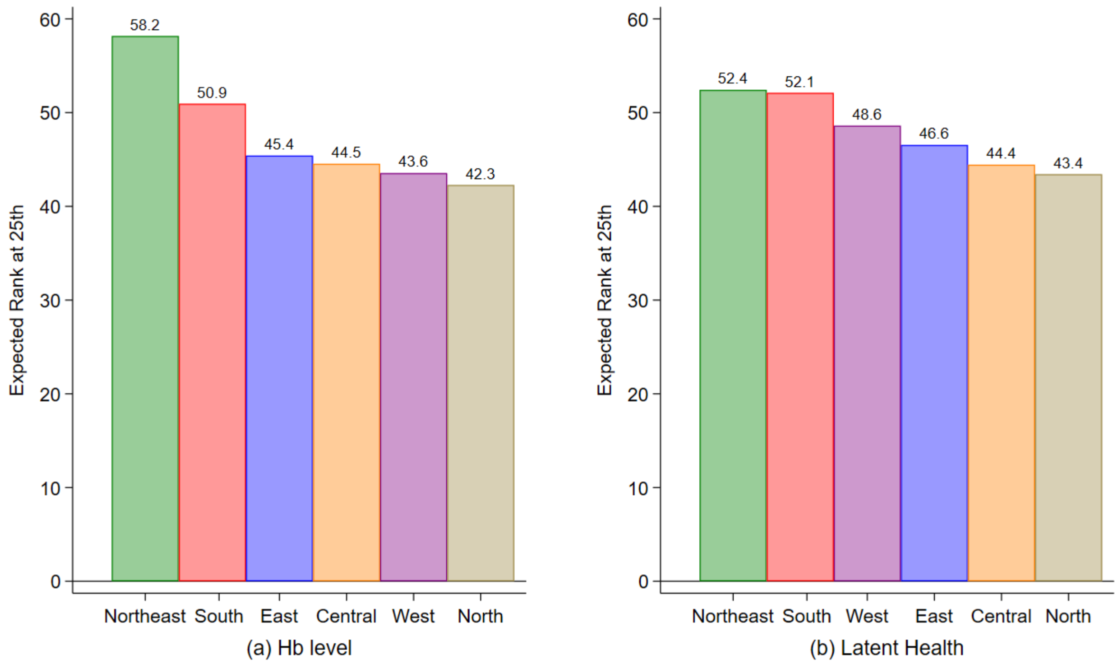

Figure 3: Expected Hb and Latent health rank at 25th percentile by region

Notes: Using the regression estimates, absolute upward mobility (P25) is defined as the sum of the intercept and $25 \times$ (rank-rank slope). The expected rank coefficient represents the predicted child rank when the mother's rank is at the 25th percentile of the distribution in a given region. Larger regression coefficients denote greater upward mobility. South region includes Andaman & Nicobar Islands, Andhra Pradesh, Karnataka, Kerala, Lakshadweep, Puducherry, Tamil Nadu, Telangana; North region: Chandigarh, Delhi, Haryana, Himachal Pradesh, Jammu & Kashmir, Ladakh, Punjab, Rajasthan, Uttarakhand; Northeast: Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura; Central region: Chhattisgarh, Madhya Pradesh, Uttar Pradesh; East region: Bihar, Jharkhand, Odisha, West Bengal; West: Dadar and Nagar Haveli, Daman and Diu, Goa, Gujarat, Maharashtra.

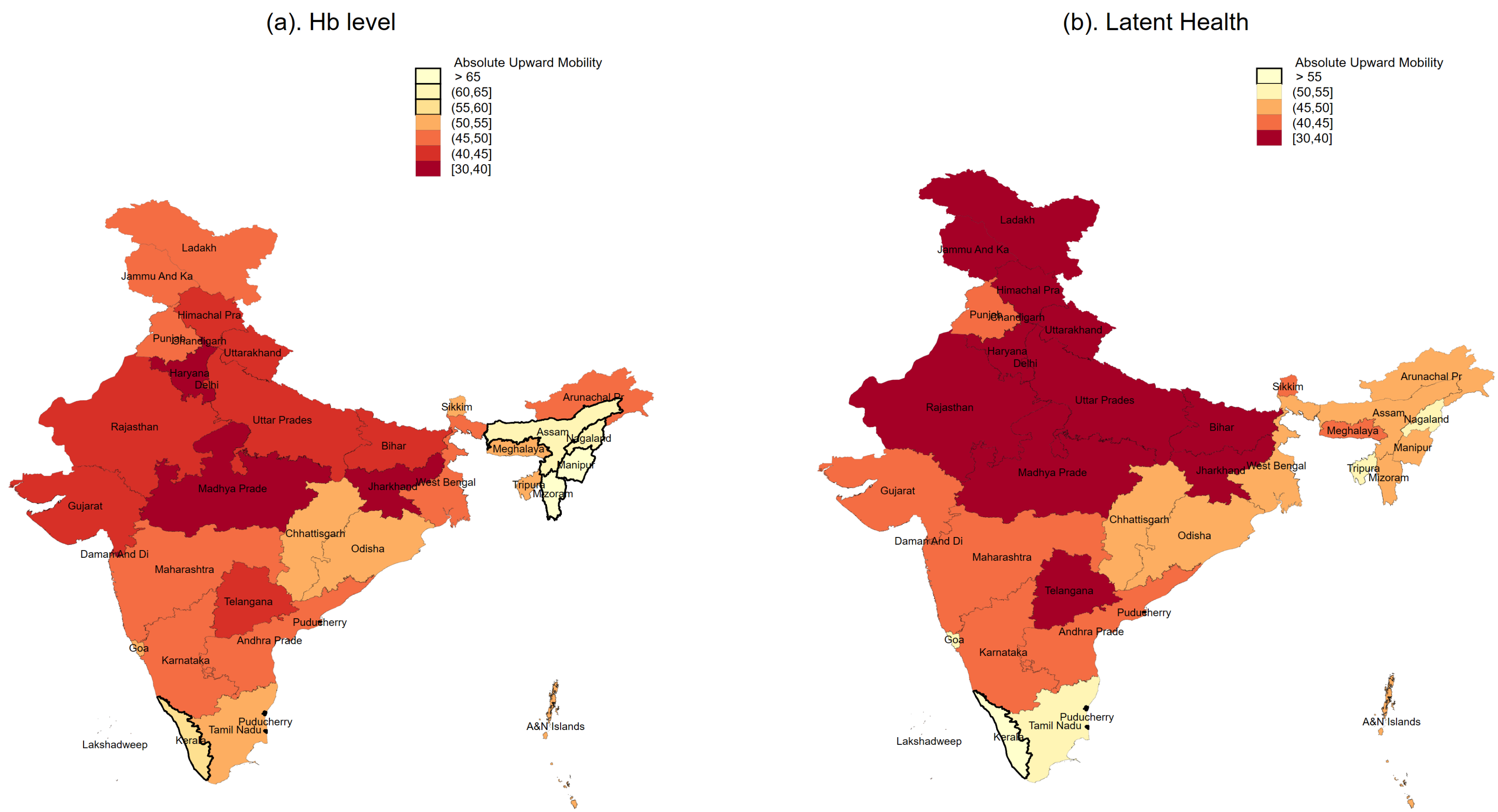

Figure 4: State-wide variation in intergenerational absolute mobility (P25) for Hb level and latent health

Notes: Using the regression estimates, absolute upward mobility ($\bar{r}_{25}$) is defined as the sum of the intercept and $25 \times$ (rank-rank slope). This represents the predicted child rank when the mother's rank is at the 25th percentile of the distribution. States with lighter colors indicate higher absolute mobility and darker colors indicate lower absolute mobility.

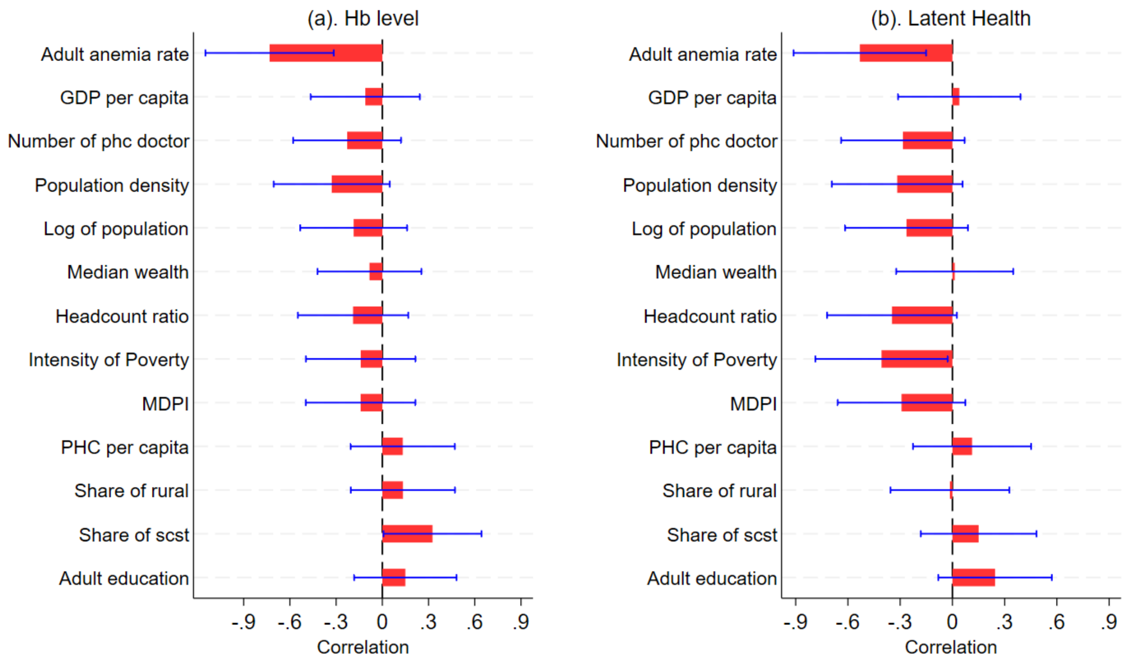

Figure 5: Correlates of intergenerational absolute mobility (P25) across states

Notes: All variables were standardized to account for differences in scale. GDP per capita is from the year 2014. MDPI denotes the Multidimensional Poverty Index and adult education refers to mean years of schooling (adult). PHC is primary health centers and GDP denotes Gross Domestic Product. Adult anemia rate is from NFHS-4. Error bars represent a 95% confidence interval.

Appendix

Table A1: Mechanisms and Robustness checks for Biomarkers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Hb levels								
Mother's Outcome	0.181***	0.144***	0.171***	0.179***	0.181***	0.179***	0.190***	0.190***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Father's Outcome	0.095***	0.078***	0.086***	0.090***	0.095***	0.090***	0.093***	0.093***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.009)	(0.013)	(0.013)
Pooled Outcome	0.216***	0.175***	0.201***	0.210***	0.215***	0.202***	0.212***	0.211***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.012)	(0.018)	(0.019)
Panel B: Anemia								
Mother's Outcome	0.132***	0.105***	0.124***	0.130***	0.132***	0.128***	0.115***	0.115***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)
Father's Outcome	0.102***	0.080***	0.090***	0.108***	0.102***	0.092***	0.080***	0.079***
	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)	(0.012)	(0.017)	(0.017)
Pooled Outcome	0.138***	0.105***	0.122***	0.147***	0.137***	0.125***	0.094***	0.093***
	(0.011)	(0.012)	(0.011)	(0.013)	(0.011)	(0.013)	(0.018)	(0.018)
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
District f.e.		✓						
SES controls			✓					
Birthweight				✓				
Mother taking iron					✓			
Antenatal iron intake						✓		
Iron-rich food							✓	
Diverse diet								✓

Notes: Hb—hemoglobin level in grams per deciliter, pooled outcome is the average parent outcome. Robust standard errors are reported in parentheses. Baseline controls include age, and square of the age of the child, as well as the age and square of the age of the mother and father. SES controls include birth order of the child, mother's education, father's education religion, caste, wealth index, and rural dummy. In column 7, the sample is restricted to children aged 6 to 23 months. Specifically, column 7 includes the youngest child in the given age group who is living with mother and consumed iron-rich food such as eggs, meat (beef, pork, lamb, chicken, etc), liver, heart, other organs, and fish or shellfish (see the guide at DHS Guide to Statistics).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Mechanisms and Robustness checks for Anthropometric outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Stunting								
Mother's Outcome	0.179***	0.158***	0.139***	0.169***	0.179***	0.172***	0.150***	0.150***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)
Panel B: Malnourished								
Mother's Outcome	0.087***	0.079***	0.077***	0.081***	0.087***	0.093***	0.101***	0.101***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.006)	(0.006)
Panel C: Latent Health								
Mother's Outcome	0.216***	0.182***	0.160***	0.205***	0.215***	0.207***	0.181***	0.180***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.006)	(0.006)
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
District f.e		✓						
SES controls			✓					
Birthweight				✓				
Mother taking iron					✓			
Antenatal iron intake						✓		
Iron-rich food							✓	
Diverse diet								✓

Notes: Robust standard errors are reported in parentheses. Baseline controls include age, and square of the age of the child, as well as the age and square of the age of the mother and father. SES controls include birth order of the child, mother's education, father's education religion, caste, wealth index, and rural dummy. In column 7, the sample is restricted to children aged 6 to 23 months. Specifically, column 7 includes the youngest child in the given age group who is living with mother and consumed iron-rich food such as eggs, meat (beef, pork, lamb, chicken, etc), liver, heart, other organs, and fish or shellfish (see the guide at DHS Guide to Statistics).