Low Transmission of Cognitive Skills across Generations in Kenya *

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Abstract

Cognitive skills drive human capital and economic productivity yet little is known about their transmission across generations in low-income settings. This study analyzes the intergenerational transmission of fluid intelligence using a 25-year longitudinal survey of over 7,000 Kenyan adults and 4,000 of their children. First, intergenerational cognitive transmission is found to be substantially lower than in high-income countries or predicted by experts, and this is not due to data quality or cognitive instability over time. Second, regression and machine learning analyses indicate that environmental factors dampen transmission. These factors are a leading, albeit partial, explanation for the lower intergenerational transmission of cognitive skills documented in Kenya relative to richer societies.

Keywords: cognitive skills, intergenerational transmission, poverty, Kenya.

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1 Introduction

Characterizing how cognitive skills are transmitted across generations is central to understanding economic productivity and the persistence of inequality within countries and globally. Cognitive skills have been associated with various dimensions of economic well-being, including greater educational attainment, higher earnings, better decision-making, and improved health, while generating beneficial "spillovers" for others in an individual's social network (Ceci and Williams 1997; Gottfredson and Deary 2004; Deary et al. 2007; Laajaj and Macours 2021; Huh et al. 2024; Nichols et al. 2026). These relationships imply that cognitive skills and their intergenerational transmission help shape broader patterns of social and economic mobility.[1]

The intergenerational correlation in cognitive skills is defined as the extent to which the variation in children's cognitive skills can be explained by a parent's cognitive score, and it provides a useful summary statistic of intergenerational processes. Evidence from large-scale economics studies from high-income and middle-income countries indicates positive correlations between parents' and children's cognitive abilities ranging from 0.23 to 0.56, implying that a sizable share of the variance in the child's cognitive skills can be explained by a parent's skills (Black et al. 2009; Hanushek et al. 2021; Grönqvist et al. 2017; Björklund et al. 2010; Anger and Heineck 2010; Byford et al. 2012; Brown et al. 2009; Zhang et al. 2025; Cockburn, Nandi, Mani, Behrman, and Ramanan Laxminarayan 2025; Calderon and Hoddinott 2010). Similarly, a review from the psychology literature based on family, adoption, and twin studies finds the average parent-offspring correlation of IQ to be within the same range, at 0.42 (Knopik et al. 2017). However, a positive correlation need not be the result of gene transmission alone (or at all), as a positive intergenerational correlation could also stem from environmental factors; thus the correlation is not equivalent to the magnitude of genetic heritability. Through the lens of behavioral genetics, the realization of a complex trait like cognitive skills is affected by a person's genetic endowment, their environment, and the interactions between the two (Turkheimer 2000; Turkheimer et al. 2003; Harden et al. 2007; Plomin and Deary 2015; Kong et al. 2018). The possibly intricate interplay of genes and environment also affects the intergenerational correlations observed in the data.

While one might expect that the biological mechanisms of passing on genes from parent to offspring are largely the same across all human societies, environmental factors and the nature of gene-environment interactions may vary markedly by income levels in ways that could not just influence the realization of cognitive levels but also the intergenerational correlations in cognitive levels across societies.[2] Furthermore, parent-child correlations may differ across societies if patterns of *assortative mating* of parents differ. (Watkins and Meredith 1981; Reynolds et al. 2000).[3] If two parents share certain traits, this can lead to a higher observed correlation between a given

1. Economics research largely estimates intergenerational income mobility in high-income countries, capturing, for example, children's propensity to end up in a higher income bracket than their parents in the US (Chetty et al. 2014). Alesina et al. (2021) estimate intergenerational mobility in African societies using census data on educational attainment, since income can be challenging to measure in low-income settings. These findings are related to intergenerational cognitive mobility in Section 3.

2. Gene-environment interactions refer to the environment influencing which genes are being expressed. For example, *Epigenetic processes* provide a mechanism through which environmental exposures can influence gene expression across generations (Dupont et al. 2009). Regardless of whether nature or nurture predominantly drives the transmission of cognitive skills across generations, poverty levels and socio-cultural factors likely affect both of these channels, as well as the interactions between them.

3. As long as there is some genetic basis of a trait (which has been posited to be the case for nearly all human behavioral traits (Turkheimer 2000)), assortative mating of parents would lead to overestimating the correlation between a parent and a child, due to omitted variable bias (confounding) driven by the other parent's genetic contribution. In the case of Raven's tests, which we use as our main

parent and child because the other parent is also contributing similar genetic endowment. It is thus unclear whether estimates of intergenerational cognitive correlations and mobility from high-income countries generalize to poorer settings, such as the study country of Kenya, especially if the strength of the transmission depends on environmental conditions and socio-cultural norms and patterns, which differ substantially across contexts.

It is not obvious ex ante whether one would expect stronger parent-child correlations in cognitive skills in wealthier or poorer societies. On the one hand, poverty often entails greater volatility in access to resources such as nutrition, healthcare, and schooling that have been linked to cognitive abilities. Fluctuations in these resources over time and across generations could weaken the intergenerational persistence in cognition, leading to lower correlations than those observed in more stably prosperous environments.[4] Thus the role of the environment could be relatively more important in low-income settings where access to resources cannot be taken for granted. This notion is in line with the Scarr-Rowe hypothesis, which posits that the environment is a more important predictor of intelligence in lower socio-economic status (SES) settings, while genes are more important predictors in higher SES settings. Research evidence has documented patterns consistent with this hypothesis by comparing interactions between genes and childhood socio-economic status in countries with less developed social security systems versus those with a stronger welfare system (Duncan et al. 1998; Turkheimer et al. 2003; Harden et al. 2007; Gottschling et al. 2019; Tucker-Drob et al. 2013; Tucker-Drob and Bates 2016; Turkheimer et al. 2015; Bates et al. 2016).

Yet there are other conceptually plausible perspectives. For instance, environmental variation might be most compressed in settings where few or no individuals have adequate access to resources, i.e., in the poorest societies, in which case the main driver of differences in realized cognitive abilities might be underlying individual genetic potential. This could increase the relative weight of genetic endowments in determining cognitive abilities, which might strengthen parent-child correlations. Taking these two perspectives together suggests that in settings where access to basic needs (such as nutrition, health care, and education) are either universally available or (nearly) universally lacking, genetic components may be more influential, which would lead to higher intergenerational correlations in cognitive performance. In contrast, environmental factors may be more influential in settings with extensive variation and inequality in access to basic needs both within and across generations, generating lower parent-child correlations. The socio-cultural setting may also influence transmission, and in particular, settings with prevailing cultural norms that do not promote individual cognitive (or academic) achievement seem likely to be characterized by weaker parent-child intergenerational correlations in cognitive performance (Bronfenbrenner and Ceci 1994; Scarr and McCartney 1983; Keller 2017; Gauvain and Munroe 2009; Greenfield 2016).

This study estimates intergenerational correlations in cognitive skills in a relatively low-income setting using detailed longitudinal (panel) data from the Kenya Life Panel Survey (KLPS). Kenya is a poor country by global standards but relatively prosperous compared to its neighbors, with better-than-average education, health, and nutrition outcomes among Sub-Saharan Africa countries (Ritchie 2026a, 2026b; World Bank 2026). So it is

cognitive outcome variable, the literature has shown spousal correlations to be in the range of 0.25 to 0.3, which could be enough induce upward bias in the estimated correlations between any one parent and a child (Watkins and Meredith 1981; Reynolds et al. 2000), although in practice it is likely to be relatively modest in magnitude. In the KLPS sample in Kenya that we use for this analysis, the correlation between spousal education (for the first marriage) is $r = 0.47$.

4. This point applies to the life experiences of both generations: a parent may have experienced such resource availability "shocks", and a child may also experience shocks, and volatility in either or both would seem likely to weaken the intergenerational correlation.

certainly not a setting in which access to basic education, health and nutrition is universally lacking, but rather — especially in the birth cohorts of parents represented in the sample — one characterized by extensive inequality in access to services and educational opportunity (Hsu et al. 2026), precisely the setting argued above that could be characterized by a lower intergenerational correlation. The main measure of cognitive abilities in this study is performance on Raven's progressive matrices (Raven 2000), which capture executive functioning and visuospatial reasoning, the latter being a central measure of fluid intelligence. The analysis below examines the extent to which these cognitive skills are transferred between generations, how the stability of these skills evolves over individuals' life course (for the parent generation, which has been surveyed since they themselves were schoolchildren), quantifies reliability using releated measures, and explores which factors moderate the transmission of cognitive skills between parents and children. The latter findings help place the results in a broader context of large-scale studies in a meta-analytic framework to characterize how intergenerational correlations vary across settings.

2 Results

A detailed description of the dataset and the methods used for analysis is presented in Section 4, and a brief summary is provided here. Data were collected from up to $N = 7,405$ respondents in the parent generation (that are either observed at least twice or are observed at least once and have a child data point attached) and $N = 4,177$ of their children (from certain birth cohorts) as part of the Kenya Life Panel Survey (KLPS), which has been tracking individuals from Western Kenya since 1998. The timing of data collection rounds, sample sizes, and respondent ages are summarized in Table 1. Not all respondents have children in the survey sample, while others have up to two children in the dataset in the relevant birth cohorts. In all, there are $N = 4,177$ unique parent-child pairs in the intergenerational analysis, and the statistical analysis is clustered at the parent level to allow for correlated outcomes among siblings. The main outcome variable of interest is the performance in Raven's matrices, which is observed up to five times per adult respondent between 2000 and 2023 (and the most recent round, KLPS-5 in 2023, included this module for the entire sample and not just smaller, randomly-selected subsamples) and once for their children, in 2024-25.[5] The following analyses estimate correlations in the Raven's matrices cognitive measures both across generations and within individuals over time, using scores that have been normalized and harmonized across rounds as described in Appendix A.3. These estimates are benchmarked against expert forecasts of the same correlations collected through the Social Science Prediction Platform (SSPP).[6] Test–retest reliability is also presented. Subsequent analyses leveraging the unusually rich KLPS dataset use ordinary least squares (OLS) and machine learning (ML) models to explore heterogeneity in the relationship between parents' and children's cognitive scores. To place findings in a larger context, a meta-analytic review of the literature around intergenerational cognitive transmission is conducted. The procedure is detailed in Section 4.

5. Raven's matrices are commonly used to measure cognitive abilities: performance has been shown to correlate with other cognitive variables (Raven 2000; Burke 1972). In the KLPS parent sample, Raven's scores also strongly predict earnings even conditional on individual educational attainment (King et al. 2026; Byambaa et al. 2025). Appendix analyses in Section A.1 correlate Raven's scores with other economic and cognitive measures.

6. The SSPP allows for the collection of precise forecasts among sociel science experts, i.e., in our context, the majority are economists and psychologists. Forecasters are provided with the exact setting and asked to estimate the value of the correlation before the research results were known. Details are descibed in Section 4.1.4.

2.1 Low Intergenerational Transmission of Cognitive Skills

The correlation between parents' and children's cognitive abilities is positive and of modest magnitude, and it is statistically significantly different from zero at high levels of confidence. The rank correlation between a parent's skills measured in KLPS-5 (mean age 37 years) and their child's measured in the KLPS Kids Round 5 data (at ages 8–12) is $r = 0.14$ as presented in Table 1 (p-value<0.001, 95% bootstrap confidence interval: [0.11, 0.17], N=3,704). This correlation implies that over 98% of the variance in children's scores is *not* explained by a parent's score. Adjusting for test-retest reliability (discussed in the next section) using Spearman's correction increases the correlation to $r = 0.22$ (Spearman 1987). While reliability adjustments are common in intraindividual studies, few intergenerational studies in the existing literautre adjust for noise (such as by testing and adjusting for test-retest reliability), and thus for comparability with existing estimates we focus on the correlation estimate of $r = 0.14$ in what follows.[7] This pattern is also found when using parents' scores at a younger age, when they were children themselves and similar in age to their children when tested (in what we refer to as KLPS-0): specifically, the magnitudes of the raw and adjusted Spearman correlations are similar to the comparison using KLPS-5 data (Table 1, second row).[8]

These findings are mirrored in estimates of intergenerational cognitive mobility: children whose parents (as adults) are in the bottom half of their own cognitive skill distribution, on average rank at the 46th percentile (95% confidence interval: [45.14, 47.72], $N = 1,862$). This is narrowly below the 50th percentile that would pertain if parents' cognitive abilities were orthogonal to children's abilities. Similarly, the probability that a child whose parents are in the bottom 75% of the cognitive distribution ranks among the top 25%, is 23% (95% confidence interval: [21.22%, 24.37%], $N = 2,780$), which is only slightly below than the 25% that would be expected if the process were purely random.

2.2 High Reliability of Cognitive Measures and Stability across Lifespan

In contrast to the relatively modest estimated intergenerational transmission, cognitive skills exhibit substantial persistence for individuals over time. First, over relatively short time horizons, performance on Raven's matrices display high test-retest reliability: Raven's scores have a correlation of $r = 0.77$ over a four-month "retest" interval in a separate convenience sample among adults in urban and rural Kenya ($N = 102$). In a separate child convenience sample in urban and rural Kenya ($N = 176$), there is a some what lower reliability correlation of $r = 0.59$ over a one-month interval. These reliability correlations allow us to carry out the reliability corrections noted in the previous subsection.

Second, cognitive correlations remain high over far longer multidecadal horizons for individuals: high rank stability prevails from childhood to midlife for the parent KLPS sample, as shown in Table 1. In the preferred

7. A unit of observation is a parent-child pair. If a parent has, say, two children, then they will be in the sample twice, once with each child. Overall, there are 5,752 distinct parents in the analysis sample drawn from KLPS-5.

8. The slightly larger reliability-adjusted estimate of $r = 0.21$ presented in the last column of Panel B of Table 1 reflects the somewhat lower test-retest reliability when cognitive scores are measured in children relative to adults which rather mechanically amplifies the Spearman correction (Breit et al. 2024). Spearman and Pearson's correlations are reported in Table 1, but Spearman rank correlations are the preferred statistic as correlating ranks across generations has a more natural, relative interpretation independent of harmonization techniques.

specification, which links KLPS-1 and KLPS-5 over a span of 20 years, the rank correlation is $r = 0.60$ ($N = 885$). Adjusting for noise due to low test-retest reliability increases this correlation to $r = 0.78$, implying that 61% of the variation in rank cognitive performance of adults in midlife (in KLPS 5, at median age 37) can be explained by the variation in cognitive scores measured in late adolescence or early adulthood (KLPS-1, at median age 19). The persistent color gradient observed in the "spaghetti plot" of harmonized cognitive scores in Figure 1 illustrates this finding graphically, demonstrating that respondents whose cognitive scores rank higher in midlife (KLPS-5) tend to rank similarly throughout the life course.

2.3 Heterogeneity in Intergenerational Transmission by Environmental Conditions

The analysis next explores which environmental characteristics (potentially relevant for parent and child cognitive development) moderate the intergenerational transmission of cognitive skills. Conceptually, both parent and child factors could affect the intergenerational correlation, since environmental factors could limit — or promote — the realization of either generation's genetic potential in terms of their cognitive development. In practice, these measures are more detailed for the childhood of the child generation, benefiting from detailed survey measures gathered in both KLPS-4 and KLPS-5. Nonetheless, several measures and proxies are available for the parent generation's childhood as well.

First, the analysis estimates ordinary least squares (OLS) regressions that interact parental cognitive scores with a set of theoretically motivated environmental characteristics. To proxy the current socio-economic status of the household the child is growing up in, the regression includes an indicator variable for whether the household currently lives in an urban or rural setting.[9] Analogously, the average educational attainment of the parents of the parent's generation, i.e., the grandparents of the child generation, broadly captures the socio-economic status of the parent's household growing up. Grandparent educational attainment is an attractive (and relatively "exogenous" in the parlance of econometrics) measure since it predates the parent's later educational and economic choices, which themselves are likely to be directly impacted by the parent's cognitive ability.[10] These two socio-economic status proxies – urban residence and grandparent education – are both statistically significant predictors of children's Raven scores (Table 2, Panel A, Columns 1-3). Columns 4-6 explore whether these factors meaningfully moderate the intergenerational transmission of cognitive skills, by interacting them with the parent score. The interaction between urban residence and the parent score is small and not statistically distinguishable from zero. The interaction with grandparent education is meaningful in magnitude and statistically significant: each additional year of grandparent education is associated with approximately a 0.01 increase in the slope relating parental and children's cognitive scores. Thus the change from having two grandparents with no formal schooling versus two grandparents who completed the seven years of Kenyan primary school (the relevant length for the grandparents' generation) is approximately 0.07, which would substantially increase the average correlation of 0.14 by roughly half — and move it far closer to the correlations observed in richer countries.

9. There is no variation in urban residence for the parent generation since they all grew up in rural western Kenya, having been sampled from rural primary schools.

10. One slight concern is that grandparent education could be a shared environmental factor that directly affects both parents' and children's realized cognitive abilities, in which case it should not be interpreted solely as a proxy for the socio-economic status of the parent's upbringing.

Second, this analysis is complemented with the use of machine learning (ML) methods that more flexibly identify heterogeneity in intergenerational transmission across a far larger set of possible moderators. Specifically, and as detailed in in Section 4, the analysis employs causal random forest models considering 101 features drawn from the KLPS dataset (listed in Table A.4) to predict children's cognitive performance.

The top 15 features that are most consistently selected by the model as meaningful predictors of effect heterogeneity are listed in Table 2, Panel B. The majority of these variables selected are features of the family environment, affecting how the child generation is growing up. In parallel to the OLS analysis, urban residence is not a consistent predictor of heterogeneity in the correlation between the parent and child cognitive score (and thus does not appear in the table list), while grandmother education does appear as one of the more consistent features, appearing in the model as a top 20 predictor in 99 out of 100 runs with a consistent positive sign. A measure of educational investments in the child generation also tends to predict a stronger correlation (although with some ambiguity across models in its sign). Parents who tend to have more routine manual labor jobs tend to see less transmission of cognitive performance to their children, as do those parents who report experiencing more ongoing stress; both may be related to lower levels of parental investment in their children's cognitive abilities. While age was often selected to be a significant predictor of the relationship–a finding potentially in line with increases in heritability as children turn into adults in the psychological literature (Knopik et al. 2017)–the random forest does not clearly sign the relationship, complicating interpretation.

It is noteworthy that, despite including multiple measures of nutrition in the child generation as features in the ML model, none are consistent predictors of heterogeneity in the parent-child correlation (and are thus not represented in the table). By contrast, a proxy for better nutrition among the parent generation — their realized height, normalized by gender — is a fairly consistent predictor of a stronger parent-child correlation, suggesting that those parents who experienced worse early life nutrition were perhaps less able to attain their genetic potential in terms of cognition. The contrast is consistent with the conceptual discussion above: there was far more under-nutrition and variation in access to adequate resources in the parent generation (when Kenya was a far poorer country overall) compared to the relatively more prosperous living conditions experienced by the child generation. The result that a proxy for parent socioeconomic status in childhood — grandparent education — significantly moderates the relationship while a proxy for child socioeconomic status (current urban residence) does not, is consistent with a view that the parent generation may have been more vulnerable to meaningful shocks to household resource and service availability relevant to cognitive development.

Appendix A.2 expands on the machine learning approaches and results, including robustness checks that largely confirm the main results. For instance, additional analyses with debiased Lasso confirm similar variable selection patterns.

2.4 Low Kenyan Transmission Rate in Global Context

It is valuable to first put the two main findings — namely, relatively low intergenerational cognitive correlation between parents and children, and relatively high intraindividual stability in cognitive performance over both short and long time horizons — in context. A meta-analytic framework compares the KLPS estimate to other intergenerational cognition studies around the globe. The intergenerational correlation Pearson correlation coefficient

of $r = 0.15$ in Kenya is lower than several large-sample studies from mostly high-income and middle-income countries (Figure 2), where Pearson estimates range from 0.19 to 0.45 among published papers (where the focus is on unadjusted Pearson's correlations throughout since these studies do not account for test-retest reliability and typically do not report rank correlations). The KLPS rank correlation estimate of 0.14 and Pearson' correlation estimate of 0.15 is also roughly half of the value of $r = 0.3$ predicted by academic experts in the SSPP for the Kenyan context (an estimate that would fall squarely in the range of existing findings from largely wealthier countries as shown in Figure 2, Panel A). When plotting these different intergenerational correlation estimates against GDP per capita in log terms in Panel B of Figure 2, Kenya is the lowest observation, both in terms of income and in terms of the corelation. The fitted line, using random-effect inverse variance weighting to account for sample sizes and heterogeneity across studies, suggests an upward slope: intergenerational correlations tend to increase in GDP per capita.

3 Discussion

3.1 Limitations

A first limitation is related to the generalizability of the Kenya Life Panel Study. KLPS is not a nationally representative sample, which raises the possibility that the patterns are cohort- or region-specific. For instance, Alesina et al. (2021) document heterogeneity in intergenerational education mobility across Africa, including heterogeneity across Kenyan regions. A further concern is the homogeneity among the parent cohort: the parents were sampled from primary schools in Western Kenya (when they were themselves children in 1998), perhaps missing out on the full distribution of baseline academic and cognitive performance (since drop-out were missed), and thus somewhat mechanically attenuating the intergenerational correlation (if the child generation has more dispersion in outcomes). However, it has been documented that the KLPS parent cohort closely resembles national averages across key dimensions including educational attainment, household size, and urban-rural composition. For example, at baseline, Busia was close to national education averages: the 2005 Kenya Integrated Household Budget Survey (KIHBS) showed that 96% of Busia children 6-17 had "ever attended" school vs 93% nationally, indicating that this school-based KLPS sample captures the vast majority of children. Similarly, 72% of the KLPS parent cohort has completed primary school and 78% of comparable cohorts nationally have completed primary school, and the KLPS child generation are slightly more likely to have ever attended school than their comparable Kenyan census cohort (Hsu et al. 2026). Furthermore, even if KLPS is reflective of the Kenyan population, the estimates may not be generalize to all of Sub-Saharan Africa. Kenya has higher average educational attainment than its African neighbors and higher incomes (Graetz et al. 2018; Ritchie 2026a, 2026b; World Bank 2026), which could make it easier for children to select into educational opportunities in line with their cognitive potential. This could also explain why Kenya boasts higher income and educational mobility than many of its neighboring countries (Van der Weide et al. 2021; Munoz and Van der Weide 2025).

Another limitation is related to the appropriatenes of Raven's scores as measures of cognitive ability. While Raven's scores have been shown to correlate with other cognitive measures and with important economic outcomes, including in Kenya and many other low- and middle-income contexts (Burke 1972; Boissiere et al. 1985;

King et al. 2026; Byambaa et al. 2025) (see Appendix A.1 for predictability of our sample), they capture only certain dimensions of cognition, a multifaceted construct. Some comparable studies in other countries rely on multidimensional cognitive indices such as verbal and mathematical tests. Since more holistic constructs tend to have higher correlations (Knopik et al. 2017), this limits the ability to generalize and compare KLPS with other studies. That said, some of the existing closely related studies also employ Raven's matrices scores as a cognitive measure (including Cockburn, Nandi, Mani, Behrman, and Ramanan Laxminarayan 2025; Calderon and Hoddinott 2010).

Another concern is that the Raven's score performance in KLPS is unincentivized, raising questions about individual effort in the activity, where low effort could lead to more random guessing of solutions and thus less signal in the measure. However, recall the relatively high reliability in scores in the short run (for both adults and children), and the high correlation of scores over the life course; none of these patterns would hold if there was considerable random guessing of answers among respondents, but the pattern is instead consistent with respondents exerting substantial effort to answer correctly. Note that nearly all other studies in this literature use similarly unincentivized cognitive tests.

The ability to draw conclusions about the exact contributions of different factors and the channels is also constrained by the lack of underlying genome data in KLPS (at the present time). The intergenerational cognitive correlations encompass shared genetic and environmental variation, as well as any interactions of the two plus any effects of assortative mating. Without genetic data or exogenous variation in the environment, it is challenging to definitively distinguish how much of the correltion documented is due to nature versus nurture.[11]

Lastly, in our current child chohort data, we only observe children once from approximately ages 8 to 13 when they are not yet fully cognitively developed. In smaller samples, Plomin and Spinath (2004) show that intergenerational persistence tends to be higher from age 16 onward, reflecting the notion that heritability increases with age and that the importance of environmental factors grows relatively weaker. Yet the other studies presented in Figure 2 also test children at similarly young ages and find far higher correlations, so the difference across studies does not appear to be due to child age.

3.2 Potential Causes of Low Intergenerational Transmission

What can account for the surprisingly low transmission of cognitive performance across generations in Kenya? An obvious concern is data quality, with the possibility that the tests were not administered as consistently in the low-income study setting. However, the test-retest reliability and rank stability in KLPS are high and in line with similar measures from high-income countries (Deary et al. 2000; Deary and Brett 2015; Poulton et al. 2022; Breit et al. 2024), suggesting that low data quality and measurement noise are not likely to be a leading cause.

A more favorable interpretation of the low intergenerational transmission is that it is related to higher levels of general social mobility in Kenya. It is has been documented that Kenya has relatively high levels of both income mobility and educational mobility (Van der Weide et al. 2021; Munoz and Van der Weide 2025) across

11. To investigate the role that assortative mating may play in the transmission of cognitive skills, we regress children's scores on their KLPS parent scores and control for the parent's first spouse's educational attainment. The coefficient estimate decreases from 0.14 to 0.10 after including the control variable. We find a spousal education correlation of r=0.45 in this sample. These back-of-the-envelope calculations suggest intergenerational transmission may indeed be confounded by assortative mating.

generations, which may themselves be related to the low cognitive correlations documented here. In other words, low intergenerational correlations and high social mobility are two sides of the same coin. For instance, in data from India, which has deeply entrenched social stratification rooted in a millenia-old caste system, data indicate that if parents are among the bottom 75% in the cognitive performance distribution, the probability that their child is among the top 25% of the child distribution is estimated to be only 15% (Cockburn, Nandi, Mani, Behrman, and Laxminarayan 2025), in contrast to the 23% found in this study's KLPS data.

The contrast between low intergenerational transmission of cognition but high rank stability for individuals over time raises questions about which factors may be weakening the transmission of cognitive skills. For example, bioecological models of development argue that the realization of genetic potential depends on sustained interactions between children and their immediate environments (Bronfenbrenner and Ceci 1994). Under this framework, genetic influences are expressed through "proximal processes" such as cognitively stimulating interactions with caregivers or teachers and other opportunities for learning. When such processes are disrupted by poverty, stress, or unstable access to education, or due to socio-cultural norms that discourage individual intellectual development, the expression of cognitive potential may be curtailed (Gauvain and Munroe 2009; Greenfield 2016). Similarly, Tucker-Drob et al. (2013) suggest that conditional on genetic potential, children from advantaged backgrounds have an easier time selecting into amplifying learning opportunities that allow them to grow and reach their potential more easily. Research on "critical periods" corroborates the idea as experiences in early childhood — including early-life shocks to nutrition, health, or schooling — can permanently alter cognitive trajectories and thus the level of cognitive skills later in life (Almond et al. 2018; Webb 2024), generating high persistence within individuals over time. At the same time, if access to resources fluctuates across generations, the cognitive trajectories of parents and children may diverge substantially, weakening intergenerational correlations. Back-of the-envelope calculations, using our regression estimates of the effect of grandparent education, suggest that if the grandparent generation, on average, had 7 more years of schooling (such that it would be closer to the average level of 14 years of education in, for example, Germany), the correlation coefficient would be around 0.22, which would put Kenya at slightly higher than the fitted line in Panel B of Figure 2.

In the Kenyan context, the sustained national economic growth experienced since roughly 2000 means that living standards are far higher on average for the KLPS child generation than the KLPS parent generation, suggesting that many parents' cognitive potential may have been constrained by greater food insecurity, health shocks, and a lack of household resources to pay for schooling. Such adversity is far less common for their children, enabling more of them to live up to their potential. Taken together, the findings suggest that the low intergenerational correlation in cognitive performance observed in Kenya is not an artifact of measurement but rather reflects attenuation of transmission through both genetic and (especially) environmental channels driven by conditions that are more prevalent in low-income settings like Kenya, such as low parental education and nutrition, and high stress. Economic growth and improved access to public goods over time may have contributed to the child generation more readily living up to their genetic potential in ways that many parents were not able to, and this could help explain lower parent-child correlations and higher levels of observed upward mobility.

4 Materials and Methods

4.1 Data: Kenya Life Panel Survey

4.1.1 Subjects and Data Collection

The Kenya Life Panel Survey (KLPS) is a longitudinal panel of individuals who attended primary school in Busia, Kenya starting in 1998. The survey has been tracking these individuals for nearly 30 years, collecting data on education, health, cognitive performance, and socioeconomic status among various other domains. The cohort was originally set up for long-term evaluation of a school-based deworming program for primary school students (Miguel and Kremer 2004). As of 2018, KLPS began collecting data on the children of these respondents (within a defined range of birth years), including cognitive tests. For each respondent, KLPS surveys one to two of their children (in the relevant birth cohorts), for a total sample size of $N = 4,177$ children for whom there is cognitive data. The respondents in KLPS thus include both: (1) the individuals who attended primary school in Busia District, Kenya that participated in a NGO-implemented deworming program (conducted from 1998-2003) and (2) (some of) their biological children. The first group is referred to as the 'parents' and the second group as the 'children'. The overall sample of the parent cohort consists of $N = 10,535$ for whom there is at least one cognitive data point, and $N = 7,049$ (67%) were surveyed for the cognitive tests in the panel at least twice across the five main KLPS rounds. For $N = 5,106$ parents, there is at least one cognitive observation throughout KLPS as well as a child score. The union of the latter two criteria is $N = 7,405$ and the intersection $N = 3,785$. The focus lies on the estimating the correlation of parent scores and child scores while understanding the trajectory through multiple parent observations. This largest round for the intergenerational estimate is KLPS 5. Its sample consists of $N = 3,202$ parental cognitive scores and $N = 3,704$ child cognitive scores ($N = 502$ parents have multiple children in relevant birth cohorts in our sample).

The primary measure of cognitive skills is performance on Raven's Progressive Matrices, which have been administered to at least a subset of respondents in every round of KLPS. These tests measure visuospatial reasoning abilities, which are considered to be a subset of fluid intelligence and high performance also requires executive functioning. Table 1 summarizes the rounds, ages, and sample sizes of cognitive tests.[12] Details on the adult cognitive assessments collected in KLPS Round 5 (as part of the Harmonized Cognitive Assessment Protocol, HCAP) can be found in Gross et al. (2025). Overall, the KLPS dataset allows one to observe thousands of individuals' cognitive performance trajectories at various points in time between the (median) ages of 14 and 37 for the parent generation, as well as their children's ability, and detailed environmental, socio-economic and other measures relevant for both parent and child cognitive development.

4.1.2 Test-Retest Reliability Validation Samples

In addition to the main panel survey, two smaller test-retest validity exercises were carried out with two independent samples of $N = 102$ adults (collected during May to September in 2025) and $N = 176$ children (collected from

12. The sample sizes vary by round because some rounds intentionally only collected data for a random subset. Table 1 gives an overview of the overlapping sample size by round. KLPS Rounds 2 and 3 are often combined because respondents sampled for cognitive tests in round 3 were not sampled in round 2 (and vice versa) and because the two rounds were collected relatively close together in time.

October to November in 2025). The convenience samples were collected in both urban and rural areas and broadly mirrored the age ranges and gender breakdown of the main KLPS parent and child samples. Each respondent in this sample takes the same test twice, 15 weeks apart on average for the adults and 5 weeks apart on average for the children. These two data points allow us to compute the intraindividual instrument reliability through pairwise correlations. For adults, we find a correlation of $r = 0.77$ over a four-month interval; for children, we find a reliability correlation of $r = 0.59$ over a one-month interval. This pattern is consistent with other studies that find that reliability is generally lower at younger ages (Breit et al. 2024).

4.1.3 Co-Calibration and Standardization of Cognitive Testing Data

The Raven's matrices items were harmonized across rounds and then standardized to ensure comparability between rounds and across individuals. The harmonization is necessary as different versions of the Raven's Progressive Matrices test were administered in KLPS rounds 0, 1, 2+3, 4, 5, and in Round 5 Kids.

For the Raven's matrices administrations in KLPS rounds 2+3, 4, 5, and 5-kids, there is item-level response data. The large overlap in items across the differently-administered tests facilitates cross-round item response theory co-calibration for that subset of rounds, and the use of a common metric facilitates pooled longitudinal analysis. This metric is constructed with a separate, independent calibration sample of $N = 406$ individuals (collected in May 2025) administered the full set of Raven's matrix items. Half of the tests were administered with colored matrices and half in black and white; some of the KLPS rounds used color and some black and white and there was interest in assessing whether this affected test performanace. This convenience sample was once again gathered in both urban and rural areas, and designed to capture a wider range of ages, education levels and similar numbers of men and women.

Within this calibration sample of $N = 406$, measurement invariance was tested by sex, education, urbanicity, and by coloring of the stimuli (i.e., color versus black and white) to test whether there are differences in the measurement model for any of these characteristics. All models fit the data well at the level of scalar invariance, suggesting measurement invariance across these characteristics. These findings suggest that Raven's scores are exchangeable across age groups and study rounds, despite differences in stimulus color. Using item response theory (IRT) co-calibration methods detailed in Gross et al. (2023), we derived a common factor representing performance on the Raven's progressive matrices test, scaled to a $N(0,1)$ distribution within the $N = 406$ calibration sample. Due to sparse data in tails, we winsorize the bottom 1% and top 0.1% of IRT-equated Raven's distributions to their next lowest and next highest values, respectively.

Although the instruments have been used for KLPS rounds 0 and 1 (and thus the exact items used are known), item-level Raven's matrix data is not available, only the total final scores. To harmonize data from these two rounds with all other rounds, random hot-deck imputation is used.[13] The Raven's tests used in the calibration

13. Equipercentile ranking is not appropriate in this setting as it would require the assumption that age is independent of other characteristics. This assumption is likely violated in the context of KLPS as older students surveyed in KLPS-1 who are of the same age as younger students in KLPS-2 are "selected" based on unobservables. Specifically, the older age cohorts who were in the higher grades of primary school were likely to have been better than average students, since in that era there were high drop-out rates before students reached the higher grades. This is in contrast to the younger cohorts in the lower grades, among whome school attendance was close to universal. We thus do not feel confident mapping scores by age percentiles across cohorts.

sample are exactly the same as those used in KLPS-0 and KLPS-1. That means for all $N = 406$ individuals in the calibration sample, a total Raven's score (just like in KLPS-0 and KLPS-1) is observed as well as an IRT-equated score. This allows us to construct a distribution of IRT scores that map to a given total Raven's score. Conversely, every total Raven's score in KLPS-0 and KLPS-1 can be matched with an IRT-equated score randomly drawn (with replacement) from the calibration sample. A detailed description of these methods can be found in Appendix A.3.

For most of the analyses and figures, all harmonized scores with respect to the mean and standard deviation observed among the parent generation in KLPS-5 are standardized. This facilitates the comparison and interpretability across rounds and cohorts.

4.1.4 Complementary Expert Forecasts

The KLPS field data are complemented with expert predictons. These are collected on the Social Science Prediction Platform SSPP described in DellaVigna and Vivalt (2025). 68 Experts forecasted the intergenerational and intragenerational correlations of cognitive scores. Exact details on age range, country, time period, and type of cognitive tests are provided. Demographic data on experts include their prior experience in the field, field of study and views on social mobility. The median forecasts for Raven's matrices are 0.6, 0.4, and 0.3 for intraindividual correlations, intergenerational correlations with parents at adult age, and intergenerational correlations with parents at child age respectively. Among the experts, 42 are economists and 23 are non-economists (psychology, sociology, political science, and others), but forecasts do not vary significantly by prior field of study.

4.2 Data Analysis

4.2.1 Pairwise Correlations

The empirical analysis focuses on documenting the strength and direction between cognitive performance measured at two instances. This involves either correlating cognitive scores longitudinally (a "younger" score against an "older" score) within the main parent cohort, or intergenerationally (a younger generation's score against an older generation's score) across parent-child pairs. Given the inherent dependency structure of the data, pairwise correlation coefficients are computed using both Spearman and Pearson's correlation. Spearman rank correlations are the preferred specification to compare the relative position in the large KLPS sample rather than changes in absolute values. This coefficient is defined as the covariance of the two cognitive score vectors, X (the 'younger' point in time) and Y (the 'older' point in time), divided by the product of their respective standard deviations (s_X and s_Y):

$$r_{raw} = \frac{Cov(\text{rank}[X], \text{rank}[Y])}{s_{\text{rank}[X]} s_{\text{rank}[Y]}}$$

Finally, t-tests were used to statistically assess whether two distinct correlation coefficients were significantly different from each other.

4.2.2 Correction for Measurement Error

Cognitive tests are imperfect signals of ability that are measured with noise. For example, an individual with the same underlying ability may perform worse on a given day due to poor sleep or because of not having eaten a proper breakfast beforehand, or due to being in a bad mood. To understand—and later correct for—the reliability of the instrument, we conduct a test-retest exercise with independent samples of individuals from urban and rural Kenya, as described above. As reported above, among adults, Raven's scores are correlated at r=0.77 over a four-month interval, and for children, the reliability correlation is r=0.59 over a one-month interval.

These reliability estimates allow us to adjust the estimated correlations with Spearman's correction for attenuation bias (Spearman 1987). In the formula below, $r_{XY,\,raw}$ denotes the observed correlation between scores in rounds X and Y, and ρ_X and ρ_Y denote the test reliabilities for the appropriate age groups of rounds X and Y, respectively. The reliability–adjusted correlations are then computed as:

$$r_{adj} = \frac{r_{XY\ raw}}{\sqrt{\rho_X \rho_Y}}$$

The resulting values are truncated at the interval $[-1, 1]$. For adults, we use $\rho_X \times \rho_Y = 0.77^2$ in the denominator. For correlations between children and adults–whether that is within or across generations–we divide by $\rho_X \times \rho_Y = 0.77 \times 0.59$. The adjusted correlations therefore represent estimates of the correlation between the underlying latent cognitive ability measures, net of classical measurement error.

4.2.3 Ordinary Least Squares Regression

Ordinary Least Squares (OLS) regressions are used relating children's cognitive outcomes to parental cognitive ability and socioeconomic background characteristics. The dependent variable is the child Raven's scores, which are harmonized across rounds and generations and normalized at the level of KLPS-5 parent scores (as described above). The unit of observation is child c of parent p. Since some parents have multiple children, the analysis uses robust standard errors that are clustered at the parent level to allow for correlations across siblings.

The baseline specification presented in Panel A in Table 2 columns 1-3 is:

$$\text{Child Ravens}_{cp} = \gamma \text{Parent Ravens}_p + X'_{cp}\beta + \varepsilon_{cp}$$

where Parent Raven's$_p$ is the measure of the parents' cognitive ability and the coefficient γ captures its effect on child cognition, while X_{cp} is the vector of socioeconomic status proxies included as covariates.

The interacted specification presented in columns 4-6 enables testing for heterogeneity—namely, whether the socioeconomic proxies differentially moderate the effect of parent cognitive ability on child ability—and is as follows:

$$\text{Child Ravens}_c = \gamma \text{Parent Ravens}_p + X'_{cp}\beta + (\text{Parent Ravens}_p \times X_{cp})'\delta + \varepsilon_{cp}$$

where the terms are defined as above and δ captures how the parent–child cognitive association varies with the socio-economic status proxies.

4.2.4 Machine Learning (ML) Approaches

The analysis is then extended to more thoroughly estimate Heterogeneous Treatment Effects (HTE), where the goal is to identify which covariates moderate the transmission of cognition from parent to child.

Random Forests. We employ Causal Forest Debiased Machine Learning (DML) in order to detect complex, non-linear interactions that may affect the relationship between parents' and children's cognitive abilities. In particular, we use the algorithm by Athey et al. (2019), and define the "Treatment" T variable as the parent's cognitive score. The outcome variable Y is the children's Raven's scores. Machine learning allows one to identify which demographic characteristics or other environmental features affect the treatment effect.

The Causal Forest operates in three phases. First, the algorithm predicts child Raven's scores Y and parent Raven scores T using only the set of 101 covariates X. It then computes the residuals ($\tilde{Y}$ and $\tilde{T}$). This step cleans the data of confounding "main effects", ideally isolating the desired exogenous variation. Second, a forest is grown using these residuals. To do so, the generalized random forest approach that we employ uses a heterogeneity-based splitting criterion. It searches for splits in the covariates X that maximize the difference in the treatment effect between the resulting child nodes. Hence it groups children into "leaves" where the transmission of cognition is most similar. Third, using "honest" trees (where the data used to determine the splits is separate from the data used to estimate the effects) and a local weighting scheme, the generalized random forest provides robust, unbiased conditional average treatment effects (CATE) estimates for each observation. The results of two example analyses are visualized using a SHAP (SHapley Additive exPlanations) values plot in Figure A.1 in Appendix A.2. For two runs with arbitary random seeds, the plots decompose exactly how much each covariate shifted an individual's estimated treatment effect away from the population average. Given the noise induced by random seeds, we estimate causal forests with 100 different random seeds. We then count the number of times a variable is ranked to be among the top 20 most important predictors as shown in Table 2 and report the modal sign along with its occurence as explained in greater detail in Appendix A.2.

LASSO. As a further robustness check, we also use a debiased Lasso approach to select relevant variables that predict the levels of children's cognitive abilities as well as variables that can explain the cognitive correlation between parents and children. Standard Lasso methods shrink coefficients toward zero for variable selection, which introduces bias and invalidates standard errors and p-values. Debiased Lasso corrects for this shrinkage post-selection, allowing one to report valid 95% confidence intervals and p-values in a high-dimensional setting.

The estimation is essentially identical to the interacted OLS specification presented above, except that the feature space (or number of covariates) considered in the vector X is far larger. By interacting X (with approximately 100 variables) with the treatment variable (the parent Ravens score), the feature space doubles. The Debiased Lasso evaluates all covariates and their interactions simultaneously, isolating the main effects on levels as well as the interactions. Results are reported in Appendix A.2.

4.2.5 Meta Analysis

To place the Kenyan estimate in global context, a meta-analysis was conducted. Scopus searches with the following keywords were conducted, and the output was reviewed by two researchers independently. In additiona, we conduct "forward searches" and screen studies that cite an initial subset of selected papers as well as papers cited in those studies. Out of this large sample, papers that were believed to capture intergenerational correlations were included. Afterwards, the high-level selected studies were reviewed in detail and the sample was restricted to those that include comparable estimates of intergenerational correlations. Afterwards, selection criteria were applied (such as peer-reviewed or sample sizes larger than $> N = 500$) to construct the samples for the respective figures.

Both main text figures only include peer-reviewed studies. The appendix repeats the same exercise including pre-prints. The forest plot in Panel A of Figure 2 was constructed with the estimates from relevant peer-reviewed studies with large samples of $N > 500$. Standard errors in the forest plot were constructed using Fisher's z scores, and 95% confidence intervals. Study estimates are sorted by GDP per capita using the World Bank database (World Bank 2026). The bubble plot in Panel B of Figure 2 plots log GDP per capita for a given study country on the x-axis and the corresponding correlation estimate on the y-axis. Bubble indicate the sample size of a given study, and studies of all sample sizes were included in this plot. A random effects regression using inverse weighting is fitted to the data. Using random effects allows for heterogeneity across studies–which the conceptual framework inspired by the Scarr-Rowe hypothesis would predict–and the inverse weighting assigns more weight to large-scale studies as these estimates are likely more precise.

5 Exhibits

5.1 Tables

Table 1: KLPS Cognitive Scores, Sample Characteristics, and Correlations.

Panel A: Data Collection and Sample Characteristics

Sample	Data Collection Year	Age Range (10^{th} to 90^{th})	Median Age	Sample Size
KLPS-0	2000	11–16	14	1,377
KLPS-1	2003–2005	15–22	19	1,198
KLPS-2	2007–2009	19–26	22	5,099
KLPS-3	2011–2014	22–29	25	3032
KLPS-4	2018–2021	30–37	33	1,455
KLPS-5	2023	34–41	37	5,752
KLPS-5-Kids	2024–2025	8–13	11	4,177

Panel B: Intergenerational Pairwise Correlations

Pair	N	$\text{Pearson}_{\text{raw}}$	$\text{Spearman}_{\text{raw}}$	$\text{Pearson}_{\text{adj}}$	$\text{Spearman}_{\text{adj}}$
Parents (at adult age) & their children	3,704	0.141	0.141	0.209	0.210
Parents (at child age) & their children	410	0.154	0.131	0.262	0.224

Panel C: Intraindividul Pairwise Ranked Correlations across Lifecourse

Variable 1	Variable 2	r_{raw}	r_{adj}	N	p-value
KLPS-4	KLPS-5	0.537	0.698	1445	0.000
KLPS-2/3	KLPS-5	0.453	0.589	6049	0.000
KLPS-1	KLPS-5	0.588	0.764	1035	0.000
KLPS-0	KLPS-5	0.405	0.602	672	0.000
KLPS-2/3	KLPS-4	0.372	0.483	1145	0.000
KLPS-1	KLPS-4	0.473	0.614	228	0.000
KLPS-0	KLPS-4	0.384	0.572	132	0.000
KLPS-1	KLPS-2/3	0.507	0.659	1263	0.000
KLPS-0	KLPS-2/3	0.371	0.551	802	0.000
KLPS-0	KLPS-1	0.617	0.918	180	0.000

Notes: **Panel A** summarizes the sample sizes and age distribution for a given round of cognitive testing. KLPS-0 to 5 refer to the main "first respondent" sample. Column 2 describes the 10^{th} to 90^{th} percentile of the age distribution of that round. Column 3 lists the median respondent age. Column 4 gives the sample size of observations for whom cognitive tests were conducted in a given round. In Rounds 0, 1, 3, and 4 testing was only comissioned for a random subset of the sample. Because not everyone is observed in every round, sample sizes for the pairwise correlations will be lower. **Panel B** reports sample size, raw pairwise Pearson's and Spearman's correlations, and adjusted pairwise correlations of harmonized cognitive test scores between parents and their children. If a parent has multiple children, we collapse the children and correlate them with the mean of both of their children. The first row correlates parents as adults, as captured in KLPS-5 in 2025, with their children's performance in 2025 at child age. The second row correlates parents's scores when they were children, captured in 2000, with their respective children's performance in 2025 at child age. Pearson and Spearman columns give the unadjusted correlations between the two rounds. Columns with the suffix $_{adj}$ adjust for measurement error following Spearman (1904) as described in Section 4. An observation is a parent-child pair, identified by the unique child. If a parent has multiple children, the parent is included multiple times. **Panel C** reports pairwise correlations of harmonized cognitive test scores for parents across rounds of testing. The unit of observation is a parent respondent. Rounds 2 and 3 are pooled because they sampled mutually exclusive subsets of respondents and were conducted close together in time. Column r_{raw} shows the unadjusted correlation between the two rounds listed in Columns 1 and 2. Column r_{adj} is the main column of interest and adjusts for measurement error following Spearman (1904) as described in Section 4. All correlations are statistically significant, as indicated by the p-values in the final column.

Table 2: Heterogeneity in Intergenerational Transmission of Cognitive Skills

Panel A: Theoretically-Motivated Heterogeneity in Transmission using Linear Regression (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	RS Kids	**RS Kids**	**RS Kids**	**RS Kids**	**RS Kids**	**RS Kids**
Urban	0.354***		0.340***	0.341***	0.339***	0.340***
	(0.034)		(0.033)	(0.033)	(0.033)	(0.033)
Grandparent ed (demeaned)	0.030***		0.025***	0.026***	0.025***	0.025***
	(0.005)		(0.005)	(0.005)	(0.005)	(0.005)
RS Parent (KLPS5)		0.165***	0.144***	0.161***	0.147***	0.168***
		(0.016)	(0.016)	(0.019)	(0.016)	(0.020)
Urban × RS Parent				-0.042		-0.052
				(0.033)		(0.033)
RS Parent × Grandparent ed (dem.)					0.010**	0.011**
					(0.005)	(0.005)
Constant	-0.594***	-0.479***	-0.588***	-0.586***	-0.591***	-0.589***
	(0.019)	(0.016)	(0.019)	(0.019)	(0.019)	(0.019)
N	3,543	3,704	3,505	3,505	3,505	3,505
R^2	0.152	0.133	0.173	0.173	0.174	0.175

Panel B: Data-Driven Selection of Predictors of Heterogeneity in Transmission using Machine Learning (GRF)

	(1)	(2)	(3)
Variable	**Top 20 Appearance**	**Modal Sign**	**Sign Occurrence**
KLPS4 Kids: Educational investment index	100	ambiguous	88
Child age	100	ambiguous	56
Parent's hours worked last week	100	(+)	86
Parent's interpersonal index	100	ambiguous	60
Parent's log wage	100	(−)	99
Neighborhood cohesion score	100	(−)	100
Parent's routine/manual occupation index	100	(−)	92
Parent's ongoing stress index	99	(−)	99
Parent's social support index	99	(−)	99
Grandmother education	99	(+)	99
Neighborhood disorder index	96	(−)	96
Parent's pro-social behavior index	92	ambiguous	79
Parent's height (std by gender)	85	(+)	50
Parent respondent gender: female	84	(+)	84
Log household consumption (KLPS4)	84	ambiguous	68

Notes: **Panel A** reports the regression coefficients of a theoretically-driven prediction exercise of children's Raven's scores with robust standard errors in parentheses in an Ordinary Least Squares (OLS) model. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The outcome variable is children's harmonized Raven's scores (RS Kids) from KLPS Round 5 Kids. Urban is a binary indicator whether the KLPS respondent grew up in an urban area. Grandparent ed (demeaned) refers to the mean of maternal and paternal years of schooling of the parents of the main respondent (i.e. one set of grandparents of the children), demeaned at the sample mean. RS Parent (KLPS5) is the harmonized and standardized Raven's score of the parent measured in Round 5. All regression include child age x gender fixed effects. Raven's Scores are harmonized and co-calibrated scores across rounds an Columns and standardized to a mean of zero and standard deviation of one. Coefficients can be interpreted in standard deviation units of latent cognitive ability. (1) and (2) show the main effects of environmental and parental cognitive variables separately. Columns (3)–(6) include both, adding interaction terms sequentially. The interaction Urban × RS Parent tests whether urban upbringing mediates intergenerational cognitive transmission. The interaction RS Parent × Grandparent ed tests whether grandparental education mediates transmission. Sample sizes vary across columns due to missing values on urban status. **Panel B** reports data-driven variable selection to predict treatment effect heterogeneity using a Generalized Random Forest (GRF) causal forest analysis and a set of 101 features. Column 1 reports the number of times that an estimator is among the top 20 predictors of treatment effect heterogeneity across 100 runs with 100 random seeds. Variables appearing more frequently in the top 20 are more robust predictors of treatment-effect heterogeneity. We report any variable that is among the top 15 more than 80% of the runs. Column 2 reports the modal sign across all runs when a variable was among the top 20 predictors. Column 3 reports the modal number of times this sign occured out of all top 20 runs.

5.2 Figures

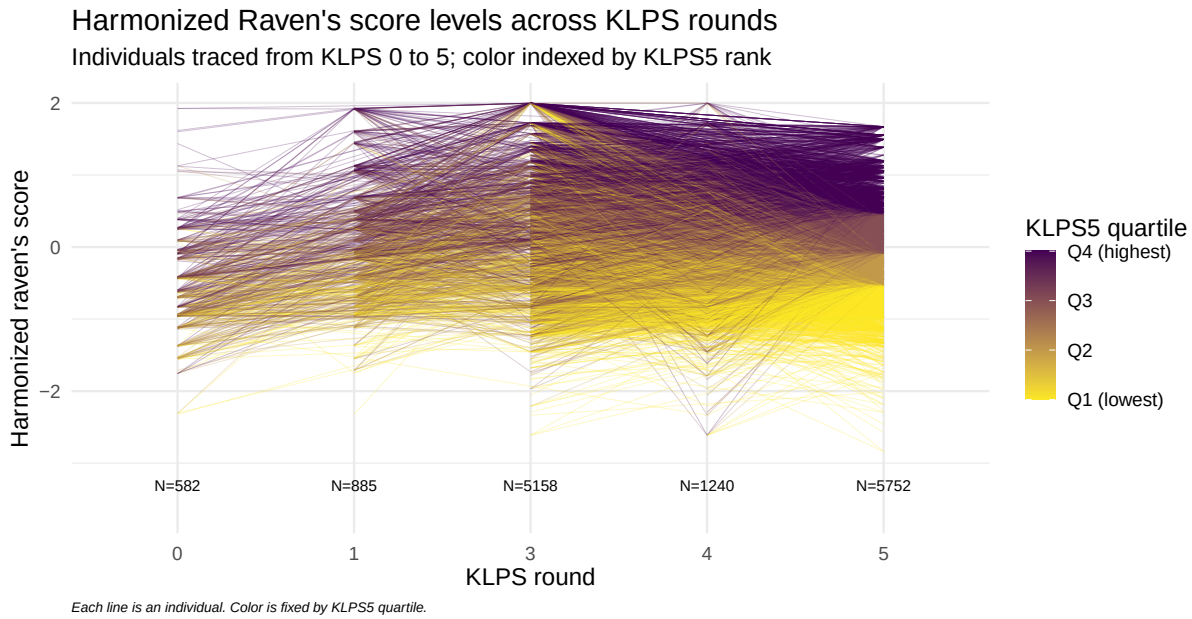
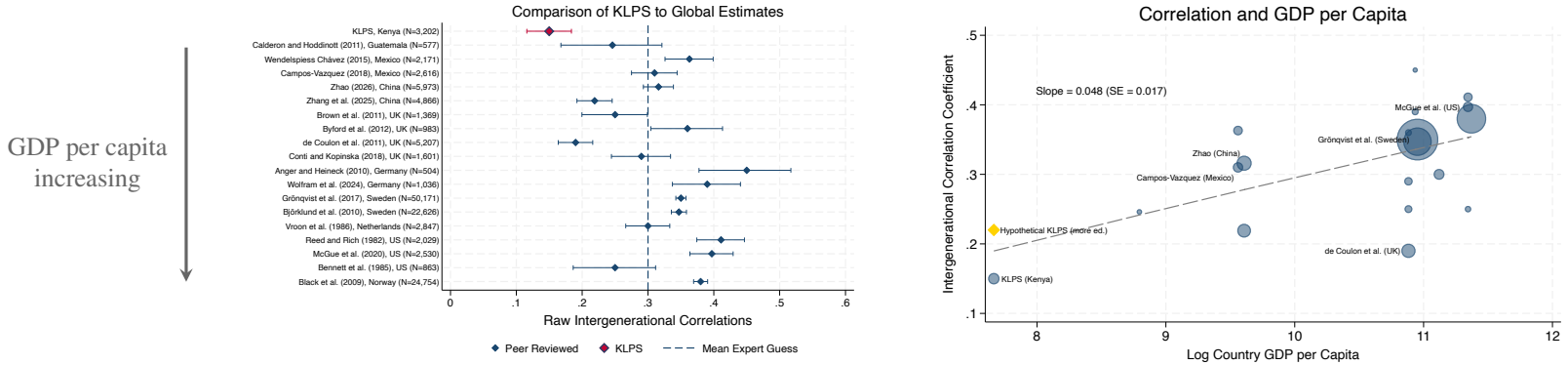


Figure 1: Evolution of Harmonized Cognitive Skills over the Life Course

Notes: This spaghetti plot traces harmonized cognitive scores among KLPS respondents from the main cohort. Each line represents an individual KLPS respondent. The y-axis captures cognitive ability. KLPS rounds are on the x-axis, starting with KLPS-0 where the median age is 14 up until KLPS-5 where the median age is 37. The color gradient is indexed to KLPS respondents' Raven's test quartiles in Round 5, with lighter colors indicating lower cognitive ability and deeper purples indicating higher ability. Persistent coloring across Rounds 1 to 5 reflects intrapersonal cognitive stability over time.



(a) Panel A

(b) Panel B

Figure 2: Correlation Estimates in Global Context

Notes: **Panel A** compares our intergenerational estimate from Kenya between parents (adult age) and children (child age) in KLPS with those found in other peer-reviewed studies. Studies are sorted by GDP per capita of the country. Sample sizes of the studies are indicated in parentheses, and we only include studies with more than 500 observations. The dashed line indicates the expert guess of the intergenerational correlation elicited through the Social Science Prediction Platform (SSPP) in 2024. The guess was obtained by asking experts to predict correlations for exactly this setting and these parent-child pairs in Kenya.

Panel B plots study-level intergenerational correlation estimates against log GDP per capita among peer-reviewed papers. Each marker represents an individual study estimate, with circle area proportional to study sample size (N). The dashed line reflects predicted values from an inverse-variance-weighted random-effects meta-regression model estimated via restricted maximum likelihood (REML) using Fisher's z transformation. The RE slope coefficient is reported in parentheses. The yellow diamond indicates a hypothetical KLPS estimate if grandparent education in Kenya were 7 years higher on average as in highly-educated, wealthy countries.

References

Alesina, Alberto, Sebastian Hohmann, Stelios Michalopoulos, and Elias Papaioannou. 2021. "Intergenerational mobility in Africa." *Econometrica* 89 (1): 1–35.

Almond, Douglas, Janet Currie, and Valentina Duque. 2018. "Childhood circumstances and adult outcomes: Act II." *Journal of Economic Literature* 56 (4): 1360–1446.

Anger, Silke, and Guido Heineck. 2010. "Do smart parents raise smart children? The intergenerational transmission of cognitive abilities" [in en]. *Journal of Population Economics* 23, no. 3 (June): 1105–1132. ISSN: 1432-1475, accessed March 2, 2026. https://doi.org/10.1007/s00148-009-0298-8. https://doi.org/10.1007/s00148-009-0298-8.

Athey, Susan, Julie Tibshirani, and Stefan Wager. 2019. "Generalized random forests."

Bates, Timothy C, Narelle K Hansell, Nicholas G Martin, and Margaret J Wright. 2016. "When does socioeconomic status (SES) moderate the heritability of IQ? No evidence for g× SES interaction for IQ in a representative sample of 1176 Australian adolescent twin pairs." *Intelligence* 56:10–15.

Björklund, Anders, Karin Hederos Eriksson, and Markus Jäntti. 2010. "IQ and family background : Are associations strong or weak?" [In eng]. Is peer reviewed, *B.E. Journal of Economic Analysis and Policy* 10 (1). ISSN: 1555-0494. https://doi.org/10.2202/1935-1682.2349.

Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes. 2009. "Like father, like son? A note on the intergenerational transmission of IQ scores." *Economics Letters* 105, no. 1 (October): 138–140. ISSN: 0165-1765, accessed March 2, 2026. https://doi.org/10.1016/j.econlet.2009.06.022. https://www.sciencedirect.com/science/article/pii/S0165176509002286.

Boissiere, Maurice, John B Knight, and Richard H Sabot. 1985. "Earnings, schooling, ability, and cognitive skills." *The American Economic Review* 75 (5): 1016–1030.

Breit, Moritz, Vsevolod Scherrer, Elliot M Tucker-Drob, and Franzis Preckel. 2024. "The stability of cognitive abilities: A meta-analytic review of longitudinal studies." *Psychological Bulletin* 150 (4): 399.

Bronfenbrenner, Urie, and Stephen J Ceci. 1994. "Nature-nurture reconceptualized in developmental perspective: a bioecological model." *Psychological review* 101 (4): 568.

Brown, Sarah, Steven McIntosh, and Karl Taylor. 2009. *Following in Your Parents' Footsteps? Empirical Analysis of Matched Parent-Offspring Test Scores* [in en]. SSRN Scholarly Paper. Rochester, NY, March. Accessed March 2, 2026. https://papers.ssrn.com/abstract=1351150.

Burke, Henry R. 1972. "Raven's Progressive Matrices: Validity, reliability, and norms." *The Journal of Psychology* 82 (2): 253–257.

Byambaa, Uyanga, Edward Miguel, Michael W Walker, and Samuel Zicheng Wang. 2025. *Beyond Education and Occupation: Unpacking the Large Gender Wage Gap in Kenya.* Working Paper, Working Paper Series 34375. National Bureau of Economic Research, October. https://doi.org/10.3386/w34375. http://www.nber.org/papers/w34375.

Byford, M, D Kuh, and M Richards. 2012. "Parenting practices and intergenerational associations in cognitive ability." *International Journal of Epidemiology* 41, no. 1 (February): 263–272. ISSN: 0300-5771, accessed March 2, 2026. https://doi.org/10.1093/ije/dyr188. https://pmc.ncbi.nlm.nih.gov/articles/PMC3304524/.

Calderon, Maria Cecilia, and John Hoddinott. 2010. "The inter-generational transmission of cognitive abilities in Guatemala." *Available at SSRN 1653410.*

Ceci, Stephen J, and Wendy M Williams. 1997. "Schooling, intelligence, and income." *American psychologist* 52 (10): 1051.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where is the land of opportunity? The geography of intergenerational mobility in the United States." *The quarterly journal of economics* 129 (4): 1553–1623.

Cockburn, Allegra, Arindam Nandi, Subha Mani, Jere Behrman, and Ramanan Laxminarayan. 2025. "Intergenerational Mobility in Cognitive Skills: New Evidence from India." *Available at SSRN 5253148.*

Cockburn, Allegra, Arindam Nandi, Subha Mani, Jere Behrman, and Ramanan Laxminarayan. 2025. *Intergenerational Mobility in Cognitive Skills: New Evidence from India* [in en]. SSRN Scholarly Paper. Rochester, NY, May. Accessed March 2, 2026. https://doi.org/10.2139/ssrn.5253148. https://papers.ssrn.com/abstract=5253148.

Deary, Ian J, and Caroline E Brett. 2015. "Predicting and retrodicting intelligence between childhood and old age in the 6-Day Sample of the Scottish Mental Survey 1947." *Intelligence* 50:1–9.

Deary, Ian J, Steve Strand, Pauline Smith, and Cres Fernandes. 2007. "Intelligence and educational achievement." *Intelligence* 35 (1): 13–21.

Deary, Ian J, Lawrence J Whalley, Helen Lemmon, John R Crawford, and John M Starr. 2000. "The stability of individual differences in mental ability from childhood to old age: Follow-up of the 1932 Scottish Mental Survey." *Intelligence* 28 (1): 49–55.

DellaVigna, Stefano, and Eva Vivalt. 2025. *Forecasting Social Science: Evidence from 100 Projects.* Working Paper, Working Paper Series 34493. National Bureau of Economic Research, November. https://doi.org/10.3386/w34493. http://www.nber.org/papers/w34493.

Duncan, Greg J, W Jean Yeung, Jeanne Brooks-Gunn, and Judith R Smith. 1998. "How much does childhood poverty affect the life chances of children?" *American sociological review,* 406–423.

Dupont, Cathérine, D Randall Armant, and Carol A Brenner. 2009. "Epigenetics: definition, mechanisms and clinical perspective." In *Seminars in reproductive medicine,* 27:351–357. 05. © Thieme Medical Publishers.

Gauvain, Mary, and Robert L Munroe. 2009. "Contributions of societal modernity to cognitive development: A comparison of four cultures." *Child Development* 80 (6): 1628–1642.

Gottfredson, Linda S, and Ian J Deary. 2004. "Intelligence predicts health and longevity, but why?" *Current Directions in Psychological Science* 13 (1): 1–4.

Gottschling, Juliana, Elisabeth Hahn, CR Beam, Frank M Spinath, Sarah Carroll, and Erik Turkheimer. 2019. "Socioeconomic status amplifies genetic effects in middle childhood in a large German twin sample." *Intelligence* 72:20–27.

Graetz, Nicholas, Joseph Friedman, Aaron Osgood-Zimmerman, Roy Burstein, Molly H Biehl, Chloe Shields, Jonathan F Mosser, Daniel C Casey, Aniruddha Deshpande, Lucas Earl, et al. 2018. "Mapping local variation in educational attainment across Africa." *Nature* 555 (7694): 48–53.

Greenfield, Patricia M. 2016. "Social change, cultural evolution, and human development." *Current Opinion in Psychology* 8:84–92.

Grönqvist, Erik, Björn Öckert, and Jonas Vlachos. 2017. "The Intergenerational Transmission of Cognitive and Noncognitive Abilities" [in en]. *Journal of Human Resources* 52, no. 4 (October): 887–918. ISSN: 0022-166X, 1548-8004, accessed March 2, 2026. https://doi.org/10.3368/jhr.52.4.0115-6882R1. https://jhr.uwpress.org/content/52/4/887.

Gross, Alden L, Madeline Duhon, Eric Ochieng, Jean N Ikanga, William H Dow, Jinkook Lee, Michael W Walker, Michelle Layvant, Anthony Ngugi, Joshua R Ehrlich, et al. 2025. "Midlife cognitive testing in Africa: validity of the harmonised cognitive assessment protocol in the Kenya life panel survey." *BMJ open* 15 (8): e096619.

Gross, Alden L, Chihua Li, Emily M Briceño, Miguel Arce Rentería, Richard N Jones, Kenneth M Langa, Jennifer J Manly, Emma Nichols, David Weir, Rebeca Wong, et al. 2023. "Harmonisation of later-life cognitive function across national contexts: results from the Harmonized Cognitive Assessment Protocols." *The lancet Healthy longevity* 4 (10): e573–e583.

Hanushek, Eric, Babs Jacobs, Guido Schwerdt, Rolf Van Der Velden, Stan Vermeulen, and Simon Wiederhold. 2021. *The Intergenerational Transmission of Cognitive Skills: An Investigation of the Causal Impact of Families on Student Outcomes* [in en]. Technical report w29450. Cambridge, MA: National Bureau of Economic Research, November. Accessed March 2, 2026. https://doi.org/10.3386/w29450. http://www.nber.org/papers/w29450.pdf.

Harden, K Paige, Eric Turkheimer, and John C Loehlin. 2007. "Genotype by environment interaction in adolescents' cognitive aptitude." *Behavior genetics* 37 (2): 273–283.

Hsu, Eric, Edward Miguel, Eric Ochieng, and Michael Walker. 2026. "Cohort profile: Kenya Life Panel Survey."

Huh, Jimi, Thalida Em Arpawong, Tara L Gruenewald, Gwenith G Fisher, Carol A Prescott, Jennifer J Manly, Dominika Seblova, Ellen E Walters, and Margaret Gatz. 2024. "General cognitive ability in high school, attained education, occupational complexity, and dementia risk." *Alzheimer's & Dementia* 20 (4): 2662–2669.

Keller, Heidi. 2017. "Culture and development: A systematic relationship." *Perspectives on psychological science* 12 (5): 833–840.

King, Wilson, Edward Miguel, and Michael W Walker. 2026. *Why Does Height Pay? Evidence from the Kenya Life Panel Survey.* Working Paper, Working Paper Series 34769. National Bureau of Economic Research, January. https://doi.org/10.3386/w34769. http://www.nber.org/papers/w34769.

Knopik, Valerie S, Jenae M Neiderhiser, John C DeFries, and Robert Plomin. 2017. *Behavioral genetics.* Worth Publishers, Macmillan Learning New York.

Kong, Augustine, Gudmar Thorleifsson, Michael L Frigge, Bjarni J Vilhjalmsson, Alexander I Young, Thorgeir E Thorgeirsson, Stefania Benonisdottir, Asmundur Oddsson, Bjarni V Halldorsson, Gisli Masson, et al. 2018. "The nature of nurture: Effects of parental genotypes." *Science* 359 (6374): 424–428.

Laajaj, Rachid, and Karen Macours. 2021. "Measuring skills in developing countries." *Journal of Human resources* 56 (4): 1254–1295.

Miguel, Edward, and Michael Kremer. 2004. "Worms: identifying impacts on education and health in the presence of treatment externalities." *Econometrica* 72 (1): 159–217.

Munoz, Ercio, and Roy Van der Weide. 2025. "Intergenerational Income Mobility around the World." *Development Research.*

Nichols, Emma, Karla Renata Flores Romero, Sirena Gutierrez, Ah-Reum Lee, Yulin Yang, Jinkook Lee, and Jacqueline M Torres. 2026. "Mechanistic pathways between adult child education and late-life parental health outcomes: cross-national comparisons across the US, Mexico, and India." *Social Science & Medicine,* 119232.

Plomin, Robert, and Ian J Deary. 2015. "Genetics and intelligence differences: five special findings." *Molecular psychiatry* 20 (1): 98–108.

Plomin, Robert, and Frank M Spinath. 2004. "Intelligence: genetics, genes, and genomics." *Journal of personality and social psychology* 86 (1): 112.

Poulton, Antoinette, Kathleen Rutherford, Sarah Boothe, Madeleine Brygel, Alice Crole, Gezelle Dali, Loren Richard Bruns Jr, Richard O Sinnott, and Robert Hester. 2022. "Evaluating untimed and timed abridged versions of Raven's Advanced Progressive Matrices." *Journal of Clinical and Experimental Neuropsychology* 44 (1): 73–84.

Raven, John. 2000. "The Raven's progressive matrices: change and stability over culture and time." *Cognitive psychology* 41 (1): 1–48.

Reynolds, Chandra A, Laura A Baker, and Nancy L Pedersen. 2000. "Multivariate models of mixed assortment: phenotypic assortment and social homogamy for education and fluid ability." *Behavior genetics* 30 (6): 455–476.

Ritchie, Hannah. 2026a. "Health." Https://ourworldindata.org/profile/health/kenya, *Our World in Data,* accessed August 7, 2026.

———. 2026b. "Population and Demography." Https://ourworldindata.org/profile/population-demography/kenya, *Our World in Data,* accessed August 7, 2026.

Scarr, Sandra, and Kathleen McCartney. 1983. "How people make their own environments: A theory of genotype → environment effects." *Child development,* 424–435.

Spearman, Charles. 1987. "Reprint: The proof and measurement of association between two things." *The American journal of psychology* 100 (3/4): 441–471.

Tucker-Drob, Elliot M, and Timothy C Bates. 2016. "Large cross-national differences in gene× socioeconomic status interaction on intelligence." *Psychological science* 27 (2): 138–149.

Tucker-Drob, Elliot M, Daniel A Briley, and K Paige Harden. 2013. "Genetic and environmental influences on cognition across development and context." *Current directions in psychological science* 22 (5): 349–355.

Turkheimer, Eric. 2000. "Three laws of behavior genetics and what they mean." *Current directions in psychological science* 9 (5): 160–164.

Turkheimer, Eric, Christopher E Beam, and Deborah W Davis. 2015. "The Scarr-Rowe interaction in complete seven-year WISC data from the Louisville twin study: Preliminary report." *Behavior genetics* 45 (6): 635–639.

Turkheimer, Eric, Andreana Haley, Mary Waldron, Brian d'Onofrio, and Irving I Gottesman. 2003. "Socioeconomic status modifies heritability of IQ in young children." *Psychological science* 14 (6): 623–628.

Van der Weide, Roy, Christoph Lakner, Daniel Gerszon Mahler, Ambar Narayan, and Rakesh Ramasubbaiah. 2021. *Intergenerational mobility around the world.* World Bank Washington, DC.

Watkins, Maria P, and William Meredith. 1981. "Spouse similarity in newlyweds with respect to specific cognitive abilities, socioeconomic status, and education." *Behavior Genetics* 11 (1): 1–21.

Webb, Duncan. 2024. "Critical periods in cognitive and socioemotional development: evidence from weather shocks in Indonesia." *The Economic Journal* 134 (660): 1637–1665.

World Bank. 2026. *World Development Indicators.* July 2026 update. Accessed: 2026-08-07. Accessed August 7, 2026. https://databank.worldbank.org/source/world-development-indicators.

Zhang, Zheyuan, Hui Xu, Ruilin Liu, and Zhong Zhao. 2025. "Free education and the intergenerational transmission of cognitive skills in rural China." *Journal of Population Economics* 38 (1): 29.

A Supplementary Analyses

A.1 Relevance of Raven's Matrices

Raven's matrices (2000) have been shown to capture visuospatial reasoning, a measure of fluid intelligence. They also hold predictive power for relevant economic measures such as earnings and educational attainment. Performance on these matrices is also correlated with performance on other cognitivie tests.

In our KLPS sample, we find that Raven's matrices are significant predictors of educational attainment (even after controlling for parents' schooling) and of earnings (even after controlling for educational attainment) (Table A.1.

In the children in our sample, we find that performance on Raven's matrices is strongly correlated with other cognitive tests (animal naming task, digit span task) and this relation is robust to including measures of parental income (Table A.2.

A.2 Machine Learning

To identify sources of heterogeneity in the relationship of parents' and children's cognitive scores, we use machine learning methods for a data-driven approach to select variables that can moderate intergenerational transmission.

Specifically, we predict children's Raven's scores as a function of parents' Raven scores and multiple characteristics using a generalized random forest. We define parents' scores to be the treatment variable, which allows us to use a generalized random forest to estimate how these other variables moderate the relationship between parents' and children's cognitive scores. The 101 characteristics are summarized in Table A.4.

Figure A.1 plots the Shapley Additive Explanations (SHAP) values from two random forests with two arbirary random seeds. The SHAP values decompose exactly how much each covariate shifted an individual's estimated treatment effect away from the population average. The features selected by this specific random seed are ranked on the y-axis by their overall global importance (mean absolute SHAP value). By looking at the horizontal distribution of the points and their color (red = high feature value, blue = low feature value), directionality can be determined. For example, if red dots cluster on the right side (positive SHAP values), it indicates that a high value of that covariate increases the treatment effect i.e., the parent-to-child transmission.

Since random forests can differ as a function of their random seeds, we grow 100 different random forests with different seeds. Panel B of Table 2 lists the frequencies with which a given variable was selected to be among the 20 most relevant out of the 101 explanatory interaction variables. The second column lists the modal sign across all 100 runs along with the frequency of this sign. To determine the sign, we rank-correlate the CATE with the feature value and use a cut-off of $p = 0.05$ for positive, negative, or ambiguous effects.

We additionally test the robustness of the generalized random forest with Debiased LASSO. The Debiased Lasso evaluates all covariates and their interactions simultaneously, isolating (1) main effects, i.e., the direct impact of baseline covariates and (2) interactions, i.e., the variables that significantly moderate the parent-to-child cognition transmission. One drawback of Debiased Lasso is that it assumes linear relationships. We report the Lasso coefficients in Appendix Table A.3.

A.3 Hot Deck Imputation and Bootstrapping

A.3.1 Approach

Since we do not have item level response data available for KLPS-0 and KLPS-1 we use the calibration sample, hot deck imputation, and bootstrapping to make the data from the earlier rounds comparable. The instrument used in the calibration study for IRT-equating contained the same full (36-items) Ravens Progressive Matrices as were used in KLPS-0 and KLPS-1. Having an identical test instrument implies that raw sum scores will be directly comparable between KLPS-0, KLPS-1, and the calibration sample. Hence the calibration sample can also be used to assign IRT-equated scores to each summed up total Raven's score observation from KLPS-0 and KLPS-1 using hot deck imputation. Bootstrap resampling further facilitates the characterization of the uncertainty introduced by the mapping procedure.

A.3.2 Data

Prior to assigning the donated IRT scores through hot deck imputation, total raw Raven's scores (`ravsum`) are winsorized at a floor of 5 and a ceiling of 31. Any scores below 5 are recoded to 5, and scores in the range of 31 to 35 are recoded to 31. Winsorizing ensures that every raw score value in KLPS-0 and 1 has a corresponding donor pool in the calibration sample as the sample size, and thus also the frequency of outliers, of the donor pool is smaller. Table A.8 reports the number of available donors and the distribution of IRT scores within each raw-score stratum of the calibration sample.

A.3.3 Implementation of Hot-Deck Imputation

The calibration sample supplied and IRT-equated value for every total sum of a Raven's test. These IRT-equated values serve as "donors". For each distinct value s of the clipped raw score:

1. We identify all calibration-sample observations with $\texttt{ravsum} = s$. This constitutes the donor pool $\mathscr{D}_s$.
2. For each KLPS-0 or KLPS-1 recipient with $\texttt{ravsum} = s$, we draw one observation uniformly at random with replacement from $\mathscr{D}_s$.
3. We assign the drawn donor's `fraven99` value to the recipient.

This procedure preserves the within-stratum variance of IRT scores, unlike mean imputation which collapses each stratum to a single value.

A.3.4 Bootstrap Uncertainty Estimation

A single hot-deck draw introduces randomness due to donor selection. To characterize this imputation uncertainty, we repeat the hot-deck procedure $B = 1000$ times, each time using a distinct random seed. This provides a distribution of B mapped IRT scores $\{\tilde{f}_{i,1}, \tilde{f}_{i,2}, \ldots, \tilde{f}_{i,B}\}$ for each KLPS-0 and KLPS-1 recipient i.

From this distribution, we compute:

$$\hat{f}_i = \frac{1}{B}\sum_{b=1}^{B} \tilde{f}_{i,b} \quad \text{(point estimate)} \tag{1}$$

$$\hat{\sigma}_i = \sqrt{\frac{1}{B}\sum_{b=1}^{B} \tilde{f}_{i,b}^2 - \hat{f}_i^2} \quad \text{(imputation SD)} \tag{2}$$

$$[\hat{f}_i^{2.5}, \hat{f}_i^{97.5}] = \text{2.5th and 97.5th empirical percentiles of } \{\tilde{f}_{i,b}\} \tag{3}$$

The point estimate $\hat{f}_i$ is used as the assigned IRT score for KLPS-0 and 1 in all downstream analyses.

A.3.5 Results

Mapped Scores by KLPS Round. Table A.9 summarizes the distribution of IRT-equated Ravens scores across all rounds after the mapping procedure is applied. For reference, the mean IRT score for KLPS-0 recipients is -0.588 (SD = 0.625, $N = 1337$) and for round 1 recipients is 0.166 (SD = 0.857, $N = 1198$).

Imputation Uncertainty. Table A.10 reports the magnitude of imputation uncertainty introduced by the hot-deck procedure. The key diagnostic is the ratio of the average bootstrap SD to the overall cross-sectional SD of IRT scores. The mean bootstrap SD across all rounds 0 and 1 recipients is 0.2537, with a maximum of 0.5797. The mean width of the empirical 95% bootstrap interval is 0.9176 IRT score units. For comparison, the overall cross-sectional SD of mapped IRT scores in rounds 0 and 1 is 0.741.

B Appendix Figures

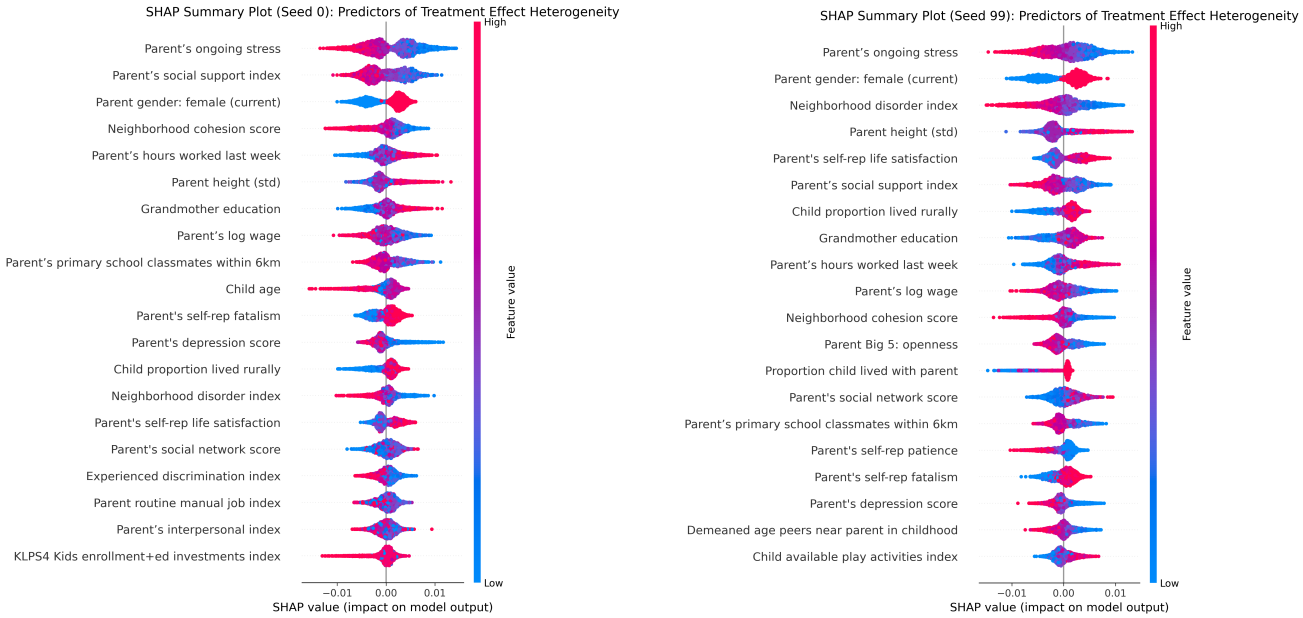
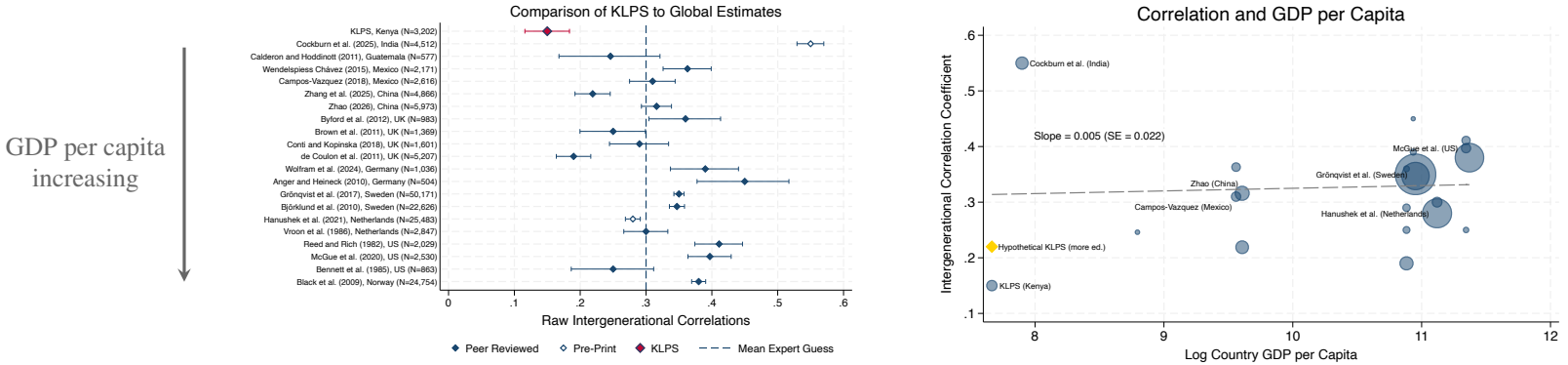


Figure A.1: SHAP Plot of Two Example Causal Random Forests

Notes: Two SHAP plots with two different random seeds (left: seed=0; right: seed=99) are depicted. Each figure ranks the 20 most important interactions to predict heterogeneity that were selected by that causal random forest run. The most important factors at listed at the top. Each row considers a given interaction term, and the Shapley value on the x-axis show how much that variable shifts the predicted intergenerational correlation for a given data point. The distribution of the data points then indicates where the mass falls, and a wide spread of the distribution means the variable is a strong predictor of treatment effect heterogeneity. The color indicates whether this data point has a high or low value of the respective variable (e.g., blue is low stress, red is high stress).



(a) Panel A

(b) Panel B

Figure A.2: Correlation Estimates in Global Context (incl. pre-prints)

Notes: **Panel A** compares our intergenerational estimate from Kenya between parents (adult age) and children (child age) in KLPS with those found in other studies, including pre-prints. Studies are sorted by GDP per capita of the country. Sample sizes of the studies are indicated in parentheses, and we only include studies with more than 500 observations. The dashed line indicates the expert guess of the intergenerational correlation elicited through the Social Science Prediction Platform (SSPP) in 2024. The guess was obtained by asking experts to predict correlations for exactly this setting and these parent-child pairs in Kenya.

Panel B plots study-level intergenerational correlation estimates against log GDP per capita among other studies, including pre-prints. Each marker represents an individual study estimate, with circle area proportional to study sample size (N). The dashed line reflects predicted values from an inverse-variance-weighted random-effects meta-regression model estimated via restricted maximum likelihood (REML) using Fisher's z transformation. The RE slope coefficient is reported in parentheses. The yellow diamond indicates a hypothetical KLPS estimate if grandparent education in Kenya were 7 years higher on average as in highly-educated, wealthy countries.

Table A.1: Predictive Power of Raven's Matrices (Parents)

	Earnings (KLPS 4)		Edudcation (KLPS 5)	
	(1)	(2)	(3)	(4)
RS parent (KLPS4)	355.116***	264.233***		
	(55.065)	(58.866)		
Educ. attained (KLPS4)		87.085***		
		(14.613)		
RS parent (KLPS5)			1.595***	1.472***
			(0.046)	(0.045)
Grandparent educ.				0.207***
				(0.010)
Constant	973.972***	157.945	9.420***	7.976***
	(44.706)	(146.737)	(0.033)	(0.077)
Observations	1250	1189	6591	6561
R sq.	0.032	0.062	0.153	0.206

Notes: This table reports the results from an OLS regression of earnings in KLPS-4 on Raven's scores in KLPS-4 in Column 1 and controlling for max educational attainment in KLPS-4 in Column 2. Estimes of the regression of max educational attainment in KLPS-5 and Raven's scores in KLPS-5 are reported in Column 3 and controlling for grandparental education in Column 4.

C Appendix Tables

Table A.2: Predictive Power of Raven's Matrices (Children)

	Animal Naming (Kids)		Digit Span (Kids)	
	(1)	(2)	(3)	(4)
Raven Score (Kids)	2.516***	2.413***	0.309***	0.326***
	(0.084)	(0.097)	(0.015)	(0.017)
Parent's earnings (KLPS4)		0.000***		-0.000
		(0.000)		(0.000)
Constant	13.368***	13.148***	0.737***	0.742***
	(0.067)	(0.088)	(0.012)	(0.016)
Observations	4177	3084	4110	3035
R sq.	0.178	0.176	0.097	0.105

Notes: This table reports the results from an OLS regression of children's performance in other cognitive tests (animnal naming, digit span) on their Raven's score as well as their parent's income in KLPS-4.

Table A.3: Significant LASSO Predictors of Treatment Effect Heterogeneity

Panel A: Covariates (Main Effects)

Variable	Coefficient	t-statistic	p-value
Child age	0.166432	11.82	0.000
Variety of play materials index (KLPS4)	0.106051	6.29	0.000
Child gender	-0.118064	-4.15	0.000
Child enrolled in private school (KLPS4)	0.119276	3.46	0.001
Self-employment (KLPS2)	0.238284	3.34	0.001
Ongoing stress index (std)	-0.049691	-3.12	0.002
Parent gender: Female	0.191051	2.88	0.004
Parent max years of schooling attained	0.027870	2.74	0.006
Parent farm hours worked last week (KLPS4)	-0.003165	-2.39	0.017
Child dietary diversity (nutritious subscore)	-0.447436	-2.39	0.017
Parent PSDP cost-sharing participant	0.083431	2.21	0.027
Food insecurity score	-0.076605	-2.18	0.029
Grandmother's education (median)	0.011963	2.11	0.035
Child urban years	0.020119	2.09	0.036
Parent average school test score	-0.079055	-2.05	0.040
Parent main occupation: other	0.291704	1.93	0.054
Parent log wage	0.023275	1.85	0.064
Parent log per capita HH consumption (KLPS4)	0.044168	1.81	0.070
Child dietary diversity score	0.319075	1.72	0.086
Parent routine/manual occupation index	0.027321	1.65	0.099
Total significant: 20			

Panel B: Interactions

Variable	Coefficient	t-statistic	p-value
Parent social support index (std)*	-0.046717	-2.98	0.003
Parent primary school classmates within 6 km *	-0.000032	-2.75	0.006
Saturation (G1/G2 ratio within 6 km)	-0.508213	-2.35	0.019
Parent non-farm hours worked last week (KLPS4) †	0.001563	2.16	0.031
Parent ongoing stress index (std)*	-0.035091	-2.13	0.033
Parent main occupation: student †	-2.165249	-2.06	0.040
Neighborhood disorder index (std)*	-0.033288	-2.04	0.041
Grandmother education (median)*	0.011164	1.99	0.047
Parent survey patience (staircase task)	-0.002480	-1.89	0.059
Play activities index (KLPS4)	0.029966	1.82	0.070
Parent job stress (binary) †	0.076710	1.79	0.074
Parent farm hours worked last week (KLPS4) †	-0.002266	-1.71	0.088
Parent attitude: people shape fate	0.026317	1.70	0.090
Total significant: 13			

Notes: This table reports LASSO-selected predictors of treatment effect heterogeneity with unadjusted $p < 0.1$. Coefficients are unscaled. Panel A reports covariate main effects; Panel B reports interaction terms. Standard errors clustered at the school level. Stars * indicate variables that were also chosen to be among the top 15 predictors of treatment effect heterogeneity with the generalized random forest. Daggers †indicate variables that were selected by lasso in a modified form (e.g., total hours worked in the GRF vs farm and non-farm hours worked with Lasso).

Table A.4: Variable Summary Statistics (1/4)

Variable	Type	Obs.	Missing(%)	Mean	Median	p25	p50	p75
Parent Age in KLPS 5	Continuous	3704	0.00	37.05	37.00	35.00	37.00	39.00
Interpersonal index	Continuous	3572	3.56	-0.10	-0.10	-0.93	-0.10	0.72
Parent job routine/manual	Continuous	3572	3.56	-0.09	-0.23	-0.64	-0.23	0.37
Parent job stress index (mean)	Continuous	3628	2.05	2.53	2.50	2.33	2.50	2.83
Decision latitute (sum)	Continuous	3627	2.08	5.73	6.00	5.00	6.00	7.00
Psychological job demand (sum)	Continuous	3627	2.08	5.09	5.00	5.00	5.00	6.00
Job Strain	Continuous	3627	2.08	0.94	0.83	0.71	0.83	1.00
KLPS5 neighborhood disorder index	Continuous	3702	0.05	-0.02	-0.02	-0.76	-0.02	0.72
KLPS5 neighborhood cohesion score	Continuous	3702	0.05	-0.05	-0.13	-0.67	-0.13	0.60
KLPS5 parent social network score	Continuous	3704	0.00	0.00	-0.21	-0.51	-0.21	0.19
KLPS5 parent loneliness index	Continuous	3702	0.05	0.01	-0.16	-0.72	-0.16	0.41
KLPS5 DISC index	Continuous	3682	0.59	-0.01	-0.11	-0.85	-0.11	0.77
KLPS5 parent social support	Continuous	3702	0.05	0.03	0.06	-0.47	0.06	0.58
Parent ongoing stress	Continuous	3702	0.05	-0.03	0.04	-0.77	0.04	0.58
KLPS 5 parent aspirations	Continuous	3700	0.11	0.01	0.05	-0.40	0.05	0.50
Parent years of schooling attained	Continuous	3612	2.48	9.26	8.00	7.00	8.00	12.00
KLPS 5 happiness-Depression symptoms	Continuous	3704	0.00	0.02	0.31	-0.84	0.31	0.89
KLPS 5 perceived stress scale (std)	Continuous	3704	0.00	-0.01	0.00	-0.56	0.00	0.57
KLPS 5 current health	Continuous	3407	8.02	1.73	2.00	1.00	2.00	2.00
KLPS 3: parent occupation 2	Continuous	2767	25.30	12.33	1.00	1.00	1.00	16.00
KLPS 2: parent occupation 2	Continuous	2269	38.74	6.77	1.00	1.00	1.00	7.00
Parent attitude: people shape fate	Continuous	3304	10.80	-0.01	0.35	-1.25	0.35	0.88
Parent life satisfaction	Continuous	3302	10.85	0.03	-0.17	-0.81	-0.17	0.80
Parent big5 extraversion	Continuous	3297	10.99	-0.04	-0.02	-0.76	-0.02	0.72
Parent big5 agreeable	Continuous	3301	10.88	-0.01	0.18	-0.71	0.18	0.63
Parent big5 consciousness	Continuous	3302	10.85	-0.02	0.48	-0.85	0.48	0.93
Parent big5 neuroticism	Continuous	3301	10.88	-0.02	-0.14	-0.55	-0.14	0.68
Parent big5 openness	Continuous	3296	11.02	-0.04	0.11	-0.99	0.11	0.48
Parent self-rep risk preference	Continuous	3331	10.07	10.45	5.00	2.00	5.00	18.00

Table A.5: Variable Summary Statistics (2/4)

Variable	Type	Obs.	Missing(%)	Mean	Median	p25	p50
Parent pro-sociality	Continuous	1312	64.58	3109.26	3100.00	1600.00	3100.00
constructed on the basis of staircase time task	Continuous	3304	10.80	9.50	2.00	1.50	2.00
KLPS 5 Parent hours worked (wk)	Continuous	3704	0.00	39.92	38.00	18.00	38.00
KLPS 5 Parent log wage	Continuous	3293	11.10	3.43	3.44	2.62	3.44
Grandfather education	Continuous	3677	0.73	8.07	7.00	6.00	7.00
Grandmother education	Continuous	3693	0.30	5.65	6.00	3.00	6.00
Child age at KLPS 5	Continuous	3704	0.00	10.99	11.00	10.00	11.00
School ID (baseline)	Continuous	3243	12.45	222.98	219.00	183.00	219.00
Number of pupils at school, 1998	Continuous	2874	22.41	409.31	366.00	268.00	366.00
Average School Test Score	Continuous	2874	22.41	-0.01	0.02	-0.27	0.02
Ratio of G1,G2 population to total pop within 6k X 0.75 (Saturation)	Continuous	2874	22.41	0.51	0.52	0.47	0.52
Demeaned Number of Primary School Students within 6km	Continuous	2874	22.41	-41.28	47.34	-1097.54	47.34
Max years of schooling attained (as of KLPS4)	Continuous	3154	14.85	9.97	9.00	8.00	9.00
KLPS4 E+ module: Ln (Total annual per capita HH consumption) (USD PPP)	Continuous	2841	23.30	7.06	7.02	6.55	7.02
KLPS4 E+ module: Farm hours worked last week	Continuous	2028	45.25	8.66	0.00	0.00	0.00
KLPS4 E+ module: Nonfarm hours worked last week	Continuous	2028	45.25	29.23	25.00	0.00	25.00
KLPS4 I module: CESD score	Continuous	3235	12.66	9.39	9.00	5.00	9.00
KLPS4: Age (at time of I module)	Continuous	2763	25.40	34.12	34.00	32.00	34.00
KLPS4 Kids: Variety of play materials index	Continuous	3240	12.53	0.12	0.42	-0.38	0.42
KLPS4 Kids: Play activities index	Continuous	3242	12.47	-0.02	-0.04	-1.00	-0.04
KLPS4 Kids: School enrollment and educational investments index	Continuous	3241	12.50	0.03	0.31	0.20	0.31

Table A.6: Variable Summary Statistics (3/4)

Variable	Type	Obs.	Missing(%)	Mean	Median	p25	p50	p75
KLPS4 Kids: Positive discipline techniques index (0 few to 1 more)	Continuous	3241	12.50	1.88	2.00	1.00	2.00	3.00
KLPS4 Kids: Negative discipline techniques index (0 few to 1 more)	Continuous	3240	12.53	1.50	1.00	1.00	1.00	2.00
Times a child moved	Continuous	3569	3.64	1.34	1.00	0.00	1.00	2.00
Child: % of life in rural	Continuous	3569	3.64	0.59	0.71	0.12	0.71	1.00
Child: % of life with parent	Continuous	3569	3.64	0.92	1.00	1.00	1.00	1.00
Child: years urban	Continuous	3569	3.64	4.35	3.00	0.00	3.00	8.00
Food insecurity score (0=none, 3=most severe)	Continuous	3701	0.08	0.47	0.00	0.00	0.00	1.00
Dietary Diversity Score (0=lowest, 6=highest)	Continuous	3702	0.05	5.71	6.00	5.00	6.00	6.00
DDS excluding other/unhealthy food group (0–5)	Continuous	3702	0.05	4.71	5.00	4.00	5.00	5.00
KLPS3 parent occupation	Categorical	3704	0.00					
KLPS2 parent occupation	Categorical	3704	0.00					
KLPS tracking wave assignment	Categorical	3243	12.45					
PSDP treatment group assignment	Categorical	2874	22.41					
Type of training voucher selected to receive (1=Unrestricted, 2=Public Only)	Categorical	1132	69.44					
Recoded 1-digit occupation (KLPS5)	Categorical	3704	0.00					
Parent gender female in KLPS5	Categorical	3704	0.00	0.59	1.00	0.00	1.00	1.00
KLPS 5 parent major health concern	Categorical	3407	8.02	0.26	0.00	0.00	0.00	1.00
KLPS 5 parent smoking	Categorical	3407	8.02	0.02	0.00	0.00	0.00	0.00
KLPS 5 parent drinking	Categorical	3407	8.02	0.36	0.00	0.00	0.00	1.00
KLPS 5 parent severe drinking	Categorical	1232	66.74	0.10	0.00	0.00	0.00	0.00
KLPS 5 parent job stress	Categorical	3704	0.00	0.46	0.00	0.00	0.00	1.00
KLPS 5 parent psych. demand of job	Categorical	3704	0.00	0.78	1.00	1.00	1.00	1.00
KLPS 5 parent job decision lat	Categorical	3704	0.00	0.87	1.00	1.00	1.00	1.00
Buy gift	Categorical	1312	64.58	0.96	1.00	1.00	1.00	1.00
PM25 2 5percentile	Categorical	3432	7.34	0.98	1.00	1.00	1.00	1.00
PM25 5percentile	Categorical	3432	7.34	0.95	1.00	1.00	1.00	1.00
PM25 10	Categorical	3432	7.34	0.47	0.00	0.00	0.00	1.00
PM25 20	Categorical	3432	7.34	0.34	0.00	0.00	0.00	1.00
PM25 30	Categorical	3432	7.34	0.10	0.00	0.00	0.00	0.00
PM25 40	Categorical	3432	7.34	0.05	0.00	0.00	0.00	0.00

Table A.7: Variable Summary Statistics (4/4)

Either parent has some primary schooling	Categorical	3697	0.19	0.82	1.00	1.00	1.00	1.00
Either parent has some secondary schooling	Categorical	3697	0.19	0.44	0.00	0.00	0.00	1.00
Both parents have some secondary schooling	Categorical	3697	0.19	0.12	0.00	0.00	0.00	0.00
Child ID	Categorical	3704	0.00	1.63	2.00	1.00	2.00	2.00
Parent female at baseline	Categorical	3243	12.45	0.59	1.00	0.00	1.00	1.00
PSDP participant indicator	Categorical	3243	12.45	0.89	1.00	1.00	1.00	1.00
PSDP treatment group assignment indicator	Categorical	2874	22.41	0.66	1.00	0.00	1.00	1.00
PSDP 2001 cost sharing school indic	Categorical	2874	22.41	0.34	0.00	0.00	0.00	1.00
GSP treatment group assignment indicator	Categorical	369	90.04	0.55	1.00	0.00	1.00	1.00
VocEd/SCY participant indicator	Categorical	3243	12.45	0.35	0.00	0.00	0.00	1.00
Indic for selected to receive information treatment	Categorical	1132	69.44	0.50	0.00	0.00	0.00	1.00
Indic for selected to receive training voucher	Categorical	1132	69.44	0.50	1.00	0.00	1.00	1.00
Indicator for chosen for SCY grant treatment group	Categorical	1132	69.44	0.45	0.00	0.00	0.00	1.00
Any secondary schooling (as of KLPS4)	Categorical	3154	14.85	0.51	1.00	0.00	1.00	1.00
KLPS4 Kids: Child coresides with KLPS respondent	Categorical	3225	12.93	0.83	1.00	1.00	1.00	1.00
KLPS4 Kids: Child enrolled in private school	Categorical	2922	21.11	0.42	0.00	0.00	0.00	1.00
Child gender	Categorical	3569	3.64	1.50	2.00	1.00	2.00	2.00
FS Severity	Categorical	3701	0.08	0.14	0.00	0.00	0.00	0.00
Minimum Dietary Diversity achieved (DDS >= 5)	Categorical	3702	0.05	0.97	1.00	1.00	1.00	1.00

Table A.8: Donor Pool by Raw Ravens Score: Summary Statistics

Raw Score	N Donors	Mean IRT	SD IRT	Min IRT	Max IRT
5	3	-1.681	0.000	-1.681	-1.681
6	3	-1.616	0.108	-1.681	-1.492
7	5	-1.612	0.116	-1.681	-1.414
8	8	-1.460	0.234	-1.681	-1.078
9	8	-1.369	0.187	-1.681	-1.147
10	11	-1.105	0.305	-1.681	-0.707
11	6	-0.935	0.123	-1.038	-0.713
12	21	-0.957	0.245	-1.638	-0.612
13	12	-0.832	0.211	-1.193	-0.358
14	30	-0.696	0.240	-1.165	-0.285
15	11	-0.615	0.469	-1.398	-0.035
16	19	-0.430	0.195	-0.814	0.114
17	21	-0.423	0.291	-0.950	-0.023
18	13	-0.163	0.312	-0.884	0.191
19	23	-0.048	0.303	-0.529	0.665
20	17	-0.094	0.239	-0.459	0.341
21	22	0.093	0.281	-0.286	0.786
22	9	0.254	0.237	-0.095	0.760
23	22	0.260	0.326	-0.246	1.029
24	24	0.385	0.207	0.073	0.787
25	22	0.491	0.290	0.051	1.155
26	23	0.683	0.196	0.325	1.099
27	16	1.060	0.351	0.593	1.765
28	18	1.124	0.179	0.793	1.519
29	19	1.444	0.254	0.898	1.997
30	17	1.594	0.316	1.009	1.997
31	3	1.860	0.119	1.785	1.997

Notes: Each row corresponds to one raw-score stratum used in the hot-deck imputation. N Donors is the number of calibration-sample observations available for random draws. IRT scores are values from the calibration study.

Table A.9: IRT-Equated Ravens Scores by Round: Summary Statistics

Round	N	Mean	SD	Min	Median	Max
KLPS 0 (mapped)	1337	-0.588	0.625	-2.321	-0.687	1.924
KLPS 1 (mapped)	1198	0.166	0.857	-2.323	0.092	1.934
KLPS 2	8131	0.241	0.880	-2.613	0.177	1.997
KLPS 4	1455	-0.090	0.857	-2.613	-0.200	1.997
KLPS 5	5752	-0.018	0.726	-2.839	-0.089	1.671
KLPS 5 Kids	4177	-0.370	0.727	-2.911	-0.486	1.671

Notes: Rounds 0 and 1 scores are assigned using random hot-deck imputation with $B = 1000$ bootstrap iterations; the point estimate is the mean across draws. Rounds 2, 4, and 5 scores are IRT co-calibrated values from the harmonization procedure.

Table A.10: Bootstrap Imputation Uncertainty: Rounds 0 and 1

Round	N	Mean BS SD	P10 BS SD	P90 BS SD	Mean CI Width	Overall IRT SD
KLPS0	1332	0.2417	0.1145	0.3092	0.8683	0.606
KLPS1	1196	0.2457	0.1673	0.3279	0.9039	0.843

Notes: Bootstrap SD is the standard deviation of `fraven99` across $B = 1000$ hot-deck draws for each individual; values reported are means and percentiles of this individual-level SD across recipients. CI Width is the average width of the empirical 95% interval $[\hat{f}_i^{2.5}, \hat{f}_i^{97.5}]$. Overall IRT SD is the cross-sectional standard deviation of the point-estimate IRT score, provided as a benchmark for gauging the magnitude of imputation uncertainty.