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INTERGENERATIONAL HUMAN CAPITAL IMPACTS AND COMPLEMENTARITIES IN KENYA

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ABSTRACT

This study exploits experimental variation in parent human capital (early-life school-based deworming) and a shock to schooling (extended Covid closures) to estimate how these factors interact in the production of child human capital within a sample of 3,500 Kenyan 3-8 year olds. Parents with additional exposure to childhood deworming have children with improved human capital, including in health, non-cognitive development, and cognition; cognitive scores are +0.26 standard deviation units higher among treated parents' school-age children, only prior to school closures. Findings are interpreted through a model where home-based and school inputs are complements in the production of child cognition.

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A data appendix is available at
http://www.nber.org/data-appendix/w32617
A randomized controlled trials registry entry is available at
https://www.socialscienceregistry.org/trials/3995/

1 Introduction

Understanding how various investments interact in the production of child cognitive and non-cognitive skills represents a key issue in the economics of human capital. Improvements in parent human capital and greater access to schooling have each been shown to independently benefit child health and educational outcomes. Less research explores how parent human capital and the local schooling environment interact in the production of child human capital, in part because few settings feature plausibly exogenous variation in both parent human capital and access to schooling, making it challenging to identify interaction effects.

To make progress on this question, this study estimates causal intergenerational impacts of a randomized human capital intervention in Kenya on child human capital – including health, non-cognitive development, and cognitive development outcomes – and leverages cross-cutting exogenous variation in access to recent schooling to explore how parent human capital and the local schooling environment interact in the production of child human capital.

The analysis draws on data from the Kenya Life Panel Survey (KLPS), a longitudinal survey spanning over twenty years and tracking over 7,000 respondents who participated in a randomized early-life human capital intervention, school-based deworming (the Primary School Deworming Project (PSDP), Miguel and Kremer, 2004) starting as early as 1998. In its fourth round of data collection (from 2017 to 2021), the KLPS extended data collection to include 3-5 year old ("younger") and 6-8 year old ("older") children of primary respondents, generating a unique intergenerational dataset that includes both extensive measures of household living standards and detailed measures of child health, non-cognitive development, and cognition. These measures, including the battery of cognitive assessments, were developed based on lessons from an earlier pilot and in collaboration with child development experts and research staff who provided in-country support throughout piloting, adaptation, and enumerator training. This provides a highly unusual set of contextually- and culturally-appropriate measures characterizing child human capital in the sample.

In contrast to high-income countries like the US, in which administrative data has been used in seminal research on intergenerational mobility (see Chetty et al. (2014, 2020); Chetty and Hendren (2018a,b)), research in low- and middle-income country settings such as Kenya often relies on original panel datasets such as KLPS. KLPS has the added advantage of having more detailed measures spanning two generations – for instance, on cognition and the home environment – than are usually found in large-scale administrative records.

The KLPS study sample is divided into two representative (randomly chosen) waves for tracking purposes. Fortuitously, data collection for the first representative wave was completed just before nine months of Covid-related school closures, and the second wave was surveyed during and immediately after the closures, providing plausibly exogenous variation in exposure to recent schooling. This data environment facilitates the estimation of causal intergenerational impacts of a parent human capital intervention on child human capital, and an investigation of how parent human capital and the local schooling environment interact.

The analysis proceeds in three steps. The paper first estimates the intergenerational impacts of the parent human capital intervention (childhood deworming) on health, non-cognitive development, and cognition in the child generation. Next, the paper leverages cross-cutting variation in access to recent schooling to explore how parent human capital and school availability interact in the production of child cognitive skills. Finally, the paper explores potential mechanisms underlying the effects, in part by replicating and extending research on long-run deworming impacts in the parent generation.

Five main findings emerge. First, the analysis finds evidence of positive intergenerational impacts among the children of deworming recipients, including health gains among older and younger children, and improvements in non-cognitive development among older children. Specifically, treatment group parents of younger children report higher overall child health, and older children score 0.15 standard deviations higher on a subjective health index (statistically significant at 10%). Further, the older children of treatment group parents score 0.20 standard deviations higher on a summary index capturing non-cognitive socioemotional development (statistically significant at 5%), driven largely by a reduction in perceived emotional difficulties and improved prosociality.

Second, the results support the existence of meaningful complementarities between parent human capital (together with household living standards) and school availability in child human capital production. Prior to extensive Covid-related school closures, older (6-8 year old; school-age) children whose parents received the early-life human capital intervention score 0.26 standard deviations higher on an academic cognitive index (statistically significant at 5%). In contrast, no positive treatment effects emerge in the sample of children assigned to be surveyed following school closures, nor among children too young to attend school (3-5 year olds).[1]

Third, the analysis provides evidence of substantial learning loss among school-age chil-

[1]Future data collection will enable tests of whether impacts emerge when these younger children themselves enter school.

dren across the survey waves as a consequence of the extended school closures. Within the control group, performance declines by 0.17 standard deviations in language and 0.10 standard deviations in math among older children who are randomly assigned to be surveyed following Covid-related school closures compared to those surveyed prior to such closures. The declines are even larger in magnitude among the treatment group, a differential effect that helps to account for the absence of positive intergenerational deworming treatment effects in the post-Covid period (treatment effect estimate of -0.09 standard deviation units, not statistically significant).

Fourth, these patterns are consistent with a model of human capital development where complementarity between school-based and home-based investments plays an important role. Cognitive gains only emerge in the pre-Covid period, but not in the post-Covid period when children had recently experienced nearly a year of "lost" schooling. No impacts arise for children too young to attend school, thus too young to benefit from said complementarities. Similarly, cognitive declines across waves are only observed among older children, with no similar declines for younger children for whom school closures are less relevant. Finally, few meaningful differences are observed across waves in terms of health and non-cognitive development, dimensions of child human capital that may be more resilient or may not be as negatively (or immediately) impacted by school closures.

Finally, the paper presents novel evidence that the early-life school-based deworming intervention leads to gains in psychological well-being later in life, in addition to improvements in multiple measures of household living standards, as documented in earlier research (Baird et al., 2016; Hamory et al., 2021b). Deworming treatment recipients in the "intergenerational sample" (KLPS respondents with children whose ages place them in the main analysis sample) report substantially fewer symptoms of depression and improved life satisfaction. While the current analysis provides little evidence of improvements in health investments, material characteristics of the home environment, or school investments, these results suggest that estimated positive intergenerational impacts of the childhood deworming intervention may emerge from some combination of improvements in parent human capital and household living standards (as documented in previous published research), as well as improvements in psychological well-being (as newly documented here).

These measures of child human capital development and the specifications for estimating intergenerational deworming impacts were pre-specified on the AEA registry (AEARCTR-0003995). While the pre-analysis plan naturally did not anticipate Covid-19 and the resulting school closures in Kenya, the two-wave data collection design and the fact that the first wave was completed just before the pandemic spread to Kenya – by chance – provides an unusual opportunity to investigate complementarities in the educational production function.[2] Specifically, the Covid-induced school closures provide an exogenous shock in access to recent schooling for those randomly assigned to the second tracking wave. In light of this, we decided to interpret this constellation of empirical findings through the lens of a standard model of child human capital development featuring complementarity between school-based and home-based investments. In such a model, improvements in home-based investments (i.e., greater parent human capital, elevated household living standards, and/or improved parent psychological well-being) enhance the productivity of school-based investments, but cannot substitute for schooling itself. Similarly, improvements in access to schooling or the quality of schooling complement home-based investments, but would prove largely ineffective when home-based investments are severely limited.

Interpreting this pattern of results as evidence of complementarities between school-based and home-based investments relies in part on differential access to recent schooling being the key aspect differentiating the experience of children assigned to the pre-Covid versus the post-Covid wave. Potential confounds would include if there were differential treatment effects on pre-Covid household economic outcomes across waves, differential Covid-related disruptions by treatment status across waves, or meaningful differences in the composition of the child sample across waves. Encouragingly, the analysis provides no evidence of differential treatment effects across waves on household economic circumstances in the pre-Covid period, nor on mid-Covid outcomes (from a phone survey) reflecting the impact of the pandemic. Finally, results persist when restricting the analysis to a subsample of children who – in addition to being eligible based on age, belong to the exact same month and year of birth cohorts – helping rule out that the results are driven by any meaningful compositional differences across waves.

The results build on several strands of existing research. First, this paper contributes to a large literature on child human capital production, and specifically to the evidence base concerned with complementarities between relevant investments. Much of this research builds on the model outlined in Cunha and Heckman (2007) (adapted by Cunha and Heckman (2008) and Cunha et al. (2010), among others), and tests for existence of dynamic complementar-

[2] Such opportunities are relatively rare, and even when the combination of two exogenous shocks does occur, investments in response to either shock may prevent detection of complementarities. For example, in a test for dynamic complementarities, Bau et al. (2020) find evidence that positive shocks to early life investment (due to favorable rainfall) increase labor market returns, inducing school dropout in later childhood.

ities (where early investments make later investments more productive) or self-productivity (where a higher stock of skills makes subsequent investments more productive). Other research examines how private investment responds to increased or higher-quality public investments as an indirect test for complementarity between public and private investments. Much of the evidence on dynamic complementarity,[3] self-productivity,[4] and public-private investment complementarity[5] comes from high income countries (HICs), with mixed findings on the importance of such complementarities.

However, a growing body of evidence within the development literature points to the important role of various complementarities in child human capital development in low- and middle-income country (LMIC) contexts (see Attanasio et al. (2022) for a related review). In early work, Glewwe et al. (2009) find that provision of textbooks in Kenyan schools enhances learning only among initially high performing students, consistent with the existence of complementarity between school-based inputs and existing child cognitive skills.[6] Özler et al. (2018) find evidence that quality improvements in informal preschools in Malawi lead to short-term learning gains, but only when paired with a parent engagement intervention. More recent work finds evidence of complementarity between teacher incentives and unconditional grants in Tanzanian schools (Mbiti et al., 2019).[7] Much of this research explores complementarities across school-based inputs alone,[8] or draws conclusions about complementarity based on how parents respond to improvements in school quality. In contrast, this study's setting enables a test for the existence of complementarity between public and private investments by exploring how existing improvements in private investments (improved parent

[3]Evidence from the US and England supports the existence of dynamic complementarities (Johnson and Jackson, 2019; Gilraine, 2016), while evidence from Denmark speaks to the absence of complementarities between early and later human capital interventions (Rossin-Slater and Wüst, 2020).

[4]Nicoletti and Rabe (2014) find evidence of positive complementarity between child skill at the end of primary school and investments during secondary school in England, while Agostinelli and Wiswall (2021) find that investments are more productive for lower-skilled children during early childhood in the US context.

[5]Gelber and Isen (2013) show that participation in Head Start crowds in parental investment. While Gensowski et al. (2024) find evidence that low-income parents in Denmark increased investments in response to higher quality public preschools, they interpret this as evidence that public and private investments act as substitutes rather than complements. Goff et al. (2023) find no evidence of complementarity between improved early childhood circumstances and later life school quality in Romania, perhaps attributable to lower parent and child effort in response to higher quality schooling.

[6]In another influential early study, Grantham-McGregor et al. (1991) provide evidence of positive complementarity between nutritional supplementation and home-based stimulation among malnourished 9-24 month old children in Jamaica, though these positive complementarities did not persist through childhood (Grantham-McGregor et al., 1997).

[7]In contrast, Das et al. (2013) investigate how parents respond to shifts in school-based investments in India and Zambia, finding that improvements in school quality crowd out parental investments. While this does not necessarily imply school- and home-based investments are substitutes, this evidence does suggest that parents may (counter-productively) behave as if they are in the presence of budget constraints.

[8]In a related point, Agostinelli et al. (2020) point out that in characterizing production of child human capital, much of the child development literature focuses primarily on the role of families and the household environment alone, while the education production function literature focuses largely on the role of school-related investments alone.

human capital and elevated living standards) interact with a subsequent shock to schooling (through Covid-related closures), leveraging exogenous variation along both dimensions. In doing so, this study aims to provide new insight regarding the existence of complementarities between parent human capital and the local schooling environment in producing child human capital. Resonant with the literature on complementarities in LMIC contexts, the results here highlight the possibility for more effective learning and child development when relevant inputs are present and where conditions allow, but also suggests that in the absence of necessary inputs or in the presence of negative external shocks, child human capital and development outcomes may suffer.[9]

Second, this study relates to a recent but growing literature documenting intergenerational transmission of human capital and estimating the intergenerational impact of specific policies or interventions in LMICs. Alesina et al. (2021) and Asher et al. (2024) document trends in intergenerational mobility in African countries and India, respectively. In related work from an experimental setting, Duflo et al. (2023) estimate the intergenerational impact of scholarships for secondary education in Ghana, finding evidence of substantial gains in cognitive scores among children of mothers who received scholarships.[10] Evidence from Indonesia (Akresh et al., 2023b; Mazumder et al., 2019, 2021), Zimbabwe (Agüero and Ramachandran, 2020), and Benin (Wantchekon et al., 2015), shows that expanded access to schooling in one generation leads to improved educational outcomes (and in some cases, health outcomes) among the next generation; in Indonesia, the strongest impacts appear among girls and children whose mothers had greater access to schooling.[11] Evidence from Nigeria shows that exposure to war during childhood – particularly during adolescence – adversely impacts later life health and educational outcomes among women and among their children (Akresh et al., 2023a). Partly consistent with this study's findings, Barham et al. (2023) find evidence of positive impacts on cognitive performance and health among children of mothers exposed to a maternal and child health program in Bangladesh (with gains

[9] A similar principle appears in Weaver et al. (2024) who find that cash transfers to mothers of young children in India increase child nutritional intake across the board, but only translate into improvements in child anthropometric outcomes in environments with sufficient sanitation, not in areas with very poor sanitation.

[10] Similar to the present study, the authors of the Ghana study find no evidence of measurable improvements in the home environment or schooling investments, pointing instead to alternate channels such as more time spent with children, and perhaps higher quality stimulation per unit of time. Also similar, positive gains are detected among children at older (5 or 7 years old), but not younger ages (3.5 years old).

[11] These findings are consistent with work showing that male and female adults may allocate spending and invest differently in female versus male children (Duflo, 2003; Dizon-Ross and Jayachandran, 2022). Further, these findings are broadly consistent with research from higher income contexts such as the US, where improved educational outcomes are detected among children of parents with greater educational attainment (due to compulsory schooling laws) (Oreopoulos et al., 2006), children of mothers who were exposed to early life educational programs such as Head Start (Barr and Gibbs, 2022), or children of parents who participated in the the Perry Preschool Project (García et al., 2023).

concentrated among female children). The present study contributes to this literature by leveraging an experimental setting to provide causal evidence of positive intergenerational impacts on health, non-cognitive development, and cognition in an LMIC setting.

Third, this study relates to the new body of research documenting the impact of Covid-related disruptions on learning. Much of this research reveals substantial learning loss among children due to school closures and/or the shift to a virtual learning environment (see Hammerstein et al. (2021) and Miguel and Mobarak (2022) for reviews),[12] particularly in LMICs, where in many contexts schools closed completely and for extended spells, and where households may have lacked resources to compensate for the absence of school-based instruction (Galevski et al., 2021; Sabarwal et al., 2023). Singh et al. (2024) document substantial learning loss among children in Tamil Nadu, India following 18 months of school closures,[13] and Dang et al. (2022) find evidence of substantial declines in learning activities across Sub-Saharan African countries during the pandemic. The present study contributes to this literature by documenting meaningful declines in academic performance among school-age children in Kenya following prolonged Covid-related school closures, echoing these other studies.

Fourth, these findings contribute to a smaller literature exploring whether human capital investments or related interventions can effectively mitigate adverse shocks that occur earlier or later in childhood. Evidence from Mexico and Colombia finds that exposure to adverse weather shocks at birth or in early childhood negatively impact later life educational outcomes, which receipt of conditional cash transfers can (partially) mitigate (Adhvaryu et al., 2024b; Duque et al., 2021). In Bangladesh, receipt of an early-life health intervention (newborn vitamin A supplementation) mitigated negative health impacts associated with exposure to natural disaster later in childhood (Gunnsteinsson et al., 2022). In the Kenyan context, however, the current paper finds that advantages associated with having a parent who received an early-life human capital intervention are unable to mitigate Covid-driven schooling disruptions to child learning, at least in the short term; future rounds of data

[12]While learning loss is widespread, it appears more pronounced among children from more socioecomomically disadvantaged backgrounds (Chetty et al., 2024; Agostinelli et al., 2022), potentially due to parents being less able to support child learning (Bacher-Hicks et al., 2021), with potential long-run consequences for educational inequality (Werner and Woessmann, 2023; Jang and Yum, 2024). As a notable exception to this pattern, schools in Sweden remained open, and Hallin et al. (2022) find no evidence of learning loss, including among socioeconomically disadvantaged students.

[13]Encouragingly, Singh et al. (2024) also document relatively rapid recovery, aided in part by a large government-provided supplementary instruction program. Similarly, experimental evidence from Botswana found that providing parents with SMS and phone-based support during school closures helped to engage parents in learning activities and mitigate potential learning loss, highlighting the important role of parental involvement in learning activities during a period of prolonged school closures (Angrist et al., 2023).

collection will allow us to assess whether these patterns persist in the longer term.

Finally, the finding of positive impacts of childhood deworming on adult psychological health among the parent generation contributes to a body of literature that investigates how early-life circumstances shape later-life mental health. Existing research shows that factors such as adverse rainfall, temperature shocks, and maternal stress in utero each lead to worse mental health outcomes as adults (Carrillo, 2020; Adhvaryu et al., 2024a; Persson and Rossin-Slater, 2018), as does exposure to war during childhood (Singhal, 2019). In contrast, positive early-life circumstances, for example, those driven by favorable cocoa prices in Ghana, reduce the likelihood of severe mental distress in adulthood (Adhvaryu et al., 2019). This paper builds on this literature by providing evidence from experimental variation in an early-life health and human capital intervention on adult mental health. The improvements in parent psychological well-being presented here could also positively impact parenting practices, investment decisions, and child outcomes (Baranov et al., 2020; Pitchik et al., 2020; Racine et al., 2024; Rogers et al., 2020; Herba et al., 2016), fostering the human capital gains observed in the next generation.

2 Data

The analysis draws on carefully collected measures of the home environment and educational investments, along with measures of child health, non-cognitive development, and cognitive performance. Such rich data linking two generations are relatively uncommon in LMIC contexts, yet critical for studying the intergenerational impacts of early-life health interventions.

The analysis uses three main sources of data. First, measures of child cognitive development in math, language, and executive function come from an extensive set of direct child assessments. These are combined into core measures of academic cognitive performance (math, language) and overall cognitive performance (math, language, executive function). Second, measures of child health, child non-cognitive development, early life health investments, the home environment, and educational investments come from a survey directly administered to each child's primary caregiver. Finally, all of these child measures are combined with information about parents, who were themselves the recipients of the deworming treatment intervention during their youth, and who have provided extensive information through various surveys over the past decades. Below is a description of the intergenerational sample, followed by more discussion on the relevant measures. More details on the data collection strategy can be found in the pre-analysis plan (Fernald et al., 2019).

2.1 Sample inclusion and tracking

The primary intergenerational sample consists of biological children of KLPS respondents ("KLPS parents") who participated in the Primary School Deworming Project (PSDP; deworming).[14] PSDP participants are those who as children attended a primary school in Busia, Kenya in 1998 which was randomly selected to receive either early (treatment) or late (control) implementation of a school-based deworming intervention (see Miguel and Kremer (2004)). Long run outcomes for the PSDP sample are measured as part of the Kenya Life Panel Survey (KLPS), an active longitudinal survey with four completed rounds of data collection so far which has maintained high respondent tracking rates.

The present sample includes up to two children per KLPS parent, with at most one child in the pre-school aged group (3 to 5 years; "younger") and at most one child in the school-age group (6 to 8 years; "older"), a distinction made to reflect that children transition to primary school between ages 5 to 7. Children were identified as eligible for one of these age groups during a prior survey (called the "Integrated (I) module"), with one eligible child per age group then randomly selected for inclusion in the sample. Eligibility was determined based on the child's date of birth; due to the passage of time between waves, the window of eligible birth dates shifted from wave 1 to wave 2, resulting in slightly different birth cohorts across waves (Figure 1). During the I module, KLPS parents identified each child's primary caregiver, a designation given to the adult that knows the child very well and spends a substantial amount of time with them. (In 59% of cases, the KLPS parent is also the designated caregiver, at 83% for female KLPS parents and 31% for male parents).

The resulting sample consists of 1,967 older children and 1,563 younger children corresponding to 2,792 KLPS parents. Tracking rates were unusually high for the two-generation sample: 86% of KLPS respondents were surveyed in the I module,[15] with some statisti-

[14] Those in the parent generation who were randomly selected into the treatment groups of subsequent cross-cutting interventions are excluded; the cross-cutting interventions impacted less than 20% of the sample and include a vocational education program (Technical and Vocational Vouchers Program, VocEd) and a small grants program (Start-up Capital for Youth; SCY) that are the subject of other research. For simplicity, the sample of KLPS respondents who participated in the PSDP but did not participate in the cross-cutting interventions are simply called "KLPS respondents" or "KLPS parents."

[15] "Surveyed" is an effective tracking rate, reflecting whether respondents where surveyed in either the regular tracking phase or in the intensive tracking phase, excluding those who were deceased (approximately 5% of the sample) or not found during regular tracking nor randomly assigned to the intensive tracking phase, but including those who were deceased but tracked for the purposes of identifying eligible children (approximately 16% of the deceased sample). Weights are adjusted appropriately to account for this

cally significant but modest differences in tracking rates between wave 1 and wave 2 and across treatment arms (Table A1; column (1)). Nearly 70% of those surveyed had a biological child eligible for inclusion; eligibility is balanced across treatment groups, with no differences across tracking waves (Table A1; columns (2)-(4)). 88% of children identified as eligible for inclusion in the sample were surveyed,[16] (columns (5)-(7)) again with balance across treatment groups, and no differences across waves.

2.2 Data collection

All children completed a battery of age-appropriate assessments ("child assessments") described in detail in the next subsection. Designated primary caregivers completed a survey (the "Primary Caregiver (PC) module") capturing measures of child health, non-cognitive development, early life health investments, features of the home environment, and educational investments. The child assessments and PC modules were completed between 2018 and 2020 (for those assigned to wave 1) or in 2021 (for those assigned to wave 2) (Figure 1).

Outcomes at the KLPS respondent or household level were typically collected during other survey modules. For example, measures of KLPS respondent psychological well-being were collected during the I module, which usually took place several weeks before the child assessments and the PC module. The present study focuses on widely-used measures broadly related to parent psychological well-being and life satisfaction (that could be relevant for parenting), including symptoms of depression (measured using the Center for Epidemiological Studies Depression (CESD) Scale (Radloff, 1977; Andresen et al., 1994)), happiness, and life satisfaction (measured as per the World Values Survey (WVS, 2017)).[17] Measures of pre-Covid household economic circumstances (earnings, urban status, etc.) were collected in an earlier "Earnings Plus (E+) module"; in contrast to the I module, the E+ module was completed substantially earlier than the child assessments and PC module, between 2017 and 2019. Finally, measures of mid-Covid household economic circumstances, labor supply, and exposure to Covid-related shocks were collected for around 95% of the sample used in the present analysis (along with some respondents who did not complete an I module and/or child-related surveys) by phone. Figure 1 depicts the timing of all relevant surveys during KLPS-4, with more details on each of these survey modules in Appendix C.

two-stage tracking methodology. See Hamory et al. (2021b) for more details.

[16] A child is considered surveyed if their primary caregiver completed the primary caregiver survey and the child completed the battery of child assessments.

[17] See the associated pre-analysis plan for more information (Baird et al., 2019). The present analysis focuses on these three closely related outcomes but not others within the pre-specified "health and well-being" domain (self-reported health, perceived stress) which appear less relevant for the present study.

KLPS uses a two-stage tracking methodology, collecting respondent data in two representative waves. Table A2 summarizes characteristics of households, parents, and primary caregivers for children in the sample across the two waves. By design, differences in observable characteristics across waves are minimal. However, differences in experience are substantial: respondents surveyed in the post-Covid period (those randomly assigned to wave 2) recently experienced a prolonged exogenous shock in access to schooling due to school closures, while those surveyed in the pre-Covid period (wave 1) had not.

2.3 Child cognitive development

Performance on an extensive battery of assessments is used to construct measures of child cognitive development across three domains: language, math and spatial abilities (simply, "math"), and executive function. These assessments were carefully selected and extensively tested and adapted during an out-of-sample "pilot" phase in Kenya prior to the launch of data collection. Any modifications to standard administration procedures were intended to ensure that assessments were age- and context-appropriate.[18] Enumerators were carefully trained over the course of several weeks to ensure standard administration, with refresher training sessions as necessary. Finally, enumerators were supervised and monitored by experienced senior field officers, field managers, and research associates, and incoming data were analyzed for data quality on a regular (weekly) basis during the course of data collection.

Older and younger children completed distinct, age-appropriate subsets of assessments within each of these three domains. Language abilities for younger children were assessed using sections one to six of the Peabody Picture Vocabulary Test (PPVT; Dunn and Dunn (2007)) and the Malawi Developmental Assessment Tool - Language and Hearing (MDAT; Gladstone et al. (2010)). Older children completed sections three to ten of the PPVT, the Early Grade Reading Assessment Swahili (EGRA-Swahili; Dubeck and Gove (2015); Gove and Wetterberg (2011)), and (for those 7 or older) certain sections from the Early Grade Reading Assessment English (EGRA-English; Dubeck and Gove (2015); Gove and Wetterberg (2011)).[19] Math and spatial abilities were captured using a Mental Transformation subtask of the Measuring Early Learning Quality and Outcomes Direct Assessment (MELQO DA; UNICEF (2017)) for younger children, and using the Early Grade Math Assessment (EGMA; Platas et al. (2014)) for older children. Measures of executive function

[18]For example, replacing images of objects with similar but more context-relevant objects (for example, a mango instead of a pear) in the Peabody Picture Vocabulary Test (PPVT).

[19]These include the oral reading and the reading comprehension sections. Instruction in the English language begins in Kenya at Grade 4.

were captured using the Forward Digit Span subtask of the MELQO DA (younger and older children), and the Dimensional Change Card Sort (DCCS; Zelazo (2006); younger children only), and the tablet-based Promoting Learning, Understanding, Self-Regulation (PLUS-EF; Obradović et al. (2018); older children only) task. With the exception of EGRA-Swahili and EGRA-English, assessments were administered in the language in which the child was most comfortable (Swahili, Luhya, Luo, or English, where Swahili was the most typical, and many younger children in rural areas completed the assessments in Luhya).

These sets of assessments are summarized in Table 1 and in Table A15. Table A3 presents an overview of raw performance on each of these assessments, and Figure B3, Figure B4, and Figure B5 present the distribution of scores on each assessment by treatment status.

Table 1: Summary of Assessments

Domain	**Assessment**	**Younger** Ages 3-5 N=1,563	**Older** Ages 6-8 N=1,967
Language			
Receptive Vocabulary	The Peabody Picture Vocabulary Test (PPVT) (Dunn and Dunn, 2007)	✓	✓
General Language	Malawi Developmental Assessment Tool (MDAT) (Gladstone et al., 2010)	✓	
Literacy	Early Grade Reading Assessment Swahili (EGRA-Swahili) (Dubeck and Gove, 2015; Gove and Wetterberg, 2011)		✓
Literacy	Early Grade Reading Assessment English (EGRA-English) (Dubeck and Gove, 2015; Gove and Wetterberg, 2011)		✓*
Math and Spatial Abilities			
Spatial Abilities	Measuring Early Learning Quality and Outcomes (MELQO): Mental Transformation (UNICEF, 2017)	✓	
Numeracy	Early Grade Math Assessment (EGMA) (Platas et al., 2014)		✓
Executive Function			
Working Memory	Measuring Early Learning Quality and Outcomes (MELQO): Forward Digit Span (UNICEF, 2017)	✓	✓
Cognitive Flexibility	Dimensional Change Card Sort (DCCS) (Zelazo, 2006)	✓	
Cognitive Flexibility, Inhibitory Control	Promoting Learning, Understanding, Self-Regulation (PLUS-EF) (Obradović et al., 2018)		✓

Note: This table summarizes the battery of assessments used to measure cognitive development.
✓*: Administered to ages 7-8 only.

Five cognitive performance indices serve as primary outcomes, including three domain-specific indices (language, math, executive function) and two summary indices (academic cognitive abilities, overall cognitive abilities). The academic cognitive index combines across language and math, and the overall cognitive index combines across all three domain-specific indices. While not pre-specified, the academic cognitive index serves as one of the primary outcomes for several reasons. First, performance in language and math is perhaps most reflective of the skills that children learn in schools, particularly for older children. Second, while valuable, measures of executive function remain somewhat experimental and exploratory in the Kenyan context, especially for younger children; associated challenges in implementing and interpreting these measures are discussed below.

To construct the summary indices, raw assessment scores are normalized within gender and 6-month age bins relative to the PSDP control group in the pre-Covid wave (wave 1), then summed and re-normalized in the same way, finally winsorizing the top and bottom 1% of the distribution to minimize the impact of outliers. Similarly, the academic cognitive index and overall cognitive abilities index are constructed by summing across normalized domain-specific index scores, then re-normalizing and winsorizing the resulting index in the same way. This procedure deviates slightly from the pre-specified procedure, which was to normalize within gender and 3-month age bins relative to the PSDP control group in both waves, without winsorizing. Designating the control group in the pre-Covid wave as the reference group facilitates interpretation of the results, given the clear differences in performance across waves (which are naturally attributed to extended school closures). As a consequence, gender- and age-based reference groups are smaller than anticipated, motivating the shift from 3-month to 6-month age bins. Finally, small cell sizes and top-coding in certain of the assessments (EGRA, EGMA) led to positive outliers in the treatment group in several age groups; while results are robust to using the pre-specified indices, winsorizing the top 1% represents a more conservative approach to treatment effect estimation given these outliers (as discussed in Section 5).

In light of various challenges described in detail below, the analysis focuses primarily on the academic cognitive index, which excludes executive function. Most related work on measuring executive function and understanding the development of executive function among children comes from HIC settings (Obradović and Willoughby, 2019), though a growing body of research focuses on measuring executive function in LMIC settings (for example, Ahmed et al. (2022); Jasińska et al. (2022); Khan et al. (2024); Willoughby et al. (2019); Obradović and Willoughby (2019)). Further, measuring executive function among younger children can be particularly challenging (Korzeniowski et al., 2021; Ahmed et al., 2019; Willoughby et al., 2010; Garon et al., 2008), and exposure to poverty and stress can adversely impact development of executive functioning, potentially leading to low assessment scores and little variation at the younger ages (Finegood and Blair, 2017; Hackman et al., 2015).

Several minor adjustments in the executive function assessment scoring and index construction are made relative to the pre-specified approach, each based on updated knowledge from the field and the evolution of thinking in the literature.[20] First, three-year olds are excluded in the analysis of executive function treatment effects, given difficulties in administering the test to such young children. Second, for older children, the executive function index only incorporates scores for one of three PLUS-EF subtasks, the Multi-Source Interference Test (MSIT), disregarding those from the Stars and Flowers[21] and Flanker subtasks. This adjustment is made in response to implementation challenges arising from the process of calibrating this novel, tablet-based assessment to the specific context. Early on in data collection, it became evident that the amount of time allocated for each item was too short, and the time allocated was lengthened accordingly. For much of wave 1 (the pre-Covid wave), tablets inadvertently reverted to the previous (incorrect) default time settings. While this was resolved for wave 2 (the post-Covid wave), given that the time settings are a critical component of this assessment, children assessed in wave 1 effectively faced a different assessment compared to those in wave 2. In contrast, time settings for the MSIT subtask were constant throughout, and thus the executive function measure only includes scores from this subtask. Finally, minor adjustments are made in the scoring of the DCCS and in the PLUS-EF relative to the pre-specified approach to be more consistent with standard scoring practices and in the interest of constructing more meaningful measures.[22]

2.4 Child health and non-cognitive development

Other measures of child human capital come from the primary caregiver module; specific components are detailed in Table A15 and the pre-analysis plan (Fernald et al., 2019).

A strengths and difficulties index serves as the primary measure of child non-cognitive development. This index is composed of five subscales capturing (1) emotional problems, (2) conduct problems, (3) hyperactivity, (4) peer problems, and (5) prosociality.[23] These subscales are derived from a 25-item Strengths and Difficulties questionnaire (Goodman, 1997), based on caregivers indicating how true statements such as "often loses temper" or "often unhappy, depressed, or tearful" describes their child. A few items differ slightly across

[20]Robustness of the main results to several different ways of constructing the executive function measures discussed below is presented Section 5.

[21]Stars and Flowers is a Kenyan context-relevant adaptation of the usual Hearts and Flowers subtask.

[22]In the DCCS, instead of simply summing indicators for passing each of the pre-switch and post-switch rounds (in which case, children who fail the pre-switch round but pass the post-switch round would score a 1), children are only considered as passing the post-switch round if they also passed the pre-switch round. In the PLUS-EF, non-responses are counted as incorrect (instead of invalid), disregarding the rule where a string of non-responses at the end is automatically considered invalid, both of which would otherwise lead to substantial data loss.

[23]All but the prosociality subscale are reverse-coded so that higher values indicate fewer emotional problems, conduct problems, etc.

older and younger children. As with the cognitive indices, each subscale and the final index are normalized within gender and 6-month age bins relative to control in wave 1. In addition, a "Total Difficulties Score" is constructed by adding scores from the emotional problems, conduct problems, hyperactivity, and peer problems subscales.

Child health outcomes are quantified using a subjective health index and measured height. The subjective health index – which serves as the primary measure of child health – is composed of (1) an indicator for no sickness over the past 7 days, (2) self-reported overall child health, (3) an indicator for no serious health problems, and (4) an indicator for no disability (Durkin et al., 1995). Height-for-age z-scores are constructed by averaging three height measurements, then constructing z-scores based on WHO child growth standards.

2.5 Health, home, and educational investments

An early-life health investments index captures parental investments in child health through early-life vaccination and parasitic prevention behaviors. The early-life health investments index is constructed from a vaccination sub-index (capturing which of five possible vaccinations a child has received) and a parasitic prevention index (capturing whether the child slept under a bed net the previous night and whether the child received deworming treatment within the last 12 months).

A modified family care indicator (FCI) index constructed from an extensive and varied set of measures serves as the primary measure capturing the richness of the home environment. This five-component index includes (1) the number of books in the household (excluding picture or story books), (2) the presence of magazines, newspapers, and other reading materials in the household, (3) sources of play materials, (4) varieties of play materials, and (5) play activities with the caregiver or other household members. These measures were adapted from a variety of sources (Bradley et al., 2001; Hamadani et al., 2010; Kariger et al., 2012; Özler et al., 2018; Fernald et al., 2017; UNICEF, 2015). Treatment effects on the number of story or picture books in the home (excluded from (1) above, but included as a component of (4) above) are estimated separately.[24]

Finally, a school enrollment and educational investment index is constructed from five components capturing enrollment, attendance, and financial investments in education.[25]

Given little variation in measures of early life health and school enrollment and edu-

[24]These are the focus of separate research (Bonds et al., 2021).

[25]The top 1% of the distribution of the school enrollment and educational investment index is winsorized, to minimize the influence of outlier observations.

cational investments (due to high vaccination, parasitic prevention, school enrollment and school attendance in the Kenyan context), these outcomes receive little focus here, with estimated treatment effects on index components presented in an appendix (Table A6, Table A7, and Table A8).

3 Model

Before presenting the empirical approach and results, a stylized model is outlined to capture how school-based and home-based investments combine to produce child human capital. This model is used to facilitate interpretation of the empirical results and to predict how exogenous variation in parent human capital (due to randomized receipt of additional years of childhood deworming) and an exogenous shock to school-based investments (due to as-good-as-random assignment to the pre-Covid or post-Covid tracking wave) alone or in combination may influence child human capital development.

3.1 Features of the model

The model characterizes how child human capital develops over time as a function of school-based and home-based investments, and is related to Cunha and Heckman (2007). The model can be applied to other dimensions of child human capital such as health and non-cognitive development (as, for example in Cunha and Heckman (2008)); for simplicity, the present discussion focuses on the cognitive dimension. Specifically, cognitive skills in the next period (θ_{t+1}) are a function of current period cognitive skills (θ_t), plus school-based and home-based investments (I_t) made during the current period (S_t and H_t, respectively). $f(\cdot)$ is increasing θ_t, S_t, and H_t, and concave in S_t, and H_t:

$$\theta_{t+1} = f(\theta_t, I_t) = f(\theta_t, S_t, H_t) \tag{1}$$

Similarly, current period cognitive skills (θ_t) are a function of previous period cognitive skills (θ_{t-1}) and investments made during the previous period (S_{t-1}, H_{t-1}). Iterating backward, cognitive skills at $t+1$ can thus be expressed in terms of cognitive skills at birth (θ_0) and the stream of all prior school-based and home-based investments ($S_0, ..., S_t, H_0, ..., H_t$); this formulation makes clear that benefits of past investments accumulate over time:

$$\theta_{t+1} = f(\theta_t, S_t, H_t) = f(\theta_0, S_0, ..., S_t, H_0, ..., H_t) \tag{2}$$

A core assumption holds that home-based investments are a function of parent human capital, household living standards, and the quality of the home environment. Parent human capital (θ^P) includes health, psychological well-being, and educational attainment, which is assumed to be fixed by adulthood. Household living standards (y_t) incorporates household earnings, consumption, and urban residence. The quality of the home environment (b_t) includes features such as books, materials, and play activities. School-based investments are a function of time in school (h_t) and school quality (q_t). Combining these components:

$$H_t = m(\theta^P, y_t, b_t) \tag{3}$$

$$S_t = n(h_t, q_t) \tag{4}$$

The assumption that school-based and home-based investments are (weakly) increasing in factors such as parent human capital, psychological well-being, and household living standards may hold for several reasons. Parents with higher human capital may earn more ($\partial y/\partial\theta^P \geq 0$), and higher-earning parents may invest more in the quality of the home environment ($\partial b/\partial y \geq 0$) and in the quantity and quality of schooling ($\partial h/\partial y \geq 0$; $\partial q/\partial y \geq 0$). Parents with higher human capital may also have more information about the importance of the home environment and schooling for child development, and so may prioritize or prefer a higher-quality environment ($\partial b/\partial\theta^P \geq 0$) and invest in additional or higher-quality schooling ($\partial h/\partial\theta^P \geq 0$; $\partial q/\partial\theta^P \geq 0$).

Parent human capital and household living standards may also influence home-based investments directly. Conditional on household living standards and the quality of the home environment, higher human capital parents may invest more productively (time spent with children may be more effective, they may be better able to help their child with homework, etc.). Conditional on parent human capital and the quality of the home environment, children in higher-income households may have advantages that make other investments more productive (they may be better nourished, better able to learn and develop, etc.). Similarly, parents with improved psychological well-being – for example, those who are less depressed – may invest more, or may invest more productively (Baranov et al., 2020; Pitchik et al., 2020; Racine et al., 2024; Rogers et al., 2020; Herba et al., 2016). Combining these,

$$\frac{\partial H_t}{\partial \theta^P} = \frac{\partial m(\theta^P, y_t, b_t)}{\partial \theta^P} \geq 0, \qquad \frac{\partial H_t}{\partial y} = \frac{\partial m(\theta^P, y_t, b_t)}{\partial y} \geq 0 \tag{5}$$

An important feature of the model allows for complementarity between school-based and home-based investments, such that additional home-based investments may enhance the productivity of school-based investments, and vice versa. In contrast, low levels of one type of investment may limit the effectiveness of the other. Establishing the sign of this interaction effect is an important goal of the empirical analysis:

$$\frac{\partial^2 \theta_{t+1}}{\partial S \partial H} = \frac{\partial^2 f(\theta_t, S_t, H_t)}{\partial S \partial H} \overset{?}{\geq} 0 \tag{6}$$

Similarly, the model allows for for complementarity between existing cognitive skills and both school-based and home-based investments, so that school-based and home-based investments could each be more effective given higher current cognitive skills:

$$\frac{\partial^2 \theta_{t+1}}{\partial \theta \partial S} = \frac{\partial^2 f(\theta_t, S_t, H_t)}{\partial \theta \partial S} \overset{?}{\geq} 0, \qquad \frac{\partial^2 \theta_{t+1}}{\partial \theta \partial H} = \frac{\partial^2 f(\theta_t, S_t, H_t)}{\partial \theta \partial H} \overset{?}{\geq} 0 \tag{7}$$

While the focus is on complementarity between school-based and home-based investments, the model can also be enriched to allow for complementarity between different dimensions of child human capital (for example, higher non-cognitive skills may enhance the productivity of investments in cognitive skills).

3.2 Model predictions: Impact of deworming

The basic framework outlined above provides several predictions for how exogenous improvements in parent human capital and household living standards – through, for example, childhood deworming – or how exogenous shocks to schooling access – through, for example, extended school closures – may impact child human capital development.

Existing analysis demonstrates positive impacts of childhood deworming on human capital and household living standards in adulthood. A growing body of research based on the KLPS sample shows that childhood deworming led to a range of benefits, including improvements in schooling and health in the short term (Miguel and Kremer, 2004), in educational attainment and labor market outcomes in the medium term (Baird et al., 2016), and in consumption, earnings, and urban residence (Hamory et al., 2021b) up to 20 years later.

This paper provides new evidence that childhood deworming also improves adult psychological well-being. Together, the body of results indicates that childhood deworming positively impacts various dimensions of parent human capital and household living standards in the households where their children grow up; using the model's notation, $\theta^P \uparrow$ and $y \uparrow$.

These impacts could lead to improvements in child cognitive development through at least four channels. First, home-based investments may be greater among recipients of childhood deworming. These effects could come through improvements in the quality of the home environment (since $\partial b_t / \partial \theta^P \geq 0$ and $\partial b_t / \partial y \geq 0$), or directly through greater human capital (since $\partial H_t / \partial \theta^P \geq 0$) or higher household income (since $\partial H_t / \partial y \geq 0$).

Second, recipients of childhood deworming may invest more in schooling, if school-based investments are increasing in parent human capital ($\partial S_t / \partial \theta^P \geq 0$) or household income ($\partial S_t / \partial y \geq 0$).

Third, childhood deworming may increase the productivity of school-based investments through positive complementarities with (elevated) home-based investments:

$$\frac{\partial}{\partial H}\left(\frac{\partial \theta}{\partial S}\right) = \frac{\partial^2 f(\cdot)}{\partial H \partial S} > 0 \tag{8}$$

Fourth, children of deworming recipients may have greater cognitive skills through the cumulative effect of past school-based and home-based investments $\{S_0, ..., S_{t-1}, H_0, ..., H_{t-1}\}$ since through these same channels:

$$\frac{\partial \theta_\tau}{\partial \theta^P} > 0, \quad \frac{\partial \theta_\tau}{\partial y} > 0 \quad \forall \quad \tau \in \{1, ..., t\} \tag{9}$$

Taken together, the model predicts that cognitive performance will be higher among children of deworming treatment group parents:

$$\bar{\theta}^{PSDP=1} > \bar{\theta}^{PSDP=0} \tag{10}$$

Similarly, the model predicts that there could be improved outcomes among children of deworming treatment group parents in other dimensions of child human capital such as health and non-cognitive development. Even if school-based investments and complementarities between school-based investments are less relevant for these dimensions of child human capital development (i.e., math lessons at school are unlikely to improve child health), developmental gains could still come through improvements in parent human capital and household living standards directly, and through the cumulative effect of complementarity between human capital and investments over time.

3.3 Model predictions: Impact of the Covid Shock

The model also provides several predictions for how tracking wave assignment – and hence exposure to recent school closures – could impact child cognitive development. Given that Kenyan schools were nearly fully closed for nine months between data collection waves, school-based investments were greatly reduced – if not essentially non-existent – for a substantial portion of the recent past for those children assigned to post-Covid (wave 2) data collection compared to those assigned to pre-Covid (wave 1) data collection. Once again, it was simply fortuitous that wave 1 data collection ended a matter of days before Covid lockdowns began in Kenya. Using the notation of the model, $S_{t-1}^{Pre-Covid} \gg S_{t-1}^{Post-Covid} \approx 0$.

Given the key role school-based investments play in child cognitive development, the first hypothesis posits that cognitive performance will be lower among children surveyed in the post-Covid wave, since

$$\begin{aligned}
\bar{\theta}^{Post-Covid} &= f(\theta_{t-1}, H_{t-1}, S_{t-1}^{Post-Covid}) \\
&\approx f(\theta_{t-1}, H_{t-1}, 0) \\
&< f(\theta_{t-1}, H_{t-1}, S_{t-1}^{Pre-Covid}) = \bar{\theta}^{Pre-Covid}
\end{aligned} \tag{11}$$

The second hypothesis holds that in the post-Covid wave, there will be at most minimal differences in cognitive performance across children of deworming treatment and control parents if there are meaningful complementarities between school-based and home-based investments. No positive treatment effects of deworming would emerge in the post-Covid period if recent school-based investments are nearly zero for both the treatment and control groups, and if home-based investments become substantially less productive in their absence. In other words, differences across treatment and control groups may not arise if school-based investments are essential for child cognitive development (alone or as complements with home-based investments) such that even elevated home-based investments are unable to compensate for their recent absence; even in the relatively high human capital homes, for instance, parents may not have had the ability or time to teach their children the math curriculum. An important issue here is that the school age children in the older sample are very early in their primary school careers, such that a lost year of schooling constitutes a large share of their total potential school exposure. In that case, the negative impact associated with recent school closures may dominate any gains attributable to the intergenerational impacts of deworming, so that

$$\bar{\theta}^{Post-Covid,PSDP=1} \approx \bar{\theta}^{Post-Covid,PSDP=0} \tag{12}$$

Finally, while there could be differences in the cognitive dimension of child human capital (and related treatment effects) across the pre-Covid and post-Covid data collection waves, differences across waves in the health and non-cognitive dimensions of child human capital may be less pronounced, since these dimensions may be less sensitive to school learning. Similarly, there could be greater differences for the older children, who would have been more impacted by school closures, than for younger children, who were not yet of school age.

The data environment allows for an empirical test of the core predictions summarized primarily in equations (10), (11), and (12). The next section outlines the empirical approach.

4 Empirical Approach

The pre-specified primary analysis estimates treatment effects associated with childhood deworming in one generation on health, non-cognitive development, and cognition in the next generation. The deworming program (PSDP) was phased in over several years across randomly-assigned groupings of schools. KLPS parents randomly assigned to early receipt of deworming (starting in 1998, for those attending Group 1 schools or starting in 1999, for those attending Group 2 schools) comprise the treatment group, while those assigned to later receipt of deworming (starting in 2001, for those attending Group 3 schools) comprise the control group. All KLPS parents in the PSDP sample eventually received the deworming medication; based on this research design, treatment parents on average received an additional 2.4 years of exposure to deworming during childhood.

Intergenerational treatment effects are estimated using the following estimating equation:

$$Y_{ijk} = \alpha + \beta T_k + X'_{ijk}\delta + \varepsilon_{ijk} \tag{13}$$

where Y_{ijk} are health, non-cognitive, cognitive, or other outcomes for child i of KLPS parent j originally in PSDP school k. T_k indicates whether the KLPS parent's school k was assigned to treatment, with their biological children considered as inheriting this same treatment status. Consequently, β captures the average impact of parent childhood deworming treatment exposure on their child's outcome Y_{ijk}. X_{ijk} is a vector of standard covariates (at the child, parent and school levels) following the pre-analysis plan and related analyses (Miguel and Kremer, 2004; Baird et al., 2016; Hamory et al., 2021b). These include an indicator for assignment to school cost-sharing treatment in 2001 (described in Kremer and Miguel (2007)), local treatment saturation within 6 km radius of 1998 PSDP school, density of children within 6 km radius of 1998 PSDP school, 1998 parent school zone indicator, population of 1998 parent school, indicator for parent inclusion in the vocational education cash grant sample, average test score of the parent school in 1996, parent gender, parent grade in 1998, and an indicator for tracking wave assignment. For this intergenerational impacts analysis, X_{ijk} also includes interviewer gender, months elapsed since survey wave start, and (for outcomes not normalized by child gender and age) child gender and age in 6-month bins. All regressions include weights to account for the two-stage tracking methodology (to maintain baseline sample representation among KLPS parents) and for total fertility (to provide a representative sample of the next generation).[26] Standard errors are clustered by 1998 PSDP school k.

The present study focuses on measures of child human capital including health, non-cognitive development, and cognitive development. For a more comprehensive analysis of intergenerational impacts, as pre-specified, treatment effects are also estimated for a broader set of outcomes, including what are here considered to be secondary outcomes (such as early life health investments), and those not emphasized in the present study (i.e., child discipline strategies), see appendix Table A17. This analysis also includes pre-specified adjustments for multiple hypotheses testing, specifically, sharpened q-values (Anderson, 2008).

An additional specification is used to examine the impact of Covid-related school closures on cognitive performance and to explore possible complementarities between parent human capital and the local schooling environment, a central goal of the present analysis. To test for such complementarities, equation (13) allows for separate deworming treatment effects for children assigned to the pre-Covid tracking wave (wave 1) and those assigned to the post-Covid tracking wave (wave 2), where the interaction between the treatment effect indicator

[26]For analyses pooling old and young children, weights are further adjusted for the number of eligible children per KLPS parent.

and the post-Covid time effect is the key term:

$$\begin{aligned} Y_{ijk} = \alpha + \beta T_k + \lambda \mathbb{1}_{ijk}^{Pre-Cov} + \gamma(T_k \times \mathbb{1}_{ijk}^{Pre-Cov}) \\ + X_{ijk}'\delta + (X_{ijk} \times \mathbb{1}_{ijk}^{Pre-Cov})'\pi + \varepsilon_{ijk} \end{aligned} \tag{14}$$

Here, the coefficient on the interaction term, γ, captures the existence of complementarities between school-based and home-based investments described in equation (6). A positive estimate for γ would indicate that the benefits associated with the parent human capital intervention are enhanced by the presence of local schooling availability. β captures estimated deworming treatment effects in the post-Covid wave, and λ captures if and how cognitive performance differs across waves (pre versus post-Covid) within the control group. If β is zero and γ large and positive, this would indicate that the parent human capital gains do not deliver benefits for child outcomes in the absence of local schooling inputs.

The comparison of the pre-Covid (wave 1) versus post-Covid (wave 2) children relies on the random allocation of KLPS respondents into these two representative tracking waves, and as such they should be balanced along both observable and unobservable dimensions. We verify that a range of respondent characteristics (many of which were collected prior to Covid, or were unlikely to be impacted by the pandemic) are in fact balanced across waves in Table A2, both for the full sample and for parents of children in the intergenerational sample (i.e., parents of those children selected for the present analysis).

For analyses estimating treatment effects on measures of household living standards (including consumption, earnings, urban status), data are pooled across as many KLPS rounds as available. Treatment effects on household living standards are estimated for the the full sample of KLPS respondents, and for parents of children in the intergenerational sample.

5 Results

This section presents and discusses the main empirical results. The overall pattern of results can be interpreted as consistent with a model of human capital development featuring meaningful positive complementarities between school-based and home-based investments.

5.1 Parent human capital and household living standards

The first analysis reproduces results of previous research showing that childhood deworming leads to lasting positive impacts on recipient human capital and household living standards, and confirms that many of these positive impacts emerge in the subset of KLPS respondents with children in the intergenerational sample. Estimates presented in Panel A of Table A5 reproduce and extend existing findings from Baird et al. (2016) and Hamory et al. (2021b), which draw on several rounds of KLPS data to estimate impacts in the full KLPS sample. KLPS respondents assigned to childhood deworming attain an additional third of a year of education (column (1); not statistically significant), are 4 percentage points more likely to live in an urban setting (column (2); statistically significant at 5%), and live in households with higher per capita consumption and total earnings (columns (3) and (4); both statistically significant at 10%). Estimated treatment effects are consistent in sign though less precisely estimated when restricting to the intergenerational sample (Panel B).

5.2 Child health and non-cognitive development

The next set of results provides evidence of positive intergenerational impacts of childhood deworming on child non-cognitive (socioemotional) development among older children, and to some extent on health outcomes among older and younger children. In contrast to cognitive performance, we show below that there are no differences observed across waves in terms of non-cognitive and health outcomes.[27] As a result, this analysis generally pools across the pre-Covid and post-Covid waves of data collection for these outcomes where recent school closures appear less relevant.[28]

We first present estimates depicting positive intergenerational impacts of childhood deworming on child health in the next generation (Table 2). The overall subjective health index is 0.15 standard deviations higher for older children of parents assigned to the deworming treatment group, significant at 10%. For older children, treatment effect estimates are positive though not statistically significant for many components of the subjective health index (columns (2)-(5) of Panel A), and there is a large (9 percentage point) and highly significant reduction in the likelihood a child exhibits any developmental delays or disability. For younger children, caregivers of children whose parents are in the treatment group report higher overall child health (column (3) of Panel B), and score 0.13 standard deviations higher on the overall subjective health index, though the latter is not significant (column

[27] These findings are consistent with evidence from Germany, where despite parents reporting negative psychological impacts of the pandemic on children, measures of non-cognitive development during the pandemic (collected using the Strengths and Difficulties Questionnaire) do not decline relative to the pre-Covid period (Werner and Woessmann, 2023).

[28] Differences in treatment effects on the summary indices capturing child health, non-cognitive development, and cognitive development across waves are presented in Table B2, which displays coefficient estimates corresponding to regressions where treatment status and all covariates are interacted with tracking wave assignment, as per equation (14).

(1) of Panel B). No differences in child height-for-age z-scores – a marker of diet quality and nutrition – emerge across treatment and control groups for older or younger children (column (6), Panels A and B); though not reported here, similar results emerge for height measured in centimeters.

Second, estimated treatment effects provide evidence of positive intergenerational impacts of childhood deworming on non-cognitive (socioemotional) development, primarily among older children (Table 3). Coefficient estimates document improvements in all five subscale outcomes for older children of deworming recipients (columns (2)-(6) of Panel A). Children of deworming recipients exhibit more prosocial behaviors, an effect significant at the 1% level (column (2)). In terms of negative behaviors, children of deworming recipients are less likely to exhibit emotional problems (significant at 5%), conduct problems, hyperactivity, or peer problems (though these are not significant), and score nearly a full point higher in the total difficulties score (3% higher relative to the control mean, significant at 10%; column (7)). Older children of deworming recipients score 0.20 standard deviations higher on the strengths and difficulties index (significant at 5%), a summary measure of non-cognitive development which incorporates the positive and negative behaviors captured in all five subscales (column (1)). For younger children, estimates in Panel B mostly suggest improvements among children of deworming recipients, though these estimates are insignificant.

Heterogeneity analysis presented in Table 5 suggests that these intergenerational health and non-cognitive gains are especially strong among younger female children compared to younger male children, consistent with several pieces of existing evidence on intergenerational transmission (Akresh et al., 2023b; Barham et al., 2023) and on differential spending and investment patterns across male and female children (Duflo, 2003; Dizon-Ross and Jayachandran, 2022). Within the sample of younger female children, children of treated parents score 0.36 standard deviation units higher on the subjective health index (column (1) in panel C of Table 5), an estimate significant at the 1% level. Similarly, the strengths and difficulties index is 0.27 standard deviation units higher among female children of deworming treatment recipients compared to those in control, significant at 5% (column (2)). No positive treatment effects emerge for younger male children for either outcome. These differences in estimated treatment effects by gender are statistically significant.

5.3 Cognitive development

5.3.1 Wave-based tracking and differential exposure to Covid school closures

Treatment effects on cognitive development are estimated separately by data collection wave to account for differences in access to recent schooling in the pre-Covid and post-Covid waves. Due to the two-wave tracking approach, each wave of data collection provides, in principle, a representative subsample of the overall study population. In practice, household and other relevant characteristics are largely similar across waves, with only minor differences in observed characteristics (as depicted in Table A2, Panel A). For example, household composition (size, number of children), earnings, agricultural employment, and educational attainment are similar across waves, while households in the post-Covid wave are marginally less likely to live in urban areas and consume less.[29] These patterns are largely similar for the intergenerational sample, though in this subsample, parents are a little over a year and a half older at the time their children were surveyed, and educational attainment is marginally higher among those assigned to the second tracking wave. Both are in part due to the fact that children eligible for the study (based on age) were born in imperfectly-overlapping cohorts across waves (Figure 1).

While households in each of the two waves are similar in terms of characteristics, they differ dramatically in terms of exposure to recent disruptions in schooling. Panel A of Figure 2 depicts how the most severe Covid-related disruptions took place precisely in between waves of data collection, so that those assigned to the post-Covid wave (from January-December 2021) experienced a prolonged period of school closures in the recent past while those assigned to the pre-Covid wave (from October 2018-March 2020) did not. Panel B of Figure 2 depicts trends in school attendance over time, separately for older and younger children. School attendance was high in the pre-Covid wave and reverted quickly following the reopening of schools in January 2021, particularly among older (school-age) children. Schools fully closed in the interim (from March 2020-January 2021) and home-based learning activities were minimal in comparison: children in only 44 to 57% of households engaged at home in any learning activities provided by the child's school, with some evidence of a downward trend over time as closures persisted.[30] These findings are broadly consistent with those reported

[29] The survey collecting household earnings and consumption was conducted prior to Covid in an earlier household visit, both for households included in the pre-Covid and post-Covid waves in the present sample; as a consequence, measures of household earnings across waves do not incorporate any impact of pandemic disruptions on household earnings, and so should be comparable, aside from the influence of normal economic fluctuations over time.

[30] Measures of home-based learning activities include engaging with any of the following activities over the

in Uwezo (2021), who find that approximately 22% of public schools and 52% of private schools in Kenya provided any form of learning continuity support during closures.

5.3.2 Pre-Covid treatment effects

Childhood deworming leads to substantial gains in cognitive outcomes among older (school-age) children in the next generation (Table 4, Panel A). Older children of deworming recipients score 0.26 standard deviations in the academic cognitive index (column (1)), which combines across the language and math and spatial abilities indices. These gains are meaningful in magnitude: to illustrate, 7 year olds score on average 0.72 standard deviation units higher than 6 year olds (in the control group, and on a separate index normalized relative to 6 year olds), so the estimated 0.26 effect equates to over one third of a year of typical cognitive gains at this age.

Scores are 0.21 and 0.28 higher in the language index (column (2)) and math and spatial abilities index (column (3), respectively. The results provide no evidence of impacts on the executive function index (column (4)), but do provide evidence of a 0.25 standard deviation unit improvement among children of deworming recipients in the overall cognitive abilities index (which combines across the language, math, and executive function domains) (column (5)).[31] No positive treatment effects emerge among younger children (Panel B), with the exception of perhaps surprisingly lower performance in the measure of executive function. As noted above in Section 2, measurement of executive function in this context – particularly among younger children – is considered exploratory and experimental.

5.3.3 Post-Covid treatment effects

There is no significant evidence of similar treatment gains in the post-Covid period. First, performance declines across the board in the post-Covid data collection wave. Within the control group, language scores decline by 0.17 standard deviations, while math and spatial scores decline by 0.10 standard deviations. Second, no positive parent deworming treatment effects are estimated for any of the cognitive indices (columns (6)-(10)).[32] Estimated

last 24 hours: (1) homework or other teaching materials prepared or assigned by the school, (2) e-learning modules prepared by the school, or (3) school textbooks. These were collected via phone, and with respect to a randomly-selected child, not necessarily the same child included in the main child sample here.

[31] Table A18 demonstrates the robustness of these results to using non-winsorized cognitive indices (as pre-specified) and to constructing indices by pooling across waves (as pre-specified), and to alternative ways of constructing scores for EGRA-Swahili and EGRA-English (equally weighting sections, or equally weighting domains.

[32] As another way of presenting these patterns, Table B2 displays coefficient estimates for regressions interacting treatment status (and all covariates) with assignment to the first tracking wave.

treatment effects differ significantly (at the 5% level[33]) across waves of data collection for all outcomes aside from the executive function index. Similar to the pre-Covid wave, no treatment effects on executive function are estimated in the post-Covid wave.

These results suggest that nine months of Covid-related school closures led to substantial average learning loss for school-age children in both treatment and control. Put differently, whatever advantages associated with the deworming treatment – among them, improved parent human capital and household living standards – led to improved cognitive outcomes in "normal" pre-Covid times were insufficient to protect against learning loss in the period following a prolonged disruption to formal schooling.

5.3.4 Heterogeneity by Gender

As with child health and non-cognitive development, the analysis points to larger treatment gains in cognitive development among younger female children specifically. While no improvements in cognitive development appear in the sample of younger children when pooling across males and females, younger female children of treated parents score 0.52 standard deviations higher on the academic cognitive index in the pre-Covid wave (column (3) of panel C in Table 5). No positive treatment effects emerge in the post-Covid wave, nor among younger males in either wave. As discussed above, school closures would have been less relevant for younger (pre-school age) children, and indeed no declines are detected in academic cognitive performance in the post-Covid relative to the pre-Covid wave for younger males or females. When pooling the pre-Covid and post-Covid waves (in unreported regressions), younger female children of treated parents score 0.23 standard deviations higher on the academic cognitive index, an estimate significant at the 10% level and significantly different (at the 10% level) from the corresponding estimate within the younger male sample. It is unclear what factors give rise to these differential treatment effects across males and females: development trajectories could differ by gender, as could the influence of parent human capital and the local schooling environment on these trajectories, and this will be the subject of further research using data from future follow-up rounds.

[33] P-values associated with coefficient estimates for the interaction term in equation (14) are 0.03 for the academic cognitive index in columns (1) and (6), 0.06 for the language index in columns (2) and (7), 0.03 for the math and spatial abilities index in columns (3) and (8), 0.19 for the executive function index in columns (4) and (9), and 0.04 for the cognitive abilities index in columns (5) and (10).

5.4 Taking stock of the different dimensions of impacts

In a summary of the study's main findings, Figure 3 plots estimated treatment effects for key outcomes, separately for older and younger children and by wave. The lower portion of this figure makes clear the positive treatment effects on both the academic cognitive index and the closely-related cognitive abilities index for older children in the pre-Covid wave. In contrast, estimated treatment effects for older children and in the post-Covid wave and for younger children in both waves are essentially zero (see also Panel C of Figure 2).

The upper portion of Figure 3 plots estimated treatment effects for health and non-cognitive outcomes, giving a slightly different view of the results compared to those presented in Table 2 and Table 3, which pooled across both waves. Estimated treatment effects on the summary indices capturing health and non-cognitive development are positive and of similar magnitude for older children in both waves (and statistically significant, when pooling both waves as shown in Table 2 and Table 3). For younger children in the pre-Covid wave, estimated treatment effects are essentially zero. In contrast, treatment effect estimates in the post-Covid wave suggest marginal improvements in health and non-cognitive outcomes among younger children similar in magnitude to estimates corresponding to older children. Though these estimates are not statistically significant, these findings suggest that some features of Covid-related disruptions may have actually promoted health and non-cognitive development among younger children; though speculative, perhaps having adults and older siblings spending more time at home provided a more stimulating environment for some children (Pitchik et al., 2021).

5.5 Mechanisms

The estimated treatment effects of deworming on the summary indices capturing early life health investments (Table 6, columns (1) and (2)), the home environment (Column (3)[34]), and school enrollment and educational investments (Columns (4) and (5)) are mostly positive, however, none are statistically significant at traditional confidence levels. (Treatment effect estimates for the full set of pre-specified outcomes in these domains are presented in Table A6, Table A7, and Table A8.)

The analysis presented here thus provides little clear evidence that the estimated gains in child human capital stem from improvements in the home environment or in health and

[34]Here results are presented pooling at the household level to accommodate cases where the home environment is shared by children selected for both the older and younger age groups.

educational investments as measured in this study. Instead, these gains could come from some other features associated with improved parent human capital and household living standards, or in non-material, quality-related features of the home environment which the measures employed are unable to detect.

The measures used in the KLPS surveys were designed to be quite comprehensive, yet it remains possible that the surveys — as detailed as they were – were still unable to detect some meaningful elements of health, home, and schooling investments. For example, behaviors such as how frequently parents speak with their young child could influence that child's development (Hoff, 2003; Weisleder and Fernald, 2013). In contrast to studies dedicated to characterizing determinants of parent-child speech patterns and investigating these important relationships (Dupas et al., 2023; Hallez et al., 2021), carefully measuring such patterns would not have been feasible in the context of the present study.[35] Further, the absence of treatment effects could to some extent reflect a lack of variation in the measures employed: encouragingly, measured early life health investments (such as childhood vaccination) and school enrollment are virtually universal across children of parents in both treatment and control, so it is unsurprising that no differences are detected across groups. Nevertheless, these results do suggest that the estimated gains in cognitive and non-cognitive development among older children are more likely to have been driven by general improvements in household standards of living (or in unmeasured improvements in the quality of investments or in parent-child interactions).

New results presented in Table 6 show that childhood deworming leads to improvements in various measures of psychological well-being among parents in adulthood. Deworming recipients score 0.71 points lower on the 0 to 30 CESD depression scale (equivalent to 0.12 standard deviation units lower), an estimate significant at the 5% level (column (6)), and Figure A3 provides evidence of reduced depressive symptoms among deworming treatment recipients throughout the distribution. Self-reported happiness is similar across respondents in treatment and control (column (7)), though deworming recipient parents report nearly half a point higher life satisfaction on a 10-point scale, an estimate statistically significant at the 5% level (column (8)).[36] Consistent with research linking parent psychological well-being to child investments and outcomes (Baranov et al., 2020; Pitchik et al., 2020; Racine et al., 2024;

[35] For example, recent research uses LENA digital language processors (Gilkerson and Richards, 2008) to capture the language environment to which infants and young children are exposed, devices which would have been logistically challenging and cost-prohibitive to implement here.

[36] Table A14 presents similar analysis for the full sample of KLPS respondents. In the full sample, depressive symptoms are substantially lower among deworming recipients (0.88 points, equivalent to 0.14 standard deviation units), with no estimated improvements for the other dimensions of psychological well-being.

Rogers et al., 2020; Herba et al., 2016), these estimated improvements in psychological well-being, together with improvements in other domains of parent human capital and household living standards, could account for some part of the positive intergenerational impacts on child human capital estimated in this study.

5.6 Robustness

The main results are largely robust to estimation using alternate weights or to estimation without sampling weights and/or covariates, or to including enumerator fixed effects, and similar treatment effects emerge for pre-specified subgroup analyses. Results are similar for male and female parents, and for parents who had been older (over 12 years) or younger (below 12) at the time of the deworming intervention.[37] Coefficient estimates for treatment effects on cognitive performance (using the academic cognitive index) and health and non-cognitive development (using the subjective health index and strengths and difficulties index) corresponding to these robustness checks and pre-specified heterogeneity analyses are plotted in Figure A1 and Figure A2, respectively.

As discussed, the disruption due to Covid-related school closures between tracking waves motivates the use of a research design where treatment effects on cognitive development in particular are estimated separately for each wave. Nevertheless, Table A17 presents treatment effect estimates for eight summary outcomes pooling across waves, for younger and older children together (panel A) and separately (panels B and C), according to the pre-specified research design.[38] For comparison, Panel D presents estimated treatment effects for older children in wave 1 as per the modified research design. Estimated effects on child health, non-cognitive development, and cognitive development among older children are not statistically significant after adjusting for multiple hypothesis testing across all eight pre-specified summary outcomes when pooling across waves (panel C) or in the smaller wave 1 sample (panel D), according to the sharpened q-values in table rows (Anderson, 2008). However, after adjusting for multiple hypothesis testing across the four pre-specified primary child outcomes (in columns (1)-(4)), estimated treatment effects on each of the cognitive abilities index, strengths and difficulties index, and subjective health index are marginally significant (q-values ranging from 0.14 to 0.19), both when pooling waves (panel C) and

[37]Meaningful differences in treatment effects for various economic outcomes across older and younger deworming recipients are reported in Hamory et al. (2021b).

[38]Here, cognitive development is measured using the pre-specified cognitive abilities index which includes executive function, rather than the academic cognitive index preferred for the main analysis. Moreover, it is presented in its non-winsorized form, again as pre-specified.

within wave 1 (panel D).[39]

Finally, results are robust to alternative methods of scoring the assessments that comprise the academic cognitive index (Table A18) and the executive function index (Table A19).

5.7 Discussion

Taken together, these empirical results indicate that there is positive intergenerational transmission of human capital, and are consistent with a model of human capital production featuring meaningful complementarities between school-based and home-based investments. The estimated improvements in health, non-cognitive development among older children, and cognitive development among older children in the pre-Covid wave point to meaningful impacts of childhood deworming in one generation on human capital development in the next. The results provide little evidence that parent deworming led to greater early life health investments, increased schooling and educational investments, or to a higher-quality home environment. (In terms of the model, there appears to be little evidence that $\partial S/\partial \theta^P > 0$, $\partial S/\partial y > 0$, $\partial b/\partial \theta^P > 0$, or $\partial b/\partial y > 0$, at least among those dimensions measured.) Instead, improvements in cognitive performance among older children are likely to be attributable to other benefits associated with improved parent human capital, psychological well-being, or household living standards. This could be through their direct effect on "effective" home-based investments ($\partial H_t/\partial \theta^P > 0$, $\partial H_t/\partial y > 0$), or through the additional benefits of positive complementarities between parent human capital and household living standards with school-based investments ($\partial^2 f(\cdot)/\partial H \partial S > 0$).

Several of the study's other findings point to the existence of meaningful complementarities between school-based and home-based investments. First, the overall decline in cognitive performance among older children following prolonged school closures, and the absence of treatment effects in the post-Covid wave suggest that the observed gains in the pre-Covid wave were not driven by advantages associated with improved parent human capital or household living standards alone. If this was the case, positive treatment effects might also emerge in the post-Covid wave.[40] Instead, if complementarity between school-based and home-based investments plays a meaningful role in the production of child human capital, any improvements in cognitive performance due to advantages associated with improved

[39] Table A17 presents results in keeping with the pre-analysis plan for summary outcomes; estimated treatment effects (and the corresponding multiple hypothesis testing adjustments) for the full set of pre-specified outcomes, including index components, are presented in a supplementary appendix.

[40] It is unlikely that Covid-related disruptions impacted parent education, and though earnings did decline somewhat at the height of the pandemic in the Kenyan context as in other LMICs (Egger et al., 2021), this living standards measure had nearly reverted to earlier levels by the post-Covid data wave.

parent human capital or household living standards would fail to materialize in the absence of (complementary) school-based investments in the previous period ($S_{t-1} = 0$). Further, the sharpest declines are found in the more academically-oriented domains of language and math, but not in executive function, nor in measures of health or non-cognitive development, domains that seem likely to be less sensitive to a recent absence of schooling-related investments.[41] Somewhat speculatively, even though schools were closed, Covid lockdowns may have been less disruptive to kids' social lives in the Kenyan context compared to many other societies, given that fewer households were fully sheltering in place at home, and given the larger number of siblings on average in Kenya (compared to high-income countries).

Second, the absence of treatment effects on cognition among younger children (in either wave) and the absence of an overall decline in performance (across waves) also support the existence of complementarities. Complementarities appear to be most relevant for older (school-age) children, less so for younger (pre-school age) children.[42] Put differently, the intergenerational benefits of parent deworming may be realized as children age and enter school, at which point school-based investments interact with improved home-based investments to more effectively produce child human capital.

Lingering concerns could be that differences in the estimated treatment effects across waves stem not from differential access to schooling alone, but from other factors that differentiate those assigned to wave 1 from those assigned to wave 2. These could include differential impacts of childhood deworming on pre-Covid outcomes across waves, the differential impact of (non-school-related) Covid disruptions by treatment status across waves, or differences in the composition of children in treatment and control across waves. As expected, and consistent with the sample being randomly divided into two representative tracking waves, there is little evidence of differential treatment effects of deworming across waves in terms of the measures of parent human capital and household living standards, as presented in Table A10. (If anything, estimated treatment effects are larger in magnitude in wave 2 for some outcomes, though not significantly so.) Further, while the sample of parents in the post-Covid wave are slightly older (partially a mechanical result, since data collection took place after data collection for wave 1) and slightly more well-educated, measures of

[41] If complementarity between school-based and home-based investments does play a strong role in driving pre-Covid effects, the strongest gains in the pre-Covid wave and the sharpest declines in the post-Covid wave might be estimated among those with greater school-related investments. However, there is no evidence of heterogeneity in estimated gains among older children in the pre-Covid period along various dimensions indicative of intensity of school investments (see Table A13), though this could to some extent again reflect a lack of variation in school-related investments as discussed in Section 5.5.

[42] Table A4 shows that only two thirds of younger children attended an educational program (primarily nursery or pre-school) in the last week, while virtually all older children did so (primarily primary school).

pre-Covid household living standards are similar across waves (Table A2).

Second, there appears to be no evidence for other differential impacts of Covid across treatment and control groups by tracking wave assignment, supporting the view that the main Covid-induced difference across waves was in recent access to schooling, rather than any other Covid-related disruptions. Drawing on data collected in 2021 (mid-pandemic, for both waves) using a phone-based survey module, treatment effects on economic outcomes such as consumption,[43] food security, agricultural employment, or disruptions such as closing a business, losing a job, or selling assets appear similar across tracking waves (Table A11). Similarly, treatment effects on changes in household membership, respondent mental health, and child home learning activities appear similar (Table A12). In general, deworming treatment recipients and their children do not appear to have been much more or less exposed to Covid-related disruptions, and importantly for the research design, there appear to be no differential treatment effects across waves.

Finally, there is no evidence that the estimated pattern of treatment effects across waves arises from meaningful differences in the composition of children across waves. While the adult samples are by design comparable across waves, the child sample was selected based on their age at the time of the survey and assessment. Given the passage of time between waves, this results in a sample of children from imperfectly overlapping cohorts, and hence from households that may not necessarily be comparable across waves.[44] Encouragingly, the pattern of results is similar when restricting the analysis to a sample of children identified as belonging to a "common cohort sample" of children whose birth month and year would have made them eligible for inclusion in the sample in either wave (see Figure 1). The estimates presented in Table A9 shows that even when adjusting the sample to eliminate the influence of any potential cohort or compositional effects, the pattern of positive treatment effects on cognition in wave 1 and null effects in wave 2 persists.

6 Conclusion

This study leverages exogenous variation in parent human capital due to a randomized intervention with cross-cutting variation in access to schooling – due to randomly-assigned tracking wave – to estimate the intergenerational impact of parent human capital and to explore how parent human capital and school availability interact. The analysis relies on

[43]Consumption was only collected for a randomly chosen 50% of respondents.

[44]For example, children eligible for inclusion in the wave 1 sample could have parents who chose to have children at an earlier age on average than children eligible for inclusion in the wave 2 sample.

data spanning two generations, including detailed measures of child health, non-cognitive, and cognitive development.

The analysis provides evidence of positive intergenerational impacts of childhood deworming on a range of outcomes, including substantial improvements in cognitive performance and non-cognitive development among older children, with more modest improvements in health-related outcomes among both older and younger children. There appears to be little clear evidence that these gains come through measured improvements in early life health investments, the home environment, or through increased educational investments. Instead, the gains appear likely to be attributable to some combination of other factors associated with long-run deworming impacts, such as improved parent health, improved psychological well-being, greater parent educational attainment, or elevated household living standards.

Importantly, gains in cognitive performance are only observed among those children surveyed prior to Covid-related school closures, and the strongest gains appear in academic-oriented domains such as language and math. Performance in these same domains declines among both treatment and control children in the period following prolonged school closures, an indication that the disruption in access to schooling led to meaningful degree of learning loss in (at least) the short term. The persistence of these patterns – within this sample, and more broadly post-Covid – is of broad policy interest and will be examined in planned future data collection.

Combining evidence on the intergenerational impacts of childhood deworming with results on the impact of Covid-related school closures provides insight into how parent human capital and the local schooling environment interact in the production of child human capital. The findings show that deworming led to substantial improvements in cognitive performance among older children prior to Covid-related school closures, but not in the period following prolonged school closures, and not among younger children in either period. Further, there is evidence of positive gains in heath and non-cognitive development, with no meaningful differences across the pre-Covid and post-Covid periods. These results are what one might expect to see if school-based inputs complement home-based inputs in the production of cognitive skills among children who attend school, during times of typical access to schooling, and in domains where access to schooling is most relevant.

The findings also carry several implications for policy. First, a better understanding of if and how educational institutions and living standards interact in the production of human capital could inform the design of policies and interventions targeted at child human capital development. The findings presented here suggest that when institutions such as public schools are functional, interventions that improve parent human capital or household living standards may yield more fruit. When such institutions are weak or largely absent, interventions that improve private living standards alone may prove less effective. Second, evidence of positive intergenerational human capital transmission builds on existing literature whose findings bolster the case for greater public and private investment in early-life health and human capital interventions. In particular, these findings contribute to a growing body of evidence that reveals positive impacts of a specific human capital intervention, childhood deworming in Kenya, on a range of outcomes in the next generation, including child survival (as in Walker et al. (2023)) and child cognitive and non-cognitive development in this study. The results here contribute further evidence of the high rate of return on such early life human capital investments, including on the next generation.

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Tables

Table 2: Child Health

	Summary Index	Index Components				Other
	Subjective Health Index	No Sickness Past 7 Days	Overall Child Health (1 to 5)	No Serious Health Problems	No Disability Indicator	Height for Age
Panel A: Older Children (Ages 6-8)	(1)	(2)	(3)	(4)	(5)	(6)
PSDP Treatment	0.15*	0.04	0.06	-0.01	0.09***	-0.03
	(0.08)	(0.04)	(0.06)	(0.04)	(0.03)	(0.08)
Control mean	0.02	0.33	4.01	0.79	0.69	-0.47
Control SD	(1.04)	(0.47)	(0.75)	(0.41)	(0.46)	(1.10)
Observations	1962	1966	1967	1967	1963	1963
P-Value: PSDP Treat × pre-Covid	0.82	0.09	0.43	0.03	0.68	0.94
Panel B: Younger Children (Ages 3-5)						
PSDP Treatment	0.13	0.05	0.16***	0.00	-0.01	0.04
	(0.09)	(0.05)	(0.06)	(0.04)	(0.03)	(0.08)
Control mean	0.06	0.23	3.98	0.81	0.81	-0.57
Control SD	(0.99)	(0.42)	(0.76)	(0.39)	(0.39)	(1.43)
Observations	1559	1562	1563	1563	1560	1557
P-Value: PSDP Treat × pre-Covid	0.17	0.67	0.02	0.49	0.24	0.55

Sample includes children of KLPS respondents who participated in the Primary School Deworming Program (PSDP), but who were not assigned to the treatment group of cross-cutting interventions (VocEd or SCY). The Subjective Health Index is constructed by normalizing each of the following four components to be mean zero with unit variance relative to the control group in wave 1, summing across components, then renormalizing in the same way. No Sickness in Past Seven Days indicates that child has not experienced fever, malaria, vomiting, cough, diarrhea, or any other infection in past seven days. Overall Child Health is a subjective health measure ranging from (1) Very Poor to (5) Very Good. No Serious Child Health Problems indicates that the child has not experienced any serious health problems since birth. No disability indicates that the child exhibits none of ten possible disabilities. The Z-score Height for Age measure is constructed by averaging across three measurements of height (taken during the child assessments) and constructing Z-scores within gender-age bands using 2004 WHO child growth standards. Table rows include p-values associated with estimated coefficients from assignment to the pre-Covid tracking wave and the interaction between PSDP treatment and assignment to the pre-Covid tracking wave (regressions not reported). PSDP treatment is an indicator for biological parent assignment to a 1998 primary school randomly assigned to early receipt of Primary School Deworming Program (group 1 or group 2 schools). Controls include child gender and age (except for height for age in column (6)), the proportion of students in schools assigned to deworming treatment within 6km of the KLPS parent's 1998 PSDP school, an indicator for parent attending a school assigned to the cost-sharing treatment in 2001, density of children in 6km radius of parent's 1998 PSDP school, indicators for parent's 1998 PSDP school zone, population of parent's 1998 PSDP school, average test score of parent's 1996 school, an indicator for parent inclusion in the VocEd or SCY sample, parent grade in 1998, parent gender, an indicator for interviewer gender, and months elapsed since the start of the survey wave. Regressions include appropriate weights to maintain representativeness of the next population (these weights account for inclusion of those parents randomly assigned to the control group, but not those randomly assigned to the treatment group of cross-cutting interventions (VocEd and SCY), for the two-stage intensive tracking strategy, and for total fertility). Standard errors are clustered at the 1998 school level. $*$ denotes significance at 10%, $**$ denotes significance at 5%, and $***$ denotes significance at 1%.

Table 3: Child Non-Cognitive (Socioemotional) Development

	Summary Index	Index Components					Other
	Strength and Difficulties Index	Prosocial Scale (0 to 10)	(-1)* Emotional Symptoms Scale (0 to 10)	(-1)* Conduct Problems Scale (0 to 10)	(-1)* Hyperactive Scale (0 to 10)	(-1)* Peer Problems Scale (0 to 10)	(-1)* Total Difficulties Score (0 to 40)
Panel A: Older Children (Ages 6-8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PSDP Treatment	0.20**	0.37***	0.42**	0.15	0.21	0.15	0.94*
	(0.09)	(0.14)	(0.19)	(0.15)	(0.19)	(0.15)	(0.52)
Control mean	0.08	7.88	6.22	8.07	5.82	7.35	27.46
Control SD	(1.02)	(2.03)	(2.61)	(1.73)	(2.11)	(1.79)	(5.87)
Observations	1966	1967	1966	1966	1967	1967	1966
P-Value: PSDP Treat × pre-Covid	0.52	0.04	0.68	0.65	0.26	0.26	0.71
Panel B: Younger Children (Ages 3-5)							
PSDP Treatment	0.07	0.08	0.30	0.04	-0.10	0.06	0.31
	(0.10)	(0.20)	(0.21)	(0.16)	(0.17)	(0.12)	(0.42)
Control mean	0.01	7.32	6.57	7.99	5.34	7.44	27.34
Control SD	(1.15)	(2.37)	(2.30)	(1.75)	(1.94)	(1.66)	(4.97)
Observations	1560	1560	1563	1561	1563	1563	1561
P-Value: PSDP Treat × pre-Covid	0.25	0.80	0.19	0.92	0.67	0.27	0.45

Sample includes children of KLPS respondents who participated in the Primary School Deworming Program (PSDP), but who were not assigned to the treatment group of cross-cutting interventions (VocEd or SCY). The Strengths and Difficulties Index is constructed by normalizing each of the scales in columns (2)-(5) within gender and 6-month age bins relative to the control group in wave 1, summing across components, then renormalizing in the same way. Regressions with the Strengths and Difficulties Index exclude controls for child gender and age since the Index is normalized within gender and 6-month age bands. Each of the scales in columns (3)-(6) are reverse-signed so that positive values indicate more positive socioemotional outcomes. The Total Difficulties Score is calculated by summing across the scales in columns (3)-(6). Table rows include p-values associated with estimated coefficients from assignment to the pre-Covid tracking wave and the interaction between PSDP treatment and assignment to the pre-Covid tracking wave (regressions not reported). PSDP treatment is an indicator for biological parent assignment to a 1998 primary school randomly assigned to early receipt of Primary School Deworming Program (group 1 or group 2 schools). Controls include child gender and age (except for the Strengths and Difficulties Index in column (1)), the proportion of students in schools assigned to deworming treatment within 6km of the KLPS parent's 1998 PSDP school, an indicator for parent attending a school assigned to the cost-sharing treatment in 2001, density of children in 6km radius of parent's 1998 PSDP school, indicators for parent's 1998 PSDP school zone, population of parent's 1998 PSDP school, average test score of parent's 1996 school, an indicator for parent inclusion in the VocEd or SCY sample, parent grade in 1998, parent gender, an indicator for interviewer gender, and months elapsed since the start of the survey wave. Regressions include appropriate weights to maintain representativeness of the next population (these weights account for inclusion of those parents randomly assigned to the control group, but not those randomly assigned to the treatment group of cross-cutting interventions (VocEd and SCY), for the two-stage intensive tracking strategy, and for total fertility). Standard errors are clustered at the 1998 school level. $*$ denotes significance at 10%, $**$ denotes significance at 5%, and $***$ denotes significance at 1%.

Table 4: Child Cognitive Development

	Wave 1 (Pre-Covid)					Wave 2 (Post-Covid)				
	Summary Index	Components		Other		Summary Index	Components		Other	
Panel A: Older Children (Ages 6-8)	Academic Cognitive Index (1)	Language Index (2)	Math and Spatial Abilities Index (3)	Executive Function Index (4)	Cognitive Abilities Index (5)	Academic Cognitive Index (6)	Language Index (7)	Math and Spatial Abilities Index (8)	Executive Function Index (9)	Cognitive Abilities Index (10)
PSDP Treatment	0.26**	0.21*	0.28**	0.12	0.25*	-0.09	-0.06	-0.10	-0.11	-0.11
	(0.12)	(0.11)	(0.13)	(0.11)	(0.13)	(0.12)	(0.11)	(0.13)	(0.11)	(0.12)
Control mean	0.00	-0.00	-0.00	0.00	0.00	-0.14	-0.17	-0.10	0.11	-0.06
Control SD	(0.98)	(0.98)	(0.98)	(0.98)	(0.98)	(1.07)	(0.97)	(1.16)	(1.16)	(1.12)
Observations	1005	1005	1005	1005	1005	962	962	962	962	962
P-Value: PSDP Treat × pre-Covid						0.03	0.06	0.03	0.19	0.04
Panel B: Younger Children (Ages 3-5)										
PSDP Treatment	0.01	0.04	0.03	-0.32**	-0.12	-0.01	-0.03	0.01	-0.04	-0.07
	(0.12)	(0.09)	(0.12)	(0.15)	(0.14)	(0.11)	(0.15)	(0.12)	(0.16)	(0.12)
Control mean	0.00	0.01	-0.00	-0.00	0.00	0.20	0.35	-0.03	-0.04	0.16
Control SD	(0.97)	(0.96)	(0.98)	(0.98)	(0.98)	(1.18)	(1.36)	(1.23)	(1.37)	(1.27)
Observations	734	735	734	545	734	828	828	828	565	828
P-Value: PSDP Treat × pre-Covid						0.94	0.72	0.90	0.22	0.83

Sample includes children of KLPS respondents who participated in the Primary School Deworming Program (PSDP), but who were not assigned to the treatment group of cross-cutting interventions (VocEd or SCY). All indices are constructed by summing across normalized components (each normalized to be mean zero with unit variance within gender and 6-month age bands relative to the control group in wave 1), then renormalizing in the same way, and winsorizing the top and bottom 1%. The Academic Cognitive Index (not pre-specified) is composed of the Language and Math and Spatial Abilities Indices. The Langauge Index is composed of the PPVT and MDAT assessments (for younger children) or the PPVT, EGRA Swahili, and EGRA English assessments (for older children). The Math and Spatial Abilities Index is composed of the Mental Transformation assessment (for younger children) or the EGMA assessment (for older children). The Executive Function Index is composed of Forward Digit Span and Dimensional Change Card Sort (DCCS) (for younger children) or Forward Digit Span and PLUS-EF (for older children). For younger children, the Executive Function index excludes those aged 3. The Cognitive Abilities Index is composed of the Language, Math and Spatial Abilities, and Executive Function Indices. PSDP treatment is an indicator for biological parent assignment to a 1998 primary school randomly assigned to early receipt of Primary School Deworming Program (group 1 or group 2 schools). Columns (1)-(5) restrict to children assigned to the pre-Covid wave (wave 1) of data collection, while columns (6)-(10) restrict to children assigned to the post-Covid wave (wave 2) of data collection. Table rows include p-values associated with estimated coefficients from assignment to the pre-Covid tracking wave and the interaction between PSDP treatment and assignment to the pre-Covid tracking wave (regressions not reported). Controls include the proportion of students in schools assigned to deworming treatment within 6km of the KLPS parent's 1998 PSDP school, an indicator for parent attending a school assigned to the cost-sharing treatment in 2001, density of children in 6km radius of parent's 1998 PSDP school, indicators for parent's 1998 PSDP school zone, population of parent's 1998 PSDP school, average test score of parent's 1996 school, an indicator for parent inclusion in the VocEd or SCY sample, parent grade in 1998, parent gender, an indicator for interviewer gender, and months elapsed since the start of the survey wave. Regressions include appropriate weights to maintain representativeness of the next population (these weights account for inclusion of those parents randomly assigned to the control group, but not those randomly assigned to the treatment group of cross-cutting interventions (VocEd and SCY), for the two-stage intensive tracking strategy, and for total fertility). Standard errors are clustered at the 1998 school level. $*$ denotes significance at 10%, $**$ denotes significance at 5%, and $***$ denotes significance at 1%.

Table 5: Child Health, Socioemotional Development, and Cognition: Heterogeneity by Gender

	Subjective Health Index	Strengths & Difficulties Index	Academic Cognitive Index (Wave 1, Pre-Covid)	Academic Cognitive Index (Wave 2, Pre-Covid)
Panel A: Older Female Children (Ages 6-8)	(1)	(2)	(3)	(4)
PSDP Treatment	0.12	0.20	0.02	-0.12
	(0.08)	(0.14)	(0.14)	(0.16)
Control mean	0.11	0.07	-0.00	-0.20
Control SD	(0.98)	(1.06)	(0.99)	(1.07)
Observations	986	983	495	488
Panel B: Older Male Children (Ages 6-8)	(1)	(2)	(3)	(4)
PSDP Treatment	0.21	0.18*	0.42***	-0.07
	(0.13)	(0.11)	(0.15)	(0.15)
Control mean	-0.07	0.09	0.00	-0.06
Control SD	(1.09)	(0.98)	(0.99)	(1.06)
Observations	984	983	510	474
P-Value: PSDP Treat × female	0.56	0.94	0.06	0.83
Panel C: Younger Female Children (Ages 3-5)	(1)	(2)	(3)	(4)
PSDP Treatment	0.36***	0.27**	0.52***	-0.03
	(0.09)	(0.13)	(0.16)	(0.13)
Control mean	0.01	0.04	0.00	0.07
Control SD	(0.98)	(1.14)	(0.97)	(1.09)
Observations	791	791	360	430
Panel D: Younger Male Children (Ages 3-5)	(1)	(2)	(3)	(4)
PSDP Treatment	-0.09	-0.14	-0.22	0.09
	(0.12)	(0.13)	(0.15)	(0.19)
Control mean	0.11	-0.02	0.00	0.32
Control SD	(0.99)	(1.16)	(0.98)	(1.25)
Observations	771	769	374	398
P-Value: PSDP Treat × female	0.00	0.02	0.00	0.62

Regressions with the Subjective Health Index and the Strengths & Difficulties Index as dependent variables (columns (1) and (2)) pool across both waves. For the Academic Cognitive Index, regressions are run separately for wave 1 (column (3)) and wave 2 (column (4)). Panel A restricts to older female children, panel B to older male children, panel C to younger female children, and panel D to younger male children. Table rows include p-values associated with estimated coefficients from the interaction between PSDP treatment and an indicator for whether the child is female. PSDP treatment is an indicator for biological parent assignment to a 1998 primary school randomly assigned to early receipt of Primary School Deworming Program (group 1 or group 2 schools). Controls include child gender and age (only for the Subjective Health Index in column (1)), the proportion of students in schools assigned to deworming treatment within 6km of the KLPS parent's 1998 PSDP school, an indicator for parent attending a school assigned to the cost-sharing treatment in 2001, density of children in 6km radius of parent's 1998 PSDP school, indicators for parent's 1998 PSDP school zone, population of parent's 1998 PSDP school, average test score of parent's 1996 school, an indicator for parent inclusion in the VocEd or SCY sample, parent grade in 1998, parent gender, an indicator for interviewer gender, and months elapsed since the start of the survey wave. Regressions include appropriate weights to maintain representativeness of the next population (these weights account for inclusion of those parents randomly assigned to the control group, but not those randomly assigned to the treatment group of cross-cutting interventions (VocEd and SCY), for the two-stage intensive tracking strategy, and for total fertility). Standard errors are clustered at the 1998 school level. $*$ denotes significance at 10%, $**$ denotes significance at 5%, and $***$ denotes significance at 1%.

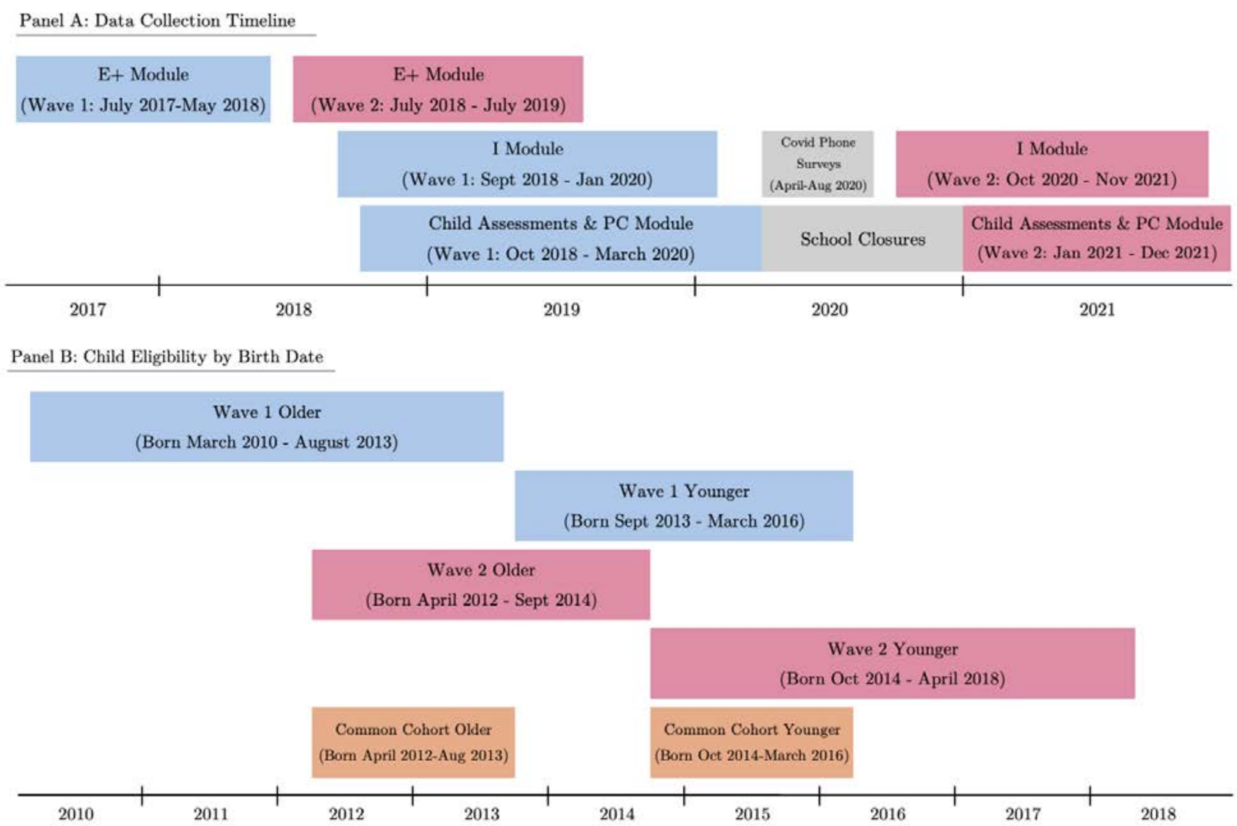
Table 6: Mechanisms: Health Investments, Home Environment, Education, and Parent Psychological Well-Being

	Health Investments, Home Environment and Educational Investments					Parent Psychological Well-Being		
	Early Life Health Investments (Younger)	Early Life Health Investments (Older)	Modified FCI Index	School Enrollment and Edu Investments Index (Younger)	School Enrollment and Edu Investments Index (Older)	(-1)* Depressive Symptoms (CESD Score, 0 to 30)	Happiness (1 to 3)	Life satisfaction (0 to 10)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PSDP Treatment	0.07	-0.01	0.06	0.03	0.01	0.71**	-0.02	0.42**
	(0.09)	(0.07)	(0.08)	(0.09)	(0.04)	(0.34)	(0.03)	(0.18)
Unit of observation	Child	Child	HH	Child	Child	Adult	Adult	Adult
Control mean	-0.14	-0.16	0.05	-0.59	0.34	-9.84	2.70	5.30
Control SD	(0.89)	(1.06)	(0.96)	(1.36)	(0.49)	(5.99)	(0.51)	(3.13)
Observations	1558	1964	2790	1572	1980	2757	2758	2739

Columns (1) and (2) present estimated treatment effects on the summary index capturing early life health investments. Column (3) presents estimated treatment effects on the summary index capturing the richness of the home environment (at the household level). Columns (4) and (5) present estimated treatment effects on the summary index capturing schooling and educational investments. Estimated treatment effects on outcomes capturing adult psychological well-being as presented in columns (6)-(8) are collected for the primary KLPS respondent in the I module; these results are for the full sample, not only those KLPS respondents with a child in the main sample for this study. Depressive symptoms reported in column (6) of Panel A are measured using the Center for Epidemiologic Studies Depression Scale, which ranges from 0 to 30. Scores are multiplied by (-1) so that positive coefficients indicate a reduction in depressive symptoms. Happiness in column (7) is measured on a three-point scale (1 = not happy, 2 = somewhat happy, and 3 = very happy). Life satisfaction in column (8) is measured on a scale from 0 to 10. PSDP treatment is an indicator for assignment to a 1998 primary school randomly assigned to early receipt of Primary School Deworming Program (group 1 or group 2 schools). Controls include the proportion of students in schools assigned to deworming treatment within 6km of the KLPS respondent's 1998 PSDP school, an indicator for attending a school assigned to the cost-sharing treatment in 2001, density of children in 6km radius of 1998 PSDP school, indicators for 1998 PSDP school zone, population of 1998 PSDP school, average test score of 1996 school, an indicator for inclusion in the VocEd or SCY sample, grade in 1998, gender, and indicators for survey wave and month of interview. Regressions include appropriate weights to maintain baseline sample representativeness (these weights account for inclusion of those randomly assigned to the control group, but not those randomly assigned to the treatment group of cross-cutting interventions (VocEd and SCY) and for the two-stage intensive tracking strategy). Standard errors are clustered at the 1998 school level. $*$ denotes significance at 10%, $**$ denotes significance at 5%, and $***$ denotes significance at 1%.

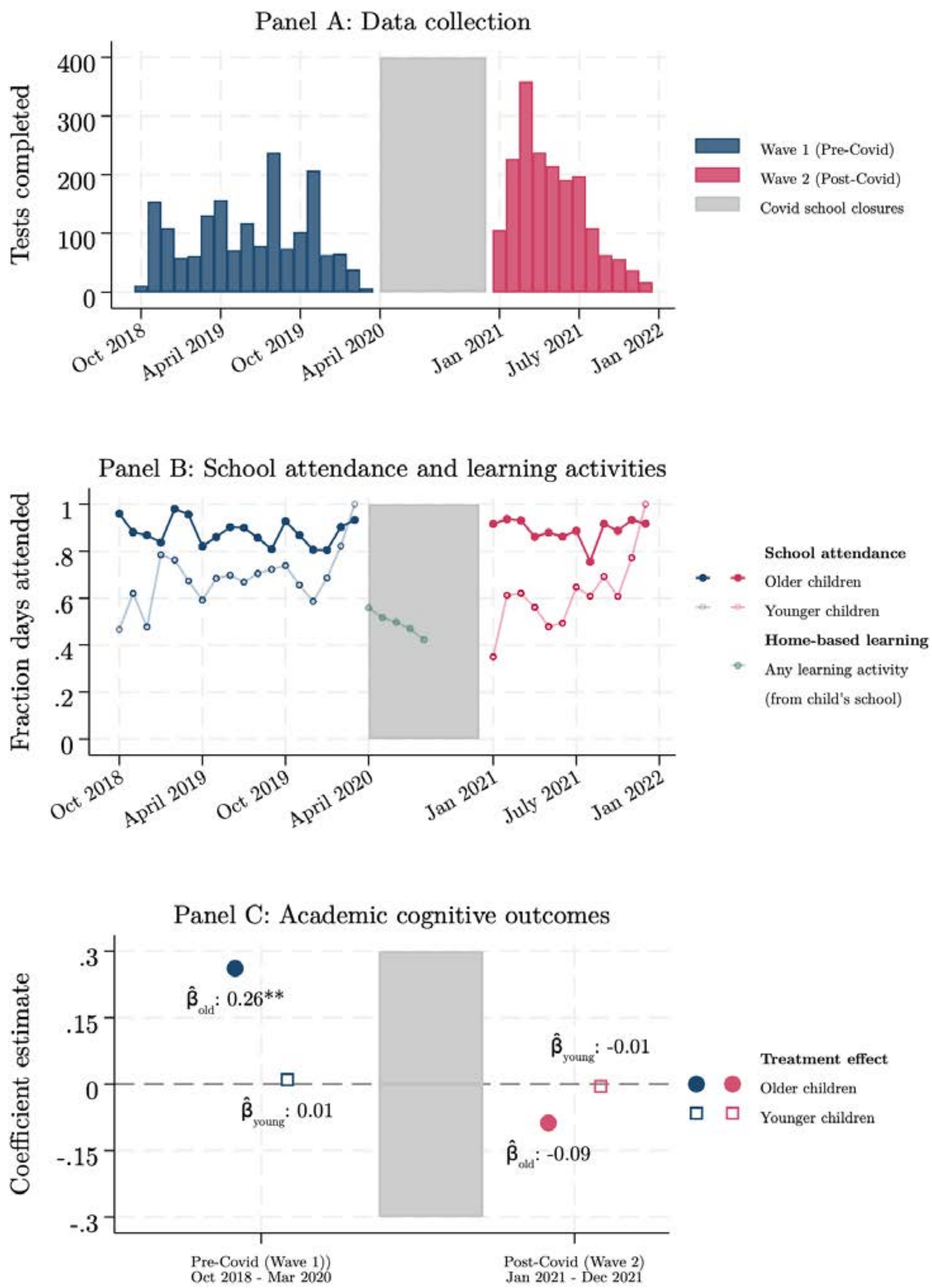
Figures

Figure 1: Data Collection and Child Eligibility Timeline



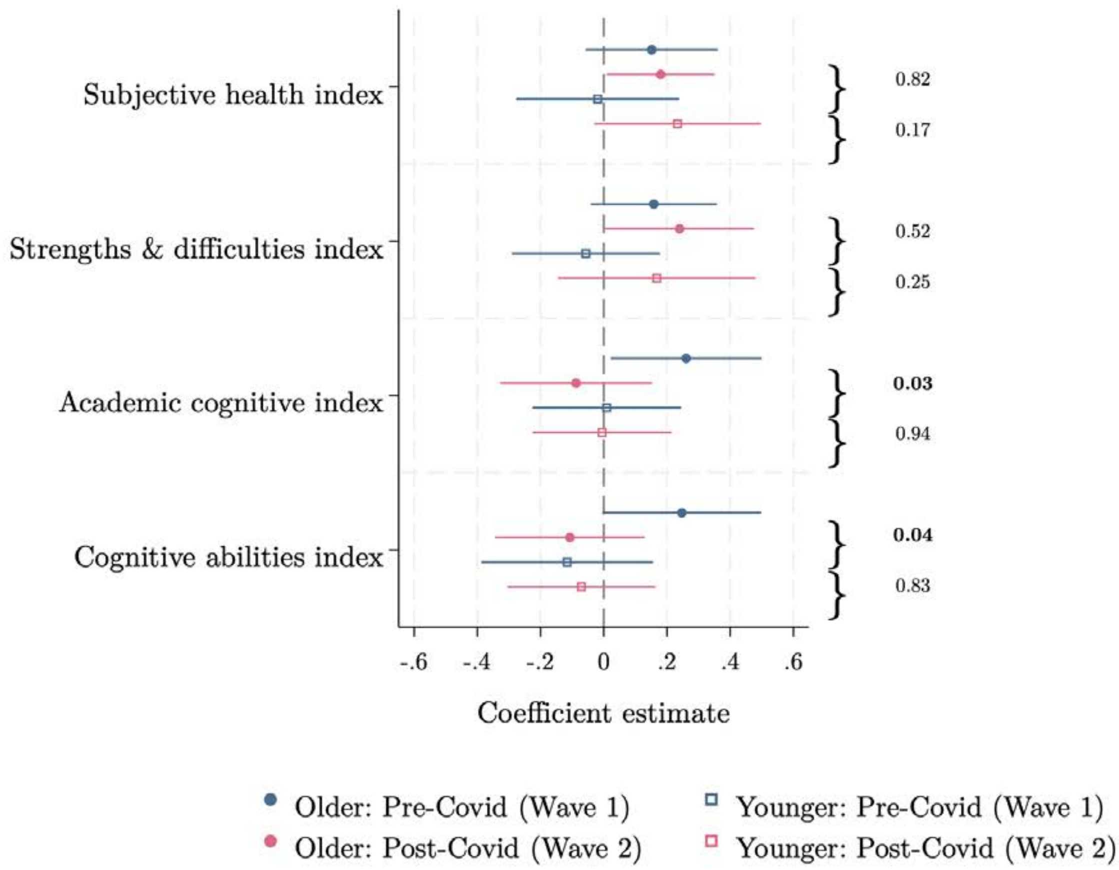
Notes: Panel A depicts the timing of the Earnings+ (E+) module, Integrated (I) module, child assessments and Primary Caregiver (PC) module, and Covid phone surveys for respondents and children assigned to wave 1 versus wave 2. Panel B depicts eligibility for inclusion in the main child sample based on birth date and for the "common cohort sample" as described in Section 5.7.

Figure 2: Data Collection Timeline, School Attendance, and Cognitive Performance



Notes: Panel A plots a histogram of surveys and tests completed by month of data collection in the pre-Covid wave (wave 1; blue) and post-Covid wave (wave 2; red). The grey box indicates months where schools were closed. Panel B shows measures of school attendance by month of data collection, separately for older children (solid dots) and younger children (hollow dots). Any learning activity (from child's school) during the Covid school closures (green circles) are collected at the household level by phone. Any school learning activity is an indicator for whether the child used homework or teaching materials prepared or assigned by the school, used e-learning modules prepared by the school, or read school textbooks. Panel C plots treatment effects on the academic cognitive cognitive index, separately for older children (solid circles) and younger children (hollow squares), and separately for the pre-Covid wave (wave 1; blue) and post-Covid wave (wave 2; red). Treatment effect estimates are noted, with ** denoting significance at the 5% level.

Figure 3: Child Health, Non-Cognitive Development, and Cognition by Wave and Age



Notes: This figure plots separate treatment effect estimates associated each of the outcomes listed on the y-axis, separately for older children (solid circles) and younger children (hollow squares), and separately for children surveyed in the pre-Covid survey wave (wave 1; blue) versus the post-Covid wave (wave 2; red). For all indices, positive values correspond to positive development outcomes. The subjective health index is constructed from four components: (1) no sickness in the past seven days, (2) overall child health, (3) no serious health problems since birth, and (4) no disabilities. The strengths and difficulties index combines across five component subscales capturing (1) emotional symptoms, (2) conduct problems, (3) hyperactivity, (4) peer problems, and (5) prosociality, reverse-signing subscales as needed so that positive values correspond to positive non-cognitive (socioemotional) development outcomes. The academic cognitive index is constructed from (1) the language index and (2) the math and spatial abilities index, and the cognitive abilities index additionally includes (3) the executive function index. Regressions include the standard covariates, clustered standard errors, and weights as per the regressions presented in Table 2, Table 3, and Table 4. P-values associated with coefficient estimates of the interaction between an indicator for pre-Covid survey wave with parent PSDP treatment status are presented on the right-hand side; bolded p-values indicate interactions are significant at 5%.