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Social protection and foundational cognitive skills during adolescence: evidence from a large Public Works Programme

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Abstract[1]

Many low- and middle-income countries have introduced Public Works Programmes (PWPs) to fight poverty. PWPs provide temporary cash-for-work opportunities to boost poor households' incomes and to provide better infrastructure to local communities. While PWPs do not target children directly, the increased demand for adult labour may affect children's development through increasing households' incomes and changing household members' time uses. This paper expands on a multidimensional literature showing the relationship between early life circumstances and learning outcomes and provides the first evidence that children from families who benefit from PWPs show increased foundational cognitive skills (FCS). We focus on four child FCS: inhibitory control, working memory, long-term memory, and implicit learning. Our results, based on unique tablet-based data collected as part of a 20-year longitudinal survey, show positive associations of family participation in the Productive Safety Net Programme (PSNP) in Ethiopia during childhood on long-term memory and implicit learning, with weaker evidence for working memory. These associations appear to be strongest for children whose households were still PSNP participants in the year of data collection. We find suggestive evidence that, the association with implicit learning may be operating through children's time reallocation away from unpaid labour responsibilities, while the association with long-term memory may be due to the programme's success in remediating nutritional deficits caused by early life rainfall shocks. Our results suggest that policy interventions such as PWPs may be able to mitigate the effects of early poverty on cognitive skills formation and thereby improve children's potential future outcomes.

Keywords: foundational cognitive skills; Ethiopia; public works programmes; PSNP; skills development

JEL Classification: J24, I2, I1

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1. Introduction

Social protection programmes that strive to combat poverty are now widespread around the world (International Labour Organization, 2021). In Africa alone, the number of social protection programmes almost tripled in the first 15 years of the 21st century (Cirillo and Tebaldi, 2016) to the extent that, today, all African countries operate at least one such programme (Beegle et al., 2018). Many low-and-middle-income countries (LMICs) have introduced Public Works Programmes (PWPs) as one such form of social protection programme for fighting poverty and to provide social safety nets in light of different types of income shocks generated by weather (e.g., Ethiopia, India, Malawi, South Africa), rising prices (e.g., Argentina, India, Mexico), and conflict and political instability (e.g., Comoros, Côte d'Ivoire, Sierra Leone) (Subbarao et al., 2012). These programs provide temporary cash-for-work opportunities to boost poor households' incomes and to develop new or improved infrastructure for local communities.

While PWPs do not target children directly, they may affect children's development through two primary, and possibly contradictory, mechanisms working through participating households (Woldehanna, 2010). First, by increasing household income, PWPs may positively impact cognition through an increase in food consumption and nutrition (Behrman, 1996; Glewwe et al., 2001; Maluccio et al., 2009). Second, given PWPs' adult work requirements, they may alter parents' and children's time uses, affecting the children's cognitive development. For example, adults may reduce their time caring for and interacting with children in order to work more, and children may substitute for adult labour in family businesses and reduce time learning (Basu and Van, 1998). Thus, PWPs may affect lifelong learning opportunities for such children, which has been advocated as a necessary condition for allowing future generations to escape poverty, as expressed in the United Nations Sustainable Development Goals (SDGs).

A small number of previous studies investigate the impacts of PWPs on children's development in LMICs. Evidence from the largest PWP in the world, India's Mahatma Gandhi National Rural Employment Guarantee Scheme, is mixed - with large positive associations with cognitive achievement tests and grade progression found in one study (Mani et al., 2020), but lower cognitive achievements and lower enrolment found in other studies (Shah and Steinberg, 2015; Hoddinott et al., 2010). For the Ethiopian Productive Safety Net Programme, Favara et al. (2019) found significant positive associations with both numeracy and vocabulary. However, a major limitation of the existing literature concerning the effect of PWPs in particular, and of social programmes more generally, on skills development in LMICs is that cognitive skills are measured using domain-specific cognitive achievement test scores (for example, test scores in maths, reading comprehension and vocabulary knowledge) rather than foundational cognitive skills (FCS).[2] A deeper understanding of how PWPs and other policy interventions can help mitigate the effects of poverty on the formation of FCS is still needed to complete the picture.

This paper contributes to filling this gap by investigating the associations of the Ethiopian Productive Safety Net Programme (PSNP), the largest PWP and the second largest social protection programme in Africa, with the development of FCS for a cohort of children tracked since infancy through adolescence. We use unique data on four FCS measures (long-term memory, inhibitory control, working memory, and implicit learning) collected in Ethiopia as

[2] We consider FCS to be a set of cognitive abilities which are considered domain-general, rather than skills such as reading, arithmetic or linguistics, which are domain-specific to certain types of knowledge (Behrman et al., 2022). FCS capture fluid intelligence skills (such as the ability to reason abstractly and solve novel problems), while domain-specific cognitive achievement tests assess crystallized intelligence skills (which involves knowledge that comes from prior learning and past experiences).

part of Young Lives Study (YLS), a longitudinal study following the same children since 2002. We test three main hypotheses. First, whether exposure to the PSNP is associated with higher FCS among children from disadvantaged backgrounds. Second, whether these associations depend on the timing and children's ages, perhaps being larger for children treated initially when younger.[3] Third, whether the associations between the PSNP and FCS differ between boys and girls.[4] To mitigate concerns about bias due to household selection based on unobserved variables, we construct a restricted comparison sample that is similar to PSNP recipients (see below), and also implement the methodology suggested by Oster (2019) for evaluating the robustness of our results to omitted-variable bias, exploiting the extensive information available on the children's households.

We find positive associations of the PSNP with long-term memory and implicit learning, and weaker evidence for working memory. These associations appear to be driven by children whose households were still recipients of the programme in 2013, the year of data collection. We do not find any associations of the PSNP with inhibitory control, and we find no significant differences in the associations by age or gender.

We also investigate what mechanisms help explain any significant associations of the PSNP with FCS. We find suggestive evidence that, in part, the association with implicit learning may reflect children's time reallocation away from unpaid-working responsibilities towards educational activities, while the association with long-term memory may be due to the programme's success in remediating early nutritional deficits.

[3] Early life intervention studies demonstrate that environmental experiences between 0-4 years shape cognitive ability later in life (Beckett et al., 2010; Muennig et al., 2009; Nelson et al., 2007; Olds, 2006; Maluccio et al., 2009).

[4] On one hand, son preferences may lead to greater impacts of the programme for boys than for girls (Behrman, 1988). On the other hand, however, girls may be treated as "luxury goods" in which investments in girls are very low for very poor households but increase relatively rapidly when income increases (Behrman and Deolalikar, 1990).

Lastly, we assess whether any associations of the PSNP with FCS may be due to remediation of negative effects caused by early life rainfall shocks. To do so, we match the Young Lives data with gridded data on monthly precipitation to generate community-level rainfall estimates. We find evidence that the positive associations of the PSNP with long-term memory are driven by children who experienced at least one rainfall shock during their first 1,000 days after conception (in-utero, and first year, in particular), suggesting that the association of the PSNP with long-term memory may, in part, be due to the programme's success in remediating early life nutritional deficits caused by rainfall shocks.

This paper offers two main contributions. First, we use unique data on FCS measured through a novel touch-screen tablet application, collected as part of a large cohort study in LMICs. Unlike most papers considering the effects of PWPs and other social protection programmes on cognitive skills, the measures we record are foundational to a wide range of learning and are not domain-specific; they should, therefore, be relatively free of bias due to the language of implementation or differences in the children's, caregivers', or communities' beliefs in the value of academic knowledge. Second, to our knowledge, it is the first study to examine the remediation role of a PWP on multiple FCS in a LMIC setting.

The rationale for investment in children's FCS hinges on their relationships with children's subsequent capabilities, learning, productivities, and welfare, and with overall economic growth and equity. A substantial body of research in high-income countries has linked cognitive function measured in laboratory settings to real-world behaviours, demonstrating that, among other functions, individual differences in FCS successfully predict educational and labour-market outcomes (Blair, 2002; Blair and Razza, 2007; Heckman et al., 2006). An increasing body of evidence also indicates that FCS may increase in response to investments of time and effort by parents and teachers. These results suggest that FCS, unlike many other developmental and cognitive processes, remain malleable into late stages of childhood and adolescence (Holmes et al., 2009; Diamond et al., 2007; Jaeggi et al., 2008).

Furthermore, family and environmental impacts on FCS precede school performance deficits related to poverty in schooling, and predict subsequent schooling outcomes (e.g., math-test performance) over and above current schooling outcomes (Blair and Razza, 2007). Therefore, policy interventions that are able to mitigate the effects of early poverty on FCS formation could have important effects that not only improve children’s current schooling, but also their potential future outcomes. Altering FCS may be one of the few means available for mitigating the adverse effects of early childhood poverty, undernutrition, and inadequate education on cognitive skills among older children.

However, to our knowledge, there is no population-based evidence from LMICs on these topics; available evidence is from small samples in high-income countries. This paper provides greater understanding of how policy interventions can help to attenuate the effects of early life deprivations in contexts of extreme poverty and promote lifelong learning opportunities for all (United Nations Sustainable Development Goal #4). Evaluation of the PSNP is of general interest, given that the programme is implemented at scale, using governmental systems, in a populous low-income country in Africa.

The rest of this article is structured as follows: the next section provides a brief outline of the PSNP structure and background. Section 3 outlines the data used, while Section 4 presents the estimation strategy used. The results are reported in Section 5, while potential mechanisms are explored in Sections 6. Section 7 concludes.

2. The PSNP in Ethiopia

The PSNP was introduced in Ethiopia in 2005 as a national safety-net programme. According to the Ministry of Agriculture and Rural Development (2004), it has an objective to provide transfers to the food-insecure population in chronically food-insecure woredas (districts)[5], as well as to assist households when food production and other sources of income are insufficient. The PSNP, which is centrally co-ordinated by the Government of Ethiopia, represented a change from previous social protection schemes, which were predominantly delivered as emergency food-for-work programmes on an irregular basis by different parties (Porter and Goyal, 2016). The PSNP was specifically conceived as a multi-year programme to provide recipients with regular and reliable transfers over several years in a way that prevents household asset depletion and creates community assets (Sabates-Wheeler et al., 2021).

The PSNP operates as a safety-net mechanism, whereby the transfers benefit poor rural households mainly through public-works participation (80%), with a small proportion of households receiving unconditional direct support (food and/or cash transfers) in the absence of available adult labour in the household. As part of the programme, PSNP beneficiaries are eligible to work five days per household member (aged 18–60) per month (Sharp et al., 2006). While the programme started with 4.5 million beneficiaries in 2005, in 2013 - the year of our study - the PSNP supported 7.2 million people (roughly 8% of the national population) in 290 chronically food-insecure woredas (Favara et al., 2019).[6]

[5] Initially, a woreda was considered chronically food insecure if: (a) it was in one of eight selected regions (Tigray, Amhara, Oromiya, SNNP, Afar, Somali, rural Harari and Dire Dawa), and (b) had been a recipient of food aid for a significant period, generally for at least three years (Sharp et al., 2006).

[6] The PSNP operates a 'scalable' safety net, scaling-up assistance to an average of 3.8 million people annually, with the eventual ambition that it will scale up to a national rural programme (Ministry of Agriculture, 2020). Consequently, in 2013, there were food-insecure households that did not have access to the PSNP simply because the programme had not been scaled-up to their woreda yet.

Despite a cash-first principle, only 15% received cash exclusively in 2012/13; 18% received food only and 67% received a mixture of cash and food. In 2010/11, median transfer values were just under 500 birr per year for a household of five, equivalent to approximately 13% of the value of the poverty line (DFID, 2013). The goal is that the programme should improve household food security up to the point that the household graduates. In the PSNP, 'A household has graduated when, in the absence of receiving PSNP transfers, it can meet its food needs for all 12 months and is able to withstand modest shocks' (FSCB, 2007). Between 2005 and 2014, approximately 500,000 beneficiaries graduated from the programme and were replaced by new households (Hoddinott, 2014).

The PSNP previously has been found to be effective in improving household food security, consumption, and children's nutritional status. Berhane et al. (2011) found significant, positive effects of the PSNP on household food security and consumption status, and Berhane et al. (2014) observed significant improvements in food security for households that received the programme for more than four years. Alderman and Yemtsov (2012) concluded that PSNP-recipient households avoided selling assets and using savings to buy food in times of food shortages, and Porter and Goyal (2016) found that the programme led to important medium-term nutritional impacts for children at different ages (from age 3 to 15).

While the impact of the PSNP on household consumption and food insecurity is well established, the work requirement of the programme means that there could be an ambiguous effect on children's outcomes, including school enrolment and cognitive development, through its effect on the time-use allocation of adults and children living in the household (Favara et al., 2019). If, for example, child labour acts as a substitute for adult labour on the family farm/enterprise or in domestic tasks, this substitution could offset the (positive) income effect of the programme, resulting in a potential worsening of children's outcomes. Additionally, if time spent with parents has a positive impact on cognitive outcomes (e.g., Sheridan et al., 2018; Sheridan and McLaughlin, 2016), an increase in parental time spent at work could have adverse effects.

While the minimum age for PWP participation is 18 years, according to Sharp et al. (2006) approximately 8% of the PSNP workers were under 18. Tafere and Woldehanna (2012) found negative effects of the PSNP on children's time use, arguing that the programme increased time spent on both paid and unpaid work among adolescents. The authors note that the PWP work requirement led households to supplement adult labour with child labour. There is also evidence that time-use implications may differ according to the child's gender. Camfield (2014) found evidence of girls working directly in the PSNP programme or increasing their household tasks in response to caregivers' participation in the programme. Hoddinott et al. (2010) found that participation in the PSNP led to a reduction in time spent on agricultural labour among boys aged 6-16, and that younger boys aged 6-10 as well as older girls aged 11-16 spent less time on household tasks. However, girls younger than 11 spent more time on tasks within the household and reduced their school enrolment.

The theoretical net effect of the programme on cognitive skills is thus ambiguous. We would expect participation in the PSNP to have a positive effect on skills development of participant household children if the positive income effect on nutrition outweighs any negative time-use effects (Behrman, 1996). However, if labour supply demands on adults change children's time use, there may be harmful time-use effects and negative effects on children's cognitive skills (Basu and Van, 1998). Favara et al. (2019) estimated the impact of the PSNP on children's domain-specific learning outcomes (measured through test scores) and found a small but significant positive effect of the programme on both numeracy and vocabulary, suggesting that the positive income effect may be dominating any negative substitution effects.

3. Data

3.1 Young Lives data

The YLS is a dual-cohort, international longitudinal study initiated in 2001 to investigate the changing nature of childhood poverty in four LMICs: Ethiopia, India (states of Andhra Pradesh and Telangana), Peru and Vietnam (Favara et al., 2021). The first survey took place in 2002, with four further in-person rounds of data collection in 2006/7 (Round 2), 2009/10 (Round 3), 2013/14 (Round 4), and 2015/16 (Round 5). The Younger Cohort of the study were aged 6-18 months in 2002, and the Older Cohort were aged 7-8 years. The RACER tests of FCS were only administered among the Younger Cohort children in Ethiopia and Peru in Round 4. In this paper, we focus on the Younger Cohort in Ethiopia only. [7]

In Ethiopia, the initial 2002 survey collected information on 1,999 Younger Cohort index children (henceforth, *index children*). These index children were selected from 20 woredas in the states of Amhara, Oromia, the Southern Nations, Nationalities and People's Region (SNNP), Tigray, and Addis Ababa. The woredas were picked in an attempt to oversample areas with food-deficit status, capture ethnic and geographic diversity, and find urban/rural and development-level balance (Outes-Leon and Sánchez, 2008). Within each woreda, a village was randomly selected, and households were randomly contacted (moving clockwise) until approximately 100 eligible families were found. Since Round 3 in 2009, additional data were

[7] An analysis of the impact of the Peruvian *Juntos* conditional cash transfer on FCS, measured via the RACER test, is provided by Scott et al., 2022

collected on the sibling born immediately after the index child, the so-called *younger sibling*.[8] The original (2009) sample of siblings is composed of 1,001 younger siblings (aged 3-8 at the time). The study managed to keep attrition rates low, compared to other longitudinal studies: after four survey rounds, only 6.2% of the 2002 sample was lost and 1,873 children were interviewed.[9]

In all rounds, three main questionnaires were administered to capture various characteristics that are expected to influence the status of the children: a child questionnaire with data on health, anthropometrics and individual characteristics; a household questionnaire including data on caregiver background, livelihood, household composition, socio-economic status, and shocks; and a community questionnaire containing information on demographic, geographic and environmental characteristics, social environment, infrastructure, the economy, health and education.

In 2013, the PSNP was operating in 14 YLS woredas, with approximately 21% of the Round 4 sample (398 out of the 1,873 households) being active beneficiaries of the programme. Households were asked whether they had received payments from public works or direct support within the PSNP framework in 2006, 2009 and 2013. They were also asked in which years they were enrolled in the PSNP, how much they had received in the past 12 months (cash or in-kind payment)[10], and whether, to their knowledge, they had been shortlisted for the programme or had graduated from the programme. Fig. 1 shows the timing of the first four YLS rounds as well as the introduction of the PSNP.

[8] If there was no younger sibling, information was collected on the next older sibling of the index child.
[9] To achieve such low levels of attrition, the study followed families that moved within the country (Sánchez and Escobal, 2020).
[10] We investigated this information to see whether it could be used to establish more nuanced treatment variables, but we found it to be too incomplete to be of use.

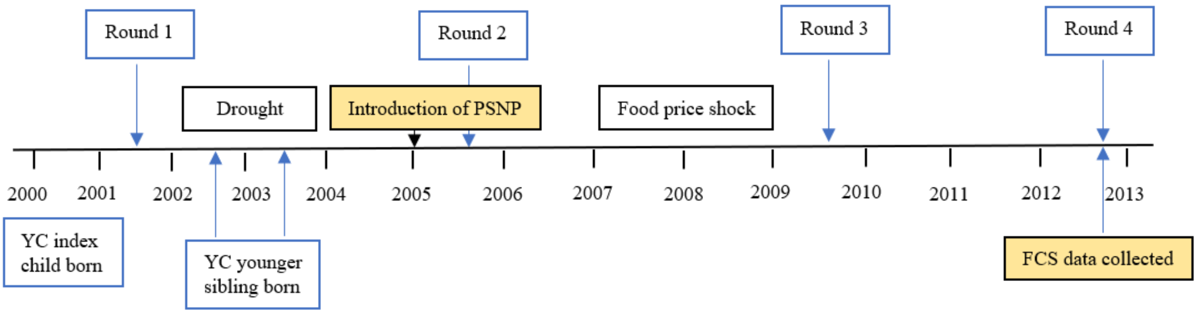

Fig 1. Timeline of PSNP introduction and data collection

3.2 Rapid Assessment of Cognitive and Emotional Regulation (RACER)

Data on FCS were obtained during the fourth YLS survey round. FCS were measured using a series of tablet-based tasks through RACER (*Rapid Assessment of Cognitive and Emotional Regulation*) (Hamoudi and Sheridan, 2015; Ford et al., 2019). RACER is a novel touch-screen tablet application that uses five short tasks (1 to 4 minutes each) to assess four components of FCS in children aged 6 years and older (and adults). In this section, we briefly describe the FCS that were assessed using RACER tasks, and the measures used in the empirical analysis. More information about RACER and the FCS measured in the YLS can be found in Behrman et al. (2022).

RACER measures four FCS: Long-term Memory (LTM), Inhibitory Control (IC), Working Memory (WM), and Implicit Learning (IL). In each cognitive task, we are interested in identifying two measures: the challenge measure and the baseline measure. Challenge measures aim to assess explicitly an individual's FCS. Baseline measures are identical to challenge measures - in terms of general concentration, visual input, and motor response - but lack the specific manipulation that requires an individual to employ FCS to get the trial correct (Ford et al., 2019). During analysis, FCS challenge measures are always compared to baseline measures so that the within-person difference is used as an indication of the person's FCS ability specifically, rather than their general ability to perform cognitive tasks or use tablets.

Below, we briefly explain how each task is performed and Figure A1 (in the Appendix) provides a schematic representation of how the tasks are presented to the child.

In Ethiopia, the RACER data were collected for 1,809 index children (aged 11-12 years old at the time) and 925 younger siblings (aged 5-13) (the distribution by age in years is reported in Figure A2 in the Appendix). Administration time ranged between 30 and 45 minutes. RACER was administered to 97% of the index-children sample and 87% of the younger-siblings sample available for interviews, with an attrition rate considerably smaller than for other cognitive test scores administered.[11] For our analysis, each component of FCS is defined so that higher values are better (see Behrman et al., 2022 for more details).

Long-term Memory: LTM is the ability to encode, retain, and retrieve new knowledge. It supports the capacity to acquire new knowledge and learn from experience. In RACER, participants are presented with a total of 20 figures, 12 of which are grouped arbitrarily into 6 pairs. For each trial, respondents see one member of a pair at the top of the screen, and at the bottom they are presented with four choices, consisting of the other shape in the pair plus three incorrect lures. Respondents see each pair a total of four times; in the first six trials (baseline trials), each pair is encountered for the first time, whereas in the second, third, and fourth cycles of six trials (challenge trials) the respondent might be able to remember each pair. In both cases, performance is measured as the average percentage of correct answers at the first touch. Tests of this kind are dependent on the function of the hippocampus in both children and adults (Bechara et al., 1995). The hippocampus is susceptible to the effects of chronic stress, which is one reason that we might expect to see an impact of poverty on performance of this task (Hanson et al., 2011; Kim and Yoon, 1998; McEwen, 2001; Shonkoff et al., 2009; Farah et al.,

[11] In comparison, the Peabody Picture Vocabulary Test, which measures receptive vocabulary, was successfully administered to 88% of the index children and 78% of the siblings.

2006). Long-term memory is necessary for the acquisition of explicit knowledge in school and other settings (Grammar, Coffman and Ornstein, 2013).

Inhibitory Control: IC is the ability to override counterproductive impulses and resist distraction by irrelevant information. Assessed skill of inhibitory control has been observed to correlate with impulse control in and out of the classroom (Barkley et al., 1992). In the RACER application, differently coloured and patterned stimuli are presented one at a time on either the right or left side of the tablet screen. Respondents are told that when a solid yellow circle appears, they should touch the centre of the circle as quickly as possible (same-side trials). However, when a striped circle appears, they should touch the opposite side of the screen from the stimulus as quickly as possible (opposite-side trials). The same-side trials and opposite-side trials correspond to the baseline and challenge trials, respectively. In both measures, performance is assessed as an equally weighted average of the inverse of response time (in milliseconds) and the inverse of the logarithm of the (Euclidean) distance (in pixels) from each touch to the nearest stimulus.

Working Memory: WM refers to the ability to hold in mind and manipulate information that is no longer present in the environment. While this is a simple cognitive function, it is a necessary component of many more complex abilities such as high-level reasoning, planning, or language comprehension (Miyake et al., 2001). Children perform better on working-memory tasks as they get older and both children and adults recruit the prefrontal cortex when performing working-memory tasks (Thomason et al., 2009). Working-memory ability in childhood is linked with performance in school even after controlling for content of knowledge (Blair, 2002), and training of working memory and executive function more generally is associated with decreased behavioural problems and increased academic performance (Diamond et al., 2007; Klingberg, 2010).

In the RACER, WM is measured using a spatial delayed-match-to-sample task. For each trial of the task, respondents are shown 1, 2, or 3 blue dots on the screen, which remain for 2 seconds. After this, the screen goes blank for either 0.1 seconds (short delay) or 3 seconds (long delay). After the delay, participants are asked to touch the screen as close as they can to where the dots used to be. Baseline trials are those with short delays and one dot. Challenge trials are those with long delays and multiple dots (2 or 3). In both measures, performance is assessed as the inverse of the logarithm of the (Euclidean) distance (in pixels) from each touch to the nearest stimulus.

Implicit Learning: IL is the ability to learn without conscious awareness (sometimes described as "muscle memory"). This ability is a very basic and primary form of learning, as it relies on the basal ganglia, deep brain structures which are conserved across species (Aron et al., 2006).

In the RACER, a total of 175 identical stimuli are presented one at a time in one of four screen locations. Each stimulus remains on the screen for up to 1 second; the respondent's task is to touch the stimulus before it disappears. The succession of screen locations follows no pattern for the first 35 stimuli (Block 1), but then the next 70 stimuli (Block 2 and 3) are presented in 10 repeated cycles of 7 locations, and then the next 35 again follow no pattern (Block 4), and the last 35 (Block 5) are 5 more repeats of the pattern observed for the first time in block 2. IL is assessed by measuring the inverse of the average response times (in milliseconds) during the patterned blocks (challenge trials), using the analogous performance in non-patterned blocks (baseline trials). In the game described above, individuals press more quickly when the movement of the dot follows a pattern, even when they themselves are unaware of the pattern (Pasupathy and Miller, 2005). The ability to speed-up with patterned presentation relative to random presentation, implicit learning, has been strongly linked with language acquisition in infancy and early childhood (Arnon, 2019).

4. Methodology

We aim to estimate whether access to the PSNP is associated with FCS among children from disadvantaged backgrounds. We test three main hypotheses. First, exposure to the PSNP is associated with higher FCS. Second, programme efficacy depends on the timing and ages when children become exposed to the programme, the impact being larger for those children treated initially when younger. Third, the associations between the PSNP and FCS differ between boys and girls.

Our main empirical concern when estimating the effects of the PSNP on FCS is that of non-random programme placement. Since access was not randomised, this leads to challenges in finding a convincing identification strategy for assessing the impact of the programme. Before the introduction of the programme, PSNP beneficiary households in the YLS sample tended to be poorer, as measured by the YLS wealth index[12], and less educated than non-beneficiary households (Table A3 in the Appendix). Thus, a naïve comparison of children in PSNP households with those in non-treated households would likely bias any estimated treatment effects downwards.

In this section we describe the sample used for the empirical analysis and the empirical approach adopted to mitigate such concerns.

4.1 Treatment and control groups

[12] The YLS wealth index takes values between zero and one, such that a larger value reflects a wealthier household. It is the simple average of a housing-quality index, an access-to-services index, and a consumer-durables index (Briones, 2017).

In our regression sample, we include only children living in rural areas (dropping 987 children), since the PSNP is a rural programme. We also drop children living in households which only started receiving the PSNP in 2012, just before the survey rounds where FCS are measured (dropping 62 children). We define households as treated if they answered *yes* to the question on PSNP participation (either food- or cash-for-work, or direct transfers of food or cash).[13]

To mitigate concerns related to systematic differences between the control and treatment group due to non-random allocation of the PSNP program, following Favara et al. (2019) and Porter and Goyal (2016), we construct a 'restricted' comparison group to use in our empirical analysis that is arguably more comparable to PSNP beneficiary households. In this we include only: *(i)* those who received any kind of governmental programme (food-for-work, cash-for-work, food aid) in 2006 since they were in some sense eligible for PSNP, and therefore likely quite similar to eventually treated households; and *(ii)* the households who reported in 2009 that they had been shortlisted for PSNP, as we know that whilst community-level shortlists were drawn up, some households did not receive PSNP due to budget allocations not being sufficient from the next level of administration (Favara et al., 2019). We assess the robustness of this approach in Section 5.2, using the methodology recommended by Oster (2019), to gain a sense of whether remaining unobserved selection effects might bias our estimates.

Panel A in Table 1 compares pre-programme (2006)[14] characteristics of the sample of children in PSNP beneficiary households to children in the restricted control group sample. It reports little difference in the average age, gender, household size, monthly food expenditure, and

[13] We investigated whether we could consider the public works employment and direct support household separately, but the sample size of households receiving direct support was too small to examine on its own.
[14] Gilligan et al. (2009) highlighted that the PSNP transfers were delayed during the first year of implementation (2005/6), and impact was not experienced in the YLS Round 2 (Woldehanna, 2010), motivating us to use 2006 (YLS Round 2) as our pre-programme comparison year.

household wealth between the groups of PSNP and restricted control children. However, it indicates slightly higher average levels of schooling among the heads of households of non-recipient control children, alongside a higher probability that the head of house is male.

Table 1. Descriptive statistics

Variable	**PSNP**	**Control**
Panel A: Pre-programme (2006), full sample		
Child's age (in years)	3.63	3.66
	(1.69)	(1.58)
Male child	0.52	0.53
	(0.50)	(0.50)
Household size	6.33	6.33
	(1.80)	(1.87)
Head of house schooling grade	1.26	1.99***
	(2.07)	(2.73)
Male head of house	0.85	0.96***
	(0.36)	(0.19)
Monthly food expenditure N(birr)	61.65	64.58
	(45.14)	(43.85)
Amhara ethnicity	0.19	0.36***
	(0.39)	(0.48)
Oromo ethnicity	0.17	0.10***
	(0.37)	(0.30)
Tigrayan ethnicity	0.50	0.13***
	(0.50)	(0.34)
Wealth index bottom tercile	0.50	0.53
	(0.50)	(0.50)
Wealth index middle tercile	0.43	0.38*
	(0.50)	(0.49)
Wealth index top tercile	0.07	0.09
	(0.25)	(0.29)
Panel B: Pre-programme (2006), index children only		
Body Mass Index	14.58	14.63
	(1.32)	(1.86)
Child is stunted	0.37	0.40
	(0.48)	(0.49)
Exposed to early life rainfall shock (first 1,000 days)	0.38	0.82***
	(0.49)	(0.39)
Engaged in educational activities	0.04	0.08
	(0.20)	(0.28)
Engaged in unpaid labour	0.29	0.35
	(0.46)	(0.48)
Engaged in household responsibilities	0.50	0.47
	(0.50)	(0.50)
Panel B: RACER outcomes (2013), full sample		
Long-term memory	-0.13	0.12*
	(0.94)	(1.01)
Inhibitory control	-0.15	-0.04
	(0.74)	(0.74)
Working memory	-0.17	-0.17
	(1.03)	(1.19)
Implicit learning	-0.03	0.01

	(0.90)	(1.00)
Long-term memory (baseline)	-0.24	0.06**
	(0.93)	(0.88)
Inhibitory control (baseline)	-0.07	-0.07
	(0.72)	(0.67)
Working memory (baseline)	-0.09	-0.28
	(1.10)	(1.19)
Implicit learning (baseline)	-0.05	0.06
	(0.52)	(1.10)
Number of children (full sample)	378	797

Notes: Panels A and C use the full, pooled sample of index children and their younger siblings. Panel B only uses the sample of index children. Standard deviations are shown in parentheses. RACER scores are standardized, according to the distribution for the non-PSNP children. Wealth terciles are based on the Young Lives wealth index (Briones, 2017). Body Mass Index is calculated by dividing weight in kilograms by the square of height in meters. Children are considered stunted if their heights are more than two standard deviations below the World Health Organization medians for a well-nourished population (WHO Multicentre Growth Reference Study Group, 2006). 'Exposed to early life rainfall shock' takes the value of one if the participant experienced at least one month in the in-utero period, or first or second years of life, where the Standardized Precipitation Index deviated at least 2 standard deviations above or below the historical monthly average of the same community. 'Engaged in educational activities' takes the value of one if children report spending any time at school or studying outside of school, and zero otherwise. 'Engaged in unpaid labour' takes the value of one if children report spending in tasks on the family farm or business, and zero otherwise. 'Engaged in household responsibilities' takes the value of one if children report spending time caring for others or in domestic tasks (fetching water, firewood, cleaning, cooking, washing, shopping, etc.), and zero otherwise. Asterisks reflect p-values for t-tests for differences in means between children in PSNP households and control households. * denotes significant at 10%, ** significant at 5% and *** significant at 1%

For index children only, Panel B provides information on a number of intermediate outcomes potentially linking enrolment in the programme to changes in FCS. It reports no significant differences in pre-programme nutritional status (Body Mass Index and the prevalence of stunting) and time-use categories. However, index children in the restricted control group were relatively more likely to experience at least one rainfall shock during their first 1,000 days of life.

Panel C compares the standardised RACER scores (both the challenge and baseline measures) for all children in the PSNP and restricted control groups. It reports no significant difference in the baseline and challenge measures for inhibitory control, working memory, and implicit learning. However, children in PSNP recipient households perform relatively worse in both long-term memory tasks than those from the restricted control group.

4.2 Empirical strategy

The primary specification used to test the association between the PSNP and FCS is as follows:

$$Challenge_{ihjk} = \alpha_0 + \delta PSNP_{hj} + \beta_1 Baseline_{ihjk} + \beta_2 \boldsymbol{X_{hj}} + \beta_3 \boldsymbol{G_{ihjk}} + \theta_{ihj} + \gamma_j + \mu_{ihjk}, \quad (1)$$

where the dependent variable *Challenge* is a variable used to denote the FCS challenge measurement of child *i* in household *h* in community *j* in RACER task *k*, and *Baseline* denotes the analogous baseline performance measurement. We standardise both the FCS challenge and baseline measures by the control group means and standard deviations. On the right side of the equation, *PSNP* is the treatment variable identifying PSNP beneficiary households; $\boldsymbol{X}$ and $\boldsymbol{G}$ are vectors of household- and child-level characteristics, and task controls respectively. γ_j represents community (unobserved) fixed effects, intended to capture community effects that may, for example, affect PSNP delivery and formation of FCS. θ_i denotes a series of year-of-birth fixed effects, to control for differences in FCS attributable to factors affecting all children born in the same year.[15] μ_{ihjk} represents a mean-zero, idiosyncratic error. The coefficient of interest, δ, denotes the association between the PSNP and FCS development.

To assess whether there are heterogeneous associations between the PSNP and FCS according to age and gender, we interact the treatment variable with age in years (in 2013) and the gender of the child (an indicator variable equal to one if the child is male and 0 otherwise), respectively. The empirical specification is:

$$Challenge_{ihjk} = \alpha_0 + \delta PSNP_{hj} + \gamma W_{ihj} + \varphi PSNP_{hj} * W_{ihj} + \beta_1 Baseline_{ihjk} + \beta_2 \boldsymbol{X_{ihj}} + \beta_3 \boldsymbol{G_{ihjk}} + \theta_{ihj} + \gamma_j + \mu_{ihjk}, \quad (2)$$

where W_{ihj} refers to age or gender.

[15] It would be inappropriate to compare FCS measurements in the pooled sample without controlling for year-of-birth because of imperfect overlap in the baseline performance distributions (Behrman et al., 2022). If challenge effects vary across the baseline distribution, the difference between average challenge effects across the age distribution will in part just reflect differences in the distribution of baseline measures.

In all specifications, we control for the gender of the child, the child's main language and religion, the socio-economic status of the household in 2002 (before the PSNP) and 2013 (the year of FCS data collection) as measured through the YLS wealth index, the household size in 2013, the household head's gender and education (the highest schooling grade achieved by the household head as reported in 2013), whether the household owns any animals, the household's non-food expenditure in 2013, and a vector of dummy variables capturing household environmental and economic negative shocks in the last three years (drought, flood, crop failure, price increase, output decrease, job loss, and livestock loss). We also control for the weekday and the time of the day when the FCS tasks were administered. However, remaining concerns of omitted-variable bias may still be justified given the non-random placement of the PSNP, motivating us to assess the robustness of our results using the methodology outlined in Oster (2019) in Section 5.2.

5. Results

5.1 Main results

In Table 2, we report the associations between each of the FCS measures and the PSNP (Equation 1).[16] To increase statistical power and allow for more variation in the FCS measures, we analyse data from the pooled sample of children (index children and their younger siblings). Our findings suggest that PSNP beneficiaries have significantly higher LTM and IL scores; on average, being a PSNP beneficiary is associated with an increase in the LTM and IL tasks of

[16] Not all children successfully completed all RACER tasks. Hence, the number of observations varies slightly across RACER measures.

0.12 and 0.16 standard deviations, respectively. We do not find any significant associations between PSNP status and IC and WM.[17]

Table 2. Associations between the PSNP and FCS

	LTM	**IC**	**WM**	**IL**
PSNP	0.124**	-0.011	0.063	0.162**
	(0.054)	(0.044)	(0.063)	(0.071)
Controls	Yes	Yes	Yes	Yes
Observations	1,044	1,047	1,045	1,046
R^2	0.277	0.437	0.388	0.509

Notes: The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at community level. LTM = long-term memory, IC = inhibitory control, WM = working memory, IL = implicit learning. RACER outcomes are standardized using the means and standard deviations of the control group. Each coefficient comes from a different estimation of Equation (1) for each FCS outcome (pooled OLS, including both index children and younger siblings). All estimations include community and year-of-birth fixed effects. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

The associations shown in Table 2 bundle the effect of PSNP among both households who received PSNP in 2009 but had graduated from the programme by 2013, and those who were still benefiting from the programme in 2013. In our sample, 37% of PSNP recipients (291) had graduated from the programme by 2013, while the remaining 506 recipients were still receiving the programme in 2013.[18] Examining the associations of the PSNP with cognitive achievement test scores, Favara et al. (2019) found significant heterogeneous effects according to graduation status, concluding that the positive associations of the programme with numeracy and vocabulary were driven by children in households that had graduated from the programme before 2013. This prompts us to explore the heterogeneity of our results across PSNP graduation status, shown in Table 3.

Table 3. Associations between PSNP and FCS by graduation status

	LTM	**IC**	**WM**	**IL**

[17] Some studies that aim to estimate a causal impact of the PSNP use propensity-score matching (PSM) to construct an appropriate counterfactual rather than constructing a restricted sample (e.g., Woldehanna, 2010; Gilligan et al., 2009; Hoddinott, Gilligan and Taffesse, 2010). We assess the robustness of our findings in Table 2 using PSM rather than our restricted control sample (results in Table A4, Table A5 and Figure A3 in the Annex). We find that using PSM does little to alter the interpretation of our results.

[18] Most households who received the programme in 2009 reported receiving it since 2007. If households received the programme in 2013 and in 2009, we assume that treatment was uninterrupted. See Table A6 for pre-programme balance according to graduation status.

2009-only PSNP beneficiaries (graduated)	0.064	-0.018	-0.008	0.111
	(0.068)	(0.050)	(0.068)	(0.072)
2009 & 2013 PSNP beneficiaries	0.165**	-0.005	0.111*	0.197**
	(0.061)	(0.055)	(0.059)	(0.074)
Controls	Yes	Yes	Yes	Yes
Observations	1,044	1,047	1,045	1,046
R^2	0.278	0.437	0.390	0.510

Notes: The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at community level. LTM = long-term memory, IC = inhibitory control, WM = working memory, IL = implicit learning. RACER outcomes are standardized using the means and standard deviations of the control group. Each coefficient estimate comes from a different estimation of Equation (1) for each FCS outcome (pooled OLS, including both index children and younger siblings). All estimations include community and year-of-birth fixed effects. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

We find that the average associations between the PSNP and both LTM and IL are driven by children in households that were still receiving the programme in 2013. Among this group of children, being a PSNP beneficiary is associated with average increases in the LTM and IL tasks of roughly 0.17 and 0.20 standard deviations, respectively. Additionally, we find that children from non-graduated households have significantly higher WM scores compared to children in the control group (coefficient significant at the 10% level). In contrast, all coefficients are statistically insignificant among the group of children in households that graduated from PSNP before the 2013 survey.

5.2 Robustness to potential selection on unobserved variables

The foregoing results provide suggestive evidence of improvements in LTM and IL outcomes due to the PSNP. However, because of non-random programme placement, it is a challenge to measure the effects of the PSNP on FCS reliably. The restriction of the control group to a more comparable subsample and the inclusion of a comprehensive set of controls both help mitigate potential concerns about omitted-variable bias due to household selection based on unobserved variables (Porter and Goyal, 2016). However, there is always a possibility that omitted variables might be correlated with both the outcome and treatment, resulting in biased estimates. In our case, it could be argued that unobserved household or family characteristics could be affecting both households' likelihoods of being selected for the PSNP and their children's FCS.

A common approach to evaluating robustness to omitted variable bias is to observe coefficient movements after the inclusion of a rich set of controls; if a coefficient is stable after the inclusion of observed controls, this is taken as a sign that omitted variable bias is limited (Altonji et al., 2005). However, Oster (2019) highlights that omitted variable bias is only proportional to coefficient movements if such movements are scaled by the change in the R^2 when controls are included. In this section, we apply the methodology suggested by Oster (2019) to assess whether the demonstrated associations between the PSNP and LTM and IL are due to selection or omitted variable bias.

One attractive aspect of the YLS data is that, for the index children, they provide an extensive list of covariates for which we can control.[19] In addition to the variables included in the main specification, we now add control variables on children's pre-programme (2006, about age 5) stunting status and cognitive test scores (measured by the Peabody Picture Vocabulary Test and the Cognitive Development Assessment), and the per-capita household food expenditures in 2013.

Oster's method requires assuming a maximum amount of variation that a hypothetical regression including all observed and unobserved covariates could explain (R_{max}); we follow the recommendation provided in Oster (2019) of using 1.3 times the R^2 value of the specification with all observed controls ($\widetilde{R^2}$).[20] The method also requires specifying the relative

[19] To utilise the richness of the Young Lives data by including additional observed control variables, we assess the robustness of the results using index children only.
[20] Oster shows that more than 90% of the results from randomized controlled trials survive this threshold. Since the experimental results are likely causal estimates, Oster suggests using this as a benchmark.

importance of observed and unobserved covariates in explaining variation in the outcome variable; again, we follow the guidance in Oster (2019) and assume observed and unobserved are equally important (δ=1).

Table 4. Robustness of LTM and IL results to omitted-variable bias

Treatment variable, outcome variable	OLS estimate (Std. error), [$\dot{R}^2$] (1)	Controlled estimate $\tilde{\beta}$ (Std. error), [$\widetilde{R^2}$] (2)	Identified set, [$\tilde{\beta}$,$\beta^*(1.3\widetilde{R^2})$] (3)	Identified set excludes zero? (4)
PSNP, LTM	0.086 (0.069)[0.156]	0.203** (0.092)[0.243]	[0.203, 0.452]	Yes
PSNP, IL	0.001 (0.052)[0.712]	0.126* (0.062)[0.735]	[0.126, 4.261]	Yes
2009 & 2013 beneficiaries, LTM	0.106 (0.756)[0.156]	0.246** (0.106)[0.244]	[0.233, 0.906]	Yes
2009 & 2013 beneficiaries, IL	0.002 (0.060)[0.712]	0.141* (0.080)[0.735]	[0.141, 7.328]	Yes

Notes: All results are estimated on the sample of index children only. The OLS regressions (column 1) have only RACER baseline and game controls. The controlled effect is estimated using an OLS regression, including community and year-of-birth fixed effects, and controlling for baseline measures, game controls, socio-economic status, demographics, negative economic shocks, language and religion, household head schooling, 2006 nutritional status and cognitive test scores, sex of the household head, household expenditure, and whether the household owns any livestock. LTM = long-term memory, IL = implicit learning. RACER outcomes are standardized using the means and standard deviations of the control group. 'PSNP' takes the value of one if the household ever received the programme, while '2009 & 2013 beneficiaries' takes the value of one if the household was still receiving the programme in 2013. The identified set in Column (3) is bounded below by $\tilde{\beta}$ and above by β^* calculated based on R_{max}=1.3$\widetilde{R^2}$ and δ=1. β^* was calculated using the Stata command psacalc provided by Oster (2019). Robust standard errors are clustered at the community level. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4 reports the results. The first two rows show results using the binary variable for any PSNP receipt, while the last two rows focus on those who received PSNP in both 2009 and 2013. The OLS treatment estimates in Column 1 control only for the baseline task and game controls. In Column 2, we then evaluate how the coefficients of interest are affected by the inclusion of the full set of controls. For all estimations, PSNP status is not significantly associated with better LTM or IL in Column 1 but is significantly associated with improved FCS in Column 2. Column 3 shows bounds on the coefficients, using the R_{max} estimate of 1.3 of $\widetilde{R^2}$ and δ = 1.

Overall, the results suggest that our findings are robust to the Oster (2019) sensitivity analysis. In all specifications, the identified set for the associations between PSNP and LTM and IL excludes zero (Column 4), and the upper-bound estimates are larger than $\tilde{\beta}$ (particularly for IL). This suggests that our results are *not* likely explained by omitted-variable bias associated with both the FCS outcomes and the treatment (PSNP status). The robustness of our results suggests that the associations found between the PSNP and FCS might in fact capture a causal relationships between the two. According to what is reported in Table 4, our results are likely to *understate* the magnitude of the PSNP's effect on LTM and IL.

5.3. Heterogeneity by age and gender

Having established that our findings are not likely to be explained by sample selection on treatment, we next move onto examining whether there are heterogeneous effects of the PSNP according to the age (Table A7) and gender of the child (Table A8). For all specifications, we find no significant difference according to the gender and age of the child.[21]

One possible reason why the association between the PSNP and FCS does not differ according to age is that the brain is malleable *across* the child lifecycle. Emerging evidence from intervention studies and natural experiments in high-income countries indicates that experiences in adolescence, as well as those in the first few years of life, significantly shape FCS (Brody et al., 2019; Colich et al., 2021). This evidence converges with recent theoretical conceptualizations of two sensitive periods in brain and behavioural development - first in very early life and then again later in adolescence (Blakemore and Mills, 2014).

[21] We also tested non-linear interactions for age (squared and cubic terms of age in years), and found no significant interaction terms.

6. Potential mechanisms

In this section, we investigate two mechanisms that may explain the positive effect of the PSNP on FCS (and more specifically LTM and IL), as suggested by the existing literature and discussed in Section 1. First, by increasing household income, the PSNP may positively impact cognition through an increase in children's food consumption and nutrition. Given that the PSNP explicitly targets food-insecure households, it is possible that the programme plays a remediation role, affecting FCS through ameliorating past nutritional deficits among those who experienced deprivations early in life.

Second, the work requirement imposed by the programme means that there may be changes in the time allocation of children, which could affect the formation of cognitive skills. For example, children may substitute in for adult labour in family businesses or household work, or they may work less as their parents are earning a more stable income. When considering this mechanism, we assume that spending more time on education (both in school and studying outside of school) improves FCS, while spending time working (paid or unpaid) and caring for others does not.[22] The programme may also affect time use of adults and time spent interacting with children, but unfortunately data are not available to test this hypothesis.

6.1 Time-use reallocation

As discussed, the work requirement among adults imposed by the PSNP means that there may be changes in the time allocation of children which could affect their cognitive development.

[22] Numerous studies, primarily for high-income countries, have documented positive associations between FCS and educational outcomes (e.g., Alloway and Alloway, 2010; Blair and Razza, 2007; Clark, Pritchard, and Woodward, 2010; Hughes and Ensor, 2011; Jacob and Parkinson, 2015, among others). Such positive associations also have been found for Ethiopia using the YLS data (Lopez et al., 2022).

Favara et al. (2019) argue that the effect of the PSNP on cognitive test scores is at least partially related to time reallocation towards educational activities, as students in PSNP households spend significantly more time in schooling in 2013 than the comparison children.

To examine whether the positive effects of the PSNP on FCS may be driven by time reallocation due to the programme, we interact the PSNP treatment variable with information on time use before the introduction of the programme (in 2006). Given the ages of the index children in 2006[23], many children reported spending zero hours in educational activities (in school or studying), caring for others or performing domestic tasks (e.g., fetching water and firewood), and performing unpaid labour on the family farm/business. Therefore, for each time category (education, household responsibilities and unpaid labour), we generated a binary variable taking the value of one if children reported *any* hours in the category, and zero otherwise.[24] For both LTM and IL, we estimate Equation (2), replacing W_i with each time-use binary variable. We focus our analysis on the index children who were aged 5 and over in 2006, as information on younger siblings was only collected from 2009 onwards and time-use information was not collected on children under five in 2006.[25] Table 9 reports the results.[26]

Table 5. Heterogenous effects according to 2006 time use

	Education	**Unpaid labour**	**Household responsibilities**
Panel A: LTM			
PSNP	0.114	0.120	0.177
	(0.116)	(0.089)	(0.141)
Reported any hours	0.162	-0.022	0.033
	(0.270)	(0.123)	(0.082)

[23] In 2006, index children were, on average, 5.2 years old.
[24] For all three time-use categories, the median number of hours reported was zero. The full distributions for number of reported hours in each category are shown in Table A8.
[25] 236 (34%) of index children were under 5 years old in 2006 and were not asked the time-use questions.
[26] The adult work requirement is only applicable to households in the public-works aspect of the PSNP, not those that receive direct support. In 2013, 19% of index children receiving the PSNP reported being in households receiving direct support. To ensure that our results in Table 9 are not unduly affected by children receiving direct support, we re-estimate our analysis on the sample of index children in public-works households only. Overall, we conclude that the interpretation of our findings is robust to this sample limitation (results in Table A10).

PSNP * Reported any hours	0.381	0.062	-0.062
	(0.418)	(0.198)	(0.151)
PSNP among those who reported any hours	0.495	0.183	0.114
	(0.356)	(0.191)	(0.108)
Observations	420	420	420
R^2	0.241	0.233	0.233
Panel B: IL			
PSNP	0.173**	0.016	0.151*
	(0.078)	(0.074)	(0.074)
Reported any hours	0.471**	-0.178*	0.121
	(0.179)	(0.099)	(0.087)
PSNP * Reported any hours	-0.633*	0.283*	-0.052
	(0.333)	(0.133)	(0.081)
PSNP among those who reported any hours	-0.460	0.299**	0.099
	(0.304)	(0.110)	(0.086)
Observations	420	420	420
R^2	0.737	0.735	0.733

Notes: Analysis performed on index children only. The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at community level. LTM = long-term memory, IL = implicit learning. RACER outcomes are standardized using the mean and standard deviation of the control group. All estimations include community and year-of-birth fixed effects. 'Reported any hours' takes the value of one if the participant reported any hours in the relevant time use category in 2006, and zero otherwise. 'PSNP among those who reported any hours' coefficient reflects the effect of the PSNP on the FCS of children who reported spending at least some time in each time-use category in 2006. It is calculated as the linear combination of the PSNP and PSNP * Reported any hours coefficients. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

In Panel A (LTM), none of the interaction terms are statistically different from zero, suggesting that the LTM result is unlikely to be related to time reallocation among PSNP beneficiary children. For IL, however, (Panel B), the interaction terms between the PSNP treatment variable and both the dummy variable for any hours spent in educational activities and in unpaid labour are statistically significant (at the 10% level). The negative interaction point estimate for educational hours suggests that the effect of the PSNP on IL is significantly lower among those who reported spending time on educational activities before the programme. In contrast, the positive point estimate for unpaid hours indicates that the effect is larger for those who had unpaid labour responsibilities in 2006. In fact, the PSNP coefficient is only statistically significant among those who reported any unpaid labour hours; among those with no unpaid labour hours in 2006, the PSNP coefficient is small and statistically insignificantly.

Taken together, these findings imply that the IL result may, in part, be due to a reallocation of time away from unpaid labour responsibilities at home towards educational activities.[27]

6.2 Remediation of early-life nutritional deficits

Using YLS data, Porter and Goyal (2016) find a positive medium-term association between PSNP participation and height-for-age z-scores for children aged 5-15, suggesting that the programme positively impacted children's long-run nutritional outcomes. Sánchez et al. (2022) investigate the impact of early undernutrition on FCS, finding that children who are well-nourished at age 5 in Ethiopia are more likely to report higher levels of LTM, IC and WM at age 12. Thus, if adequate nutrition engenders higher FCS, we would expect the PSNP to have a larger effect on FCS among those who were undernourished in early childhood.

As a first step, we estimate Equation (1) using the Body Mass Index (BMI) in 2013 as the outcome to assess whether, among our sample, being a PSNP beneficiary is associated with improved short-run nutritional status (Table 6). Consistent with Porter and Goyal (2016), our results suggest that PSNP beneficiaries have significantly higher BMI scores; on average, being a PSNP beneficiary is associated with an increase in BMI of 0.20 kg/m^2. Given that the beneficiaries tend to be undernourished (see Table 1), this is a positive gain.

Table 6. Association between the PSNP and Body Mass Index

	Body Mass Index
PSNP	0.204**
	(0.084)
Controls	Yes
Observations	1,047
R^2	0.195

[27] This is consistent with the finding that, among the pooled sample of index children and younger siblings, being a PSNP beneficiary is associated with significantly fewer unpaid domestic-task hours in 2013 (Table A11 in the Annex).

Notes: The table reports the OLS estimate with robust standard errors (reported in parentheses) clustered at community level. Estimation includes community and year-of-birth fixed effects. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

To test the possible remediation role of the programme, we interact the PSNP treatment with information on whether the participants were stunted before their households started receiving the programme (in 2006).[28] Stunting is a well-established measure of individual health status, especially among children, which typically reflects the persistent, cumulative effects of inadequate nutrition (Dewey and Begum, 2011; Hoddinott et al., 2013). Children are considered stunted if their heights are more than two standard deviations below the World Health Organization medians for a well-nourished population (WHO Multicentre Growth Reference Study Group, 2006). We focus our analysis on the index children only, as information on younger siblings was only collected once households were enrolled in the PSNP (from 2009 onwards). Table 8 reports the results.

Table 7. Heterogenous effects according to 2006 stunting status

	LTM	**IL**
PSNP	0.063	0.073
	(0.089)	(0.078)
Stunted (2006)	-0.356**	-0.017
	(0.123)	(0.081)
PSNP*Stunted (2006)	0.367**	0.090
	(0.131)	(0.094)
PSNP among stunted (2006)	0.430***	0.164*
	(0.105)	(0.079)
Controls	Yes	Yes
Observations	628	628
R^2	0.241	0.733

Notes: Analysis performed on index children only. The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at community level. LTM = long-term memory, IL = implicit learning. RACER outcomes are standardized using the means and standard deviations of the control group. All estimations include community and year-of-birth fixed effects. 'Stunted (2006)' takes the value of one if the participant was stunted in 2006, and zero otherwise. 'PSNP among stunted (2006)' coefficient reflects the effect of the PSNP on FCS of children who were stunted in 2006. It is calculated as the linear combination of the PSNP and PSNP*Stunted (2006) coefficients. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

[28] This is estimated using Equation (2), replacing W_i with an indicator that takes the value of one if the child was stunted in 2006, and zero otherwise.

For LTM (but not IL), the interaction term is positive and statistically significant, suggesting that the positive effect of PSNP on LTM is significantly larger for those who were stunted before receiving the programme. For both tasks, the PSNP coefficient is positive and statistically significant (at least at the 10% level) among those who were stunted in 2006; in contrast, for both FCS tasks, the PSNP coefficient among those who were not stunted in 2006 is small and statistically insignificant. This provides suggestive evidence that the observed effect of the PSNP on FCS may, in part, be due to the programme's success in remediating past nutritional deficits (particularly for LTM).

6.2.1. Remediation of early life rainfall shocks

The above results provide suggestive evidence that the positive effects of the PSNP on LTM may be due to improvements in nutrition. This raises an interesting question of whether part of the programme's success may be due to the remediation of negative effects due to early life rainfall shocks, which may have affected nutritional and other investments in children.

As a country in which 80% of the population lives in rural areas and relies on rain-fed agriculture, Ethiopia is highly vulnerable to extreme climate conditions (UN DESA, 2019). In recent decades, the country has been exposed to multiple, severe droughts - with adverse short- and long-term consequences (Webb and Braun, 1994; Dercon, 2004; Porter, 2012). In particular, a growing body of international evidence finds that early life rainfall shocks negatively impact children's nutritional outcomes (e.g., Dimitrova and Muttarak, 2020; Hirvonen et al., 2020; Skoufias and Vinha, 2012; Yamano et al., 2005; Dercon and Porter, 2012), suggesting that the PSNP have been able to affect FCS through partially offsetting the negative nutritional, as well as possibly other, effects of rainfall shocks.

To analyse whether part of the PSNP's positive effects on FCS may be due to the remediation of early life rainfall shocks, we combine the YLS data with gridded data on monthly precipitation to generate monthly community-level rainfall estimates. Rainfall data are obtained from the University of Delaware, a commonly used climate dataset in the literature (e.g., Shah and Steinberg, 2017; Rocha and Soares, 2015; Thai and Falaris, 2014), which contains high-spatial-resolution (0.5°) gridded estimates of monthly total precipitation across land surfaces between 1900 and 2014 (Matsuura and Wilmott, 2018). For each YLS community, the survey collected GPS coordinates using, as a reference point, the centre of the community, either identified as the centre of the main square or, in the absence of it, of another point of interest (e.g., city hall, school, post office, church). Using this information, we matched the grid points for which rainfall data were available to the GPS locations of the YLS communities, using the main square in each community as the reference point. For each community, monthly rainfall precipitation was calculated as an inverse-distance-weighted average of the monthly rainfall registered at the four closest grid points to that community.

To identify rainfall shocks and their intensity, for each community, we construct a Standardised Precipitation Index (SPI). The SPI was first proposed by McKee et al. (1993) and is recommended by the World Meteorological Organisation for the characterization of meteorological droughts (Wu et al., 2007). The SPI derives a value for a month's rainfall in terms of standard deviations from the long-term mean of the transformed standardised normal distribution for that month-of-year and community specifically. Deviations from the mean are more relevant than absolute rainfall because individual and communities typically adapt to local conditions on average (e.g., with regard to composition of agricultural products). The SPI is preferred to using raw precipitation data as, unlike a deviation from the simple long-term average, the non-negative and positively skewed nature of rainfall is accounted for prior to normalisation. Another advantage of this measure is that it requires only precipitation to calculate and is computationally simple, unlike other measures such as the Palmer Drought Index (Lloyd-Hughes and Saunders, 2002). To calculate the SPI, precipitation data are fitted to a gamma distribution, and then transformed to a standard normal distribution with a mean value of zero (McKee et al., 1993; Agnew, 2000). This is conducted for each month of the year at each community separately, providing a month-community specific measure of rainfall anomalies relative to long-run conditions.

Following the definition of an 'extreme' weather condition ('extremely wet' or 'extremely dry') in McKee et al. (1993), for each community, we define a rainfall shock as any monthly SPI deviation of at least 2 standard deviations above or below the historical monthly average of the same community. For each YLS respondent, information about the date and place of birth is used to identify whether children experienced at least one rainfall shock during the gestation (in-utero, pre-natal) period and/or during the early childhood period (the first and second years of life after birth).[29] For LTM and IL, we then estimate Equation (2) three times, replacing W_i with three binary variables that take the value of one if children experienced at least one rainfall shock during the in-utero period, the first year of life, and the second year of life, respectively, and zero otherwise. Table 8 presents the results.

Table 8. Heterogenous effects according to early life rainfall shocks

	In-utero **(1)**	**Year 1** **(2)**	**Year 2** **(3)**
Panel A: LTM			
PSNP	0.102	0.028	0.070
	(0.069)	(0.063)	(0.063)
Rainfall shock	-0.079	-0.246**	-0.268

[29] We dropped 12 index children who moved/migrated communities between conception and Round 1 (children ~ 6-18 months old), or between Round 1 and Round 2 (children ~ 4.5-5.5 years old). 100 index children were also excluded as they did not have complete community GPS information.

	(0.250)	(0.099)	(0.417)
PSNP * Rainfall shock	0.196**	0.353***	0.105
	(0.076)	(0.093)	(0.109)
PSNP among rainfall shock sample	0.298***	0.381***	0.174*
	(0.083)	(0.083)	(0.096)
Observations	520	520	520
Controls	Yes	Yes	Yes
R^2	0.201	0.205	0.201
Panel B: IL			
PSNP	0.088	0.094	0.133
	(0.072)	(0.065)	(0.103)
Rainfall shock	-0.010	0.078	-0.136
	(0.051)	(0.059)	(0.158)
PSNP * Rainfall shock	0.002	-0.019	-0.074
	(0.066)	(0.124)	(0.157)
PSNP among Rainfall shock sample	0.090	0.075	0.059
	(0.077)	(0.127)	(0.099)
Observations	520	520	520
Controls	Yes	Yes	Yes
R^2	0.724	0.724	0.724

Notes: Analysis performed on index children who did not move between communities between conception and Round 2 (~age 5). The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at community level. LTM = long-term memory, IL = implicit learning. RACER outcomes are standardized using the mean and standard deviation of the control group. All estimations include community and year-of-birth fixed effects. 'Rainfall shock' takes the value of one if the participant experienced at least one month in the in-utero period, first, or second year of life, respectively, where the SPI deviated at least 2 standard deviations above or below the historical monthly average of the same community. 'PSNP among Rainfall shock sample' coefficient reflects the effect of the PSNP among children who experienced at least one rainfall shock in each period. It is calculated as the linear combination of the PSNP and PSNP * Rainfall shock coefficients. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

For LTM, the interaction term is positive and statistically significant in Columns (1) and (2), suggesting that the effect of PSNP on LTM is significantly larger for those who experienced at least one rainfall shock during the gestation period, or in their first year of life. In contrast, none of the interaction coefficients are significant for IL.[30]

One interpretation of these results is that, while we observe a lower level of LTM among those exposed to early life rainfall shocks (particularly among those who experienced a rainfall shock in their first year), this negative effect is partially offset within the group of PSNP-recipients.

[30] Previous research shows that findings can be sensitive to how rainfall shocks are defined (Sohnesen, 2020). Therefore, in Table A12 in the Appendix, we show that our findings are robust to using 2.5 SPI as a cut-off for defining a rainfall shock (using 2.5 SPI, the interaction coefficient for Year 2 is also positive and statistically significant at the 5% level).

In fact, for LTM, the PSNP coefficient is positive and statistically significant among those who experienced a rainfall shock; in contrast, the coefficient among those who did not experience any rainfall shocks is consistently insignificant.[31] This, combined with the findings in Table 7, provides evidence that the positive effect of the PSNP on LTM may, at least in part, be due to the programme's success in remediating early life deficits in nutritional and other investments in children, caused by rainfall shocks. Indeed, we find that early life rainfall shocks likely represent one important determinant of malnutrition, as 63% of index children who were stunted at age 5 experienced at least one rainfall shock during their first 1,000 days after conception.[32]

7. Conclusion

We find significant, positive associations of a large Public Works Programme, the Ethiopian PSNP, with foundational cognitive skills of young adolescents who grew up in poverty, but received transfers from the programme during their childhood. The effects are most robust for long-term memory and implicit learning, and positive, but weaker for working memory. These associations appear to be strongest for children whose households were still recipients of the PSNP in the year of data collection. We also find suggestive evidence that, in part, the association with implicit learning may be operating through the income effect of the programme allowing time reallocation away from unpaid labour hours, while the association with long-term memory may be due to the programme's success in remediating past nutritional deficits caused by early life rainfall shocks.

[31] This is unlikely to be due to insufficient power, as in each period in question, the majority of the PSNP sample did not experience a rainfall shock.
[32] The Pearson correlation coefficient between stunting status at age 5 and rainfall shocks during the first 1,000 days is 0.163, significant at the 1% level.

We acknowledge a number of key limitations in our analysis, related to the fact that we only observe foundational cognitive skills in one time period. First, we are limited in our empirical strategy and are not able to utilise longitudinal data techniques (such as individual fixed effects). Second, we are not able to analyse dynamics over time, to assess whether the observed benefits of the PSNP persist into adolescence and early adulthood.

In spite of the limitations described above, the link between enrolment in the PSNP and foundational cognitive skills is relevant for the future design and targeting of the PSNP, and other similar Public Works Programmes. Taken together, our findings suggest that Public Works Programmes can have positive effects on child foundational cognitive skills, and in particular, that policy interventions may be able to mitigate the effects of early poverty on cognitive skills formation, and could improve children's potential future outcomes. We also note that recent changes to make the PSNP more nutrition-sensitive, combined with targets for improved delivery, may increase the effectiveness of the programme for children in future (Roelen et al., 2017).

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Appendix

Figure A1. RACER in practice

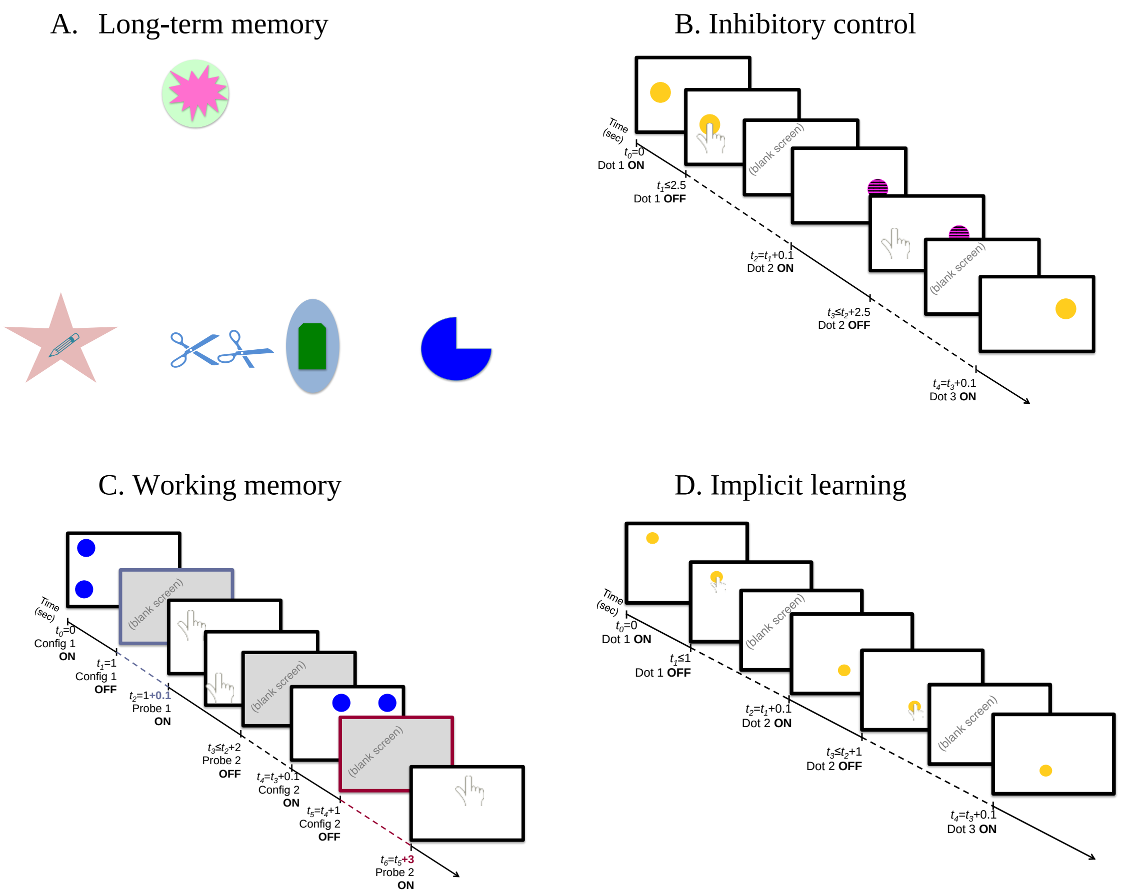

Figure A2. Age distribution in year of RACER collection

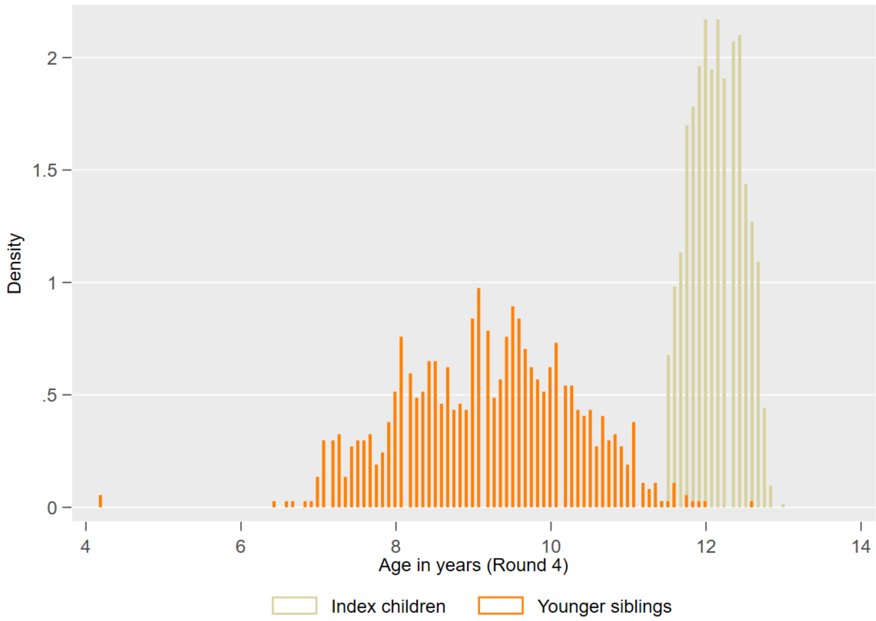

Table A3. Non-PSNP households and PSNP households: pre-programme balance (full sample)

	Non-PSNP households	PSNP households
Age (in years)	3.72	3.63
Male	0.52	0.52
Household size	6.37	6.33
Head of house schooling grade	2.17	1.26***
Male head of house	0.95	0.85***
Has attended pre-primary	0.12	0.02***
Wealth index		
Bottom tercile	0.49	0.50
Middle tercile	0.38	0.43**
Top tercile	0.13	0.07***
Amhara ethnicity	0.29	0.19***
Oromo ethnicity	0.16	0.17
Tigrayan ethnicity	0.07	0.50***
Observations	1,111	797

Notes: All variables are measured at Round 2 (2006). Wealth terciles are based on the Young Lives wealth index (Briones, 2017). Asterisks reflect p-values for a t-test for differences in means between control households and PSNP households. *<0.1 **<0.05 ***<0.01.

Table A4. Robustness of associations between the PSNP and FCS using propensity-score matching

	LTM	**IC**	**WM**	**IL**
PSNP	0.147*	0.058	0.086	0.143**
	(0.070)	(0.056)	(0.060)	(0.057)
Controls	Yes	Yes	Yes	Yes
Observations	1,407	1,411	1,408	1,409
R^2	0.376	0.520	0.428	0.625

Notes: The table reports OLS estimates weighted using inverse probability weights generated from propensity scores. Robust standard errors (reported in parentheses) are clustered at community level. Propensity scores are estimated using information on pre-PSNP (2006) wealth index score, pre-primary education attendance, community of residence, and negative economic shocks (crop failure, death of livestock, and illness or death of household member). RACER outcomes are standardized using the means and standard deviations of all children in non-PSNP households. Each coefficient estimate comes from a different estimation of equation (1), for each FCS outcome (pooled OLS, including both index children and younger siblings). All estimations include community and year-of-birth fixed effects. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

Table A5. Logistic Model for Probability of Participating in The PSNP

	Dependent variable: PSNP participation
Number of males aged 0-5	-0.198
	(0.141)
Number of males aged 6-12	-0.237**
	(0.101)
Number of males aged 13-17	-0.068
	(0.131)
Number of males aged 18-60	-0.573***
	(0.137)
Number of males aged 61+	-0.331
	(0.361)
Number of females aged 0-5	0.030
	(0.140)
Number of females aged 6-12	-0.004
	(0.095)
Number of females aged 13-17	-0.111
	(0.139)
Number of females aged 18-60	-0.094
	(0.174)
Number of females aged 61+	0.695*
	(0.367)
Shock (crops failed) 2002-2006	0.242
	(0.153)
Shock (death of livestock) 2002-2006	-0.129
	(0.144)
Shock (death of father) 2002-2006	-0.084
	(0.562)
Shock (death of mother) 2002-2006	0.611
	(0.683)
Shock (death of other household member) 2002-2006	0.196
	(0.348)
Shock (illness of father) 2002-2006	0.279
	(0.207)
Shock (illness of mother) 2002-2006	-0.465**
	(0.207)
Shock (illness of other household member) 2002-2006	0.076
	(0.190)
Household wealth index score (2006)	-6.461***
	(0.814)
Attended pre-primary education	0.281
	(0.464)
Community dummies (2006)	Yes

Pseudo R^2	0.366
Log likelihood	-666.270
Observations	1,516

Notes: * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

Figure A3. Propensity score common support

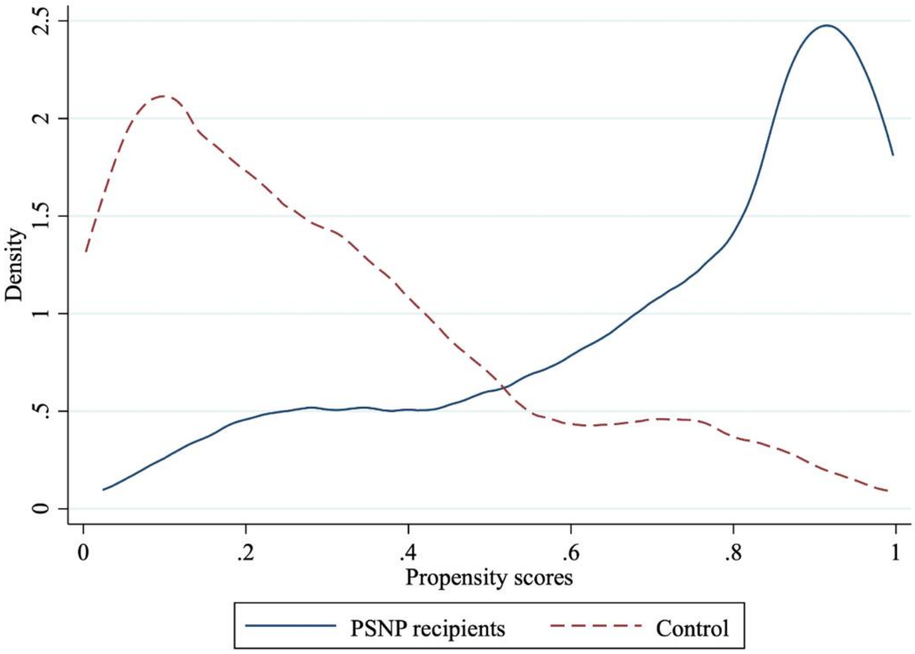

Table A6. Pre-programme balance, according to PSNP graduation status

	Non-PSNP households	2009 PSNP only	2009 & 2013 PSNP	p-value (2009 only)	p-value (2009 & 2013)
Age (in years)	3.66	3.57	3.66	0.47	0.98
Male	0.53	0.55	0.50	0.67	0.34
Household size	6.33	6.60	6.17	0.06	0.21
Head of house education grade	1.99	1.22	1.28	0.00	0.00
Male head of house	0.96	0.89	0.82	0.00	0.00
Monthly food expenditure (birr)	64.58	62.95	60.90	0.65	0.21
Amhara ethnicity	0.36	0.24	0.16	0.00	0.00
Oromo ethnicity	0.10	0.08	0.22	0.24	0.00
Tigrian ethnicity	0.13	0.59	0.45	0.00	0.00
Wealth index					
Bottom tercile	0.53	0.54	0.48	0.89	0.11
Middle tercile	0.38	0.42	0.44	0.29	0.07
Top tercile	0.09	0.04	0.08	0.02	0.75
Observations	378	291	506		

Notes: All variables are measured at Round 2 (2006). Wealth terciles are based on the Young Lives wealth index (Briones, 2017). The p-values for t-tests for differences in means between control group and the PSNP groups are reported in the last two columns.

Table A7. Heterogeneous associations of PSNP with FCS according to age

	LTM	**IC**	**WM**	**IL**
	(1)	(2)	(3)	(4)
PSNP	-0.341	0.009	0.088	0.123
	(0.291)	(0.039)	(0.299)	(0.305)
Age	-0.018	0.005	0.114***	0.098***
	(0.024)	(0.004)	(0.018)	(0.025)
PSNP*Age	0.043	-0.000	-0.002	0.003
	(0.026)	(0.004)	(0.025)	(0.026)
Observations	1,044	1,047	1,045	1,046
Controls	Yes	Yes	Yes	Yes
R^2	0.271	0.716	0.386	0.502

Notes: The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at the community level. LTM = long-term memory, IC = inhibitory control, WM = working memory, IL = implicit learning. RACER outcomes are standardized using the means and standard deviations of the control group. Each coefficient estimate comes from a different estimation of equation (1), for each FCS outcome (pooled OLS, including both index children and younger siblings). All estimations include community fixed effects. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

Table A8. Associations between PSNP and FCS, by gender

	LTM	**IC**	**WM**	**IL**
	(1)	(2)	(3)	(4)
PSNP	0.189**	-0.001	0.071	0.136
	(0.077)	(0.006)	(0.079)	(0.108)
PSNP*Male	-0.117	0.011	-0.005	0.060
	(0.115)	(0.009)	(0.090)	(0.111)
PSNP among males	0.071	0.010	0.066	0.171**
	(0.080)	(0.007)	(0.075)	(0.068)
Observations	1,044	1,048	1,046	1,047
Controls	Yes	Yes	Yes	Yes
R^2	0.277	0.713	0.358	0.476

Notes: The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at the community level. LTM = long-term memory, IC = inhibitory control, WM = working memory, IL = implicit learning. RACER outcomes are standardized using the means and standard deviations of the control group. Each coefficient estimate comes from a different estimation of equation (1), for each FCS outcome (pooled OLS, including both index children and younger siblings). All estimations include community and year-of-birth fixed effects. The dependent variable is the challenge outcome for LTM, IC, WM and IM. 'PSNP among males' coefficient reflects the association between the PSNP and FCS among male children. It is calculated as the linear combination of the PSNP and PSNP*Male coefficients. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

Table A9. Full distribution of time-use in 2006, index children only

Hours	**Educational activities**	**Unpaid labour**	**Household responsibilities**
0	431	313	232
1	1	29	45
2	0	31	68
3	2	17	33
4	4	35	40
5	5	8	7
6	11	11	16

7	2	0	7
8	1	9	7
9	0	0	0
10	0	3	2
11	0	0	0
12	0	1	0
Total	*457*	*457*	*457*

Notes: Hours refer to the number of hours a respondent spent in each category during a typical day (from Monday to Friday) in the week before the survey. 'Educational activities' refers to time spent at school or studying outside of school. 'Unpaid labour' refers to time in tasks on the family farm or business. 'Household responsibilities' refers to time spent caring for others or in domestic tasks (fetching water, firewood, cleaning, cooking, washing, shopping, etc.). Time use information was only asked about index children aged five and over in 2006.

Table A10. Heterogenous associations according to 2006 time-use, public works households only

	Education	Unpaid labour	Household responsibilities
Panel A: LTM			
PSNP	0.136	0.108	0.207
	(0.117)	(0.094)	(0.142)
Reported any hours	0.184	-0.039	0.017
	(0.257)	(0.116)	(0.086)
PSNP * Reported any hours	0.280	0.145	-0.084
	(0.424)	(0.183)	(0.140)
PSNP among those who reported any hours	0.416	0.254	0.123
	(0.375)	(0.181)	(0.104)
Observations	382	382	382
R^2	0.255	0.251	0.250
Panel B: IL			
PSNP	0.187*	0.026	0.201**
	(0.088)	(0.087)	(0.076)
Reported any hours	0.451**	-0.179*	0.118
	(0.185)	(0.095)	(0.084)
PSNP * Reported any hours	-0.550*	0.315**	-0.104
	(0.298)	(0.140)	(0.081)
PSNP among those who reported any hours	-0.364	0.341**	0.097
	(0.265)	(0.114)	(0.095)
Observations	382	382	382
R^2	0.754	0.753	0.750

Notes: Analysis performed on index children only. PSNP households only include those benefitting from the public works programme (not those receiving direct support). The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at community level. LTM = long-term memory, IL = implicit learning. RACER outcomes are standardized using the means and standard deviations of the control group. All estimations include community and year-of-birth fixed effects. 'Reported any hours' takes the value of one if the participant reported any hours in the relevant time use category in 2006, and zero otherwise. 'PSNP among those who reported any hours' coefficient reflects the association between the PSNP and FCS among children who reported spending at least some time in each time use category 2006. It is calculated as the linear combination of the PSNP and PSNP * Reported any hours coefficients. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

Table A11. Association between the PSNP and unpaid labour hours in 2013

	Unpaid labour hours

PSNP	-0.421*
	(0.221)
Controls	Yes
Observations	1,052
R^2	0.315

Notes: Analysis performed on pooled sample of both index children and younger siblings. The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at community level. Estimations include community and year-of-birth fixed effects. Estimations include controls for socio-economic status, demographics, negative economic shocks, language and religion, household head schooling, sex of the household head, household expenditure, and whether the household owns any livestock. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.

Table A12. Heterogenous effects according to early life rainfall shocks, using 2.5 SPI cut-off

	In-utero (1)	Year 1 (2)	Year 2 (3)
Panel A: LTM			
PSNP	0.098	0.060	0.009
	(0.064)	(0.061)	(0.092)
Rainfall shock	-0.138	-0.220**	-0.346
	(0.386)	(0.095)	(0.239)
PSNP * Rainfall shock	0.270**	0.329**	0.239**
	(0.118)	(0.113)	(0.104)
PSNP among rainfall shock sample	0.368***	0.388***	0.249***
	(0.106)	(0.107)	(0.058)
Observations	520	520	520
Controls	Yes	Yes	Yes
R^2	0.202	0.204	0.203
Panel B: IL			
PSNP	0.081	0.081	0.078
	(0.070)	(0.062)	(0.085)
Rainfall shock	-0.054	0.112	-0.438*
	(0.035)	(0.109)	(0.235)
PSNP * Rainfall shock	0.046	0.032	0.012
	(0.063)	(0.153)	(0.142)
PSNP among Rainfall shock sample	0.126	0.114	0.090
	(0.082)	(0.160)	(0.107)
Observations	520	520	520
Controls	Yes	Yes	Yes
R^2	0.724	0.724	0.724

Notes: Analysis performed on index children who did not move communities between conception and Round 2 (~age 5). The table reports the OLS estimates with robust standard errors (reported in parentheses) clustered at community level. LTM = long-term memory, IL = implicit learning. RACER outcomes are standardized using the mean and standard deviation of the control group. All estimations include community and year-of-birth fixed effects. 'Rainfall shock' takes the value of one if the participant experienced at least one month in the in-utero period, first, or second year of life, respectively, where the SPI deviated at least 2.5 standard deviations above or below the historical monthly average of the same community. 'PSNP among Rainfall shock sample' coefficient reflects the effect of the PSNP among children who experienced at least one rainfall shock in each period. It is calculated as the linear combination of the PSNP and PSNP * Rainfall shock coefficients. * denotes significant at 10%, ** significant at 5% and *** significant at 1%.