WORKING WITH THE THRIVE BY FIVE INDEX 2024:
EXPLORATIONS OF EARLY LEARNING SYSTEMS IN SOUTH AFRICA

COGNITIVE GAINS FROM EARLY LEARNING PROGRAMME ENROLMENT IN THREE SOUTH AFRICAN PROVINCES

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Abstract

Early learning is a critical determinant of later educational and life outcomes, yet enrolment gaps persist in South Africa, particularly among disadvantaged households. This study investigates whether participation in early learning programmes (ELPs) is associated with improved developmental outcomes, and how programme quality and duration of exposure shape these associations. The analysis draws on the 2024 Thrive by Five Index, which for the first time, includes a sub-sample of non-enrolled children in three provinces, providing novel evidence on the developmental consequences of non-enrolment for children ages 50-59 months. Coarsened Exact Matching is applied to balance observable characteristics and construct comparable groups of non-enrolled and enrolled children. Ordinary least squares models are then used to estimate sample average treatment effects on the treated (SATT), using the Early Learning Outcomes Measure (ELOM) assessment for 4-5-year-olds as the outcome measure. Differences between enrolled and non-enrolled children depend strongly on programme quality. While an overall gap is observed between the two groups—non-enrolled children in the matched sample score 5.8 ELOM points lower on average, equivalent to roughly five to six months of cognitive delay—this advantage is concentrated among children attending programmes where instructional quality meets at least a basic threshold. These findings provide the first matched comparison in South Africa showing that, under the right conditions, enrolment in an ELP is associated with at least moderate cognitive gains, even after accounting for child and household characteristics. Gains are more pronounced in higher-order cognitive domains, including emergent literacy and language, emergent numeracy and mathematics, and cognition and executive functioning, and among children with sustained programme exposure of two years or more. By contrast, children attending programmes with inadequate instructional quality exhibit no meaningful advantage over comparable non-enrolled peers. While enrolment advantages are observed across most structural characteristics, including registration status, subsidy receipt, infrastructure compliance and practitioner qualifications, the pattern changes once instructional quality is considered. While these estimates are associational rather than causal, the results suggest that enrolment alone is insufficient: meaningful cognitive gains emerge primarily when participation occurs in programmes with at least basic instructional quality.

1. Introduction

South Africa has made notable strides in expanding access to early childhood care and education (ECCE) services - also referred to locally as Early Learning Programmes (ELPs) - yet many young children remain excluded. Recent national estimates indicate that nearly one-third (29%) of 4-year-olds (around 350,000 children) are not enrolled in any organised learning programme (Hall, 2025). Those left out are largely from the poorest and most vulnerable households, deepening early inequalities (Moses, 2021). Although ELP access has grown substantially since the end of apartheid, there is limited evidence on whether participation in ELPs improves children's learning outcomes compared to those who are not enrolled. Understanding these differences is critical for ensuring that expansion in access translates into real gains in child development. As government advances the 2030 Strategy for Early Childhood Development Programmes and implements the Bana Pele Blueprint, expanding access to quality programming remains a central policy objective.

While international evidence generally supports the benefits of participation in an ELP for children's cognitive and language development, the findings remain mixed and contingent on programme quality and context. Studies from low- and middle-income countries (LMICs) show that centre-based care tends to improve cognitive outcomes, yet the observed advantages may dissipate when programme quality is low relative to children's home learning environments (Blimpo et al., 2022; Bouguen et al., 2018; Evans et al., 2024). In South Africa, emerging evidence suggests that participation in ELPs is associated with cognitive benefits primarily for children in better-resourced or higher-quality settings (Van der Berg, 2023; Kika-Mistry, forthcoming). These findings highlight that access alone may be insufficient, as the magnitude and distribution of developmental benefits depend critically on the quality of provision; yet evidence remains limited on whether ELP participation improves cognitive outcomes for disadvantaged children and how far such gains hinge on programme quality.

As part of the 2024 South African Thrive by Five Index, a small-scale sub-study was undertaken alongside a nationally representative study of enrolled children to test the feasibility of identifying and assessing children aged 50-59 months who were not enrolled in any ELP. This sub-study exercise produced a unique dataset that offers a window into whether enrolment in an ELP is associated with improved cognitive outcomes for a non-representative sample of children aged 50-59 months. In doing so, it begins to address a critical evidence gap in South Africa, where the extent to which ELP participation contributes to children's cognitive development remains largely unknown. This paper makes three contributions. First, it directly compares the cognitive outcomes of children enrolled in an ELP with those of children not enrolled in any programme in three provinces in South Africa, using the sub-study dataset from the 2024 Thrive by Five Index.

Second, it extends the international literature from LMICs (Bornstein & Hendricks, 2012; Evans et al., 2024; Jakiela et al., 2024; Sosu & Pimenta, 2023; Tran et al., 2017; Willoughby et al., 2019) by examining not only whether enrolment matters, but also how the benefits of enrolment differ across dimensions of ELP quality. Third, by situating the South African experience within a broader global debate on the returns to early childhood investment, the paper contributes context-specific evidence on whether expanding access to centre-based early childhood education alone is sufficient, and whether improvements in programme quality are essential to realising developmental gains for disadvantaged children. This paper seeks to answer three research questions:

1. Is enrolment in an ELP associated with measurable cognitive differences among children from disadvantaged backgrounds?
2. How does the duration of enrolment relate to these cognitive outcomes?
3. Under what conditions do enrolment advantages emerge, and does programme quality shape their magnitude?

The findings from this study indicate that the developmental advantages associated with ELP enrolment are conditional on programme quality. Using the Early Learning Outcomes Measure (ELOM) assessment for children aged 4–5 years, the analysis compares enrolled and non-enrolled children in low-income communities across three South African provinces—Gauteng, KwaZulu-Natal, and the Western Cape. After constructing comparable groups using Coarsened Exact Matching and adjusting for a rich set of child, household, and contextual characteristics, an overall gap is observed: non-enrolled children score on average the equivalent of five to six months behind comparable enrolled peers in typical age-related development. However, this average difference masks an important quality threshold. Children attending programmes with inadequate instructional quality show no meaningful advantage over comparable non-enrolled peers, whereas substantial enrolment advantages emerge once instructional quality reaches at least a basic standard.

Enrolment differences are also larger in programmes with stronger structural characteristics, including better infrastructure and more highly qualified practitioners. By documenting both the average differences between enrolled and non-enrolled children and the conditions under which these differences emerge, this study provides new and policy-relevant evidence for South Africa and contributes to a growing international literature showing that participation in early learning programmes supports foundational cognitive development primarily when children are exposed to sufficiently high-quality learning environments. The remainder of this paper proceeds as follows: Section 2 provides the background for the analysis, Section 3 describes the data and sample used, Section 4 outlines the methodological approach and presents the results, while Section 5 provides a discussion of the findings and Section 6 concludes.

2. Background

Across high-income countries, the expansion of early childhood care and education has been driven by the twin aims of improving child development and enabling women's labour-force participation. Yet evidence from long-term studies suggests that while high-quality, targeted interventions can generate large and lasting benefits, rapid or low-quality scale-up may produce unintended consequences for children's development. Seminal small-scale experiments such as the HighScope Perry Preschool Project in the United States (Heckman et al., 2010; Schweinhart, 2005) and the Abecedarian Project in North Carolina (Campbell et al., 2002; Campbell & Ramey, 1994) demonstrate substantial returns to intensive, high-quality programmes for disadvantaged children - improving educational attainment, employment, and social outcomes well into adulthood. However, when similar principles were implemented at scale without equivalent investment in quality, the results were less promising. The Quebec Universal Childcare reform, introduced in 1997, expanded access to full-day, low-cost care from infancy to age four, and led to sharp increases in maternal employment but was also associated with higher rates of behavioural and socio-emotional problems and no measurable long-term gains in learning (Baker et al., 2005, 2019). These contrasting cases illustrate a central lesson from decades of research in high-income settings: quality, dosage, and target population determine whether early learning investments yield developmental dividends or developmental risks.

While the evidence from high-income contexts lends support to the importance of quality and dosage, much less is known about how these dynamics play out in low- and middle-income countries (LMICs), where early learning systems are still emerging. A recent systematic review by Evans et al. (2024) synthesises evidence from 71 studies on childcare interventions in LMICs[1]. They find that centre-based care is generally associated with improvements in children's cognitive and language development: 81% of interventions focusing on learning outcomes for preschool and kindergarten children show positive impacts, but only 55% are positive and statistically significant.[2] However, these gains observed in LMICs are often contingent on programme quality.

[1] These studies were mostly from Latin America and East Asia.
[2] Around 39% of interventions had statistically insignificant impacts, while 5% were negative and statistically significant.

Research shows that participation in a structured group setting offering high-quality early childhood education (ECE) can enhance cognitive stimulation (Engle et al., 2011; Garcia et al., 2016); whereas exposure to low-quality early learning environment may yield few or no developmental benefits (Blimpo et al., 2022; Bouguen et al., 2018; Wong et al., 2013). Further, when the quality of a programme is low relative to a plausible counterfactual, such as the child's educational experience under the care of a parent or primary caregiver, enrolment in an ELP may offer no measurable advantage, highlighting that the developmental returns to ELP participation are not guaranteed (Blimpo et al., 2022; Bouguen et al., 2018; Jakiela et al., 2024).

Evidence on the role of dosage — the length or intensity of a child's exposure to an ELP — suggests that longer enrolment is often associated with stronger developmental outcomes. Studies from both low- and middle-income and high-income settings find that children who spend two or more years in preschool tend to exhibit stronger cognitive, language, and executive-function outcomes than peers with shorter or irregular attendance (Koshy et al., 2024; Kvintová et al., 2025; Loeb et al., 2007; Magnuson et al., 2007). In many cases, these associations persist after controlling for family background and, in some studies, classroom quality, suggesting that sustained participation may provide cumulative cognitive stimulation. However, the magnitude and persistence of these gains appear to depend critically on programme quality. Reviews and experimental studies indicate that extended enrolment in high-quality early childhood settings is associated with improved cognitive and socioemotional outcomes, whereas prolonged exposure to low-quality environments yields minimal or no gains (Bouguen et al., 2018; Melo et al., 2022; Zaslow et al., 2016).

This mixed international evidence on the impacts of ECE programmes resonates with a broader debate on the returns to early investment, often framed through the Heckman Curve. The Heckman Curve is widely cited as evidence that the highest returns to human capital investment, particularly for disadvantaged children, occur in the earliest years of life (Heckman, 2006). Later interventions at school or post-school levels remain valuable, but their effectiveness is substantially constrained in the absence of strong early foundations. As Heckman (2006, p. 192) argues, "Early interventions targeted toward disadvantaged children have much higher returns than later interventions such as reduced pupil-teacher ratios, public job training, convict rehabilitation programmes, tuition subsidies or expenditure on police." While the Heckman Curve has become influential in advocating for prioritising early childhood investment, Rea and Burton (2020) challenge its empirical foundations. Reviewing a wide range of cost-benefit analyses across interventions targeted at different age groups, they find no systematic evidence that early interventions consistently yield higher benefit-cost ratios than later interventions. Instead, they argue that the effectiveness of interventions depends heavily on contextual and implementation factors, including how well programmes are targeted, the discount rates applied, the trajectory of benefits over time, and the quality and fidelity of programme delivery, rather than the age at which beneficiaries are reached (Rea & Burton, 2020).

This suggests that the relative returns to investment in education and social policy may not be fixed by developmental stage but may be contingent on context and quality.

The evidence on the applicability of the Heckman Curve to South Africa is still emerging, particularly in relation to cognitive outcomes linked to participation in ELPs. The Early Learning Programme Outcome (ELPO) Study assessed the relative effectiveness of different programmes (two centre-based models, one mobile playgroup and one site-based playgroup) and found that higher levels of programme exposure were significantly associated with stronger cognitive performance on the ELOM assessment (Dawes, Biersteker, Girdwood, Snelling, & Horler, 2020). Van der Berg (2023) used extended enrolment[3] in an ELP from the 2021 Thrive by Five Index survey as a proxy for 'treatment' to investigate whether prolonged exposure to an ELP was associated with gains in cognitive outcomes measured using the ELOM 4&5 Assessment.

The analysis found benefits largely concentrated among children in more affluent ELP settings, particularly those located near Quintile 5 schools[4] (Van der Berg, 2023). A similar pattern was observed in an impact evaluation of Grade R (the year before Grade 1), where the positive effects of attendance were found among children in Quintiles 4 and Quintile 5 schools (Van der Berg et al., 2013). Analysis from several school datasets in South Africa also shows two data-generating processes – that is, two distinct patterns linking educational inputs with outcomes (Spaull & Jansen, 2019). In better-resourced schools, educational inputs such as teacher qualifications and learning materials are associated with meaningful improvements in outcomes. In contrast, in historically disadvantaged and low-resourced schools, the same inputs yield much smaller or negligible gains. These findings indicate that a large part of the education system in South Africa is functioning too weakly to convert additional resources into improvements in learning outcomes for all children, regardless of their socioeconomic status (Van der Berg, 2021)

More recent work from South Africa suggests that the cognitive gains from participation in an ELP depend heavily on the conditions under which children attend. Van der Berg (2023) argued that expanding access without simultaneously improving quality is unlikely to yield the returns suggested by the Heckman Curve. Kika-Mistry (forthcoming) finds that elements of programme quality, particularly teaching strategies as a sub-component of process or instructional quality, are associated with better cognitive outcomes, though these effects are strongly moderated by children's socioeconomic status (SES). Together, these studies highlight the importance of quality in reducing SES-related disparities and enhancing child development. What remains unclear is whether enrolment in an ELP improves cognitive outcomes for children from disadvantaged households in South Africa, and how far such gains are contingent on the quality of provision.

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[3] Extended enrolment was calculated as the length of enrolment in an ELP minus ten months (the average length of enrolment in 2021 at the time of the survey) (Van der Berg, 2023).

[4] The National Norms and Standards for School Funding (NNSSF) classify public ordinary schools into nationally divided poverty quintiles based on the socioeconomic status of the area in which they are located. The quintiles determine funding allocations and fee policies. Quintile 1 – 3 schools are designated as "no-fee" schools and may not charge fees and receive higher per-learner allocations from the government. Quintile 4 and 5 schools receive smaller allocations from the government and can charge fees to supplement resources.

3. Data

This analysis makes use of data from the Thrive by Five Index 2024, the second round of South Africa's nationally representative survey of preschool child outcomes. Compared to the inaugural 2021 round, the 2024 Index broadened its scope, applied more rigorous methodological approaches, and incorporated a sub-study that assessed children not enrolled in an ELP. This addition provides rare insight into the circumstances and developmental outcomes of children who are not enrolled in centre-based early learning programmes.

Comparisons between key outcomes from the 2021 and 2024 Index surveys, however, are not possible for several methodological reasons. First, the 2021 Index was conducted during the COVID-19 pandemic, when lockdowns and health restrictions led to the closure of many ELPs, and some families either chose or were compelled to keep their children at home (Wills & Kika-Mistry, 2023). As a result, data collection was affected both in terms of which ELPs were included and which children were assessed (Pettersson et al., 2025). Second, the 2024 Index employed a new sampling strategy that incorporated smaller ELPs - those enrolling one or more children, whereas the 2021 Index focused only on centres enrolling six or more children (Pettersson et al., 2025). Finally, at the time of the 2021 Index, no national database of ELPs existed; by contrast, the 2024 Index sampling frame was constructed using data from the 2021 Early Childhood Development (ECD) Census, enabling broader and more representative coverage of the sector. This analysis, therefore, focuses on the cross-sectional data from the 2024 Index survey.

3.1. Non-enrolled sub-study sample

The sample of non-enrolled children from the sub-study was purposively selected and was not intended to be statistically representative of the underlying population, either nationally or provincially. Children were drawn from the same geographic areas as the enrolled sample in three provinces: Gauteng, KwaZulu-Natal, and the Western Cape. Of the 432 enumeration areas selected for the national component of the study of children attending an ELP, 45 enumeration areas were chosen for the sub-study, specifically from the bottom three weighted school quintiles (proxying for the poorest 60%), where the weights are based on the number of Grade 3 learners in each school.

These enumeration areas included informal settlements, rural communities, and urban formal neighbourhoods. Gauteng and KwaZulu-Natal were selected because they have the largest populations of 3–5-year-old children and the highest absolute numbers of non-enrolled children, making them critical for understanding barriers to early learning participation. The Western Cape was included for logistical reasons and to draw on operational insights from the pre-test phase (Pettersson et al., 2025).

Fieldworkers successfully visited over 20 000 households in the selected areas, administering a short screening questionnaire to assess eligibility. To qualify for inclusion in the non-enrolled sub-study, households needed to have a child: (1) aged 50-59 months at the time of the survey, (2) who was not enrolled in any ELP in 2024, and (3) had no reported disabilities such as vision, hearing, or mobility difficulties, or challenges in understanding spoken language (Pettersson et al., 2025). The sub-study initially sought to include 540 non-enrolled children. In practice, identifying eligible non-enrolled children through household-based fieldwork proved substantially more challenging than anticipated and only 272 children were identified, yielding a success rate of approximately 1.5%. Several factors contributed to this low yield.

First, non-enrolment status was often difficult to verify, as caregivers were reluctant to disclose non-participation due to concerns that this might affect access to social grants. Second, early learning participation was found to be highly fluid, with children moving in and out of programmes in response to short-term income shocks, caregiving arrangements, or local availability. Finally, fieldwork in economically deprived communities posed significant logistical and safety constraints, including restricted access in high-crime areas, and disruptions in the home, which constrained sustained engagement with eligible households (Giese et al., 2025). As a result of these combined operational, informational, and safety-related challenges, the final sample comprised 272 children from 262 households across the three provinces (Table 1).

Table 1: Number of children aged 50-59 months and their households in non-enrolled sub-study sample, by province

Province	**Children**		**Households**	
	N	%	**N**	%
Gauteng	127	47	123	47
KwaZulu-Natal	36	13	34	13
Western Cape	109	40	105	40
Total	**272**	**100**	**262**	**100**

Source: Own calculations, 2024 Thrive by Five Index. Note: There are fewer households than children in the non-enrolled sample since the study design allowed for multi-family arrangements, for example, cousins living in the same household (Pettersson et al., 2025).

3.2. Enrolled sample

By contrast, the 2024 Thrive by Five Index sample of enrolled children was designed to be representative at both the national and provincial levels. A stratified, multi-stage sampling approach was applied, involving three distinct stages. At the first stage, wards served as the primary sampling units (PSUs), except in a few cases where multiple wards were combined to create viable enumeration areas. The second stage focused on ELPs within the selected PSUs. To qualify, an ELP needed to have at least one child aged 50-59 months enrolled, operate for a minimum of eight hours per week, and be functional at the time of fieldwork. In the final stage, individual children attending these ELPs were sampled. Eligible children were those aged 50-59 months at the time of data collection, whose Primary Caregivers (PCGs) consented to participation, who did not present with disabilities and who were present at the ELP on the day of assessment (Pettersson et al., 2025). The realised sample of enrolled children for the 2024 Thrive by Five Index is 5 001 children across 1 388 ELPs.

To ensure comparability between the enrolled and non-enrolled samples, the full sample of enrolled children was restricted in three steps that mirror the selection criteria used for the non-enrolled sub-study. First, the enrolled sample was limited to the three provinces selected for the non-enrolled analysis - Gauteng, KwaZulu-Natal and the Western Cape for reasons described above. Second, within these provinces, the enrolled sample was further restricted to children attending ELPs located in enumeration areas (EAs) classified within the bottom three weighted school quintiles, reflecting the focus of the non-enrolled sample on disadvantaged communities. Finally, because the PCG interview was the only additional instrument administered to 77% of enrolled and all non-enrolled children, and it provides key information on child, caregiver and household characteristics, the analysis was restricted to enrolled children with completed PCG responses. Exploratory checks showed that ELP quality indicators did not differ between enrolled children whose PCGs completed the interview and those whose PCGs did not, suggesting that the final restriction to completed PCG interviews is unlikely to bias comparisons by programme quality. This final restriction reduced the enrolled sample to 1 050 children across 305 ELPs (Table 2).

Table 2: Number of children and ELPs in the enrolled sample in three provinces that meet criteria for inclusion in counterfactual sample

Province	**Children**		**Households**	
	N	%	**N**	%
Gauteng	460	44	139	45
KwaZulu-Natal	391	37	106	35
Western Cape	199	19	60	20
Total	1050	100	305	100

Source: Own calculations, 2024 Thrive by Five Index.

3.3. Child Cognitive Outcomes

The ELOM 4&5 assessment provides a reliable measure of child cognitive outcomes. The tool was designed specifically for South Africa and has undergone extensive psychometric testing, with evidence supporting its content, construct, age, and concurrent validity (with the Wechsler Preschool and Primary Scale of Intelligence, Fourth Edition), as well as strong test–retest reliability (Dawes, Biersteker, Girdwood, Snelling, & Tredoux, 2020). It aligns with the South African National Curriculum Framework for Children from Birth to Four and was standardised for use with children between the ages of 50-69 months, with performance bands for two separate groups: 50-59 months and 60-69 months (Pettersson et al., 2025). The 2024 Index focuses on the 50–59-month age range and a total of 5 001 children enrolled in 1 388 ELPs, and 272 children not enrolled in ELPs, were assessed in their home language.

The specific ELOM domains in the ELOM 4&5 assessment include Gross Motor Development (GMD), Fine Motor Coordination and Visual Motor Integration (FMC and VMI), Emergent Numeracy and Mathematics (ENM), Cognition and Executive Functioning (CEF), and Emergent Literacy and Language (ELL). For each of the domain items, a raw score is allocated according to the child's performance on the assessment, which is then transformed into a scaled score. The item standard scores are then summarised to provide a total domain score out of 20. A total ELOM 4&5 score out of 100 is derived by summing the scores for the five domains (Dawes, Biersteker, Girdwood, Snelling, & Horler, 2020). For each developmental domain, as well as the overall ELOM score, children are classified into one of three performance bands: On Track, Falling Behind, or Falling Far Behind. Scores at or above the 60th percentile are classified as On Track, scores between the 32nd and 59th percentiles as Falling Behind, and scores below the 32nd percentile as Falling Far Behind (Pettersson et al., 2025).

The ELOM 4&5 assessment also includes characteristics of the child that are also used in the analysis, such as age in months, gender, province, the language that they were assessed in and child height measured using a stadiometer.

3.4. Socioeconomic and primary caregiver characteristics

A Primary Caregiver (PCG) Interview form was administered telephonically for 3 841 enrolled children - 77% of the Thrive by Five Index 2024 enrolled sample, and for all PCGs of children in the non-enrolled sample (272 children). The form captures information about the child's socioeconomic circumstances, the home learning environment, and some characteristics of the PCG. The majority of PCGs are biological mothers (71% of the 3 841 PCGs of enrolled children, and 73% of PCGs of non-enrolled children), followed by grandmothers, biological fathers, aunts and others. It is important to account for who the primary caregiver is, as the relationship between the child and caregiver shapes both the child's home learning experience and the relevance of caregiver characteristics such as education and employment.

A categorical variable was created for PCG education using three sequentially asked questions: (1) the highest school grade successfully completed, (2) if the PCG passed Grade 12 with a Matric or National Senior Certificate, and (3) if they have successfully completed any tertiary qualifications such as a certificate, diploma or degree. This analysis does not look at the type of tertiary qualification obtained by the PCG. There was no significant difference between total ELOM scores of children whose PCGs passed matric and had a diploma or certificate to those whose PCGs passed matric and had a tertiary qualification (Giese et al., 2025).

Further, only 5% of PCGs of non-enrolled children have successfully completed Grade 12 and have a tertiary qualification. The categorical variable for PCG education therefore includes three levels of education attainment: (1) PCG has not passed Grade 12 ("No Matric") – this includes PCGs with no schooling, those with some primary education, those who completed primary education, those with some secondary education and those who indicate that they have successfully completed Grade 12; (2) those who completed secondary school (Grade 12) and passed with a Matric or National Senior Certificate, but do not have a tertiary qualification ("Matric"); and (3) those who have successfully completed secondary school, passed with a Matric or National Senior Certificate, and has a tertiary qualification such as a certificate, diploma or degree ("Tertiary").

The PCG employment categorical variable was used in the analysis, grouping those who are paid employees and employers or owners of their own businesses, and those who are unemployed and doing unpaid family work, including being a housewife. The PCG education and employment variables were both constructed separately for each category of primary caregiver, allowing comparisons by the caregiver's relationship to the child. PCGs were also asked if the child has a birth certificate and if they receive the Child Support Grant for the child.

3.5. Sample characteristics

The descriptive statistics in Table 3 provide an initial comparison of the enrolled and non-enrolled children in the analysis samples – that is, children in Gauteng, KwaZulu-Natal and the Western Cape, residing in enumeration areas in weighted school quintiles 1-3, and have completed PCG interviews. Although enrolled children appear to have higher average ELOM scores and higher height-for-age outcomes, these differences in estimates are not directly comparable and cannot provide a causal account of enrolment. The two groups differ for several reasons.

First, the sampling strategies used differ (as discussed above). Second, the groups differ in observable characteristics between enrolled and non-enrolled children that are not adjusted for in these comparisons, such as socioeconomic circumstances, the child's primary caregiver, and household characteristics. Third, the groups may differ in unobserved ways associated with both enrolment decisions and children's development. As a result, simple mean differences between enrolled and non-enrolled children reflect a combination of sampling design, observable background differences and unobserved factors, and therefore cannot be interpreted as evidence of the effect of ELP participation. For example, it would be incorrect to conclude that 18% of non-enrolled children are "on track" compared to 37% of enrolled children or that non-enrolled children exhibit greater growth faltering or lower height-for-age z-scores (-1.06 standard deviations) compared to enrolled children (-0.55 standard deviations); such a comparison would overstate the role of enrolment.

Table 3: Mean early learning performance, on-track proportions, and height-for-age scores for the adjusted enrolled and non-enrolled samples, before matching

	Mean	Lower 95% CI	Upper 95% CI	Number of Children
Non-enrolled sub-study sample				
Total ELOM scores	35.16	33.61	36.72	272
On track – total ELOM	0.18	0.13	0.23	272
On track – GMD	0.31	0.25	0.36	272
On track – FMC-VMI	0.12	0.08	0.16	272
On track – ENM	0.19	0.14	0.23	272
On track – CEF	0.17	0.12	0.21	272
On track – ELL	0.37	0.31	0.43	272
Height-for-age (z-scores)	-1.06	-1.18	-0.94	270

	Mean	Lower 95% CI	Upper 95% CI	Number of Children
Adjusted enrolled sample				
Total ELOM scores	42.49	41.70	43.27	1050
On track – total ELOM	0.37	0.34	0.40	1050
On track – GMD	0.40	0.37	0.43	1050
On track – FMC-VMI	0.26	0.23	0.28	1050
On track – ENM	0.31	0.28	0.34	1050
On track – CEF	0.39	0.36	0.42	1050
On track – ELL	0.48	0.45	0.51	1050
Height-for-age (z-scores)	-0.55	-0.61	-0.50	1050

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) CI – Confidence Interval. (ii) The five ELOM domains include Gross Motor Development (GMD), Fine Motor Coordination and Visual Motor Integration (FMC and VMI), Emergent Numeracy and Mathematics (ENM), Cognition and Executive Functioning (CEF), and Emergent Literacy and Language (ELL).

Table 4 presents the pre-matching differences in baseline child, caregiver, household, and home-learning characteristics between enrolled and non-enrolled children, reported primarily as proportions. Although the two groups are broadly similar in gender composition (51% compared to 49% female), enrolled children are, on average, slightly older – by just over half a month (54.73 compared to 54.15 months) – and this difference is statistically significant at the 1% level.

This potentially reflects the larger sample size for enrolled children rather than substantially meaningful age differences. Enrolled children are also more likely to possess a birth certificate, with a 12-percentage-point gap significant at the 1% level. In contrast, receipt of the Child Support Grant (CSG) is high and similar across both groups (77% compared to 75%), and the 2-percentage-point difference is not statistically significant, indicating that CSG uptake does not meaningfully differentiate the samples. Linguistic differences, however, are pronounced with the differences significant at the 5% level or lower.

The dominant languages spoken by enrolled and non-enrolled children closely mirror the provinces from which each group was sampled. The proportion of isiZulu-speaking children is nearly double among the enrolled (51% compared to 26%), and nearly one-third of non-enrolled children (30%) speak isiXhosa compared with 12% of enrolled children. Afrikaans is also more concentrated among the non-enrolled (15% compared to 6%). English-speaking children make up a small share of both samples, though they remain more common among the enrolled (6% compared to 1%). Differences across the remaining African languages are more mixed and reflect, in part, the much smaller number of children in the sample who speak these languages.

Although the distribution of primary caregiver types is similar, with biological mothers comprising 73% of PCGs of both enrolled and non-enrolled children, their human capital profiles differ significantly. The proportion of caregivers who have completed Grade 12 (Matric) but do not have any post-school qualifications, is more than twice as high among non-enrolled children (26% versus 11%), whereas PCGs who have a Matric certificate plus tertiary education are over five times (more common among the enrolled (28% versus 5%) – with differences significant at the 1% level. Similar magnitudes arise across caregiver subgroups. For biological mothers, the share with Matric plus tertiary education is over five times higher (24 percentage points) in the enrolled sample (28% versus 5%), and among grandparents, it is 19 percentage points higher for the enrolled group versus the non-enrolled sample. In instances where biological fathers are the PCG, 30% of the enrolled sample have a Matric without any post-school qualifications, versus none in the non-enrolled sample. Differences between the groups in whether biological fathers have completed Matric and have a tertiary qualification are statistically insignificant. When the aunt is the PCG (for 4% of the enrolled sample and 5% of the non-enrolled sample), they all have less than a Matric for the non-enrolled group compared to half of the enrolled group.

PCG employment shows larger gaps. The proportion of caregivers with stable paid employment is more than three times higher among the enrolled (45% versus 13%), significant at the 1% level. These patterns persist across caregiver types: employed biological mothers are over three times more common among enrolled children (46% compared to 13%), and grandparents of enrolled children are nearly ten times more likely to be employed (29% compared to 3%). Biological fathers of enrolled children are also close to 30 percentage points more likely to be employed compared to non-enrolled children. There are no aunts or other caregivers of non-enrolled children with paid employment. These educational and employment gaps translate into pronounced differences in material living conditions. Ownership of basic durable goods in working condition is consistently higher among households of enrolled children.

Enrolled households are 29 percentage points more likely to own a refrigerator (92% vs 63%), 26 percentage points more likely to own a washing machine (47% vs 22%), and 25 percentage points more likely to have a television (92% vs 67%), with similarly large differences for computers (16 percentage perpoints), pay-TV subscriptions (39 percentage points), and motor vehicles (24 percentage points); all of these gaps are statistically significant at the 1% level. Internet access also differs markedly, with enrolled households being 24 percentage points more likely to have internet connectivity at home (94% vs 70%), again significant at the 1% level. By contrast, items such as cell phones and vacuum cleaners show very little variation between groups: cell phone ownership is nearly universal, while vacuum cleaners are extremely uncommon in both samples. These differences culminate in a 1.1 standard deviation difference in the standardised household asset index (-0.05 versus -1.16), significant at the 1% level, signalling a large underlying wealth gradient between the two groups.

Substantial differences are also evident in the home learning environment. More than three-quarters of non-enrolled children (77%) have no children's books at home compared with only 30% of enrolled children, a 47 percentage point difference significant at the 1% level. Enrolled children are also substantially more likely to live in households with 2-5 books (42% versus 13%), a 29-percentage point difference. These material disparities are mirrored in parental engagement. Caregivers of enrolled children are 16 percentage points more likely to have told stories (35% versus 19%), 32 percentage points more likely to have sung songs (69% versus 38%), 25 percentage points more likely to have read books or looked at pictures together (37% versus 12%), and 34 points more likely to have drawn or painted with the child (45% versus 11%) in the past week. They are also 27 percentage points more likely to have counted objects with the child (64% versus 37%). All of these differences are statistically significant at the 99% confidence level. The resulting standardised parental engagement index differs by more than one full standard deviation (0.16 compared to –0.91), reflecting a large and systematic gap in the cognitive stimulation environments of enrolled and non-enrolled children.

Table 4: Sample characteristics for adjusted enrolled and non-enrolled children before matching (proportions)

	Enrolled (N= 1050)	Non-enrolled (N = 272)	Difference
Child age (Months)	54.73	54.15	0.58***
Child sex (Female)	0.51	0.49	0.02
Child received Child Support Grant	0.77	0.75	0.02
Child has a birth certificate	0.96	0.84	0.12***
Province			
Gauteng	0.44	0.47	-0.03
KwaZulu Natal	0.37	0.13	0.24***
Western Cape	0.19	0.40	0.21***
Language spoken by the child in the home			
English	0.06	0.01	0.05**
Afrikaans	0.06	0.15	-0.09***
isiZulu	0.51	0.26	0.25***
isiXhosa	0.12	0.30	-0.18***

	Enrolled (N= 1050)	Non-enrolled (N = 272)	Difference
Sesotho	0.05	0.12	-0.07***
Setswana	0.13	0.07	0.06**
Sepedi	0.06	0.01	0.05**
Xitsonga	0.00	0.07	-0.07***
Primary caregiver relationships of person completing PCG			
Biological mother	0.73	0.73	0.01
Biological father	0.07	0.07	0.00
Grandmother	0.13	0.13	0.00
Aunt	0.05	0.04	0.01
Step/adopt./foster parent/sibling/other	0.02	0.04	-0.01
PCG education			
All PCGs: Matric only	0.26	0.11	0.15***
All PCGs: Matric and tertiary	0.28	0.05	0.22***
Biological mother: Matric only	0.29	0.15	0.14***
Biological mother: Matric + tertiary	0.28	0.05	0.24***
Biological father: Matric only	0.30	0.00	0.30**
Biological father: Matric + tertiary	0.31	0.22	0.09
Grandmother: Matric only	0.11	0.03	0.09
Grandmother: Matric + tertiary	0.19	0.00	0.19**
Aunt: Less than Matric	0.51	1.00	-0.49**
Other caregiver: Matric only	0.32	0.10	0.22
Other caregiver: Matric + tertiary	0.32	0.10	0.22

	Enrolled (N= 1050)	Non-enrolled (N = 272)	Difference
PCG paid employee/employer/business owner			
All PCGs	0.45	0.13	0.32***
Biological mother	0.46	0.13	0.33***
Biological father	0.73	0.44	0.29*
Grandparent	0.29	0.03	0.26**
Aunt	0.35	0.00	0.35*
Other caregiver	0.44	0.00	0.44*
Household assets in working condition			
Fridge	0.92	0.63	0.29***
Electrical or gas stove	0.96	0.79	0.17***
Vacuum cleaner	0.05	0.02	0.03*
Washing machine	0.47	0.22	0.26***
Computer or laptop	0.23	0.07	0.16***
TV set	0.76	0.62	0.14***
Pay TV subscription, e.g. DSTV	0.72	0.33	0.39***
Motor car	0.32	0.08	0.24***
Radio	0.60	0.38	0.22***
Cell phone	1.00	0.90	0.10***
Internet access in dwelling or uses cell phone/other mobile device	0.94	0.70	0.24***
Standardised index of HH assets (z-score)	-0.05	-1.16	1.11***

	Enrolled (N= 1050)	Non-enrolled (N = 272)	Difference
Children's/picture books in the home			
No children's/picture books	0.30	0.77	-0.47***
1 children's/picture book	0.19	0.09	0.11***
2-5 children's/picture books	0.42	0.13	0.29***
6-10 children's/picture books	0.06	0.02	0.04**
10 or more children's/picture books	0.02	0.00	0.02*
PCG learning activities with the child in the past 7 days (3 or more times)			
Told stories to the child	0.35	0.19	0.16***
Sang songs to/with the child, including when putting the child to sleep	0.69	0.38	0.32***
Read books to/looked at a picture book with the child	0.37	0.12	0.25***
Played with the child	0.79	0.61	0.18***
Told the child the names of things	0.52	0.46	0.06
Drew or painted things with the child	0.45	0.11	0.34***
Counted things with the child	0.64	0.37	0.27***
Standardised index of parental engagement (z-score)	0.16	-0.91	1.07***

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) Significance levels of differences: *** p<0.01, ** p<0.05, * p<0.1; (ii) Samples of children speaking isiNdebele, siSwati and Tshivenda were very small (5 children or less), (iii) There are no aunts in the non-enrolled sample with at least a Matric or a Matric and tertiary qualification.

Taken together, the magnitude and consistency of these differences show that the enrolled and non-enrolled groups are highly imbalanced across most observable characteristics. These imbalances underscore the need for matching to construct comparable samples prior to estimating associations between ELP enrolment and children's early learning outcomes. It is important to emphasise that this comparison is restricted to enrolled and non-enrolled children living in low-income areas, as defined by the bottom three weighted school quintiles.

Even within this relatively disadvantaged segment of the population, substantial socioeconomic, educational, and home-learning disparities persist, indicating that meaningful heterogeneity exists even among households located in similarly low-resourced settings. This further reinforces the need for careful adjustment to isolate the role of ELP enrolment from underlying differences in children's circumstances.

To address this, matching methods will be used to create sub-samples of enrolled and non-enrolled children who are similar across a set of observable covariates. Matching improves internal validity by balancing observed characteristics, thereby constructing a pseudo-counterfactual group that better approximates what outcomes would look like if the non-enrolled children had been enrolled. This approach has been widely used in programme evaluation and causal inference to address selection bias (Hui et al., 2023; Iacus et al., 2012; Rosenbaum & Rubin, 1983; Stuart, 2010).

4. Results

4.1. Enrolment effects before matching

Ordinary Least Squares (OLS) estimates are presented first to show the unadjusted association between enrolment (enrolled versus not enrolled in 2024) and cognitive outcomes (as measured by total ELOM scores) and to illustrate the extent of selection bias before matching. In this specification, the coefficient on the non-enrolled indicator in model (1) represents the simple mean difference in outcomes between children who did not attend an ELP and those who did. However, it is important to consider child demographic and socioeconomic characteristics as well as the home learning environment, controlled for by the number of children's/picture books in the home and the frequency of parental engagement. Models (2) to (9) incrementally introduce additional covariates and investigate how these characteristics affect the estimate of the overall difference in total ELOM scores between enrolled and non-enrolled children.

Table 5: Estimating total ELOM scores, before matching

Variables	1 Total ELOM Score	2 Total ELOM Score	3 Total ELOM Score	4 Total ELOM Score	5 Total ELOM Score	6 Total ELOM Score	7 Total ELOM Score	8 Total ELOM Score	9 Total ELOM Score	10 Total ELOM Score
Non-enrolled	-7.321*** (0.882)	-6.453*** (0.847)	-6.361*** (0.839)	-7.118*** (0.910)	-6.654*** (0.910)	-6.640*** (0.912)	-5.732*** (0.940)	-5.145*** (0.992)	-4.324*** (1.038)	-4.412*** (1.083)
Child age in months (Average)		1.498*** (0.134)	1.503*** (0.133)	1.480*** (0.133)	1.466*** (0.133)	1.458*** (0.133)	1.451*** (0.132)	1.440*** (0.132)	1.442*** (0.132)	1.437*** (0.132)
Child sex (Female)			3.655*** (0.675)	3.689*** (0.673)	3.774*** (0.669)	3.772*** (0.670)	3.794*** (0.667)	3.634*** (0.665)	3.587*** (0.664)	3.561*** (0.665)
Language of assessment (Reference: English)										
Afrikaans				0.576 (1.960)	-0.160 (2.123)	-0.068 (2.129)	-0.004 (2.120)	1.075 (2.158)	0.729 (2.157)	0.815 (2.174)
isiZulu				-0.884 (1.603)	-3.267* (1.792)	-3.210* (1.795)	-3.026* (1.787)	-1.679 (1.814)	-1.794 (1.810)	-1.752 (1.810)
isiXhosa				2.019 (1.764)	1.172 (1.834)	1.106 (1.844)	1.534 (1.839)	2.923 (1.869)	2.958 (1.865)	2.974 (1.866)
Sesotho				1.494 (2.038)	1.491 (2.051)	1.601 (2.056)	1.589 (2.048)	2.823 (2.071)	3.086 (2.069)	3.095 (2.068)
Setswana				0.680 (1.809)	1.228 (1.896)	1.359 (1.901)	1.346 (1.895)	2.474 (1.913)	2.389 (1.909)	2.567 (1.912)
Sesotho se Leboa (Sepedi)				4.871** (2.113)	5.447** (2.185)	5.647** (2.191)	5.771*** (2.182)	6.869*** (2.200)	6.799*** (2.195)	6.783*** (2.195)
Xitsonga				3.156 (3.183)	3.323 (3.216)	3.363 (3.220)	4.056 (3.212)	5.357* (3.216)	5.476* (3.209)	5.429* (3.219)
Tshivenda				17.113 (12.336)	17.294 (12.269)	16.467 (12.312)	16.793 (12.256)	16.892 (12.226)	15.478 (12.210)	15.629 (12.214)

Variables	1 Total ELOM Score	2 Total ELOM Score	3 Total ELOM Score	4 Total ELOM Score	5 Total ELOM Score	6 Total ELOM Score	7 Total ELOM Score	8 Total ELOM Score	9 Total ELOM Score	10 Total ELOM Score
Province (Reference: Gauteng)										
KwaZulu-Natal					4.370*** (0.993)	4.331*** (1.007)	4.544*** (1.004)	4.639*** (1.003)	4.836*** (1.004)	4.851*** (1.004)
Western Cape					1.179 (1.471)	1.270 (1.477)	1.563 (1.472)	1.237 (1.472)	1.179 (1.469)	1.178 (1.469)
PCG relationship (Reference: Biological mother)										
Biological Father						0.443 (1.355)	0.347 (1.349)	0.072 (1.346)	0.027 (1.343)	0.019 (1.343)
Grandmother						0.948 (1.047)	1.484 (1.057)	1.439 (1.053)	1.378 (1.051)	1.355 (1.052)
Aunt						-0.606 (1.604)	-0.423 (1.599)	-0.694 (1.595)	-0.744 (1.591)	-0.777 (1.591)
Step/adopt/foster/sibling/other						-2.032 (2.108)	-2.136 (2.098)	-2.475 (2.096)	-2.454 (2.092)	-2.467 (2.092)
Primary caregiver education (Reference: Less than Matric)										
Matric only							2.080** (0.864)	1.820** (0.865)	1.487* (0.872)	1.487* (0.872)
Matric + tertiary							3.103*** (0.885)	2.504*** (0.900)	1.922** (0.925)	1.956** (0.925)

Variables	1 Total ELOM Score	2 Total ELOM Score	3 Total ELOM Score	4 Total ELOM Score	5 Total ELOM Score	6 Total ELOM Score	7 Total ELOM Score	8 Total ELOM Score	9 Total ELOM Score	10 Total ELOM Score
Children's picture books in the home (Reference: No children's/picture books in the home)										
1 children's/picture book								0.558 (1.005)	0.380 (1.005)	0.412 (1.015)
2-5 children's/picture books								1.173 (0.851)	0.751 (0.864)	0.799 (0.883)
6-10 children's/picture books								3.066* (1.577)	2.440 (1.591)	2.821* (1.620)
10 or more children's/picture books								10.316*** (2.892)	9.679*** (2.895)	9.759*** (2.908)
Standardised index of household assets (z-scores)									1.048*** (0.398)	1.070*** (0.398)
Standardised index of parental engagement (z-scores)										-0.139 (0.409)
Constant	42.485*** (0.400)	-39.488*** (7.361)	-41.645*** (7.294)	-40.721*** (7.306)	-40.601*** (7.312)	-40.301*** (7.323)	-41.659*** (7.300)	-42.882*** (7.282)	-42.400*** (7.268)	-42.168*** (7.284)
Observations	1,322	1,322	1,322	1,322	1,322	1,322	1,322	1,322	1,322	1,320
R-squared	0.050	0.131	0.150	0.165	0.177	0.178	0.187	0.197	0.201	0.201

Source: Own calculations, 2024 Thrive by Five Index. Note: Significance levels of differences: *** p<0.01, ** p<0.05, * p<0.1

Before matching, non-enrolled children perform substantially worse than their enrolled peers in the ELOM assessment. In the unadjusted model (1), the enrolment gap is -7.32 ELOM points, significant at the 1% level. Adding controls for child age and gender reduces the magnitude of the gap slightly, and introducing language and province explains additional variation but leaves the enrolment coefficient largely unchanged. The most notable shift occurs when introducing socioeconomic and home-learning environment variables, such as primary caregiver education, a household asset index and having children's books in the household.

Together, these factors reduce the enrolment gap to approximately 4.4 ELOM points, also significant at the 1% level. This pattern suggests that roughly one-third of the initial enrolment gap (2.92 ELOM points) is explained by differences in socioeconomic status and home-learning environments between enrolled and non-enrolled children, while the remaining gap is not explained by the observable characteristics included in the model. The coefficients on the socioeconomic (PCG education and HH asset) and home learning environment variables behave as expected, reinforcing the role of household resources and parental education in shaping early learning outcomes. The attenuation of the enrolment coefficient following the inclusion of socioeconomic and home-learning controls highlights substantial selection on observable characteristics between enrolled and non-enrolled children, underscoring the need for matching to improve comparability prior to estimating enrolment effects.

For this reason, the subsequent analysis applies coarsened exact matching (CEM) to balance the samples on key covariates, thereby providing more credible estimates of the enrolment effect. CEM was selected as the primary matching method because of its ability to reduce imbalance deterministically, and it has fewer modelling assumptions compared to alternative approaches. It is described as a monotonic imbalance-reducing method since the imbalance on matched covariates can only decrease or remain unchanged relative to the original data; it cannot increase. By construction, units without overlap are discarded, so balance is improved ex-ante rather than checked ex-post (Iacus et al., 2012). In contrast, propensity score matching (PSM) can increase imbalance when the propensity score model is mis-specified (King & Nielsen, 2019), and weighting methods such as inverse probability weighting (IPW) can produce extreme or unstable weights (Chesnaye et al., 2022; Zhou et al., 2020).

While entropy balancing ensures mean balance, it requires iterative weight adjustments (Hainmueller, 2012). Pre-processing with CEM, therefore, offers a more transparent and assumption-light approach for achieving covariate balance before estimating treatment effects. These properties make CEM well-suited to this analysis, where the non-enrolled group is relatively small and retaining all non-enrolled observations is important for estimating the Sample Average Treatment Effect (SATT), where the SATT represents the average difference in outcomes between non-enrolled and enrolled children, conditional on being in the matched sample.

In this paper, non-enrolment is defined as the treatment, while being enrolled in an ELP is the counterfactual or control. Defining non-enrolment as the treatment allows the matching procedure to construct a comparison group of enrolled children around the full set of non-enrolled children without discarding them due to a lack of common support. In other words, the matching process finds comparable enrolled children for each non-enrolled child, rather than dropping non-enrolled observations to match to a larger, more heterogeneous enrolled sample. The core algorithm of CEM consists of the following steps (Blackwell et al., 2009):

i. Coarsen: Pre-treatment covariates are temporarily coarsened into practical, interpretable categories (for example, grouping exact ages into age bands).
ii. Create strata: Create one stratum per unique observation of each covariate and place each observation into a stratum.
iii. Restrict to common support: Assign these strata to the original data and drop any strata that do not contain at least one treated and one control observation, by setting the new weight to zero. This ensures common support and that the comparison groups are balanced. Once complete, these strata form the basis for calculating treatment effects.

Given the substantial baseline differences between enrolled and non-enrolled children (Table 4), CEM was implemented to improve comparability between the two groups prior to estimating the associations between enrolment and early learning outcomes. Matching was performed using the CEM command in STATA (Blackwell et al., 2009) on child age and gender, province and primary caregiver education. These matching covariates were selected on the basis that they plausibly affect both treatment assignment (non-enrolment in an ELP) and child cognitive outcomes.

Although other covariates differed between enrolled and non-enrolled children in the descriptive balance table, they were not included in the CEM specification because matching on too many dimensions would eliminate common support and lead to excessive sample loss. These variables are instead included as regression controls after matching, which allows adjustment for remaining observable differences while preserving the integrity of the matched sample.

Age and gender capture biological and developmental heterogeneity relevant for performance on the ELOM assessment, while province accounts for geographic variation in access to ELPs and socioeconomic context. Primary caregiver education is included as a proxy for household socioeconomic status and the home learning environment, both of which are strongly correlated with enrolment decisions and developmental outcomes. Adding ward to the CEM specification greatly increased the number of strata and caused most to be dropped due to a lack of common support.

This occurred because several wards were highly imbalanced or sparse (for example, one ward had 10 non-enrolled children but only 2 enrolled). Even in cases where the numbers appeared similar (for example, 10 non-enrolled and 10 enrolled children), combining the ward with other matching variables, such as PCG education, further fragmented the strata and led to a loss of treated observations. As a result, the province was used as the geographic matching variable. Conditioning on these variables reduces confounding[5] and ensures that comparisons are drawn between treated and control units with similar demographic, socioeconomic, and contextual characteristics.

The age categories[6], gender, province and PCG education combinations resulted in 90 strata in the coarsened covariate space, of which 59 contained at least one enrolled and one non-enrolled child. All 272 non-enrolled children (100%) were retained in the matched strata, while 767 of the 1050 enrolled children (73%) were matched to comparable non-enrolled children. The remaining 283 enrolled children were dropped because no comparable non-enrolled children existed in their strata. The final matched sample, therefore, comprises 1039 children, representing the region of common support between both groups.

Unlike propensity score matching, which typically assesses balance using mean or standardised mean differences, coarsened exact matching (CEM) evaluates balance by comparing the entire joint distribution of covariates across treatment groups. The central diagnostic is the multivariate L1 statistic, which ranges from 0 (perfect overlap) to 1 (no overlap) and measures the distance between the treated and control groups' multivariate distributions of the coarsened matching variables, rather than differences in their means alone. By construction, CEM enforces exact balance within strata defined by the coarsened bins, retaining only strata that contain both enrolled and non-enrolled children. Overall balance in the matched sample therefore follows from the weighted aggregation across these balanced strata.

In this application, age is coarsened into bins (2-month categories), while categorical variables—including gender, province, and primary caregiver education—are not further coarsened and are therefore, matched exactly. As a result, differences in these covariates in the matched sample are zero or statistically insignificant, as shown in Appendix Table A1, even when assessed using the raw (uncoarsened) variables.

[5]Confounding happens when a variable affects both who becomes enrolled and how well children perform on the ELOM assessment. If these variables are not accounted for, it can look like enrolment causes differences in scores when part of that difference is actually due to underlying characteristics of the children and their households. Conditioning on covariates in CEM means that the matching algorithm constructs treated and control groups that are similar with respect to these confounders. In doing so, it reduces the degree to which differences in outcomes can be attributed to unequal distributions of these background characteristics.
[6]Age was derived as a continuous variable and was coarsened into two-month categories. Missing values were treated as a separate category.

While post-matching standardised mean differences are reported for completeness and comparability with the applied literature, they are secondary in the CEM framework and may be uninformative when exact balance within coarsened strata has been achieved. Interpretation therefore focuses on the L1 statistic and the CEM-specific univariate imbalance measures, which include differences in means and differences across the empirical distribution (minimum, 25th, 50th, 75th percentiles, and maximum), with perfect balance indicated by values of zero.

Before matching, the two groups were highly imbalanced. The multivariate L1 distance was 0.58, indicating substantial divergence in the joint distribution of the matching covariates. Univariate imbalance statistics confirm this pattern (Table 6) - PCGs of non-enrolled children had markedly lower education levels than caregivers of enrolled children (L1 = 0.37), enrolled and non-enrolled children were distributed differently across the three provinces (L1 = 0.24), and smaller but systematic differences existed in child age and sex. Median and upper quartile differences in PCG education corresponded to shifts of one or two educational categories. After applying CEM, the balance improves significantly. The multivariate L1 statistic fell to approximately zero (3.6 x 10-15), indicating perfect distributional alignment between non-enrolled and enrolled children within matched strata. Univariate imbalance for the covariates used in the match also approached zero (Table 7): all differences in means and empirical quantiles (minimum, 25th, 50th, 75th and maximum) were exactly zero.

This pattern is consistent with near-perfect overlap created by CEM's strata-based design, where children are only compared within coarsened cells defined by identical values of the matching variables. Together, these diagnostics show that CEM generated a highly balanced analytical sample with good common support, eliminating pre-existing distributional differences between the groups. The matched enrolled group can therefore be interpreted as a credible synthetic counterfactual for the non-enrolled children along the matched dimensions. Table A2 in the Appendix documents the variations in the counterfactual enrolled sample that were considered for the matching exercise, along with the number of strata, number of observations matched in enrolled and non-enrolled samples, as well as the overall imbalance before and after matching.

Table 6: Pre-matching CEM imbalance table

Variable	L1	Mean Diff	Min	25%	50%	75%	Max
Child age	0.119	-0.579	0	0	-0.696	-0.608	-0.516
Child sex	0.024	-0.024	0	0	0	0	0
Province	0.240	1.027	0	0	0	5	0
PCG education	0.372	-0.595	0	0	-1	-2	0

Source: Own calculations, 2024 Thrive by Five Index. Note: L1 statistic ranges from 0 (perfect overlap) to 1 (no overlap).

Table 7: Post-matching CEM imbalance table

Variable	L1	Mean Diff	Min	25%	50%	75%	Max
Child age	0	0	0	0	0	0	0
Child sex	0	0	0	0	0	0	0
Province	0	0	0	0	0	0	0
PCG education	0	0	0	0	0	0	0

Source: Own calculations, 2024 Thrive by Five Index. Note: L1 statistic ranges from 0 (perfect overlap) to 1 (no overlap).

With balance achieved and comparable samples constructed, the next step is estimation of the SATT using OLS regressions with CEM weights applied, where the weights account for strata imbalances and ensure valid estimates of the treatment effect for the non-enrolled group. CEM weights are constructed at the stratum level, where each matched stratum contains at least one treated and one control observation. Treated (non-enrolled) children retain a weight of 1, while control observations are weighted in proportion to the ratio of the total number of treated children to the number of controls in their stratum, ensuring that the weighted control group reflects the distribution of the treated group (Iacus et al., 2012).

4.2. Enrolment effects after matching

4.2.1. Non-enrolled vs enrolled

Applying CEM allows for a more balanced comparison of enrolled and non-enrolled children. The post-matching estimates presented below using OLS regressions show the extent to which enrolment gaps persist after adjusting for observed child, household, and contextual characteristics. To assess whether the CEM-weighted OLS specification satisfies the assumptions required for valid inference, a set of standard post-estimation diagnostic plots was examined.

These include a Q–Q plot of residuals, a residuals-versus-fitted plot, and a scale–location plot, all of which are provided in the Appendix (Figures A1–A3). Together, the diagnostics indicate that the model provides a good approximation of the data: residuals are approximately normally distributed, the linear functional form appears adequate, and heteroskedasticity, while present, is mild and fully addressed through the use of heteroskedasticity-robust standard errors. There is no evidence of influential outliers or structural violations that would warrant alternative modelling approaches. The post-matching OLS estimates may therefore be interpreted as reliable estimates of the SATT.

Across specifications (Table 8), non-enrolment is consistently associated with significantly lower ELOM scores. The estimated SATT ranges from 5.45 to 6.31 ELOM points across models (1)-(9), with all estimates statistically significant at the 1% level. As additional controls are introduced – including child age, sex, language of assessment, province, primary caregiver relationship, primary caregiver education, children's/picture books in the home, a standardised index of household assets and a standardised index of primary caregiver engagement – the magnitude of the estimated enrolment gap narrows only modestly.

In the fully adjusted specification (10), the gap remains large at 5.8 ELOM points – a difference comparable to 5 to 6 months of a year of typical gains from maturation[7] for children aged 50-59 months. Compared with the raw OLS differences reported in Table 6, these CEM-weighted estimates indicate that part of the initial enrolment gap reflects differences in observable child and household characteristics. However, even after balancing the samples on key background characteristics and adjusting for a wide set of covariates, non-enrolled children continue to perform meaningfully worse than their enrolled peers.

[7] Dawes and Henry (2023) recommend using 1.04 total ELOM 4&5 points as the benchmark for maturation gains per month.

Table 8: Estimating total ELOM scores, after matching and applying CEM weights

Variables	1 Total ELOM Score	2 Total ELOM Score	3 Total ELOM Score	4 Total ELOM Score	5 Total ELOM Score	6 Total ELOM Score	7 Total ELOM Score	8 Total ELOM Score	9 Total ELOM Score	10 Total ELOM Score
Non-enrolled	-6.063*** (1.008)	-5.872*** (0.966)	-5.871*** (0.960)	-6.203*** (1.019)	-6.340*** (1.026)	-6.251*** (1.026)	-6.314*** (1.022)	-6.157*** (1.083)	-5.484*** (1.169)	-5.770*** (1.206)
Observations	1,039	1,039	1,039	1,039	1,039	1,039	1,039	1,039	1,039	1,038
Controls										
Child age		Y	Y	Y	Y	Y	Y	Y	Y	Y
Child sex			Y	Y	Y	Y	Y	Y	Y	Y
Language of assessment				Y	Y	Y	Y	Y	Y	Y
Province					Y	Y	Y	Y	Y	Y
PCG relationship						Y	Y	Y	Y	Y
PCG education							Y	Y	Y	Y
Children's/picture books in the home								Y	Y	Y
Standardised index of HH assets									Y	Y
Standardised index of parental engagement										Y

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1, (ii) CEM weights applied, (iii) Robust standard errors in parentheses, (iv) Variance inflation factors (VIFs) were examined to assess multicollinearity among the covariates. All VIF values were below 5, with a mean VIF of 1.9, indicating no evidence of problematic multicollinearity.

Inverse Probability Weighted Regression Adjustment (IPWRA) is a doubly robust estimator that combines inverse-probability weighting with regression adjustment, producing consistent treatment-effect estimates when either the treatment model or the outcome model is correctly specified (Słoczyński & Wooldridge, 2018; Wooldridge, 2007). Applying IPWRA to this analysis provides a rigorous robustness check that complements the main CEM-based estimates. The estimated Average Treatment Effect on the Treated (ATET) indicates that non-enrolled children score 5.09 ELOM points lower than comparable enrolled children (significant at a 1% level), after adjusting for observable child, household, and contextual characteristics. This effect size closely mirrors the post-matching OLS results using CEM weights, reinforcing confidence that the observed enrolment gap is not sensitive to the choice of adjustment method. Given that typical maturation contributes about 1.04 ELOM points per year (Dawes & Henry, 2023), a deficit of 5.09 points corresponds to nearly five years of age-related developmental progress among children aged 50–59 months.

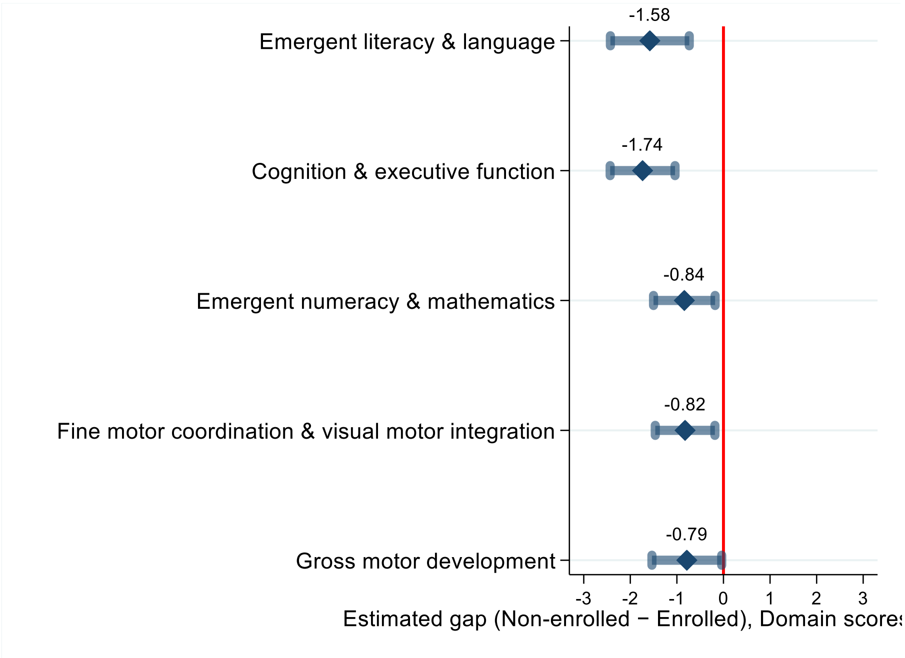
Figure 1 presents the estimated enrolment gaps across the five developmental domains after applying CEM and adjusting for observable child, household, and contextual characteristics. Across all domains, the estimated coefficients are negative, indicating that non-enrolled children score lower than comparable enrolled peers. The largest gaps are observed in higher-order cognitive domains, particularly Cognition and Executive Function and Emergent Literacy and Language. In these areas, the adjusted differences range from approximately 1.6 to 1.7 ELOM points, equivalent to roughly seven to eight months of typical developmental progress at this age.[8]

Although the gap in Emergent Numeracy and Mathematics is smaller in absolute score terms, around 0.8 ELOM points, when translated into age-equivalent developmental progress it still corresponds to approximately seven months of expected learning gains. Differences in the motor domains are somewhat smaller but remain statistically significant, with estimated gaps of around three to four months of typical maturation. Together, these results indicate that the developmental disadvantage associated with non-enrolment extends across multiple domains of early development, although the largest differences are concentrated in cognitive and language-related skills.

These larger effects for cognitive and language domains align with findings from international studies such as Sosu and Pimenta (2023) and Evans et al. (2024), who find that early childhood care and education attendance significantly improves school readiness competencies for children in LMICs, but these improvements are strongly geared towards higher-order cognitive outcomes.

[8] Domain score maturation gains per month recommended by (Dawes & Henry, 2023): GMD (0.23), FMC&VMI (0.23), ENM (0.12), CEF (0.25), ELL (0.21).

Figure 1: Domain-specific enrolment gaps (Non-enrolled - Enrolled) from CEM-weighted OLS regression



Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) 95% confidence intervals shown, (ii) The red line represents zero difference between enrolled and non-enrolled children, (iii) If the confidence interval crosses the red line, the estimate is not statistically significant, (iv) CEM weights applied, (v) Regression controls include child age in months, child sex, language of assessment, province, PCG relationship, PCG education, children's/picture books in the home, a household asset index and a primary caregiver engagement index.

4.2.2. Heterogeneous effects of enrolment

While enrolment is treated as the primary intervention of interest, ELPs differ substantially in their regulatory status, access to public financing, infrastructure quality, and staff qualifications. As a result, enrolment does not represent a uniform treatment. To account for this supply-side heterogeneity, heterogeneous treatment effects were estimated by key programme characteristics—including registration status, receipt of the ECD subsidy, practitioner qualifications, and infrastructure quality. This allows us to assess whether observed enrolment effects vary systematically across different types of early learning provision, rather than assuming uniform returns to enrolment.

Previous research by Van der Berg (2023) also found that prolonged exposure to an ELP was associated with improvements in cognitive outcomes in South Africa, though these benefits were largely concentrated among children in more affluent ELP settings. Accordingly, the duration of enrolment is also considered in the estimation of heterogeneous treatment effects. This approach allows for examining whether the advantages of enrolment differ according to ELP quality, and other features that may shape children's learning experiences.

Several countries use the minimum standards that ELPs are required to meet as a benchmark of the structural quality of a programme (Barnett et al., 2005; Harbach, 2017; Mashburn et al., 2008; OECD, 2015). In South Africa, ELPs must fully comply with the prescribed national norms and standards to achieve full registration, which provides some measure of programme quality. All ELPs are legally required to register as partial-care facilities with the Department of Basic Education (DBE), demonstrating compliance with minimum administrative, health, and safety standards. This registration is also a prerequisite to qualifying for the government ECD subsidy (Giese et al., 2025).

In each ELP, an interview was conducted with the principal to collect detailed information on the programme's characteristics, funding sources, and the principal's own background and qualifications. Principals were asked whether the ELP was registered as a partial care facility with the DBE (or previously, the Department of Social Development). This variable was considered to establish the registration status of ELPs for enrolled children. Principals were asked whether their ELP received income from any of the following sources during the survey year: parent fees, the ECD subsidy, donations, fundraising, learnerships, or other sources. Responses to this question were used to derive a variable indicating receipt of the ECD subsidy.

Structural quality encompasses observable aspects of an ELP's environment, including infrastructure, child-practitioner ratios, and practitioner qualifications and experience (Slot, 2018). Given that infrastructure is often the focus of policy interventions, through subsidies, conditional grants, and budget allocations, it is examined separately from practitioner characteristics to better understand its association with enrolment gaps. A standardised index of infrastructure compliance[9] was created using Principal Component Analysis (PCA), and programmes were subsequently grouped into terciles of infrastructure compliance, ranging from low to high compliance. Programmes in the highest tercile represent those with more adequate or well-resourced infrastructure, meeting a greater number of compliance standards relative to those in the lower terciles.

Practitioner qualifications represent another central dimension of structural quality beyond infrastructure. The same three sequential questions administered to primary caregivers were also posed to practitioners (through a practitioner interview) and used to construct a categorical variable capturing their highest level of educational attainment. Practitioners were grouped into three categories: those without a Matric, those with a Matric, and those with a tertiary qualification. In addition, practitioners were asked whether they held any accredited qualifications specifically in ECD - ranging from an accredited skills programme to a National Qualifications Framework (NQF) Level 7 qualification, such as a Bachelor's Degree in Education, Early Childhood Care and Education (ECCE), or Grade R teaching, as well as postgraduate certificates or higher.

[9] The following variables from the facility observation were included in the infrastructure compliance index: having a fence around the ELP, a lockable gate, indoor floor space large enough for children to move around, an outdoor play area on the premises, formal building (conventional or pre-fab), tap water in building or on-site, ELP has flush toilet, toilets clean and safe for children to use, handwashing facility at ELP or tippy-tap, area for preparing meals separately from children, ELP has refrigeration facilities, ELP has electricity from mains. The infrastructure index was standardised to have a mean of zero and standard deviation of one.

For the purposes of analysis, ECD-specific qualifications were coded into two categories: those with and those without such a qualification. Matric status is not used in this categorisation because several accredited ECD qualifications (e.g., skills programmes and certain certificates/diplomas) can be obtained without completing Grade 12; hence, Matric does not consistently indicate ECD-specific qualification status. In instances where the principal also served as a practitioner, the principal's qualification variables were substituted for missing practitioner data.

Process quality is associated with improvements in child development and learning outcomes (Black et al., 2017; Burchinal et al., 2011; Soliday Hong et al., 2019; Vandell et al., 2010). Kika-Mistry (forthcoming) provides an indication of process quality driving improvements in cognitive outcomes in South Africa using the 2021 Thrive by Five Index data. The Lesson Programme Quality Assessment (LPQA) tool) is used as a measure of ELP process quality for enrolled children.

The LPQA rating, used as a measure of instructional quality, is comprised of 22 items across the following five domains: (i) Materials and Equipment which evaluates available learning materials and their use in the classroom; (ii) Planning and Assessment which measures the use of the curriculum, programme planning and how children are monitored; (iii) Learning Programme which examines the daily schedule and the quality of activities related to literacy, numeracy, group sessions, and free play; (iv) Teaching Strategies, that evaluates the strategies used by practitioners to support and extend children's learning, and whether practitioners encourage independence; and (v) Relationships and Interactions, which looks at the interactions between staff and children, and how staff encourage positive peer interactions among children (Giese et al., 2025).

Each item was rated and coded numerically as 1 (Inadequate), 2 (Basic) and 3 (Good), and the numeric codes for all 22 items were summed and divided by the maximum possible score of 66. The derived percentages were then mapped to the following three categories: (i) inadequate (Less than 60% of the domain total score), (ii) basic (60% - 80% of the domain total), and (iii) good (80% or more of the domain total).

Van der Berg (2023) found that prolonged exposure to an ELP was associated with gains in cognitive outcomes, although these benefits were largely concentrated among children attending more affluent programmes. For the 2024 Index, primary caregivers were asked when their child began attending their current ELP. Based on this information, the DataDrive2030 team derived a variable capturing the average number of months each child had been enrolled. This continuous measure was then used to construct a categorical variable representing duration of enrolment (or ELP exposure) in 12-month intervals: 0–12 months, 13–24 months, 25–36 months, and more than 36 months.

Having established the key dimensions along which early learning programmes differ, the analysis now turns to the estimated heterogeneous effects of enrolment on child outcomes across these programme characteristics. The results are presented sequentially, beginning with duration of enrolment as a measure of cumulative exposure to early learning, and then examining whether the association between enrolment and child outcomes varies by registration status, access to the ECD subsidy, infrastructure compliance, practitioner qualifications, and instructional quality as a measure of process quality. This ordering reflects both the salience of exposure length in the literature, and the central role of programme features in shaping children's learning environments.

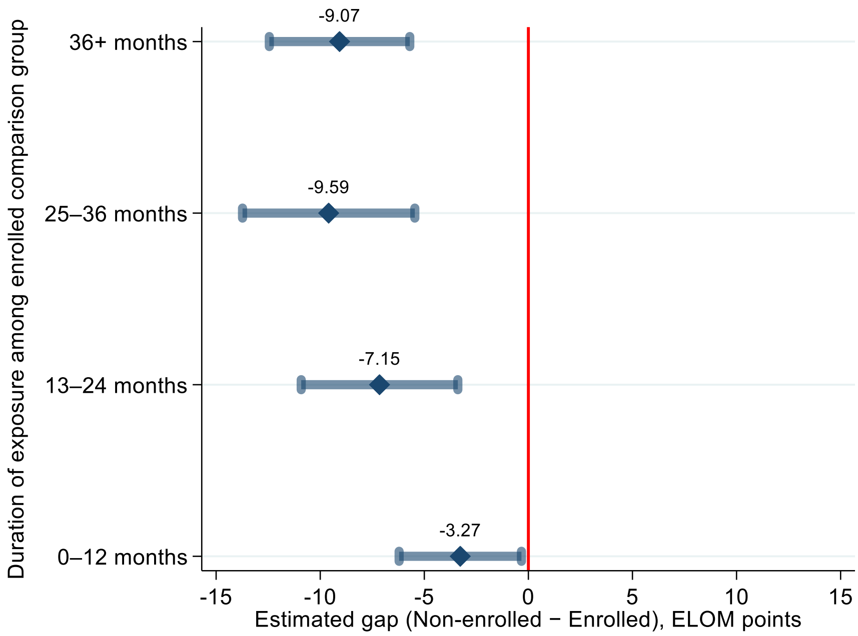
Non-enrolled versus enrolled by duration of enrolment

Figure 2 examines whether the enrolment gap varies with the duration of exposure to early learning programmes (ELPs). The estimates compare non-enrolled children with otherwise comparable enrolled peers within four exposure categories: 0–12 months, 13–24 months, 25–36 months, and more than 36 months of enrolment. Across all exposure groups, non-enrolled children score significantly lower on the ELOM assessment than their matched enrolled counterparts.

When non-enrolled children are compared to peers enrolled for 0–12 months, the adjusted gap is approximately 3.3 ELOM points, equivalent to roughly three months of typical developmental progress at this age. The gap widens when comparisons are made with children who have been enrolled for longer periods. Relative to children enrolled for 13–24 months, non-enrolled children score about seven months behind in age-equivalent developmental progress. When compared to children enrolled for 25 months or more, the estimated gap increases further to approximately nine months of typical development.

Importantly, these estimates are derived from separate matched comparisons within each duration band and therefore should not be interpreted as causal evidence that longer exposure mechanically increases the treatment effect. Rather, the results indicate that the developmental advantage associated with enrolment is larger when non-enrolled children are compared to peers who have remained enrolled in ELPs for longer periods.

Figure 2: Enrolment gaps in ELOM scores by duration of exposure to ELPs (CEM-weighted estimates)



Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) 95% confidence intervals shown, (ii) The red line represents zero difference between enrolled and non-enrolled children, (iii) If the confidence interval crosses the red line, the estimate is not statistically significant, (iv) CEM weights applied, (v) Regression controls include child age in months, child sex, language of assessment, province, PCG relationship, PCG education, children's/picture books in the home, a household asset index and a primary caregiver engagement index.

Non-enrolled vs enrolled by registration status

Among the 1 050 enrolled children included in the study, 51% were attending fully registered ELPs, 42% were attending unregistered ELPs, and 6% were attending conditionally registered ELPs. Table 9 presents the SATT estimates comparing non-enrolled children to two groups of enrolled children - those attending fully registered ELPs and those attending unregistered ELPs. Matching was conducted separately within each registration category, meaning that each estimate reflects a distinct within-group comparison between non-enrolled children and a matched subset of enrolled children with similar observable characteristics. The regression-adjusted SATTs – after controlling for observable characteristics (Columns 2 and 4) represent the primary estimates, consistent with recommended practice following CEM.

Across both registration categories, non-enrolled children score significantly lower on the ELOM assessment than their matched enrolled peers. When compared to children attending fully registered ELPs, non-enrolled children score approximately 7.22 points lower and relative to children in unregistered ELPs, the corresponding gap is approximately 4.47 points – both significant at a 1% level. Benchmarking against typical gains from maturation for children aged 50–59 months, the deficit of 7.22 points corresponds to roughly seven months of expected maturation, while the 4.47-point difference relative to unregistered ELPs represents around four months of developmental progress.

This pattern suggests that while enrolment in an ELP, regardless of registration status, appears to be beneficial relative to non-enrolment, attending a fully registered ELP confers an additional advantage, consistent with the expectation that compliance with registration standards may signal higher programme quality. Yet, even non-registered ELPs appear to offer benefits relative to non-enrolment, while the differences in cognitive outcomes for children in registered versus non-registered ELPs are comparatively modest.

Table 9: Estimating total ELOM scores, comparing non-enrolled to enrolled by registration status for matched samples and applying CEM weights

	Enrolled: Fully registered		**Enrolled: Not registered**	
	(1) **Unadjusted**	**(2)** **Adjusted**	**(3)** **Unadjusted**	**(4)** **Adjusted**
Variables	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**
Non-enrolled	-7.052*** (1.251)	-7.218*** (1.392)	-4.628*** (1.264)	-4.469*** (1.407)
Observations	635	635	618	618
Controls		Y		Y

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1, (ii) CEM weights applied, (iii) Robust standard errors in parenthesis, (iv) Controls include child age in months, child sex, language of assessment, province, PCG relationship, PCG education, children's/picture books in the home, a household asset index and a primary caregiver engagement index.

Non-enrolled vs enrolled by subsidy receipt

Table 10 presents the SATT estimates comparing gaps in total ELOM scores between non-enrolled children and enrolled children, separately for ELPs that receive the ECD subsidy and those that do not. Matching was conducted independently within each group, so each set of estimates reflects a distinct comparison between non-enrolled children and an enrolled group with similar observable characteristics. As with previous tables, the regression-adjusted estimates (columns 2 and 4) are the primary results. Across both subsidy categories, non-enrolled children score significantly lower than their matched enrolled peers.

When compared to children attending subsidised ELPs, non-enrolled children score about 7.87 ELOM points lower than their enrolled peers (significant at a 1% level) and equivalent to roughly seven to eight months of maturation. Among children in unsubsidised ELPs, the corresponding deficit is approximately 4.97 ELOM points, significant at a 1% level and equivalent to about five months relative to gains from maturation. Again, these magnitudes highlight the benefits of participation in an ELP, regardless of subsidy receipt.

Although the estimated enrolment gap is somewhat larger when the comparison group consists of subsidised ELPs, this difference should not be interpreted as evidence that the subsidy itself generates substantially stronger learning gains. Several factors may explain the modest differences observed.

First, the subsidy amount has historically been low (R17 per child per day for seven years, increased to R24 per child per day in 2025), likely limiting its potential to translate into meaningful improvements in structural or instructional quality. Second, subsidised ELPs often pass on the benefits of receiving the subsidy to parents/caregivers by reducing parent fees. As a result, the net financial resources available to subsidised ELPs may not differ meaningfully from unsubsidised providers. Third, families of children who are in ELPs that are not subsidised are not necessarily better off than those in subsidised ELPs.

Many ELPs operate in poor communities but are unable to meet the norms and standards required to access the subsidy, often due to resource constraints or onerous compliance requirements (Kika-Mistry & Wills, 2024). As a result, children in both subsidised and non-subsidised ELPs could come from similarly disadvantaged backgrounds, and both types of ELPs often lack the quality improvements needed to generate stronger developmental returns. These findings indicate that enrolment in an ELP, whether subsidised or not, is associated with significant developmental advantages relative to non-enrolment. However, the relatively small differences between subsidised and non-subsidised ELPs suggest that the current subsidy level may not be sufficient to generate markedly stronger cognitive benefits.

Table 10: Estimating total ELOM scores, comparing non-enrolled to enrolled by subsidy receipt for matched samples and applying CEM weights

	Receives subsidy		**Does not receive subsidy**	
	(1) Unadjusted	**(2) Adjusted**	**(3) Unadjusted**	**(4) Adjusted**
Variables	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**
Non-enrolled	-6.548*** (1.413)	-7.872*** (1.576)	-5.509*** (1.188)	-4.968*** (1.332)
Observations	564	563	731	731
Controls		Y		Y

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1, (ii) CEM weights applied, (iii) Robust standard errors in parenthesis, (iv) Controls include child age in months, child sex, language of assessment, province, PCG relationship, PCG education, children's/picture books in the home, a household asset index and a primary caregiver engagement index.

Non-enrolled vs enrolled by infrastructure terciles

Table 11 reports the SATT estimates comparing non-enrolled children to enrolled children across three levels of infrastructure compliance. A standardised infrastructure compliance index was divided into terciles (low, medium, and high). Matching was performed separately within each tercile, meaning that each set of estimates reflects a distinct comparison between non-enrolled children and the subset of enrolled children with similar characteristics participating in ELPs with different levels of infrastructure quality. Across all terciles, non-enrolled children score significantly lower on the ELOM assessment than their matched enrolled counterparts, all significant at the 1% level. Among ELPs in the lowest infrastructure compliance tercile, non-enrolled children perform approximately 5.74 points worse, and when the comparison group consists of children attending ELPs in the middle tercile, the enrolment gap is approximately 5.13 points, between five and six months of maturation gains.

The largest difference emerges when non-enrolled children are compared with those in the highest infrastructure compliance group, with an adjusted deficit of around 9.04 points – about three-quarters of a year of maturation. These findings further highlight that participation in an ELP, regardless of infrastructure quality, is associated with better learning outcomes relative to non-enrolment. Although the estimates should not be interpreted as strictly comparable across terciles, the larger deficits observed in the high-infrastructure category are consistent with the expectation that children attending better-resourced ELPs may experience stronger developmental support. Infrastructure quality may therefore play a supporting role in strengthening the association between ELP enrolment and early learning outcomes.

Table 11: Estimating total ELOM scores, comparing non-enrolled to enrolled by terciles of infrastructure compliance for matched samples and applying CEM weights

	Low infrastructure compliance		**Medium infrastructure compliance**		**High infrastructure compliance**	
	(1) Unadjusted	**(2) Unadjusted**	**(3) Unadjusted**	**(4) Unadjusted**	**(5) Unadjusted**	**(6) Unadjusted**
Variables	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**
Non-enrolled	-5.134*** (1.764)	-5.738*** (2.067)	-7.148*** (1.464)	-5.128*** (1.574)	-6.708*** (1.280)	-9.042*** (1.566)
Observations	483	483	528	527	536	536
Controls		Y		Y		Y

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1, (ii) CEM weights applied, (iii) Robust standard errors in parenthesis, (iv) Controls include child age in months, child sex, language of assessment, province, PCG relationship, PCG education, children's/picture books in the home, a household asset index and a primary caregiver engagement index.

Non-enrolled vs enrolled by practitioner qualifications

Table 12 presents adjusted SATT estimates comparing non-enrolled children to matched samples of enrolled children, stratified by the highest qualification of the practitioner. Each comparison is based on CEM-matched subsamples, ensuring that non-enrolled children are compared only to enrolled peers with similar observable characteristics. Across all qualification levels, non-enrolled children score significantly lower on the ELOM assessment than comparable enrolled children, all significant at a 1% level.

However, the size of the enrolment gap increases monotonically with practitioner qualification. Non-enrolled children score 5.39 ELOM points lower than their enrolled counterparts, taught by practitioners with less than a Matric, equivalent to approximately 5 months of expected age-related progress. When practitioners of enrolled children hold a Matric, the gap widens to 6.26 points, corresponding to roughly 6 months of maturation. The largest enrolment gap appears in the group where enrolled children are taught by practitioners with a tertiary qualification, where non-enrolled children score 8.48 ELOM points lower, equivalent to about 8 months or three-quarters of a year of typical developmental gains.

These findings suggest that while enrolment in an ELP is consistently associated with improved developmental outcomes, the magnitude of the benefit is greatest in settings where practitioners possess higher levels of formal training. This is consistent with the broader literature showing that practitioner qualifications are linked to more effective instructional practices and richer learning environments.

Table 12: Estimating total ELOM scores, comparing non-enrolled to enrolled by the highest qualification of practitioner and applying CEM weights

	Less than matric		**Matric**		**Matric + Tertiary**	
	(1) **Unadjusted**	**(2)** **Unadjusted**	**(3)** **Unadjusted**	**(4)** **Unadjusted**	**(5)** **Unadjusted**	**(6)** **Unadjusted**
Variables	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**
Non-enrolled	-5.428*** (1.213)	-5.393*** (1.412)	-3.811* (2.044)	-6.259*** (1.707)	-7.847*** (1.499)	-8.476*** (1.735)
Observations	552	551	398	398	533	533
Controls		Y		Y		Y

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1, (ii) CEM weights applied, (iii) Robust standard errors in parenthesis, (iv) controls include child age in months, child sex, language of assessment, province, PCG relationship, PCG education, children's/picture books in the home, a household asset index and a primary caregiver engagement index.

Building on this, Table 13 examines whether the developmental advantage associated with enrolment differs depending on whether the child's practitioner holds an ECD-specific qualification. Two matched samples are constructed: one comparing non-enrolled children to those enrolled with practitioners who do not hold any ECD-specific qualification, and one comparing non-enrolled children to those taught by practitioners who do have such a qualification. For children enrolled in an ELP, close to 60% of practitioners who had less than a Matric had some ECD-specific qualification – ranging from accredited skills certificates to a national Diploma in Grade R (NQF level 6). The results show that non-enrolled children perform significantly worse than their enrolled peers in both cases, but the magnitude of the enrolment gap varies meaningfully by practitioner training.

When practitioners do not hold an ECD-specific qualification, non-enrolled children score 4.49 ELOM points lower (significant at a 1% level) after adjusting for child, household, and contextual characteristics. This disadvantage corresponds to roughly 4 months of typical developmental gains. However, when practitioners do have an ECD-specific qualification, the gap widens substantially: non-enrolled children score 6.89 ELOM points lower (also significant at a 1% level), equivalent to close to 7 months of expected gains from maturation. While the estimated non-enrolment penalty is larger in magnitude in settings where practitioners hold ECD-specific qualifications, these coefficients are estimated on different matched samples and cannot be directly compared using a formal statistical test. This pattern is therefore interpreted descriptively as suggestive of heterogeneous effects by programme quality, rather than as evidence of a statistically significant difference across groups.

Table 13: Estimating total ELOM scores, comparing non-enrolled to enrolled by whether the practitioner holds an ECD-specific qualification for matched samples and applying CEM weights

	Practitioner has no ECD-specific Qualification		**Practitioner has some ECD-specific qualification**	
	(1) **Unadjusted**	**(2)** **Unadjusted**	**(3)** **Unadjusted**	**(4)** **Unadjusted**
Variables	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**
Non-enrolled	-4.655*** (1.311)	-4.488*** (1.445)	-7.035*** (1.092)	-6.887*** (1.380)
Observations	527	526	771	771
Controls		Y		Y

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1, (ii) CEM weights applied, (iii) Robust standard errors in parenthesis, (iv) controls include child age in months, child sex, language of assessment, province, PCG relationship, PCG education, children's/picture books in the home, a household asset index and a primary caregiver engagement index.

Non-enrolled vs enrolled by categories of instructional quality

Table 14 presents estimates of the enrolment gap after matching and adjusting for child, household, and contextual characteristics, disaggregated by categories of instructional quality. Across all quality categories, non-enrolled children score lower on the ELOM assessment than their matched enrolled counterparts. However, the magnitude and statistical significance of these differences vary with instructional quality. For programmes with inadequate instructional quality, the estimated enrolment gap is 2.63 ELOM points and only weakly significant at the 10% level. This suggests that when instructional practices are very weak, the developmental advantage of enrolment, relative to remaining outside an ELP, is limited.

By contrast, the gaps become both large and statistically robust in settings where instructional practices meet at least a basic threshold. In the basic instructional quality category, non-enrolled children score 9.45 ELOM points lower than comparable enrolled peers (significant at a 1% level), while in the good instructional quality category, the gap remains sizeable at 7.43 ELOM points (significant at a 1% level). These estimated differences are equivalent to roughly 7–9 months of typical developmental gains. Importantly, while the point estimate is slightly larger for Basic than Good instructional quality, the difference between these two categories is not statistically significant. This suggests that the key distinction is not between basic and good, but between inadequate instruction and instruction that meets at least a basic quality threshold.

Table 14: Estimating total ELOM scores, comparing non-enrolled to enrolled by categories of instructional quality for matched samples and applying CEM weights

	Inadequate instructional quality		Basic instructional quality		Good instructional quality	
	(1) Unadjusted	(2) Unadjusted	(3) Unadjusted	(4) Unadjusted	(5) Unadjusted	(6) Unadjusted
Variables	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**	**Total ELOM score**
Non-enrolled	-0.211 (1.144)	-2.629* (1.451)	-8.801*** (1.053)	-9.449*** (1.314)	-6.870*** (1.095)	-7.434*** (1.424)
Observations	433	431	600	601	524	525
Controls		Y		Y		Y

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1, (ii) CEM weights applied, (iii) Robust standard errors in parenthesis, (iv) Controls include child age in months, child sex, language of assessment, province, PCG relationship, PCG education, children's/picture books in the home, a household asset index and a primary caregiver engagement index.

5. Discussion

This study investigated whether enrolment in ELPs is associated with improved early learning outcomes among 4- to 5-year-old children in three provinces in South Africa, using rich child-level assessment data from the 2024 Thrive by Five Index. Descriptive analyses revealed substantial initial differences between enrolled and non-enrolled children across socioeconomic characteristics, linguistic background, and home-learning environments - even after restricting the sample to low-income communities in Gauteng, KwaZulu-Natal, and the Western Cape.

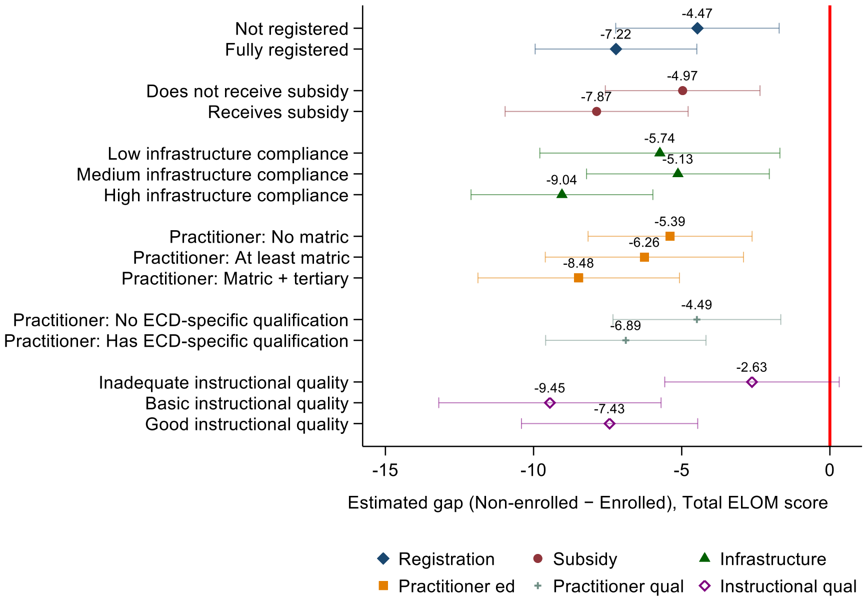
These disparities highlighted the need to construct comparable groups before estimating the effects of enrolment. Coarsened Exact Matching (CEM) provided a transparent approach to achieving balance across key demographic and contextual variables, producing a matched sample suitable for estimating sample average treatment effects on the treated (SATT) i.e., the developmental outcomes that might be observed for this group of non-enrolled children if they had been enrolled.

The results indicate that the developmental advantages associated with ELP enrolment are conditional on programme quality, particularly the quality of instructional practices within programmes. In settings where instructional quality is inadequate, enrolment is not associated with measurable developmental advantages relative to comparable non-enrolled children. By contrast, once instructional quality reaches at least a basic threshold, substantial enrolment gaps emerge.

Figure 3 illustrates how the enrolment gap varies across different dimensions of programme quality. Across most structural programme characteristics—including registration status, subsidy receipt, infrastructure compliance, and practitioner qualifications—non-enrolled children score significantly lower than comparable enrolled peers. Even in unregistered or unsubsidised programmes, enrolment remains associated with measurable cognitive advantages.

However, the pattern changes markedly when instructional quality is considered. In programmes rated as having inadequate instructional quality, the adjusted enrolment gap is small—approximately 2.6 ELOM points—and statistically insignificant at the 5% level of confidence. By contrast, once instructional quality reaches at least a basic threshold, the gap becomes large and robust, ranging between roughly 7 and 9 ELOM points. Importantly, the estimated differences between programmes classified as “basic” and “good” instructional quality are not statistically significant. This finding reinforces the interpretation that the critical distinction lies between inadequate instructional practices and those that meet at least a minimal quality standard.

Figure 3: Enrolment gaps in ELOM scores by quality indicators (CEM-weighted estimates)



Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) 95% confidence intervals shown, (ii) The red line represents zero difference between enrolled and non-enrolled children, (iii) If the confidence interval crosses the red line, the estimate is not statistically significant, (iv) CEM weights applied, (v) Regression controls include child age in months, child sex, language of assessment, province, PCG relationship, PCG education, children's/picture books in the home, a household asset index and a primary caregiver engagement index.

Across the matched sample, non-enrolled children score approximately 5.8 ELOM points lower than comparable enrolled peers, equivalent to roughly five to six months of typical developmental progress at this age. However, the heterogeneity analysis indicates that this overall gap masks important variation across programme quality conditions. In practice, the observed average enrolment difference largely reflects the gains experienced by children attending programmes where instructional quality meets at least a basic level in the Lesson Programme Quality Assessment.

Domain-specific analyses corroborate this pattern. The largest enrolment gaps appear in Cognition and Executive Function, Emergent Literacy and Language and Emergent Numeracy and Mathematics, where non-enrolled children lag by the equivalent of seven to eight months of typical development. Smaller but statistically significant differences are observed in the motor domains. These findings are consistent with international evidence showing that participation in early childhood care and education programmes most directly enhances higher-order cognitive and language skills (Evans et al., 2024; Sosu & Pimenta, 2023).

The analysis also reveals that the developmental advantages associated with enrolment vary with the duration of programme exposure. Comparisons between non-enrolled children and peers enrolled for different lengths of time show that the enrolment gap widens as exposure increases. When non-enrolled children are compared to peers enrolled for less than one year, the adjusted gap corresponds to roughly three months of developmental progress. When compared to children enrolled for one to two years, the difference increases to approximately seven months.

The largest differences are observed when non-enrolled children are compared to peers who have been enrolled for more than two years, corresponding to roughly nine months of typical developmental gains. Although these estimates should not be interpreted as causal dose–response effects—since each estimate is derived from a separate matched comparison—they suggest that the developmental advantage associated with enrolment tends to be larger when children remain enrolled for longer periods. This pattern is consistent with evidence that cumulative exposure to structured early learning environments can reinforce developmental progress over time (Koshy et al., 2024; Kvintová et al., 2025; Loeb et al., 2007; Magnuson et al., 2007).

Structural features of programme quality also appear to reinforce the developmental advantages associated with enrolment. Across indicators such as infrastructure compliance and practitioner qualifications, non-enrolled children consistently score lower than comparable enrolled peers, with the largest gaps observed when children attend programmes with stronger structural characteristics. For example, enrolment advantages are larger in programmes located in the highest infrastructure compliance tercile and in programmes led by practitioners with higher academic or ECD-specific qualifications. These patterns suggest that the physical environment and practitioner human capital may strengthen the developmental returns to enrolment.

Overall, the heterogeneity analyses suggest that enrolment advantages are most pronounced under three conditions. First, sustained participation appears to reinforce developmental gains, with larger differences emerging when children remain enrolled for longer periods. Second, structural features of programme quality—including stronger infrastructure and more qualified practitioners—tend to amplify the benefits associated with enrolment. Third, and most critically, instructional quality determines whether enrolment translates into meaningful developmental gains at all. While structural characteristics may strengthen these gains, the presence of at least minimally adequate instructional practices appears to be a necessary condition for enrolment to generate measurable improvements in children's developmental outcomes.

These findings align with a growing body of international research emphasising the importance of process quality in early childhood education. Evidence from multiple contexts shows that what practitioners do with children during daily interactions—through language-rich engagement, guided play, and structured learning activities—is more strongly associated with child development than structural inputs alone (Black et al., 2017; Soliday Hong et al., 2019). The results presented here reinforce this conclusion, highlighting instructional quality as a key mechanism through which participation in early learning programmes translates into improved developmental outcomes.

Several limitations of this analysis should be acknowledged. The estimates presented are associational SATTs rather than causal treatment effects and therefore cannot be generalised to the wider population. The sample of non-enrolled children in the Thrive by Five sub-study is relatively small and is not nationally or provincially representative. Although Coarsened Exact Matching substantially reduces observable differences between enrolled and non-enrolled children, unobserved selection into enrolment cannot be ruled out. Finally, the cross-sectional nature of the data limits the ability to draw conclusions about longer-term developmental trajectories. Despite these limitations, the study provides new and policy-relevant evidence on the developmental penalties associated with non-enrolment and the programme conditions under which enrolment advantages are most likely to emerge in the South African early learning system.

6. Conclusion

This study provides new evidence that the developmental advantages associated with participation in ELPs are conditional on the quality of instructional practices within programmes. Using matched comparisons based on child-level assessment data from the 2024 Thrive by Five Index, the results show that enrolment does not automatically translate into improved developmental outcomes. In programmes where instructional quality is inadequate, enrolled children do not exhibit measurable developmental advantages relative to comparable non-enrolled peers. By contrast, once instructional quality reaches at least a basic threshold, substantial enrolment gaps emerge, corresponding to roughly seven to nine months of typical developmental progress. These findings highlight instructional quality as a critical mechanism through which participation in early learning programmes translates into meaningful cognitive gains.

Across the matched sample, non-enrolled children score on average 5.8 ELOM points lower than comparable enrolled peers, equivalent to roughly five to six months of typical developmental progress at this age. However, the heterogeneity analyses show that this overall difference masks important variation across programme conditions. The developmental advantages associated with enrolment are concentrated among children attending programmes with at least basic instructional quality and tend to be larger for children who remain enrolled for longer periods and for those attending programmes with stronger structural characteristics, such as better infrastructure and more highly qualified practitioners.

These findings contribute to the South African and broader LMIC literature by providing rare child-outcome-linked evidence on how different dimensions of programme quality shape the developmental returns to early learning participation. In particular, the results underscore the central role of process quality—what practitioners do with children during daily interactions—as the key determinant of whether enrolment translates into developmental gains.

The policy implications are as follows: Expanding access to early learning programmes, while important, is unlikely to generate meaningful developmental improvements if instructional quality remains weak. Efforts to strengthen the early learning system must therefore prioritise improving pedagogical practice within programmes, including investments in practitioner training, ongoing professional support, and systems that incentivise improvements in instructional quality. Aligning access expansion with sustained improvements in programme quality offers a critical pathway for reducing early developmental inequalities and strengthening school readiness among children in disadvantaged communities in South Africa.

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8. Appendix

Table A1: Sample characteristics for adjusted enrolled and non-enrolled children after matching (proportions)

	Enrolled (N= 767)	**Non-enrolled (N = 272)**	**Difference**
Child age (Months)	54.28	54.15	0.13
Child sex (Female)	0.49	0.49	0.00
Child received Child Support Grant	0.76	0.75	0.00
Child has a birth certificate	0.95	0.84	0.10***
Language spoken by the child in the home			
English	0.08	0.01	0.07***
Afrikaans	0.12	0.15	-0.03
isiZulu	0.30	0.26	0.05
isiXhosa	0.23	0.30	-0.07*
Sesotho	0.05	0.12	-0.07***
Setswana	0.14	0.07	0.07***
Sepedi	0.07	0.01	0.05***
Xitsonga	-0.00	0.07	-0.07***
Primary caregiver relationships of person completing PCG			
Biological mother	0.74	0.73	0.01
Biological father	0.07	0.07	0.01
Grandmother	0.13	0.13	0.00
Aunt	0.04	0.04	0.00
Step/adopt./foster parent/sibling/other	0.02	0.04	-0.01

	Enrolled (N= 767)	Non-enrolled (N = 272)	Difference
PCG education			
All PCGs: Matric only	0.11	0.11	0.00
All PCGs: Matric and tertiary	0.05	0.05	0.00
Biological mother: Matric only	0.13	0.15	-0.02
Biological mother: Matric + tertiary	0.05	0.05	0.00
Biological father: Matric only	0.16	0.00	0.16***
Biological father: Matric + tertiary	0.05	0.22	-0.18*
Grandmother: Matric only	0.03	0.03	0.00
Grandmother: Matric + tertiary	0.03	0.00	0.03**
Aunt: Less than Matric	0.88	1.00	-0.12**
Other caregiver: Matric only	0.07	0.10	-0.03
Other caregiver: Matric + tertiary	0.13	0.10	0.03
PCG paid employee/employer/business owner			
All PCGs	0.47	0.13	0.34***
Biological mother	0.48	0.13	0.35***
Biological father	0.80	0.44	0.36**
Grandparent	0.21	0.03	0.18***
Aunt	0.49	0.00	0.49***
Other caregiver	0.56	0.00	0.56***

	Enrolled (N= 767)	Non-enrolled (N = 272)	Difference
Household assets in working condition			
Fridge	0.90	0.63	0.27***
Electrical or gas stove	0.96	0.79	0.17***
Vacuum cleaner	0.04	0.02	0.03*
Washing machine	0.49	0.22	0.28***
Computer or laptop	0.15	0.07	0.08***
TV set	0.77	0.62	0.15***
Pay TV subscription, e.g. DSTV	0.67	0.33	0.34***
Motor car	0.27	0.08	0.19***
Radio	0.56	0.38	0.19***
Cell phone	1.00	0.90	0.09***
Internet access in dwelling or uses cell phone/other mobile device	0.93	0.70	0.23***
Standardised index of HH assets (z-score)	-0.16	-1.16	1.00***
Children's/picture books in the home			
No children's/picture books	0.32	0.77	-0.45***
1 children's/picture book	0.17	0.09	0.09***
2-5 children's/picture books	0.44	0.13	0.31***
6-10 children's/picture books	0.06	0.02	0.04**
10 or more children's/picture books	0.01	0.00	0.01**
PCG learning activities with the child in the past 7 days (3 or more times)			
Told stories to the child	0.33	0.19	0.14***
Sang songs to/with the child, including when putting the child to sleep	0.66	0.38	0.28***

	Enrolled (N= 767)	Non-enrolled (N = 272)	Difference
Read books to/looked at a picture book with the child	0.36	0.12	0.25***
Played with the child	0.81	0.61	0.20***
Told the child the names of things	0.54	0.46	0.09**
Drew or painted things with the child	0.40	0.11	0.29***
Counted things with the child	0.62	0.37	0.26***
Standardised index of parental engagement (z-score)	0.11	-0.91	1.02***

Source: Own calculations, 2024 Thrive by Five Index. Notes: (i) Significance levels of differences: *** p<0.01, ** p<0.05, * p<0.1; (ii) Samples of children speaking isiNdebele, siSwati and Tshivenda were very small (5 children or less), (iii) There are no aunts in the non-enrolled sample with at least a Matric or a Matric and tertiary qualification.

This table summarises the quality of the Coarsened Exact Matching (CEM) procedure across all heterogeneous comparisons conducted in the study. For each enrolled subsample- for example, by duration, registration status, or subsidy receipt - the table reports (i) the total number of strata created by CEM, (ii) how many of those strata successfully included matched pairs of enrolled and non-enrolled children, and (iii) the number of observations retained in the matched enrolled and matched non-enrolled groups. Across all specifications, between 49 and 59 strata are retained, indicating a high degree of overlap between treatment and comparison cases. The “overall imbalance” statistic shows substantial imbalance between groups prior to matching (ranging from 0.425 to 0.576), but CEM reduces imbalance to zero in every matched sample, indicating perfect balance on the coarsened covariates. This confirms that the matching procedure performs strongly and yields comparable treatment and control groups for all subsequent SATT estimates.

Table A2: Matched samples after CEM, by different enrolled samples

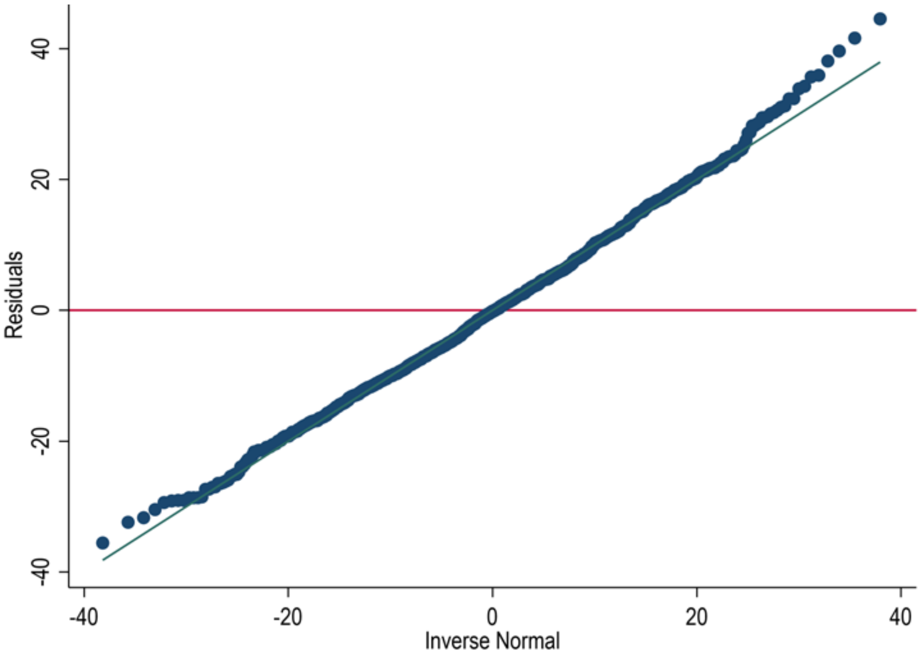
	Enrolled Samples	Number of Strata	Number of matched strata	Matched-enrolled sample of children	Matched-non-enrolled sample of children	Overall imbalance before CEM	Overall imbalance after CEM
1	All enrolled	90	59	767	272	0.576	0
2	Enrolled: 0-12 months	85	54	279	263	0.425	0
3	Enrolled: 13-24 months	86	57	195	269	0.472	0
4	Enrolled: 25-36 months	82	51	159	256	0.454	0
5	Enrolled: More than 36 months	82	49	134	252	0.525	0

Table A2: Matched samples after CEM, by different enrolled samples

	Enrolled Samples	Number of Strata	Number of matched strata	Matched-enrolled sample of children	Matched-non-enrolled sample of children	Overall imbalance before CEM	Overall imbalance after CEM
6	Enrolled: Fully registered	89	56	367	268	0.467	0
7	Enrolled: Not registered	83	56	350	268	0.425	0
8	Enrolled: Subsidy	88	57	294	270	0.466	0
9	Enrolled: No subsidy	88	57	461	270	0.452	0
10	Enrolled: Low infrastructure compliance	85	48	240	243	0.413	0
11	Enrolled: Medium infrastructure compliance	87	56	260	268	0.436	0
12	Enrolled: High infrastructure compliance	85	56	267	269	0.514	0
13	Enrolled: Practitioner – Less than Matric	84	55	286	266	0.400	0
14	Enrolled: Practitioner - Matric	87	48	157	241	0.491	0
15	Enrolled: Practitioner - tertiary	85	59	261	272	0.476	0

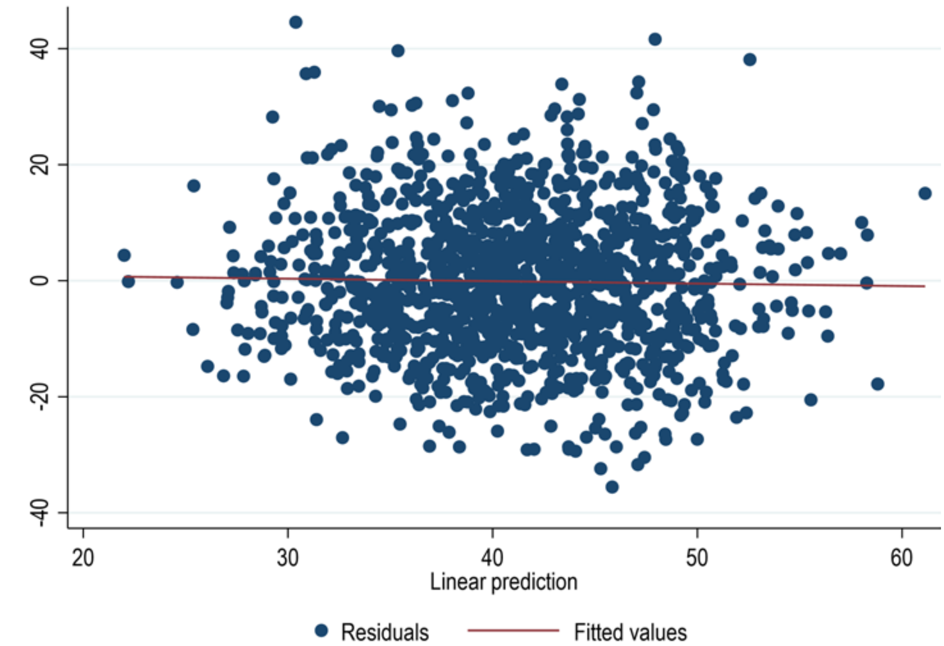
	Enrolled Samples	Number of Strata	Number of matched strata	Matched-enrolled sample of children	Matched-non-enrolled sample of children	Overall imbalance before CEM	Overall imbalance after CEM
16	Enrolled: Practitioner – no ECD specific qualification	88	53	263	264	0.452	0
17	Enrolled: Practitioner – some ECD specific qualification	89	59	499	272	0.455	0
18	Enrolled: Inadequate instructional quality	273	44	71	106	0.653	0
19	Enrolled: Basic instructional quality	351	77	141	160	0.621	0
20	Enrolled: Good instructional quality	280	71	140	154	0.598	0

Figure A1: Q-Q plot of OLS residuals



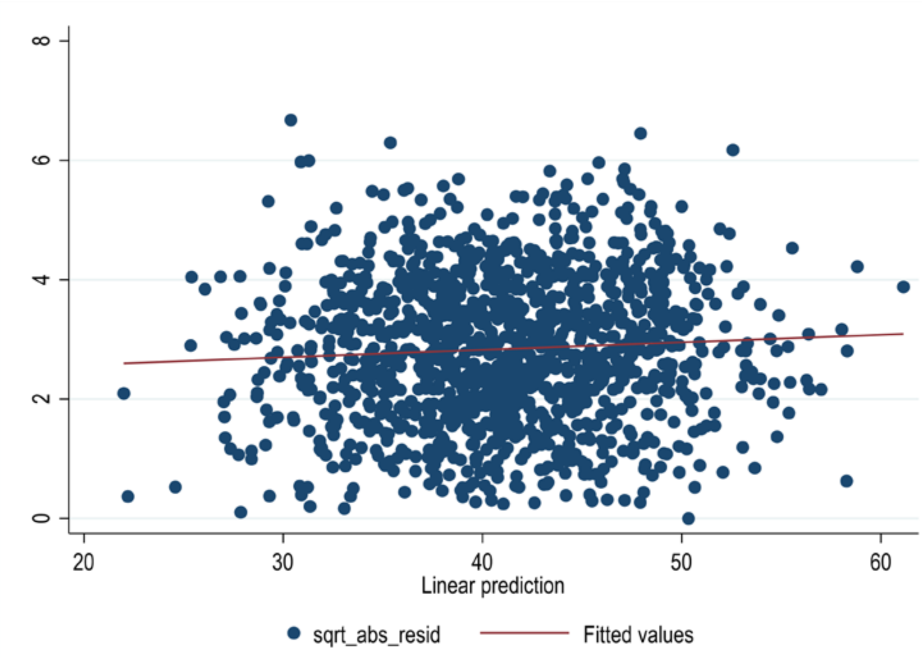
Source: Own calculations, 2024 Thrive by Five Index.

Figure A2: Residuals vs fitted values from OLS regression



Source: Own calculations, 2024 Thrive by Five Index.

Figure A3: Scale-location plot of standardised residuals



Source: Own calculations, 2024 Thrive by Five Index.

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