Cognitive Gains from Early Learning Programme Enrolment in Three South African Provinces: Analysis of the 2024 Thrive by Five Index

Jesal Kika-Mistry | June 2026

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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 Thrive by Five Index 2024, which, for the first time, includes a sub-sample of non-enrolled children across three provinces, providing novel evidence on the developmental consequences of non-enrolment among children aged 50–59 months.

Coarsened Exact Matching (CEM) is applied to balance observable characteristics and to construct comparable groups of non-enrolled and enrolled children on a limited set of key background characteristics. Ordinary least squares models are then used to estimate regression-adjusted sample average treatment effects on the treated (SATT) within the matched sample, using the Early Learning Outcomes Measure (ELOM) as the outcome measure.

The subgroup comparisons suggest that enrolment advantages are not uniform across programme conditions. In separate matched comparisons, the estimated gap is small and only weakly significant for children attending programmes with inadequate instructional quality. It is substantially larger in programmes where instructional quality is rated as basic or good.

Across the matched sample as a whole, non-enrolled children score 5.8 ELOM points lower on average than comparable enrolled peers, equivalent to roughly 5–6 months of typical developmental progress at this age. This overall estimate should therefore be read as an average across heterogeneous programme conditions, rather than as a uniform enrolment effect across all ELPs.

Estimated enrolment advantages are also larger in higher-order cognitive domains, including emergent literacy and language, emergent numeracy and mathematics, and cognition and executive functioning, as well as in comparisons involving children with sustained programme exposure of two years or more.

Enrolment advantages are also observed across most structural programme characteristics, including registration status, subsidy receipt, infrastructure compliance, and practitioner qualifications. Because these subgroup estimates are derived from separate matched comparisons, they are interpreted as conditional descriptive patterns rather than formal tests of moderation. Although the estimates are associational rather than causal, the findings suggest that participation in an ELP is more strongly associated with improved cognitive outcomes in settings with higher programme quality.

Keywords: early learning programmes (ELPs), early childhood development, enrolment, cognitive development, programme quality, Thrive by Five Index, South Africa

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 with those who are not enrolled. Understanding these differences is critical to ensure that expanded access translates into real gains in child development. As the government advances the 2030 Strategy for Early Childhood Development and implements the Bana Pele Shared 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, 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). Findings highlight that access alone may be insufficient, as the magnitude and distribution of developmental benefits depend critically on the quality of provision. However, 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 South African Thrive by Five Index 2024, a small sub-study tested the feasibility of identifying and assessing children aged 50–59 months who were not enrolled in any ELP, alongside the nationally representative study of enrolled children. This sub-study 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 across three provinces in South Africa, using the sub-study dataset from the Thrive by Five Index 2024. 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 vary across dimensions of ELP quality. Third, by situating the South African experience within a broader global debate on the returns of 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 realise 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 indicate that the developmental advantages associated with ELP enrolment vary across programme conditions, particularly with respect to instructional 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 (CEM) 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 5–6 months behind comparable enrolled peers in typical age-related development.

However, this average difference masks important heterogeneity across separate matched comparisons. Descriptively, enrolment advantages appear small and only weakly significant when instructional quality is inadequate, but larger in programmes where instructional quality is rated as basic or good. Enrolment gaps are also larger in comparisons involving programmes with stronger structural characteristics, including better infrastructure and more highly qualified practitioners.

Because these subgroup estimates are derived from separate matched samples, they should be interpreted as conditional descriptive comparisons rather than formal tests of moderation. Even so, they provide new and policy-relevant evidence for South Africa and contribute to growing international literature suggesting that participation in ELPs is more strongly associated with improved cognitive outcomes in settings where programme quality is stronger.

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 discusses the findings, and Section 6 concludes.

2. Literature review

Across low- and middle-income countries (LMICs), the literature generally points to positive associations between centre-based early childhood care and education and child development outcomes, particularly in cognitive and language domains (Evans et al., 2024). A recent systematic review of 71 studies on childcare interventions in LMICs[1] finds that, among interventions focused on preschool- and kindergarten-aged children, 81% report positive effects, although only 55% report effects that are both positive and statistically significant[2] (Evans et al., 2024). This suggests an encouraging overall pattern, but not one that is uniform or unconditional.

Estimated impacts vary considerably across countries, programme models, and implementation contexts. Evidence from large-scale expansions and evaluations indicates that programme effects depend not only on whether children participate, but also on how services are delivered, which populations they reach, and the institutional conditions under which provision occurs. The international evidence therefore points less to a single average effect of enrolment than to substantial heterogeneity in impacts across contexts (Attanasio et al., 2022; Bernal et al., 2019; Nores et al., 2019).

A related theme in the literature is that gains from participating in early childhood education programmes are not evenly distributed across developmental domains. Effects tend to be more pronounced for cognitive and language outcomes than for broader developmental measures (Evans et al., 2024; Sosu & Pimenta, 2023). This is important for interpreting the benefits of enrolment, since average effects may obscure substantial variation in the types of capabilities that are most responsive to early learning experiences. It also suggests that evaluations of programme effectiveness should distinguish between domains, rather than treating child development as a single, undifferentiated outcome.

The literature is less conclusive on the extent to which early learning participation reduces socioeconomic disparities. In some settings, disadvantaged children appear to benefit most from participation; in others, gains are concentrated among children already able to access better-resourced programmes or more supportive home environments (Berlinski et al., 2009; Bouguen et al., 2021). This points to an important distributional question: early learning participation does not automatically equalise opportunity and may instead interact with pre-existing inequalities in ways that either narrow or reinforce developmental gaps. The equity effects of participation therefore depend not only on access, but also on the quality of the programme relative to the care and learning environment the child would otherwise have experienced.

This helps explain why programme quality features so prominently in the international evidence. Participation in a structured group setting can improve cognitive stimulation and school readiness when programmes provide developmentally appropriate interactions, routines, and teaching practices (Engle et al., 2011; Garcia et al., 2016). However, enrolment alone does not guarantee developmental gains. Where programme quality is weak, relative to the alternative care environment available to the child, measured benefits may be small or absent (Blimpo et al., 2022; Bouguen et al., 2018; Jakiela et al., 2024). The emerging consensus in the literature is therefore not simply that access matters, but that the developmental returns to access are conditional on the nature of the learning environment to which children are exposed.

Relatedly, a growing body of work suggests that exposure matters. Longer exposure to ELPs is often associated with stronger developmental outcomes, including gains in cognitive, language, and executive-function domains (Koshy et al., 2024; Kvintová et al., 2025; Loeb et al., 2007; Magnuson et al., 2007). Yet here too, the evidence points to interaction rather than simple accumulation. Sustained participation appears to generate the largest gains where programme quality is adequate, while prolonged exposure to low-quality provision yields limited benefits (Bouguen et al., 2021; Melo et al., 2022; Zaslow et al., 2016). Duration and quality should therefore be understood as complementary dimensions of participation rather than independent sources of benefit.

The South African evidence is consistent with these broader patterns but remains limited. The Early Learning Programme Outcome study found that greater programme exposure was associated with stronger performance on the ELOM assessment (Dawes et al., 2020). Using the Thrive by Five Index 2021, Van der Berg (2023) similarly shows that the benefits of longer enrolment are concentrated in more affluent programme settings. Evidence from Grade R points in the same direction, with positive effects strongest in better-resourced parts of the school system (Van der Berg et al., 2013). More broadly, South African education research suggests that similar inputs do not produce similar returns across contexts: educational resources tend to translate into stronger learning gains in better-functioning settings than in historically disadvantaged ones (Spaull & Jansen, 2019; Van der Berg, 2021). In Chapter 3, the analysis further shows that elements of programme quality, particularly teaching strategies, are associated with stronger cognitive outcomes, although these relationships are themselves shaped by children's socioeconomic circumstances.

This literature suggests that access alone is insufficient. What remains unclear is whether enrolment in an ELP is associated with improved cognitive outcomes for children from disadvantaged backgrounds in South Africa, and the extent to which these enrolment advantages depend on duration of exposure and programme quality.

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 with the inaugural 2021 round, the 2024 Index broadened its scope, applied more rigorous methodological approaches, and incorporated a sub-study that assessed children who were not enrolled in an ELP. This addition provides rare insight into the circumstances and developmental outcomes of non-enrolled children.

However, comparisons of key outcomes from the 2021 and 2024 Index surveys 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 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 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, 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 study, 45 were chosen for the sub-study, including informal settlements, rural communities, and urban formal neighbourhoods. These were specifically selected from the bottom three weighted school quintiles (proxying for the poorest 60%), with weights based on the number of Grade 3 learners in each school.

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 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) who 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. 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 highly fluid, with children moving in and out of programmes in response to short-term income shocks, caregiving arrangements, or local availability. Finally, fieldwork teams faced significant logistical and safety challenges in economically deprived communities. High-crime areas limited access, while disruptions within households made sustained engagement with eligible families difficult (Giese et al., 2025).

As a result, the final sample comprised 272 children from 262 households across the three provinces (Table 1).

Table 1: Number of children and their households in the non-enrolled sub-study sample

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 using Thrive by Five Index 2024 data.
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 Thrive by Five Index 2024 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 involved selecting ELPs within the 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 Thrive by Five Index 2024 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 the 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 because 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 enrolled children and ELPs meeting the criteria for inclusion in the 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 using Thrive by Five Index 2024 data.

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 fourth edition of the Wechsler Preschool and Primary Scale of Intelligence), as well as strong test–retest reliability (Dawes et al., 2020). It aligns with the South African National Curriculum Framework for Children from Birth to Four and was standardised for use with children aged 50–69 months, with performance bands for two separate groups: children aged 50–59 months and children aged 60–69 months (Pettersson et al., 2025). The 2024 Index focuses on children aged 50–59 months. 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 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 domain item, 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 et al., 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 used in the analysis, including age in months, gender, province, the language of assessment, and height (measured using a stadiometer).

3.4. Socioeconomic and primary caregiver characteristics

A Primary Caregiver (PCG) interview was administered telephonically for 3,841 enrolled children, representing 77% of the enrolled sample, and for all PCGs of children in the non-enrolled sample (272 children). The interview form captured information about the child's socioeconomic circumstances, the home learning environment, and selected PCG characteristics.

The majority of PCGs are biological mothers (71% among enrolled children and 73% among non-enrolled children), followed by grandmothers, biological fathers, aunts, and others. Accounting for the identity of the primary caregiver is important because the relationship between child and caregiver shapes both the child's home learning experience and the relevance of caregiver characteristics such as education and employment.

Primary caregiver education and employment

A categorical variable was created for PCG education using three sequentially asked questions: (1) the highest school grade completed, (2) whether the PCG passed Grade 12 with a Matric or National Senior Certificate, and (3) whether they have completed any tertiary qualifications such as a certificate, diploma, or degree. This analysis does not consider 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 and those whose PCGs passed Matric and had a tertiary qualification (Giese et al., 2025). Further, only 5% of PCGs of non-enrolled children have completed Grade 12 and completed a tertiary qualification.

The categorical variable for PCG education therefore includes three levels of educational attainment:

1. **No Matric:** PCGs who have not passed Grade 12. This includes PCGs with no schooling, those with some primary education, those who completed primary education, those with some secondary education, and those who completed Grade 12 but did not obtain a Matric pass.
2. **Matric:** PCGs who completed secondary school (Grade 12) and passed with a Matric or National Senior Certificate, but do not have a tertiary qualification.
3. **Tertiary:** PCGs who completed secondary school, passed with a Matric or National Senior Certificate, and have a tertiary qualification such as a certificate, diploma, or degree.

The PCG employment categorical variable was used in the analysis, grouping those who are paid employees, employers, or owners of their own businesses, and those who are unemployed and engaged in unpaid family work, including household caregiving responsibilities.

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 whether the child had a birth certificate and whether they received the Child Support Grant for the child.

Household socioeconomic measures

A standardised household asset index was constructed to capture the long-term wealth of a household. The asset index was derived using Principal Component Analysis (PCA) based on household ownership of the following assets (in working condition) and subscriptions available in the household: fridge, electric or gas stove, computer/laptop, TV set, pay TV subscription, radio, and internet access in the dwelling (using a cell phone or other mobile device).

Ownership of children's books, which reflects aspects of the home learning environment rather than household wealth, was excluded from the asset index and entered separately as a control variable.

Following Vyas and Kumaranayake (2006), variables that showed limited variation across households, such as washing machine ownership (rare) or cell phone ownership (near-universal), were excluded to improve discrimination in the PCA.

The asset index was standardised to have a mean of zero and a standard deviation of one. Higher index values indicate relatively wealthier households with greater access to durable assets in working condition.

Home learning environment

A parental engagement index was constructed to capture the frequency of interactive activities that PCGs engaged in with their children during the reference week. This measure draws on seven caregiver-reported activities. Caregivers were asked how often they read books or looked at picture books, told stories, sang songs, played with the child, named objects or identified things in the environment, counted or compared things, and drew or scribbled with the child.

Each activity was coded on a three-point ordinal scale (0 = never, 1 = once or twice, 2 = three or more times), with "don't know" and "refused" responses treated as missing. PCA was applied to these items to form a continuous index representing the intensity of parental engagement, which was standardised to have a mean of zero and a standard deviation of one. Higher scores on the parental engagement index indicate more frequent engagement in learning and play activities within the home.

3.5. Sample characteristics

3.5.1. Pre-matching comparisons

The descriptive statistics in Table 3 provide an initial comparison of enrolled and non-enrolled children in the analysis samples – namely, children in Gauteng, KwaZulu-Natal, and the Western Cape, residing in enumeration areas in weighted school quintiles 1–3, with completed PCG interviews.

Although enrolled children appear to have higher average ELOM scores and higher height-for-age outcomes, these differences are not directly comparable and cannot provide a causal account of enrolment. The two groups differ for several reasons. First, the sampling strategies differ (as discussed above). Second, the groups differ in observable characteristics 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 with 37% of enrolled children, or that non-enrolled children exhibit greater growth faltering or lower height-for-age z-scores (-1.06 standard deviations) than enrolled children (-0.55 standard deviations); such comparisons would overstate the role of enrolment.

Table 3: Mean early learning performance, On Track proportions, and height-for-age scores for adjusted 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
Non-enrolled sub-study sample				
Total ELOM scores	42.49	41.70	43.27	1,050
On Track – total ELOM	0.37	0.34	0.40	1,050
On Track – GMD	0.40	0.37	0.43	1,050
On Track – FMC-VMI	0.26	0.23	0.28	1,050
On Track – ENM	0.31	0.28	0.34	1,050
On Track – CEF	0.39	0.36	0.42	1,050
On Track – ELL	0.48	0.45	0.51	1,050
Height-for-age (z-scores)	-0.55	-0.61	-0.50	1,050

Source: Own calculations using Thrive by Five Index 2024 data.
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).

3.5.2. Child characteristics

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 with 49% female), enrolled children are, on average, slightly older – by just over half a month (54.73 compared with 54.15 months) – and this difference is statistically significant at the 1% level. This may reflect the larger sample size for enrolled children rather than a substantively meaningful age difference.

Enrolled children are also more likely to have a birth certificate, with a 12-percentage-point gap that is significant at the 1% level. In contrast, receipt of the Child Support Grant (CSG) is high and similar across both groups (77% compared with 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 more pronounced, with several 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 with 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 with 6%). English-speaking children make up a small share of both samples, though they remain more common among the enrolled (6% compared with 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.

3.5.3. Primary caregiver characteristics

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 enrolled children (26% versus 11%), whereas PCGs with a Matric certificate plus tertiary education are more than five times more common among enrolled children (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 group. In instances where biological fathers are the PCG, 30% of the enrolled sample have a Matric without any post-school qualifications, compared with 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), all non-enrolled caregivers have less than a Matric compared with half in the enrolled sample.

Employment shows larger gaps; the proportion of caregivers with stable paid employment is more than three times higher among the enrolled sample (45% versus 13%), significant at the 1% level. These patterns persist across caregiver types: employed biological mothers are more than three times more common among enrolled children (46% compared with 13%), and grandparents of enrolled children are nearly ten times more likely to be employed (29% compared with 3%). Biological fathers of enrolled children are also close to 30 percentage points more likely to be employed compared with 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 14 percentage points more likely to have a television (76% vs 62%), with similarly large differences for computers (16 percentage points), 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.

3.5.4. Home learning environment characteristics

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 percentage 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 with –0.91), reflecting a large and systematic gap in the cognitive stimulation environments of enrolled and non-enrolled children.

Table 4: Sample characteristics before matching (selected proportions)

	Enrolled	**Non-enrolled**	**Difference**
	(N = 1050	**(N = 272)**	
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***
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 to child			
Biological mother	0.73	0.73	0.01

	Enrolled	Non-enrolled	Difference
	(N = 1050	(N = 272)	
Biological father	0.07	0.07	0.00
Grandmother	0.13	0.13	0.00
Aunt	0.05	0.04	0.01
Step/adopted/foster parent, sibling or 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 and tertiary	0.28	0.05	0.24***
Biological father: Matric only	0.30	0.00	0.30**
Biological father: Matric and tertiary	0.31	0.22	0.09
Grandmother: Matric only	0.11	0.03	0.09
Grandmother: Matric and 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 and tertiary	0.32	0.10	0.22
PCG employed			
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***
Electric 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***

	Enrolled	**Non-enrolled**	**Difference**
	(N = 1050	**(N = 272)**	
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 household (using cell phone or other device)	0.94	0.70	0.24***
Standardised household assets index (z-score)	-0.05	-1.16	1.11***
Children's/picture books in the home			
No books	0.30	0.77	-0.47***
1 book	0.19	0.09	0.11***
2–5 books	0.42	0.13	0.29***
6–10 books	0.06	0.02	0.04**
10 or more books	0.02	0.00	0.02*
Learning activities with child past 7 days (3+ times)			
Told stories to the child	0.35	0.19	0.16***
Sang songs to/with the child (including when putting to sleep)	0.69	0.38	0.32***
Read books to/looked at a picture book together	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 using Thrive by Five Index 2024 data.
*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.*

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 meaningful heterogeneity 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 were used to create comparable sub-samples of enrolled and non-enrolled children based on 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 status (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 (Table 5).

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 primary caregiver engagement. Models (2) to (9) in Table 5 incrementally introduce additional covariates and investigate how these characteristics affect the estimated 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)
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/adopted/foster parent, sibling, or 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 and tertiary							3.103*** (0.885)	2.504*** (0.900)	1.922** (0.925)	1.956** (0.925)
Children's/picture books in the home (Reference: no books in the home)										
1 book								0.558 (1.005)	0.380 (1.005)	0.412 (1.015)
2–5 books								1.173 (0.851)	0.751 (0.864)	0.799 (0.883)
6–10 books								3.066* (1.577)	2.440 (1.591)	2.821* (1.620)
10 or more 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 using Thrive by Five Index 2024 data. 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 modestly reduces the magnitude of the gap, and introducing language of assessment, province, and primary caregiver relationship explains additional variation, reducing the estimated gap to -6.64 points in model (6).

The more notable attenuation occurs once socioeconomic and home learning environment variables are added. Introducing primary caregiver education, children's books in the home, the household asset index, and parental engagement reduces the estimated gap further to -4.41 ELOM points in model (10), also significant at the 1% level.

This pattern suggests that demographic and geographic differences account for a relatively small share of the initial enrolment gap, while socioeconomic status and home learning environments explain a larger share. Specifically, of the total 2.91-point reduction in the enrolment coefficient between models (1) and (10), about 0.68 points is associated with the inclusion of demographic and geographic controls in models (2) to (6), while a further 2.23 points is associated with the addition of socioeconomic and home learning variables in models (7) to (10).

The remaining gap is not explained by the observable characteristics included in the model. 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 with 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 enrolment 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 strata based on the unique combinations of the coarsened covariates 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 several other child, household and home learning 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 have sharply reduced common support and led to substantial sample loss among the treated group. The post-matching regressions therefore combine exact balance on the matched covariates with regression adjustment for selected additional observables. This improves comparability, but it does not imply that the matched samples are balanced on variables not included in the CEM design.

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 the 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 two enrolled). Even in cases where the numbers appeared similar (for example, 10 non-enrolled and 10 enrolled), 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[3] and ensures that comparisons are drawn between treated and control units with similar demographic, socioeconomic, and contextual characteristics.

The age categories[4], 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 1,039 children, representing the region of common support across both groups.

Unlike propensity score matching, which typically assesses balance using mean or standardised mean differences, 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 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 of these balanced strata.

In this application, age is coarsened into 2-month bins, while the categorical variables included in the matching procedure, namely gender, province, and primary caregiver (PCG) education, are matched exactly. Balance should therefore be assessed primarily with reference to the variables included in the CEM design.

In the CEM framework, the main diagnostic is the multivariate L1 statistic, supplemented by variable-specific imbalance measures that compare the distribution of each matched covariate through differences in means and selected quantiles (minimum, 25th, 50th, 75th, and maximum), with values closer to zero indicating greater overlap. These diagnostics are reported in Tables 6 and 7.

Appendix Table A1 serves a different purpose: it reports post-matching differences across a broader set of child, household, and home learning characteristics, including variables that were not included in the match. It is therefore useful for showing residual differences after matching, but not for assessing whether the CEM procedure achieved balance on the matched covariates.

Before matching, the two groups were highly imbalanced on the covariates used in the match. The multivariate L1 distance was 0.58, indicating substantial divergence in the joint distribution of child age, sex, province, and PCG education. The univariate imbalance statistics in Table 6 confirm this pattern: the largest imbalance was observed for PCG education (L1 = 0.37), followed by province (L1 = 0.24), while smaller but still systematic differences were present for age and sex.

After applying CEM, the multivariate L1 statistic fell to approximately zero (3.6×10^{-15}), and the univariate imbalance statistics for the matched covariates also fell to zero, as shown in Table 7. This indicates exact balance on the coarsened variables used to define the matched strata

and strong overlap within the region of common support. At the same time, Appendix Table A1 shows that meaningful differences remain in several unmatched characteristics, including birth certificate status, PCG employment, household assets, books in the home, and parental engagement.
The contribution of CEM in this setting is therefore to improve comparability along the matched dimensions and restrict the analysis to common support, rather than to eliminate all differences between enrolled and non-enrolled children. The subsequent CEM-weighted OLS estimates should therefore be interpreted as regression-adjusted associational differences within the matched sample.

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						
PCG education	0.372						

Source: Own calculations using Thrive by Five Index 2024 data.
Notes: (i) L1 statistic ranges from 0 (perfect overlap) to 1 (no overlap), (ii) Mean or quantile differences are not reported for unordered categorical variables since they are challenging to interpret methodically.

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						
PCG education	0						

Source: Own calculations using Thrive by Five Index 2024 data.
Notes: (i) L1 statistic ranges from 0 (perfect overlap) to 1 (no overlap), (ii) Mean or quantile differences are not reported for unordered categorical variables since they are challenging to interpret methodically

With balance achieved and comparable samples constructed, the next step is to estimate 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. This ensures 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 by using 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 (model 10), the gap remains large at 5.8 ELOM points. This difference is comparable to 5 to 6 months of a year of typical gains from maturation[5] for children aged 50–59 months. Compared with the raw OLS differences reported in Table 5, 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.

Table 8: Estimated effect of non-enrolment on 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 household assets index									Y	Y
Standardised index of parental engagement										Y

Source: Own calculations using Thrive by Five Index 2024 data.
*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.*

As an additional robustness check, Inverse Probability Weighted Regression Adjustment (IPWRA) method was used to estimate the treatment effect. This 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 5 months of age-related developmental progress among children aged 50–59 months.

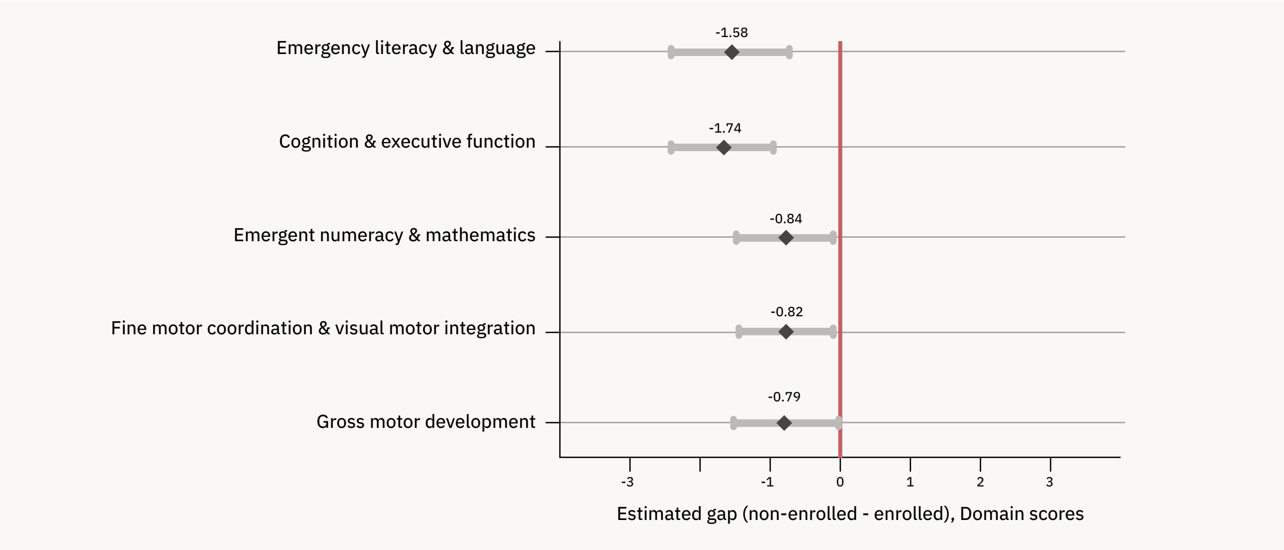
Figure 1 presents the estimated enrolment gaps across the five developmental domains after applying CEM and adjusting for observable child, household, and contextual characteristics. Across all domains, the estimated coefficients are negative, indicating that non-enrolled children score lower than comparable 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 7–8 months of typical developmental progress at this age.[6]

Although the gap in Emergent Numeracy and Mathematics is smaller in absolute score terms, at around 0.8 ELOM points it, when translated into age-equivalent developmental progress, still corresponds to approximately 7 months of expected learning gains. Differences in the motor domains are somewhat smaller but remain statistically significant, with estimated gaps of around three to 4 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), which 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.

Figure 1: Domain-specific enrolment gaps from CEM-weighted OLS regression



Source: Own calculations using Thrive by Five Index 2024 data.
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 the analysis 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 the analysis to examine 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 for a programme's structural quality (Barnett et al., 2005; Harbach, 2017; Mashburn et al., 2008; OECD, 2015). In South Africa, ELPs must comply with prescribed national norms and standards to achieve full registration, which provides a measure of programme quality. All ELPs are legally required to register as partial-care facilities with the Department of Basic Education (DBE) to demonstrate compliance with minimum administrative, health, and safety standards. This registration is also a prerequisite for qualifying for the government ECD subsidy (Giese et al., 2025).

During the Thrive by Five Index 2024 survey, an interview was conducted with the principal of each ELP 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 used to determine 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 whether the ELP received 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, such as 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[7] was created using Principal Component Analysis (PCA), and programmes were subsequently grouped into terciles of infrastructure compliance, ranging from low to high. 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 qualifications. For the purposes of analysis, ECD-specific qualifications were coded as a binary indicator distinguishing practitioners who reported holding any accredited ECD qualification from those who did not.

This classification was based directly on reported ECD-specific credentials, rather than being inferred from general schooling attainment. No additional consistency restriction was imposed requiring practitioners with an ECD qualification to have completed Matric, since some accredited ECD pathways, including skills programmes and certain certificates or diplomas, can be obtained without completing Grade 12. The variable therefore captures whether a practitioner holds any recognised ECD-specific qualification, irrespective of their general schooling level.

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 Thrive by Five Index 2021 data.

To account for variation in process quality across ELPs, the analysis also incorporates measures derived from the ELOM Learning Programme Quality Assessment Tool (LPQA). The LPQA is used to assess ELP programme quality and comprises 22 items across 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, which evaluates the strategies used by practitioners to support and extend children's learning, and whether practitioners encourage independence;
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 ELPs 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.

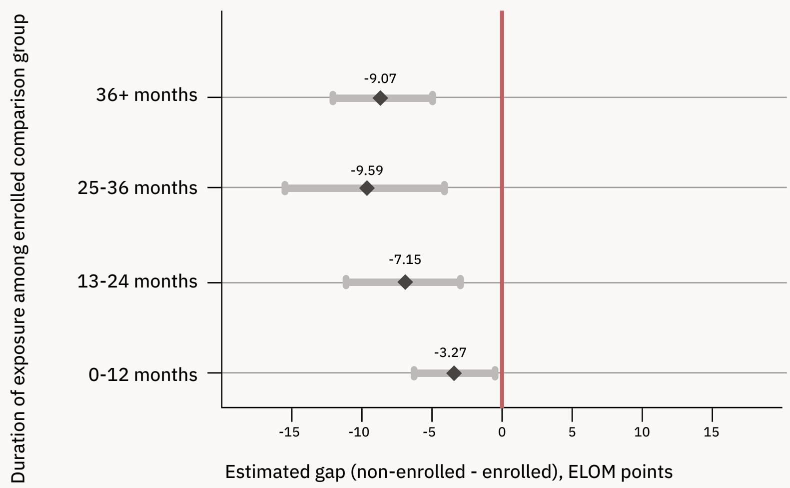
4.2.3. Non-enrolled versus enrolled by duration of enrolment

Figure 2 examines whether the enrolment gap varies with the duration of exposure to 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 with peers enrolled for 0–12 months, the adjusted gap is approximately 3.3 ELOM points, equivalent to roughly 3 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 7 months behind in age-equivalent developmental progress. When compared with children enrolled for 25 months or more, the estimated gap increases further to approximately 9 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 with 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 using Thrive by Five Index 2024 data.
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.

4.2.4. 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 with 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 7 months of expected maturation, while the 4.47-point difference relative to unregistered ELPs represents around 4 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 by registration status, for matched samples 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 using Thrive by Five Index 2024 data.
*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) 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.*

4.2.5. 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 with children attending subsidised ELPs, non-enrolled children score about 7.87 ELOM points lower than their enrolled peers (significant at a 1% level), equivalent to roughly 7–8 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 5 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 those available to unsubsidised providers. Third, families of children attending unsubsidised ELPs 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 by subsidy receipt for matched samples 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 using Thrive by Five Index 2024 data.
*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.*

4.2.6. 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, between 5–6 months of maturation gains. When the comparison group consists of children attending ELPs in the middle tercile, the enrolment gap is approximately 5.13 points, approximately 5 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, equivalent to approximately 9 months 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 by terciles of infrastructure compliance for matched samples applying CEM weights

	Low infrastructure compliance		Medium infrastructure compliance		High infrastructure compliance	
	(1) Unadjusted	(2) Adjusted	(3) Unadjusted	(4) Adjusted	(5) Unadjusted	(6) Adjusted
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 using Thrive by Five Index 2024 data.
*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) 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.*

4.2.7. 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, significant at the 1% level in the adjusted models. 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 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 by the highest practitioner qualification for matched samples applying CEM weights

	Less than matric		Matric		Matric and tertiary	
	(1) Unadjusted	(2) Adjusted	(3) Unadjusted	(4) Adjusted	(5) Unadjusted	(6) Adjusted
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 using Thrive by Five Index 2024 data.
*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) 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.*

4.2.8. Non-enrolled vs enrolled by ECD-specific practitioner qualifications
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 the 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 by whether the practitioner holds an ECD-specific qualification for matched samples applying CEM weights

	Practitioner has NO ECD-specific qualification		Practitioner has some ECD-specific qualification	
	(1) Unadjusted	(2) Adjusted	(3) Unadjusted	(4) Adjusted
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 using Thrive by Five Index 2024 data.
*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) 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.*

4.2.9. 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 estimated gaps are larger and more precisely estimated in programmes where instructional quality is rated as basic or good.

In the basic instructional quality category, non-enrolled children score 9.45 ELOM points lower than comparable enrolled peers (significant at the 1% level), while in the good instructional quality category, the gap remains sizeable at 7.43 ELOM points (significant at the 1% level). These estimated differences are equivalent to roughly 7–9 months of typical developmental progress at this age.

Importantly, these results are derived from separate matched comparisons between non-enrolled children and different subsets of the enrolled sample and therefore do not constitute a formal test of whether the enrolment gap differs across instructional-quality categories. The estimates should instead be interpreted as conditional descriptive comparisons. On this basis, the evidence suggests that enrolment advantages are more likely to be observed in settings where instructional quality meets at least a basic standard.

Table 14: Estimating total ELOM scores by categories of instructional quality for matched samples applying CEM weights

	Inadequate instructional quality		Basic instructional quality		Good instructional quality	
	(1) Unadjusted	(2) Adjusted	(3) Unadjusted	(4) Adjusted	(5) Unadjusted	(6) Adjusted
Variables	Total ELOM score	Total ELOM score	Total ELOM score	Total ELOM score	Total ELOM score	Total ELOM score
Non-enrolled	-0.211 (1.567)	-2.629* (1.503)	-8.801*** (1.375)	-9.449*** (1.914)	-6.870*** (1.298)	-7.434*** (1.517)
Observations	434	433	601	601	525	525
Controls		Y		Y		Y

Source: Own calculations using Thrive by Five Index 2024 data.
*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) 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, (v) 23.4% of ELPs in the sample have inadequate instructional quality, 43.1% basic and 33.4% good.*

5. Discussion

This study investigated whether enrolment in ELPs is associated with improved early learning outcomes among 4–5-year-old children in three provinces in South Africa, using rich child-level assessment data from the Thrive by Five Index 2024.

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 disadvantaged communities in Gauteng, KwaZulu-Natal, and the Western Cape.

Coarsened Exact Matching (CEM) provided a transparent way of restricting comparisons to children with common support and achieving exact balance on a limited set of key covariates: child age, sex, province, and PCG education. Because non-enrolment is defined as the treatment, the analysis targets the Sample Average Treatment Effect on the Treated (SATT), that is, the average difference in outcomes for non-enrolled children relative to their matched enrolled counterparts within the matched sample. At the same time, important differences remained on several unmatched household and home learning characteristics, so the estimates that follow are best understood as regression-adjusted associational differences for the treated group within the matched sample, rather than as causal effects of enrolment.

The results indicate that the developmental advantages associated with ELP enrolment vary across programme conditions, particularly with respect to instructional quality. In the subgroup comparisons, enrolment advantages are small and only weakly significant when instructional quality is inadequate, but larger and more precisely estimated in programmes rated as having basic or good instructional quality. Because these estimates are derived from separate matched comparisons between non-enrolled children and different subsets of the enrolled sample, they should not be interpreted as a formal test of whether the enrolment gap differs significantly across instructional-quality categories. Rather, they point to a descriptive pattern in which enrolment advantages appear more likely to be observed in settings where instructional quality meets at least a basic standard. 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 looks different 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 only weakly significant. In the basic and good instructional quality categories, by contrast, the estimated gaps are much larger, at roughly 7–9 ELOM points. These subgroup estimates are obtained from separate matched samples and should therefore be interpreted as conditional descriptive comparisons, not as formal evidence that the enrolment effect differs significantly across quality categories. On this basis, the results suggest that enrolment advantages are more likely to be concentrated in programmes where instructional quality is at least basic.

Across the matched sample, non-enrolled children score approximately 5.8 ELOM points lower than comparable enrolled peers, equivalent to roughly 5–6 months of typical developmental progress at this age. The heterogeneity analysis suggests that this overall gap masks important variation across programme conditions. In particular, the average enrolment difference appears to be driven more strongly by comparisons involving children in programmes with at least basic instructional quality, while the corresponding estimate is smaller in the subgroup attending programmes rated as inadequate on instructional quality. Because these estimates are generated from separate matched comparisons, this interpretation remains descriptive rather than causal or formally comparative across categories.

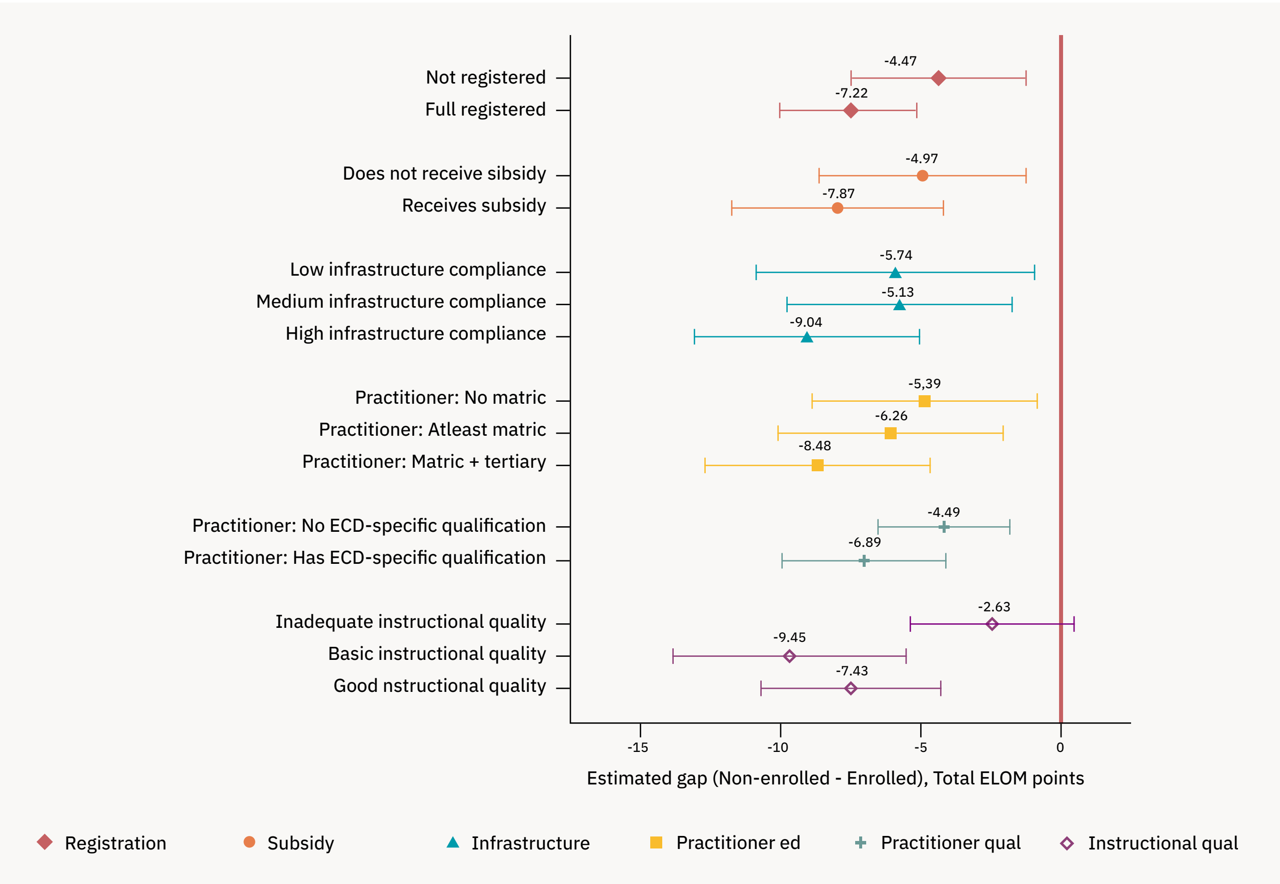
Domain-specific analyses corroborate this pattern. The largest enrolment gaps appear in Cognition and Executive Function, Emergent Literacy and Language and Emergent Numeracy and Mathematics, where non-enrolled children lag by the equivalent of 7–8 months of typical development. Smaller but statistically 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 with peers enrolled for less than one year, the adjusted gap corresponds to roughly 3 months of developmental progress. When compared with children enrolled for one to two years, the difference increases to approximately 7 months. The largest differences are observed when non-enrolled children are compared with peers who have been enrolled for more than two years, corresponding to roughly 9 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 point to three descriptive patterns. First, enrolment advantages tend to be larger when non-enrolled children are compared with peers with longer durations of programme exposure.

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



Source: Own calculations using Thrive by Five Index 2024 data.
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.

Second, the estimated gaps are often larger in comparisons involving programmes with stronger structural characteristics, including stronger infrastructure and more highly qualified practitioners. Third, the subgroup estimates by instructional quality suggest that enrolment advantages are less evident when instructional practices are inadequate and more pronounced in programmes rated as basic or good. Because each of these heterogeneous estimates is derived from a separate matched comparison, they should be interpreted as conditional descriptive patterns rather than formal evidence of moderation. Even so, they are consistent with the view that both sustained exposure and stronger programme quality are associated with larger enrolment advantages.

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 are consistent with this broader literature and suggest that instructional quality may be an important channel through which participation in ELPs is associated with improved developmental outcomes.

Several limitations of this analysis should be acknowledged. The estimates presented are associational SATTs rather than causal treatment effects due to potential unobserved confounding within the study sample. The results cannot be generalised to the wider population since the sample of non-enrolled children in the Thrive by Five Index 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. In addition, the matched samples remain imbalanced on several contemporaneously measured household and home learning variables not included in the CEM design. 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 vary across programme conditions, particularly with respect to instructional quality. Using matched comparisons based on child-level assessment data from the Thrive by Five Index 2024, the results show that enrolment does not automatically translate into improved developmental outcomes. In subgroup comparisons involving programmes with inadequate instructional quality, the estimated enrolment gap is small and only weakly significant. By contrast, the estimated gaps are considerably larger in comparisons involving programmes rated as having basic or good instructional quality. These patterns are consistent with the view that instructional quality matters for whether enrolment is associated with meaningful cognitive advantages, although the subgroup estimates are derived from separate matched samples and therefore should be interpreted as descriptive rather than as formal tests of threshold effects or moderation. Across the matched sample as a whole, non-enrolled children score on average 5.8 ELOM points lower than comparable enrolled peers, equivalent to roughly 5–6 months of typical developmental progress at this age.

The heterogeneity analyses suggest that this overall difference masks important variation across programme conditions. Enrolment advantages appear larger in comparisons involving children who have remained enrolled for longer periods and 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 are associated with the developmental returns to early learning participation.

The policy implications are clear. Expanding access to ELPs, while important, is unlikely to generate meaningful developmental improvements if instructional quality remains weak. Efforts to strengthen the early learning system should 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.

Endnotes

[1] These studies were mostly from Latin America and East Asia.

[2] Around 39% of interventions has statistically insignificant impacts, while 5% were negative and statistically significant.

[3] 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 distribution of these background characteristics.

[4] Age was derived as a continuous variable and was coarsened into two-month categories. Missing values were treated as a separate category.

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

[6] 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).

[7] 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, 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.

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Appendix

Table A1: Sample characteristics after matching (proportions)

	Enrolled	Non-enrolled	Difference
	(N = 1050	(N = 272)	
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***
Province			
Gauteng	0.47	0.47	0.00
KwaZulu-Natal	0.13	0.13	0.00
Western Cape	0.40	0.40	0.00
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 to child			
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/adopted/foster parent, sibling or other	0.02	0.04	-0.01
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

	Enrolled	Non-enrolled	Difference
	(N = 1050	(N = 272)	
Biological father: Matric and tertiary	0.05	0.22	-0.18*
Grandmother: Matric only	0.03	0.03	0.00
Grandmother: Matric and 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 and tertiary	0.13	0.10	0.03
PCG employed			
All PCGs		0.13	0.34***
Biological mother	0.47	0.13	0.35***
Biological father	0.48	0.44	0.36**
Grandmother	0.80	0.03	0.18***
Aunt	0.21	0.00	0.49***
Other caregiver	0.49	0.00	0.56***
Household assets in working condition	0.56		
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 household (using a cell phone or other device)	0.93	0.70	0.23***
Standardised household asset index (z-score)	-0.16	-1.16	1.00***
Children's/picture books in the home			
No books	0.32	0.77	-0.45***

	Enrolled	Non-enrolled	Difference
	(N = 1050	(N = 272)	
1 book	0.17	0.09	0.09***
2–5 books	0.44	0.13	0.31***
6–10 books	0.06	0.02	0.04**
10 or more books	0.01	0.00	0.01**
Learning activities with child past 7 days (3+times)			
Told stories to the child	0.33	0.19	0.14***
Sang songs to/with the child (including when putting to sleep)	0.66	0.38	0.28***
Read books to/looked at a picture book together	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 using Thrive by Five Index 2024 data.
*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.*

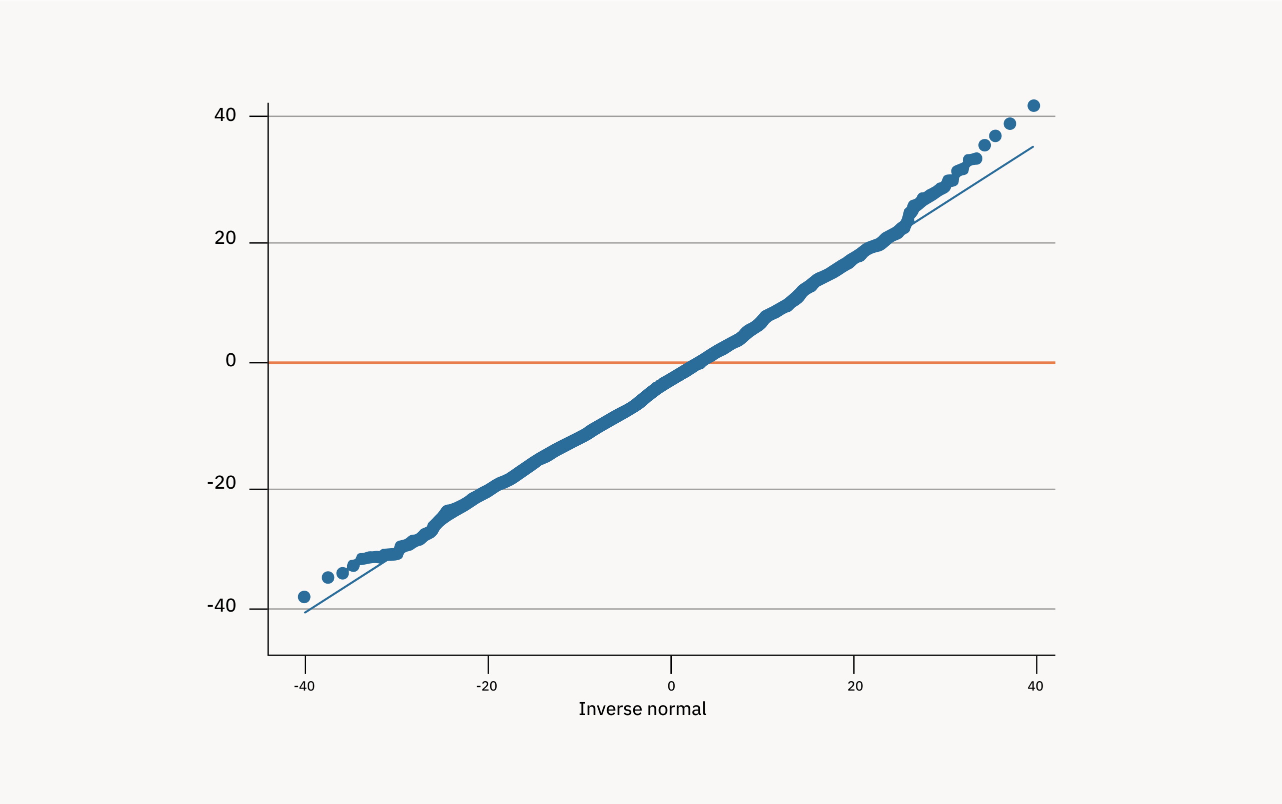
Table A2: Matched samples after CEM, by different enrolled samples

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.

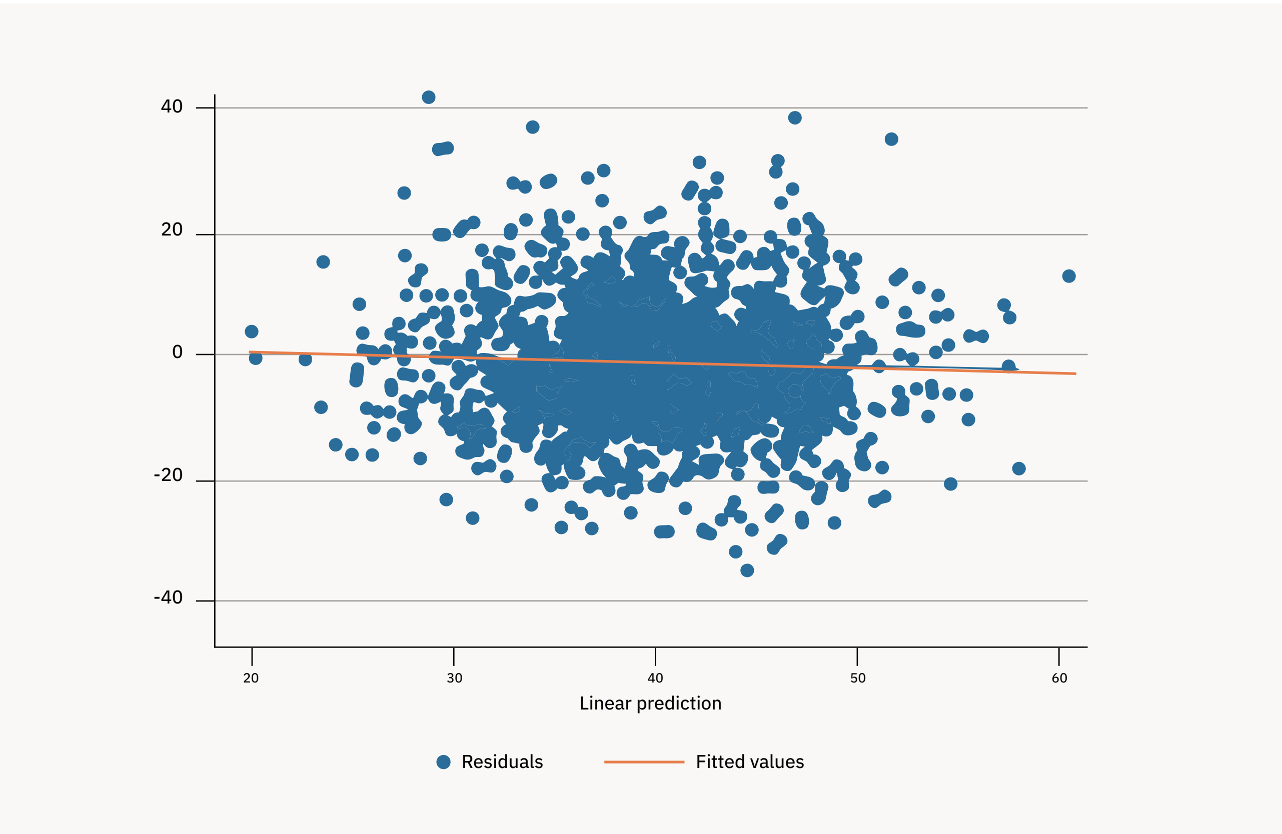
	Enrolled samples	Number of strata	Number of matched strata	Matched-enrolled sample of children	Matched-non-enrolled sample of children	Overall imbalance before CEM	Overall imbalance after CEM
1	All enrolled	90	59	767	272	0.576	0
2	Enrolled: 0–12 months	85	54	279	263	0.425	0
3	Enrolled: 13–24 months	86	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
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
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	83	54	179	255	0.397	0
19	Enrolled: Basic instructional quality	88	56	332	269	0.442	0
20	Enrolled: Good instructional quality	86	57	256	269	0.493	0

Figure A1: Q-Q plot of OLS residuals



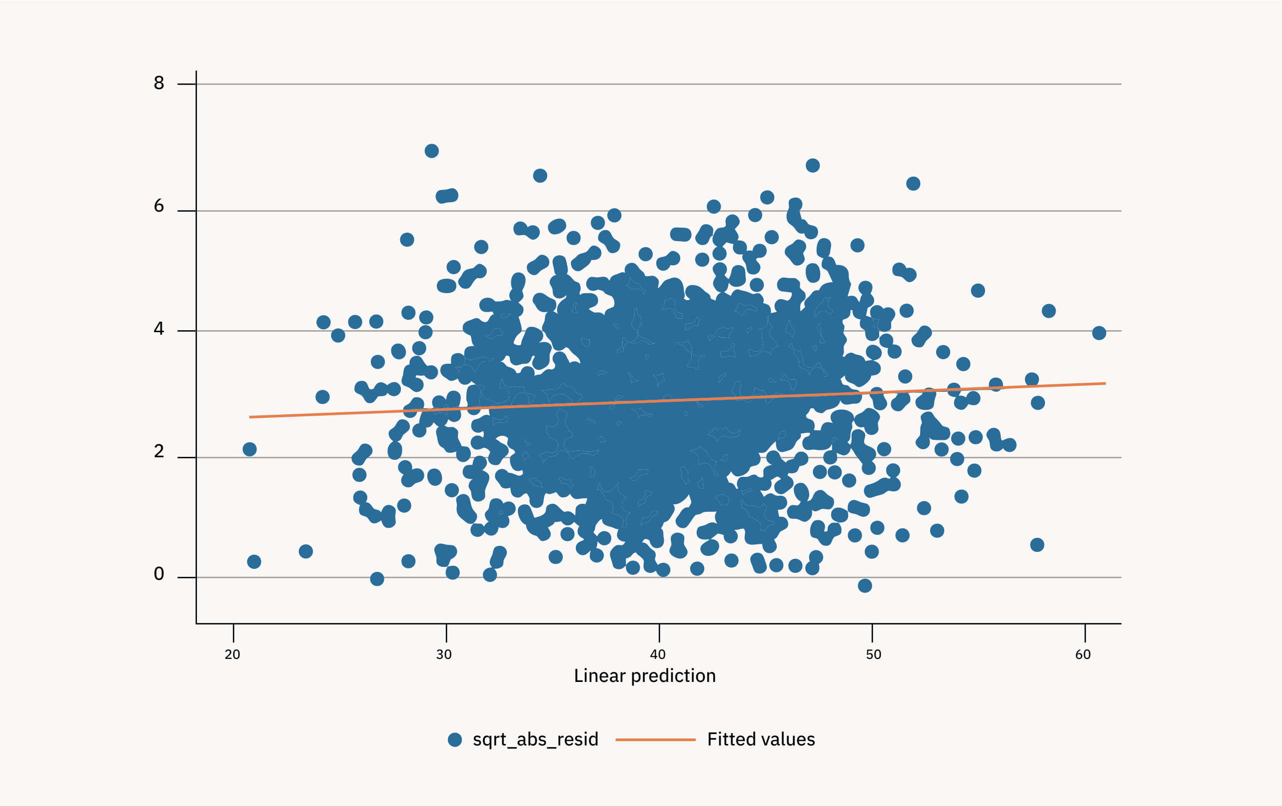
Source: Own calculations using Thrive by Five Index 2024 data.

Figure A2: Residuals vs fitted values from OLS regression



Source: Own calculations using Thrive by Five Index 2024 data.

Figure A3: Scale-location plot of standardised residuals



Source: Own calculations using Thrive by Five Index 2024 data.

www.ilifalabantwana.co.za
info@ilifalabantwana.co.za
Ilifa Labantwana
@ilifalabantwana9729
Cape Town, South Africa