The Role of Early Life Conditions on the Development of Children's Adaptive Behavior Skills

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Abstract

This paper examines how early-life factors, including perinatal and neonatal conditions, shape children's communicative, physical, and socio-emotional skills by age three in the United Kingdom. These three domains are measured by adaptive behaviour scales, widely used in the UK to assess early developmental delays and support clinical diagnosis. Using data on 4,335 children from the Understanding Society: Pregnancy and Early Childhood (PEACH) dataset between 2011 and 2023, we study how infant health at birth and breastfeeding are associated with the development of adaptive behavior skills at age 3. We rely on selection on observables models, including rich-controlled OLS, propensity score matching, and correlated random-effects models, drawing on detailed child, maternal, and household covariates measured from birth through age three. We find that poorer perinatal health is associated with slower physical development, whereas breastfeeding is linked to enhanced communication and socio-emotional development. Heterogeneity analyses indicate more pronounced perinatal-health effects for boys and non-firstborn children. We further implement a parametric mediation analysis and show that maternal engagement explains around 15% of the total benefits of breastfeeding for adaptive behavior, but does not positively mediate the relationship between adverse perinatal health and skill development. Our findings underscore the importance of public health policies that target support for children born in poorer perinatal health, helping to reduce early-life inequalities and promote more equitable child development.

Keywords: child adaptive behavior, breastfeeding, perinatal health, mediation analysis
JEL Codes: I12, I14, I18, J13, J16, J24

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1. INTRODUCTION

Early childhood is a sensitive developmental period for the formation of cognitive, socio-emotional, and motor skills that underpin later educational achievement, labour-market success, and health (Currie and Stabile 2006). Children's early skill development can be captured using adaptive behaviour scales, which measure the everyday communication, physical, and social competencies that enable children to function in their environments. Deficits in adaptive behaviour are strong predictors of early developmental delay and form a core component of clinical assessments of developmental disabilities in the United Kingdom (Furnier et al. 2024). While economic research has identified a range of early-life determinants of child development, typically defined using clinical diagnoses or educational test scores (Heckman and Mosso 2014), evidence remains limited on whether early-life conditions shape broader, functionally grounded measures of early skills. This study examines how perinatal health and breastfeeding are associated with children's communication, physical, and socio-emotional skills by age three, and investigates the role of maternal engagement underlying these relationships, thereby contributing to our understanding of early skill formation.

Severe neurodevelopmental conditions, such as autism spectrum disorder and intellectual disability, are often viewed as the lower tail of a continuum of developmental functioning and affect around 15% of children and adolescents worldwide (Thapar et al. 2017; Dietrich et al. 2005). In the United States, the share of children aged 3–17 diagnosed with developmental disabilities rose from 7.40% to 8.56% between 2019 and 2021 (boys: 10.76%; Black children: 9.07%; ages 3–7: 8.42%) (Zablotsky et al. 2019), while in the United Kingdom around 3–4% of children are affected by neurodevelopmental disorders and autism prevalence is among the highest globally at 700.07 cases per 100,000 children (Zeidan et al. 2022).[1] These figures capture only the diagnosed tip of the iceberg: many children with meaningful developmental difficulties never receive a formal diagnosis but nonetheless experience limitations in everyday functioning (Centers for Disease Control and Prevention 2025). While prior studies link early-life conditions to child development, evidence remains limited on how perinatal

[1] See Figure A1.1 in Appendix A1 for the global prevalence of autism in children (per 100k) by country in 2019.

and neonatal factors shape early skills using broader measures of development, and on the extent of heterogeneity in these effects across children.

Awareness of the value of early identification has increased among clinicians and parents (Rabba et al. 2019; Okoye et al. 2023), alongside the widespread adoption of screening tools such as adaptive behaviour scales, now routinely used in UK assessments of intellectual and developmental disabilities (Tassé and Kim 2023). Advances in neonatal care have increased survival among infants with adverse perinatal outcomes such as low birth weight and preterm birth (Mercurio and Drago 2022; Silva et al. 2023), with potential long-run developmental consequences shaped by both biology and early environments (Faraone et al. 2024). These risks unfold amid persistent socioeconomic inequalities (Spencer et al. 2022; Potijk et al. 2013), shifting parenting practices (Modesto-Lowe et al. 2008), and declining breastfeeding (Fitzsimons and Vera-Hernández 2022). The medical literature points to nutritional and mother–child bonding pathways through which breastfeeding may shape child development (Colaizy et al. 2024), yet most studies of perinatal and neonatal factors do not use robust methods to address selection bias and endogeneity.

In this paper, we use data from the UK Household Longitudinal Study, which gathers information on children's development through an adaptive behavior scale consisting of 20 items across three key areas: communication, physical, and social-emotional skills (see Table A3.1 in Appendix A3). This dataset contains rich information on child, maternal and household characteristics throughout the child's first years of life (ages 0–3). Our analytical sample includes 4,335 children with information on adaptive behavior at age three, observed between January 2011 and May 2023. To study the relationship between early-life factors and adaptive behavior, we rely on three complementary empirical approaches: ordinary least squares with rich controls, propensity score matching, and correlated random-effects (Mundlak-type) models. All three strategies are based on a selection-on-observables assumption: conditional on the observed child, maternal and household characteristics, differences in early-life conditions are assumed to be independent of unobserved determinants of adaptive behavior. The correlated random-effects specification additionally allows us to include time-invariant covariates in a framework that models the correlation between these covariates and the child-specific unobserved effect.[2] These methods allow us to assess how sensitive the estimated associations are to different ways of accounting for observed and (partly) unobserved family characteristics.[3] Across our three main approaches, we find that breastfeeding is positively associated with higher adaptive behavior scores at age three compared with children who are not breastfed. We also find that worse perinatal health is associated with slower developmental skills. Our results also highlight distinct patterns across developmental domains. Poorer perinatal health is more strongly related to lower scores in physical skills, whereas breastfeeding is more strongly related to higher scores in communication and social-emotional development.

We further assess heterogeneity by sex, ethnicity, household income, and maternal mental health, and find limited evidence of differential associations across these dimensions, with statistically significant differences concentrated among girls and first-born children. To investigate mechanisms, we implement a parametric causal mediation analysis following Imai et al. (2010), using maternal engagement in early childhood as the key mediator. This framework decomposes the overall association between each early-life exposure (perinatal health and breastfeeding) and adaptive behaviour at age three into an indirect component operating through maternal engagement and a residual direct component capturing pathways not mediated by engagement. The mediation results indicate that maternal engagement accounts for around 15% of the breastfeeding–adaptive behavior association, consistent with a bonding/interaction channel, but provides no evidence of positive mediation of the perinatal-health gradient in adaptive behavior.

This paper makes three key contributions to the literature on early-life conditions and child development, each relating to a different strand of literature. First, we introduce a rich, clinically grounded measure of early developmental skills into the economics literature on early-life human capital (e.g. Currie and Stabile 2006). In contrast to most existing economic studies, which typically rely on teacher-reported behavior indices or diagnosed neurodevelopmental conditions, our outcome captures multiple domains of everyday functioning that are a more broadly measured of develop-

[2] Yet, it does not in itself identify a causal effect of time-invariant variables such as breastfeeding status if unobserved preferences or behaviors remain correlated with both exposure and outcome.

[3] We also estimate within-sibling fixed-effects models and an instrumental-variables specification, reported in Appendix B2 and B3. Yet, the sibling fixed-effects estimates are imprecise because of limited within-family variation, while the instrumental-variables estimates are severely underpowered due to a weak first stage.

mental delays. To our knowledge, this is the first study to exploit these adaptive behavior scales to examine the relationship between perinatal and neonatal factors and early skills development.

Second, we contribute to the empirical literature on early-life conditions and later outcomes (e.g. Currie and Stabile 2006; Rothstein 2013) by exploiting the unusually rich longitudinal information in PEACH to implement a selection-on-observables research design with extensive confounder adjustment. Specifically, we estimate three models: rich-controlled OLS, propensity score matching, and correlated random-effects models. We then go beyond documenting reduced-form associations by embedding these results in a mediation framework to explore mechanisms, quantifying the extent to which maternal engagement explains the breastfeeding–adaptive behaviour gradient and assessing whether it also accounts for the perinatal-health penalty in early skill development.

Third, we contribute to the literature on socioeconomic inequalities in child development by estimating heterogeneity in the associations between early-life conditions and adaptive behaviour across subgroups defined by child sex, ethnicity, and socioeconomic status. The results show that important distributional patterns are masked by aggregate estimates: the developmental penalties associated with adverse perinatal health and the advantages associated with breastfeeding are concentrated among boys and non-first-born children.

2. BACKGROUND

2.1. *Related Literature*

In the first years of life, developmental delays often manifest gradually as children fall behind age-appropriate milestones. Early developmental difficulties often present in infancy as subtle lags in attention, social engagement, and early communication, indicating slower acquisition of age-appropriate cognitive and socio-emotional skills. Human capital theory characterises early socio-emotional development as a sequence from basic responsivity in the neonatal period to increasingly coordinated caregiver interaction and emerging self-regulation across the first three years (Saarni et al. 2007;

Rochat 2014).[4] Over roughly the first two years, infants become increasingly capable of understanding their own emotions and those of others, engaging in purposeful communication, and sharing intentionally with caregivers and peers (Rochat 2014). By the age of three, diagnoses of neurodevelopmental disabilities are generally considered to be relatively stable and are routinely based on instruments such as adaptive behavior scales (Webb and Jones 2009).

The medical literature has examined several pathways through which early-life conditions may influence children's development. A number of studies document that children born with low birth weight (Lampi et al. 2012; Isaksson et al. 2023; Kim et al. 2024) or prematurely (Franz et al. 2018) are at higher risk of developmental delays. Other studies explore the association between breastfeeding and the risk of neurodevelopmental conditions, with some studies suggesting that breastfeeding reduces this risk (Khushaym et al. 2024), while others report no significant association between infant feeding practices and autism spectrum disorder (Zhan et al. 2023). Among preterm infants, maternal milk feeding during birth hospitalisation has been associated with better neurodevelopmental outcomes than formula (Vohr et al. 2007). However, a recent clinical trial by Colaizy et al. (2024) finds no differences in neurodevelopmental outcomes at 22 to 26 months between infants fed donor milk and those fed preterm formula. Overall, this literature highlights important links between perinatal and neonatal factors and later neurodevelopmental outcomes, but studies often focus on specific diagnostic categories or narrow cognitive measures, and many do not fully address potential biases arising from unobserved maternal characteristics, family background, or selection into early-life conditions and investments.

The economics literature shows the importance of the early years of life for later outcomes, emphasising the cumulative and dynamic nature of human capital formation (Gertler et al. 2014; Heckman and Mosso 2014; Currie and Almond 2011; Walker et al. 2011; Cunha and Heckman 2007; Cunha et al. 2010; Attanasio et al. 2022). A number of studies have examined how breastfeeding relates to children's cognitive development (Todd and Wolpin 2007). Four main empirical strategies have

[4] Phase 1 (prenatal to 6 weeks) involves rudimentary but balanced reactions to emotional signals; Phase 2 (6 weeks to 9 months) is characterised by pre-referential communication, with infants engaging in synchronous interactions with caregivers; Phase 3 (9 to 18 months) sees the emergence of referential emotional communication and behavioural regulation, where others' emotions begin to shape a child's expressive behavior; and Phase 4 (18 months to 3 years) marks the development of self-conscious emotions such as shame, guilt, and pride.

been used in this work. First, several papers employ instrumental variables to address endogeneity in breastfeeding, using, for example, mode of delivery (caesarean vs. vaginal birth) (Denny and Doyle 2010) or hospital-level breastfeeding promotion programmes (Del Bono and Rabe 2011). Second, a number of studies rely on selection-on-observables assumptions and use propensity score matching to compare breastfed and non-breastfed children with similar observed characteristics (Belfield and Kelly 2012; Iacovou and Sevilla-Sanz 2010; Jiang et al. 2011). With a few exceptions, least squares, propensity score matching, and instrumental variables estimates tend to point to positive associations between breastfeeding and children's cognitive test scores (Neidell 2000; Belfield and Kelly 2012; Del Bono and Rabe 2011; Denny and Doyle 2010; Gibson-Davis and Brooks-Gunn 2006; Iacovou and Sevilla-Sanz 2010; Jiang et al. 2011). Third, several studies exploit mother fixed effects in sibling samples to control for unobserved time-invariant family characteristics (Belfield and Kelly 2012; Der et al. 2006; Evenhouse and Reilly 2005; Neidell 2000); within-sibling analyses often find attenuated or null effects of breastfeeding on cognitive outcomes (Belfield and Kelly 2012; Der et al. 2006; Neidell 2000). Fourth, and most commonly, researchers estimate ordinary least squares models that include a rich set of potentially confounding variables in child test score equations (Gibson-Davis and Brooks-Gunn 2006). Yet, this literature has largely treated breastfeeding as the primary early-life factor, with comparatively limited evidence on the role of perinatal and neonatal conditions and their interaction with postnatal investments in shaping early skill formation.

Our study fits into this broader literature on early-life conditions and children's development, but departs from most existing work in two key respects. First, we focus on a multi-dimensional, clinically grounded index of adaptive behavior at age three, rather than on later cognitive test scores or diagnosed neurodevelopmental disorders. Second, we examine how perinatal and neonatal factors and breastfeeding are related to adaptive behavior in a large, population-representative sample, while drawing on the methodological insights from the economics literature to assess the robustness of the observed associations.

2.2. *The Use of Adaptive Behavior Scales in the English NHS*

In NHS England, a range of standardised instruments is employed to assess children's skills development, particularly in the context of diagnosing intellectual and developmental disabilities (NHS England 2015). These tools measure an individual's ability to perform everyday tasks and function independently in different contexts. Commonly used assessments include the Vineland Adaptive Behavior Scales, Third Edition (Vineland-3); the Adaptive Behavior Assessment System (ABAS-3); and the Bayley Scales of Infant and Toddler Development (Bayley-III) (Hong and Matson 2019). Importantly, adaptive behavior scales are also available in longitudinal studies such as Understanding Society to proxy early human capital (Furnier et al. 2024). Adaptive behavior scales have several functions in the diagnostic process (Pilling et al. 2012). First, they are central to confirming deficits in skills development, which is a key criterion in the diagnosis of neurodevelopmental impairments. Second, they inform the development of personalised care plans and interventions based on specific areas of functional difficulty. Third, they allow for the longitudinal monitoring of adaptive development, which supports evaluating intervention efficacy over time. In this paper, we use the adaptive behaviour scale available in PEACH, a 20-item measure of children's communication, physical/motor, and socio-emotional skills that is closely comparable to the Vineland-3.

3. DATA

We use a unique dataset known as the Pregnancy and Early Childhood data from Understanding Society, the UK Household Longitudinal Study (Benzeval et al. 2023).[5] Understanding Society is among the largest and most detailed longitudinal household panel surveys globally, and it has been operating since 2009. It gathers annual data from individuals and households throughout the UK, encompassing various social, economic, and behavioural factors. The survey tracks core sample members over time, documenting their life circumstances and outcomes, as well as those of their family members, which provides an exceptional opportunity to study the dynamic processes within families. The PEACH dataset is a specialised component of UKHLS, aimed at supporting research on pregnancy, early childhood, and family environments. It offers age-specific, time-constant data,

[5] More details about the PEACH database and its available variables are in Appendix A, Table A1.

such as birth weight, developmental benchmarks, health conditions, and parenting practices for all children reported in the households.

In UKHLS, parents or guardians are asked to answer a set of questions about each child under 10 living in their home, with questions tailored to the child's age. Notably, adaptive behavior questions are gathered once children reach age 3. These questions were first introduced in wave 3 of UKHLS and compiled in the PEACH dataset. A key aspect of this dataset is that all children in a household are Understanding Society participants, allowing for comparing child development measures among siblings at similar stages of development within the family context. In this study, we have pooled data from waves 3 to 13 (January 2011 – May 2023). The availability of comprehensive perinatal information and detailed adaptive behavior scores information defines our sample.

The analysis benefits from highly granular child-level information, including the day and month of birth, accessed through a secure data environment. We have extensive maternal and paternal information, as well as household characteristics, encompassing employment history, household monthly net income, and marital status from birth until the collection of the adaptive behavior measure. Moreover, we capture detailed health information, tracking child health conditions at age 3, alongside parental mental health status and maternal quality time spent with the kid. This is further complemented by healthcare utilisation data, including the mother's GP visits in the past 12 months, which enables an in-depth analysis of early-life factors that influence child developmental outcomes. The final sample consists of 4,335 children from 3,262 families, with 39.1% having at least one sibling for whom adaptive behavior measures were also collected in the study. These children were born between February 2007 and October 2020.

3.1. *Measures of communication, physical and social-emotional development*

Communication, physical and social-emotional development in children is measured using adaptive behavior scales (Caselman and Self 2008). These instruments capture the practical, social, and conceptual skills that children use to function in daily life. These skills include conceptual competencies, such as literacy, numeracy, and time management; social skills, including interpersonal relationships, social responsibility, and effective problem-solving; as well as practical abilities pertinent to daily living activities, such as personal care, safety, and mobility (Tassé and Kim 2023). Unlike cognitive ability tests (e.g. maths or language tests), adaptive behavior represents the capacity to apply acquired skills in real-world contexts, providing a more comprehensive evaluation of an individual's functional competence in everyday life (Sparrow 2011).

In this study, a subset of 20 questions, drawn from broader assessment instruments developed to appraise adaptive behavior, was used - refer to Table A1.1 in Appendix A1. These questions are administered annually to parents or responsible adults of children aged three years, focusing on essential aspects of early adaptive functioning, including communication, daily living skills, socialisation, and developmental competencies. By addressing these three pivotal areas, we can evaluate early indicators of adaptive behavior difficulties. Parents rated each question on a 3-point Likert-type scale. We computed a composite adaptive behavior score by summing the scores of individual items. We reverse-scored and rescaled the item values, resulting in a final index ranging from 0 to 40, where higher scores signify higher adaptive behavior skills. Figure 1 illustrates a map displaying the average adaptive behavior scale for age 3 (2011-2023) across government office regions in the United Kingdom. A standardised version of the adaptive behavior scale is used in our analysis.[6]

[Insert Figure 1 around here]

3.2. *Measures of early life conditions and child's circumstances*

To analyse early life conditions, we focus on perinatal and neonatal factors. A key neonatal factor is breastfeeding, which is collected when babies are first reported as newborns in Understanding Society. Biological mothers are asked whether they breastfed the child, even if only for a short time, with response options *yes*, *no*, or *currently breastfeeding*. If the mother reports that the child is still being breastfed, a follow-up question in the next annual interview asks whether breastfeeding is still ongoing. Whenever the mother indicates that breastfeeding has stopped, she is then asked the age of the child when breastfeeding was discontinued, allowing the construction of breastfeeding duration.

[6] We adjust the scores to achieve a mean of zero and a standard deviation of one (refer to the online data appendix for further details). The scores are normalised based on nationally representative samples; therefore, we refrain from standardising the scores within our subsamples. Consequently, the means and standard deviations in the dataset will not precisely equal zero and one. However, we interpret the results following the national sample norms of a standard deviation of one.

For the purposes of this analysis, however, we focus on a binary indicator equal to 1 if the child was ever breastfed and 0 otherwise. We deliberately abstract from duration to avoid substantial loss of sample size, as complete breastfeeding histories are only available for a subset of children due to non-response.

Birth weight is collected in either kilograms or pounds and ounces, and the survey provides a harmonised measure in kilograms. For mothers who are unsure of the exact birth weight, a follow-up question asks whether the child weighed more than 5.5 lbs/2.5 kg. Using this information, we construct an indicator for low birth weight equal to 1 if the child weighed less than or equal to 2.5 kg at birth and 0 otherwise, following the standard clinical definition. Mothers are also asked whether the child was born within one week of the expected due date (*yes*, *no*, *do not know*). If the answer is *no*, they are asked whether the child was born early or late and by how many weeks. These questions allow us to derive gestational age and to construct an indicator for preterm birth, defined as birth before 37 completed weeks of gestation. Breastfeeding, low birth weight, and preterm birth constitute our main early-life variables of interest.

Rich set of covariates at child's, mother's and household level.—We include a rich set of explanatory variables to account for potential confounding factors. First, we include fixed effects for region at birth and survey year to capture geographic and temporal variation. We further control for child-level characteristics, including gender and an indicator for being the firstborn child, to account for potential birth-order effects. Birth order is derived using information on adult respondents' fertility histories: we compare the recorded birth date of the respondent's first child with the focal child's date of birth and code a dummy equal to 1 if the focal child is the firstborn.

Maternal characteristics are also central to our specification. At their first interview, adult sample members report their ethnic group, categorised (among others) as White British, Mixed, Asian, Black, or Other. As expected, most mothers in our sample identify as White British. Given the relatively small number of observations in other categories, we create a binary indicator equal to 1 if the mother identifies as White British and 0 otherwise. We additionally control for maternal age at childbirth and maternal educational attainment. Education is coded as a binary variable equal to 1 for mothers with a degree or higher qualification and 0 for mothers with no formal qualifications, GCSEs, or A-levels. Marital status is coded as 1 if the mother is married or cohabiting and 0 otherwise, and employment status is coded as 1 if the mother is employed and 0 if not. We also capture maternal psychological well-being. We use the short version of the General Health Questionnaire (GHQ-12), a widely used, validated self-reported measure of psychological distress. The GHQ-12 consists of 12 items covering concentration, decision-making, coping with everyday life, and other aspects of mental health, each recorded on a four-point scale ranging from *much more than usual* to *not at all*. Following standard practice, we recode responses so that categories indicating no or minimal distress are scored 0 and those indicating greater distress are scored 1, yielding a total score from 0 to 12. We then dichotomise this scale at the threshold of 4 to identify mothers at increased risk of psychological distress.

Household characteristics capture the broader socioeconomic context in which the child is raised. We use an urban–rural indicator coded as 1 if the address falls within an urban settlement with a population of 10,000 or more and 0 otherwise. Household income is measured using total equivalised net household income as a continuous measure. We apply the OECD equivalence scale to account for differences in needs across households of varying size and composition, and then define an indicator for low-income households equal to 1 if the equivalised income falls below 60% of the median income, a commonly used threshold for relative poverty. We also control for household size, measured as the total number of individuals living in the household. These child, maternal and household characteristics are also used in our heterogeneity analysis to examine how the associations between early-life conditions and adaptive behavior vary across socioeconomic and demographic groups.

Mediation analysis: maternal engagement with the child.—For the mediation analysis, we construct an index capturing maternal engagement in quality time with the child, using information from the "Parents and Children" module collected in waves 1, 3, 5, 7, 9, 11, and 13. For mothers with data in multiple waves, we retain the observation from the wave closest in time to the wave in which the child's adaptive behavior is reported. The index summarises the frequency of various mother–child interactions, including shared meals, outings, conversations and disciplinary practices, and ranges from 0 to 27, with higher scores indicating more favourable patterns of maternal engagement. While this measure is not child-specific, it provides a meaningful proxy for the broader maternal environment in which the child is embedded. Details on the individual items used to construct this index are reported in Table A2.3 in the Appendix.

Sample weights.—PEACH provides weights for cross-sectional analysis across multiple waves, enabling researchers to examine children at a specific age without being constrained to data from a singular time point. This approach facilitates the amalgamation of information from various waves, as demonstrated in our study analysis. We are employing the weights provided in the PEACH dataset to ensure that our findings are representative through data aggregation across multiple waves.

4. EMPIRICAL APPROACHES

In this paper, we implement three complementary selection-on-observables estimators to account for confounding in the relationship between perinatal/neonatal conditions and children's adaptive behaviour. Our empirical strategy follows the approach in Rothstein (2013), which leverages rich longitudinal observational data and extensive covariate adjustment to study early-life conditions and child development. We begin with a baseline linear regression that controls for a detailed set of child, maternal, and household characteristics, specified as follows:

$$Y_i = \alpha + \mathbf{P}_i'\omega + \mathbf{X}_i'\phi + \lambda_s + \gamma_c + \delta_r + \varepsilon_i, \tag{1}$$

where Y_i is the outcome variable of child i (adaptive behavior score at age 3), P_i is a vector of early-life conditions (low birth weight, preterm birth, breastfeeding indicators), X_i^E is a vector of observed child, maternal, and household covariates measured from birth through age 3, λ_s is the survey years in which the outcome variables is collected; γ_c is year of birth fixed effects and δ_r regional dummies fixed effect, and e_i which includes unobserved characteristics relevant to the child's development. This linear model is estimated using Ordinary Least Squares (OLS), and the parameter ω measures the effect of perinatal/neonatal factors on a child's adaptive behavior at age 3. Although we rely on longitudinal information on mother and parents' characteristics from children's first three years of life, unobservable characteristics may still be driving the results.

As a second approach, we implement propensity score weighting to adjust for differences in observed characteristics between treated and untreated children. We first estimate propensity scores for each treatment using a rich set of child, maternal, and household covariates, and construct inverse probability weights. We then use these weights in a weighted least squares regression to estimate the average treatment effect on the treated (ATT). Reported standard errors are heteroskedasticity-robust and clustered at the mother level.

Our third empirical strategy is a Correlated Random Effects (CRE), which is specified and estimated by a pooled maximum-likelihood estimator (Wooldridge 2019). This statistical approach allows us to control for individual-level time-invariant unobserved heterogeneity in the absence of individual time-variant outcome variables. This is particularly useful in our setting because adaptive behaviour is observed at age three, while key predictors (early-life conditions and investments) and controls are measured over the first three years of life. The CRE approach allows correlations between X_{it} and e_i via the average over the sample period of all time-varying explanatory variables ($\bar{X}_l$). This is effectively equivalent to the approach proposed by Mundlak (1978) where the individual effect is specified as:

$$e_i = \varphi + \bar{X}_l \xi + c_l \tag{2}$$

where c_i is purely random error term with $c_i|\bar{X}_l \approx N(0, \sigma_c^2)$. A pooled Maximum Likelihood Estimation (MLE) is implemented to obtain average partial effects (APEs), which impose no restriction on the serial correlation of the idiosyncratic error. Plugging Equation (1) into Equation (2) leads to a CRE model. If the conditional distribution of e_i is correctly specified, unobserved heterogeneity is captured by time averages and random elements, and all parameters can be consistently estimated:

$$y_i^* = \omega P_i + \phi X_i^E + \omega \bar{X}_i + S_i + Y_i + R_i + c_i \tag{3}$$

In addition to the baseline effect, we also examine the heterogeneous effects of the outcomes. As outlined in Equation 1, we interact the main explanatory variables, early life conditions (preterm, low weight and breastfeeding) , with a subset of control variables. These include child's gender, mother's characteristics (e.g., race and ethnicity, education attachment) and socioeconomic status indicators (e.g., equivalenced household income).

For completeness, we also estimated two additional models to address remaining concerns about unobserved confounding: a sibling fixed-effects specification and an instrumental-variable specification. The sibling fixed-effects model, estimated on a much smaller sample with limited within-family variation in perinatal and neonatal conditions, yields very imprecise estimates with wide confidence intervals. The instrumental-variable approach based on timing of birth (Friday and weekend births, and their interactions with region) likewise suffers from a weak first stage, with instruments only weakly correlated with the early-life variables of interest. We therefore treat the sibling fixed-effects and instrumental-variable estimates as supplementary robustness checks, reported in the Appendix B2 and B3, and place primary weight on the OLS, propensity score matching, and CRE results.

4.1. *Validity of the empirical strategy*

Our empirical strategy combines complementary selection-on-observables estimators: (i) rich-controlled OLS, (ii) IPWRA, and (iii) CRE or Mundlak–Wooldridge. We use these approaches to assess sensitivity to modeling assumptions and to directly evaluate key threats to validity, particularly covariate balance and common support.

OLS with rich controls.—Our baseline OLS specifications relate adaptive behaviour at age 3 to early-life conditions, controlling for a comprehensive set of child, maternal, and household characteristics measured at age 3 (e.g., parental education and employment, household income and composition, maternal mental health, region, and cohort). Under conditional independence, the coefficient on each early-life indicator captures its association with adaptive behaviour net of observed differences in the child's environment at age 3. We assess the plausibility of this assumption in two ways. First, we estimate balance regressions that relate each age-3 covariate to the early-life indicators and summarise selection using standardised differences and goodness-of-fit measures. Second, we examine coefficient stability across increasingly saturated specifications and complement this with a data-driven covariate selection procedure that retains controls predictive of the treatment and or the outcome and materially relevant for the early-life coefficient. Because some age-3 covariates may lie on the causal pathway (e.g., household income or maternal mental health), we interpret the OLS estimates as controlled direct effects and therefore potentially conservative relative to total effects.

Matching strategy.—IPWRA complements OLS by reducing functional-form dependence and explicitly addressing overlap. The estimator combines a treatment model to construct inverse-probability weights with an outcome model for regression adjustment and is doubly robust: treatment effects are consistently estimated if either model is correctly specified, provided common support holds. We estimate propensity scores for each early-life condition using the same rich covariate set and reweight the sample to improve comparability between treated and control children. Diagnostics indicate substantial improvements in balance, with kernel-density plots showing close overlap in weighted covariate distributions and joint balance tests based on overidentification restrictions failing to reject post-weighting balance. We also verify adequate propensity-score overlap and show robustness to common-support restrictions, suggesting results are not driven by extreme weights. Under conditional independence and common support, IPWRA identifies causal ATT effects, with consistency guaranteed when either the propensity-score or outcome model is correctly specified. Appendix B1 reports the full set of balance and overlap diagnostics.

Mundlak–Wooldridge CRE.—To probe the role of time-invariant unobservables, we exploit the panel information from birth to age three and estimate a Mundlak–Wooldridge correlated random effects (CRE) model. Time-varying covariates (e.g., household income) enter both in levels and as child-specific averages over ages 0–3, so that coefficients on within-child deviations have a fixed-effects interpretation, while the averages absorb correlation between unobserved child effects and the covariates. We use this framework primarily as a diagnostic tool. First, joint tests on the time-averaged covariates assess whether conventional random effects would be inconsistent due to correlation with unobservables. Second, we compare CRE estimates with fixed-effects estimates for time-varying covariates and with OLS and IPWRA estimates for early-life conditions. The similarity of estimates across specifications once rich controls are included suggests that residual bias from time-invariant heterogeneity is likely limited, although it cannot be ruled out.

As in any selection-on-observables design, causal interpretation hinges on the assumption that the observed covariates adequately capture confounding relevant for both treatment assignment and outcomes. We therefore interpret the consistency of results across OLS, IPWRA (together with strong balance and overlap diagnostics in Appendix B1), and CRE-based checks as supporting the credibility of our findings.

5. RESULTS

5.1. *Descriptive Statistics*

Table 1 presents weighted descriptive statistics by population subgroups based on whether the child was breastfed, had low birth weight (<2.5 kg) or was born preterm (<37 weeks). Overall, 73.68% of children aged 3 years were breastfed, 7.72% were born with low weight and 6.09% were born prematurely. The adaptive behavior scores show that breastfed children outperform the overall sample average. In contrast, those born with low birth weight or prematurely show lower adaptive behavior scores compared to the average of the whole sample. The descriptive statistics also show differentials in pretreatment characteristics, favouring breastfed children. Mothers of breastfed children, on average, have higher years of education, spend more quality time with their kids, are older, and have higher household monthly net income than mothers of children with low birth weight or premature.

[Insert Table 1]

Figure 2 shows kernel density histograms of the adaptive behavior scale by subgroups of perinatal and neonatal factors, with similar results but compared to their counterparts. Appendix A1 provides additional descriptive insights into the key variables of interest, further illustrating the patterns observed in Table 1. Figure A1.2 presents the mean values of key variables for children born between 2007 and 2020, offering a broad overview of the sample characteristics. Figure A1.3 displays a kernel density histogram of the adaptive behavior scale at age 3 in both its standardised and non-standardised forms, highlighting the distribution of scores across the sample. Similarly, Figure A1.4 disaggregates this distribution by income quintiles, shedding light on socioeconomic disparities in early childhood development. Figure A1.5 presents a correlation plot between the adaptive behavior scale and household monthly net equivalised income, emphasising the positive association between socioeconomic status and child development outcomes. Figures A1.6 and A1.7 illustrate yearly and subgroup-specific trends in adaptive behavior scores, respectively, demonstrating stability and variation over time.[7]

5.2. *Early life conditions and child's adaptive behavior*

Table 2 shows the effects of early life conditions on the adaptive behaviour scale at age three by estimating Equation (1). The entries in columns 1 to 4 are ordinary least squares estimates with robust standard errors clustered at the mother level in parentheses. Column 1 does not include any control variables or fixed effects, column 2 adjusts for the region at birth and year of survey fixed effects, column 3 adds children's and maternal characteristics (education level, marital status, employment, ethnicity and age at birth), column 4 adds household measures (including household equivalised income and household size). Entries in column 5 are propensity score matching estimates (ATT).

Results from Table 2 show a negative correlation between low birth weight and preterm birth and children's adaptive behaviour at age 3, while a positive relationship is found for those children who are breastfed. The magnitude of the association is reduced when controlling for children, maternal and household characteristics. The attenuation of the estimates after adding controls implies that part of the observed effect is mediated through socioeconomic and family characteristics. Similar results are found using a propensity score matching strategy in column (5) in Table 2. This suggests that when we compare children with similar characteristics but differing in their perinatal health status or breastfeeding experience, those with worse perinatal health tend to exhibit lower adaptive behaviour

[7] Table D1.1 provides additional descriptive statistics without using sample weights.

scores at age 3, while those who were breastfed show higher scores. Considering the results shown in column (4), on average, low birth weight is associated with a 0.27 SD lower adaptive behaviour score, while premature children score 0.16 SD lower than their peers. In contrast, being breastfed increases, on average, their adaptive behaviour score by 0.09 SD compared to children who were not breastfed. The persistence of significant associations across specifications suggests a direct link between early life conditions and adaptive behaviour development.

[Insert Table 2]

Figure 3 presents estimates of the effects of early life conditions on three adaptive behaviour subgroups at age 3: communication skills, physical abilities, and socio-emotional development, using both OLS and PSM approaches.[8] The results highlight distinct patterns across these developmental domains. Worse perinatal health is primarily associated with slower development in physical abilities, suggesting that early health complications may have lasting effects on physical skills and coordination. In contrast, breastfeeding is positively linked to higher scores in communication and social-emotional development, indicating its potential developmental benefits. These findings remain consistent across estimation methods.

[Insert Figure 3]

Table 3 presents the results of the correlated random effects (CRE) estimations. The CRE-Mundlak approach accounts for the potential correlation between unobserved individual (or household) characteristics and the explanatory variables. Instead of assuming random effects are purely exogenous, the Mundlak adjustment includes the individual-level means of time-varying covariates as additional regressors, which helps control for unobserved heterogeneity that could bias the estimates. The CRE estimates largely align with previous findings, reinforcing the associations observed in prior models while accounting for time-invariant unobserved heterogeneity. This suggests that the relationships between perinatal health, breastfeeding, and adaptive behaviour remain consistent even after controlling for unobserved family-level characteristics.

[8] Tables XX, XX and XX in Appendix, shows the estimated coefficients of the effects of early life conditions by subgroups of adaptive behaviour scale at age 3 using OLS and IPWRA approaches.

[Insert Table 3]

5.3. *Heterogeneous Effects Across Child and Family Contexts*

Table 4 presents heterogeneous analyses examining the relationship between early life conditions and adaptive behaviour development across different population subgroups. The analysis explores variations by gender in rows (a-b), birth order (whether the child is the mother's firstborn) in row (c), maternal ethnicity (Non-white British) in row (d), and household location (urban vs rural) in row (e). Estimates are reported using three empirical methodologies: OLS (columns 1-4), propensity score matching (column 5), and correlated random effects (column 6). The heterogeneous analyses show differences in how early life conditions influence adaptive behaviour across subgroups of populations. Gender-based estimates suggest that the effects of breastfeeding and perinatal health factors may differ between boys and girls, with more pronounced effects for boys in terms of magnitude and statistical significance. Firstborn children can exhibit different adaptive behaviours, likely influenced by parental investment, experience, or differences in resource distribution (Lehmann et al. 2018). However, we do not find significant effects supporting this hypothesis as results are mostly not statistically significant, except for low birth weight. Moreover, maternal ethnicity does not seem to play an important role in this relationship, as children of non-white British mothers do not show systematically different adaptive behaviour scores. Lastly, children in rural areas do not experience worse developmental scores in the UK, suggesting similar trajectories for those in rural and urban areas, as shown in previous studies (Currie and Almond 2011).

[Insert Table 4]

5.4. *Mediation Effect Analysis*

Here, we want to understand the channels through which these associations between early life conditions and physical, communication, and cognitive skills emerged. Thus, a mediation analysis is conducted to examine the potential mechanisms underlying the treatment effects, following Imai et al. (2010). This approach goes beyond simply establishing whether early-life conditions influence adaptive behavior skills; it allows us to uncover how and why these effects occur by decomposing the total effect into direct and indirect pathways (Imai et al. 2010; Doyle 2024). Mediation analysis decomposes the total effect of an exposure on the outcome into an indirect component operating through an intermediate variable (the mediator) and a direct component capturing all remaining pathways, as illustrated in Appendix Figure C1 (Zhao et al. 2010). We focus on maternal engagement as the mediator because it captures early parental time investments and mother–child interaction, allowing us to quantify the extent to which the breastfeeding and child development operates through a bonding channel highlighted in the medical literature. In Appendix C, we describe a mediation model on how these direct and indirect effects are estimated.

Table 5 reports the results of the mediation effect analysis with maternal engagement (double-standardised index) as the mediator. Each panel summarises, for a given early-life condition, the average causal mediation effect (ACME, $\delta(t)$ in Equation (C.7)), the average direct effect (ADE, $\zeta(t)$ in Equation (C.8), Appendix C), the total effect (τ in Equation (C.9), Appendix C), and the proportion of the total effect that is mediated. Rounded brackets report robust standard errors and square brackets 95% confidence intervals. A mediation effect is statistically significant when the corresponding confidence interval does not include zero.

[Insert Table 5]

Panel A shows that maternal engagement at age 3 is positively associated with overall adaptive behavior and several of its domains. A one–standard deviation increase in the maternal engagement index is associated with an increase of 0.041 standard deviations in the overall adaptive behavior scale, 0.042 in physical ability, and 0.039 in socioemotional development, with a smaller and imprecisely estimated association for communication skills. Thus, maternal engagement is itself a meaningful correlate of children's adaptive skills.

Panels B and C examine whether maternal engagement mediates the detrimental effects of low birth weight and preterm birth, respectively. For both exposures, the estimated ACMEs are very small in magnitude and statistically indistinguishable from zero across all outcomes. For low birth weight, maternal engagement explains at most 4.9% of the total effect on socio-emotional development and less than 1% of the total effects on the other domains. Similarly, for preterm birth, the proportion of the total effect mediated never exceeds about 10%, and is below 5% for most outcomes. The harmful consequences of adverse birth conditions for adaptive behavior therefore appear to operate almost entirely through pathways other than maternal engagement at age 3, with the large negative total effects in Panels B and C being driven by the direct components.

By contrast, Panel D indicates that maternal engagement is an important mechanism through which breastfeeding benefits children's development. Breastfeeding is associated with higher maternal engagement, and the ACMEs for breastfeeding are positive and statistically significant for all outcomes. For the overall adaptive behavior scale, the estimated ACME is 0.015 (95% CI: 0.003, 0.027), while the total effect is 0.105 (95% CI: 0.021, 0.188), implying that maternal engagement mediates roughly 15% of the overall impact of breastfeeding on adaptive behavior at age 3. For communication skills, the ACME is 0.011 (95% CI: 0.001, 0.022) and accounts for about 11% of the total effect (0.101; 95% CI: 0.014, 0.188). For socio-emotional development, the ACME is 0.017 (95% CI: 0.004, 0.030) and explains approximately 15% of the total effect of breastfeeding (0.120; 95% CI: 0.035, 0.204). Although we also find a statistically significant indirect effect for physical ability, the corresponding total effect of breastfeeding on this outcome is imprecisely estimated, so we place less weight on the implied 35% share mediated.

5.5. *Robustness checks*

To assess the robustness of our findings and our empirical approach, we conducted a series of sensitivity analyses addressing potential concerns regarding measurement, omitted variables, sampling bias and model specification. Appendix D shows the results of all the sensitivity analyses performed in our study.

First, to examine sensitivity to sampling design and survey weights, we estimated weighted least squares (WLS) using cross-sectional survey weights that account for the complex sampling structure and differential non-response. Results in Table D1.2-D.1.3 are similar to those of Table 2 and Table 3, supporting the robustness of our main estimates. The similarity across weighted and unweighted specifications indicates that sampling design is unlikely to bias the main results. Fourth, a sample selection test was performed using the Mundlak fixed-effects approach to address potential biases arising from unobserved heterogeneity within families. These results can be found in Table D1.5, in which the estimates of the selection bias estimator ($\hat{s}$) are not statistically significant. This implies that selection on unobservables across siblings does not substantially bias our core estimates.

Second, to evaluate the role of paternal socioeconomic characteristics and potential omitted variable bias, we include additional controls for father's socioeconomic characteristics: age, education (A-level or above), married or living with a partner, employment status, and ethnicity (white-British). Table D1.4. presents similar results in terms of magnitude and statistical significance, although the sample size is reduced due to the inclusion of these control variables. Therefore, our main estimated equation does not include these control variables. The stability of coefficients suggests that our main estimates are nor substantially confounded by paternal characteristics.

Overall, these sensitivity checks reinforce the robustness of the main results. These results increase confidence that out findings are not driven by sample selection bias or omitted variable bias.

6. DISCUSSIONS AND CONCLUSION

This study quantifies the association between perinatal and neonatal conditions and children's adaptive behaviour at age three using the Understanding Society Pregnancy and Early Childhood data. Across complementary selection-on-observables estimators, breastfeeding is positively associated with adaptive behaviour, whereas adverse perinatal health is negatively associated with early skill development. We further investigate mechanisms using a mediation framework, showing that maternal engagement accounts for a non-trivial share of the breastfeeding association, but does not explain the perinatal-health penalty.

Across specifications, the estimated associations are highly stable. IPWRA estimates closely track rich-controlled OLS, and CRE estimates that absorb correlation between time-varying covariates and time-invariant unobservables deliver similar conclusions, supporting the credibility of the selection-on-observables design. By contrast, sibling fixed-effects estimates are imprecise and typically insignificant, consistent with limited within-family variation and attenuation from measurement error. The results also vary by domain: adverse perinatal health is most strongly related to poorer physical development, whereas breastfeeding is more strongly related to communication and socio-emotional skills, in line with human-capital models in which early endowments and parental investments jointly shape skill formation. Heterogeneity analyses indicate larger penalties and gains for boys, with comparatively limited differences by ethnicity or place of residence. Mechanism analyses reinforce these patterns. Maternal engagement does not account for the perinatal-health penalty, suggesting predominantly direct pathways, but it mediates a meaningful share of the breastfeeding association. Specifically, maternal engagement explains around 15% of the breastfeeding association with overall adaptive behaviour and socio-emotional development, and about 11% of the association with communication skills.

Despite the consistency of results across empirical approaches, several limitations merit consideration. First, breastfeeding is measured imperfectly: PEACH does not capture duration in detail or distinguish exclusive from partial breastfeeding, which may attenuate estimated associations. Second, our instrumental-variable exercises deliver weak and unstable estimates, indicating that the proposed instruments (date of birth and region) do not generate sufficiently strong exogenous variation for credible IV identification in this setting. While the richness of PEACH enables extensive adjustment for observed confounders and the use of multiple selection-on-observables estimators, causal interpretation still hinges on the assumption that the included covariates adequately proxy for unobserved determinants of both early-life conditions and child development. Finally, the mediation results should be interpreted cautiously: the causal mediation framework relies on strong identifying assumptions, including no unobserved confounding of the exposure–mediator and mediator–outcome relationships, which may be violated if latent traits jointly influence maternal engagement and child skills. Accordingly, our mediation estimates are best viewed as suggestive evidence on channels rather than definitive causal decomposition, and future work should refine identification and examine longer-run outcomes as additional data become available.

Our findings are consistent with household production models in which early endowments and parental investments jointly determine child skill formation, and they speak to the intergenerational transmission of disadvantage through early-life health and parenting environments. From a policy perspective, the results support a dual emphasis on improving prenatal and neonatal health and strengthening early parenting investments. Interventions that expand access to high-quality antenatal care and reduce adverse birth outcomes, alongside policies that remove barriers to breastfeeding and promote early parent–child interaction (for example through postnatal support services and parental leave arrangements), are likely to yield gains in early development. Targeting these resources toward families facing socioeconomic constraints may be especially effective in reducing early gaps in communication and socio-emotional skills and, in turn, longer-run inequalities in human capital.

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TABLES

Table 1. Descriptive Statistics by early life conditions – Weighted.

Variables	Whole sample	Breastfed	Low birth weight (<2.5 Kg)	Preterm birth (<37 weeks)
Adaptive Behavior measures				
Adaptive Behavior Scale [0–40]	35.769	35.973	34.083	34.324
	(5.011)	(4.578)	(6.938)	(6.789)
Communication Skills score [0–12]	11.464	11.574	11.065	11.191
	(1.513)	(1.318)	(2.228)	(2.108)
Physical Ability score [0–18]	15.144	15.178	14.212	14.257
	(2.839)	(2.734)	(3.598)	(3.627)
Socio-emotional Development score [0–10]	9.160	9.221	8.805	8.875
	(1.486)	(1.349)	(1.945)	(1.825)
Child characteristics				
Female	0.492	0.496	0.544	0.485
	(0.500)	(0.500)	(0.498)	(0.500)
Child is first born for mother	0.401	0.428	0.487	0.498
	(0.490)	(0.494)	(0.500)	(0.500)
Year of birth	2012.011	2012.037	2012.284	2012.286
	(3.187)	(3.213)	(3.527)	(3.377)
Maternal characteristics				
Age at birth	30.445	31.137	30.434	30.667
	(5.664)	(5.418)	(6.045)	(5.871)
Marital status: married or living with partner	0.805	0.851	0.795	0.818
	(0.396)	(0.355)	(0.403)	(0.386)
A-levels, degree or higher than a degree	0.692	0.768	0.616	0.659
	(0.461)	(0.421)	(0.487)	(0.474)
White British	0.822	0.791	0.670	0.798
	(0.381)	(0.405)	(0.470)	(0.402)
Employment status: paid employment (full time or part time)	0.529	0.573	0.433	0.485
	(0.499)	(0.494)	(0.496)	(0.500)
Risk of mental health problems (GHQ-12)$^{\pm}$	0.239	0.243	0.278	0.266
	(0.426)	(0.429)	(0.448)	(0.443)
Household characteristics				
Household size	4.093	4.069	4.225	4.206
	(1.147)	(1.058)	(1.218)	(1.213)
Tenure: owned outright or own mortgage	0.545	0.621	0.437	0.532
	(0.497)	(0.484)	(0.496)	(0.499)
Above 60% of median income	0.827	0.868	0.790	0.852
	(0.377)	(0.338)	(0.407)	(0.355)
Urban	0.795	0.781	0.827	0.767
	(0.403)	(0.413)	(0.378)	(0.423)
Observations	4,335	3,193	329	263

Notes: This table reports weighted means of children's adaptive behaviour outcomes (age 3) and selected child, maternal, and household characteristics for the full sample and by early-life condition (breastfed, low birth weight <2.5kg, preterm birth <37 weeks). Standard deviations are reported in parentheses; for indicator variables, means can be interpreted as proportions. All statistics use PEACH sample weights to account for the survey design and differential non-response/attrition. Observations are unweighted counts. Maternal mental health risk is measured using the GHQ-12 indicator, defined as $^{\pm}$GHQ-12 ≥ 4.

Table 2. Early life conditions and adaptive behavior scale at age 3 – OLS and IPWRA estimates.

	Ordinary Least Squares (OLS)				IPWRA
Dep. Var → *Standarized Adaptive Behavior Scale*	(1)	(2)	(3)	(4)	(5)
(a) Low birth weight (<2.5 Kg)	-0.366***	-0.362***	-0.330***	-0.316***	-0.311***
	(0.109)	(0.106)	(0.102)	(0.103)	(0.107)
R-squared	0.009	0.032	0.075	0.079	
(b) Preterm birth (<37 weeks)	-0.299**	-0.279**	-0.248**	-0.238**	-0.235**
	(0.121)	(0.116)	(0.110)	(0.110)	(0.116)
R-squared	0.005	0.027	0.071	0.075	
(c) Breastfeeding	0.167***	0.186***	0.150***	0.138***	0.159***
	(0.049)	(0.049)	(0.049)	(0.050)	(0.061)
R-squared	0.006	0.029	0.071	0.075	
Control variables: children			✓	✓	✓
Control variables: maternal			✓	✓	✓
Control variables: household				✓	✓
Year of birth FE		✓	✓	✓	✓
Region of birth FE		✓	✓	✓	✓
Survey wave FE		✓	✓	✓	✓
Observations	4,335	4,335	4,335	4,335	4,335

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The Adaptive Behavior Scale is standardised (mean = 0, SD = 1), with higher scores indicating better adaptive behavior skills. Columns 1–4 report ordinary least squares estimates with robust standard errors clustered at the mother level in parentheses. Column 1 includes no control variables or fixed effects. Column 2 adjusts for year of birth, region of birth and survey wave fixed effects. Column 3 further controls for child characteristics (gender and first-born status) and maternal measures postbirth (education level, marital status, employment, ethnicity, age at birth, and risk of mental health problems). Column 4 additionally includes household characteristics (household size, urban residence, home ownership, and above-60%-of-median-income indicator). Column 5 presents IPWRA estimates (average treatment effect on the treated), with robust standard errors clustered at the mother level; propensity scores are estimated using an inverse probability weighting strategy based on all child, maternal and household characteristics. OLS and IPWRA estimates using sample weights.

Table 3. Early life conditions and adaptive behavior scale at age 3 - CRE estimates.

	Correlated Random Effects (CRE)			
Dep. Var → *Standarized Adaptive Behavior Scale*	(1)	(2)	(3)	(4)
(a) Low birth weight (<2.5 Kg)	-0.322***	-0.317***	-0.302***	-0.296***
	(0.106)	(0.102)	(0.102)	(0.100)
R-squared	0.035	0.057	0.083	0.086
(b) Preterm birth (<37 weeks)	-0.282**	-0.255**	-0.229**	-0.224**
	(0.115)	(0.111)	(0.109)	(0.107)
R-squared	0.032	0.054	0.080	0.083
(c) Breastfeeding	0.103**	0.114**	0.122**	0.122**
	(0.049)	(0.049)	(0.049)	(0.049)
R-squared	0.030	0.052	0.080	0.082
Control variables: children			✓	✓
Control variables: maternal			✓	✓
Control variables: household				✓
Mundlak FE	✓	✓	✓	✓
Year of birth FE		✓	✓	✓
Region of birth FE		✓	✓	✓
Survey wave FE		✓	✓	✓
Observations	4,335	4,335	4,335	4,335

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The Adaptive Behavior Scale is standardised (mean = 0, SD = 1), with higher scores indicating better adaptive behavior. Columns 1–4 report correlated random effects estimates (average treatment effects) with robust standard errors clustered at the mother level in parentheses. The CRE specification includes time-varying averages from birth to age 3 (Mundlak FE), such as household size, urban residence, home ownership, low-income household indicator, and maternal characteristics including education level, marital status, employment, ethnicity and risk of mental health problems. Column 1 includes only Mundlack fixed effects. Column 2 adds year of birth, region of birth and survey wave fixed effects. Column 3 additionally controls for child characteristics (gender and first-born status) and maternal characteristics. Column 4 further adds household characteristics (household size, urban residence, home ownership, and above 60% of median income indicator). All estimates use sample weights.

Table 4. Heterogenous analyses.

	Linear Model (OLS)				Correlated Random Effects
Dependent Variable → *Standarized Adaptive Behavior Scale*	(1)	(2)	(3)	(4)	(5)
a) Child sex (female = 1) interacted with...					
Low birth weight (< 2.5 Kg)	0.513**	0.530**	0.519**	0.533***	0.512**
	(0.221)	(0.211)	(0.205)	(0.206)	(0.201)
Pre-term birth (< 37 weeks)	-0.549***	0.524**	0.528**	0.540**	0.546**
	(0.209)	(0.227)	(0.220)	(0.221)	(0.217)
Breastfeeding	0.047	0.026	0.016	0.012	0.016
	(0.094)	(0.092)	(0.089)	(0.089)	(0.088)
b) First-born status (firstborn = 1) interacted with...					
Low birth weight (< 2.5 Kg)	0.418**	0.452**	0.395**	0.404**	0.380**
	(0.210)	(0.204)	(0.195)	(0.194)	(0.190)
Pre-term birth (< 37 weeks)	0.344	0.340	0.324	0.347	0.334
	(0.238)	(0.229)	(0.216)	(0.214)	(0.210)
Breastfeeding	0.045	0.053	0.064	0.085	0.073
	(0.102)	(0.097)	(0.092)	(0.091)	(0.090)
c) Maternal education (degree or higher qualifications = 1) interacted with...					
Low birth weight (< 2.5 Kg)	0.028	0.019	0.019	0.034	0.023
	(0.237)	(0.230)	(0.223)	(0.223)	(0.220)
Pre-term birth (< 37 weeks)	0.282	0.252	0.247	0.269	0.247
	(0.274)	(0.265)	(0.254)	(0.254)	(0.249)
Breastfeeding	-0.062	-0.021	-0.029	-0.027	-0.030
	(0.104)	(0.104)	(0.101)	(0.101)	(0.100)
d) Maternal ethnicity (white–British = 1) interacted with...					
Low birth weight (< 2.5 Kg)	0.002	-0.007	-0.035	-0.044	-0.045
	(0.218)	(0.211)	(0.207)	(0.207)	(0.205)
Pre-term birth (< 37 weeks)	-0.009	-0.032	-0.036	-0.045	-0.043
	(0.264)	(0.258)	(0.240)	(0.243)	(0.238)
Breastfeeding	0.038	0.099	0.069	0.075	0.056
	(0.147)	(0.146)	(0.147)	(0.149)	(0.149)
e) Maternal risk of mental health problems (high risk = 1) interacted with...					
Low birth weight (< 2.5 Kg)	-0.450	-0.439	-0.385	-0.386	-0.400
	(0.310)	(0.299)	(0.290)	(0.291)	(0.287)
Pre-term birth (< 37 weeks)	-0.449	-0.436	-0.394	-0.390	-0.413
	(0.368)	(0.360)	(0.347)	(0.348)	(0.340)
Breastfeeding	0.204	0.205	0.236*	0.244*	0.238*
	(0.142)	(0.139)	(0.136)	(0.136)	(0.134)
f) Equivalised net household income (above 60% of the median income = 1) interacted with...					
Low birth weight (< 2.5 Kg)	-0.250	-0.229	-0.247	-0.223	-0.217
	(0.243)	(0.245)	(0.244)	(0.246)	(0.247)
Pre-term birth (< 37 weeks)	-0.067	-0.051	-0.036	-0.018	0.028
	(0.314)	(0.316)	(0.303)	(0.305)	(0.301)
Breastfeeding	0.015	0.019	-0.015	-0.027	-0.022
	(0.124)	(0.122)	(0.120)	(0.120)	(0.121)
Control variables: children			✓	✓	✓
Control variables: maternal			✓	✓	✓
Control variables: household				✓	✓
Year of birth FE		✓	✓	✓	✓
Region of birth FE		✓	✓	✓	✓
Survey wave FE			✓	✓	✓
Observations	4,335	4,335	4,335	4,335	4,335

Notes: This table shows estimates for the interaction effects between early life conditions and population sub-group characteristics on adaptive behavior development. Standard errors clustered at mother level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

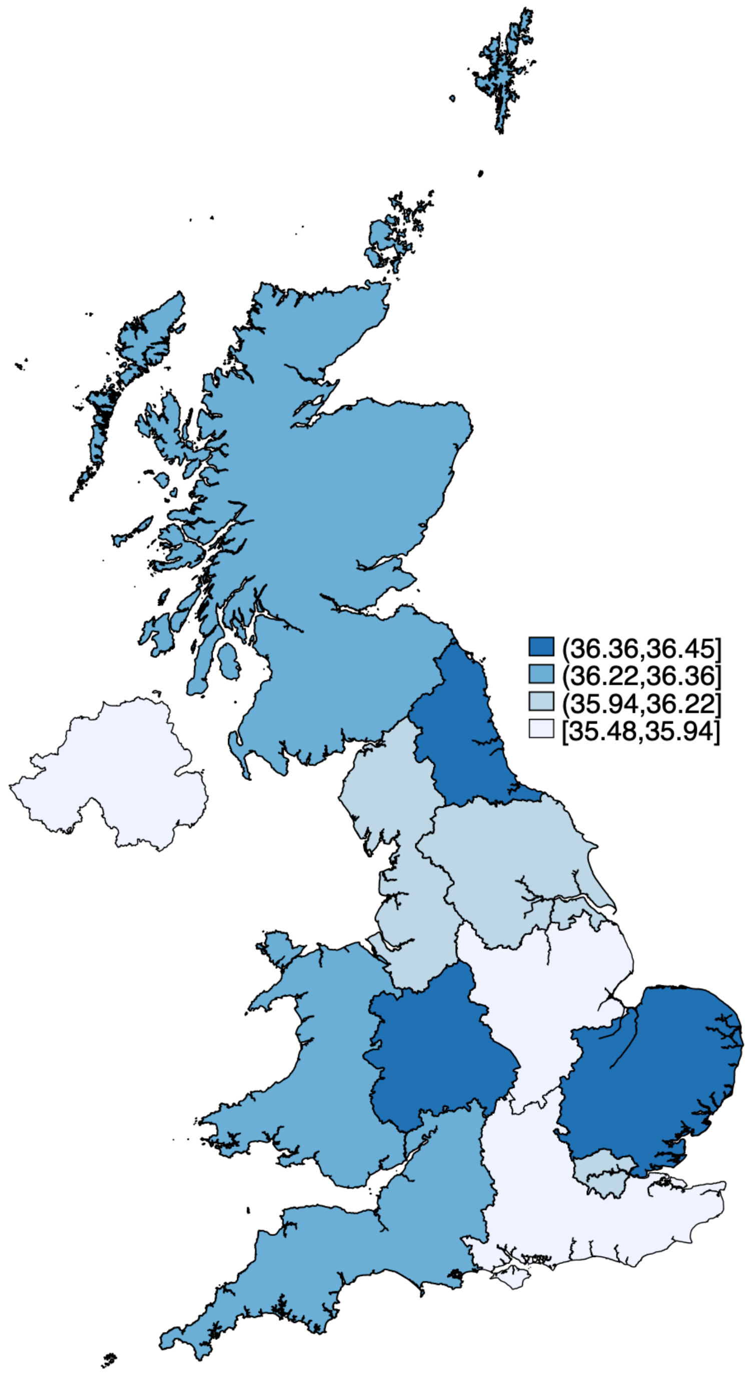
Table 5. Mediation effect analysis results for maternal engagement.

	(1)	(2)	(3)	(4)
Dependent Variable →	*Adaptive Behavior Scale*	*Communication skills*	*Physical ability*	*Socioemotional development*
Panel A: Mediator → Maternal engagement				
Mediator	0.041**	0.110	0.042**	0.039**
	(0.020)	(0.095)	(0.020)	(0.020)
Panel B: Treatment →Low birth weight (< 2.5 Kg)				
Treatment	-0.293***	-0.988*	-0.301***	-0.238**
	(0.103)	(0.509)	(0.098)	(0.094)
ACME	-0.001	0.001	-0.001	-0.010
	(0.009)	(0.007)	(0.008)	(0.011)
	[-0.018, 0.017]	[-0.014, 0.016]	[-0.016, 0.015]	[-0.032, 0.012]
Direct effect	-0.268***	-0.177**	-0.299***	-0.197***
	(0.078)	(0.081)	(0.079)	(0.071)
	[-0.422, -0.113]	[-0.336, -0.018]	[-0.454, -0.144]	[-0.338, -0.056]
Total effect	-0.269***	-0.175**	-0.300***	-0.207***
	(0.076)	(0.079)	(0.077)	(0.072)
	[-0.419, -0.118]	[-0.331, -0.020]	[-0.453, -0.148]	[-0.350, -0.064]
% of total effect mediated	0.3%	0.08%	0.2%	4.9%
Panel C: Treatment → Preterm birth (< 37 weeks)				
Treatment	-0.106	-0.114	-0.203*	-0.018
	(0.194)	(0.492)	(0.106)	(0.093)
ACME	-0.003	0.002	-0.002	-0.009
	(0.009)	(0.007)	(0.009)	(0.013)
	[-0.022, 0.014]	[-0.011, 0.015]	[-0.021, 0.016]	[-0.035, 0.016]
Direct effect	-0.142*	-0.044	-0.263***	-0.083
	(0.082)	(0.080)	(0.089)	(0.075)
	[-0.304, 0.019]	[-0.202, 0.113]	[-0.439, -0.087]	[-0.230, 0.063]
Total effect	-0.146*	-0.042	-0.266***	-0.093
	(0.081)	(0.077)	(0.089)	(0.075)
	[-0.305, 0.012]	[-0.195, 0.110]	[-0.440, -0.091]	[-0.241, 0.055]
% of total effect mediated	2.6%	4.8%	1.04%	10.23%
Panel D: Treatment → Breastfeeding				
Treatment	0.113**	0.552**	0.068	0.115**
	(0.052)	(0.251)	(0.049)	(0.051)
ACME	0.015***	0.011**	0.017***	0.017***
	(0.006)	(0.005)	(0.006)	(0.006)
	[0.003, 0.027]	[0.001, 0.022]	[0.004, 0.030]	[0.004, 0.030]
Direct effect	0.089**	0.090**	0.032	0.102**
	(0.043)	(0.045)	(0.041)	(0.043)
	[0.004, 0.174]	[0.001, 0.178]	[-0.049, 0.114]	[0.016, 0.188]
Total effect	0.105**	0.101**	0.050	0.120***
	(0.042)	(0.044)	(0.040)	(0.043)
	[0.021, 0.188]	[0.014, 0.188]	[-0.030, 0.130]	[0.035, 0.204]
% of total effect mediated	14.84%	11.31%	34.69%	14.92%
Observations	3,833	3,769	3,769	3,769

Note: Four standarized dependent variables: Adaptive behavior scale, and communication, physical and socioemotional scores. Panel A presents the results from Equation (12) with each potential channel that may explain the effect of the mediator on adaptive behavior skills. The potential channel is the maternal engagement index, double-standardised. The set of explanatory variables is identical to that in columns (4) and (5) in Table 2. This table presents the results of the mediation effect analysis from Equations (C.7) and (C.8) for the maternal engagement index. The data source is PEACH Understanding Society (2011–2023). Each panels summarise the average causal mediation effect (ACME), the average direct effect (ADE), the total effect, and the percentage of the total effect mediated for each early-life condition. All models are adjusted for attrition using sample weights. Rounded brackets show robust standard errors; square brackets show 95% confidence interval. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

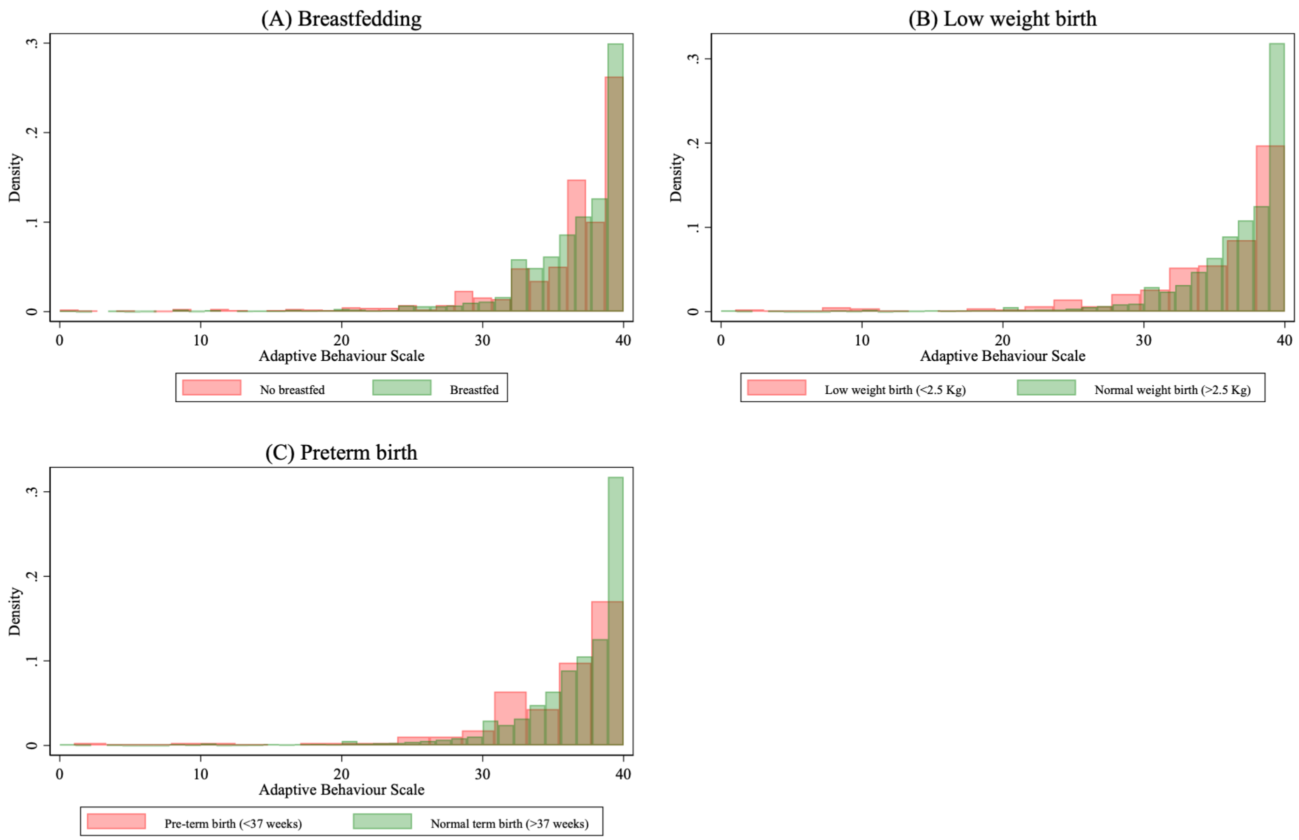
FIGURES

Figure 1. Average of Adaptive Behavior Scale at Age 3 by regions (2011-2023)



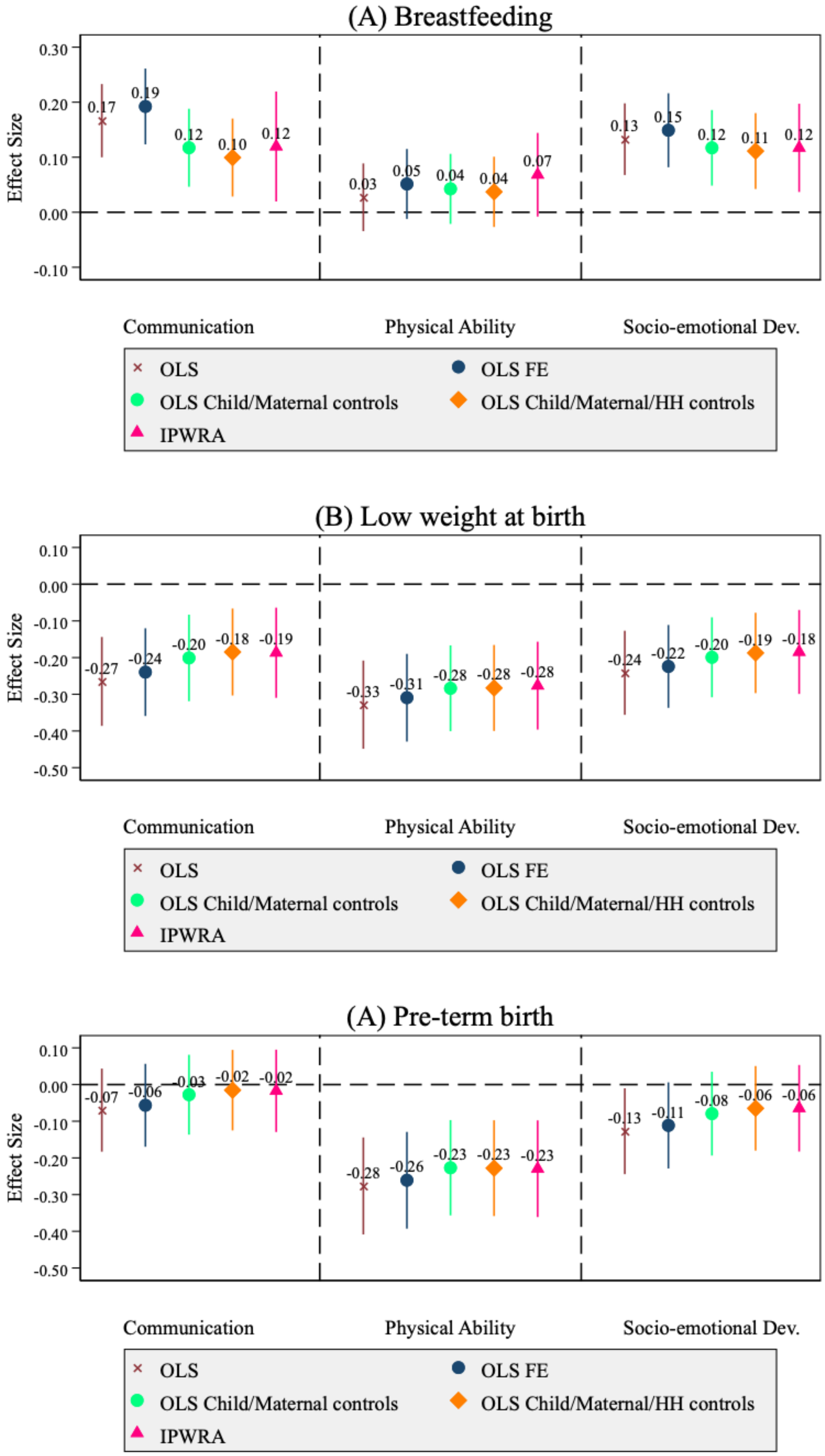
Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* Adaptive Behavior Scale: [f0-40] higher values represent better adaptive behavior. This figure shows the average of Adaptive Behavior Scale at Age 3 (2011-2023) by government office regions.

Figure 2. Kernel density histograms of adaptive behavior scale by subgroups



Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* This figure shows the kernel density histograms of adaptive behavior scale [f0-40] by subgroups of perinatal and neonatal factors between 2011-2023.

Figure 3. Estimates for the association between early life conditions and communication, physical ability and socio-emotional development at age 3

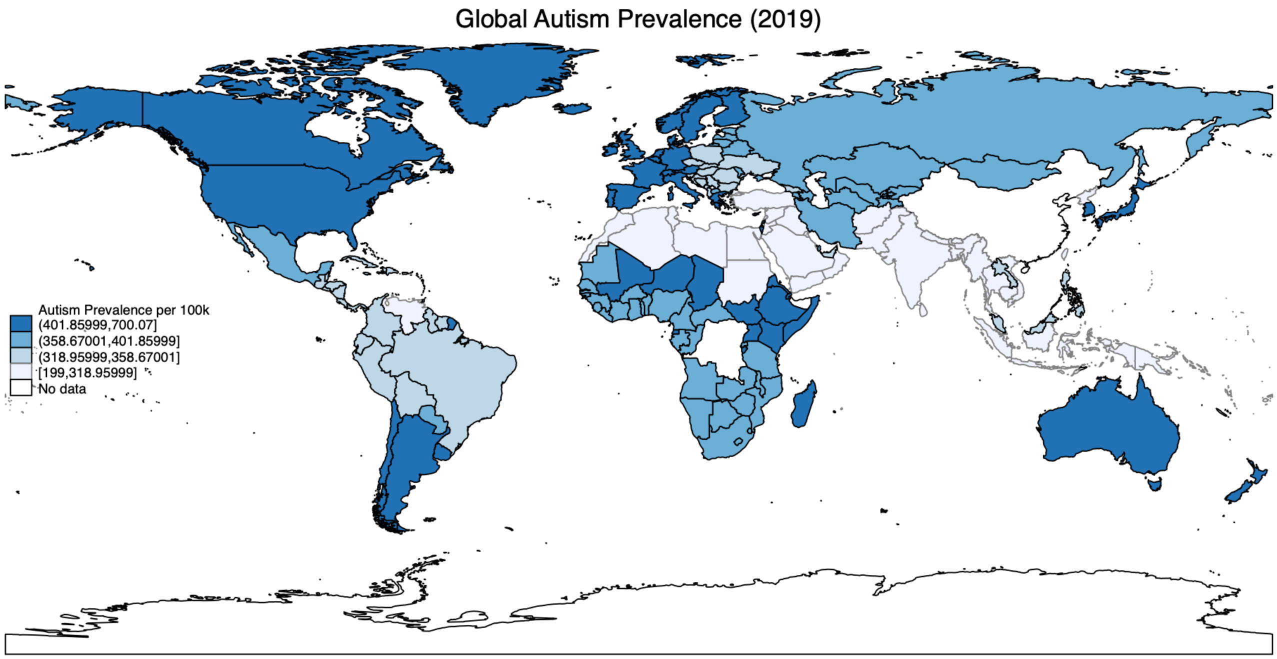


Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* Standardised outcome of variable capturing three subgroups of Adaptive Behavior Scale: Communication, physical ability, and socio-emotional development indexes. Three dummy variables of interest: a) low-weight at birth, b) preterm birth and c) breastfeeding. This figure plots estimates for the OLS and IPWRA approaches. 90% confidence intervals shown from standard errors clustered at the mother level. HH= households.

APPENDIX A. CONTEXT, DESCRIPTIVE ANALYSIS & DATA

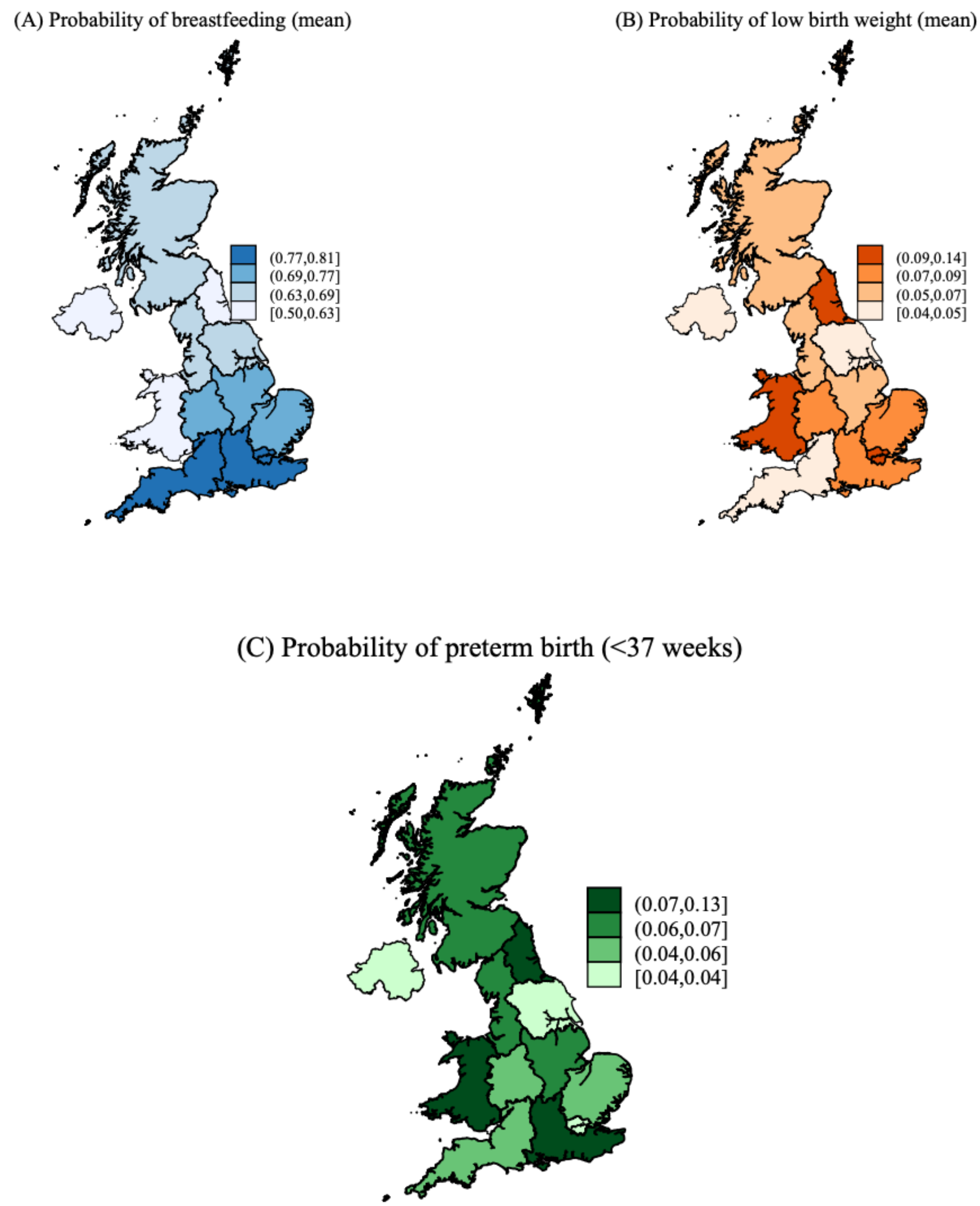
A1. Context and Descriptive Figures

Figure A1.1. Global prevalence of autism in children (per 100k) by country in 2019



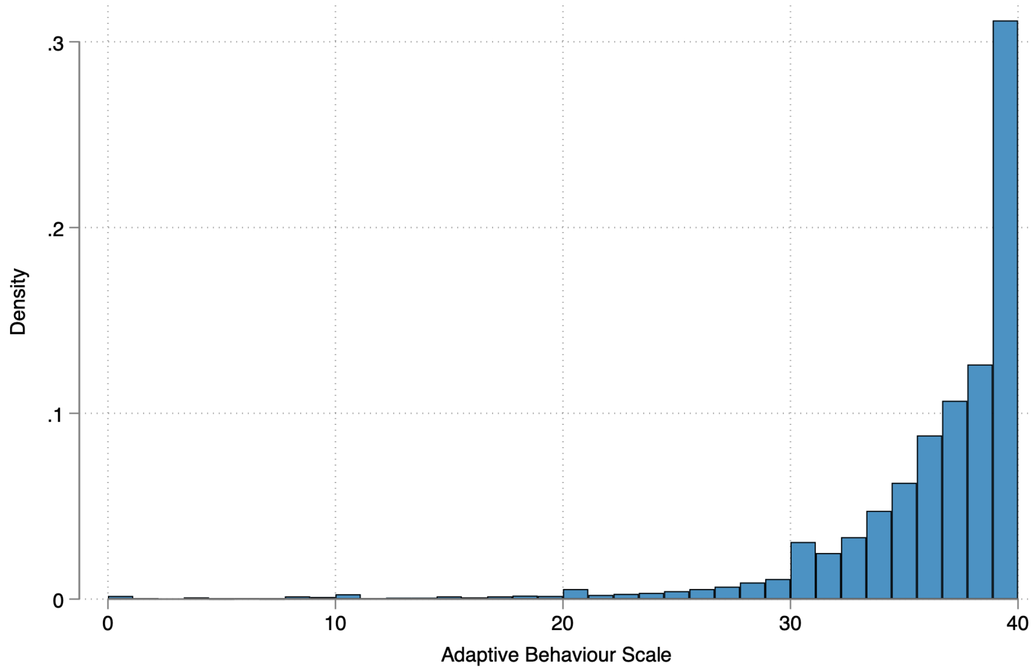
Source: Global Burden of Disease Collaborative Network—Global Health Data Exchange. *Notes:* The rates shown indicate the number of children out of 100,000 who have been diagnosed with autism at any age. Country-to-country comparisons of autism rates can be misleading. A higher rate of autism diagnoses does not necessarily indicate more autism. It may instead indicate that the country's healthcare system is better at detecting and diagnosing autism than the healthcare systems of other countries.

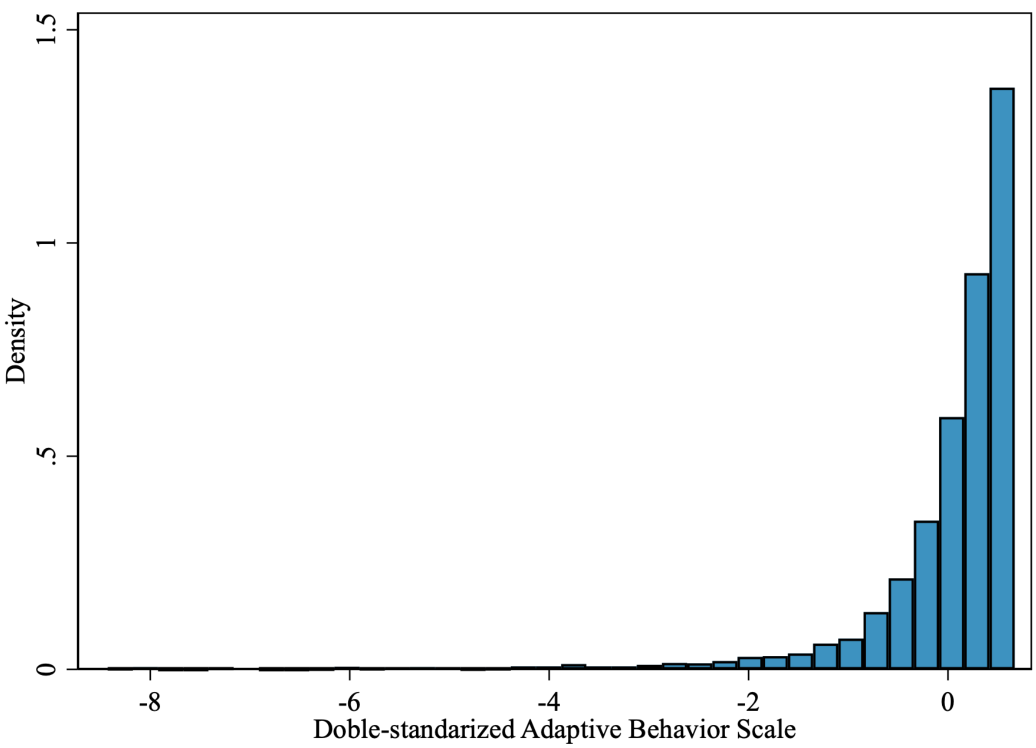
Figure A1.2. Mean of key interest variables for our sample of children born between 2007 and 2020



Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* Table A1.2 shows the spatial distribution of early-life conditions across regions in the UK.

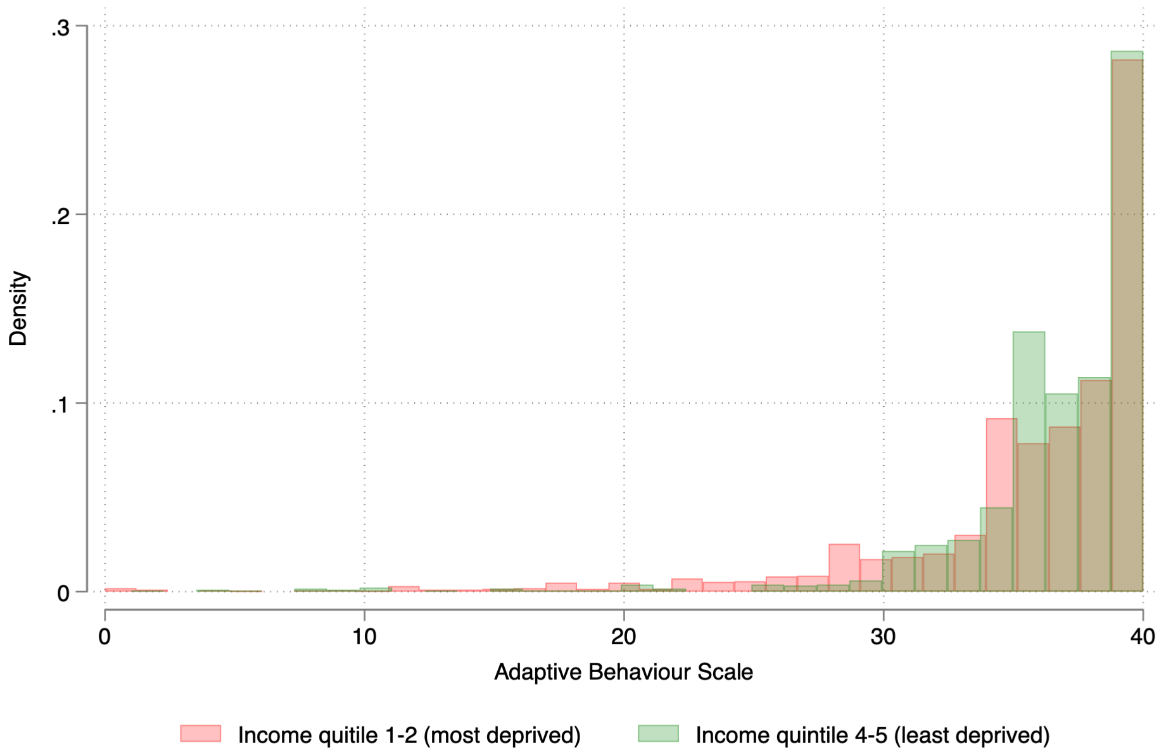
Figure A1.3. Kernel density histograms of adaptive behavior scale and standardised index at age 3





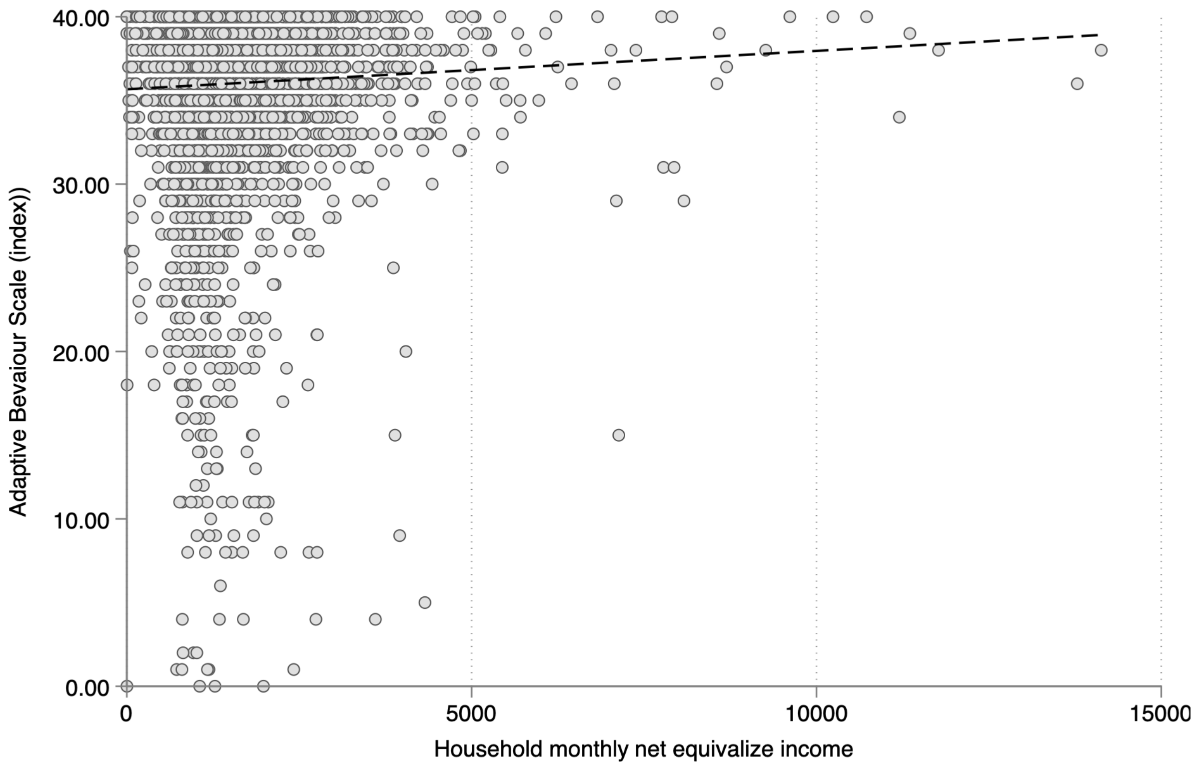
Source: PEACH UK Understanding Society. *Notes:* Kernel density histograms of the raw adaptive behavior scale and the standardised index at age 3.

Figure A1.4. Kernel density histogram of adaptive behavior sale at age 3 by income quintiles



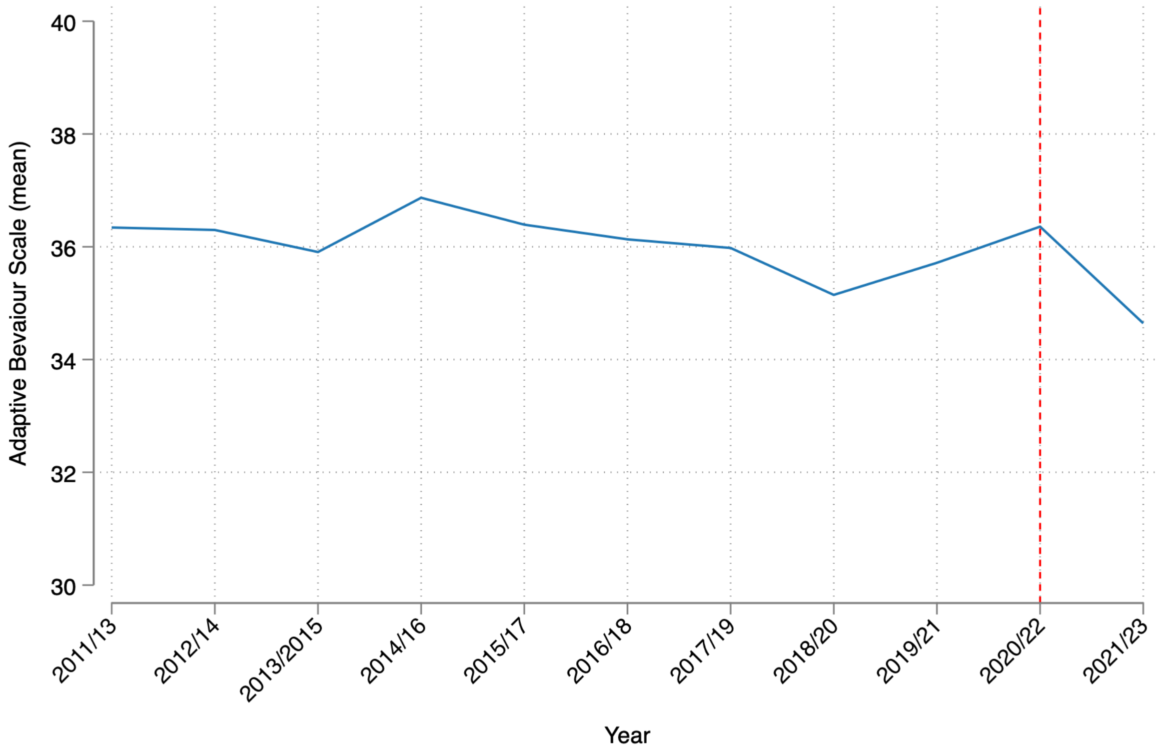
Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* This figure shows the kernel density histogram of adaptive behavior sale at age 3 by income quintiles.

Figure A1.5. Correlation plot between the adaptive behavior scale and household monthly equivalised net income



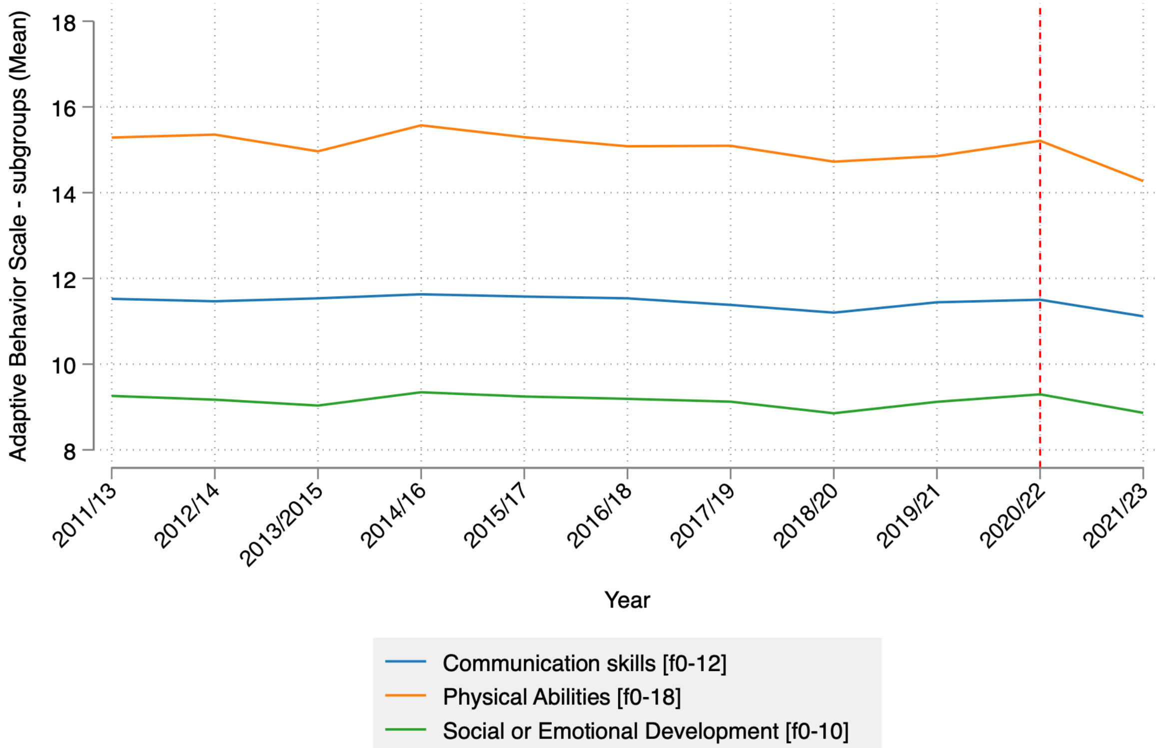
Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* This figure shows the correlation distribution between the adaptive behavior scale and household monthly equivalised net income.

Figure A1.6. Yearly mean trends of adaptive behavior scale



Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* This figure shows yearly mean trends of adaptive behavior scale.

Figure A1.7. Annual mean trends of adaptive behavior scale by subgroups



Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* This figure shows annual mean trends of adaptive behavior scale by subgroups.

A2. Adaptive Behavior Scale and Maternal Engagement Index

Table A2.1. Adaptive behavior questions collected in Understanding Society

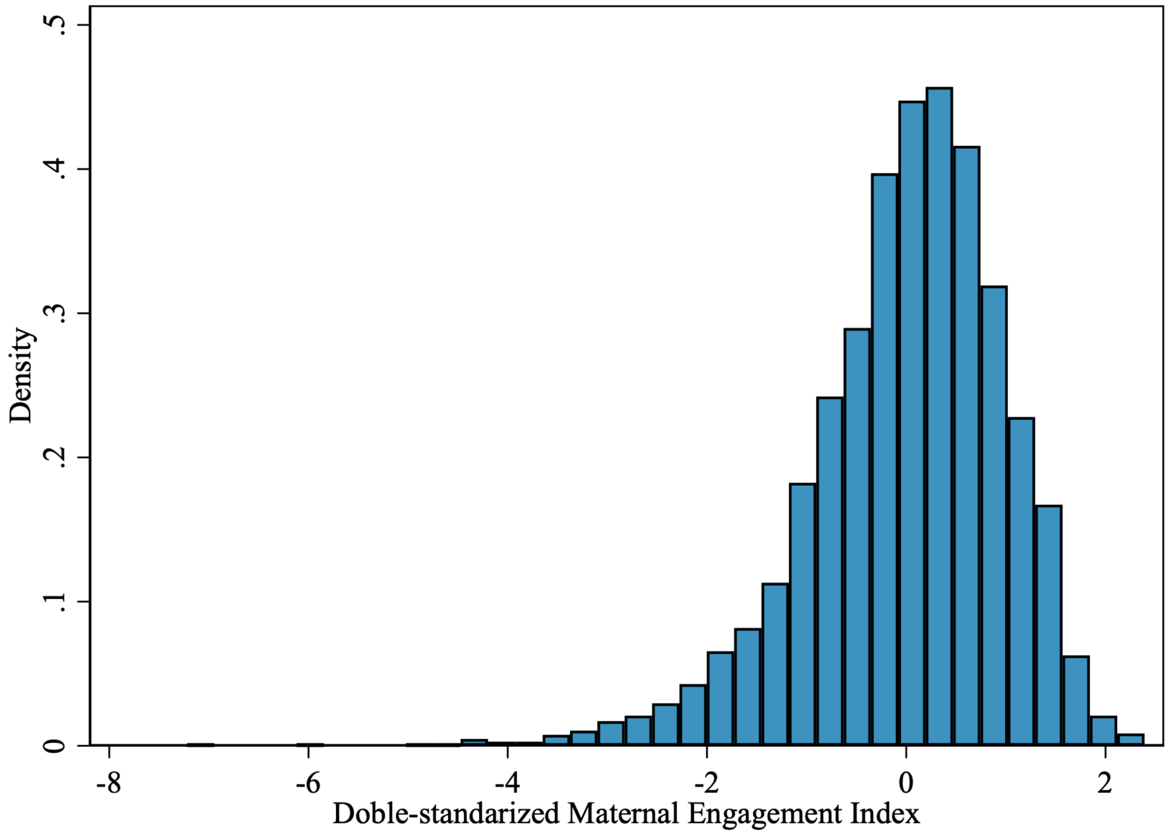
Domain	Question
Communication skills	1. Understands brief instructions such as "go get your shoes"
	2. Forms sentences with at least two words
	3. Speaks in full sentences (with four or more words)
	4. Listens attentively to a story for five minutes or longer
	5. Passes on simple messages such as "dinner is ready"
	6. Calls familiar people by name (e.g., "Mummy" and "Daddy") or uses the father's first name
Physical abilities	7. Uses a spoon to eat, without assistance and without dripping
	8. Blows his/her nose without assistance
	9. Uses the toilet to do "number two"
	10. Puts on pants and underpants the right way around
	11. Brushes his/her teeth without assistance
	12. Walks forward down the stairs
	13. Opens doors with the door handle
	14. Climbs up playground climbing equipment and other high playground structures
	15. Cuts paper with scissors
Socio-emotional skills	16. Paints/draws recognizable shapes on paper
	17. Participates in games with other children
	18. Gets involved in role-playing games ("playing pretend")
	19. Shows a special liking for particular playmates or friends
	20. Calls his/her own feelings by name (e.g., "sad", "happy", "scared")

Note: Parents or responsible adults are asked to assess whether their 3-year-old child can perform each task by selecting one of three options: "Yes," "To some extent," or "No".

Table A2.2. Maternal Engagement Index

Question	**Likert scale**	**Reverse coded**	**Final scoring**
1. How often do you allow your child to help set rules? 2. How often do you praise your child? 3. How often do you hug or cuddle your child?	Never – 0 Seldom – 1 Sometimes – 2 Very often – 3	No	Never – 0 Seldom – 1 Sometimes – 2 Very often – 3
4. How often do you spank or slap your child? 5. How often do you shout at your kid?	Never – 0 Seldom – 1 Sometimes – 2 Very often – 3	Yes	Never – 3 Seldom – 2 Sometimes – 1 Very often – 0
6. How often do you quarrel with your child?	Most days – 1 More than once a week – 2 Less than once a week – 3 Hardly ever – 4	No	Most days – 0 More than once a week – 1 Less than once a week – 2 Hardly ever – 3
7. How often does your child talk to you about things that matter to them?	Most days – 1 More than once a week – 2 Less than once a week – 3 Hardly ever – 4	Yes	Most days – 3 More than once a week – 2 Less than once a week – 1 Hardly ever – 0
8. In the past 7 days, how many times have you eaten an evening meal together with your child and other family members who live with you?	None – 1 1 to 2 times – 2 3 to 5 times – 3 6 to 7 times – 4	No	None – 0 1 to 2 times – 1 3 to 5 times – 2 6 to 7 times – 3
9. How often do you and your child spend time together on leisure activities or outings outside the home such as going to the park or zoo, going to the movies, sports or to have a picnic?	Never or rarely – 1 Once a month or less – 2 Several times a month – 3 About once a week – 4 Several times a week – 5 Almost every day – 6	No	Never or rarely – 0 Once a month or less – 0 Several times a month – 1 About once a week – 2 Several times a week – 3 Almost every day – 3

Figure A2.1. Kernel density histogram for Doble-standardized Maternal Engagement Index



Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* This figure shows kernel density histogram for the maternal engagement scale after the doble-standardization process.

A3. A conceptual framework of children's adaptive behavior development

We set up a conceptual framework to study the relasionship between children's adaptive behavior develoment and early life factors. In our paper, adaptive behavior is measured at age 3, and we follow a simple static model of early life factors and child human capita outcomes (adaptive behavior here) based on a dynamic utility maximisation model of child health and parental investment presented in Blau et al. (1996) and Rothstein (2013). We assume a household receives utility from the human capital of its child (h), consumption good (c), and leisure of the mother (L). For simplicity, we assume that a household consists of a mother with one child, given the following parental utility function:

$$U = U(h, C, L; Z, m) \tag{A1.1}$$

Where Z is a vector of observed exogenous determinants of preferences and μ is an unobserved fixed determinant of preferences. Two key assumptions implicit in this specification preferences are the separability of preferences over time and no serial correlation of preferences than through the fixed effect.

The production function of children's human capital (h), is a function of health initial endowments (E), for example, perinatal outcomes including birthweight and gestational age, parental time investments (I), breastfeeding practices (B), a vector of exogenous determinants of health (X), for example, the child's age and sex, and child's unobserved initial endowments (α_0), such as genes and ability:

$$h = h(E, I, B; X, \alpha_0) \tag{A1.2}$$

The parental time constraint is based on the following equation:

$$I + B + W_h + D_h + L = 1 \tag{A1.3}$$

Where W_h is the hours of work if mothers decide to return to work after pregnancy and D_h is time spent on domestic and family tasks. The full household budget constraint is:

$$A + w * W_h = C + p_f * F \tag{A1.4}$$

A is the stock of financial assets and any interest rate returns and w is the mother's wage rate, p_f is the price of food and the consumption of good C is the numeraire. Substituting equation (2) into (1) and maximising utility subject to time and budget constraints (3) and (4) and solving the first-order conditions give us that children's human capital formation (adaptive behavior here) is represented by the following equation:

$$h = h(E, B, X, Z, Ap_f, w, m, \alpha_0) \tag{A1.5}$$

As Cunha and Heckman (2007) show, the human skill formation process is governed by a multistage technology, in which stage corresponds to a period of the life cycle of a child. Therefore, inputs or investments at each stage produce outputs in the next stage. Here, our human capital outcome is measured at age 3, which is a measure of a child's cognitive development. Potential shocks to parental preferences (e_1) and child human capital (e_2) can occur during these first years of life given the following equation:

$$U = U(h, C, L; Z, m, \epsilon_1) \tag{A1.6}$$

$$h = h(I, B; X, \alpha_0, \epsilon_2) \tag{A1.7}$$

This framework of children's cognitive development aims to provide guidance for the empirical analysis and the mediation analysis studied. In practice, we focus on maternal engagement as main mediator on the relationship between neonatal and perinatal factors and adaptive behavior skills.

A4. Pregnancy and Early Childhood (PEACH) from UK Understanding Society

In our analysis, we use the PEACH dataset, which consolidates information across multiple waves about children, thereby offering a cumulative sample size encompassing all children for whom adaptive behavior measures are available. Furthermore, we incorporate data from the Understanding Society's main release to associate this sample with comprehensive details regarding maternal and household characteristics, both at the juncture when the children's adaptive behavior measures were collected at the age of three and prior, facilitating a more profound understanding of their circumstances from birth onward.

Like other longitudinal surveys, attrition and non-response present significant challenges that must be considered, particularly after 14 waves of data collection. Over time, the population of children in each wave diminishes. Furthermore, the UK Household Longitudinal Study (UKHLS) includes boosts for ethnic minority groups, which can introduce bias if these demographics are not adequately considered in our analysis. To mitigate this issue, the PEACH dataset provides weights for cross-sectional analysis across multiple waves, enabling researchers to examine children at a specific age without being constrained to data from a singular time point. This approach facilitates the amalgamation of information from various waves, as demonstrated in our study analysis.

We are employing the weights provided in the PEACH dataset to ensure that our findings are representative through data aggregation across multiple waves. It is essential to highlight that the most recent release of PEACH encompasses data up to wave 13. To further enhance the sample size for our analysis, we have also incorporated adaptive behavior measures from the main release of Understanding Society Wave 14. While this inclusion broadens the sample, it is important to note that weights for these additional observations have not yet been available. Consequently, it is pertinent to state that we only apply weights for the data up to wave 13, as noted in the annotations of each table containing the results of the reported estimation.

A reduced sample size is evident in particular subsamples, such as those examining maternal smoking, alcohol consumption, and caesarean section deliveries. This constraint emerges as the relevant data is recorded at the maternal rather than the child level, resulting in the potential for missing data due to the correlation between maternal and child information. In Table A4.1 below, we present a comprehensive description of the information incorporated into our analysis.

Sample weights.—PEACH provides weights for cross-sectional analysis across multiple waves, enabling researchers to examine children at a specific age without being constrained to data from a singular time point. This approach facilitates the amalgamation of information from various waves, as demonstrated in our study analysis. We are employing the weights provided in the PEACH dataset to ensure that our findings are representative through data aggregation across multiple waves.

Table A4.1. Key variables – Concentrated

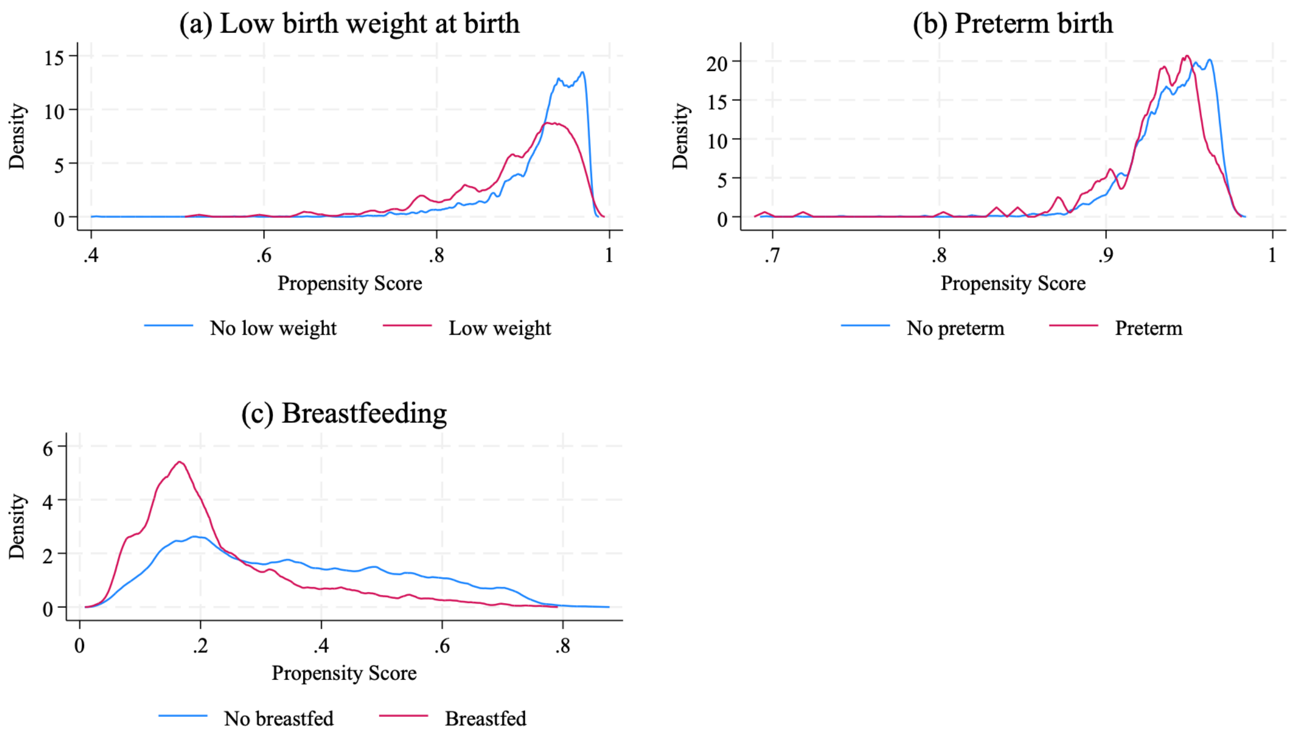
Measure	**Variable**	**Description**
Personal identifier	Child `pidp`	Child's unique identifier.
	Mother `pidp`	Mother's unique identifier.
	Father `pidp`	Father's unique identifier.
Child's characteristics	Adaptive behavior	Adaptive Behavior Scale – Sum of 20 questions reverse-scored and rescaled (range: 0–40). Higher scores indicate better adaptive behavior. See details in Table A3.1.
	Sex	Sex: 1 = Girl, 0 = Boy.
	Survey year	Year when the child's adaptive behavior measure was recorded.
	First born	Mother's firstborn: 1 = Yes, 0 = No.
Early life conditions	Breastfeeding	Breastfed child: 1 = Yes, 0 = No.
	Birth weight	Low birthweight: 1 < 2.5 kg, 0 > 2.5 kg.
	Preterm birth	Preterm birth: 1 = Born before 37 weeks, 0 = Born at 37 weeks or later.
Maternal characteristics†	Education	Mother's education: 1 = Degree or higher degree, 0 = No qualification, other qualification, GCSE or A-levels.
	Marital status	Mother's marital status: 1 = Married or living with partner, 0 = Otherwise.
	Employment	Mother's employment status: 1 = In paid employment (full-time/part-time), 0 = Otherwise.
	Ethnicity	Ethnicity: 1 = White British, 0 = Otherwise.
	Age	Mother's age.
	Psychological distress	Mother's General Health Questionnaire (GHQ): 1 = Higher risk of psychological distress, 0 = No or minimal distress.
	Quality time	Maternal engagement in quality time with children. Sum of 9 questions (range: 0 to 27). Higher scores indicate more positive maternal engagement. See details in Table A3.2.
Household characteristics†	Income	Low-income: 1 = Equivalised monthly household income < 60% of the median income, 0 = Otherwise.
	Urban	Urban: 1 = Population of 10,000 or more, 0 = Otherwise.
	Household size	Number of individuals in the household.
	Region	Government office region of the child's household location.

† Data on maternal and household characteristics is available from birth.

APPENDIX B. VALIDITY OF STRATEGY & OTHER EMPIRICAL METHODOLOGIES

B1. Validity of Strategy

Figure B1.1. Matching validity check: Common support test for propensity score matching strategy



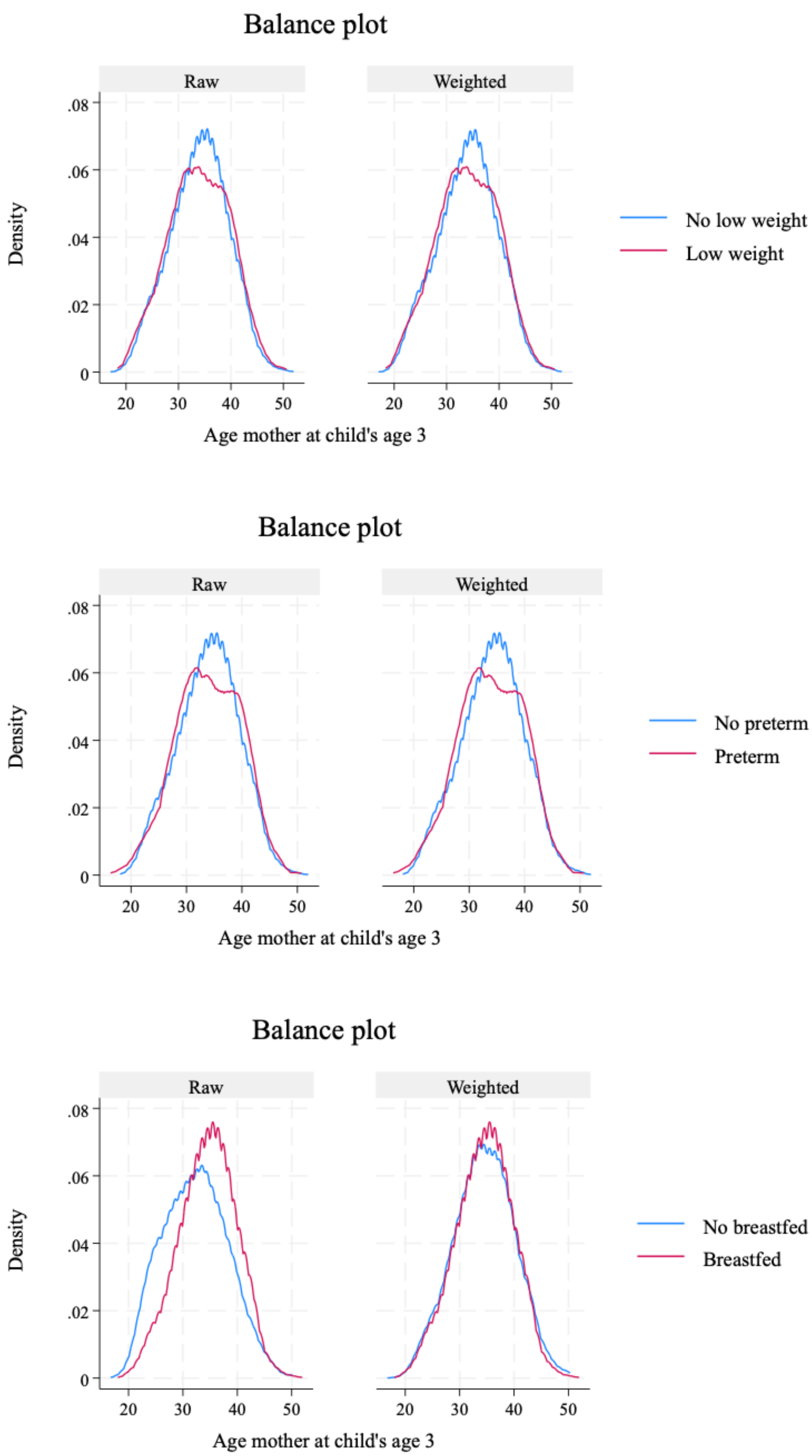
Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* Each panel plots kernel densities of the estimated propensity score $\widehat{p}(X) = \Pr(D = 1 \mid X)$ separately for the treated group ($D = 1$, red) and the control group ($D = 0$, blue), where D denotes (a) low birth weight, (b) preterm birth, and (c) breastfeeding. Propensity scores are obtained from the treatment model used in the IPWRA estimator (logit) and are estimated using the full set of pre-treatment covariates included in the main specification. Visual overlap of the two distributions provides evidence in support of the positivity/common-support assumption; limited overlap or mass near 0/1 would indicate potential violations and motivates common-support restrictions or trimming as robustness checks.

Table B1.1. Covariate balance diagnostics for IPWRA – Treatment: Low weight birth

	Means (baseline)			Baseline dispersion	
Covariate	Control	Treated	Treated − Control	Var ratio (T/C)	Std. diff.
Female	0.490	0.532	0.042	0.999	0.085
Firstborn (mother)	0.395	0.438	0.043	1.033	0.087
Mother education: A-levels / degree	0.734	0.635	-0.099	1.190	-0.214
Married mother	0.845	0.830	-0.015	1.080	-0.040
Employed mother	0.559	0.453	-0.106	1.008	-0.213
White mother	0.775	0.574	-0.201	1.407	-0.439
Mother age at birth	30.96	30.95	-0.01	1.085	-0.002
Risky GHQ (mother)	0.228	0.243	0.016	1.050	0.037
Above median 60	0.830	0.793	-0.037	1.167	-0.095
Household size	4.125	4.328	0.203	1.477	0.161
Urban	0.783	0.839	0.056	0.798	0.143
Housing tenure	0.627	0.505	-0.122	1.072	-0.248

Notes: Baseline means/variances are reported by treatment status for the covariates included in the treatment model. Std. differences are computed using the pooled standard deviation based on baseline variances. Raw sample size is $N = 4{,}335$ (treated = 329, controls = 4,006). Weighted group totals (sum of IPWRA weights) are treated = 2,135.5 and controls = 2,199.5. The joint covariate-balance overidentification test after IPWRA weighting fails to reject the null of balance: $\chi^2(13) = 8.82296$, $p = 0.7862$ (Stata: `tebalance overid`).

Figure B1.2. Balance diagnostics for maternal age (child age 3)



Source: The Pregnancy and Early Childhood (PEACH): UK Understanding Society. *Notes:* Each row shows kernel density estimates of maternal age (measured when the child is age 3) for the treated group (red) and control group (blue). The left sub-panel ("Raw") uses the unweighted sample, while the right sub-panel ("Weighted") uses the inverse-probability weights from the IPWRA treatment model. The weighted densities exhibit substantially greater overlap than the raw densities—especially for breastfeeding—indicating improved covariate balance with respect to maternal age and supporting the plausibility of the overlap (positivity) assumption for this covariate.

Table B1.2. Covariate balance diagnostics for IPWRA – Treatment: Preterm birth

	Means (baseline)			Dispersion (baseline)	
Covariate	Control	Treated	Treated − Control	Var ratio (T/C)	Std. diff.
Female	0.490	0.532	0.042	0.999	0.085
Firstborn (mother)	0.395	0.438	0.043	1.033	0.087
Mother education: A-levels / degree	0.734	0.635	-0.099	1.190	-0.214
Married mother	0.845	0.830	-0.015	1.080	-0.040
Employed mother	0.559	0.453	-0.106	1.008	-0.213
White mother	0.775	0.574	-0.201	1.407	-0.439
Mother age at birth	30.957	30.945	-0.011	1.085	-0.002
Risky GHQ (mother)	0.228	0.243	0.016	1.050	0.037
Above median 60	0.830	0.793	-0.037	1.167	-0.095
Household size	4.125	4.328	0.203	1.477	0.161
Urban	0.783	0.839	0.056	0.798	0.143
Housing tenure	0.627	0.505	-0.122	1.072	-0.248

Notes: Baseline means/variances are reported by treatment status for the covariates included in the treatment model. Raw sample size is $N = 4{,}335$ (treated = 263, controls = 4,072). Weighted group totals (sum of IPWRA weights) are treated = 2,163.1 and controls = 2,171.9. The joint covariate-balance overidentification test after IPWRA weighting fails to reject the null of balance: $\chi^2(13) = 10.3652$, $p = 0.6638$ (Stata: `tebalance overid`).

Table B1.3. Covariate balance diagnostics for IPWRA – Treatment: Breastfeeding

	Means (baseline)			Dispersion (baseline)	
Covariate	Control	Treated	Treated − Control	Var ratio (T/C)	Std. diff.
Female	0.464	0.503	+0.039	1.005	+0.078
Firstborn (mother)	0.342	0.418	+0.077	1.081	+0.159
Mother education: A-levels / degree	0.541	0.793	+0.252	0.661	+0.554
Married mother	0.756	0.875	+0.119	0.592	+0.311
Employed mother	0.458	0.584	+0.126	0.978	+0.254
White mother	0.862	0.724	-0.138	1.676	-0.345
Mother age at birth	29.293	31.550	+2.257	0.813	+0.405
Risky GHQ (mother)	0.220	0.232	+0.012	1.039	+0.029
Above median 60	0.743	0.858	+0.115	0.638	+0.291
Household size	4.181	4.126	-0.055	0.708	-0.046
Urban	0.791	0.786	-0.005	1.016	-0.011
Housing tenure	0.462	0.673	+0.211	0.885	+0.435

Notes: Baseline means/variances are shown by treatment status for the covariates included in the treatment model. Std. differences are computed using the pooled standard deviation from baseline variances. Raw sample size is N = 4,335 (treated = 3,193, controls = 1,142). Weighted group totals (sum of IPWRA weights) are treated = 2,087.9 and controls = 2,247.1. The joint covariate-balance overidentification test after IPWRA weighting fails to reject the null of balance: $\chi^2(13) = 10.37$, $p = 0.66$ (Stata: `tebalance overid`).

B2. Sibling Fixed-Effects Analysis

Another potential way to correct for unobserved family-level heterogeneity biases is to use sibling fixed-effects models. The sibling fixed-effects model controls for unobserved family factors (F_i), like shared environment (e.g., socioeconomic status, parental characteristics) and genetics, that impact adaptive behavior. This model compares siblings within the same family who experienced different perinatal and neonatal experiences to isolate the effects on the child's adaptive behavior development by focusing on within-family variation. This sibling fixed effects model is estimated as follows:

$$Y_i = \alpha + \omega P_i + \phi X_i^E + F_i + T_i + R_i + e_i \tag{B2.1}$$

This methodology is widely used in the literature concerning the impact of early childhood inputs (refer to Currie and Almond (2011)). Its primary advantage is the ability to eliminate confounding effects arising from fixed, unobserved shared background characteristics. However, as noted by Currie and Almond (2011), this method is not without limitations. It does not adequately control for unobserved sibling-specific factors, which raises concerns in light of prior research indicating that their children's characteristics may influence mothers' breastfeeding decisions at birth (Loughran et al. 2006). All robust standard errors are clustered by mother.

For some exposures, such as preterm birth, the point estimates also differ in sign from those obtained in our OLS, propensity score matching, and CRE models. This pattern is in line with the concerns highlighted by Currie and Almond (2011) that sibling fixed-effects designs may remain vulnerable to unobserved child-specific factors (e.g. child health at birth) that can influence both parental decisions, such as breastfeeding, and later developmental outcomes (see also Loughran et al. 2006). More information on the availability of siblings in our dataset can be seen in Tables B1.1-B1.2.

Table B2.1. Sample's family composition

Siblings			**Families**		
	Obs.	**%**		**Obs.**	**%**
Only child	2,309	53.3	Families with only 1 child	2,309	70.8
Two siblings	1,696	39.1	Families with 2 siblings	848	26.0
Three siblings	273	6.3	Families with 3 siblings	91	2.8
Four siblings	52	1.2	Families with 4 siblings	13	0.4
Five siblings	5	0.1	Families with 5 siblings	1	0.0
Total of observations	*4,335*	*100.0*	*Total of families*	*3,262*	*100.0*

Table B2.2. Outcome variation in the number of siblings within families

	Only 1 child		2 siblings		3 siblings		4 siblings		5 siblings	
	Obs.	%	Obs.	%	Obs.	%	Obs.	%	Obs.	%
a) Breastfeeding										
None breastfed	631	27.3	144	17.0	20	22.0	1	7.7	-	-
One breastfed	1,678	72.7	116	13.7	10	11.0	1	7.7	1	100.0
Two breastfed	-	-	588	69.3	9	9.9	2	15.4	-	-
Three breastfed	-	-	-	-	52	57.1	3	23.1	-	-
Four breastfed	-	-	-	-	-	-	6	46.2	-	-
Five breastfed	-	-	-	-	-	-	-	-	-	-
Total of families	*2,309*	*100.0*	*848*	*100.0*	*91*	*100.0*	*13*	*100.0*	*1*	*100.0*
b) Low birthweight										
None low birthweight	2,146	92.9	747	88.1	74	81.3	11	84.6	1	100.0
One low birthweight	163	7.1	70	8.3	7	7.7	-	-	-	-
Two low birthweight	-	-	31	3.7	9	9.9	-	-	-	-
Three low birthweight	-	-	-	-	1	1.1	2	15.4	-	-
Four low birthweight	-	-	-	-	-	-	-	-	-	-
Five low birthweight	-	-	-	-	-	-	-	-	-	-
Total of families	*2,309*	*100.0*	*848*	*100.0*	*91*	*100.0*	*13*	*100.0*	*1*	*100.0*
c) Preterm birth										
None preterm	2,180	94.4	772	91.0	73	80.2	11	84.6	1	100.0
One preterm	129	5.6	49	5.8	9	9.9	2	15.4	-	-
Two preterm	-	-	27	3.2	7	7.7	-	-	-	-
Three preterm	-	-	-	-	2	2.2	-	-	-	-
Four preterm	-	-	-	-	-	-	-	-	-	-
Total of families	*2,309*	*100.0*	*848*	*100.0*	*91*	*100.0*	*13*	*100.0*	*1*	*100.0*

Table B1.3 presents OLS and maternal fixed effects estimates of the association of perinatal health and breastfeeding on children's adaptive behaviour outcomes using a sibling subsample. Previous studies suggest that within-sibling analysis helps address selection bias by leveraging variation within families. Here, the effects of perinatal and neonatal factors are identified only from sibling sets where at least one child was breastfed while another was not, or where one child is born prematurely or with low birth weight and another not. Comparing the results in Table B1.3 with those in Table 2, OLS estimates for the sibling subsample are generally attenuated, likely due to sample selection effects from excluding singletons. Yet, running the regression on the singleton subsample shows that the positive effects of breastfeeding are slightly more pronounced in column (3) and not statistically significant when adding household characteristics. As seen in prior research (Rothstein 2013), once sibling fixed effects are included, removing fixed characteristics related to mothers (but not children), the effects of breastfeeding and perinatal health are no longer statistically significant. This may be explained by the limited variation in these measures among sibling groups.

Table B2.3. Effects of early life conditions on adaptive behavior scale at age 3 – Siblings subsample

	Ordinary Least Squares				**S7blings FE**
Outcome variable: Standarized Adaptive Behavior Scale	(1)	(2)	(3)	(4)	(5)
(a) Low birth weight (<2.5 Kg)	-0.253**	-0.274**	-0.244**	-0.224**	-0.160
	(0.121)	(0.120)	(0.114)	(0.114)	(0.190)
R-squared	0.005	0.033	0.087	0.097	0.037
(b) Preterm birth (<37 weeks)	-0.165	-0.148	-0.141	-0.123	0.202
	(0.121)	(0.122)	(0.113)	(0.112)	(0.166)
R-squared	0.001	0.028	0.084	0.095	0.033
(c) Breastfeeding practices	0.150**	0.171***	0.102	0.075	-0.059
	(0.066)	(0.066)	(0.066)	(0.066)	(0.092)
R-squared	0.005	0.033	0.085	0.095	0.036
Control variables: children			✓	✓	✓
Control variables: maternal			✓	✓	✓
Control variables: household				✓	✓
Mundlak FE	✓	✓	✓	✓	✓
Year of birth FE		✓	✓	✓	✓
Region of birth FE		✓	✓	✓	✓
Survey wave FE		✓	✓	✓	✓
Observations	2,121	2,121	2,121	2,121	2,121

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The Adaptive Behavior Scale is standardised (mean = 0, SD = 1), with higher scores indicating better adaptive behavior skills. Columns 1–4 report ordinary least squares estimates with robust standard errors clustered at the mother level in parentheses. Column 1 includes no control variables or fixed effects. Column 2 adjusts for year of birth, region of birth and survey wave fixed effects. Column 3 further controls for child characteristics (gender and first-born status) and maternal measures postbirth (education level, marital status, employment, ethnicity, age at birth, and risk of mental health problems). Column 4 additionally includes household characteristics (household size, urban residence, home ownership, and above-60%-of-median-income indicator). Column 5 presents sibling FE estimates. OLS estimates using sample weights. Because identification relies on within-family comparisons, survey weights, which vary across siblings, cannot be applied in the sibling fixed-effects models. Estimates are therefore unweighted but include family fixed effects and cluster robust standard errors at the mother level.

B3. Instrumental Variables Analysis

We consider using an instrumental variable approach to handle this type of endogeneity. This requires finding a variable (Z_i) that impacts children's adaptive behavior development only indirectly by influencing perinatal and neonatal factors (P_i). Previous studies have used different approaches, such as whether the birth was by caesarean (Denny and Doyle 2010) or whether the hospital where the child was born participated in a breastfeeding promotion program (Del Bono and Rabe 2011). We build upon earlier research concerning development outcomes, using being born during a Friday or/and weekend as an instrumental variable. We have employed various combinations of the day of the week at birth and its interaction with the region of birth as instrumental variables, alongside caesarean section delivery, following prior literature. We also used combined instrumental variables of regions that interacted with being born during weekends. Previous literature has found that children born on or just before the weekend are less likely to be breastfed or show worse perinatal outcomes due to poorer healthcare services in hospitals on weekends (Fitzsimons and Vera-Hernández 2022). However, we were not convinced that the exclusion restriction was valid or that the instruments were powerful enough in the first stage. Therefore, selection issues may remain. Results for a set of instrumental variables can be found in Tables B2.1-B2.3.

Table B3.1. IV-2SLS a set of instrumental variables

IV-2SLS→	Weekend	Friday & weekend	Friday	Regions & weekends	Regions, Friday & weekends	C-section	
Dependent variable: Low birth weight	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Standarized Adaptive Behaviour Scale	-0.165	10.911	36.761	2.841	1.384	-6.472*	-6.660*
	(12.511)	(11.670)	(54.012)	(4.630)	(3.822)	(3.765)	(3.700)
First stage (day of week)	0.013	0.015*	0.008				
	(0.009)	(0.008)	(0.011)				
First stage (regions)							
North East				0.069	0.081*		
				(0.052)	(0.044)		
North West				0.006	0.029		
				(0.023)	(0.021)		
Yorkshire and The Humber				0.034	0.009		
				(0.032)	(0.023)		
East Midlands				-0.016	-0.008		
				(0.023)	(0.019)		
West Midlands				0.009	-0.003		
				(0.028)	(0.021)		
East of England				0.009	0.018		
				(0.024)	(0.021)		
London				0.011	0.014		
				(0.027)	(0.022)		
South East				0.015	0.024		
				(0.024)	(0.020)		
South West				0.008	0.0003		
				(0.028)	(0.021)		
Wales				0.089**	0.067**		
				(0.041)	(0.028)		
Scotland				-0.015	0.004		
				(0.022)	(0.021)		
Northern Ireland				-0.003	-0.018		
				(0.034)	(0.023)		
First stage (c-section)						0.057***	0.057***
						(0.011)	(0.011)
Weak instrument test (F-test)	2.072	3.621	0.613	0.774	1.15		
Durbin–Wu–Hausman Test (p-value)	0.912	0.189	0.065	0.329	0.434		
R-squared	0.059	.	.	0.009	0.038	0.041	0.041
Observations	4,445	4,445	4,445	4,445	4,445	3,547	3,547

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Doble-standarized Adaptive Behaviour Scale. “Weekend” includes *Saturday* and *Sunday*.

Table B3.2. IV-2SLS a set of instrumental variables

IV-2SLS→	Weekend	Friday & weekend	Friday	Regions & weekends	Regions, Friday & weekends	C-section	
Dependent variable: Pre-term birth (< 37 weeks)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Standarized Adaptive Behaviour Scale	-5.759	11.197	13.684	5.584	5.351	-5.532*	-5.667*
	(76.217)	(0.361)	(10.458)	(4.764)	(4.424)	(3.198)	(3.120)
First stage (day of week)	0.002	0.014*	0.023**				
	(0.008)	(0.007)	(0.011)				
First stage (regions)							
North East				0.071	0.084*		
				(0.052)	(0.044)		
North West				0.010	0.032		
				(0.022)	(0.019)		
Yorkshire and The Humber				-0.006	0.002		
				(0.023)	(0.019)		
East Midlands				0.003	0.016		
				(0.025)	(0.022)		
West Midlands				0.002	0.001		
				(0.023)	(0.018)		
East of England				-0.049***	-0.013		
				(0.009)	(0.015)		
London				-0.029*	-0.016		
				(0.016)	(0.014)		
South East				-0.011	0.028		
				(0.018)	(0.019)		
South West				0.035	0.028		
				(0.032)	(0.024)		
Wales				0.048	0.038		
				(0.036)	(0.025)		
Scotland				0.031	0.030		
				(0.031)	(0.024)		
Northern Ireland				0.012	-0.015		
				(0.034)	(0.019)		
First stage (c-section)						0.067***	0.068***
						(0.011)	(0.011)
Weak instrument test (F-test)	0.076	3.753	4.563	3.249	1.426		
Durbin–Wu–Hausman Test (p-value)	0.949	0.239	0.061	0.137	0.114		
R-squared	0.012	.	.	.	.	0.050	0.084
Observations	4,441	4,441	4,441	4,441	4,441	3,543	3,476

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Doble-standarized Adaptive Behaviour Scale. "Weekend" includes *Saturday* and *Sunday*.

Table B3.3. IV-2SLS a set of instrumental variables

IV-2SLS →	Weekend	Friday & weekend	Friday	Regions & weekends	Regions, Friday & weekends	C-section	
Dependent variable: Breastfeeding practices	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Standarized Adaptive Behaviour Scale	1.892	-18.006	80.661	0.637	0.455	20.983	9.928
	(13.255)	(32.954)	(337.030)	(1.915)	(1.328)	(21.570)	(6.422)
First stage (day of week)	-0.013	-0.008	0.004				
	(0.014)	(0.505)	(0.016)				
First stage (regions)							
North East				-0.220**	-0.197		
				(0.076)	(0.061)		
North West				-0.040	-0.028		
				(0.037)	(0.029)		
Yorkshire and The Humber				-0.061	-0.031		
				(0.046)	(0.037)		
East Midlands				0.018	0.051		
				(0.043)	(0.034)		
West Midlands				0.006	0.031		
				(0.039)	(0.032)		
East of England				0.034	0.030		
				(0.038)	(0.031)		
London				0.038	0.031		
				(0.029)	(0.023)		
South East				0.069**	0.061		
				(0.033)	(0.027)		
South West				0.090**	0.107		
				(0.041)	(0.032)		
Wales				-0.059	-0.101		
				(0.052)	(0.041)		
Scotland				-0.037	-0.061		
				(0.047)	(0.038)		
Northern Ireland				-0.193**	-0.195		
				(0.062)	(0.044)		
First stage (c-section)						-0.018	-0.039***
						(0.016)	(0.016)
Weak instrument test (F-test)	0.859	0.444	0.057	2.824	5.299		
Durbin–Wu–Hausman Test (p-value)	0.916	0.302	0.086	0.934	0.984		
R-squared	0.047	.	.	0.056	0.057	.	.
Observations	4,402	4,402	4,402	4,402	4,402	3,537	3,470

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Doble-standarized Adaptive Behaviour Scale. "Weekend" includes *Saturday* and *Sunday*.

APPENDIX C. MEDIATION MODEL

To explore the potential pathways linking early-life conditions (low birth weight, preterm birth, and breastfeeding) to children's adaptive behavior, we implement a parametric causal mediation analysis following Imai et al. (2010). Let $M_i(t)$ denote the potential value of the mediator for child i under treatment status $t \in \{0, 1\}$, and let $Y_i(t, m)$ denote the potential outcome if treatment is set to t and the mediator to m. The observed outcome is $Y_i = Y_i(T_i, M_i(T_i))$, where $T_i \in \{0, 1\}$ is the observed treatment status. The average total treatment effect can then be written as:

$$\tau = \mathbb{E}\left[Y_i(1, M_i(1)) - Y_i(0, M_i(0))\right]. \tag{C.1}$$

Following Imai et al. (2010), we decompose τ into an average causal mediation effect (ACME) and an average direct effect (ADE) for each treatment level $t \in \{0, 1\}$:

$$\delta(t) = \mathbb{E}\left[Y_i(t, M_i(1)) - Y_i(t, M_i(0))\right], \tag{C.2}$$

$$\zeta(t) = \mathbb{E}\left[Y_i(1, M_i(t)) - Y_i(0, M_i(t))\right]. \tag{C.3}$$

Here, $\delta(t)$ captures the ACME (indirect effect) when treatment is fixed at t, and $\zeta(t)$ captures the ADE (direct effect) when the mediator is fixed at the level it would take under t. The total effect can be written as:

$$\tau = \delta(t) + \zeta(1 - t). \tag{C.4}$$

Because we consider several candidate mediators, we focus on the average causal mediation effects, $\delta(t)$, and average direct effects, $\zeta(t)$, in what follows.

We identify the ACME under the sequential ignorability assumption for the treatment and the mediator, which is sufficient for identifying both the average total effect and the ACME (Imai et al. 2010; Doyle 2024). Let X_i be the vector of pre-treatment confounders for child i. Sequential ignorability can be written as:

$$\{Y_i(t', m), M_i(t)\} \perp\!\!\!\perp T_i \mid X_i = x, \tag{C.5}$$

$$Y_i(t', m) \perp\!\!\!\perp M_i(t) \mid T_i = t,\ X_i = x, \tag{C.6}$$

for all $t', t \in \{0, 1\}$, all x in the support of X_i, and all m in the support of M_i, with the additional overlap conditions

$$P(T_i = t \mid X_i = x) > 0 \quad \text{and} \quad P(M_i = m \mid T_i = t, X_i = x) > 0.$$

Intuitively, conditional on rich pre-treatment covariates, the treatment assignment mechanism is independent of both potential outcomes and potential mediator values, and the mediator is independent of potential outcomes given the treatment and the same covariates. In addition, the joint assumptions in Equations (C.5) and (C.6) rule out causal dependence across multiple mediators that would otherwise complicate identification (Imai et al. 2010).

Our mediation analysis is based on the following linear mediator and outcome models:

$$M_i = \alpha_3 + \beta_1 \text{Breastfed}_i + \beta_2 \text{LowWeight}_i + \beta_3 \text{Preterm}_i + \gamma X_i + \lambda_t + \varepsilon_i, \tag{C.7}$$

$$Y_i = \alpha_4 + \xi M_i + \beta_4 \text{Breastfed}_i + \beta_5 \text{LowWeight}_i + \beta_6 \text{Preterm}_i + \gamma X_i + \lambda_t + \varepsilon_i. \tag{C.8}$$

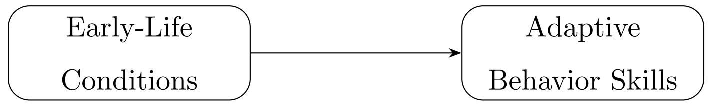
In the outcome equation, the direct effects of breastfeeding, low birth weight, and preterm birth are given by β_4, β_5, and β_6, respectively. The mediation (indirect) effect of each treatment operates through the product $\xi\beta_1$, $\xi\beta_2$, and $\xi\beta_3$ for breastfeeding, low birth weight, and preterm birth, respectively. This specification allows us to estimate the causal mediation effects (ACME) of each early-life condition by quantifying its indirect effect through the mediator while controlling for its direct effect and for pre-treatment confounders. Standard errors are obtained using nonparametric bootstrap methods.

We recognise three main threats to the validity of our mediation analysis. First, the sequential ignorability assumption is ultimately untestable and remains demanding in our setting. We partly address the first component of this assumption (ignorability of treatment) by conditioning on a rich set of maternal and household characteristics measured at birth, which are plausibly pre-treatment with respect to both the mediator (maternal engagement) and the outcome (adaptive behavior). These baseline controls, drawn from the PEACH sample of UK *Understanding Society*, include maternal socio-demographic characteristics and indicators of household socio-economic conditions at the time of birth. Conditioning on these variables helps reduce confounding in the relationship between early-life conditions and later outcomes. However, the second component of sequential ignorability requires that, conditional on treatment and these baseline characteristics, there are no remaining unobserved factors that jointly affect maternal engagement and adaptive behavior. We cannot fully rule out such unobserved time-varying determinants, so we interpret the estimated average causal mediation effects as informative about potential pathways rather than as fully identified causal parameters.

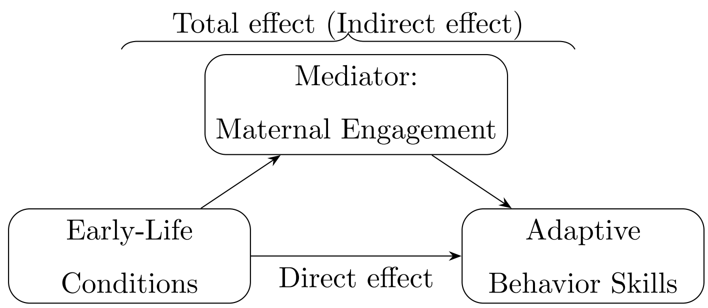
Second, because PEACH is embedded in the UK *Understanding Society* longitudinal household panel, attrition may affect both external and internal validity. Parents of children who drop out of the study before age three are likely to come disproportionately from more disadvantaged or poorer-health backgrounds, consistent with evidence from other health-related panel studies (e.g. **??**). In our context, such selective attrition is likely to induce a conservative bias: as the panel ages, the analytic sample becomes progressively healthier and more socio-economically advantaged, compressing the variation in early-life risk factors, mediators, and outcomes. This tends to attenuate (rather than exaggerate) the estimated associations between early-life conditions, maternal engagement, and adaptive behavior. To limit the impact of differential non-response, we use the child-level longitudinal weights provided in PEACH, which are constructed to correct for observed patterns of non-response and attrition.

Third, the construction of the maternal engagement mediator could, in principle, introduce scaling bias if items with greater dispersion mechanically receive more weight in the index. Our mediator is based on ten maternal engagement items. To avoid overweighting items with higher variance or different response scales, we double-standardise this index. Specifically, we first standardise each of the ten items at the individual level and then construct the maternal engagement index as the simple average of these standardised items. We then standardise this composite index again. This procedure ensures that (i) each of the ten activities contributes equally to the mediator, rather than being implicitly weighted by its raw variability, and (ii) the final mediator is expressed in standard-deviation units, which improves interpretability and comparability across specifications. While this transformation does not itself relax the sequential ignorability assumptions, it reduces the risk that our mediation results are driven by arbitrary differences in item scaling and thus mitigates an important source of potential measurement and aggregation bias in the mediator.

Figure C.1. Illustration of a direct effect and a mediation design



(1) Without mediator



(2) With mediator

APPENDIX D. ROBUSTNESS CHECKS

Table D1.1. Descriptive Statistics by early life conditions – without sample weights

Variables	Whole sample	Breastfed	Low birth weight (< 2.5kg)	Preterm birth (< 37 weeks)
Adaptive Behavior measures				
Adaptive Behavior Scale [0–40]	35.721	35.856	34.184	34.678
	(5.117)	(4.830)	(6.426)	(5.896)
Communication Skills score [0–12]	11.474	11.545	11.093	11.357
	(1.512)	(1.392)	(2.010)	(1.699)
Physical Ability score [0–18]	15.112	15.128	14.302	14.383
	(2.879)	(2.807)	(3.460)	(3.358)
Socio-emotional Development score [0–10]	9.134	9.181	8.788	8.937
	(1.548)	(1.450)	(1.871)	(1.699)
Child characteristics				
Female	0.493	0.504	0.533	0.476
	(0.500)	(0.500)	(0.499)	(0.500)
Child is first born for mother	0.398	0.419	0.434	0.442
	(0.489)	(0.493)	(0.496)	(0.497)
Year of birth	2012.192	2012.249	2012.279	2012.576
	(3.350)	(3.383)	(3.600)	(3.570)
Maternal characteristics				
Age at birth	30.986	31.570	31.014	31.029
	(5.506)	(5.257)	(5.701)	(5.653)
Marital status: married or living with partner	0.845	0.876	0.835	0.867
	(0.361)	(0.328)	(0.371)	(0.340)
Eduation status: A-levels, degree or higher	0.730	0.796	0.648	0.697
	(0.443)	(0.402)	(0.478)	(0.460)
Ethnicity: White British	0.759	0.722	0.577	0.734
	(0.427)	(0.447)	(0.494)	(0.442)
Employment status: paid employment (full part or part time)	0.550	0.582	0.454	0.498
	(0.497)	(0.493)	(0.498)	(0.500)
Risk of mental health problems (GHQ-12)$^{+}$	0.228	0.231	0.252	0.269
	(0.420)	(0.421)	(0.434)	(0.444)
Household characteristics				
Household size	4.143	4.129	4.343	4.354
	(1.150)	(1.094)	(1.368)	(1.267)
Tenure: owned outright or own mortgage	0.618	0.673	0.504	0.575
	(0.485)	(0.469)	(0.500)	(0.495)
Above 60% of median income	0.829	0.859	0.797	0.867
	(0.376)	(0.347)	(0.402)	(0.340)
Urban	0.787	0.786	0.829	0.763
	(0.409)	(0.410)	(0.376)	(0.425)
Observations	4,447	3,281	341	271

Notes: mean (std. errors). Wave at responses and region statistics are in the appendix. $^{+}$GHQ-12 $\geq$ 4.

Table D1.2. The role of early life conditions on adaptive behavior scale at age 3 – without sample weights

	Ordinary Least Squares (OLS)				IPWRA
Dep. Var → *Standarized Adaptive Behavior Scale*	(1)	(2)	(3)	(4)	(5)
(a) Low birth weight (<2.5 Kg)	-0.326***	-0.302***	-0.267***	-0.257***	-0.254***
	(0.072)	(0.071)	(0.069)	(0.069)	(0.072)
R-squared	0.007	0.025	0.067	0.070	
(b) Preterm birth (<37 weeks)	-0.190***	-0.173**	-0.137*	-0.128*	-0.129*
	(0.073)	(0.073)	(0.071)	(0.072)	(0.073)
R-squared	0.002	0.020	0.063	0.067	
(c) Breastfeeding	0.119***	0.144***	0.101**	0.090**	0.113**
	(0.039)	(0.040)	(0.041)	(0.041)	(0.050)
R-squared	0.002	0.022	0.064	0.067	
Control variables: children			✓	✓	✓
Control variables: maternal			✓	✓	✓
Control variables: household				✓	✓
Year of birth FE		✓	✓	✓	✓
Region of birth FE		✓	✓	✓	✓
Survey wave FE		✓	✓	✓	✓
Observations	4,447	4,447	4,447	4,447	4,447

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The Adaptive Behavior Scale is standardised (mean = 0, SD = 1), with higher scores indicating better adaptive behavior skills. Columns 1–4 report ordinary least squares estimates with robust standard errors clustered at the mother level in parentheses. Column 1 includes no control variables or fixed effects. Column 2 adjusts for year of birth, region of birth and survey wave fixed effects. Column 3 further controls for child characteristics (gender and first-born status) and maternal measures postbirth (education level, marital status, employment, ethnicity, age at birth, and risk of mental health problems). Column 4 additionally includes household characteristics (household size, urban residence, home ownership, and above 60% of median income). Column 5 presents IPWRA estimates (average treatment effect on the treated), with robust standard errors clustered at the mother level; propensity scores are estimated using an inverse probability weighting strategy that incorporates all child, maternal and household characteristics.

Table D1.3. The role of early life conditions on adaptive behavior scale at age 3 – without sample weights

	Correlated Random Effects (CRE)			
Dep. Var → *Adaptive Behavior Scale*	(1)	(2)	(3)	(4)
(a) Low birth weight (<2.5 Kg)	-0.278***	-0.262***	-0.252***	-0.250***
	(0.071)	(0.070)	(0.069)	(0.069)
R-squared	0.035	0.050	0.074	0.075
(b) Preterm birth (<37 weeks)	-0.161**	-0.141*	-0.122*	-0.119*
	(0.072)	(0.072)	(0.072)	(0.072)
R-squared	0.031	0.047	0.071	0.071
(c) Breastfeeding	0.065	0.080*	0.084**	0.084**
	(0.039)	(0.041)	(0.041)	(0.041)
R-squared	0.030	0.047	0.071	0.072
Control variables: children			✓	✓
Control variables: maternal			✓	✓
Control variables: household				✓
Mundlak FE		✓	✓	✓
Year of birth FE		✓	✓	✓
Region of birth FE		✓	✓	✓
Survey wave FE		✓	✓	✓
Observations	4,447	4,447	4,447	4,447

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The Adaptive Behavior Scale is standardised (mean = 0, SD = 1), with higher scores indicating better adaptive behavior. Columns 1–4 report correlated random effects estimates (average treatment effects) with robust standard errors clustered at the mother level in parentheses. The CRE specification includes time-varying averages from birth to age 3 (Mundlak FE), such as household size, urban residence, home ownership, low-income household indicator, and maternal characteristics including education level, marital status, employment, ethnicity and risk of mental health problems. Column 1 includes no control variables or fixed effects. Column 2 adjusts for year of birth, region of birth and survey wave fixed effects. Column 3 additionally controls for child characteristics (gender and first-born status) and maternal characteristics. Column 4 further adds household characteristics (household size, urban residence, home ownership, and above 60% of median income indicator).

Table D1.4. Controlling for father's socioeconomic circumstances

Dep. Var.: Standardized Adaptive Behaviour Scale	Ordinary Least Squares (OLS)			IPWRA
	(1)	(2)	(3)	(4)
a) Low birth weight (< 2.5 kg)	-1.552***	-1.501***	-1.480***	-1.606***
	(0.438)	(0.427)	(0.429)	(0.437)
R-squared	0.033	0.065	0.066	
Observations	3,353	3,320	3,309	3,366
b) Pre-term birth (< 37 weeks)	-1.134**	-0.974**	-0.940**	-1.128**
	(0.480)	(0.463)	(0.465)	(0.485)
R-squared	0.028	0.061	0.062	
Observations	3,350	3,317	3,306	3,363
c) Breastfeeding practices	0.769***	0.567**	0.533**	0.739***
	(0.251)	(0.250)	(0.247)	(0.285)
R-squared	0.031	0.062	0.063	
Observations	3,218	3,190	3,180	3,230
Control variables: children		✓	✓	✓
Control variables: maternal		✓	✓	
Control variables: paternal	✓	✓	✓	✓
Control variables: household			✓	✓
Year of survey FE	✓	✓	✓	✓
Region at birth FE	✓	✓	✓	✓
Survey wave FE	✓	✓	✓	✓

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The dependent variable is the standardized Adaptive Behaviour Scale (higher values indicate better adaptive behaviour). Columns (1)–(3) report OLS estimates and column (4) reports IPWRA estimates. Robust standard errors clustered at the mother level are reported in parentheses. Column (1) includes paternal controls and fixed effects; column (2) adds child and maternal controls; column (3) further adds household controls. Paternal socioeconomic controls include father's age, education (A-level or above), marital/partnership status, employment, and ethnicity (white British).

Table D1.5. Correlated Random Effects (CRE) with Tobit estimator and selection-bias estimator

Dep. Var.: Standardized Adaptive Behaviour Scale	Correlated Random Effects (CRE)		
	(1)	(2)	(3)
a) Low birth weight	-1.624***	-1.569***	-1.497***
	(0.365)	(0.358)	(0.352)
Selection-bias estimator (s)	0.567	0.069	-0.249
	(0.378)	(0.373)	(0.389)
R-squared	0.011	0.012	0.011
Observations	4,698	4,698	4,648
b) Pre-term birth (< 37 weeks)	-1.279***	-1.130***	-1.025***
	(0.387)	(0.375)	(0.364)
Selection-bias estimator (s)	0.558	0.039	-0.310
	(0.378)	(0.369)	(0.379)
R-squared	0.010	0.011	0.011
Observations	4,753	4,694	4,644
c) Breastfeeding practices	0.558***	0.431**	0.385*
	(0.203)	(0.205)	(0.205)
Selection-bias estimator (s)	1.832	0.987	1.363
	(1.834)	(0.945)	(4.338)
R-squared	0.010	0.011	0.011
Observations	4,574	4,524	4,475
Control variables: child		✓	✓
Control variables: maternal		✓	✓
Control variables: household			✓
Mundlak FE	✓	✓	✓
Year of survey FE	✓	✓	✓
Region at birth FE	✓	✓	✓
Survey wave FE	✓	✓	✓

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The dependent variable is the standardized Adaptive Behaviour Scale (higher values indicate better adaptive behaviour). Columns (1)–(3) report correlated random effects (CRE) estimates from a Tobit specification. The CRE specification follows Mundlak–Wooldridge by including child-specific averages of time-varying covariates over ages 0–3 ("Mundlak FE"), including (among others) household income, number of siblings, and household size. Standard errors clustered at the mother level are reported in parentheses. Column (1) includes fixed effects and Mundlak terms; column (2) additionally controls for child and maternal characteristics; column (3) further adds household controls.

APPENDIX E. FURTHER FIGURES AND TABLES

Table E1. The role of early life conditions on three adaptive behavior subgroups at age 3

	Ordinary Least Squares (OLS)				IPWRA
Dependent variables → Variables A/B/C	(1)	(2)	(3)	(4)	(5)
A) Communication skills					
Low birth weight (<2.5 Kg)	-0.265***	-0.239***	-0.201***	-0.184***	-0.186**
	(0.073)	(0.072)	(0.071)	(0.072)	(0.074)
Preterm birth (<37 weeks)	-0.069	-0.056	-0.027	-0.015	-0.017
	(0.068)	(0.068)	(0.067)	(0.066)	(0.068)
Breastfeeding practices	0.166***	0.192***	0.117***	0.099***	0.119**
	(0.040)	(0.041)	(0.043)	(0.043)	(0.060)
B) Physical ability					
Low birth weight (<2.5 Kg)	-0.328***	-0.309***	-0.283***	-0.282***	-0.276***
	(0.073)	(0.072)	(0.071)	(0.071)	(0.072)
Preterm birth (<37 weeks)	-0.276***	-0.260***	-0.226***	-0.227***	-0.229***
	(0.080)	(0.080)	(0.078)	(0.079)	(0.080)
Breastfeeding practices	0.027	0.051	0.042	0.037	0.068
	(0.037)	(0.038)	(0.038)	(0.038)	(0.046)
C) Social and emotional development					
Low birth weight (<2.5 Kg)	-0.241***	-0.224***	-0.199***	-0.187***	-0.184***
	(0.069)	(0.068)	(0.066)	(0.066)	(0.069)
Preterm birth (<37 weeks)	-0.127*	-0.111	-0.079	-0.064	-0.064
	(0.071)	(0.071)	(0.069)	(0.070)	(0.071)
Breastfeeding practices	0.132***	0.148***	0.117***	0.111***	0.117**
	(0.039)	(0.040)	(0.041)	(0.041)	(0.048)
Control variables: children			✓	✓	✓
Control variables: maternal			✓	✓	✓
Control variables: household				✓	✓
Year of birth FE		✓	✓	✓	✓
Region at birth FE		✓	✓	✓	✓
Survey wave FE				✓	✓
Observations	4,447	4,447	4,447	4,447	4,447

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Continuous outcome variable capturing three subgroups of Adaptive Behavior Scale: communication, physical ability, and social and emotional development indices. Three dummy variables of interest: (a) low weight at birth, (b) preterm birth and (c) breastfeeding. The table reports estimates for the OLS and IPWRA approaches. Standard errors clustered at the mother level; 90% confidence intervals are implied. HH = households.