LifeSim Childhood: Extrapolating Intervention Effects and Public Cost Savings from Birth to Adolescence in the UK

Shrathinth Venkatesh[1*], Ieva Skarda[1], Aase Villadsen[2], Miqdad Asaria[3], Jan R. Boehnke[4], Alan Brennan[5], Christian Krekel[3], Mark Mon-Williams[6], George Ploubidis[2], Paul A Tiffin[1], Richard Cookson[1]

[1]University of York, [2]University College London, [3]London School of Economics, [4]University of Dundee, [5]University of Sheffield, [6]University of Leeds

5 November 2025

Abstract

Economic evaluation of early childhood interventions is challenging because it is hard to extrapolate the full range of long-term benefits and public cost savings from short-term effectiveness evidence. It is also cumbersome and expensive to gather long-term evidence. One way to address this issue is through the use of microsimulation. This paper introduces a childhood microsimulation model, LifeSim Childhood, that is capable of extrapolating the long-term effects of many childhood risk factors on a broad range of health, educational, and social outcomes and public cost savings up to age 17 in the UK. It is based on bespoke modelling of longitudinal birth cohort data. The aims of this paper are to describe the general modelling approach and methods underpinning LifeSim Childhood, to present a simple illustration of how the model can be used to simulate the effects of early childhood poverty, and to compare our illustrative results with estimates from quasi-experimental studies.

Our model is based on analysis of data from the Millennium Cohort Study which follows children born in the UK around the year 2000. Our causal inference strategy is to focus on causal pathways that can be explicitly justified by existing inter-disciplinary scientific knowledge and to estimate the total magnitude of long-term causal effects by controlling for an explicitly justified set of confounding variables. As well as describing our data inputs, regression analysis methods and simulation methods, we illustrate how the model can be used to evaluate four hypothetical income-shifting scenarios in early childhood and estimate the general magnitude of long-term public cost savings and wellbeing benefits, alongside a battery of more specific outcomes.

[*]Centre for Health Economics, University of York, York, UK, YO10 (*Email*:shrathinth.venkatesh@york.ac.uk). This work was supported by the Medical Research Council Prevention Research Partnership ("ActEarly Programme", Grant # MR/S037527/1) and UK Research and Innovation (Grant # MMR/X002837/1). We thank Lucy Andrews, Sarah Bates, Patryk Bronka, Emma Brookes, Eric John Brunner, Sara Evans-Lacko, Rowena Jacobs, Brooke Johnson, Isaac J Parkes, Liina Mansukoski Matteo Richiardi, Matthew Warburton, Emir Zaidi, and seminar participants at HESG, University of Aberdeen, University of Leeds and University of York for helpful comments on this paper. All remaining errors are our own.

1 Introduction

Early childhood circumstances from conception to age five have been shown to have important long-term effects on individual life chances across a range of domains including health, education, employment and crime (Heckman, 2012; Almond et al., 2018). However, it is challenging to estimate the magnitude of the full range of long-term life outcomes and associated public cost savings across varying policy domains. This is because the data collected from specific intervention studies tends to focus on a narrow set of short-term intervention-specific outcomes (e.g. Melhuish et al. (2017)) and follow-up data on long-term outcomes takes decades to accumulate. Previous attempts at long-term early childhood policy modelling have tended to use special-purpose models that focus on a specific intervention or a limited set of outcomes. These have generally only encompassed a narrow range of policy domains or estimated outcomes over relatively short time periods (Milne et al., 2015; García et al., 2020). This means that there is no standardised approach capable of producing comparable value for money estimates. In particular, there is no general childhood modelling approach capable of producing cost-effectiveness estimates based on a general summary measure of public value such as the "WELLBY" measure recommended by the UK Treasury (Frijters and Krekel, 2021; Krekel and Layard, 2023). Microsimulation gives us the flexibility to create a re-useable general-purpose long-term model by combining multiple data sources that can be continuously updated.

We have previously started the process of developing a general long-term childhood policy model that can be re-used to evaluate different interventions, known as LifeSim (Skarda et al., 2021, 2022).

Our prototype model, which we call "LifeSim 1.0", was a discrete event simulation of annual outcomes from birth to death. However, from age 0 to 17 it was primarily based on simply carrying forward observations from longitudinal data, rather than explicit modelling, and so the main capability of LifeSim 1.0 was extrapolating outcomes from late adolescence to late adulthood, rather than extrapolating risk factors from early childhood to outcomes up to late adolescence. Consequently, here we present the first general childhood microsimulation model capable of extrapolating risk factors in childhood to a rich set of outcomes in later childhood and adolescence, which we call LifeSim Childhood. This new model is capable of inputting short-term effects on childhood risk factors (age 0 to 14) and outputting a wide range of extrapolated outcomes and public cost savings up to age 17. The model builds on LifeSim 1.0 by analysing the effects of early childhood circumstances on important adolescent outcomes known to have long-term effects on health and other life outcomes in adulthood (Villadsen et al., 2023). The main purpose of this paper is to describe and illustrate the use of LifeSim Childhood. Using an increase in early childhood income as an example, we describe our model and causal inference strategy for estimating the magnitude of impacts, and illustrate how it can be used to extrapolate the consequences up to age 17. The risk factor (early years income), the change to risk factor (increasing income for a specific population) and model used for estimation can be updated and changed as necessary for future research. Our model simulates various childhood outcomes that could subsequently be plugged into our adulthood model to estimate life-course outcomes, and we plan to do that and describe the methods and results in subsequent papers. Our model is a micro-economic evaluation tool that aims to predict the specific costs and benefits of specific interventions, rather than a macro-economic forecasting tool that aims to predict future trends in general population outcomes. Where possible, we compare our model simulated estimates to external experimental and quasi-experimental estimates from the literature, to ensure that our estimates are in the right ballpark.

To illustrate how the model can be used in practice, we follow (Villadsen et al., 2023) in modelling the potential effect of four simple hypothetical income-increasing scenarios for groups of households split by their position in each fifth of the MCS household income distribution: (1) increasing the income of the poorest fifth to that of the second poorest fifth; (2) increasing the income of the two poorest fifths up to that of the middle fifth; (3) increasing the income of the poorest to the richest fifth, and (4) increasing everyone's income to that of the richest fifth. We report outcomes and costs by age and disaggregate costs by source (hospitalisation, disability, conduct disorder, special education needs (SEN), truancy and exclusion). These scenarios are not realistic policy options for specific tax-benefit reforms but are just simple illustrative examples asking what would happen if in theory it were possible to make perfectly targeted cash transfers with no administrative costs or deadweight losses due to the effects of tax-benefit reforms on economic behaviour.

We use Millennium Cohort Study (MCS) birth cohort data on about 15,380 babies born in the UK around 2000/2001 and followed up to age 17. We use multiple imputation to handle missing values due to attrition and non-response. We model a set of policy-relevant outcomes from age 3 to 17, including cognitive skills, socio-emotional and behavioural problems, educational attainment, smoking, obesity, self-reported health, psychological distress, wellbeing, and six cost-bearing outcomes. In this study, as an illustrative example, we focus on a single early years risk factor - mean household income age 0 to 5. However, the same approach can be applied to a wide range of other risk factors and circumstances during childhood and adolescence that policy makers often target for prevention, support services or both. We take an explicitly justified approach to causal inference based on the principles set out by Pearl (2009). We focus on estimating the total magnitude of causal effects that are already well-established or at least can be given a plausible justification on the basis of current inter-disciplinary scientific knowledge, and we only include confounders for which there is a plausible justification based on a clear set of causal inference rules. We make our causal inference assumptions explicit, we identify theory and evidence to support them, and we identify important uncertainties and controversies about our assumptions and how far this might materially impact our conclusions. We chose income as an illustrative risk factor as there have been many experimental and quasi-experimental studies of the long-term effects of early childhood income on specific later childhood outcomes (Cooper and Stewart, 2021). These are reviewed later in section 3.6 to provide evidence for the external validity of our estimates, derived from observation data, which control only for measured confounding factors.

2 Methods

An overview of the structure of LifeSim childhood is presented in Figure 1. Modelling using LifeSim begins with the data drawn from the Millennium Cohort Study (MCS) from which we identify "risk factors" (ages 0 to 14) and "outcomes" (ages 3 to 17). In this sense, "risk factors" represent any early years variable that could be a potential policy intervention target for improving the "outcomes". Our current list of risk factors and outcomes has been chosen through consultation with an interdisciplinary group of academics, policy experts, stakeholders and policy makers.[1]

We make explicitly justified assumptions about causal inference based on principles set out by Pearl (2009), and follow Squires et al. (2016) in taking a systematic approach to developing those assumptions and selecting appropriate models for estimating the magnitude of causal effects of risk factors on outcomes, based on review of the scientific literature and iterative consultation with stakeholders, experts, and members of the team. Through this process we have set up a set of

[1] A non-exhaustive list of those consulted as part of our advisory group are included in appendix section A.9

causal inference rules[2] to put together models of the effect of risk factors on each outcome based on directed acyclic graphs (DAGs). We then use regression analyses run on the MCS data to estimate the relationships.

For the simulation we extract not only coefficients but also their standard errors and the distribution of residuals from the regressions to parametrise uncertainty. These are used as parameters in our simulation of the outcomes. We attach unit costs to various cost-bearing outcomes to estimate public costs. We use a parent-reported emotional problems score as a proxy indicator of life satisfaction - one domain of the parent-reported strengths and difficulties questionnaire (SDQ) - with sensitivity analysis using a two-item version that includes a peer problems domain score as well. This allows us to calculate public costs, subjective wellbeing and other life outcomes from age 3 to 17.[3]

Short term intervention effects from external studies, (e.g. improvements to birth weight or reduction in socio-emotional problems) or policy changes (e.g. increases in income due to changes to the tax benefit system or direct money transfer) can be input into the model to simulate long-term effects. If the exact risk factor is not available, the effects can be mapped onto an equivalent risk factor available in the MCS and input into the model.

2.1 Data

The main data source used in LifeSim childhood is the Millennium Cohort Study (MCS), a longitudinal cohort study of around 19,000 children born in the UK around the year 2000.

The MCS surveys were conducted when the children were 9 months, 3 years, 5 years, 7 years, 11 years, 14 years, and 17 years[4]. After excluding twins and triplets and limiting our sample to those who responded to the age 3 survey, the final analytical sample consisted of 15,380 cohort members[5]. The response rate for the MCS cohort declined over time, affecting the availability of outcomes measured at later ages. To deal with missing data we use multiple imputation using chained equations. We work with 30 sets of the multiply imputed data for the 15,380 children which

[2]These rules are described in detail with examples in appendix section A.6.

[3]We assume our risk factor "permanent income " affects outcomes from birth but we only model public costs and wellbeing gains from age three to age 17 in an effort to be conservative.

[4]The study is ongoing and the next sweep of data from when the cohort members are around 23 is expected to be released in late 2025

[5]3,705 children are dropped due to non response in the second sweep ate age 3 and 396 children who are twins or triplets are dropped. Twin and triplet households are dropped entirely.

we use for the regression analysis and simulation.[6]

The variables we use for our estimation from the MCS can be roughly divided into three categories: risk factors, confounders, and outcomes.[7]

2.1.1 Risk Factors

The list of risk factors whose effect could be estimated in LifeSim childhood is broad and can be expanded based on availability in the MCS. This can include anything from the mother's perinatal characteristics (e.g. teenage parent, perinatal smoking, perinatal drinking), birth circumstances (e.g. low birth weight, pre-term birth, parents income at birth), and childhood circumstances (e.g. disability, school readiness, socio-emotional development).

The primary risk factor used in our illustrative results is early years income; the average OECD equivalised weekly income of the household measured when the child is 9 months, 3 years, and 5 years. We use this pooled measure to capture the household's permanent income during early childhood. This avoids the risk of bias due to temporary income shocks that would occur if we focused only on income measured in one specific sweep of the survey. Our results specifically look at the effect of increasing income for families, thereby moving them up the income distribution[8] We assume that the timing of change to this "permanent income" starts prior to the point of measurement when the child is 9-months old and continues throughout early childhood to at least the age of five.

2.1.2 Confounders

The MCS data includes detailed information about the child, their parents and household at each sweep of the survey. Any of this information can be included as a potential confounder, but the final selection for each model is based on our DAG rules and consultation with experts.

For example, in our illustrative example with income as a risk factor we use a set of eight confounders in our preferred model. We include basic demographic characteristics at age 9 months which we assume to be the same as that at birth: country, region within England, and ethnicity of

[6]The imputation process is described in more detail in Appendix section A.5

[7]In this paper the three groups of variables will be mutually exclusive but this is not be the case for LifeSim in general.

[8]Income fifths are based on the distribution of household income within the multiply-imputed MCS data with age 3 UK population weights.

the child. We also include some maternal characteristics: mother's age at birth of the child, and maternal smoking during pregnancy. Finally we include some household characteristics: education of parents, parental disability and having a single parent.[9]

2.1.3 Outcomes

LifeSim Childhood can simulate the effect of a risk factor on a broad range of outcomes, limited only by data availability. However, in this paper we focus on three broad outcome categories, important adverse outcomes, wellbeing, and outcomes with direct public costs.

Adverse Outcomes We simulate a set of five adverse health and educational outcomes measured in the MCS at age 17. These outcomes are all both important in their own right and also predictive of poor outcomes throughout adulthood (Villadsen et al., 2023; Hale et al., 2015; Patton et al., 2016; Akasaki et al., 2019; Ploubidis et al., 2021; Gondek et al., 2021; Berg et al., 2022).

The first, poor GCSEs, is a binary measure for poor self reported academic performance at the end of secondary school [10]. Specifically poor GCSEs is defined as not having 5 or more GCSEs[11], including maths and english, graded C or above.

The second adverse outcome is psychological distress determined by self reported Kessler score (K6). This is a self-report measure based on a 6 item questionnaire about anxiety and depression. Each response is scored from 1-4 and a score of 13 or over is considered to represent the screening threshold for probable clinical levels of psychological distress (Kessler et al., 2003).

The third adverse outcome is obesity based on a respondent meeting the UK90 growth reference chart obesity threshold for their age and sex at the time of interview (Freeman et al., 1995).

The fourth adverse outcome is 'regular smoker'; an indicator for regular cigarette smoking based on self reported smoking of more than six cigarettes per week.

The final adverse outcome is poor/fair health an indicator for poor self reported health. Respondents are asked "*How would you describe your health generally?*" and pick a response of 'excellent', 'very good', 'good', 'fair' and 'poor'. A response of 'poor' or 'fair' is considered as representing a

[9] The confounders are described in more detail in section 2.3.1 and appendix section A.2.2.

[10] General Certificate of Secondary Education (GCSE) results in England, Wales, and Northern Ireland, and National 5 (N5) results in Scotland.

[11] or 4 or more N5 results in Scotland graded D or above

report of being in poor health.

Wellbeing Subjective wellbeing is an important policy outcome, which can be converted into the "wellbeing-year-point" (WELLBY) summary unit of benefit recommended by the UK Treasury, based on a one point improvement in life satisfaction for one year, valued at about £13,000 (MacLennan et al., 2021). We use the parent-reported Strength and Difficulties Questionnaire (SDQ) emotional symptoms scale from ages 3 to 17[12], as an imperfect proxy indicator for life satisfaction as SDQ scores are consistently available throughout childhood in the MCS. The 0-10 scale for SDQ emotional symptoms is converted to a life satisfaction score (0-10) between 2 and 10 using a simple linear mapping.[13]

Using this simple 0-10 scale allows us to directly translate our results to WELLBYs.

Outcomes with Public Costs We were able to capture many, though not all, of the childhood public costs that are potentially modifiable with early intervention using six outcomes available in the MCS: hospitalisation, disability, conduct disorder, special education needs (SEN), truancy and exclusion. In the following section, we describe each cost-bearing outcome, the source of annual unit costs, and any adjustments and assumptions made.[14]

Hospitalisation is based on parent report of admission to a hospital at ages 3, 5, 7, 11, 14 and 17 years. We do not distinguish between "avoidable" and "unavoidable" hospitalisation, so the baseline costs captured here should not be interpreted as the "costs of late intervention" as usually defined in terms of the incremental costs associated with children experiencing significant challenges in life compared with the standard health care costs needed for all children (Chowdry and Fitzsimons, 2016). Instead, we rely on our estimates to tell us how many instances of any hospitalisation are prevented by a change in the specific risk factor. We therefore rely on our causal inference modelling to estimate effects on public costs, rather than attempting to do this by distinguishing "avoidable" and "unavoidable" categories of public expenditure. Since MCS does not specify the details around

[12] We provide more information about using this measure in appendix section A.4. We also present simulation estimates with SDQ internalising - the sum of emotional and peer problem scores - as the life satisfaction measure instead in appendix table A7.

[13] We map only to life satisfaction of 2 or above because the distributions of life satisfaction and SDQ emotional symptoms do not match perfectly and such a mapping results in a much higher rate of very low life satisfaction than other studies of life satisfaction in the UK. The simple linear transformation of SDQ emotion (SDQE) to life satisfaction (LS) is $LS = SDQE * (10 - 2)/(10 - 0)$.

[14] Appendix tables A1 and A2 summarises the details of the costs and their sources.

recorded hospital admissions we use the average cost of a single inpatient hospitalisation for a child (age <18) in the UK of £1,587 (Dale et al., 2024). We do not capture all healthcare costs using this outcome and cost measure, just inpatient costs and not costs of primary care, outpatient care, and community care utilisation which are not possible reliably to estimate in the publicly available MCS data. However, inpatient costs make up a much larger proportion of preventable healthcare costs than primary, outpatient and community care costs (Chowdry and Fitzsimons, 2016).

Disability, based on parent reported long-term illness that affects the child's daily activity, is available at ages 3, 5, 7, 11, 14 and 17 years. We do not have a good cost estimates for the disability in the UK. We limit ourselves to the health costs associated with disability. We use a cost of £1,008 per year per child to the NHS, the average annual cost of healthcare for a child in the UK (Kelly et al., 2018). This is likely an underestimate of the total cost of disability.

'Conduct Disorder' classification is based on the scores derived from the parent reported version of the SDQ conduct problems scale at ages 5, 7, 11, 14 and 17 years[15]. We follow Skarda et al. (2021); Goodman et al. (2000, 2003) in using a simple algorithm to estimate the probability of conduct disorder for each individual using their SDQ conduct problems scale. Age specific costs for conduct disorder are derived from Bonin et al. (2011). We use a unit cost (annual cost per child with conduct disorder) of £3,092 between ages 5 and 10, £1,963 between ages 11 to 16, and £236 for age 17 and beyond. These costs decline as the child gets older as they only capture costs to the NHS, Social Services and Department of Education. The costs to the the justice system which may increase with age are not currently included in the model.

Special Education Needs (SEN) is based on teacher/parent report of the child having a statement of special education needs. Costs for students with SEN statement are based on calculations for the average costs for students with an Education, Health and Care Plan (EHCP) for children in schools in 2023 amounting to an additional cost of £25,500 per year per EHCP student over the cost of a non EHCP student.[16] The cost was based on analysis by the Department for Education of costs associated with around 400,000 pupils with EHCPs in mainstream schools, special schools and independent special schools in 2023. Costs per EHCP pupil in 2023 are comparable to costs

[15]SDQ scores are also available at age 3 but we do not have a cost at that age and the algorithm we use to identify conduct disorder is not appropriately calibrated for this age group so we omit these outcomes.

[16]The average cost per EHCP student is estimated at around £31,000 and the average cost for a non-EHCP student is estimated at around £5,500 in 2023.

per SEN pupil in the early 2010s, since SEN statements were gradually phased out and replaced by EHCP plans during the early 2010s. The full (non-incremental) cost breaks down as £25,000 for place and top-up funding per EHCP, £2,000 for additional costs (e.g. SEN support services, support for inclusion, and therapies), £2,500 for additional cost of transport per EHCP (cost additional to expenditure on mainstream transport), and further administration and education psychology costs of £1,500. (Department for Education, 2024a,b; Acton et al., 2024)

Truancy in the MCS is measured by parent reported absence from school at ages 11 and 14 years. A binary indicator for any truancy is used for the simulation. We cost truancy using the average cost to the Department of Education from regular truancy per child who is regularly absent from school, which is £943 per year per child (Brookes et al., 2007). The parents in the MCS are also asked about number of weeks of absence, a response of more than 5 weeks a year is considered regular truancy. We assume there is no cost to the public for any truancy that is not regular truancy.

Exclusion in the MCS is measured by parent reported exclusion from school ages 11 and 14 years. Parents are also asked about permanent exclusion at age 11. We cost exclusion using the cost of alternate provision, an alternative school for permanently excluded children to complete their schooling. Consequently, permanent exclusion is costed at £21,848 per year per child in alternative provision(Bryant et al., 2018). We assume no cost to the public for temporary exclusion.

2.2 Simulation Structure

The simulation in LifeSim Childhood runs a cohort of children picked from the MCS through the course of childhood several times or across several "universes" and produces the outcomes for each individual in the cohort in every universe. We perform a probabilistic sensitivity analysis using universes by introducing an element of randomness to the models built using the MCS.

We use the MCS data for the baseline characteristics of the cohort we run through the simulation. We use “long-jump” modelling which goes directly from the risk factor at the time of exposure to the outcome in each subsequent period without tracing out the mediating pathways at individual level (e.g. directly from age 3 to age 17). This is different from many other microsimulation models such as (Skarda et al., 2021) (the prior version of LifeSim) which use a “relay” approach, modelling outcomes sequentially period by period and tracing out the pathways at individual level. Both the long-jump and relay approaches to simulation have their benefits and downsides. The main difference is that the relay approach traces out full individual level casual pathways including mediating effects, whereas the long-jump approach only estimates outcomes. As a consequence, the relay approach allows changes to the risk factor and confounders at any time. On the other hand the long-jump approach, does not allow this variation in risk factor and confounders, but it also does not require observation and modelling of every mediating relationship between risk factor and outcome to estimate the final effect.

However, we prefer the long-jump modelling approach for LifeSim Childhood as a way to simplify models required to be estimated and minimise possible bias due to propagating bias and error from one period to the next. Since each effect is measured with some error/bias the error in the simulation when using the relay approach will likely increase with the number of years modelled. The long-jump simulation approach helps guard against this error being propagated and compounded through the model giving us estimates that are less likely to be biased.

In order to estimate the parameters for our long-jump modelling approach we run regressions estimating the effect of each risk factor on each outcome in each simulated year. We use linear regressions for cognitive ability (normal distribution), negative binomial regressions for SDQ scores and Kessler (count variables), and logistic regressions for the binary outcomes (Hospitalisation, disability, special education needs, truancy, exclusion, poor GCSEs, obesity, regular smoking, poor health). The point estimates as well as the variance of the estimates are extracted from the regression for use in the simulation. To get a nationally representative sample for estimation we use weights included in the MCS dataset, they adjust for attrition between the initial survey and the second sweep and the MCS's sampling strategy.

The short-term intervention effect estimated in an external study such as a trial, is applied to the MCS initial population and the long-term outcomes are simulated using the regression estimates. The simulation is not deterministic, rather parameter uncertainty is captured in the model in the following two ways. First, the coefficients used to simulate the outcomes are randomly drawn from a normal distribution with a mean equal to the point estimate and standard deviation equal to the standard error from the estimates obtained[17]. Second, an error term is added based on a random draw from the distribution of residuals to each estimate. Doing this allows us to capture some element of the variance of the outcomes. Additionally, in the case of binary outcomes, our estimates

[17] In the case of logistic regressions

allow us to come up with a predicted probability of the outcome for each individual, we predict success for each individual by comparing the predicted probability with an individual random draw from a uniform distribution between 0 and 1.

2.3 Estimation Strategy

In order to estimate causal relationships between each risk factor and outcome in the absence of experimental or quasi-experimental data we follow Pearl (2009) in drawing causal diagrams (DAGs). This allows us to bring together prior scientific knowledge to determine causal links between risk factors and outcomes in our data.[18] The depth of information about the individuals and parents in the MCS allows us to capture a rich set of confounders in the relationship between our risk factors and outcomes using a set of model selection rules[19] so our models are credible, conservative, and parsimonious. The main limitation of MCS in terms of relevant confounders relates to genetic variables and biomarkers that provide information about genetically inherited traits. This is a potential source of unobserved confounding, though some of these genetic traits will be indirectly captured through observed parental variables such as parental education, mental health, smoking and other parental circumstances and behaviours. The main limitation of MCS in terms of relevant confounders relates to genetic variables and biomarkers that provide information about inherited biological traits. This could introduce unobserved confounding. However, many genetic influences on later adverse outcomes are only realised through cumulative processes of childhood development involving sustained interactions between social and biological factors rather than being predetermined impairments at age 5 (Krieger, 2024; O'Donnell, 2024; Almond et al., 2018; Cunha and Heckman, 2007). In the general population, outcomes such as conduct disorder at age 17 typically arise from gradual processes of skills formation and responses to material and social environments. For example, a genetic susceptibility to conduct problems may only manifest under persistent stress or adverse parenting conditions. The rich set of parental characteristics and family circumstances included in our models - such as parental education, mental health, smoking, and socioeconomic conditions - therefore captures much of the relevant pathway through which genetic traits influence child outcomes. For the sake of comparison we also estimate an un-adjusted relationship between

[18] Appendix section A.3 provides justification for assuming a causal relationship between early years income and our chosen outcomes.

[19] The rules along with examples of their application are presented in Appendix section A.6

each risk factor and outcome and an "extra conservative" model where we include an expanded confounder set where we relax some of the rules and include further potential confounding variables that are also partly mediating variables to err on the side of caution.

2.3.1 Model used for income as a risk factor

For our illustrative example, to keep our example simple, we construct a single model to estimate the effect of early years income on a broad set of the outcomes described above, following our model selection rules. We run the simulation across three versions of our model, our preferred model that follows all the model selection rules, an "extra conservative" model that relaxes some of the rules, and unadjusted correlation. A simplified version of the DAG is presented in Figure 2.

The confounders we include in the preferred model are indicators for country (England, Wales, Scotland and Northern Ireland, with England as baseline) at age 9 months, indicators for region within England[20] (with London as baseline) at age 9 months, indicators for ethnicity[21] of the child (with White as baseline), indicator for the mother's smoking status during pregnancy, age of the mother at birth, indicators for highest education of parents at age 9 months (NVQ levels 1 to 5, with level 5 as baseline), indicator for any disability in the household at age 9 months[22], and indicator for parent being the sole carer at age 9 months.

In our extra conservative model we include an additional set of five confounders.

These include neighbourhood deprivation measured using the Index of Multiple Deprivation (IMD) fifth (with least deprived fifth as baseline) at age 9 months, poor maternal mental health (based on Rutter malaise score) at age 9 months, participation of at least one parent in the labour force at age 9 months, grandparents' education reported at age 17 (NVQ levels 1 to 5, with level 5 as baseline), and disability of the child at age 3[23].

IMD, maternal mental health, and disability of the child are not included in the main analysis as they may be mediators, i.e. they could all be affected by the parent's permanent income and could affect the child's outcomes.[24] Additionally maternal mental health is also not included because

[20] North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, and South West

[21] White, mixed, Indian, Pakistani and Bangladeshi, Black or Black British, and other ethnic group (inc. Chinese and other Asian)

[22] Measured by receipt of any disability benefits by either the main parent or partner.

[23] This is excluded as a control when estimating the effect of income on disability.

[24] Since mediators(M) lie on the causal pathway between the risk factor (RF) and outcome (O), their

it is measured at 9 months, post-partum mental health may not be a perfect measure for mental health prior to birth/pregnancy. Parental labour force participation is not included as it is a major determining factor of income and its inclusion may not have a large effect on the child's outcomes. Its inclusion could result in underestimating the effect of income. Finally, grand parent's education is not included in the original model as it is used as a measure of wealth and is unlikely to have a large effect on the child's outcomes except that through the parents education which we already account for.

The relationship between income and each of the outcomes we simulate is complex. Both risk factor and outcomes are affected by household composition, parental education, parental age,parental physical and mental health, parental wealth, parental socio-economic status, access to resources, child health, and genetics. The richness of data in the MCS about the child and the family allow us to control for most if not all potential confounders in these relationships either directly or indirectly. However, the MCS does not include explicit information on genetic traits that may be confounders. However, many relevant genetic traits are likely to be captured indirectly by things like parental education and socioeconomic status (Wang et al., 2021).

3 Results

As an illustrative example for this paper we simulate four simple income increasing scenarios, as used in Villadsen et al. (2023)[25]. We chose these scenarios as simple thought experiments that illustrate our methodology. These scenarios are based on increasing the income for families grouped by each fifth of the income distribution

- **Scenario 1** - increasing the income for families with children in the **poorest** fifth **to** that of the **second poorest** fifth.
- **Scenario 2** - increasing the income for families with children in the **two poorest** fifths **to** that of the **middle** fifth.
- **Scenario 3** - increasing the income for families with only children in the **poorest** fifth **to**

inclusion in the regression (assuming direction of the effect is the same in all three relationships, RF->O, RF->M, and M->O) will result in smaller estimates of the effect of the risk factor on the outcome.

[25]They examined the effects of scenarios 1, 2 and 4 on the five adverse outcomes at age 17.

that of the **richest** fifth.

- **Scenario 4** - increasing the income for **all** families with children **to** that of the **richest** fifth.

The weekly mean equivalised household incomes in each fifth of the birth cohort are, £123.47 (£0 to £163) for the poorest, £207.40 (£164 to £254) for the second poorest fifth, £304.54 (£255 to £356) for the middle fifth, £419.29 (£357 to £495) for the next fifth, and £659.05 (£496 to £1,298) for the richest fifth for families with a child born around 2000.[26]

In scenario 1, the equivalised income for the poorest fifth of households increases to £207 a week, an annual average increase of £4,368 a year for these households. On average this cash transfer is about four times the current child benefit amount for single child families, however, families would be eligible for this transfer for only five years instead of between 16 and 20 years and fewer families would be eligible for a cash transfer in scenario 1.

3.1 Adverse Outcomes

The simulation estimates that at age 17, 38% of the population have poor GCSEs, 25% experience psychological distress, 26% are obese, 13% are regular smokers, and 10% have poor self reported health.[27] Figure 3 shows the percentage reduction in these adverse outcome across the entire population associated with each intervention. The error bars show the range in which 95% of the simulated sample effects lie.

Scenario 1, increasing the income of the poorest fifth to that of the second poorest fifth results in a 4% (1.6 (0.44 - 2.66) percentage points) reduction in poor GCSEs, 0.4%(0.1 (-0.49 - 0.69) percentage points) reduction in psychological distress, 0.4% (0.1 (-1.10 - 1.31) percentage point) increase in obesity, 3.9% (0.5 (-0.65 - 1.63) percentage point) reduction in regular smoking, and 5.7% (0.6 (-0.3 - 1.44) percentage point) reduction in self reported poor health.

The other scenarios lead to reductions in all five adverse outcomes, including obesity, with larger reductions (percentage) in Poor GCSEs, self reported poor health, and regular smoking than in obesity or psychological distress.

[26] The distribution is presented in Appendix Figure A1.

[27] The prevalence of these adverse outcomes in the MCS are slightly lower. 37% of the population have poor GCSEs, 23% experience psychological distress, 23% are obese, 10% are regular smokers, and 8% have poor self reported health.

3.2 Wellbeing

Wellbeing in our case is measured by parent reported SDQ emotional symptoms scale linearly transformed to life satisfaction on a 0 to 10 scale. The simulated baseline levels of life satisfaction do not fluctuate significantly with age. Life-satisfaction peaks at age 5 with a mean of 7.9 and is lowest at age 17 with a mean of 7.14.

Figure 4 shows the average increase in life satisfaction for each scenario, to illustrate the size of the effects on life satisfaction we convert the results into WELLBYs. WELLBYs are defined as a one point increase in life satisfaction on a 10 point scale per child per year. In scenario 1, increasing the income of the poorest fifth to that of the second poorest fifth results in an increase in life satisfaction between 0.028 (-0.009 - 0.652, at age 5) and 0.043 (-0.003 - 0.090, at age 17) in a single year, for an annual average wellbeing increase (between ages 3 and 17) of 0.027 (0.016 - 0.038) or 0.404 (0.238 - 0.570) over the entire 15 year period.

The other scenarios lead to greater improvements in wellbeing at every age resulting in a 15 year average wellbeing increase of 1.048 (0.796 - 1.299) in scenario 2, 1.312 (1.170 - 1.455) in scenario 3 and 3.214 (2.906 - 3.522) in scenario 4.

3.3 Costs

Our public cost estimates capture the costs associated with hospitalisation (ages 3 to 17), disability (ages 3 to 17), conduct disorder (ages 5 to 17), special education needs (ages 7 to 17[28]), persistent truancy (ages 11 to 17[28]) and permanent exclusion (ages 11 to 17[28]).

The annual cost per child at the baseline increases with age as presented in Figure 5. The total annual cost per child is £396 at age 3, £604 at age 5, £1,185 at age 7, £1,507 at age 11, £1,530 at age 14, and £1,516[29] at age 17. This averages to an annual cost per child between the ages of 3 and 17 years of £804[30]. This annual cost per child between 3 and 17 can be broken down into £187 for hospitalisation, £71 for disability, £128 for conduct disorder, £364 for special education needs, £3 for persistent truancy, and £50 for permanent exclusion.

[28]This outcome is not available at age 17 in the MCS but the value from age 14 is assumed to carry over to age 17.

[29]Special education needs, Truancy and Exclusion are not measured at age 17 and are carried over from age 14, the total cost when excluding those three is £538.

[30]Calculated at birth and discounted at 3.5 percent a year. The un-discounted annual average is £1,180.

Figure 6 shows the cost savings associated with the implementation of each scenario. Note we do not account for the cost of achieving poverty reduction, rather we only show public cost savings. The figure shows four clustered bar graphs at each age, each bar is an estimate for scenarios 1 to 4 in order (from left to right). The area below the x-axis represents cost increases and the area above represents cost savings.

Scenario 1 does not result in overall public cost savings (based on our six outcomes) at age 3 due to an increase in hospital costs compared to the baseline. The cohort average annual cost increases by £1.42 (-13.47 - 16.30) at age 3[31], and results in savings of £7.60 (-8.15 - 23.35) at age 5, £4.62 (-96.72 - 105.96) at age 7, £49.63 (-59.67 - 158.93) at age 11, £28.21 (-69.90 - 126.32) at age 14, and £23.75 (-76.48 - 123.98) at age 17. This translates to an average annual cost between ages 3 and 17 of £13.46 (-15.04 - 41.95)[30], which can be broken down into an increase of £0.41 for hospitalisation, and savings of £0.67 for disability, £2.43 for conduct disorder, £4.89 for special education needs, £0.10 for persistent truancy, and £5.78 for permanent exclusion.

The cost savings in the other scenarios are statistically significant and increase (though there is still an increase in hospitalisation costs in scenario 2) as the money transferred increases. The cohort average annual savings between ages 3 and 17 years [30] are £31.45 (14.32 - 48.58) for scenario 2, £36.13 (25.45 - 46.80) for scenario 3, and £81.47 (60.77 - 102.18) for scenario 4.

While our results are primarily a demonstration of the tool, the increase in hospital utilisation with increase in income, though not significant, may be unexpected. From the literature, there is a plausible mechanism for increased inpatient hospitalisation due to an increase in parental income causing more proactive care seeking behaviour and earlier diagnosis of conditions, resulting in a general increase in non-emergency healthcare utilisation. However, there are very few studies (outside of the US and LMICs) looking at the effect of changes to family income on healthcare utilisation. Reinhold and Jürges (2012) find that healthcare utilisation among German children has an income gradient. Coughlan et al. (2022) find that children living in the most deprived parts of the UK were less likely to use primary and secondary health care but more likely to have emergency visits.

[31] This is due to increases in costs to the public associated this hospitalisation

3.4 Total effects

Table 1 summarises the effects of each scenario on a cohort of 700,000 (rough size of 2021 UK birth cohort) children over the full fifteen year period from age 3 to age 17.

The first part of the table shows the number of children who avoid each adverse outcome under each simulated scenario as compared to the base-case model.

The next part of the table shows the public cost savings compared to the base-case model in millions of 2023 £s. There is a cost saving[30] of 141 million £s with scenario 1 despite an increase in hospitalisation costs, driven mostly by savings from reductions in school exclusions. The costs savings are higher for the other scenarios.

The third part of the table shows the improvement in wellbeing in terms of WELLBYs, and the value of that increase with WELLBYs being valued at £13,000. For scenario 1 this results in £3,677 million[32] worth of wellbeing generated over 15 years[30] for a cohort of 700,000. The amount of wellbeing generated increases with the scale of the money transferred across scenarios.[33]

The final part of the table contains a rough estimate of the cost of the program, based on the minimum amount of money that would have to be transferred to each eligible household to move them to the target fifth of the income distribution. The amount of money that would have to be transferred to household with newborns over the first five years[30] in the poorest fifth to ensure they have at least as much as the lowest income in the second poorest fifth is £2,134 million. [34]

The public cost savings (up to age 17) from each of the scenarios do not offset their costs. However, for scenario 1 this cost is more than offset by the value gained in terms of wellbeing, before taking into account the public costs savings and savings due to improvement in adverse outcomes and improved outcomes beyond age 17. However, the cost increases exponentially with each scenario with Scenario 2's cost just about matching the sum of value generated in wellbeing and the public cost savings. For scenarios 3 and 4 the value of wellbeing generated and public cost

[32] The Treasury green book (MacLennan et al., 2021) suggests the value of a WELLBY is £13,000 with an upper limit of £16,000 and lower limit of £10,000. In which case the wellbeing gain can be valued between £2,828 million and £4,525 million. There is also the much lower supply side valuation of about £2,755 a WELLBY which values the WELLBY gain at £779 million.

[33] We also present simulation estimates with SDQ internalising - the sum of emotional and peer problem scores - as the life satisfaction measure instead in appendix table A7. The increase in life satisfaction is about 30% lower when using this measure.

[34] It is likely undertaking a program like this will involve significantly more in administrative costs but we do not calculate them here.

savings are dwarfed by the costs.

3.5 Sensitivity analysis

As a check of our model selection criteria and to get a sense of the effect of controlling for potentially missed confounders we compare our preferred model to an "extra conservative" model and an unadjusted model. Table 2 summarises the effects of each of the models in scenario 1 on a cohort of 700,000 (rough size of 2021 UK birth cohort) children over the full fifteen year period from age 3 to age 17.

The preferred model shows a reduction in all adverse outcomes except for obesity. In the extra conservative model, there is an increase in psychological distress and a larger increase in obesity than the preferred model, the improvements to the other adverse outcomes are more conservative as may be expected. The unadjusted model shows greater improvements than the preferred model in all adverse outcomes except psychological distress, where there is an increase in the number of cases.

The preferred model suggests with scenario 1 there is a cost savings of £141 million, compared to -£46 with the "extra conservative" model and £242 million [30]) for the unadjusted model. This difference in cost is driven by increases in hospitalisation, disability and special education needs relative to the baseline in the conservative model coupled with lower savings on the other outcomes. The savings are higher across all six outcomes and positive across the board in the unadjusted model.

The preferred model shows greater wellbeing gains than the conservative model, both of which are much lower than the gains in the unadjusted model. Assuming the cost of implementing scenario 1 is £2,127 million as used above, the gain in value from wellbeing from any of the three models are greater than the cost.

3.6 Comparison with other studies

Villadsen et al. (2023) look at the effects of scenarios 1, 2 and 4 on adverse outcomes using the MCS. However, they do not include any covariates in their base case estimation of the effects of these income shifting scenarios, and only include two covariates in sensitivity analysis. Consequently, the effects of each of the income shifting scenarios they report, after adjusting for just two covariates, are much larger than our more conservative estimates, roughly varying between 0% (obesity) and 6% (poor health) for scenario 1, between 2% (obesity) and 15% (poor health) for scenario 2, and between 13% (psychological distress) and 35% (poor health) for scenario 4. The general trend and ranking of effect sizes on the adverse outcomes however, is similar to ours.

We use a continuous measure of household income and report findings in terms of effect sizes so that we can compare our estimates with those from a recent systematic review Cooper and Stewart (2021). The review compares findings from different studies by reporting the effect of a \$1000 (in year 2000 dollars) increase in income on effect sizes in terms of standard deviation changes for a wide range of outcomes including cognitive development, educational outcomes, child health, and social and behavioural scores. Using LifeSim we estimate the effect of a £676 (Year 2000 equivalent of \$1000) increase in income on some of the human capital outcomes reported by Cooper and Stewart (2021) that have an analogue in the MCS. The effect estimates are the change in standard deviation of each outcome with an increase in income of £676. The estimates from Cooper and Stewart (2021) and LifeSim are reported in Table 3.

The estimates from LifeSim closely match those from Blau (1999), Votruba-Drzal (2006), Dearing et al. (2006), and Zachrisson and Dearing (2015). However the estimates from Fernald et al. (2008), Dahl and Lochner (2012) and Gennetian and Miller (2002) who limit their study to poor households in Mexico, the US and Minnesota respectively and find are much larger than those in LifeSim Childhood. The effect sizes measured based on the equivalent sub-population in the simulation cohort. For example, results of a study focusing on poor households are compared to households in the bottom fifth of the income distribution. However, the estimates used in the simulation are still based on the full population and not specific sub groups. This may partially explain why estimates are more similar for the full population estimates in the systematic review. The estimates from Cooper and Stewart (2021) while broadly being similar to those from the MCS are not perfect for the purposes of our comparison as the interventions are different, they are not UK specific and are not all contemporary.

4 Discussion

LifeSim Childhood is a versatile childhood microsimulation model that can be used to estimate the long-term effects of wide range of childhood risk factors on multiple later life outcomes. In this paper we describe our methodology in creating LifeSim Childhood, set out our model, the data, the estimation strategy and simulation. We estimate the effect of increasing income to illustrate it's use, and present sensitivity analysis of our model selection. We also compare estimates from our model to those in the literature.

Summary of results In our illustrative example, we find that increased early years income substantially reduces adverse outcomes and improves wellbeing. However, the public cost savings are relatively small compared with the monetary value of the wellbeing gains. Indeed, in the case of inpatient hospital utilisation we even see a small and non-significant increase in cost in scenario 1, involving a move from the poorest to the second poorest income quintile group. In a cohort of 700,000 newborns we estimate that public costs savings up to age 17 would be £100 million (discounted at 3.5%) compared with a gain of 279,520 WELLBYs (a one point increase in life satisfaction for one year for one child) which would be valued at £3,677 million (discounted at 3.5%) using the standard UK Treasury value of £13,000 per WELLBY. The monetary value of wellbeing gains is thus more than 30 times larger than the estimated public cost savings. Assuming a cost of £2,127 per family in the birth cohort over five years, scenario 1 results in a net benefit of £1,684 million over 15 years for a single birth cohort - but this benefit is almost entirely due to wellbeing gains rather than public cost savings. The cost per WELLBY for this scenario is £7,545, below the Treasury's standard values of a WELLBY of £13,000 and also below its lower bound value of £10,000. However, we likely under-estimate the cost of this scenario as we do not include administrative costs or dead weight losses and our simple hypothetical scenario unrealistically assumes perfect targeting of additional benefits on those in the poorest fifth. On the other hand, our results can also be considered conservative since we are estimating only the wellbeing benefits of one child in the household and ignoring potential effects of income on the wellbeing of adults and other children in the household as well, and also spillover wellbeing benefits from the wellbeing of the child to the wellbeing of others. The more ambitious scenarios resulted in larger public cost savings and wellbeing gains, but these were offset by the increasing costs of the scenario resulting in higher costs per WELLBY.

In our extra conservative model, we found a slightly larger increase in hospitalisation costs, and also an increase in disability and special education needs, though none of these were statistically significant. These increases might potentially be due to increased identification of needs for these services, but our sample size and power do not allow robust statistical conclusions to be drawn about the existence and magnitude of these potential cost increases. In our unadjusted model, with no control for confounding, all public cost savings and benefits to health and wellbeing and other life outcomes are higher across the board.

Finally, we compare LifeSim Childhood estimates to the effects of a $1,000 increase in income on several cognitive and socio-emotional scores in the in the US, Canada, Mexico and Norway. We find our estimates to largely match those in the literature, particularly when looking at full population effects. Some of the studies looking specifically at the poor find larger effects than we do using LifeSim.

Strengths First, with LifeSim Childhood we can estimate the long term effects of modifying a range of early childhood risk factors on a variety of life outcomes across several important policy domains up to age 17, including their effects on wellbeing and public costs. Second, the MCS data, on which LifeSim Childhood is based, is a detailed, high-quality and nationally representative longitudinal dataset following the lives of more than 15,000 Gen Z individuals from birth to age 17. Third, we use a conservative causal inference strategy based on pre-existing scientific theory and evidence about the relevant causal pathways, together with validation against existing estimates of the magnitude of the effects from a previously published systematic review. Fourth, we use simulation modelling to synthesise our MCS findings and incorporate unit costs and other sources of information, and to allow us to address uncertainty. Fifth, The output from MCS can easily be plugged in to LifeSim adulthood to simulate the entire life-course of each individual.

Limitations First, we do not use trial or quasi-experimental data to estimate the magnitude of causal effects for each risk-factor outcome pair as such data is currently unavailable and unlikely to be easily available in the future. Instead we use observational data from the MCS and are limited in the confounders we can include in the model by what is available in the MCS. Second, we estimate causal effects for Gen Z, born 2000/01, but then apply these to Gen A, born today. There is therefore a risk of cohort bias in our estimates, due to generational change. Third, our unit cost estimates omit important rare but expensive outcomes such as the costs of being taken into care and costs from the justice system. In addition our cost estimates are not complete, such as non-inpatient healthcare costs, social care costs associated with disability and exclusion. Fourth, LifeSim Childhood focuses on outcomes for the child and does not capture spillover effects on outcomes for parents, siblings and classmates. Fifth, the current measure of life satisfaction is based on parent-reported SDQ Emotional Symptoms, a measure of negative mental health problems, instead of a measure of a more clear measure of wellbeing. The simulated effect on life satisfaction is dependent on which scales of the SDQ are included in its construction and it is unclear which would be best to use in our case.

Future Work We plan to address some of the limitations in future work on LifeSim Childhood. We aim to determine the extent of bias in the model due to cohort changes and update the parameters with the most recent estimates available from external data sources. We are in the process of updating our unit costs so they are more accurate and describe the distribution of costs for each outcome, and also plan to model the rare but extremely expensive outcomes such as being taken into care and contact with the justice system using administrative data. We also plan to improve our life satisfaction measurement using other self reported measures available from age 11 onward and refine it to better reflect wellbeing at earlier ages. We will also validate our current measure and its mapping onto life satisfaction using other UK data. Our current models are simple, we do not capture any interaction between multiple risk factors or moderators due to the complexity in properly specifying such a model. Future work will explore the inter-relationship between the risk factors, beginning with looking at moderation effects.

Policy implications Researchers and policy makers could use LifeSim Childhood to evaluate a wide range of interventions and policy scenarios, by mapping their intervention's short-term effect onto one of our early childhood risk factors and describing their population of interest. That should then allow them to plug the effect of the intervention into LifeSim Childhood and estimate its long-term consequences for public spending, wellbeing and other life outcomes.

Such methods are sought after by policy analysts, who otherwise find it difficult to quantify the full long-term consequences of early-years policies. These methods can help them to build a better economic case for investing in these policies, as well as for understanding the most effective ways to invest in the early years from a long-term perspective.

References

Acton, C., Johnson, H. H., Martin, R., Raraty, D., Taylor, A., and Willson, E. (2024). Support for children and young people with special educational needs. Technical Report HC 299, UK National Audit Office Report.

Aizer, A., Devereux, P., and Salvanes, K. (2022). Grandparents, moms, or dads? why children of teen mothers do worse in life. *Journal of Human Resources*, 57(6):2012–2047.

Akasaki, M., Ploubidis, G. B., Dodgeon, B., and Bonell, C. P. (2019). The clustering of risk behaviours in adolescence and health consequences in middle age. *Journal of adolescence*, 77:188–197.

Almond, D., Currie, J., and Duque, V. (2018). Childhood circumstances and adult outcomes: Act ii. *Journal of Economic Literature*, 56(4):1360–1446.

Bailey, M. J., Hoynes, H., Rossin-Slater, M., and Walker, R. (2024). Is the social safety net a long-term investment? large-scale evidence from the food stamps program. *Review of Economic Studies*, 91(3):1291–1330.

Barr, A., Eggleston, J., and Smith, A. A. (2022). Investing in infants: The lasting effects of cash transfers to new families. *The Quarterly Journal of Economics*, 137(4):2539–2583.

Bastian, J. and Michelmore, K. (2018). The long-term impact of the earned income tax credit on children's education and employment outcomes. *Journal of Labor Economics*, 36(4):1127–1163.

Baughman, R. A. and Duchovny, N. (2016). State earned income tax credits and the production of child health: Insurance coverage, utilization, and health status. *National Tax Journal*, 69(1):103–131.

Berg, N., Nummi, T., Bean, C. G., Westerlund, H., Virtanen, P., and Hammarström, A. (2022). Risk factors in adolescence as predictors of trajectories of somatic symptoms over 27 years. *European Journal of Public Health*, 32(5):696–702.

Black, S. E., Devereux, P. J., Løken, K. V., and Salvanes, K. G. (2014). Care or cash? the effect of child care subsidies on student performance. *Review of Economics and Statistics*, 96(5):824–837.

Blau, D. M. (1999). The effect of income on child development. *Review of Economics and Statistics*, 81(2):261–276.

Bonin, E.-M., Stevens, M., Beecham, J., Byford, S., and Parsonage, M. (2011). Costs and longer-term savings of parenting programmes for the prevention of persistent conduct disorder: a modelling study. *BMC public health*, 11(1):1–10.

Brookes, M., Goodall, E., and Heady, L. (2007). Misspent youth. *The cost of truancy and exclusion. New Philanthropy Capital*.

Bryant, B., Parish, N., Swords, B., Gray, P., Kulawik, K., and Saied-Tessier, A. (2018). Alternative provision market analysis. Technical report, Research Report. Department of Education.

Bullinger, L. R., Packham, A., and Raissian, K. M. (2023). Effects of universal and unconditional cash transfers on child abuse and neglect. Technical report, National Bureau of Economic Research.

Chowdry, H. and Fitzsimons, P. (2016). The cost of late intervention: Eif analysis. Technical report, Early Intervention Foundation.

Clark-Kauffman, E., Duncan, G. J., and Morris, P. (2003). How welfare policies affect child and adolescent achievement. *American Economic Review*, 93(2):299–303.

Cooper, K. and Stewart, K. (2021). Does household income affect children's outcomes? a systematic review of the evidence. *Child Indicators Research*, 14(3):981–1005.

Coughlan, C. H., Ruzangi, J., Neale, F. K., Maldonado, B. N., Blair, M., Bottle, A., Saxena, S., and Hargreaves, D. (2022). Social and ethnic group differences in healthcare use by children aged 0–14 years: a population-based cohort study in england from 2007 to 2017. *Archives of Disease in Childhood*, 107(1):32–39.

Cunha, F. and Heckman, J. (2007). The technology of skill formation. *American economic review*, 97(2):31–47.

Currie, J. (2009). Healthy, wealthy, and wise: Is there a causal relationship between child health and human capital development. *Journal of Economic Literature*, 47(1):87–122.

Dahl, G. B. and Lochner, L. (2012). The impact of family income on child achievement: Evidence from the earned income tax credit. *American Economic Review*, 102(5):1927–1956.

Dale, V., Gutacker, N., Bradshaw, J., and Bloor, K. (2024). Examining the hospital costs of children born into relative deprivation in england. *J Epidemiol Community Health*.

de Gendre, A., Lynch, J., Meunier, A., Pilkington, R., and Schurer, S. (2021). Child Health and Parental Responses to an Unconditional Cash Transfer at Birth. IZA Discussion Papers 14693, Institute of Labor Economics (IZA).

Dearing, E., McCartney, K., and Taylor, B. A. (2006). Within-child associations between family income and externalizing and internalizing problems. *Developmental psychology*, 42(2):237.

Department for Education (2024a). School funding statistics: Financial year 2023-24. Technical report.

Department for Education (2024b). Special educational needs: an analysis and summary of data sources. Technical report.

Doyle, M.-A., Schurer, S., and Guthridge, S. (2024). Income and immunity: The consequences of a pre-and neo-natal income shock on childhood infection risk. *Available at SSRN 5003887*.

Duncan, G. J., Morris, P. A., and Rodrigues, C. (2011). Does money really matter? estimating impacts of family income on young children's achievement with data from random-assignment experiments. *Developmental psychology*, 47(5):1263.

East, C. N. (2020). The effect of food stamps on children's health: Evidence from immigrants' changing eligibility. *Journal of Human Resources*, 55(2):387–427.

Elstad, J. I. and Bakken, A. (2015). The effects of parental income on norwegian adolescents' school grades: A sibling analysis. *Acta Sociologica*, 58(3):265–282.

Fernald, L. C., Gertler, P. J., and Neufeld, L. M. (2008). Role of cash in conditional cash transfer programmes for child health, growth, and development: an analysis of mexico's oportunidades. *The lancet*, 371(9615):828–837.

Freeman, J., Cole, T., Chinn, S., Jones, P., White, E., and Preece, M. (1995). Cross sectional stature and weight reference curves for the uk, 1990. *Archives of disease in childhood*, 73(1):17–24.

Frijters, P. and Krekel, C. (2021). *A handbook for wellbeing policy-making: History, theory, measurement, implementation, and examples.* Oxford University Press.

García, J. L., Heckman, J. J., Leaf, D. E., and Prados, M. J. (2020). Quantifying the life-cycle benefits of an influential early-childhood program. *Journal of Political Economy*, 128(7):2502–2541.

Gennetian, L. A. and Miller, C. (2002). Children and welfare reform: A view from an experimental welfare program in minnesota. *Child development*, 73(2):601–620.

Gondek, D., Bann, D., Brown, M., Hamer, M., Sullivan, A., and Ploubidis, G. B. (2021). Prevalence and early-life determinants of mid-life multimorbidity: evidence from the 1970 british birth cohort. *BMC Public Health*, 21:1–11.

Goodman, R., Ford, T., Simmons, H., Gatward, R., and Meltzer, H. (2003). Using the strengths and difficulties questionnaire (sdq) to screen for child psychiatric disorders in a community sample. *International Review of Psychiatry*, 15(1-2):166–172.

Goodman, R., Renfrew, D., and Mullick, M. (2000). Predicting type of psychiatric disorder from strengths and difficulties questionnaire (sdq) scores in child mental health clinics in london and dhaka. *European child & adolescent psychiatry*, 9:129–134.

Hale, D. R., Bevilacqua, L., and Viner, R. M. (2015). Adolescent health and adult education and employment: a systematic review. *Pediatrics*, 136(1):128–140.

Hamad, R. and Rehkopf, D. H. (2015). Poverty, pregnancy, and birth outcomes: a study of the earned income tax credit. *Paediatric and perinatal epidemiology*, 29(5):444–452.

Heckman, J. J. (2012). The developmental origins of health. *Health economics*, 21(1):24.

Jones, L. E., Milligan, K., and Stabile, M. (2019). Child cash benefits and family expenditures: Evidence from the national child benefit. *Canadian Journal of Economics/Revue canadienne d'économique*, 52(4):1433–1463.

Kelly, E., Lee, T., Sibieta, L., and Waters, T. (2018). Public spending on children in england: 2000 to 2020. *London: Institute for Fiscal Studies*, pages 2–55.

Kessler, R. C., Barker, P. R., Colpe, L. J., Epstein, J. F., Gfroerer, J. C., Hiripi, E., Howes, M. J., Normand, S.-L. T., Manderscheid, R. W., Walters, E. E., et al. (2003). Screening for serious mental illness in the general population. *Archives of general psychiatry*, 60(2):184–189.

Ko, H., Howland, R. E., and Glied, S. A. (2020). The effects of income on children's health: Evidence from supplemental security income eligibility under new york state medicaid. Technical report, National Bureau of Economic Research.

Krekel, C. and Layard, R. (2023). A lifetime wellbeing ready reckoner : A feasability study. Technical report, Department of Education, UK.

Krieger, N. (2024). *Epidemiology and the people's health: theory and context*. Oxford University Press.

Kuehnle, D. (2014). The causal effect of family income on child health in the uk. *Journal of health economics*, 36:137–150.

MacLennan, S., Stead, I., and Little, A. (2021). Wellbeing guidance for appraisal: Supplementary green book guidance. Guidance, Social Impacts Task Force, HM Treasury.

Melhuish, E. C., Gardiner, J., and Morris, S. (2017). Study of early education and development (seed): impact study on early education use and child outcomes up to age three. Technical Report DFE-RR706, Department for Education.

Milligan, K. and Stabile, M. (2011). Do child tax benefits affect the well-being of children? evidence from canadian child benefit expansions. *American Economic Journal: Economic Policy*, 3(3):175–205.

Milne, B., Lay-Yee, R., Mc Lay, J., Pearson, J., von Randow, M., and Davis, P. (2015). Modelling the early life-course (melc): A microsimulation model of child development in new zealand. *International Journal of Microsimulation*, 8(2):28–60.

O'Donnell, O. (2024). What we know, can know and need to know about the causes of health inequality. EsCHER Working Paper Series 2024005, Erasmus University Rotterdam.

Page, M. E. (2024). New advances on an old question: Does money matter for children's outcomes? *Journal of Economic Literature*, 62(3):891–947.

Patton, G. C., Sawyer, S. M., Santelli, J. S., Ross, D. A., Afifi, R., Allen, N. B., Arora, M., Azzopardi, P., Baldwin, W., Bonell, C., et al. (2016). Our future: a lancet commission on adolescent health and wellbeing. *The Lancet*, 387(10036):2423–2478.

Pearl, J. (2009). *Causality*. Cambridge university press.

Ploubidis, G. B., Batty, G. D., Patalay, P., Bann, D., and Goodman, A. (2021). Association of early-life mental health with biomarkers in midlife and premature mortality: evidence from the 1958 british birth cohort. *JAMA psychiatry*, 78(1):38–46.

Reinhold, S. and Jürges, H. (2012). Parental income and child health in germany. *Health economics*, 21(5):562–579.

Skarda, I., Asaria, M., and Cookson, R. (2021). Lifesim: a lifecourse dynamic microsimulation model of the millennium birth cohort in england. *International Journal of Microsimulation*, 14(1):2–42.

Skarda, I., Asaria, M., and Cookson, R. (2022). Evaluating childhood policy impacts on lifetime health, wellbeing and inequality: Lifecourse distributional economic evaluation. *Social Science & Medicine*, 302:114960.

Squires, H., Chilcott, J., Akehurst, R., Burr, J., and Kelly, M. P. (2016). A framework for developing the structure of public health economic models. *Value in Health*, 19(5):588–601.

Tennant, P. W., Murray, E. J., Arnold, K. F., Berrie, L., Fox, M. P., Gadd, S. C., Harrison, W. J., Keeble, C., Ranker, L. R., Textor, J., et al. (2021). Use of directed acyclic graphs (dags) to identify confounders in applied health research: review and recommendations. *International journal of epidemiology*, 50(2):620–632.

Villadsen, A., Asaria, M., Skarda, I., Ploubidis, G. B., Williams, M. M., Brunner, E. J., and Cookson, R. (2023). Clustering of adverse health and educational outcomes in adolescence following early childhood disadvantage: population-based retrospective uk cohort study. *The Lancet Public Health*, 8(4):e286–e293.

Votruba-Drzal, E. (2003). Income changes and cognitive stimulation in young children's home learning environments. *Journal of Marriage and Family*, 65(2):341–355.

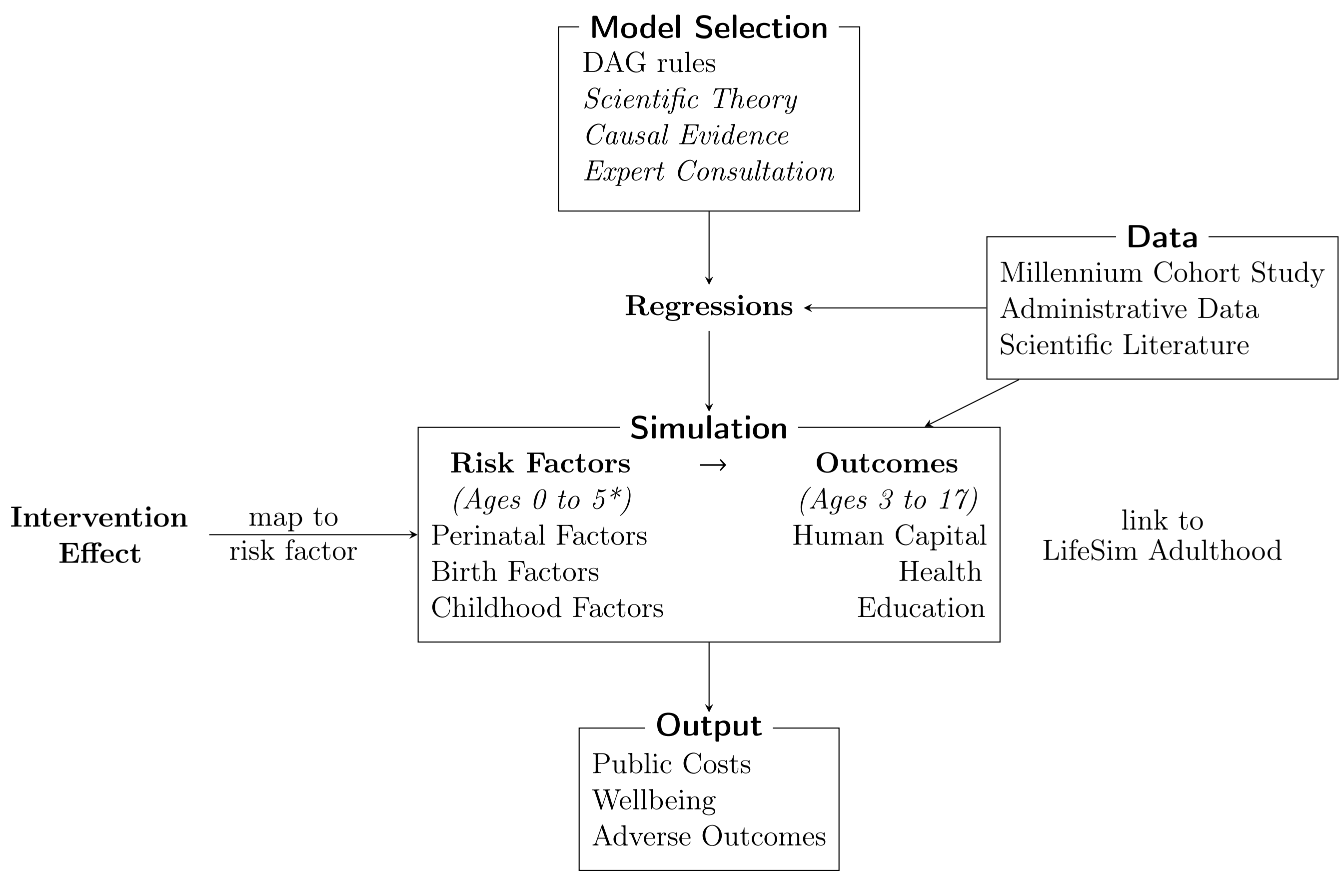
Votruba-Drzal, E. (2006). Economic disparities in middle childhood development: Does income matter? *Developmental psychology*, 42(6):1154.

Wang, B., Baldwin, J. R., Schoeler, T., Cheesman, R., Barkhuizen, W., Dudbridge, F., Bann, D., Morris, T. T., and Pingault, J.-B. (2021). Robust genetic nurture effects on education: A systematic review and meta-analysis based on 38,654 families across 8 cohorts. *The American Journal of Human Genetics*, 108(9):1780–1791.

Zachrisson, H. D. and Dearing, E. (2015). Family income dynamics, early childhood education and care, and early child behavior problems in norway. *Child development*, 86(2):425–440.

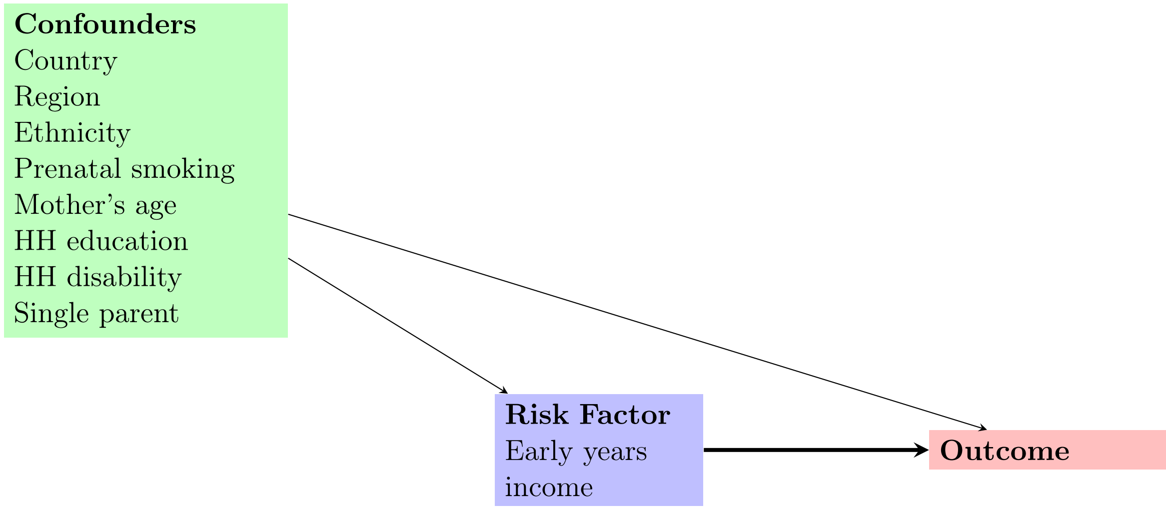
Figures

Figure 1: Structure of LifeSim Childhood



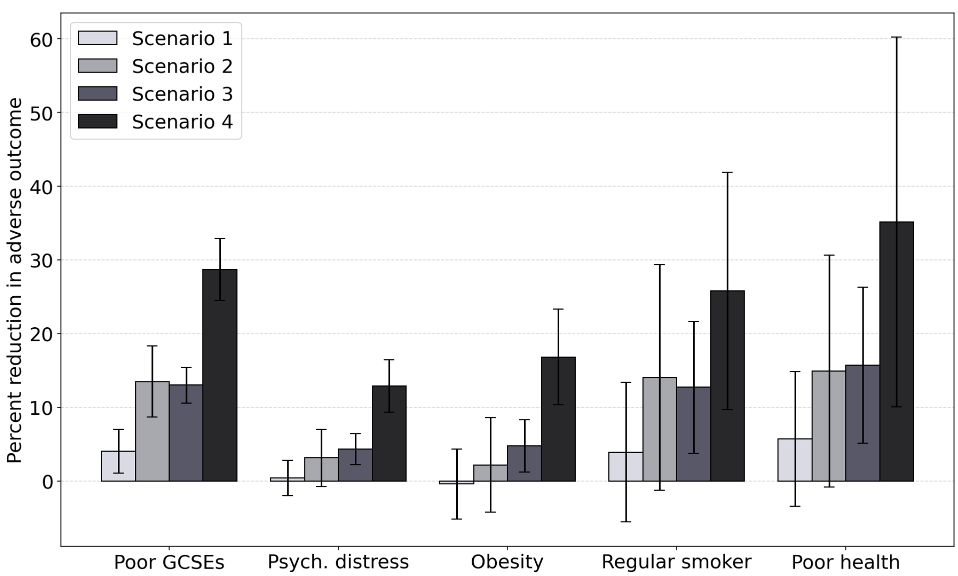
* - Ongoing work will extend this to include risk factors up to age 14. The current list of risk factors includes early years household income, having a teenage mother, low birth weight, disability, delayed school readiness, etc. Outcomes are estimated from the age of the risk factor up to age 17, and will be extended to age 23 when the new sweep of the MCS is available. Our current outcomes include cognitive ability, socio-emotional scores, hospitalisation, exclusion from school, etc. The important adverse outcomes at age 17 we currently focus on are poor GCSE performance, psychological distress, obesity, smoking and poor health.

Figure 2: Simplified directed acyclic diagram (DAG) for the effect of early childhood income



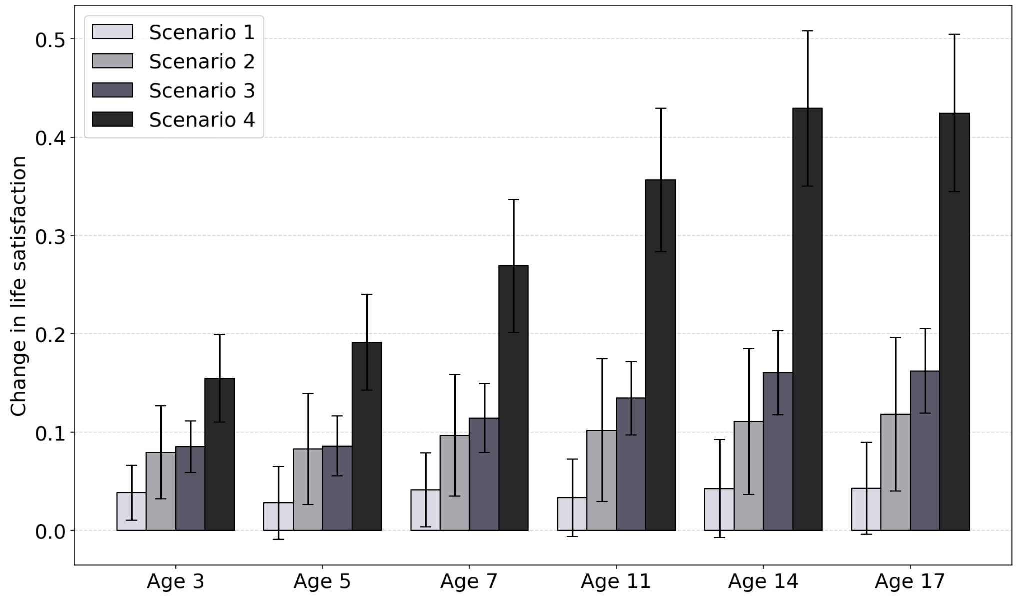
The preferred model controls for everything in the "Confounders" list. We also run an "extra conservative" model which controls for additional variables about which there is room for disagreement because they partly mediators as well as partly confounders - we call these "partly confounding mediators". These additional control variables in the extra conservative model are: X Y Z. HH education is highest education in the household, HH disability is an indicator for any parental disability in the household, IMD is the index of multiple deprivation, Perinatal MH is Maternal malaise measured at 9 months, HH employment is an indicator for labour force participation in the household and the child's disability is observed at age 3. IMD MM Health HH Employment GP Education Child's disability

Figure 3: Percentage reduction in adverse outcomes with each intervention.



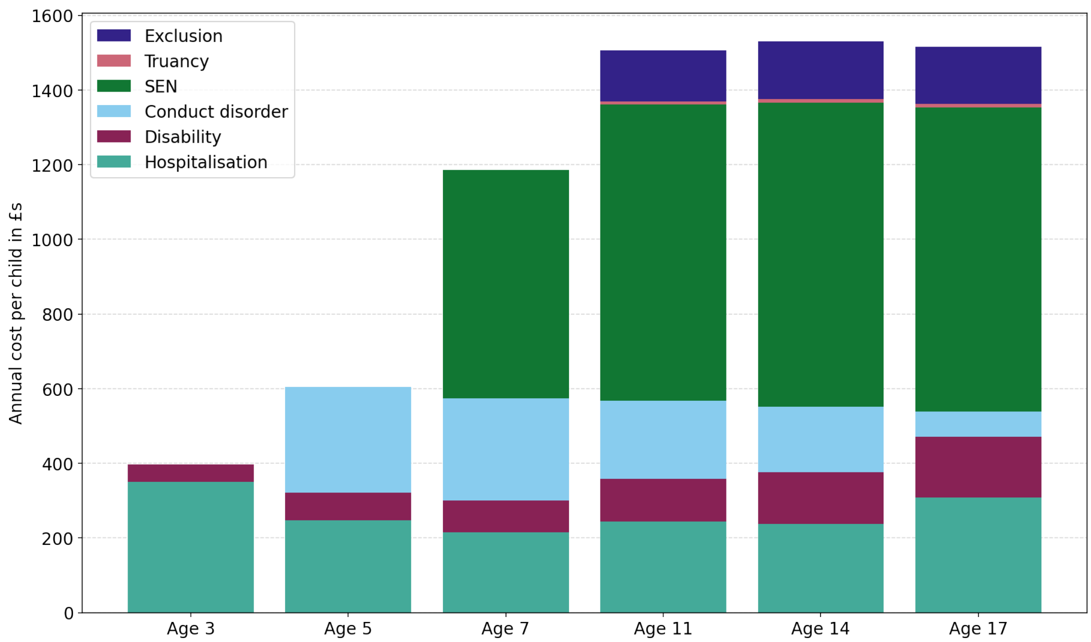
Income increase scenarios - Scenario 1 - Poorest to second poorest, Scenario 2 - Poorest two to middle, Scenario 3 - Poorest to richest, Scenario 4 - All to richest. Outcomes are measured at MCS sweep 7 when respondents are around age 17. Poor GCSEs also includes N5 results for Scotland, Psychological distress is identified using the Kessler scale, Obesity is based on UK90 thresholds for sex and age, Regular smoking is more than 6 cigarettes a week.

Figure 4: Estimated gain in annual average WELLBYs per child in the general population cohort.



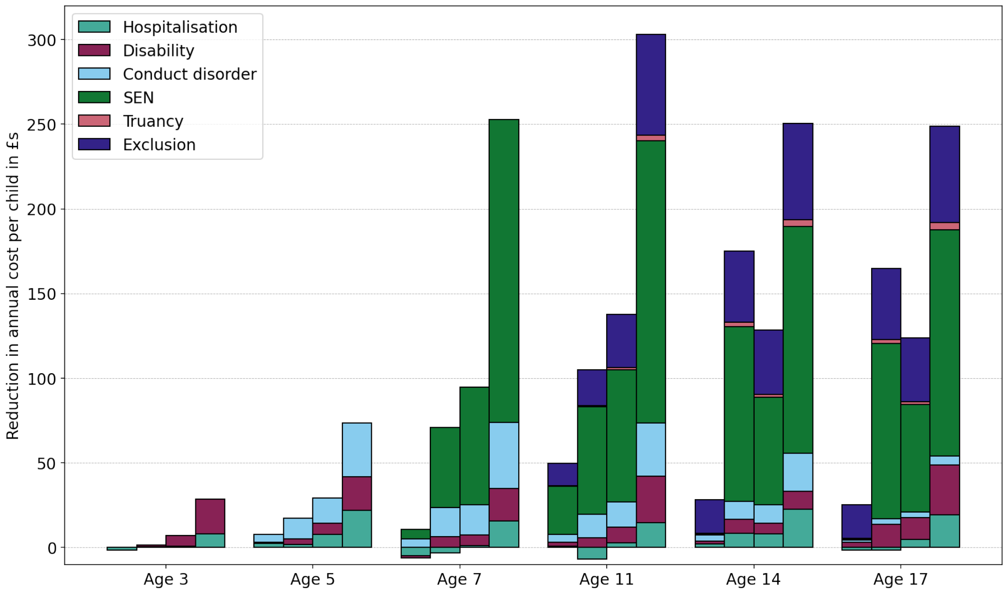
Income increase scenarios - Scenario 1 - Poorest to second poorest, Scenario 2 - Poorest two to middle, Scenario 3 - Poorest to richest, Scenario 4 - All to richest. Life satisfaction is based on a simple linear transformation of parent reported SDQ internalising, the sum of SDQ emotional problems and SDQ peer problems.

Figure 5: Baseline annual cost per child in each MCS sweep broken down by source.



Truancy, exclusion and special education needs are not measured at age 17 so age 14 values are carried over. Conduct disorder does not include justice costs and the unit cost is lower from age 11.

Figure 6: Annual cost savings per child for each scenario in each MCS sweep broken down by source.



The bar plots cluster at each age represent scenarios 1, 2, 3, and 4. Income increase scenarios - Scenario 1 - Poorest to second poorest, Scenario 2 - Poorest two to middle, Scenario 3 - Poorest to richest, Scenario 4 - All to richest. Truancy, exclusion and special education needs are not measured at age 17 so age 14 values are carried over. Conduct disorder does not include justice costs and the unit cost is lower from age 11.

Tables

Table 1: Simulated effects of scenarios for a UK birth cohort of 700,000 children

	Outcome	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Adverse outcomes *(Number of cases prevented by age 17)*					
	Poor GCSEs	10,857	36,267	34,980	77,186
	Psychological distress	697	5,576	7,685	22,916
	Obesity	−745	4,022	8,745	31,055
	Regular smoker	3,425	12,328	11,155	22,618
	Poor health	3,937	10,344	10,897	24,396
Public cost savings *(Cost savings between ages 3 and 17, in millions of 2023 £s)*					
	Total savings	141	628	657	1,482
By source	Any hospitalisation	−4	−3	30	127
	Disability	7	46	57	155
	Conduct disorder	26	78	84	178
	Special education needs	51	382	356	805
	Persistent truancy	1	6	5	13
	Permanent exclusion	61	118	124	205
Wellbeing improvement *(WELLBYs gained between ages 3 and 17)*					
	WELLBYs	282,840	733,257	918,563	2,249,815
	Value (in millions of 2023 £s)	3,677	9,532	11,941	29,248
Scenario cost *(Cost to increase income to quintile minimum, in millions of 2023 £s)*					
	Cost estimate	−2,134	−9,717	−20,240	−52,020

Number of births in the UK in 2021 was around 700,000. Costs are discounted at 3.5% per year calculated at birth. Tables with baseline levels and unadjusted figures can be found in the appendix. Income increase scenarios - Scenario 1 - Poorest to second poorest, Scenario 2 - Poorest two to middle, Scenario 3 - Poorest to richest, Scenario 4 - All to richest. Negative values in the table are increases in cases or public costs. Poor GCSEs also includes N5 results for Scotland, Psychological distress is identified using the Kessler scale, Obesity is based on UK90 thresholds for sex and age, Regular smoking is more than 6 cigarettes a week. The program cost is based on minimum the amount that would need to be transferred to each household over five years to move them across fifths of the income distribution.

Table 2: Simulated effects from three models of increasing the income of families with children in the poorest fifth to that of the second poorest fifth for a UK birth cohort of 700,000 children

	Outcome	Preferred Model	Extra Conservative	Unadjusted
Adverse outcomes *(Number of cases prevented by age 17)*				
	Poor GCSEs	10,857	6,015	15,189
	Psychological distress	697	−152	−298
	Obesity	−745	−1,118	2,742
	Regular smoking	3,425	1,458	5,764
	Poor Health	3,937	2,499	5,254
Public cost savings *(Cost savings between ages 3 and 17, in millions of 2023 £s)*				
	Total cost	141	−46	242
By source	Hospitalisation	−4	−17	13
	Disability	7	−7	10
	Conduct disorder	26	15	43
	Special education needs	51	−90	104
	Truancy	1	1	2
	Exclusion	61	32	68
Wellbeing improvement *(WELLBYs gained between ages 3 and 17)*				
	WELLBYs	282,840	180,847	435,380
	Value (in millions of £s)	3,677	2,351	5,660

Number of births in the UK in 2021 was around 700,000. Costs are discounted at 3.5% per year calculated at birth. Tables with baseline levels and unadjusted figures can be found in the appendix. All results are the estimated impact of income increase shift scenario 1 - Poorest to second poorest. Negative values in the table are increases in cases or public costs. Poor GCSEs also includes N5 results for Scotland, Psychological distress is identified using the Kessler scale, Obesity is based on UK90 thresholds for sex and age, Regular smoking is more than 6 cigarettes a week.

Table 3: Effects of increasing income by $1000 (£676) in Lifesim compared to estimates from Cooper and Stewart (2021)

	Cooper and Stewart (2021)			LifeSim Childhood		
Paper	**Outcome**	**Age**	**Effect**	**Outcome**	**Age**	**Effect**
Blau (1999) *(All families in US)*						
	PIAT Maths	5+	0.01	NFER Progress in maths	7	0.02
	PIAT Reading	5+	0.01	BAS Word reading	7	0.02
	PPVT	3+	0.01	BAS Naming vocabulary	3-5	0.01
Votruba-Drzal (2006) *(All families in US)*						
	PIAT Maths	5+	0.02	NFER Progress in maths	7	0.02
	PIAT Reading	5+	0.02	BAS Word reading	7	0.02
Fernald et al. (2008) *(Poor households in Mexico)*						
	PPVT	4-6	0.21	BAS Naming vocabulary	3-5	0.03
Milligan and Stabile (2011) *(Low education households in Canada)*						
	PIAT Maths	6-10	0.07	NFER Progress in maths	7	0.03
	Hyperactivity	4-10	0.07	SDQ Hyperactivity	5-11	0.0
	Conduct disorder	4-10	0.10	SDQ Conduct problems	5-11	0.03
Dahl and Lochner (2012) *(Poor families in US)*						
	Maths	8-14	0.21	NFER Progress in maths	7	0.03
	Reading	8-14	0.21	BAS Word reading	7	0.03
Gennetian and Miller (2002) *(Poor families in Minnesota)*						
	BPI Internalising	5-13	0.12	SDQ Internalising	5-14	0.03
	BPI Externalising	5-13	0.11	SDQ Externalising	5-14	0.02
Dearing et al. (2006) *(Poor households in US)*						
	CBCL Internalising	2-5	0.02	SDQ Internalising	3-5	0.03
	CBCL Externalising	2-5	0.03	SDQ Externalising	3-5	0.01
Zachrisson and Dearing (2015) *(All families in Norway)*						
	CBCL Internalising	2-3	0.02	SDQ Internalising	3	0.01

Effect sizes are based on standard deviation increases in outcome for a $1000 increase in income. The most similar available test, based on concept measured and age at measurement, in the MCS is used for comparison with those presented in Cooper and Stewart (2021). The age range for the LifeSim estimates are based on the sweep age rather than actual age at time of testing. All MCS measures, except the SDQ scores, are age and ability adjusted measures that are standardised within sample. PIAT - Peabody individual achievement test, NFER - National foundation for educational research, PPVT - Peabody picture vocabulary test, BAS - British ability scales, SDQ - Strength and difficulties questionnaire, BPI - Basic personality inventory, and CBCL - Child behaviour checklist. Ages in MCS correspond to MCS sweeps and not age at observation (age 3 - sweep 2, age 5 - sweep 3 and so on until age 17 - sweep 7).

A Supplementary material

A.1 Definitions

- **Risk factors** are early childhood targets for policy intervention with long-term consequences to be extrapolated into the future using LifeSim; they may include protective factors with "good" consequences as well as adverse factors with "bad" consequences [35]
  - E.g. when examining the effect of low birth weight on school results, low birth weight is the risk factor.
- **Outcomes** are the policy relevant long-term consequences of risk factors [36], i.e. the measures of the long term effects of changes to risk factors.
  - E.g. when examining the effect of low birth weight on school results, school results are the outcome.
- **Confounders** are factors that have an independent causal effect on both the risk factor and the outcome. The effect of the confounder on the outcome must be independent i.e. must not entirely go through its effect on the risk factor.[37] Confounders generally occur temporally before both the risk factor and the outcome.
  - For example, when examining the effect of low birth weight on school results, parental income is a confounder that influences both the risk of low birth weight and the risk of poor school results. The influence on poor school results is independent, and goes via a number of mechanisms other than it's affect on low birth weight.
- **Mediators** are on the causal pathway between the risk factor and the outcome. Controlling for mediators will result in biased estimates of the total causal impact of the risk factor, since it will remove indirect effects of the risk factor that are mediated via the effect on the mediating factor.

[35] They can also be considered as short-term effects from intervention studies that are then harmonised with and plugged into LifeSim.

[36] from the point of view of LifeSim, they may be important human capital variables, outcomes that have significant costs to the public, wellbeing, etc.

[37] We consider factors that have an effect on the measurement of the risk factor or outcome to also be a confounder, even if they have no effect on the "true" risk factor or outcome.

- E.g. when examining the effect of low birth weight on school results, low birth weight will affect school readiness which in turn will affect school results. School readiness is a mediator in this relationship.

- **Moderators** influence the size of the causal effect of the risk factor on the outcome. Moderators generally are temporally before the outcome. Allowing for moderators is not necessary if we are primarily interested in the general population average effect of the risk factor on the outcome, rather than the conditional average effect for a subset of the population with a specific level of the moderating factor.

  - E.g. when examining the effect of low birth weight on school results, parental income may influence the impact of low birth weight on school results by influencing access to support, thus mitigating harmful affects for the best oof and exacerbating harmful effects for the worst off.

A.2 MCS variables

A.2.1 Risk Factors

In this paper the risk factor used is early childhood income, the average OECD equivalised income of the household measured around when the child is 9 months, 3 years and 5 years. We use this pooled measure to capture the household's permanent income during early childhood, thus avoiding the risk of bias due to temporary income shocks that would occur if we focused only on income when the child was about 9 months old. The main results specifically look at the effect of increasing income for families to move them up the income distribution[38] We assume that the timing of change to this "permanent income" starts prior to the point of measurement when the child is approximately 9 months old and continues throughout early childhood to at least the age of five.

In addition to income, LifeSim can be used to evaluate a wide range of other risk factors both in childhood and adolescence such as low birth weight, pre-term birth, disability, school readiness, socio-emotional development, etc.

[38] Income fifths are based on the distribution of household income within the multiply-imputed MCS data with age 3 UK population weights.

A.2.2 Confounders

For the current version of LifeSim with Income as a risk factor, we use a set of eight confounders in the preferred model and an additional five confounders in the "extra conservative" model. We include basic demographic characteristics at age 9 months which we assume to be the same as at birth, country (England, Wales, Scotland and Northern Ireland), region[39] within England, and ethnicity[40] of the child. Besides this we also include some maternal characteristics, mother's age at birth of the child, and maternal smoking during pregnancy. Finally we include some household characteristics, highest education level of parents (NVQ levels 1 to 5), disability in the household[41] and the child having a single carer.

In the extra conservative model in addition the the variables above we include indicators for the Index of Multiple Deprivation (IMD) fifths (with the least deprived as baseline) at age 9 months, an indicator for poor maternal mental health based on the mother's Rutter Malaise score when the child is 9 months old, an indicator for at least one parent participating in the labour force when the child is 9 months old, indicators for the NVQ education level of the grandparents at measured when the child is 17 years old, and an indicator for the child having a disability at age 3.

A.3 Relationship between early childhood income and outcomes

In this paper we estimate the effect of income on five outcomes at age 17 (poor GCSEs, Kessler score, obesity, regular smoking, and self reported poor health) and ten outcomes through childhood and adolescence (SDQ emotional symptoms, SDQ conduct problems, SDQ hyperactivity, SDQ peer relationships, hospitalisation, truancy, exclusion, special educational needs statement, disability and cognitive ability). We believe that early childhood income affects each of these outcomes either directly or indirectly through effects to the cognitive ability, socio-emotional/ mental health, or physical health of the child. Two recent systematic reviews of the literature (Cooper and Stewart, 2021; Page, 2024), present evidence of the effect of income on cognitive ability. The studies they include show than increase in income improved cognitive ability as measured by maths, reading

[39] North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, and South West

[40] White, mixed, Indian, Pakistani and Bangladeshi, Black or Black British, and other ethnic group (inc. Chinese and other Asian)

[41] Measured by receipt of any disability benefits by either the main parent or partner.

and verbal test scores (Blau, 1999; Votruba-Drzal, 2006; Fernald et al., 2008; Duncan et al., 2011; Milligan and Stabile, 2011; Dahl and Lochner, 2012), improved cognitive development as measured by memory and visual integration (Fernald et al., 2008), improved academic performance in school (Gennetian and Miller, 2002; Clark-Kauffman et al., 2003; Votruba-Drzal, 2003; Duncan et al., 2011; Black et al., 2014; Elstad and Bakken, 2015) and increased years of schooling (Votruba-Drzal, 2006; Bastian and Michelmore, 2018; Bailey et al., 2024).

Similarly they present evidence of the effect of income on mental health measured in terms of socio-emotional development. Increasing income during early childhood improves the socio-emotional health of children (Blau, 1999; Gennetian and Miller, 2002; Dearing et al., 2006; Votruba-Drzal, 2006; Hamad and Rehkopf, 2015; Zachrisson and Dearing, 2015) , improved engagement, and reduced inattention, anxiety and aggression (Milligan and Stabile, 2011).

There are fewer studies looking into the causal effect of early years income on health outcomes after birth. Despite a large number associational and descriptive research on the subject, the causal literature is still relatively sparse. Some of the literature looking at the specific physical health outcomes of interest finds no statistically significant effect during childhood but finds an effect in adulthood (Currie, 2009; Kuehnle, 2014). Ko et al. (2020); de Gendre et al. (2021) find that early years income results in lower likelihood of hospitalisations, and Doyle et al. (2024) found a reduction in income lead to increases in hospitalisation. Baughman and Duchovny (2016); East (2020) find that early years income increases leads to reduced likelihood of poor/fair health and increased likelihood of excellent health. Aizer et al. (2022) show that an increase in income leads to increases life expectancy, increases BMI (but not obesity) reduces probability of being underweight. East (2020); Ko et al. (2020) also find early years income leads to lower rates of developmental delay and reduced incidences of acute and chronic conditions up to age 3. Since we define disability as a long term illness that affects day to day activity we believe a reduction in chronic conditions will translate to a reduction in disability among the children as well. The most studied mechanism through which income affects physical health is nutrition, particularly for low income households, Milligan and Stabile (2011) provide evidence for this, they show a reduction in reports of children going hungry following an increase in income during early childhood.

Another indirect mechanism we also hope to capture is the indirect effects on the outcomes through effects on the parents, either by increasing their income beyond the transfers (Barr et al., 2022), improved parental mental health / reduction in stress (Jones et al., 2019), changes in parental behaviour (Votruba-Drzal, 2003; Jones et al., 2019; Bullinger et al., 2023).

A.4 Measurement of wellbeing

The current model uses parent-reported SDQ Emotional Symptoms as the primary measure of wellbeing as parent reported SDQ scores are available consistently across all current sweeps. Alternative wellbeing measures are available at ages 11, 14 (Wellbeing grid) and 17 (SWEMWBS) which we hope to use in the future at those ages and help map the SDQ scores to a better wellbeing measure for us to use at earlier ages.

An alternative that is available at all ages is parent-reported SDQ Internalising, the sum of SDQ emotional symptoms and Peer problems scales. We choose to use SDQ emotional symptoms instead of SDQ internalising for a few reasons. SDQ scores used in our model are parent-reported and therefore may not reflect the actual levels of each attribute but rather the level perceived by the parent. The relationship between the actual levels and parent-reported levels for peer problems may be less correlated than that for emotional symptoms for school-aged children. While we do not have a wellbeing measure, SDQ emotional symptoms scale is predictive of a number of outcomes that are closely related to wellbeing (such as mental disorders, school performance.) whereas the concepts associated with the peer problems scale are more tenuously associated with wellbeing.

A version of Table 1 with wellbeing measured by SDQ internalising instead of just emotional symptoms is presented in appendix table A7.

A.5 Multiple Imputation

Of the cohort of 19,519 children in the MCS only 10,757 children provided any data at age 17, this is without accounting for incomplete responses to specific questions even in years they did participate. To deal with this attrition and missingness in the data we use multiple imputation. We believe this helps increase the statistical power and reduce bias in our estimation of effects.

We used chained equations to impute missing data back to the second sweep (age 3) of the MCS. We use the second sweep instead of the first as more than a thousand eligible households were added to the cohort in that sweep that were missed in the first sweep. We follow Villadsen et al. (2023) and include a number of the same auxiliary variables that are predictive of the our outcomes at age 17 and earlier in the imputation to improve the accuracy of our estimates. These variables are from various sweeps and included child physical health, parental substance use, maternal mental health, and other household characteristics. We generate 30 datasets using multiple imputation. Post-imputation, the final sample used in our analyses consists of 15,380 cohort members.

A.6 Model selection rules

To build our models we follow a set of rules, described below with examples of their application, so our models are **credible**, **conservative**, **parsimonious** and **focused on population averages**. The rules below are used in the current version of LifeSim Childhood, but may change in the future as we develop LifeSim further. We will follow the DAG reporting recommendations of Tennant et al. (2021) in future work and include detailed documentation for each DAG produced along with the code.

1. **Credible**: Confounder selection must be based on strong theoretical framework, scientific evidence and expert opinion. There must be a credible story that justifies why the variable is a well-founded confounder.

2. **Conservative**: We include confounders that are also partly mediators, even though this will remove part of the total causal effect. Similarly, we also include confounders that are also moderators. [42] That makes our approach conservative. However, we do not wish to be over-conservative by over-adjusting the total causal effect downwards by controlling for too many mediating effects. So we do not control for "partly confounding mediators" that we consider to be primarily mediators rather than confounders - i.e. we make a scientific judgement that the mediating impact is more important than the confounding impact. This requires a scientific judgement drawing on prior knowledge about the temporal sequence of events and, if necessary, the expected relative strength of the causal impacts and correlations. If there is doubt about whether a variable is “primarily” a confounder or a mediator then we do not include it in the base model but do in the “extra conservative” model as a robustness check.

[42] This also includes moderators that can be seen a special type of “collider” that involves selection into the risk factor but does not involve “collider bias”.

- E.g. 1 a "partly confounding mediator": when examining the effect of having a teenage mother on school results at age 17 (GCSEs), it is unclear if maternal mental health (MMH) at age 9 months primarily a confounder or mediator. We judge it is primarily a mediator because we expect variation in MMH age 9 months to be strongly driven by having a baby, and the relevant timing of MMH for causing teen pregnancy is at least 2 years before that at conception, so even though MMH at 9 month may be correlated with MMH 2 years before, the confounding impact is expected to be less strong than the mediating impact.
- E.g.

  2 a "partly mediating confounder". when examining the effect of having a teenage mother on school results at age 17 (GCSEs), we do control for smoking in pregnancy because this is a proxy for risky behaviour which may confound the teen pregnancy effect. This is debatable, however, insofar as teen pregnancy itself might be conceptualised as related to risky behaviour which partly relates to some of the social causal pathways from teen pregnancy to child outcomes. We therefore do not include this in our preferred model but do include this as a confounder in our "extra conservative" model. (A similar example is whether to control for IMD, which turns on whether pregnancy is more likely to cause the parents to move out of the grandparents house to a deprived neighbourhood, or whether living in a deprived neighbourhood is more likely to cause teenage pregnancy).
- E.g. 3 a "confounding moderator". When examining the effect of disability at age 3 on school results at age 17 (GCSEs), income between ages 0 and 5 is included as a confounder even though we expect it to have a moderating effect. This moderating effect is not explicitly modelled because we are not including interaction terms. We just want the population average effect.

3. **Parsimonious**: We prefer a simple model unless additional complexity is clearly justified and makes an important difference. As well as the general scientific virtue of keeping things as simple as possible but not simpler, parsimony in relation to confounder selection has the further advantage of reducing the variance of the effect estimate: adding further possible confounding variables that are not distinctive from the preferred set of confounding variables

will tend to increase the variance of the effect estimate without improving its accuracy.

(a) Use a simple functional form with fewer parameters to estimate and interpret where possible.

(b) Exclude confounders that are not distinctive i.e. they are likely measuring the same thing as other confounders.

   i. A confounder is considered distinct if the causal pathway to either the risk factor or the outcome is distinct from other confounders. The causal pathway to both the risk factor and the outcome do not have to be distinct.

   ii. When multiple options are available choose the measure most relevant for the causal pathway.

   - E.g. when examining the effect of low birth weight on school results at age 17 (GCSEs), being a single parent could be a potential confounder as it could capture some economic characteristics of the household (it likely will not capture anything else, such as time with child because of exposure timing) that may affect birth weight and later education outcomes. However, we include household income and IMD as confounders and that should capture everything that single parent captures in this instance. This will not be the case if the exposure is disability at age 5.

(c) Exclude prior measurements of outcome and/or risk factor. We are not interested in modelling the effect of changes or the trajectory of outcomes by each sweep, we are interested only in the full direct effect.

   - E.g. when examining the effect of cognitive ability at age 7 on wellbeing at age 17, we do not include measures of cognitive ability or wellbeing as confounders. We are currently interested in modelling the direct effect of a specific cognitive ability level on wellbeing and not on how changes in cognitive ability affects wellbeing or cognitive ability affects wellbeing trajectory.

   - Note: An alternative approach to causal inference would be to include a prior measure of the risk factor as a control variable - for example, estimating the effect of income at age 5 controlling for income at age 3. However, we believe this would be an over-adjustment that would under-estimate the causal effect of the exposure level at T on the outcome level at T+1. Including a prior measure would estimate the effect of the exposure trajectory (first difference) rather than the effect of the exposure level which is our parameter of interest.

(d) Do not include both linear and non-linear forms of the same confounder. But the linear or non-linear measures can be used individually as appropriate for the model.

- E.g. when examining the effect of disability at age 3 on school results at age 17 (GCSEs), income between ages 0 and 5 is included as a confounder. Poverty between ages 0 to 5 is not currently included as a confounder as income and poverty are seen to capture the same causal pathway, even though those below the poverty line may have different effects for those above.

(e) For an outcome risk factor pair, the model used is specific to risk factor timing only. i.e. for a particular risk factor and outcome pair the same model should be used for outcomes at all ages as long as risk factor timing is constant. However if the risk factor timing changes the model should also change.

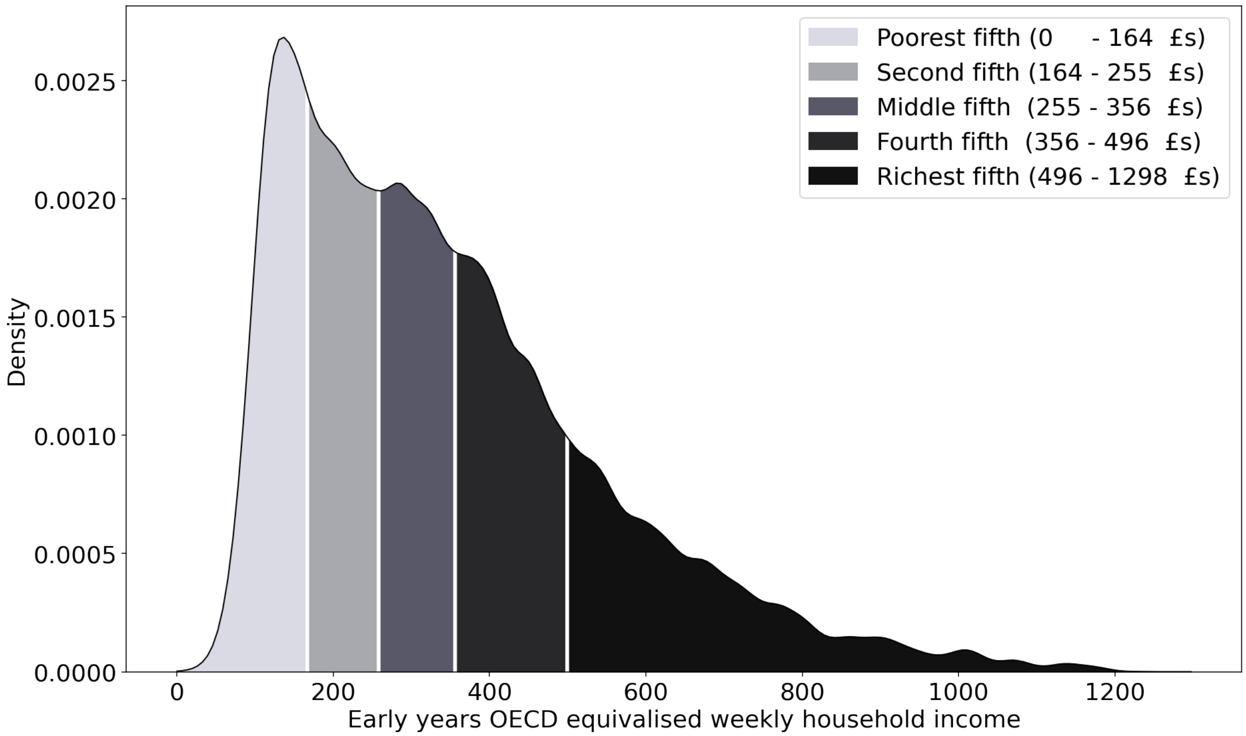
- E.g. when examining the effect of cognitive ability at age 7 on wellbeing, we use the same model to simulate wellbeing from ages 11 upto 17. However, if we want to examine the effect of cognitive ability at age 5 on wellbeing, we use a different model to simulate the effects on wellbeing from ages 7 to 17.

4. **Focused on population averages** Do not include interaction terms, since our primary interest lies is in the unconditional population average effect rather than the moderating effects for sub-populations with specific levels of the moderating variable.

   - E.g. when examining the effect of disability at age 3 on school results at age 17 (GCSEs), we do not include interaction between age 3 disability and parental income age 0-5, since we currently just want the population level effect of age 3 disability and not how this effect is modified by parental income.

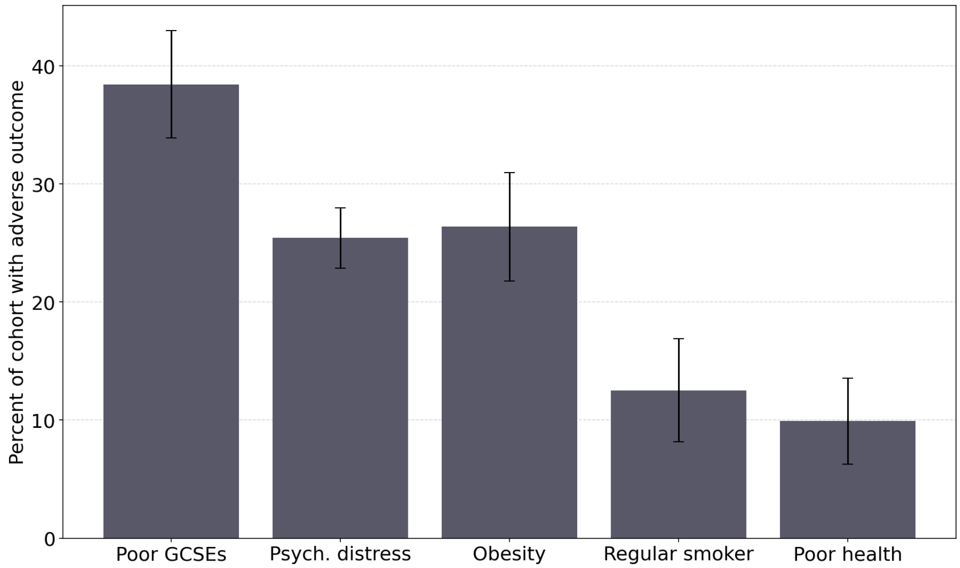
A.7 Figures

Figure A1: Density plot of early years OECD equivalised weekly household income in the MCS split into quintiles.



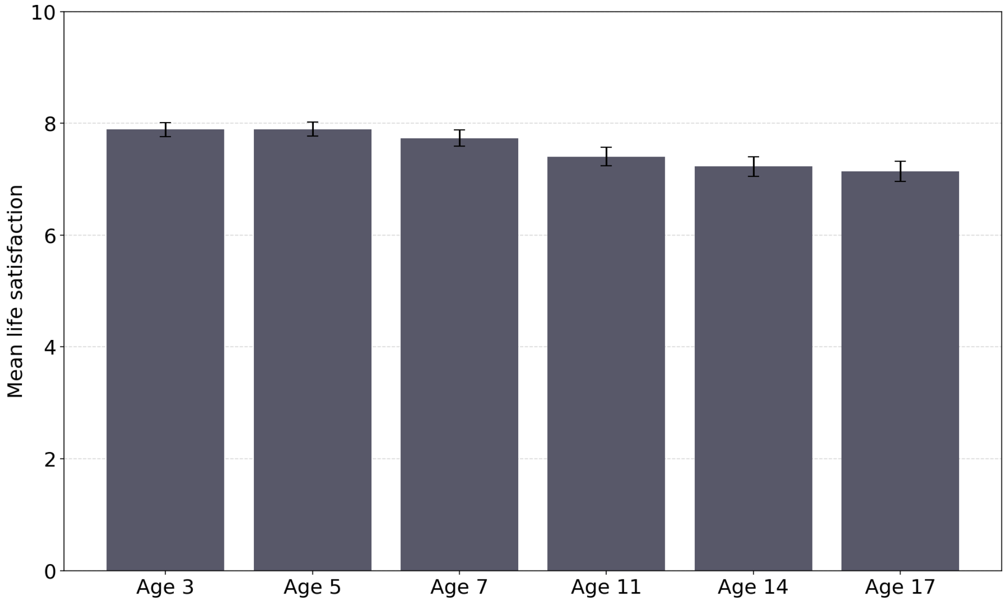
The means for each quintile or fifth of the distribution are £123.47, £207.40, £304.54, £419.29 and £659.05 respectively.

Figure A2: Baseline prevalence of adverse outcomes at age 17.



Outcomes are measured at MCS sweep 7 when respondents are around age 17. In Scotland, Poor GCSEs refers to N5 exam results, Psychological distress is identified using the Kessler scale, Obesity is based on UK90 thresholds for sex and age, Regular smoking is more than 6 cigarettes a week.

Figure A3: Baseline life satisfaction proxied by SDQ internalising in each MCS sweep.



Life satisfaction is based on a simple linear transformation of parent reported SDQ emotional symptoms scale.

A.8 Tables

Table A1: Summary of unit costs currently used in LifeSim Childhood

Simulated Outcomes	Ages Available in MCS	Public Cost Sector: NHS	Social	Education	Criminal Justice	Outcome Costed	Annual Unit Cost(2023 £)
Hospital Admission	3, 5, 7, 11, 14, 17	X				Inpatient visit for children	1,587
Disability	3, 5, 7, 11, 14, 17	X				Per child cost to NHS	1,009
Conduct Disorder	3, 5, 7, 11, 14, 17	X	X	X		Conduct disorder	3,092 (5 to 10) 1,963 (11 to 16) 235 (17+)
Special Education Needs	7, 11, 14			X		EHC Plan	25,500
Any Truancy	11, 14 11, 14			X		Persistent Truancy	943
Any Exclusion	11, 14 11, 14			X		Alternate Provision	21,848

Ages in MCS correspond to MCS sweeps and not age at observation (age 3 - sweep 2, age 5 - sweep 3 and so on until age 17 - sweep 7).

Table A2: Sources of unit costs currently used by LifeSim childhood

Simulated Outcome	MCS Source	Cost Outcome	Ages costed	Cost year	Cost source
Hospital Admission	Parent admission	Hospital	0-18	2020	Average cost of a single inpatient hospitalisation for a child aged between 0 and 17 in the UK in 2003/2004 at 2019/2020 prices. (Dale et al., 2024)
Disability	Parent	Healthcare		2016	average annual cost of healthcare for a child in the UK. (Kelly et al., 2018)
Conduct disorder	Parent	Conduct disorder	5 to 18	2008	Costs from 4 papers published between 2000 and. 2007. (Bonin et al., 2011)
Special Educational Needs	Teacher	EHC Plan	5 to 18	2023	Average incremental cost to DfE of student with EHC plan in 2023 (Acton et al., 2024) (Department for Education, 2024a,b)
Persistent truancy	CM	Persistent Truancy	11 to 12	2005	Cost education welfare services in England and number of persistent truants in 2005. (Brookes et al., 2007)*
Permanent School Exclusion	Parent	Alternative Provision	5 to 18	2018	Survey of 101 LAs by ISOS for the Department for Education in FY 2017-2018. (Bryant et al., 2018)

* - also source for costs in the Greater Manchester unit cost database.

Table A3: Simulation population descriptive statistics for confounders and exposure

	Characteristic	Mean/ Proportion	Standard Error
Sex	Male	0.503	
Ethnicity	White	0.860	
	Mixed	0.032	
	Indian	0.018	
	Pakistani or Bangladeshi	0.044	
	Black	0.027	
	Other	0.013	
Country	England	0.826	
	Wales	0.047	
	Scotland	0.091	
	Northern Ireland	0.037	
Region	North East	0.037	
	North West	0.103	
	Yorkshire and the Humber	0.089	
	East Midlands	0.071	
	West Midlands	0.081	
	East of England	0.088	
	London	0.130	
	South East	0.148	
	South West	0.078	
Household Highest	No qualifications	0.119	
Education	NVQ level 1	0.081	
	NVQ level 2	0.340	
	NVQ level 3	0.098	
	NVQ level 4	0.293	
	NVQ level 5	0.037	
Household	Disability in household	0.029	
Characteristics	Single parent	0.146	
	Age of mother (at birth)*	28.723	0.041
	Annual early years income*	18226.072	74.836

*- mean and standard error, all other numbers are proportion of population in category.

Table A4: Simulated baseline outcome means

Outcome	Age 3	Age 5	Age 7	Age 11	Age 14	Age 17
Poor GCSEs						0.38
						(0.045)
Psychological distress						0.25
						(0.026)
Obesity						0.26
						(0.046)
Regular smoker						0.13
						(0.044)
Poor health						0.10
						(0.036)
Life satisfaction	7.89	7.90	7.73	7.41	7.23	7.14
	(0.125)	(0.125)	(0.146)	(0.166)	(0.173)	(0.181)
Any hospitalisation	0.22	0.16	0.14	0.15	0.15	0.19
	(0.034)	(0.033)	(0.032)	(0.031)	(0.041)	(0.043)
Disability	0.05	0.07	0.08	0.11	0.14	0.16
	(0.022)	(0.024)	(0.026)	(0.033)	(0.033)	(0.046)
Conduct disorder		0.09	0.09	0.09	0.09	0.08
		(0.005)	(0.005)	(0.006)	(0.007)	(0.006)
Special education needs			0.05	0.06	0.06	
			(0.030)	(0.028)	(0.030)	
Any truancy				0.04	0.05	
				(0.031)	(0.025)	
Any exclusion				0.06	0.09	
				(0.066)	(0.043)	

Terms in brackets are the standard deviation of the distribution of means across simulations. Ages correspond to MCS sweeps and not age at observation (age 3 - sweep 2, age 5 - sweep 3 and so on until age 17 - sweep 7).

Table A5: Simulated baseline cost means by source

Outcome	Age 3	Age 5	Age 7	Age 11	Age 14	Age 17
Any hospitalisation	349.49	246.68	215.45	243.71	237.38	308.90
	(54.33)	(51.84)	(51.02)	(49.26)	(65.29)	(67.54)
Disability	46.67	73.89	84.12	114.43	138.30	161.57
	(21.74)	(24.25)	(26.00)	(33.64)	(33.13)	(46.54)
Conduct disorder		283.86	273.90	209.21	175.65	67.39
		(16.04)	(16.19)	(13.89)	(13.49)	(4.48)
Special education needs			143.97	186.74	191.82	191.82
			(89.96)	(82.66)	(89.18)	(89.18)
Permanent exclusion				137.77	154.34	154.34
				(148.40)	(73.18)	(73.18)
Persistent truancy				7.79	8.91	8.91
				(5.37)	(4.38)	(4.38)

Costs for special education needs, permanent exclusion, and persistent truancy are carried over from age 14 to age 17 as those outcomes are not measured at age 17. Terms in brackets are the standard deviation of the distribution of means across simulations. Ages correspond to MCS sweeps and not age at observation (age 3 - sweep 2, age 5 - sweep 3 and so on until age 17 - sweep 7).

Table A6: Simulated undiscounted effects of scenarios for a UK birth cohort of 700,000 children

	Outcome	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
Adverse outcomes *(Number of cases prevented by age 17)*					
	Poor GCSEs	10,857	36,267	34,980	77,186
	Psychological distress	697	5,576	7,685	22,916
	Obesity	−745	4,022	8,745	31,055
	Regular smoker	3,425	12,328	11,155	22,618
	Poor health	3,937	10,344	10,897	24,396
Public cost savings *(Cost savings between ages 3 and 17, in millions of 2023 £s)*					
	Total savings	215	970	982	2,184
By source	Any hospitalisation	−5	−3	44	181
	Disability	11	69	82	217
	Conduct disorder	36	109	117	248
	Special education needs	74	594	532	1,193
	Persistent truancy	2	10	9	21
	Permanent exclusion	97	192	198	324
Wellbeing improvement *(WELLBYs gained between ages 3 and 17)*					
	WELLBYs	398,629	1,042,533	1,326,571	3,293,455
	Value (in millions of 2023 £s)	5,182	13,553	17,245	42,815
Scenario cost *(Cost to increase income to quintile minimum, in millions of 2023 £s)*					
	Cost estimate	−2,364	−10,760	−22,414	−57,607

Number of births in the UK in 2021 was around 700,000. Tables with baseline levels and unadjusted figures can be found in the online appendix. Income increase scenarios - Scenario 1 - Poorest to second poorest, Scenario 2 - Poorest two to middle, Scenario 3 - Poorest to richest, Scenario 4 - All to richest Negative values in the table are increases in cases or public costs. Poor GCSEs also includes N5 results for Scotland, Psychological distress is identified using the Kessler scale, Obesity is based on UK90 thresholds for sex and age, Regular smoking is more than 6 cigarettes a week.

Table A7: Simulated effects of scenarios for a UK birth cohort of 700,000 children with SDQ internalising as the wellbeing measure

	Outcome	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Adverse outcomes *(Number of cases prevented by age 17)*					
	Poor GCSEs	10,857	36,267	34,980	77,186
	Psychological distress	697	5,576	7,685	22,916
	Obesity	−745	4,022	8,745	31,055
	Regular smoker	3,425	12,328	11,155	22,618
	Poor health	3,937	10,344	10,897	24,396
Public cost savings *(Cost savings between ages 3 and 17, in millions of 2023 £s)*					
	Total savings	100	330	379	855
By source	Any hospitalisation	−4	−3	30	125
	Disability	7	45	56	153
	Conduct disorder	25	77	83	176
	Special education needs	12	89	83	187
	Persistent truancy	1	6	5	13
	Permanent exclusion	60	116	122	201
Wellbeing improvement *(WELLBYs gained between ages 3 and 17)*					
	WELLBYs	197,879	629,453	678,858	1,656,902
	Value (in millions of 2023 £s)	2,572	8,183	8,825	21,540
Scenario cost *(Cost to increase income to quintile minimum, in millions of 2023 £s)*					
	Cost estimate	−2,127	−9,682	−20,168	−51,833

Number of births in the UK in 2021 was around 700,000. Costs are discounted at 3.5% per year calculated at birth. Tables with baseline levels and unadjusted figures can be found in the online appendix. Income increase scenarios - Scenario 1 - Poorest to second poorest, Scenario 2 - Poorest two to middle, Scenario 3 - Poorest to richest, Scenario 4 - All to richest Negative values in the table are increases in cases or public costs. Poor GCSEs also includes N5 results for Scotland, Psychological distress is identified using the Kessler scale, Obesity is based on UK90 thresholds for sex and age, Regular smoking is more than 6 cigarettes a week.

Table A8: Simulated effect size of scenarios per child in birth cohort

	Outcome	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Adverse outcomes *(Percentage point reduction in probability by age 17)*					
	Poor GCSEs	0.02	0.05	0.05	0.11
	Psychological distress	0.0	0.01	0.01	0.03
	Obesity	0.0	0.01	0.01	0.04
	Regular smoker	0.0	0.02	0.02	0.03
	Poor health	0.01	0.01	0.02	0.03
Public cost savings *(Cost savings between ages 3 and 17, in 2023 £s)*					
	Total savings	281	1,452	1,445	3,283
By source	Any hospitalisation	−6	−4	43	181
	Disability	10	65	81	221
	Conduct disorder	36	111	120	254
	Special education needs	153	1,102	1,015	2,316
	Persistent truancy	2	9	8	19
	Permanent exclusion	86	169	178	292
Wellbeing improvement *(WELLBYs gained between ages 3 and 17)*					
	WELLBYs	0.4	1.05	1.31	3.21
	Value (in 2023 £s)	5,253	13,618	17,059	41,782

Costs are discounted at 3.5% per year calculated at birth. Tables with baseline levels and unadjusted figures can be found in the online appendix. Income increase scenarios - Scenario 1 - Poorest to second poorest, Scenario 2 - Poorest two to middle, Scenario 3 - Poorest to richest, Scenario 4 - All to richest Negative values in the table are increases in cases or public costs. Poor GCSEs also includes N5 results for Scotland, Psychological distress is identified using the Kessler scale, Obesity is based on UK90 thresholds for sex and age, Regular smoking is more than 6 cigarettes a week.

Table A9: Simulated effect size of scenarios per recipient in birth cohort

	Outcome	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Adverse outcomes *(Percentage point reduction in probability by age 17)*					
	Poor GCSEs	0.08	0.13	0.26	0.14
	Psychological distress	0.01	0.02	0.06	0.04
	Obesity	−0.01	0.02	0.07	0.06
	Regular smoker	0.03	0.05	0.08	0.04
	Poor health	0.03	0.04	0.08	0.04
Public cost savings *(Cost savings between ages 3 and 17, in 2023 £s)*					
	Total savings	1,482	3,762	7,618	4,128
By source	Any hospitalisation	−33	−10	229	227
	Disability	53	169	429	278
	Conduct disorder	192	288	633	320
	Special education needs	806	2,854	5,350	2,912
	Persistent truancy	8	22	42	24
	Permanent exclusion	455	438	936	367
Wellbeing improvement *(WELLBYs gained between ages 3 and 17)*					
	WELLBYs	2.13	2.71	6.92	4.04
	Value (in 2023 £s)	27,682	35,274	89,903	52,537

Costs are discounted at 3.5% per year calculated at birth. Tables with baseline levels and unadjusted figures can be found in the online appendix. Income increase scenarios - Scenario 1 - Poorest to second poorest, Scenario 2 - Poorest two to middle, Scenario 3 - Poorest to richest, Scenario 4 - All to richest Negative values in the table are increases in cases or public costs. Poor GCSEs also includes N5 results for Scotland, Psychological distress is identified using the Kessler scale, Obesity is based on UK90 thresholds for sex and age, Regular smoking is more than 6 cigarettes a week.

Table A10: Effects of increasing income by $1000 (£676) in Cooper and Stewart (2021) compared to three LifeSim models

Cooper and Stewart (2021)			**LifeSim Childhood**			
Paper	**Outcome**	**Effect**	**Outcome**	**Preferred Model**	**Extra Conservative**	**Unadjusted**
Blau (1999) *(All families in US)*						
	PIAT Maths	0.01	NFER Progress in maths	0.02	0.01	0.02
	PIAT Reading	0.01	BAS Word reading	0.02	0.01	0.03
	PPVT	0.01	BAS Naming vocabulary	0.01	0.01	0.03
Votruba-Drzal (2006) *(All families in US)*						
	PIAT Maths	0.02	NFER Progress in maths	0.02	0.01	0.02
	PIAT Reading	0.02	BAS Word reading	0.02	0.01	0.03
Fernald et al. (2008) *(Poor households in Mexico)*						
	PPVT	0.21	BAS Naming vocabulary	0.01	0.01	0.03
Milligan and Stabile (2011) *(Low education households in Canada)*						
	PIAT Maths	0.07	NFER Progress in maths	0.03	0.03	0.05
	Hyperactivity	0.07	SDQ Hyperactivity	0.0	0.0	0.0
	Conduct disorder	0.10	SDQ Conduct problems	0.03	0.02	0.05
Dahl and Lochner (2012) *(Poor families in US)*						
	Maths	0.21	NFER Progress in maths	0.03	0.03	0.05
	Reading	0.21	BAS Word reading	0.03	0.03	0.05
Gennetian and Miller (2002) *(Poor families in Minnesota)*						
	BPI Internalising	0.12	SDQ Internalising	0.03	0.02	0.05
	BPI Externalising	0.11	SDQ Externalising	0.02	0.01	0.04
Dearing et al. (2006) *(Poor households in US)*						
	CBCL Internalising	0.02	SDQ Internalising	0.03	0.02	0.05
	CBCL Externalising	0.03	SDQ Externalising	0.01	0.01	0.03
Zachrisson and Dearing (2015) *(All families in Norway)*						
	CBCL Internalising	0.02	SDQ Internalising	0.01	0.02	0.05

Effect sizes are based on standard deviation increases in outcome for a $1000 increase in income. The most similar available test, based on concept measured and age at measurement, in the MCS is used for comparison with those presented in Cooper and Stewart (2021). The age range for the LifeSim estimates are based on the sweep age rather than actual age at time of testing. All MCS measures, except the SDQ scores, are age and ability adjusted measures that are standardised within sample. PIAT - Peabody individual achievement test, NFER - National foundation for educational research, PPVT - Peabody picture vocabulary test, BAS - British ability scales, SDQ - Strength and difficulties questionnaire, BPI - Basic personality inventory, and CBCL - Child behaviour checklist. Ages in MCS correspond to MCS sweeps and not age at observation (age 3 - sweep 2, age 5 - sweep 3 and so on until age 17 - sweep 7).

Table A11: Coefficients - marginal effects on life satisfaction (0-10)

	Life satisfaction age 17		
Intercept	8.456	Mixed	0.041
	(0.114)		(0.085)
Poorest fifth	-0.65	Indian	0.172
	(0.058)		(0.096)
Second poorest fifth	-0.451	Pakistani or Bangladeshi	0.204
	(0.048)		(0.07)
Middle fifth 3	-0.273	Black	0.158
	(0.042)		(0.092)
Second richest fifth	-0.198	Other	0.118
	(0.039)		(0.132)
Wales	-0.033	Smoked during pregnancy	-0.198
	(0.065)		(0.034)
Scotland	0.014	Age of mother at birth	0.004
	(0.062)		(0.003)
Northern Ireland	0.219	No qualifications	-0.237
	(0.071)		(0.07)
North East	0	NVQ level 1	-0.233
	(0.08)		(0.072)
North West	0.007	NVQ level 2	-0.103
	(0.058)		(0.057)
Yorkshire and the Humber	-0.051	NVQ level 3	-0.108
	(0.065)		(0.064)
East Midlands	-0.009	NVQ level 4	-0.02
	(0.067)		(0.053)
West Midlands	-0.125	Disability in household	-0.516
	(0.059)		(0.082)
East of England	-0.107	Single parent	-0.056
	(0.057)		(0.046)
South East	-0.048		
	(0.052)		
South West	-0.044		
	(0.063)		

Life satisfaction is a linear transformation of SDQ emotional symptoms scale. The estimates presented are from an OLS regressions using the preferred specification on Life satisfaction on a 0 o 10 scale.

A.9 Advisory group

The advisory group for the two grants from the Medical Research Council Prevention Research Partnership ("ActEarly Programme", Grant # MR/S037527/1) and UK Research and Innovation (Grant # MMR/X002837/1) include those below.

Anna Freud: Jessica Deighton

Bradford Institute for Health Research: David Ryan, John Wright

Department for Education: Catherine Newsome

Department of Health and Social Care: Lucy Andrews

Department for Work Pensions: Mike Daly

Institute for Fiscal Studies: Sarah Cattan

London School of Economics: Miqdad Asaria, Sara Evans-Lacko, Paul Frijters

Public Health England: Annalisa Belloni

The Behavioral Insights Team: Tom McBride

Tower Hamlets: Somen Banerjee

University College London: Nichola Christie, Peter Goldblatt, Heather Joshi, Catherine Law, George Ploubidis, Aase Villadsen

University of Dundee: Jan Boehnke, Louise Marryat

University of Essex: Patrick Bronka, Matteo Ricciardi

University of Leeds: Mark Mon-Williams

University of Liverpool: David Taylor-Robinson

University of Oxford: Leon Feinstein

University of Sheffield: Sarah Bates, Alan Brennan

University of York: Karen Bloor, Jonathan Bradshaw, Richard Cookson, Tim Doran, Ruth Helstrip, Rowena Jacobs, Ruth Patrick, Kate Pickett, Ieva Skarda, Shrathinth Venkatesh

Young Person Representative: Brooke Johnson

Youth Futures Foundation: Andrea Barry