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], Richard Cookson[1]

[1]University of York, [2]University College London, [3]London School of Economics

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Abstract

Economic evaluation of early childhood interventions is difficult because it is hard to extrapolate the full range of long-term benefits and public cost savings from short-term effectiveness evidence. This paper presents the first childhood microsimulation model of a wide range of health, educational and social outcomes and public cost savings up to age 17 based on bespoke modelling of longitudinal birth cohort data. Our model is based on regression analysis of the Millennium Cohort Study (MCS), which includes 15,380 children born in the UK around 2000/2001. We use a conservative causal inference strategy controlling for a rich set of confounders. As well as describing our data analytical and simulation strategy, we illustrate how the model can be used to evaluate four hypothetical income-shifting scenarios in early childhood. We found that shifting the poorest fifth to the next poorest would increase public costs, due to increased hospitalisation and identification of special educational needs, but deliver considerable gains in wellbeing. For example, in a cohort of 700,000 newborns we estimate that public costs up to age 17 would increase by £14.8 million (discounted at 3.5%) alongside a gain of 134,761 WELLBYs (a one point increase in life satisfaction for one year for one child) which would be valued at £1,752 million (discounted at 3.5%) using the standard UK Treasury value of £13,000 per WELLBY. More ambitious scenarios resulted in public cost savings and larger WELLBY gains.

*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 (Grant # MR/S037527/1) and UK Research and Innovation (Grant # MMR/X002837/1). We thank Jan Boehnke, Alan Brennan, Patryk Bronka, Eric John Brunner, Sara Evans-Lacko, Rowena Jacobs, Brooke Johnson, Christian Krekel, Liina Mansukoski, Mark Mon-Williams, George Ploubidis, Matteo Richiardi, Paul Tiffin, and Matthew Warburton for helpful comments on this paper. All remaining errors are our own. An updated version of the paper with the appendix can be found online.

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 policy domains including health, education, employment and crime (Heckman, 2012; Almond et al., 2018; Conti et al., 2019). However, it is difficult to estimate the full range of long-term life outcomes and associated public cost savings across different policy domains. Previous attempts at long-term early childhood policy modelling have tended either to use simplistic methods of causal inference or to develop specific models that focus on a specific intervention or a specific set of outcomes in a narrow range of policy domains or do so over a shorter time period (Milne et al., 2015; García et al., 2020).

We have previously started the process of developing a rigorous general long-term childhood policy model that can be re-used to evaluate different interventions, known as LifeSim (Skarda et al., 2021, 2022). However, our previous prototype model focused on discrete event simulation of outcomes in adulthood and for outcomes in childhood relied on raw observational data combined with simple carrying forward of short-term effects on basic cognitive and social skills into adolescence. Building on this work and a descriptive study of associations between early childhood circumstances and adolescent outcomes (Villadsen et al., 2023) we have developed the first general childhood microsimulation model capable of inputting short-term effects on early years risk factors (age 0 to 5) and outputting a wide range of extrapolated outcomes and public cost savings up to age 17 based on bespoke modelling of longitudinal data. In this paper we aim to describe our model and illustrate how it can be used to extrapolate the long-term consequences of a reduction in early childhood poverty.

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, using multiple imputation to handle missing values due to attrition and non-response. We select 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 and subjective wellbeing. In this paper 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 further early years circumstances that policy makers often target for prevention or for support services or both, and we are in the process of modelling

five further risk factors: teenage mother, preterm birth, low birth weight, disability and school readiness. We take a conservative approach to causal inference by only including causal effects for which there is a plausible theoretical story, by including a rich set of confounding variables (country, region, ethnicity, neighbourhood deprivation, child disability, mother's age at birth, smoking during pregnancy, maternal mental health and education (NVQ level), single parent, household size and composition, parental disability and employment) based on a clear set of causal inference rules, by identifying theory and evidence to support our causal inference assumptions, and by comparing the magnitude of our estimated effects with external estimates from a previous systematic review of causal inference studies of the effects of early childhood income on later life outcomes (Cooper and Stewart, 2021). We run one regression for each outcome from ages 3-17 to estimate causal effects and their standard errors. Based on these estimates we then use discrete event simulation to extrapolate those outcomes between ages 3 to 17 by progressing a birth cohort to age 17, allowing for uncertainty around both causal effect coefficients and individual-level outcomes.

We use six outcomes to quantify public costs potentially amenable to policy intervention: truancy, exclusion, hospitalisation, special education needs, conduct disorder, and disability (parent reported activity limiting long-term condition). We model the potential effect of four income-shifting scenarios based on quintile groups of household income - shifting the poorest fifth to the next poorest, shifting the two poorest fifths to the middle, shifting the poorest to the richest fifth, and shifting everyone to the richest fifth. We report outcomes and costs by age and further disaggregate costs by source (hhospitalisation, disability, conduct disorder, special education needs (SEN), truancy and exclusion).

2 Data and Methods

Modelling using LifeSim begins with the data, the Millennium Cohort Study (MCS), from which we identify "risk factors" (age 0 to 5) and "outcomes" (age 3 to 17). By "risk factors" we mean any early years variable that could be a potential policy target for improving the "outcomes". We use regressions to estimate the relationships between the risk factor and outcomes using our estimation strategy based on directed acyclic graphs (DAGs)[1]. From these estimates we extract coefficients,

[1] described in detail section 2.2 below

standard errors and the distribution of residuals to feed into the simulation of the outcomes. We attach unit costs to various cost-bearing outcomes to estimate public costs, and we use a parent-reported emotional and peer problems score as a proxy indicator of life satisfaction. This allow us to calculate public costs, subjective wellbeing and other life outcomes from age 3 to 17.[2]

LifeSim Childhood uses a direct microsimulation strategy, i.e. we simulate the outcomes for a cohort of individuals from the time of risk factor onset to age 17 and every sweep in between. We do not progress an individual between each sweep of the MCS but instead go directly from the age of risk factor onset to every subsequent sweep. This strategy allows us to minimise error propagation that might occur if we took an indirect "relay" approach that progressed individuals wave-by-wave.

2.1 Data

The Millennium Cohort Study (MCS) follows 18,800 children born in the UK around 2000/1, we exclude twins and triplets which brings the initial sample size down to 15,380. Surveys were conducted when the children were 9 months, 3 years, 5 years, 7 years, 11 years, 14 years and 17 years[3]. The response rate for the MCS cohort declines over time, but we use multiple imputation of 30 data sets to handle non-response and attrition and thereby maintain the full initial sample size.

The variables we use for our estimation from the MCS can be roughly divided into three categories: risk factors, outcomes and confounders.[4] We will describe the risk factors and confounders first and then go into more detail about the outcomes.

In this paper we will discuss early childhood income quintile groups[5] as our primary risk factor, where early childhood income is the average OECD equivalised income of the child's 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. We assume that the timing of change to this "permanent income" starts

[2]We assume our early risk factors affect outcomes from birth but we only model public costs and wellbeing gains from age three to age 17 in an effort to be conservative.

[3]The study is ongoing and the next wave of data from when the children were around 23 is expected to be released in late 2025

[4]For the example risk factor in this paper the three groups of variables will be mutually exclusive but this will not be the case for the larger model.

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

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. We therefore only use confounders from the first sweep of the MCS at around month 9.

2.1.1 Adverse Outcomes

We begin with a set of five adverse health and educational outcomes measured in the 7th sweep of the MCS (around age 17). These outcomes are all both important in their own right and also predictive of poor outcomes throughout adulthood (Villadsen et al., 2023). The first, poor GCSEs, is a binary measure for poor self reported academic performance at the end of secondary school [6]. Specifically poor GCESs is defined as not having 5 or more GCSEs[7], including maths and english, graded C or above. Psychological distress is determined by self reported Kessler score, a measure of distress 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 have serious mental illness or be under psychological distress(Kessler et al., 2003). Regular smoker is an indicator for regular cigarette smoking based on self reported smoking of more than 6 cigarettes per week. Poor/Fair Health is a 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 being in poor health. Obesity is based on a respondent meeting the UK90 growth reference chart obesity threshold for their age and sex at the time of interview.

2.1.2 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) internalising scale from age 3 to 17, a sum of emotional symptoms scale and peer relationship problems scale, as an imperfect proxy indicator of life satisfaction. The 0-20 scale for SDQ internalising is converted to

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

[7] or 4 or more N5 results in Scotland

a life satisfaction score (0-10) between 2[8] and 10 using a simple linear mapping[9]. Using this simple 0-10 scale allows us to directly translate our results to WELLBYs.

Self-reported subjective wellbeing measures are available in the MCS at ages 11, 14 and 17 but they vary from one sweep to another and we do not use them to avoid breaks in the time series from 3 to 17. At age 17, for example, neither the self-reported SDQ internalising score nor the self-reported Short Form Warwick-Edinburgh Mental Wellbeing Scale (SWEMWBS) matches the mean and variance of the parent-reported SDQ internalising score.

2.1.3 Outcomes with Public Costs

We are 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. Below we describe each cost-bearing outcome, the source of annual unit costs[10] and any adjustments and assumptions made.

Hospitalisation is based on parent reporting of admission to a hospital in sweeps 2, 3, 4, 5, 6, and 7. 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" i.e. the total potential savings from all kinds of early intervention (Chowdry and Fitzsimons, 2016). Instead, we rely on our causal estimates to tell us how many hospitalisations are prevented by a change in the specific risk factor. Since we do not know the number and nature of admissions we use the cost of a single inpatient hospitalisation in the UK, £3,313 (GMCA, 2022). This cost is potentially an over estimate as it is the cost of inpatient hospitalisation for everyone in the UK and costs for children may be lower than the rest of the population. We will update these with more specific childhood costs in future work.

Disability, based on parent reported long term illness that affects daily activity, is available at sweeps 2, 3, 4, 5, 6 and 7. Currently we use a temporary place holder for the health costs associated

[8] We map only to life satisfaction of 2 or above because the distributions of life satisfaction and SDQ Internalising 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.

[9] We are working to better map the SDQ internalising scale to other wellbeing measures at every age and plan to move away from the measure based on a simple linear transformation.

[10] The unit costs we use currently are likely to change and improve as we update the model. We also plan to account for the distribution of the unit costs and increase the number of costs captured.

with disability of £800 per year per child, the average annual cost of healthcare for a child in the UK (Kelly et al., 2018) and needs to be updated.

Conduct Disorder is based on parent reported SDQ conduct problems scale at sweeps 3, 4, 5, 6, and 7[11]. We follow Skarda et al. (2021); Goodman et al. (2000, 2003) in using an algorithm to estimate the probability of conduct disorder for each individual using their SDQ conduct problems scale which is then compared with the randomly generated probabilities to determine the final outcome. Costs for conduct disorder are from Bonin et al. (2011), who calculate the cost of conduct disorder from the literature. They suggest an average annual cost per child of £2,943 between ages 5 and 10, and a cost of £1,968 between ages 11 to 16 [12]. These costs do not include costs to the justice system (which we plan to include in the future), but rather are just costs to the NHS, education and social services.

Special Education Needs (SEN) is based off of a teacher/parent report of the child having a statement of special education needs. We use the average cost of SEN support, £3,000 per year per child, from the government notional SEN guidance (DoE, 2023) as the unit cost.

Truancy in the MCS is measured by parent reported absence from school at sweeps 5 and 6. A binary indicator for any truancy is used for the simulation. We cost truancy using the cost to education from regular truancy, which is £911 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 use the proportion of sample with any truancy with regular truancy to calculate the average cost of any truancy, assuming no cost for non-regular truancy.

Exclusion in the MCS is measured by parent reported exclusion from school at sweeps 5 and 6. A binary indicator for any exclusion (permanent or temporary) is used for the simulation. We cost exclusion using the cost of alternate provision, a consequence of permanent exclusion, £21,100 per year per child (Bryant et al., 2018). The parents in the MCS are also asked about permanent exclusion in sweep 5. We use the proportion of sample with any exclusion with permanent exclusion to calculate the average cost of any exclusion, assuming no cost for temporary exclusion.

[11] SDQ scores are also available at sweep 2 when the child is 3 but we do not have a cost at that age and algorithm we follow to identify conduct disorder predicts high rates at that age.

[12] Which we extend to age 17

2.2 Estimation Strategy

We want to estimate causal relationships between each risk factor and outcome. We do not have access to experimental or quasi-experimental data to do this, instead we use follow Pearl (2009) in drawing causal diagrams (DAGs) to estimate the relationship. This allows us to bring together prior scientific knowledge to determine causal links between risk factors and outcomes in our data. We believe the depth of information available about the individuals and parents in the MCS allows us to capture most confounders (factors that have an effect on both the risk factor and outcome) in the relationship between our risk factors and outcomes.

For building our model we attempt to follow a set of rules, described below, so our models are **conservative**, **credible**, and **parsimonious**. We detail the rules we use below and will describe the confounders we actually use here.

2.2.1 DAG Rules

1. **Parsimonious**: Simple functional form without interaction terms (i.e. no moderators)
2. **Conservative**: Adjust for a broad set of well-founded and distinctive confounders
    - Include confounders that are also moderators, mediators (even if the mediating effect is likely to be strong), other risk factors in LifeSim Childhood (to avoid double counting). We only exclude confounders that are not well-founded or distinctive. In the case of multi-year risk factors we include all confounders for the full period.
3. **Credible**: Scientifically credible causal inference story in every case.
4. Do not adjust for prior or interim measurements of the same outcome or risk factor.
5. Use the same DAG as outcome timings change, but not as risk factor timings change.
6. Quality of data also be considered for inclusion decision
    - Exclude confounders with low response rate, difficult to parse structure, or clearer or simpler alternatives.

In our effort to be conservative we include a wide range of potential confounders as controls[13]. These can be split into three broad groups - basic demographics, child and maternal characteristics, and finally household/family characteristics.

We include basic demographic characteristics such as country, region within England, six level ethnicity and Index of multiple deprivation (IMD) quintile using binary indicators. We also include some characteristics of the child such as disability at age 3 and the mother's perinatal characteristics such as indicators for being a teen parent, for being over 35 at birth, smoking during pregnancy, poor maternal mental health (based on mother's Rutter score at 9 months), and education (NVQ levels). Finally we account for characteristics of the household and family unit such as single parent/carer, number of children in the household, number of adults in the household, parental disability, and labour force participation of parents.

To estimate these models we use different types of regressions based on the type of outcome variable. For continuous outcomes we use simple linear regression and for binary outcomes we use logistic regressions. We also have outcomes that are discreet scores based on responses in the survey, for these we use negative binomial regressions.

2.3 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. Since we use direct modelling, progress from time of exposure to risk factor directly to each outcome year, the baseline characteristics from the MCS form the basis for simulated outcomes in all years.

Randomness is introduced to each universe in a couple of 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. 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, but we do

[13]Descriptive statistics for these confounders can be found in the online appendix.

not account for covariance. Additionally, in the case of binary outcomes, our estimates 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.

3 Results

In this section we present the baselines for the simulated population and the simulated policy effects of several income shifting policies on public costs, wellbeing and the five adverse outcomes. In these policies we shift children across income quintile groups[14]. While do model uncertainty in the simulations we are unable to present confidence intervals in these estimates.[15]

We simulate four simple income quintile shifting scenarios, as used in Villadsen et al. (2023)[16],

- **Scenario 1** - shifting children in the **bottom** income quintile **to** the **second** quintile.
- **Scenario 2** - shifting children in the **bottom two** quintiles **to** the **middle** quintile.
- **Scenario 3** - shifting only children in the **bottom** quintile **to** the **top** quintile.
- **Scenario 4** - shifting **all** children **to** the **top** quintile.

The first and third scenarios look at the effect of only moving the bottom quintile group and so show the effects of changes only to 20% of the population.

3.1 Adverse Outcomes

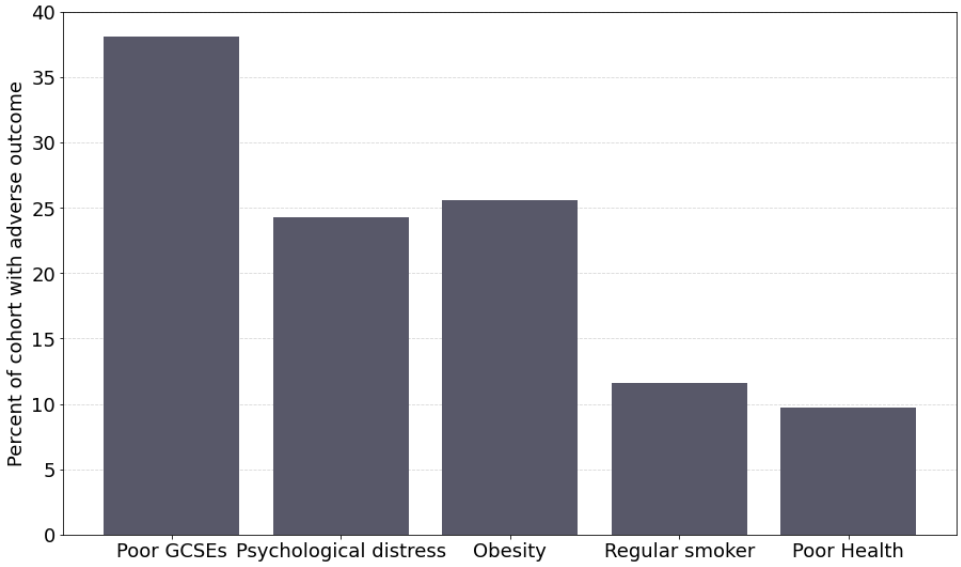
The simulated prevalence of five adverse outcomes in the cohort is presented in Figure 1. At age 17 12% of the cohort are regular smokers, 38% of the cohort have poor GCSEs, 26% are obese, 10% have poor self reported health, and 24% are under psychological distress.

[14]Income quintiles are based on the distribution of average early years (9months to age 5) OECD equivalised household income within the multiply-imputed MCS data with age 3 UK population weights.

[15]We hope to update our online appendix with estimates that include uncertainty soon.

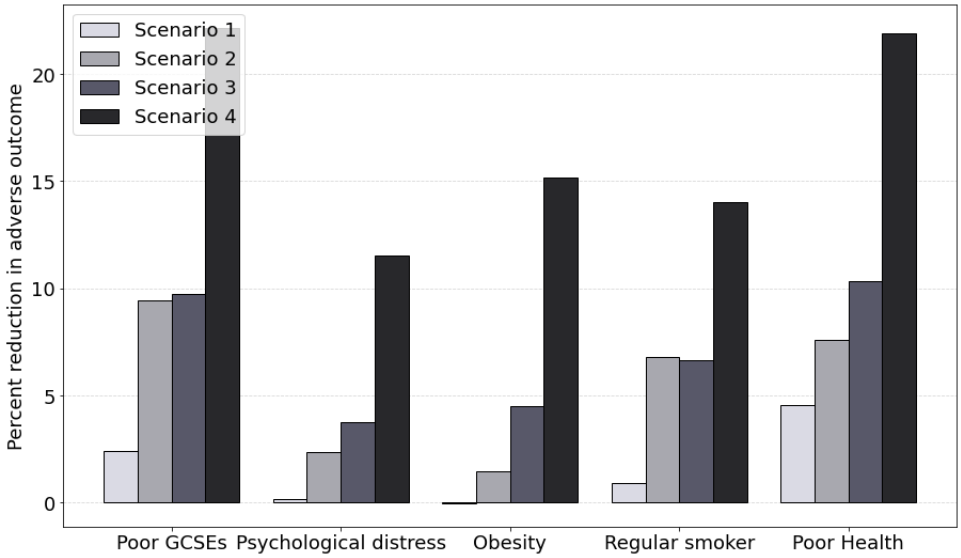
[16]They examined the effects of scenarios 1, 2 and 4 on the five adverse outcomes at age 17.

Figure 1: 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 2: Percentage reduction in adverse outcomes with each intervention.



Income quintile shift scenarios - Scenario 1 - Bottom to second, Scenario 2 - Bottom two to middle, Scenario 3 - Bottom to top, Scenario 4 - All to top. 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.

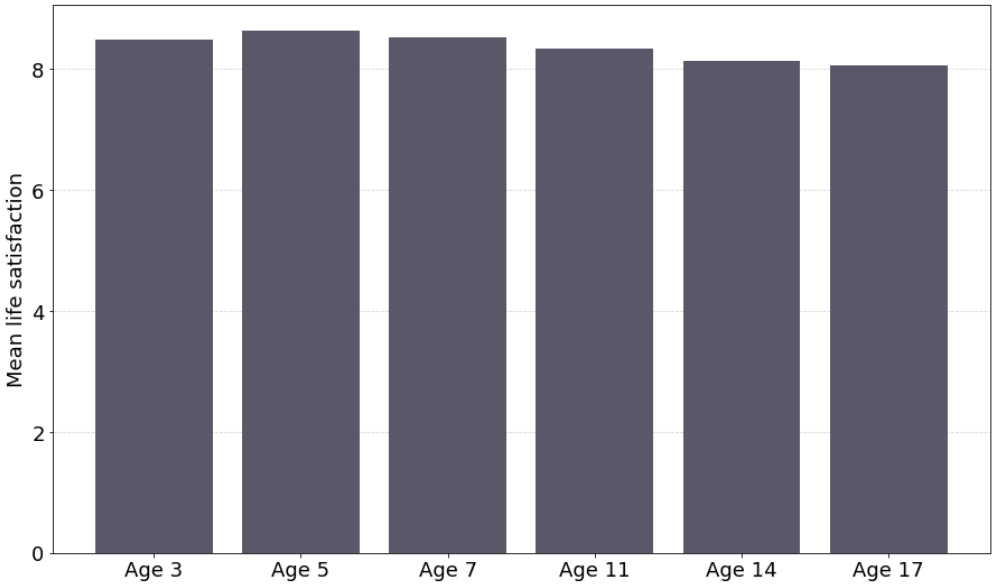
Figure 2 shows the percentage reduction in an adverse outcome associated with each intervention. Scenario 1, moving the bottom quintile to the next quintile results in a 1% reduction in Regular smoking, 2.4% reduction in Poor GCSEs, 4.55% reduction in poor health, 0.2% reduction

in psychological distress, and no reduction in obesity. Scenario 2, moving the bottom two quintiles to the third quintile results in a 6.8% reduction in Regular smoking, 9.4% reduction in Poor GCSEs, 1.5% reduction in Obesity, 7.6% reduction in poor health and 2.3% reduction in psychological distress. Scenario 3, moving the bottom quintile to the top quintile results in a 6.6% reduction in Regular smoking, 9.7% reduction in Poor GCSEs, 4.5% reduction in Obesity, 10.4% reduction in poor health and 3.8% reduction in psychological distress. Scenario 4, moving everyone to the top quintile results in a 14.0% reduction in Regular smoking, 22.2% reduction in Poor GCSEs, 15.2% reduction in Obesity, 21.9% reduction in poor health and 11.5% reduction in psychological distress.

3.2 Wellbeing

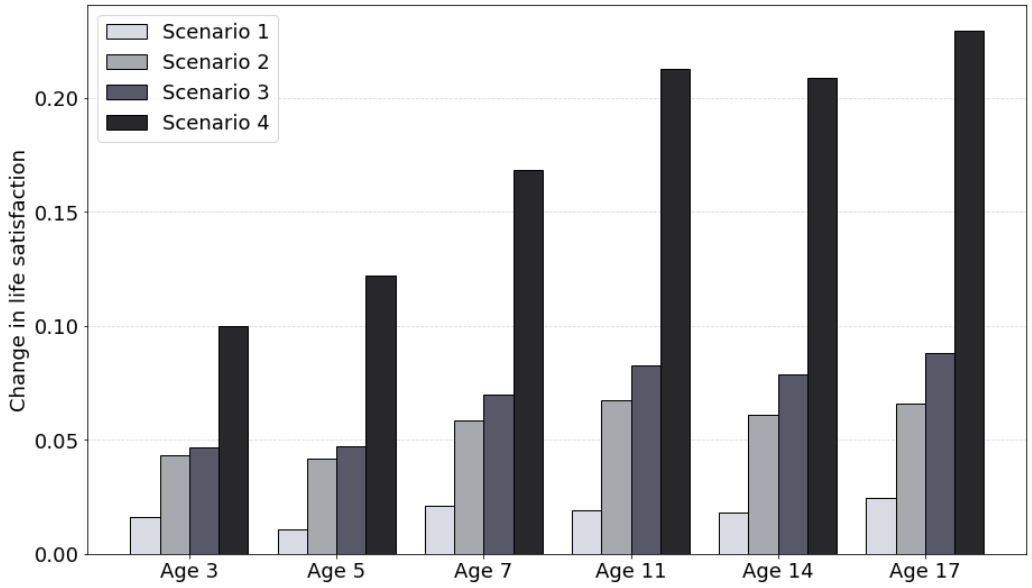
Wellbeing in our case is measured by parent reported SDQ internalising scale, a sum of the SDQ emotional symptoms and peer relationship problems scales, linearly transformed to life satisfaction on a 0 to 10 scale. The simulated baseline life satisfaction levels in the cohort is presented in Figure 3. The baseline levels of life satisfaction do not fluctuate significantly with age, it peaks at age 5 with a mean of 8.63 and is lowest at age 17 with a mean of 8.07.

Figure 3: Baseline life satisfaction proxied by SDQ internalising in each MCS sweep.



Life satisfaction is based on a simple linear transformation of parent reported SDQ internalising, the sum of emotional problems and peer problems.

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



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

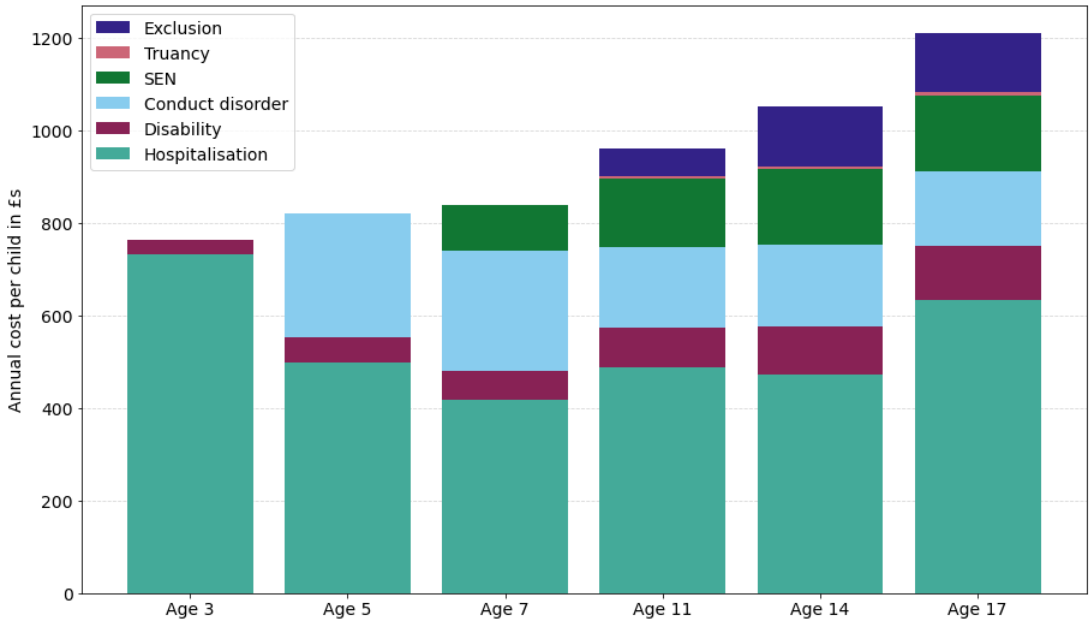
Figure 4 shows the average increase in life satisfaction for each scenario, to illustrate the size of the effects on life satisfaction we convert the results into WELLBYs. WELLBYs are defined as a one point increase in life satisfaction on a 10 point scale per child per year. In scenario 1, moving the bottom quintile to the next quintile results in an increase in life satisfaction between 0.011 (at 5) and 0.024 (at 17) for an annual average wellbeing increase (between ages 3 and 17) of 0.018 or 0.277 over the entire 15 year period. In scenario 2, moving the bottom two quintiles to the third quintile results in an increase in life satisfaction between 0.042 (at 5) and 0.067 (at 11) for an annual average wellbeing increase (between ages 3 and 17) of 0.058 or 0.863 over the entire 15 year period. In scenario 3, moving the bottom quintile to the top quintile results in an increase in life satisfaction between 0.047 (at 3) and 0.088 (at 17) for an annual average wellbeing increase (between ages 3 and 17) of 0.070 or 1.056 over the entire 15 year period.And in scenario 4, moving everyone to the top quintile results in an increase in life satisfaction between 0.1 (at 3) and 0.229 (at 17) for an annual average wellbeing increase (between ages 3 and 17) of 0.178 or 2.671 over the entire 15 year period.

3.3 Costs

Our public cost estimates are currently limited to 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[17]), persistent truancy (ages 11 to 17[17]) and permanent exclusion (ages 11 to 17[17]).

The annual cost per child at the baseline increases with age as presented in Figure 5. This is partially expected as we also include more cost bearing outcomes at later ages as noticed in the figure which breaks down the costs by source. The total annual cost per child is £764.81 at age 3, £821.28 at age 5, £838.22 at age 7, £960.09 at age 11, £1,050.99 at age 14, and £1,210.38[18] at age 17. This combines to an annual cost per child between the ages of 3 and 17 to about £942.59[19]. This annual cost per child between 3 and 17 can be broken down into £524.17 for hospitalisation, £77.32 for disability, £179.24 for conduct disorder, £103.95 for special education needs, £3.52 for persistent truancy, and £54.39 for permanent exclusion.

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.

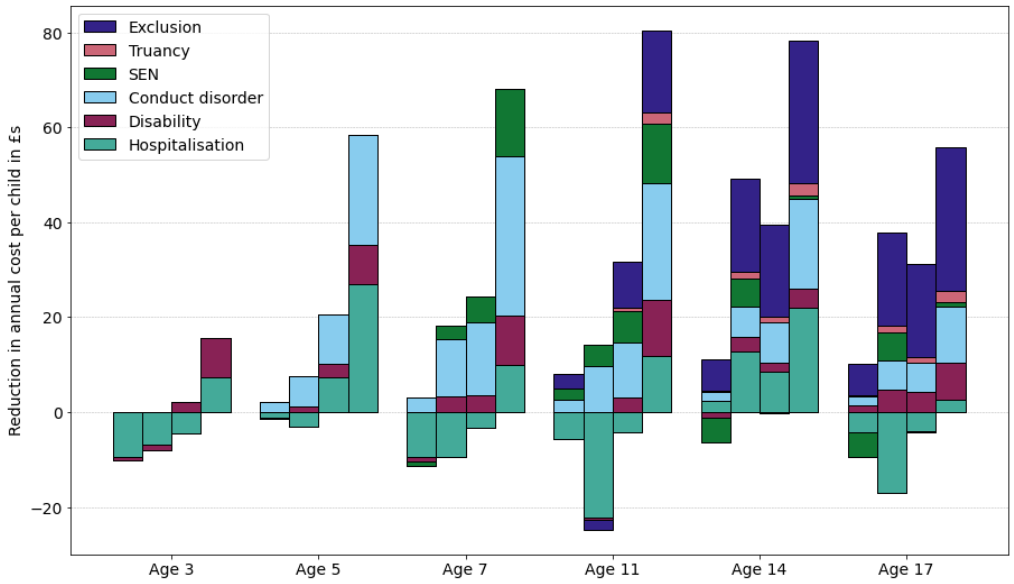
[17]This outcome is not available at age 17 in the MCS but the value from age 14 is assumed to carry over to age 17.

[18]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 £912.

[19]Calculated at birth and discounted at 3.5 percent a year.

Figure 6 shows the cost savings associated with the implementation of each scenario. Here we do not account for the cost of each scenario to present net costs and only show public cost savings. The graph shows four clustered graphs at each age, each bar on the of the cluster is an estimate for scenario 1 to 4 in order (from left to right). The area below the x-axis represents cost increases and area above represents cost savings.

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



The bar plots cluster at each wave represent scenarios 1, 2, 3, and 4. Income quintile shift scenarios - Scenario 1 - Bottom to second, Scenario 2 - Bottom two to middle, Scenario 3 - Bottom to top, Scenario 4 - All to top. 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.

Scenario 1 does not result in overall public cost savings (based on our six outcomes) with an increase in hospital costs and special education needs costs compared to the baseline driving this result. The average annual cost is £-10.27 at age 3, £0.72 at age 5, £-8.29 at age 7, £2.38 at age 11, £4.85 at age 14, and £0.79 at age 17. This translates to an average annual cost between ages 3 and 17 of £-1.38[19], which can be broken down into £-4.51 for hospitalisation, £-0.36 for disability, £2.01 for conduct disorder, £-1.50 for special education needs, £0.10 for persistent truancy, and £2.88 for permanent exclusion. Scenario 2 does result in cost savings despite an increase in public costs associated with hospitalisation. The average annual cost is £-8.07 at age 3, £4.58 at age 5, £8.91 at age 7, £-10.48 at age 11, £49.24 at age 14, and £20.92 at age 17. This translates to an average annual cost between ages 3 and 17 of £11.86[19], which can be broken down into £-7.40 for hospitalisation, £1.89 for disability, £7.31 for conduct disorder, £3.44 for special education needs,

£0.47 for persistent truancy, and £6.14 for permanent exclusion. Scenario 3 once again results in cost savings despite an increase in costs associated with hospitalisation in sum years (but an overall reduction). The average annual cost is £-2.33 at age 3, £20.63 at age 5, £21.15 at age 7, £27.26 at age 11, £39.20 at age 14, and £26.75 at age 17. This translates to an average annual cost between ages 3 and 17 of £23.53[19], which can be broken down into £0.06 for hospitalisation, £2.87 for disability, £9.34 for conduct disorder, £2.30 for special education needs, £0.54 for persistent truancy, and £8.41 for permanent exclusion. Scenario 4 results in cost savings across the board. The average annual cost is £15.60 at age 3, £58.33 at age 5, £68.06 at age 7, £80.41 at age 11, £78.23 at age 14, and £55.69 at age 17. This translates to an average annual cost between ages 3 and 17 of £62.62[19], which can be broken down into £13.64 for hospitalisation, £8.50 for disability, £20.06 for conduct disorder, £5.66 for special education needs, £1.27 for persistent truancy, and £13.50 for permanent exclusion.

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

	Outcome	**Scenario 1**	**Scenario 3**	**Scenario 2**	**Scenario 4**
Adverse outcomes *(Number of cases prevented by age 17)*					
	Poor GCSEs	6,395	25,135	25,946	59,110
	Psychological distress	277	3,975	6,374	19,572
	Obesity	-29	2,646	8,080	27,156
	Regular smoking	744	5,517	5,373	11,350
	Poor Health	3,084	5,159	7,027	14,868
Public cost savings *(Cost savings between ages 3 and 17, in millions of 2023 £s)*					
	Total cost	-14.8	73.6	163.8	451.2
By source	Hospitalisation	-36.1	-55.6	-0.5	102.5
	Disability	-3.1	12.6	21.2	64.2
	Conduct disorder	14.7	53.2	68.7	147.8
	Special education needs	-9.2	23.0	17.4	42.1
	Truancy	0.6	2.9	3.5	8.3
	Exclusion	18.3	37.4	53.6	86.4
Wellbeing improvement *(WELLBYs gained between ages 3 and 17)*					
	WELLBYs	134,761	418,935	507,847	1,276,226
	Value (in millions of £s)	1,752	5,446	6,602	16,591

Number of births in the UK in 2021 was around 700000. 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 quintile shift scenarios - Scenario 1 - Bottom to second, Scenario 2 - Bottom two to middle, Scenario 3 - Bottom to top, Scenario 4 - All to top

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 five rows show the number of children who do not have each adverse outcome compared to the baseline population. Scenario 1 reduces the number of children with adverse outcomes by between 0 (Obesity) and 4.5% (Poor health). The effects of scenario 2 are slightly higher varying between 1.5 (obesity) and 9.4% (poor GCSEs). The effects of scenario 3 are similar varying between 3.8 (psychological distress) and 10.4% (poor health). Finally, the effects of scenario 4 are much higher varying between 11.2 (psychological distress) and 22.1% (poor GCSEs).

The next six rows show the public cost savings compared to the baseline population in millions of 2023 £s. There is a cost increase of 14.8 million £s with scenario 1 but cost savings of 73.6, 163.8 and 451.2 million £s[19]) for each of scenarios 2 to 4 respectively. The final row shows the improvement in wellbeing in terms of WELLBYs, there is a steady increase in the value of the WELLBYs generated across the scenarios, 1,752, 5,446, 6,602 and 16,591, million £s[19]) for scenarios 1 to 4 respectively.

4 Discussion

LifeSim Childhood estimates a broad range of long-term effects of modifying early childhood risk factors. To use it researchers and policy makers would have to map their intervention's short-term effect onto one of our early childhood risk factors and describe 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 currently particularly 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.

Summary of results

We find that increased early years income substantially reduces adverse outcomes and improves wellbeing. However, this does not necessarily lead to public cost saving in the least ambitious but plausible policy scenario of shifting the poorest fifth to the next poorest fifth. In this scenario, there is an increase in public costs driven by increased hospitalisation, disability and special education needs, which is presumably due to increased identification of needs for these services. For example,

in a cohort of 700,000 newborns we estimate that public costs up to age 17 would increase by £14.8 million (discounted at 3.5%) alongside a gain of 134,761 WELLBYs (a one point increase in life satisfaction for one year for one child) which would be valued at £1,752 million (discounted at 3.5%) using the standard UK Treasury value of £13,000 per WELLBY. More ambitious scenarios resulted in public cost savings and larger WELLBY gains.

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 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. This allows us to estimate effects for a relatively recent birth cohort. In future, it will also allow us to extend the model directly to age 23, once this next sweep of MCS data becomes available in late 2025. 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 discrete event simulation to synthesise our MCS findings and incorporate unit costs and other sources of information, and to allow us to address uncertainty.

Limitations First, we do not use trial or quasi-experimental data to estimate the magnitude of causal effects for each risk-factor outcome pair. 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. Our next step will therefore be to validate the magnitude of our estimates against those in the literature. 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. In future work we would address this by updating our parameters with most recent estimates available from exteranl soruces studies for specific outcomes where this cohort bias is likely to be of concern. Third, in this paper we do not yet present uncertainty in our estimates, but will do so soon. Fourth, our unit cost estimates are partial, out of date, and lack information on the distribution of costs. We plan to improve our unit costs in future, by accessing more up-to-date data sources including linked administrative data. For example, we do not capture costs of being taken into care and costs from the justice system, both of which are important. Fifth, LifeSim Childhood focuses on outcomes for

the child and does not capture spillover effects on outcomes for parents, siblings and classmates.

Comparison with other studies As we improve our model we plan to directly compare our estimates with those from past research on both long term and short term effects. Villadsen et al. (2023) looks 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 conservative estimates, roughly varying between -1 (obesity) and 6% (poor health) for scenario 1, between 4 (obesity) and 18% (poor health) for scenario 2, and between 23% (psychological distress) and 47% (poor GCSEs) for scenario 4. The general trend and ranking of effect sizes on the adverse outcomes are similar to ours. For the next step we plan to 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). They comparing findings from different studies by reporting the effect of a $1000 increase in income on effect sizes for a wide range of outcomes including cognitive development, education, child health, and social and behavioural scores. For now we report our own adjusted and unadjusted effect estimates in our online appendix.

We are continuing to work to improve LifeSim Childhood and would be most grateful for any comments and feedback from HESG members.

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