Evaluating Childhood Policy Impacts on Lifetime Health, Wellbeing and Inequality: Framework and Illustrative Application

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Highlights

- Childhood policies have long-term impacts on adult health, wellbeing and inequality
- We introduce a new interdisciplinary framework for quantifying these impacts
- The framework uses a general index of lifetime health and wellbeing
- This facilitates comparisons of value-for-money between diverse policies
- It also facilitates policy targeting analysis and distributional analysis
- We illustrate by re-evaluating a parent training programme in England

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Abstract

We introduce and illustrate a new, inter-disciplinary framework for economic evaluation of cross-sectoral childhood policies that takes a long and broad view of the impacts on health, wellbeing and inequality from a whole-lifetime perspective. Lifecourse distributional economic evaluation starts by estimating total lifetime costs and benefits using detailed underpinning information about diverse health, social and economic outcomes for each individual in the general population from birth to death. It then conducts cost-effectiveness analysis, policy targeting analysis and distributional analysis of inequality impacts using a multi-dimensional index of lifetime health and wellbeing. This index allows comparisons of both value-for-money (efficiency) and distributional impact (equity) from a lifetime perspective between different childhood policies with different kinds of costs and benefits for different populations over different time horizons. It also has a simple, intuitive interpretation – the number of good years of life the individual enjoys over their whole lifetime. We illustrate how this framework can be applied in practice by conducting a lifecourse distributional economic evaluation of a training programme in England for parents of children at risk of conduct disorder. Our illustration uses a simple index of lifetime health and wellbeing based on health-related quality of life and consumption outcomes, but other indices could be used based on other kinds of outcomes data. We create the detailed underpinning data needed to apply the framework by using a previously published meta-analysis of randomised controlled trials to estimate the short-term outcomes and a previously published lifecourse microsimulation model to estimate the long-term outcomes.
1 Introduction

Recent scientific advances in epidemiology, neuroscience, economics and other disciplines have established beyond reasonable doubt that childhood development and childhood programmes can have important effects on adult health and wellbeing many decades in the future, during working years and retirement (Goodman et al., 2015; Almond, Currie and Duque, 2018; Conti, Mason and Poupakis 2019; Heckman 2012). There is therefore a strong case for taking a long and broad view of childhood policy that accounts for these important long-term impacts over the whole lifecourse, as well as short-term impacts over the next year or two and medium-term impacts over the next five or ten years.

However, standard economic evaluation frameworks do not provide the full information needed to support national and local decision making about cross-sectoral childhood policy investments (Feinstein, Chowdry and Asmussen 2017; Allen 2011; Dalziel, Halliday and Segal 2015). Policy makers do not just want information about potential short- and medium-term cash savings and benefits in monetary terms. They also want information about potential long-term benefits in terms of lifetime health and wellbeing (Coast 2019; Adler and Fleurbaey 2016; De Neve et al. 2020; Layard et al. 2014); they want the ability to re-design programmes in line with available budgets by identifying which kinds of children benefit most in the long-term and evaluating alternative policy targeting options (Heckman and García 2017); and they want distributional analysis of long-term impacts on inequalities in health and wellbeing within the general population (Hills 2017).

In this paper we introduce a new, inter-disciplinary framework for lifecourse distributional economic evaluation of childhood policies that is capable of providing this information, and we illustrate how it can be applied in practice and the kinds of new insights it can generate. As well as calculating the total programme costs and benefits, this lifetime health and wellbeing approach also includes cost-effectiveness analysis, policy targeting analysis and distributional analysis based on a multi-dimensional index of lifetime health and wellbeing for each individual in the general population. This index allows comparisons of value-for-money and inequality impact from a lifetime perspective between different childhood policies with different kinds of costs and benefits for different populations over different time horizons. It also has a simple,

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1For general audiences we think ‘lifetime health and wellbeing approach’ is a suitable label, while for specialist audiences we suggest ‘lifecourse distributional economic evaluation’ or ‘distributional cost-wellbeing analysis’.

2
intuitive interpretation – the number of good years of life the individual enjoys over their whole lifetime – and its theoretical underpinnings have been extensively explored in the ethics and economics literature (Adler, 2019). There are many ways of constructing an index of this kind based on different kinds of individual-level outcomes data. In our illustrative application we use a simple index based on data on health-related quality of life and consumption (Cookson and Culyer, 2010) but other indices could be used instead based on other kinds of outcomes data (Coast, 2019; Adler and Fleurbaey, 2016; Mukuria et al., 2018; Frijters and Krekel, 2021).

Our contribution is to show how lifecourse distributional economic evaluation can be conducted in practice, using the example of a training programme for parents of young children at risk of developing conduct disorder. Specifically, we show how to extrapolate short-term childhood effect estimates from randomised controlled trials or quasi-experiments across the rest of the lifecourse, and then how to use the resulting data not only to estimate total costs and benefits but also to conduct cost-effectiveness analysis, policy targeting analysis and distributional analysis based on a multi-dimensional index of lifetime health and wellbeing. We take estimates of short-term effects from a published meta-analysis of trials (Gardner et al., 2017), and we extrapolate the long-term outcomes using a published lifecourse microsimulation model of the Millennium Cohort Study (Skarda, Asaria and Cookson, 2021). We also check for robustness using different policy effect fade-out assumptions and perform a simple external validity check by comparing our sub-group predictions against data from a 7-year follow-up study of two randomised controlled trials.

We lay no claim to conceptual originality in developing any of the individual components of lifecourse distributional economic evaluation – concepts and methods for measuring lifetime health and wellbeing, for discrete event simulation of lifecourse outcomes, and for conducting cost-effectiveness analysis, policy targeting analysis and distributional analysis have all been developed and published elsewhere in various different strands of literature on ethics and economics, epidemiological modelling and economic evaluation. Rather, our contribution lies in bringing these diverse components together into a useful inter-disciplinary framework that can be applied in practice using existing data and models to yield new information and insights for decision makers who wish to take a long and broad view of the consequences of childhood policy for health, wellbeing, public cost and inequality.
2 Lifecourse Distributional Framework

2.1 Comparison with Standard Economic Evaluation Framework

Standard frameworks for economic evaluation of childhood programmes are usually known as cost-benefit analysis and cost-effectiveness analysis. Cost-benefit analysis of a childhood programme can provide useful policy insights about public costs and savings, about the social benefits in terms of money, and about overall value for money. For example, Hendren and Sprung-Keyser (2020) conducted cost-benefit analysis of 133 US policies based on previous careful causal inference studies. They compared the “marginal value of public funds” – the ratio of monetary social benefit to net public cost, which is considered to be infinite if the long-run public cost savings outweigh the initial cost investment – and found that childhood programmes tended to have higher returns than adult programmes. Cost-benefit analyses typically present a “dashboard” of detailed information about many different specific kinds of costs and benefits over different time horizons. This information is then summarised using one or more standard headline measures of value for money – for example, a benefit-cost ratio, a marginal value of public funds, a rate of return on investment, or a number of years before the financial savings and/or social benefits recoup the initial policy investment. To create these summary measures of value for money, each specific cost and benefit is valued in monetary terms, after applying appropriate discount rates and other adjustments, and then added up to calculate the sum total. Childhood policies are also sometimes evaluated using cost-effectiveness analysis in terms of one specific primary policy effect – for example, a cost per case of conduct disorder prevented. However, this is less common and less useful because evaluation studies of different childhood policies use a bewildering variety of different specific childhood effect measures which do not allow comparisons of value-for-money between different policies with different effects on different aspects of childrens’ lives.
Lifecourse distributional economic evaluation adds three main kinds of policy insight, as illustrated in Figure 1. First, it provides insight into overall social benefit and value for money in terms of gains in lifetime health and wellbeing, measured in a way that allows comparisons between different kinds of childhood policy with different specific childhood effects – a broad form of cost-effectiveness analysis that one might call “cost-wellbeing analysis”. Second, it provides insight into which kinds of children benefit most and how the programme can be re-targeted towards different kinds of children at different ages to deliver better value for money in terms of lifetime health and wellbeing – a broad form of policy targeting analysis. Third, it provides insight into the inequality impacts of the policy in terms of inequality in lifetime health and wellbeing in the general population – a broad form of distributional equity analysis. Distributional analysis often focuses on short-term financial outcomes (Bourquin and Waters, 2019; United States Congress Joint Committee on Taxation, 2019), which only provides a snapshot of inequality impacts at a point in time and can potentially be misleading if the underlying concern relates to inequalities in lifetime opportunities and outcomes (Hills, 2017). There is a literature on modelling policy impacts on lifetime earnings (Dearden et al., 2008; Altig and Carlstrom, 1999), but this does not take into account dynamic interactions with mental and physical health outcomes and does not provide information about impacts on lifetime health and wellbeing as well as lifetime earnings.

Delivering this additional insight requires additional underpinning information. Standard eco-

<table>
<thead>
<tr>
<th>POLICY INSIGHTS:</th>
<th>STANDARD ECONOMIC EVALUATION</th>
<th>LIFECOURSE DISTRIBUTIONAL ECONOMIC EVALUATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public Costs and Savings</td>
<td>Social Benefit in Terms of Money</td>
<td>Public Costs and Savings</td>
</tr>
<tr>
<td>Cost-Benefit Analysis</td>
<td>Cost-Effectiveness Analysis</td>
<td>Social Benefit in Terms of Health and Wellbeing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Policy Targeting Analysis</td>
</tr>
<tr>
<td>POPULATION:</td>
<td>General Population</td>
<td>Recipients</td>
</tr>
<tr>
<td>EFFECT ESTIMATION:</td>
<td>Population Average</td>
<td>Population Subgroup</td>
</tr>
<tr>
<td>LIFECOURSE COVERAGE:</td>
<td>Partial</td>
<td>Full (Birth to Death)</td>
</tr>
</tbody>
</table>

**Figure 1: Lifecourse Distributional Economic Evaluation Framework**
conomic evaluation focuses on modelling outcomes in the recipient population, including diverse policy effects and their associated costs and benefits. Lifecourse distributional economic evaluation broadens this out to look at outcomes in the whole general population including the non-recipient population. It requires information about the broader non-recipient population for three reasons: (i) costs borne by non-recipients – including the opportunity costs of foregone public programmes – may have impacts on the health and wellbeing of non-recipients, (ii) distributional equity analysis needs to look at inequality within the whole general population, not just within the recipient population, and (iii) policy targeting analysis requires analysis of different recipient populations (i.e. different kinds of children at different ages), which may be broader than the original recipient population included in a trial or quasi-experiment.

Standard economic evaluation ultimately only requires estimates of population-level average policy effects, though sometimes sophisticated individual-level modelling is undertaken to estimate these effects (Bernal 2008; Caucutt and Lochner 2020; Gayle, Golan and Soytas 2018; Del Boca, Flinn and Wiswall 2014; Bolt et al., 2018; Attanasio, Meghir and Nix 2020). By contrast, lifecourse distributional analysis is directly interested in population-subgroup-level effects, not only to facilitate policy targeting analysis and distributional analysis but also because health and wellbeing are multi-dimensional concepts that require joint estimation of many different specific pieces of information about similar types of individuals (e.g. mental and physical health, mortality risk, income and other specific outcomes that contribute to individual health and wellbeing). In cost-benefit analysis it is common practice to measure various specific effects as population-level averages, then monetise them, and then add them up. Population-level modelling is often undertaken to extrapolate short-term average effects from trials or quasi-experiments into long-term effects (Lee et al. 2012; Paull and Xu 2017). Each outcome is usually modelled using separate estimated production functions, often using a simple linear ‘multiplier’ that converts a marginal effect on the short-term outcome, such as a change in social problems score at age 5, into a corresponding marginal effect on the long-term outcome, such as a change in adult earnings. Even though this approach allows many long-term outcomes to be modelled

\[^2\] A notable example of sophisticated modelling is [García et al. (2020)] which conducts a cost-benefit analysis of a childhood programme implemented in the 1950s by linking data from cohort studies of similar individuals at successive stages of their lives. This study includes many outcomes at individual level from birth to death for the recipient population. However, it does not include this data for the general population, does not construct multi-dimensional indices of health and wellbeing, and does not conduct cost-wellbeing analysis, policy targeting analysis or distributional equity analysis. Furthermore, this analysis is entirely backward looking and does not provide prospective information about the likely costs and benefits of programmes implemented in today’s society.
in a simple way, it ignores dynamic interactions between individual-level outcomes and does not allow the construction of multi-dimensional indices of lifetime health and wellbeing. In lifecourse distributional economic evaluation, by contrast, specific effects are first simulated at an individual level in order to then estimate the effects and health and wellbeing impacts at population-subgroup level. As necessary, these then can also be added up across the population.

Finally, lifecourse distributional economic evaluation requires information on the full lifecourse from birth to death. This is more demanding than most applications of standard economic evaluation, which typically only require estimates of outcomes for part of the lifecourse – for example, from the age at which the policy is implemented (e.g. age 5) to the time horizon of the analysis, which might only be 10 or 20 years into the future.

2.2 Indices of Lifetime Health and Wellbeing

Policy makers are increasingly interested in analysis of the impacts of policies in terms of individual health and wellbeing, rather than just money. There is a large literature on the theoretical and practical shortcomings of standard unweighted cost-benefit analysis and the advantages of alternative utilitarian and prioritarian approaches to economic evaluation based on explicit individual wellbeing and social welfare functions (Adler and Fleurbaey, 2016). However, the construction of these functions imposes a requirement for individual-level datasets in terms of several outcomes.

There are many different ways of computing an index of lifetime health and wellbeing. In our illustrative evaluation we apply the wellbeing measure proposed by Cookson et al. (2020), who suggest a simple approach based on the quality-adjusted life year (QALY) concept in health economics but adjusting for consumption as well as health-related quality of life. They refer to this as an “equivalent life” approach (Canning, 2013), and the resulting wellbeing metric as “good life years” or “wellbeing QALYs”. The good life years metric represents individual wellbeing in year t by a function \( w_t() \) increasing in both consumption and health (see the online Appendix A for details). The interpretation is that a good year is a year lived enjoying full health and consuming a good income. However, in principle many other multidimensional indices of wellbeing could be used for lifecourse distributional economic evaluation, including measures based on multidimensional questionnaire instruments and life satisfaction (Coast, 2019; Adler and Fleurbaey, 2016; Mukuria et al., 2018; Frijters and Krekel, 2021).
3 Methods

3.1 Illustrative Policy Analysis

We illustrate how lifecourse distributional economic evaluation can be conducted in practice by evaluating a national parent-training programme for parents with children at risk of developing conduct disorder. We initially make a simple comparison between delivering publicly funded parent training to all eligible parents in England versus none, before evaluating various targeted policy options.

We take short-term effect data from a recent systematic review of randomised control trial evidence about the effects of the “Incredible Years” (IY) programme (Gardner et al., 2017) – a particular parent-training programme to improve child conduct problems. We extrapolate these effects across the rest of the lifecourse using an existing microsimulation model (Skarda, Asaria and Cookson, 2021) and then use the detailed resulting information to evaluate programme impacts in terms of lifetime health, wellbeing and inequality.

3.2 Modelling Conduct Disorder Incidence

We model the child’s individual age-specific probability of developing conduct disorder and the actual outcome of whether a child develops conduct disorder or not, using parent reported scores on their child’s problems. More specifically, we measure parent-reported conduct problems during childhood using the parent-reported Strengths and Difficulties Questionnaire (SDQ) conduct problem subscale and a further parent-reported “behavioural impact” score. These scores range from 0-10, with a higher score representing more conduct problems and a higher impact of problems.

We then model the child’s actual probability of developing conduct disorder using a predictive algorithm based on a combination of SDQ conduct problem and impact scores, which provides a specific probability of conduct disorder based on a classification as “unlikely”, “possible”, or “probable” (Goodman et al., 2003; Goodman, Renfrew and Mullick, 2000). More specifically, the algorithm allocates a probability of 0.61 for children with SDQ conduct problem score of at least 5 combined with impact score of at least 2; a probability of 0.31 for children with SDQ conduct problem score of 4 (irrespective of impact score) and a probability of 0.06 for all other children with SDQ scores below 4. Whether a child develops conduct disorder or not is then
determined by comparing their probability with a random draw from a uniform distribution over the interval 0-1.

3.3 Modelling the Training Programme

There are various ways of selecting the eligible population for parent training. We assume that parents are selected by parent-reported screening for potential conduct problems, based on a SDQ conduct problem score value of 4 or above, as an indicator of children at risk of developing a conduct disorder.

We assume that the parent training:

(i) is delivered to parents of all five-year old children screened as being at risk of developing a conduct disorder, based on a parent-reported SDQ conduct problem score at age 5 within the abnormal range (4 or above);

(ii) causes an average 0.46 standard deviation decrease in the SDQ conduct problem and impact scores of a child recipient, with heterogeneous effects conditional on child and parental characteristics (larger effects for the children of parents with mental health problems and for children with a higher baseline conduct problems score, and correspondingly smaller effects for other children (Gardner et al. 2017)). The effect persists for the rest of the childhood. See details in online Appendix C.

This modelled decrease in the SDQ conduct problem and impact scores then reduces the child’s risk of developing childhood conduct disorder, which then improves child’s mental health and chances of obtaining a university degree in early adulthood. The positive effects then translate into various benefits during the working years, including more earnings and higher consumption level, lower chances of ending up in prison, lower probability of smoking, better physical and mental health and lower mortality risk. Finally, these benefits persist and accumulate into retirement years.

We also conduct sensitivity analysis using alternative assumptions about effectiveness, including a random error reflecting individual heterogeneity and a conservative assumption of effect fadeout over time (Feinstein, Chowdry and Asmussen 2017; Van Aar et al. 2017) (see online

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3This cut-off value is suggested on the SDQ official website http://www.sdqinfo.org/py/sdqinfo/b3.py?language=English$q2(UK).
3.4 Modelling the Costs and Opportunity Costs

The positive effects of the intervention then translate into cost savings, which are modelled using the costs associated with different outcomes (see table B.1 in online Appendix B). We assume that the following outcomes incur costs to the public service: CHD, depression, other healthcare, conduct disorder, prison, residential care.

We also model the opportunity cost of the programme in two simple ways. First, our base case assumption is that the upfront intervention costs fall upon other public services over a period of five years and that expenditure on public services has the same value to an individual as private consumption. In other words, we assume that everyone in the cohort experiences a reduction in their consumption during the next five years post intervention. This reduction in consumption is modelled to precisely cover the direct costs of the parent training programme.

Second, in a separate cost-effectiveness analysis, we model opportunity costs based on evidence and assumptions about the marginal cost of producing a good life year from public expenditure (Frijters and Krekel 2021). We start by taking an existing estimate of the marginal productivity of public expenditure in England in terms of the cost of a one point improvement in life satisfaction - known as a “wellbeing-year” or WELLBY. Frijters and Krekel (2021) estimate that a WELLBY costs £2,156 in 2008 prices, which equals £2,408 in 2015 prices. We then convert this into a cost per good year gained by assuming that a good year is equivalent to a year at the national average level of life satisfaction (7.7), that a life as bad as death is equivalent to a year with a life satisfaction of 2, and that a one point improvement in life satisfaction is equally valuable at all levels of life satisfaction. These assumptions imply that producing a good year requires a 5.7 point improvement in life satisfaction for one year and so the marginal productivity of public expenditure in terms of the cost of a good year is £13,724 (=£2,408×5.7). Further details of this calculation are in online Appendix A.
3.5 Microsimulation Modelling

To extrapolate long-term effects we use a lifecourse microsimulation model which has been extensively documented elsewhere. LifeSim is a dynamic microsimulation model that undertakes discrete event modelling of a rich set of developmental, social, health and economic outcomes of interest to policy makers, from birth to death for each child in a simulated cohort. It draws initial conditions up to age 14 from the Millennium Cohort Study (MCS) by re-sampling a population of 100,000 English children born in the year 2000-01, and simulates their long-term outcomes after age 14 using life-stage specific stochastic equations. These equations are parameterised using effect estimates from existing studies combined with target outcome levels from up-to-date administrative and survey data.

Figure 2 summarises the general structure and modelled outcomes of LifeSim.

![Figure 2: Summary of the Model Structure](image)

4 Results

We present the results of the illustrative lifecourse distributional economic evaluation and discuss how it leads to new insights into economic evaluation, policy targeting and distributional equity.

Skarda, Asaria and Cookson (2021) have published detailed information on all LifeSim assumptions, equations, data sources and the complete open source programming code. They also compare LifeSim predictions with external sources of survey data on adult outcomes for older cohorts.
4.1 Total Costs and Benefits

Figure 3 presents the effects on the primary outcome of interest in childhood – conduct disorder from age 5 to 14.

![Figure 3: Prevalence of Conduct Disorder Over Time](image)

The assumed short term average effect size stated earlier of 0.46 standard deviations implies a decrease of 0.70 points in the SDQ conduct problem score and 0.09 points in the SDQ impact score\(^5\) which then translate into preventing around 16% of the children from developing conduct disorder at age 5 (see Figure 3). However, the effect on conduct disorder diminishes over time, with only around 5% of conduct disorder cases prevented by age 18, even though our base case assumption is that the effect on SDQ does not fade out. This occurs because, independently from the parent training programme, many children with high parent-reported conduct problem scores at age 5 progress to scores within the normal range by age 7. These normal to low scores are associated with a low probability of developing conduct disorder, and so a small improvement in SDQ score no longer makes a big difference in reducing the probability of developing conduct disorder. This also explains the substantial reduction in conduct disorder after age 5 for child recipients in the ‘without policy’ scenario in Figure 3.

We use these primary effects in childhood to model a wide range of secondary effects in childhood and adulthood (summarised in Table D.2 in online Appendix D). We then use these effects to model the long-run cost savings presented in Figure 4. There are substantial initial savings due to reduced costs to social, educational and health services for children with conduct disorders.

\(^5\)The specific effects on the SDQ scores and a wide range of other lifecourse outcomes are summarised in Table D.2 in online Appendix D.
with further savings in adulthood due to reduced costs to the criminal justice system, additional tax revenues and lower benefit payments.\footnote{\textcite{Bonin et al., 2011}} The cost of the “Incredible Years” programme falls within the range £1,773-2,660 per recipient, depending on the training group size (\textcite{Edwards et al., 2016}; uprated to 2015/16 prices). This implies that the initial savings would cover the costs of the programme within a ten to fifteen year period, with further public cost savings in adulthood. The total government budget savings over lifetime sum up to £19,457 per recipient.

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure4.png}
\caption{Cumulative Cost Savings Over Time}
\end{figure}

Note: Savings as a result of the parent training programme estimated per young child at risk of conduct disorder, in 2015/16 prices and discounted at 1.5% annual rate. The dashed lines represent the range of estimated unit costs of the “Incredible Years” programme (\textcite{Edwards et al., 2016}). See table B.1 for the full list of sources used to model costs.

If the policymaker has a time horizon of 15 years or more, then from a social perspective the programme is cost saving and there is no need for a cost benefit ratio.

In principle, we could also calculate the full long-term benefits of the policy in monetary terms, by placing monetary values on various specific effects in childhood and adulthood - though as usual with cost-benefit exercises involving multiple different benefits there would be a risk of\footnote{The savings from residential care are so much more lower than savings from prison due to ‘residential care’ being modelled only after age 69.}
double counting the value of different specific effects. However, since the policy is cost-saving we can conclude it is cost-beneficial without undertaking this further step.

In sensitivity analysis in online Appendix F, we find that reducing the SDQ effect by 50% would have little impact on the time taken to recoup the initial investment, though would substantially reduce lifetime savings. However, with a fadeout of 65% after year 1 then the time taken to recoup costs would increase substantially to 45 years. It is unlikely that fadeout will be as high as this, however. A meta-analysis of randomized controlled trials with long-term follow up on child conduct problem interventions by Van Aar et al. (2017) found that the maximum observed policy effect fadeout in any of the 40 randomized controlled trials was 0.65, but the average fade-out effects were small and insignificant.

We also compare our estimated effects with findings from two long-term trial follow up studies. Scott, Briskman and O’Connor (2014) find positive effects from “Incredible Years” in an indicated child sample (with conduct problems above 97th percentile) but no effect in a selectively screened child sample (with conduct problems above 82nd percentile). We find that our estimated effects for the subgroups of children with similar conduct problem levels are consistent with the findings of these authors.

4.2 Cost-Effectiveness Analysis

Policymakers are sometimes interested in cost-effectiveness from the perspective of their own current budget. For this purpose, we can calculate a simple cost effectiveness ratio based on the upfront investment cost divided by the average gain in lifetime wellbeing or any other outcome. Table [I] presents these cost per unit of effect ratios, both for overall wellbeing and for various more specific outcomes, together with the effects per child recipient and the total population effect across all 9,228 child recipients. On average, the intervention increases the consumption of child recipients by around £287 per year, lifetime health by 0.43 healthy years, and lifetime wellbeing by 0.69 good years.
Table 1: Cost Effectiveness in Terms of Good Years and Various Specific Outcomes

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Individual effect</th>
<th>Population effect (in 9,228 recipients)</th>
<th>Cost per unit of effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good life years</td>
<td>0.69</td>
<td>6,367</td>
<td>3,212</td>
</tr>
<tr>
<td>Healthy life years</td>
<td>0.43</td>
<td>3,968</td>
<td>5,155</td>
</tr>
<tr>
<td>Life years</td>
<td>0.17</td>
<td>1,569</td>
<td>13,038</td>
</tr>
<tr>
<td>Annual consumption (£)</td>
<td>287</td>
<td>2,644,929</td>
<td>8</td>
</tr>
<tr>
<td>Conduct disorder at age 5 (% and number)</td>
<td>-16.17</td>
<td>-1,492</td>
<td>13,708</td>
</tr>
<tr>
<td>Conduct disorder at age 18 (% and number)</td>
<td>-5.19</td>
<td>-479</td>
<td>42,707</td>
</tr>
<tr>
<td>University graduates (% and number)</td>
<td>0.71</td>
<td>66</td>
<td>312,185</td>
</tr>
<tr>
<td>Working years in unemployment</td>
<td>-0.71</td>
<td>-6,552</td>
<td>3,122</td>
</tr>
<tr>
<td>Life years in poverty</td>
<td>-0.99</td>
<td>-9,136</td>
<td>2,239</td>
</tr>
<tr>
<td>Working years in prison</td>
<td>-0.41</td>
<td>-3,783</td>
<td>5,406</td>
</tr>
<tr>
<td>Retirement years in residential care</td>
<td>-0.09</td>
<td>-831</td>
<td>24,628</td>
</tr>
<tr>
<td>Adult years as a smoker</td>
<td>-1.03</td>
<td>-9,505</td>
<td>2,152</td>
</tr>
<tr>
<td>Life years with mental illness</td>
<td>-1.27</td>
<td>-11,720</td>
<td>1,745</td>
</tr>
<tr>
<td>Premature mortality ≤ 75 (% and number)</td>
<td>-0.47</td>
<td>-43</td>
<td>471,599</td>
</tr>
</tbody>
</table>

Note: The individual effect is calculated on average per child recipient (9,228 child recipients in total). The population effect is the aggregate effects summed across the entire recipient population.

We find that the cost per good life year for the policy is £3,212, which is substantially below our suggested supply-side cost-effectiveness threshold of £13,724 per good life year (based on a marginal productivity calculation by Frijters and Krekel [2021], see section 3.4 and online Appendix [A]). We also find that the cost per healthy life year is £5,155, which is above the corresponding supply-side threshold for preventative public health expenditure in England of around £3,800 per healthy life year (Martin, Lomas and Claxton [2020]), but substantially below the decision thresholds used for health care expenditure in England – around £30,000 per healthy life year (Masters et al. [2017]).

4.3 Policy Targeting Analysis

We show how lifecourse distributional analysis can enable intelligent policy re-targeting to improve value for money. This could be useful, for example, to a local government agency considering how best to invest in parent-training programmes. Delivering training to all eligible parents has a large total up front cost that may be considered excessive by a cash-strapped decision maker. Therefore, decision makers are often looking for ways of targeting programmes towards people who are likely to benefit the most.

Table 2 reveals that even though the average benefits in terms of lifetime wellbeing are relatively
small, some individuals benefit substantially, in particular 354 children (3.83% of the recipients) gain at least five good years over their lifetime, and 109 children (1.18% of the recipients) gain at least ten good years. We refer to the people who gain at least five good years as ‘top gainers’.  

**Table 2: Distribution of Policy Gains**

<table>
<thead>
<tr>
<th>Good years gained</th>
<th>Recipient children</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>less than 1</td>
<td></td>
<td>7,785</td>
<td>84.36</td>
</tr>
<tr>
<td>1-2</td>
<td></td>
<td>732</td>
<td>7.93</td>
</tr>
<tr>
<td>2-3</td>
<td></td>
<td>194</td>
<td>2.10</td>
</tr>
<tr>
<td>3-4</td>
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<td>99</td>
<td>1.07</td>
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<tr>
<td>4-5</td>
<td></td>
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<tr>
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<td></td>
<td>245</td>
<td>2.65</td>
</tr>
<tr>
<td>10+</td>
<td></td>
<td>109</td>
<td>1.18</td>
</tr>
</tbody>
</table>

To identify what predicts a top gainer, we conduct a linear regression of good years gained on various child characteristics and conditions that could be used in policy targeting, as well as their interactions. We present details of the procedure in online Appendix G. We find that high baseline conduct problems (SDQ conduct problem score at age 5 equal to 7 or above), being born in poverty and having a parent with a university degree are all independently strongly associated with higher wellbeing gains. When analysing the interactions, we find that the combination of ‘high conduct problems’, ‘in poverty’, and ‘parental degree’ is strongly associated with larger wellbeing gains. The combination of only ‘high conduct problems’ and ‘in poverty’ is also associated with larger wellbeing gains.

Based on this information, in Table 3 we evaluate two alternative ways of targeting the programme more narrowly, and compare these to the initial policy (scenario 1): (i) offering training only to parents who live in poverty and have a 5 year old child with high conduct problems, i.e. SDQ conduct problem score 7 or above (scenario 2); and (ii) offering training only to the subset of such parents who also have a university degree (scenario 3). Both re-targeted options substantially reduce the total up-front programme cost and increase the wellbeing gain per recipient. This lowers the cost per good year gained from £3,212 in scenario 1, to £1,745 in scenario 2 and to only £407 in scenario 3 – an almost eight-fold increase in cost-effectiveness.

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5In Figure G.3 in online Appendix E we show that the top gainers are predominantly individuals who experience a cluster of multiple bad life outcomes at baseline, and for whom the policy is beneficial in preventing the clusters of bad life outcomes.

8These should be variables that are relatively easy to identify and there should be no obvious ethical obstacles to using them for policy targeting.
Re-targeting also substantially increases the lifetime cost savings per recipient (£19,457 in scenario 1 vs. £147,041 in scenario 3) and reduces the return on investment payback period (15 years in scenario 1 vs. 4 years in scenario 3).

### Table 3: Cost-Effectiveness Analysis of Three Targeting Options

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Number of child recipients</th>
<th>Total policy cost, 1000 £</th>
<th>Good years per recipient</th>
<th>Total good years gained</th>
<th>Cost per good year gained, £</th>
<th>Lifetime cost savings per recipient, £</th>
<th>Payback period, years</th>
<th>Opportunity cost, good years lost</th>
<th>Net total good years gained</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9,228</td>
<td>20,454</td>
<td>0.69</td>
<td>6,367</td>
<td>3,212</td>
<td>19,457</td>
<td>15</td>
<td>1,490</td>
<td>4,877</td>
</tr>
<tr>
<td>2</td>
<td>494</td>
<td>1,095</td>
<td>1.27</td>
<td>627</td>
<td>1,745</td>
<td>40,080</td>
<td>15</td>
<td>80</td>
<td>548</td>
</tr>
<tr>
<td>3</td>
<td>42</td>
<td>93</td>
<td>5.45</td>
<td>229</td>
<td>407</td>
<td>147,041</td>
<td>4</td>
<td>7</td>
<td>222</td>
</tr>
</tbody>
</table>

Note: It is assumed that the parent-training programme costs £2,217 per recipient, and the opportunity cost of a good year to other public services is £13,724 (see online Appendix A). We use 2015/16 prices.

However, because re-targeting substantially reduces programme scale, the total sum of good years gained is substantially reduced, as is the net total after allowing for the wellbeing opportunity costs of reduced expenditure on other programmes. This is because in scenario 1 training is offered to parents of 9,228 children, but only to parents of 494 children in scenario 2 and 42 children in scenario 3. This highlights a trade-off that exists between increased cost-effectiveness and reduced total impact in terms of total good years gained across the whole population, when re-targeting the programme more narrowly.

#### 4.4 Distributional Equity Analysis

We illustrate various ways of conducting distributional equity analysis of inequality impacts on lifetime health and wellbeing in the general population.

Figure 5 summarises the average policy gains in terms of lifetime wellbeing for various recipient subgroups. Each bar represents the good years gained on average for different subgroups. Figure 5 shows that the intervention has a larger impact on lifetime wellbeing of the poorest 20% recipient children, children whose parent has mental illness, children whose parent is without degree and children with high baseline conduct problems. We also find that boys gain more

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9 On average, children with university educated parents benefit less than children with less educated parents. However, as our policy targeting analysis showed, there is a small sub-group of children with university-educated parents who are among the top gainers – i.e. those in poverty and with high conduct problems.
from the intervention, a finding consistent with previous literature (Gardner et al. 2017).

Figure 5: Lifetime Impacts by Childhood Circumstances

Note: The average lifetime wellbeing gains for the subgroups among the group of recipients (n=9,228). Whiskers represent 95% confidence intervals.

Next, we look at the gap in average lifetime wellbeing between the best-off and worst-off 20% children in terms of lifetime wellbeing at baseline, which is a simple measure of inequality that is easy to communicate to policymakers. Figure 6 shows the baseline good years and policy gains for each wellbeing percentile and quintile group. The intervention reduces inequality between the best-off and worst-off 20% children by 0.1 good life years.
In online Appendix H we conduct further distributional analyses, including an analysis of expected lifetime wellbeing that identifies worse-off children in terms of early years circumstances that predict low lifetime wellbeing. We also provide summary indices of inequality and social welfare impact using an Atkinson index approach, which reveals a trade-off between narrower policy targeting being more cost-effective but yielding a smaller population-level reduction in inequality.

5 Discussion

We develop and apply a lifecourse distributional economic evaluation framework for analysing the long-term consequences of alternative childhood policy options for health, wellbeing and inequality. As well as cost-benefit analysis in monetary terms, this framework is capable of cost-effectiveness analysis, targeting analysis and distributional analysis based on multidimensional indices of lifetime health and wellbeing. We show how this framework can be applied in
practice by conducting a life-course distributional economic evaluation of a training programme for parents of young children at risk of developing conduct disorder.

We find that the beneficial short-term effects of parent training demonstrated in trials become less useful in preventing conduct disorder over time, because many apparent socio-behavioural problems would resolve for these children in due course without parent training. This suggests that there may be a trade-off between delivering childhood programmes at an earlier age when the dynamic skills formation benefits are greater (Cunha and Heckman, 2007) versus delivering them at a later age when problems can be more accurately diagnosed. Despite this, however, we estimate that public cost savings cover the cost of the programme within the first ten to fifteen years, and that substantial further savings accrue into adulthood. Previous studies have tended to be more optimistic, in finding that parenting programmes break even after only five or ten years (Bonin et al., 2011; O’Neill et al., 2013; Edwards et al., 2007, 2016).

Our cost-effectiveness analysis finds that the parent training programme is highly cost-effective with a cost per good year gained of £3,212. This compares favourably with the cost per good year from marginal public expenditure in England, which we estimate to be £13,724 based on figures from Frijters and Krekel (2021). We also find that lifetime benefits are small on average but a subset of recipient children enjoy substantial gains – about 4% of them gain five or more years of good life. The long-term benefits for these children are large and cumulative: improved conduct problems in childhood leads to improved educational and employment outcomes, the avoidance of spells in prison and premature mental and physical illness and mortality, and the saving of substantial sums of money over the life-course in public services and the social protection system. Our policy targeting analysis was able to identify a set of family circumstances and child characteristics that predict capacity to benefit, and showed how this information can be used to identify and evaluate intelligent ways of re-targeting the programme to increase cost-effectiveness and reduce total up-front cost. Finally, our distributional analysis suggests that the programme disproportionately benefits children from socially disadvantaged backgrounds and contributes to reducing inequality of opportunity for lifetime wellbeing on various measures of distributional equity. For example, we estimate that the programme reduces the lifetime inequality gap of 27.5 good years between the best-off and worst-off fifth of children by 0.1 good years.
The main strength of lifecourse distributional economic evaluation is its ability to take a long and broad view of childhood policy consequences by conducting cost-effectiveness analysis, policy targeting analysis and distributional analysis using multidimensional indices of lifetime health and wellbeing that have been proposed in the theoretical literature (Cookson et al., 2020; O’Donnell et al., 2014; Adler and Fleurbaey, 2016). In this paper we illustrate the application of one simple multidimensional metric – good life years based on income and health-related quality of life (Cookson et al., 2020), but different general wellbeing metrics could be constructed based on different kinds of outcomes data. Health and income are both fundamentally important general-purpose goods that are valuable to people throughout their lives, and so this index can be viewed as a simple general measure of a child’s opportunity for lifetime wellbeing.

From a conceptual perspective, the main limitation of this proposed framework for distributional economic evaluation is that it focuses on a single birth cohort, and does not evaluate effects on the health and wellbeing of future generations or issues of inter-generational equity. There are also limitations to the simple index of lifetime health and wellbeing used in our illustrative application. First, it only looks at health-related quality of life and consumption, not broader dimensions of health and wellbeing, and second, it focuses on these same outcomes valued in the same way across all stages of the lifecourse without allowing for potentially important changes in the outcomes people value at different stages of life (Coast, 2019). Further research is needed to broaden the framework to address inter-generational issues and to develop and compare different indices of lifetime health and wellbeing that can be used for comparing value for money and distributional equity impact between different childhood programmes. Future work could also help to produce better estimates of the appropriate threshold for assessing cost-effectiveness in units of wellbeing. Our own indirect estimate of the marginal productivity of public expenditure in England in terms of the cost of producing a good life year is £13,724, but this is based on numerous strong assumptions and direct estimation would be preferable.

Our illustrative application also has various specific limitations. For example, our benefit estimates are likely to be conservative, because we do take into account cross-productivity effects of conduct problems on cognitive and other skills, nor spillovers on other children (e.g., siblings, class-mates), parents, and future co-workers, which are likely to generate further positive cumulative effects. Nor do we take into account macro-level general equilibrium effects, though that this is a reasonable assumption in this context since a parent-training programme for a
few hours a week is unlikely to have large labour market effects on wages and prices.

There are also specific limitations relating to the type of microsimulation model we use to estimate long-term effects. We use a type of dynamic microsimulation model known as a “discrete event simulation” which is common in epidemiology and health economics and has also been used in labour economics and pension policy analysis (Zhang, 2018; Emmerson, Reed and Shephard, 2004). This approach models the evolution of future life outcomes as stochastic processes estimated using longitudinal data on the observed life outcomes of past cohorts of individuals. It rests on the fundamental assumption that the relevant stochastic processes – for example, the transition from childhood poverty to smoking, or from smoking to coronary heart disease – are invariant to social change (such as the Covid-19 crisis) and to policy change. In principle, lifecourse distributional economic evaluation of childhood policies could be conducted using other kinds of models that relax this fundamental assumption to some extent. For example, agent-based models based on classical economic rational choice theory can explicitly model behavioural responses to childhood programmes, such as changes in parental investment and labour supply (Bernal, 2008; Caucutt and Lochner, 2020; Gayle, Golan and Soytas, 2018; Del Boca, Flinn and Wiswall, 2014; Bolt et al., 2018; Attanasio, Meghir and Nix, 2020). Such models, however, can become intractable when they attempt to handle more than a few outcomes over long time periods (Emmerson, Reed and Shephard, 2004; Richiardi, 2017). Nevertheless, it may in future be possible to create the detailed underpinning data for our approach using agent-based modelling of complex adaptive systems comprising individuals who are thoughtful but not super-human (Miller and Page, 2007) and what economists call “quasi-structural” modelling that explicitly analyses behavioural responses without using the full apparatus of classical rational choice theory (Bernal and Keane, 2010). More generally, in considering what kind of underpinning microsimulation model to use to evaluate a particular childhood policy, there are likely to be trade-offs between complexity and tractability, and in some cases it may be preferable to combine findings from more than one model.

Lifecourse distributional economic evaluation provides a flexible and informative new approach to long-term childhood policy analysis which opens up an exciting research agenda. Policymakers are often accused of “short-termism”, and the lifecourse perspective often receives short shrift in public debates. Lifecourse distributional economic evaluation can potentially help keep the lifecourse perspective in view, by routinely providing policymakers with detailed and
credible information about long-term policy consequences for health, wellbeing and inequality.

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