



Deposited via The University of York.

White Rose Research Online URL for this paper:

<https://eprints.whiterose.ac.uk/id/eprint/185391/>

Version: Published Version

Article:

Skarda, Ieva, Asaria, Miqdad and Cookson, Richard Andrew (2022) Evaluating Childhood Policy Impacts on Lifetime Health, Wellbeing and Inequality: Lifecourse Distributional Economic Evaluation. *Social Science & Medicine*. 114960. ISSN: 1873-5347

<https://doi.org/10.1016/j.socscimed.2022.114960>

Reuse

This article is distributed under the terms of the Creative Commons Attribution (CC BY) licence. This licence allows you to distribute, remix, tweak, and build upon the work, even commercially, as long as you credit the authors for the original work. More information and the full terms of the licence here:

<https://creativecommons.org/licenses/>

Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.



Evaluating childhood policy impacts on lifetime health, wellbeing and inequality: Lifecourse distributional economic evaluation

Ieva Skarda^{a,*}, Miqdad Asaria^b, Richard Cookson^a

^a Centre for Health Economics, University of York, Heslington, York, YO10 5DD, UK

^b Department of Health Policy, Cowdray House, London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, UK

ABSTRACT

We introduce and illustrate a new framework for distributional economic evaluation of childhood policies that takes a broad and long view of the impacts on health, wellbeing and inequality from a cross-sectoral whole-lifetime perspective. Total lifetime benefits and public cost savings are estimated using lifecourse microsimulation of diverse health, social and economic outcomes for each individual in a general population birth cohort from birth to death. Cost-effectiveness analysis, policy targeting analysis and distributional analysis of inequality impacts are then conducted using an index of lifetime wellbeing that allow comparisons of both value-for-money (efficiency) and distributional impact (equity) from a cross-sectoral lifetime perspective. We illustrate how this framework can be applied in practice by re-evaluating a training programme in England for parents of children at risk of conduct disorder. Our illustration uses a simple index of lifetime wellbeing based on health-related quality of life and consumption, but other indices could be used based on other kinds of outcomes data such as life satisfaction or multidimensional quality of life. 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 effects and a previously published lifecourse microsimulation model to extrapolate the long-term effects.

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 et al., 2018; Conti et al., 2019; Heckman, 2012). When making decisions about the funding and implementation of childhood programmes across different policy sectors - including education, welfare, social care and justice as well as health care and public health - there is therefore a strong case for taking a long and broad view that accounts for these important long-term impacts over the whole lifecourse.

Unfortunately, however, standard cost-effectiveness and cost-benefit studies fail to do this and hence do not provide the full information needed to support decision making about cross-sectoral childhood policy investments (Feinstein et al., 2017; Allen, 2011; Dalziel et al., 2015). Cost-effectiveness studies of childhood policies outside the health sector typically focus on short-term effects during childhood only, and although cost-benefit studies sometimes take a longer time horizon they

focus on monetary benefits rather than lifetime health and wellbeing and do not provide information about how benefits vary for different children living in different circumstances. Yet policy makers do not just want information about total public cost 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; HM Treasury, 2021); 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 framework for lifecourse distributional economic evaluation of cross-sectoral childhood policies in terms of lifetime wellbeing 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 wellbeing approach also includes cost-effectiveness analysis, policy targeting analysis and distributional

* Corresponding author.

E-mail address: ieva.skarda@york.ac.uk (I. Skarda).

analysis based on a multi-dimensional index of lifetime wellbeing for each individual in the general population.¹ Measuring effects in terms of lifetime wellbeing 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. The concept of lifetime wellbeing has a simple, 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; Cookson et al., 2022). 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, including life satisfaction and multi-dimensional quality of life scores (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. We selected this example because strong trial evidence is available and parent training programmes are of widespread international interest. For example, the specific programme that we evaluate, known as the “Incredible Years Parenting Programme for Preschoolers”, has been trialled and at least partially rolled out in England, Scotland, Wales, Ireland, Northern Ireland, Denmark, Norway, Sweden, Estonia, Finland, Netherlands, Spain, Malta, Portugal, Slovenia, United States, Canada, Australia, New Zealand, Hong Kong, Russia, Singapore (<https://incredibleyears.com/programs/>). 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 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 et al., 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.

Guidelines for cost-effectiveness and cost-benefit analysis often recommend doing the kinds of things that we do in our illustrative application - for example, using a lifetime time horizon, capturing a broad range of costs and benefits, using general indices of wellbeing, and conducting policy targeting analysis and distributional analysis (Husereau et al., 2022; HM Treasury, 2020). These things are easier said than done, however, especially in the challenging case of childhood policy. Our contribution is to show how to accomplish all of these daunting childhood policy evaluation tasks in practice, within a clear analytical framework, based on dynamic microsimulation modelling of the complex lifecourse causal pathways involved.

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 cross-sectoral 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 economic evaluation framework

2.1. Comparison with standard economic evaluation framework

Standard frameworks for economic evaluation of cross-sectoral 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 sector-specific primary effect – for example, a cost per point improvement in a specific measure of childhood social and behavioural problems, or per case of conduct disorder prevented, or per health-adjusted life-year gained during childhood. However, this is less useful because cross-sectoral childhood programmes usually have a broad range of health and non-health benefits, rather than just one sector-specific effect, and because evaluation studies 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. It is possible to conduct cost-effectiveness analysis based on health sector costs and effects and then provide a separate list or “inventory” of non-health costs and effects. This is not entirely satisfactory, however, as decision makers then have to informally compare, combine and weigh up the different kinds of costs and effects themselves before they can draw conclusions about overall value for money.

Lifecourse distributional economic evaluation adds three main kinds of policy insight, as illustrated in Fig. 1. First, it provides insight into overall social benefit and value for money in terms of gains in lifetime 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 “lifecourse 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 lifecourse 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 lifecourse distributional analysis. Distributional analysis often focuses on short-term financial outcomes (Bourquin and Waters, 2019; United States

¹ For general audiences we think ‘lifetime health and wellbeing approach’ is a suitable label, while for specialist audiences we suggest selecting a more specific technical term for the study design in hand - for example ‘lifecourse economic evaluation’ if there is no distributional component or ‘lifecourse distributional economic evaluation’ if distributional analysis is included.

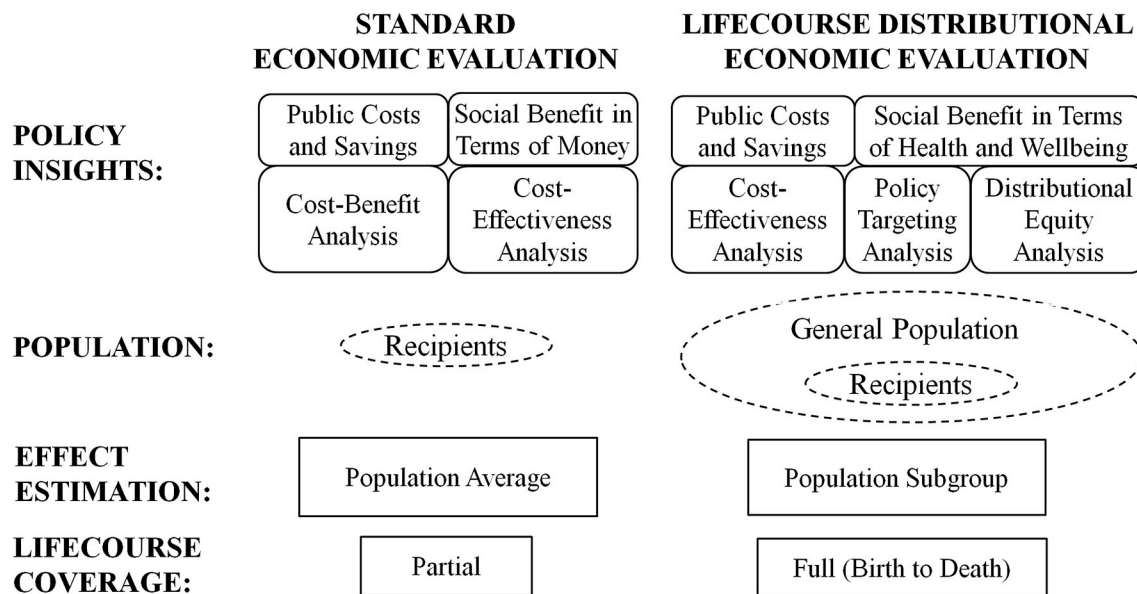


Fig. 1. Lifecourse distributional economic evaluation framework.

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 economic 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 et al., 2018; Del Boca, Flinn and Wiswall, 2014; Bolt et al., 2018; Attanasio et al., 2020).² 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 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 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.

2.2. Indices of lifetime wellbeing

Policy makers are increasingly interested in analysis of the impacts of policies on individual wellbeing (De Neve et al., 2020). For example, UK Treasury guidance on economic appraisal recommends that wellbeing impacts can be evaluated either alongside other impacts as part of a cost-benefit analysis, or in some cases as the primary outcome variable in a cost-effectiveness analysis, and that this “may be particularly useful in certain policy areas, for example community cohesion, children and

families” (HM Treasury, 2020, chapter 6). The practical advantages of a general wellbeing metric for childhood policy evaluation are clear, since childhood policies are currently evaluated using diverse and incomparable metrics - for example, previous cost-effectiveness studies of parent training programmes have used a cost per SDQ point, per ECBI-I point, per PSOC point and per DALY gained. There is also a large theoretical literature on the 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 wellbeing suitable for economic evaluation. The theoretical properties of such indices have been extensively investigated, and they go by various names including “equivalent life” (Canning, 2013), “good life years”, “wellbeing QALYs”, “wellbeing years” and “wellbeing adjusted life years”. The basic theoretical requirement is that individual wellbeing during a specific period (e.g. a year) needs to be measured on an interpersonally comparable ratio scale, with zero representing a level of wellbeing as bad as death and 1 representing a period of time lived at a good level of wellbeing. This ensures that wellbeing can be added up across the lifetime and that lifetime wellbeing is measured on the same simple and intuitive scale as length of life. Within those (demanding) theoretical constraints, many different kinds of data can be used in many different ways to construct a suitable index.

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. This 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). One wellbeing QALY can then be interpreted as one year lived in full health at an average level of income, and concisely labelled as a “healthy and wealthy” life-year or a “good” life-year. This aligns the value scale with the health QALY, such that one wellbeing QALY has approximately the same value as one health QALY for someone with an average level of income - though the number of health and wellbeing QALYs gained will differ in line with differences in consumption. Lifetime wellbeing can then be described as the number of good life-years enjoyed by an individual over their whole lifetime. For cost-effectiveness analysis and policy targeting analysis, we construct a remaining-lifetime wellbeing index - the sum of period-specific wellbeing from the time of intervention over the individual’s remaining lifetime. For distributional analysis, however, we construct a whole-lifetime wellbeing index that also looks backwards to include past period-specific wellbeing.

In principle, however, 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). For example, UK Treasury wellbeing guidance for appraisal proposes evaluating wellbeing impacts using “WELLBYs”, defined as a one point increase in life satisfaction for one year on a scale from 0 to 10 (HM Treasury, 2021). This guidance assumes that a life satisfaction score of 1 can be considered “as bad as death” (corresponding to a QALY value of zero) and a score of 8 (the UK average) can be considered to represent full health (corresponding to a QALY value of 1). One WELLBY is therefore worth approximately one seventh of a wellbeing QALY - i.e. just under two months of life for someone with an average life satisfaction score of 8. This is because it would take 7 WELLBYs to bring someone from a life satisfaction score of 1, valued at zero on the QALY scale, to a life satisfaction score of 8, valued at 1 on the QALY scale. Further details about the relationship between the wellbeing QALY and the WELLBY are included in online Appendix A.

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 et al., 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 to 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 et al., 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.³

We assume that the parent training:

1. 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);
2. 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,

³ This cut-off value is suggested on the SDQ official website [http://www.sdqinfo.org/py/sdqinfo/b3.py?language=Englishqz\(UK\)](http://www.sdqinfo.org/py/sdqinfo/b3.py?language=Englishqz(UK)).

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 leads to improvements in many outcomes across the lifecourse, leading to better health and wellbeing, as described in more detail in Section 3.5.

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 et al., 2017; Van Aar et al., 2017) (see online Appendix F).

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 B1 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 a simple but strong assumption about the marginal cost of producing a good life year from public expenditure (Frijters and Krekel, 2021). We assume that this is constant across all types of

government expenditure, including health expenditure, and make use of the fact that a health QALY is worth approximately the same as a wellbeing QALY for someone living on average income. Based on these assumptions, we simply reuse an existing estimate of the production cost of a health QALY by Claxton et al. (2015), of £13,724. 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.⁴ 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.

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

The modelled policy effect described in section 3.3 then activates various LifeSim pathways which translate into improved lifetime outcomes for the modelled children. Firstly, the improvement in a child’s SDQ conduct problem and impact scores reduces the child’s risk of developing childhood conduct disorder, which then improves the 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.

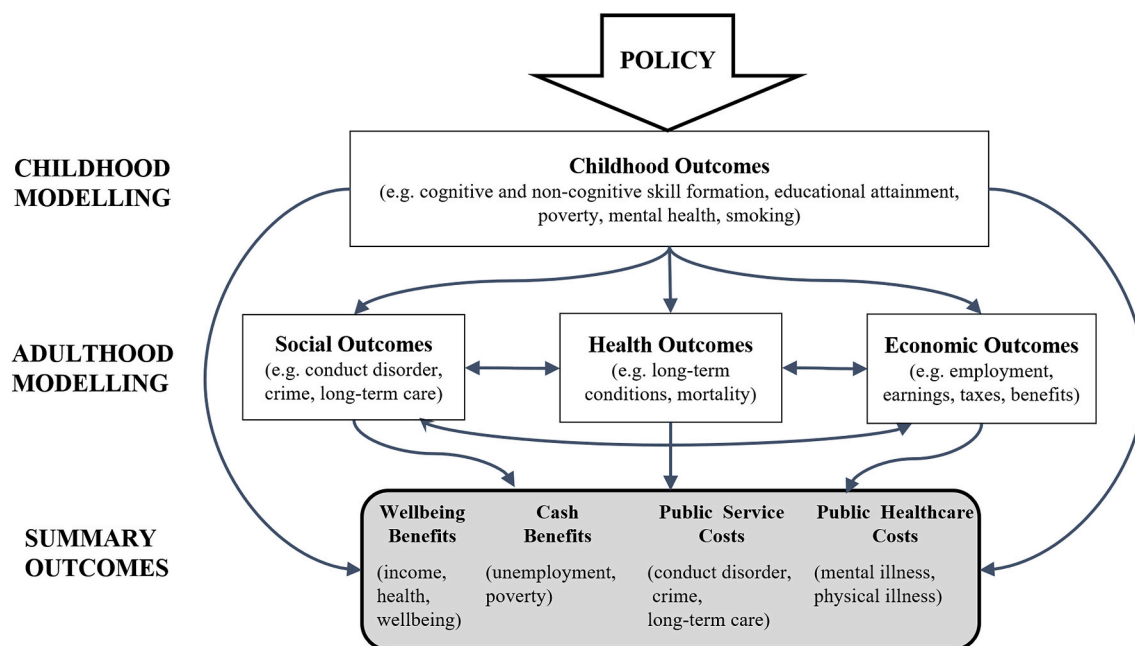


Fig. 2. Summary of the model structure.

⁴ Skarda et al. (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.

Finally, these benefits persist and accumulate into retirement years. [Table 1](#) summarises the LifeSim pathways activated by the parent training programme leading to general wellbeing benefits (consumption, health-related quality of life and mortality). Other key pathways leading to specific public cost outcomes are summarised in [Table C.2](#) in the online [Appendix C](#).

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.

4.1. Total costs and benefits

[Fig. 3](#) presents the effects on the primary outcome of interest in childhood – conduct disorder from age 5 to 14.

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 [Fig. 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 [Fig. 3](#).

We use these primary effects in childhood to model a wide range of secondary effects in childhood and adulthood (summarised in [Table D.3](#) in online [Appendix D](#)). We then use these effects to model the long-run cost savings presented in [Fig. 4](#). There are substantial initial savings due to reduced costs to social, educational and health services for children with conduct disorders ([Bonin et al., 2011](#)), with further savings in adulthood due to reduced costs to the criminal justice system, additional tax revenues and lower benefit payments.⁶ The cost of the “Incredible Years” programme falls within the range £1773–2660 per recipient, depending on the training group size ([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.

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 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

⁵ The specific effects on the SDQ scores and a wide range of other lifecourse outcomes are summarised in [Table D.3](#) in online [Appendix D](#).

⁶ The savings from residential care are so much lower than savings from prison due to ‘residential care’ being modelled only after age 69.

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 2](#) 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 9228 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.

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 (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 £3800 per healthy life year ([Martin et al., 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 3](#) 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’.⁷

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.⁸ We

⁷ In [Figure G.5](#) 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.

⁸ These should be variables that are relatively easy to identify and there should be no obvious ethical obstacles to using them for policy targeting.

Table 1
LifeSim causal pathways activated by the parent training programme.

Pathways to Consumption
SDQ conduct problem and impact scores → conduct disorder → childhood mental illness → education → earnings, taxes and benefits → consumption
SDQ conduct problem and impact scores → conduct disorder → prison → employment status → earnings, taxes and benefits → consumption
SDQ conduct problem score → earnings, taxes and benefits → consumption
SDQ conduct problem score → employment status → earnings, taxes and benefits → consumption
... consumption → mental illness → prison → employment status → earnings, taxes and benefits → consumption
Pathways to Health Related Quality of Life
SDQ conduct problem and impact scores → conduct disorder → childhood mental illness → health-related quality of life
SDQ conduct problem and impact scores → conduct disorder → childhood mental illness → adulthood mental illness → health-related quality of life
SDQ conduct problem and impact scores → conduct disorder → childhood mental illness → education → unhealthy behaviour → physical illness → health-related quality of life
SDQ conduct problem and impact scores → conduct disorder → childhood mental illness → adulthood mental illness → unhealthy behaviour → physical illness → health-related quality of life
... consumption → adulthood mental illness → health-related quality of life
... consumption → physical illness → health-related quality of life
... consumption → unhealthy behaviour → physical illness → health-related quality of life
Pathways to Mortality
SDQ conduct problem and impact scores → conduct disorder → childhood mental illness → education → unhealthy behaviour → physical illness → mortality
SDQ conduct problem and impact scores → conduct disorder → childhood mental illness → adulthood mental illness → unhealthy behaviour → physical illness → mortality
SDQ conduct problem and impact scores → conduct disorder → childhood mental illness → mortality
SDQ conduct problem and impact scores → conduct disorder → childhood mental illness → adulthood mental illness → mortality
... consumption → mortality

Note: This table only shows pathways to the general wellbeing benefits shown in bold i.e. consumption, health-related quality of life and mortality. There are further pathways to more specific benefits (e.g. reductions in smoking). Feedback loops between final benefits are written with the prefix "...". For example, higher consumption can improve future consumption by preventing adverse outcomes such as mental illness, prison and unemployment.

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 4](#) 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 £3212 in

scenario 1, to £1745 in scenario 2 and to only £407 in scenario 3 – an almost eight-fold increase in cost-effectiveness. 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).

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 9228 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.

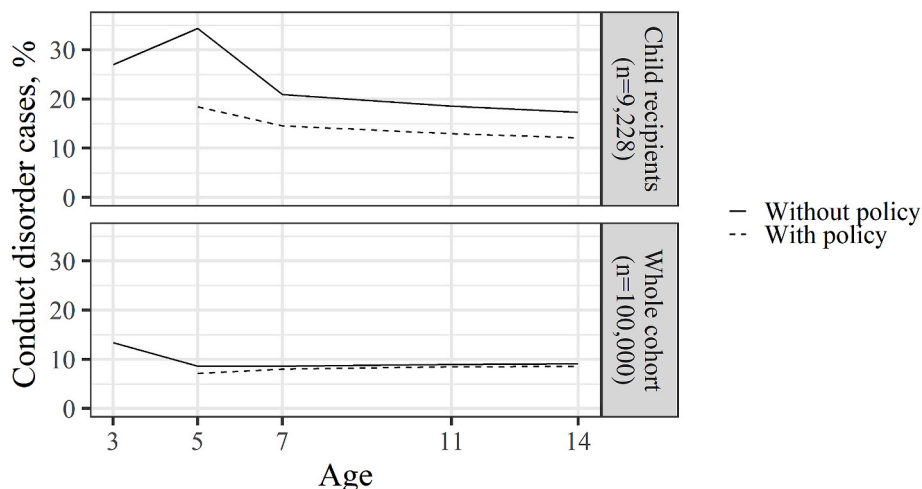


Fig. 3. Prevalence of conduct disorder over time.

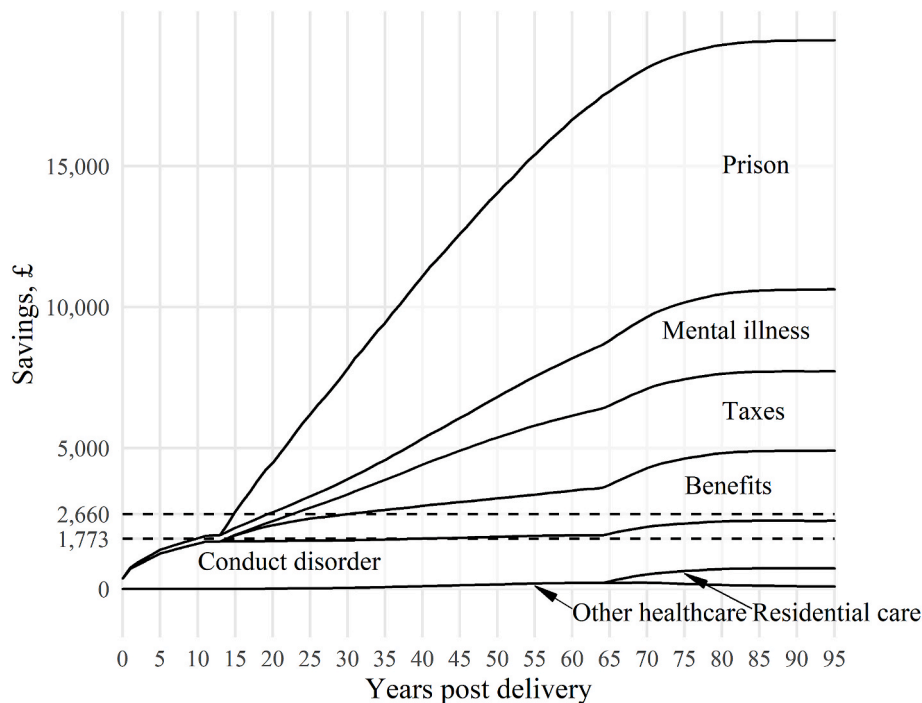


Fig. 4. Cumulative Cost Savings Over Time. Note: Savings as a result of the parent training programme estimated per young child at risk of conduct disorder, in 2015/16 prices and discounted at 1.5% annual rate. The dashed lines represent the range of estimated unit costs of the “Incredible Years” programme (Edwards et al., 2016). See table B.1 for the full list of sources used to model costs.

Table 2
Cost effectiveness in terms of good years and various specific outcomes.

Outcome	Individual effect	Population effect (in 9228 recipients)	Cost per unit of effect
Good life years	0.69	6367	3212
Healthy life years	0.43	3968	5155
Life years	0.18	1569	13,038
Annual consumption (£)	287	2,644,929	8
Conduct disorder at age 5 (% and number)	-16.18	-1492	13,708
Conduct disorder at age 18 (% and number)	-5.19	-479	42,707
SDQ conduct problem subscore at age 5	-0.7	-6460	3166
SDQ conduct problem subscore at age 18	-0.61	-5629	3634
University graduates (% and number)	0.71	66	312,185
Working years in unemployment	-0.71	-6552	3122
Life years in poverty	-0.99	-9136	2239
Working years in prison	-0.41	-3783	5406
Retirement years in residential care	-0.09	-831	24,628
Adult years as a smoker	-1.03	-9505	2152
Life years with mental illness	-1.27	-11,720	1745
Premature mortality ≤75 (% and number)	-0.47	-43	471,599

Note: The individual effect is calculated on average per child recipient (9228 child recipients in total). The population effect is the aggregate effects summed across the entire recipient population.

Table 3
Distribution of policy gains.

Good years gained	Recipient children	
	N	%
less than 1	7785	84.36
1-2	732	7.93
2-3	194	2.10
3-4	99	1.07
4-5	72	0.78
5-10	245	2.65
10+	109	1.18

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.

Fig. 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. Fig. 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,⁹ and children with high baseline conduct problems. We also find that boys gain more from the intervention, a finding consistent with previous literature (Gardner et al., 2017).

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

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.

Table 4
Cost-effectiveness analysis of three targeting options.

Scenario	Number of child recipients	Total policy cost, 1000£	Good years gained per recipient	Total good years gained	Cost per good year gained, £	Lifetime cost savings per recipient, £	Payback period, years	Opportunity cost, good years lost	Net total good years gained
1	9228	20,454	0.69	6367	3212	19,457	15	1490	4877
2	494	1095	1.27	627	1745	40,080	15	80	548
3	42	93	5.45	229	407	147,041	4	7	222

Note: It is assumed that the parent-training programme costs £2217 per recipient, and the opportunity cost of producing a good life-year from expenditure on other public services is £13,724 (see online [Appendix A](#)). We use 2015/16 prices.

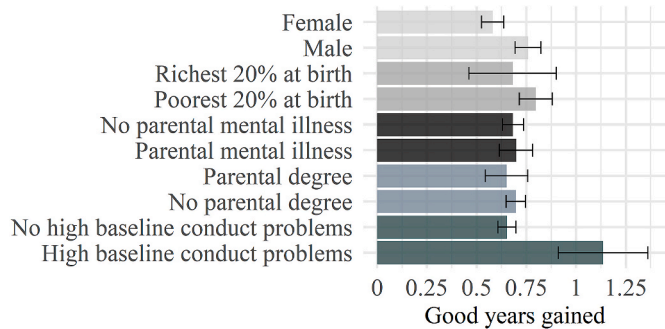


Fig. 5. Lifetime Impacts by Childhood Circumstances.
Note: The average lifetime wellbeing gains for the subgroups among the group of recipients (n = 9228). Whiskers represent 95% confidence intervals.

baseline, which is a simple measure of inequality that is easy to communicate to policymakers. [Fig. 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 evaluating the total benefits and public cost savings, this framework is capable of cost-effectiveness analysis, targeting analysis and distributional analysis based on multidimensional indices of lifetime wellbeing. We show how this framework can be applied in practice by conducting a lifecourse 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

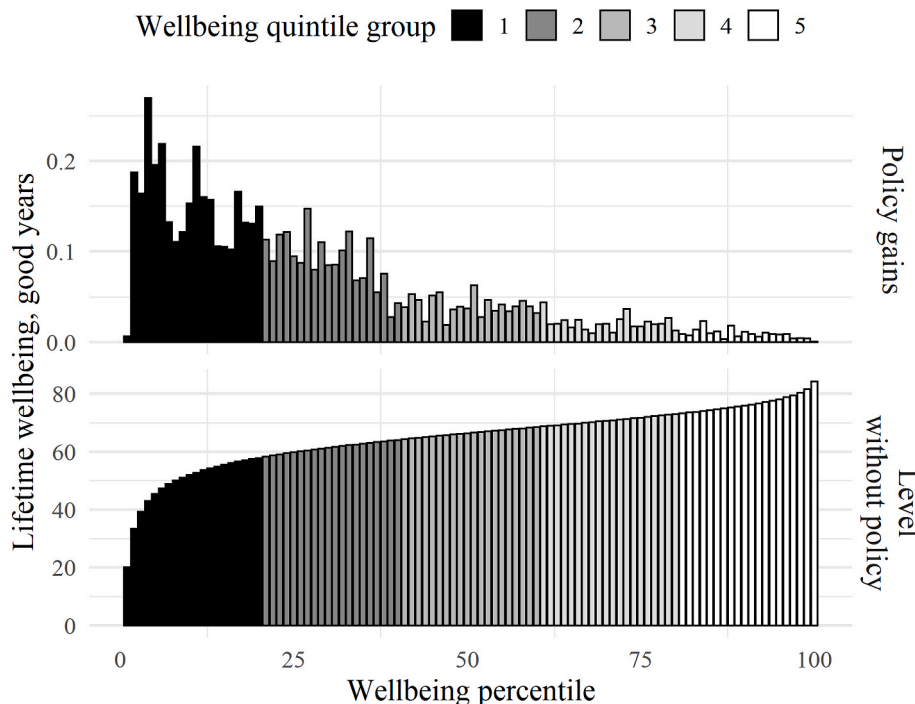


Fig. 6. Change in Wellbeing Distribution.
Note: The analysis is for the cohort of 100,000 children. The bottom panel presents the average good years at baseline for each baseline wellbeing percentile/quintile group, the top panel – the average good years gained by each group.

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 in England 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 also finds that the parent training programme is highly cost-effective with a cost per good year gained of £3212. This compares favourably with the cost per good life-year from marginal public expenditure in England, which we estimate to be £13,724 based on by re-using an estimate of the marginal productivity of the health sector from Claxton et al. (2015).

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 lifecourse 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.

Findings from 6 previous cost-effectiveness studies and 4 previous cost-benefit studies of similar parenting programmes are summarised in the [supplementary Appendix I \(Table I.12 and I.13\)](#). Previous cost-effectiveness studies all adopted short time horizons, typically 6–18 months though in one case up to age 18, and measured effectiveness using diverse and incomparable sector-specific measures (cost per SDQ point, per ECBI-I point, per PSOC point and per DALY gained). Insofar as one can make limited comparisons between studies using diverse metrics and methodologies, previous studies generally seemed more optimistic about cost-effectiveness than our study - for example, we estimated a cost per point improvement in SDQ conduct score of £3116 around age 5 while Edwards et al. (2016) estimated a cost per point improvement in SDQ total score of £1423 around age 5. Previous cost-benefit studies modelled a broad range of public cost savings up to early adulthood (age 25 or 30) in England and one US study went up to age 50 (Washington State Institute for Public Policy, 2019). Our study thus added value by capturing various beneficial health and wellbeing effects beyond early adulthood - including reductions in unemployment, poverty, imprisonment, residential care, smoking, mental illness, physical illness and mortality. In terms of the public cost savings, our approach also adds value by enabling fine-grained time profiling of the composition of public cost savings over the entire remaining lifetime. This revealed that public costs start rising sharply after age 18 and that over a lifetime the prison, tax-benefit and mental illness cost savings during adulthood swamp all the childhood public cost savings up to age 18.

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 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 such as life satisfaction and multi-dimensional quality of life. 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.

Often the costs and benefits to some sectors (e.g. health) accrue much later in the lifecourse than costs and benefits to other sectors (e.g. education). The long and broad view afforded by lifecourse distributional economic evaluation can thus help to support a shift towards more joined-up institutional structures that shift money between sectors more appropriately. A future extension of this approach would be portfolio analysis that looks at the impact of multiple childhood policy interventions implemented jointly by different government agencies at different points in childhood, to help optimise the mix of policy interventions.

Lifecourse distributional economic evaluation can be applied to many different kinds of cross-sectoral programmes that are funded and delivered outside the health sector - for example, in the education, welfare, social care or justice spheres. It could also be useful for evaluating childhood health care and public health programmes with preventive elements that address health risk factors (e.g. obesity, smoking, drug abuse, mental health problems). As well as delivering short-term health benefits in childhood, of a kind which can be potentially be measured using parent-reported or child-reported measures of health-related quality of life, addressing childhood health risk factors can also deliver important long-term benefits to both health-related quality of life and mortality in adulthood. In some cases, these long-term health benefits may be larger than the short-term health benefits - for example, adolescents who are obese, or smoke, or abuse drugs, or experience elevated mood symptoms may report good current health-related quality of life even though they are at risk of future poor health-related quality of life and mortality in adulthood. These long-term health benefits in adulthood are missing from standard cost-effectiveness studies which focus on short-term health benefits during childhood. There is currently a substantial research effort going into developing new measures of short-term health-related quality of life in childhood - for example the new EQ-5D index for childhood. However, this research effort needs to be complemented with effort to develop better dynamic microsimulation modelling tools for estimating the long-term health benefits in adulthood of preventive care that targets health risk factors in childhood.

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 wellbeing used in our illustrative application. First, it only looks at health-related quality of life and consumption, not broader dimensions of 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 wellbeing. Future work could also help to produce better estimates of appropriate supply-side and demand-side thresholds 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 not 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. Also, we have evaluated a programme which has been previously shown to be cost-effective using conventional evaluation methods. In future work, it would be of interest to explore the conditions under which evaluation of lifetime health and wellbeing is likely to reverse conventional conclusions and find illustrative examples to illustrate various different cases.

There are also specific limitations relating to the 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 et al., 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, lifecycle 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 et al., 2018; Del Boca, Flinn and Wiswall, 2014; Bolt et al., 2018; Attanasio et al., 2020). Such models, however, can become intractable when they attempt to handle more than a few outcomes over long time periods (Emmerson et al., 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.

Lifecycle 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 lifecycle perspective often receives short shrift in public debates. Lifecycle distributional economic evaluation can potentially help keep the lifecycle perspective in view, by routinely providing policymakers with detailed and credible information about long-term policy consequences for health, wellbeing and inequality.

Credit author statement

<https://www.elsevier.com/authors/policies-and-guidelines/credit-author-statement>.

Ieva Skarda: Conceptualization, Writing - Original Draft, Writing - Review & Editing, Methodology, Software, Validation, Formal analysis, Investigation, Visualization. **Miqdad Asaria:** Conceptualization, Methodology, Writing - Review & Editing. **Richard Cookson:** Conceptualization, Writing - Original Draft, Writing - Review & Editing, Methodology, Supervision, Project administration, Funding acquisition.

Funding

This is independent research supported by the National Institute for Health Research (SRF-2013-06-015), the Wellcome Trust (205427/Z/16/Z), and the UK Prevention Research Partnership (ActEarly Programme, MR/S037527/1). The views expressed in this publication are those of the authors and not necessarily those of the National Institute for Health Research, the Wellcome Trust, the NHS, the Department of Health and Social Care, or the UK Prevention Research Partnership.

Declaration of competing interest

Dr. Cookson was supported by the National Institute for Health Research, Wellcome Trust, and the UK Prevention Research Partnership during the conduct of the study, Dr. Skarda by the National Institute for Health Research and the Wellcome Trust, and Dr. Asaria by the National Institute for Health Research and the UK Prevention Research Partnership. The authors have no other conflicts of interest to declare.

Acknowledgements

We would first like to thank the members of our advisory group: Annalisa Belloni, Sarah Cattan, Leon Feinstein, Paul Frijters, Peter Goldblatt, Heather Joshi, Catherine Law, Lara McClure and Christine Power.

For useful comments we also are grateful to Shehzad Ali, Mark Ashworth, Karen Bloor, Laura Bojke, Eva Maria Bonin, Jonathan Bradshaw, Penny Breeze, Alan Brennan, Eric Brunner, Tracey Bywater, Simon Capewell, Maria Guzman Castillo, Bette Chambers, Brendan Collins, Gabriella Conti, Peter Diggle, Tim Doran, Susan Griffin, Nils Gutacker, James Heckman, Nathan Hendron, Bruce Hollingsworth, Andrew Jones, Noemi Kreif, Christodoulos Kyriopoulos, Richard Mattock, Cheti Nicoletti, Owen O'Donnell, Martin O'Flaherty, Kate Pickett, George Ploubidis, Gerry Richardson, Jemimah Ride, Matthew Robson, Tracey Sach, Filipa Sampaio, Trevor Sheldon, Tushar Srivastava, Mark Strong, David Taylor-Robinson, Valentina Tonei, Aki Tsuchiya, Simon Walker, Margaret Whitehead and Mark Mon Williams, and several anonymous reviewers of previous versions of the manuscript.

The errors and opinions expressed in this paper are our own.

Appendix. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.socscimed.2022.114960>.

References

- Adler, Matthew D., 2019. *Measuring Social Welfare: an Introduction*. Oxford University Press, USA.
- Adler, Matthew D., Fleurbaey, Marc, 2016. *The Oxford Handbook of Well-Being and Public Policy*. Oxford University Press, Oxford, United Kingdom.
- Allen, Graham, 2011. *Early Intervention: the Next Steps, an Independent Report to Her Majesty's Government by Graham Allen MP*. The Stationery Office from. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/284086/early-intervention-next-steps2.pdf. (Accessed 10 December 2020).
- Almond, Douglas, Currie, Janet, Duque, Valentina, 2018. Childhood circumstances and adult outcomes: act II. *J. Econ. Lit.* 56 (4), 1360–1446.
- Altig, David, Carlstrom, Charles T., 1999. Marginal tax rates and income inequality in a life-cycle model. *Am. Econ. Rev.* 89 (5), 1197–1215.
- Attanasio, Orazio, Meghir, Costas, Nix, Emily, 2020. Human capital development and parental investment in India. *Rev. Econ. Stud.* 87 (6), 2511–2541.
- Bernal, Raquel, 2008. The effect of maternal employment and child care on children's cognitive development. *Int. Econ. Rev.* 49 (4), 1173–1209.
- Bernal, Raquel, Keane, Michael P., 2010. Quasi-structural estimation of a model of childcare choices and child cognitive ability production. *J. Econom.* 156 (1), 164–189.
- Bolt, Uta, French, Eric, Maccuishi, Jamie Hentall, O'Dea, Cormac, 2018. *Intergenerational Altruism and Transfers of Time and Money: A Life-Cycle Perspective*. Michigan Retirement Research Center Research Paper (2018-379). Retrieved 29 October 2020, from. <https://deepblue.lib.umich.edu/handle/2027.42/144781>.
- Bonin, Eva-Maria, Stevens, Madeleine, Beecham, Jennifer, Byford, Sarah, Parsonage, Michael, 2011. *Costs and longer-term savings of parenting programmes*

- for the prevention of persistent conduct disorder: a modelling study. *BMC Publ. Health* 11 (1), 803.
- Bourquin, Pascale, Waters, Tom, 2019. The Effect of Taxes and Benefits on UK Inequality. The Institute of Fiscal Studies Briefing Note BN249. Retrieved 23 March 2020, from: <https://www.ifs.org.uk/uploads/BN249.pdf>.
- Canning, David, 2013. Axiomatic foundations for cost-effectiveness analysis. *Health Econ.* 22 (12), 1405–1416.
- Caucutt, Elizabeth M., Lochner, Lance, 2020. Early and late human capital investments, borrowing constraints, and the family. *J. Polit. Econ.* 128 (3), 1065–1147.
- Claxton, Karl, Martin, Steve, Soares, Marta, Rice, Nigel, Spackman, Eldon, Hinde, Sebastian, Devlin, Nancy, Smith, Peter C., Sculpher, Mark, 2015. Methods for the estimation of the national institute for health and care excellence cost-effectiveness threshold. *Health Technol. Assess.* 19 (14), 1.
- Coast, J., 2019. Assessing capability in economic evaluation: a life course approach? *Eur. J. Health Econ.: HEPAC: Health Econ. Prev. Care* 20, 779–784. <https://doi.org/10.1007/s10198-018-1027-6>. Retrieved 11 October 2021, from.
- Conti, Gabriella, Mason, Giacomo, Poupakis, Stavros, 2019. Developmental Origins of Health Inequality. *Oxford Research Encyclopedia of Economics and Finance*. Retrieved 11 May 2021, from: <https://oxfordre.com/economics/view/10.1093/acrefore/9780190625979.001.0001/acrefore-9780190625979-e-4>.
- Cookson, Richard, Culyer, Anthony, 2010. Measuring Overall Population Health: The Use and Abuse of QALYs. Evidence-based public health: effectiveness and efficiency, p. 148.
- Cookson, Richard, Skarda, Ieva, Cotton-Barrett, Owen, Adler, Matthew D., Asaria, Miqdad, Ord, Toby, 2020. Quality adjusted life years based on health and consumption: a summary wellbeing measure for cross-sectoral economic evaluation. *Health Econ.* 30 (1), 70–85.
- Cookson, Richard, Norheim, Ole, Skarda, Ieva, 2022. Prioritarian analysis in health. In: Adler, M.D., Norheim, O.F. (Eds.), *Prioritarianism in Practice*. Cambridge University Press.
- Cunha, Flavio, Heckman, James, 2007. The technology of skill formation. *Am. Econ. Rev.* 97 (2), 31.
- Dalziel, Kim M., Halliday, Dale, Segal, Leonie, 2015. Assessment of the cost–benefit literature on early childhood education for vulnerable children: what the findings mean for policy. *Sage Open* 5 (1). <https://doi.org/10.1177/2158244015571637>. Retrieved 11 October 2021, from.
- Dearden, Lorraine, Fitzsimons, Emla, Goodman, Alissa, Kaplan, Greg, 2008. Higher education funding reforms in England: the distributional effects and the shifting balance of costs. *Econ. J.* 118 (526), F100–F125.
- Daniela, Del Boca, Flinn, Christopher, Wiswall, Matthew, 2014. Household choices and child development. *Rev. Econ. Stud.* 81 (1), 137–185.
- Edwards, Rhiannon T., Céilleachair, Alan, Bywater, Tracey, Hughes, Dyfrig A., Hutchings, Judy, 2007. Parenting programme for parents of children at risk of developing conduct disorder: cost effectiveness analysis. *Br. Med. J.* 334 (7595), 682.
- Edwards, Tudor, Rhiannon, Jones, Carys, Berry, Vashti, Charles, Joanna, Linck, Pat, Bywater, Tracey, Hutchings, Judy, 2016. Incredible years parenting programme: cost-effectiveness and implementation. *J. Child. Serv.* 11 (1), 54–72.
- Emmerson, Carl, Reed, Howard, Shephard, Andrew, 2004. An Assessment of PenSim2.” (No. 04/21). Institute for Fiscal Studies Working Papers. Retrieved 29 October 2020, from: <https://www.econstor.eu/handle/10419/71475>.
- Feinstein, Leon, Chowdry, Haroon, Asmussen, Kirsten, 2017. On estimating the fiscal benefits of early intervention. *Natl. Inst. Econ. Rev.* 240 (1), R15–R29.
- Frijters, Paul, Krekel, Christian, 2021. A Handbook of Well Being Decision-Making in the UK: History, Measurement, Theory, Implementation, and Examples. Oxford University Press.
- García, Jorge Luis, Heckman, James J., Duncan Ermini Leaf, María José Prados, 2020. Quantifying the life-cycle benefits of an influential early childhood program. *J. Polit. Econ.* 128 (7) <https://doi.org/10.1086/705718>. Retrieved 11 October 2021, from.
- Gardner, Frances, Leijten, Patty, Mann, Joanna, Landau, Sabine, Harris, Victoria, Beecham, Jennifer, Bonin, Eva-Maria, Hutchings, Judy, Scott, Stephen, 2017. Could scale-up of parenting programmes improve child disruptive behaviour and reduce social inequalities? Using individual participant data meta-analysis to establish for whom programmes are effective and cost-effective. *Publ. Health Res.* 5 (10) <https://doi.org/10.3310/phr05100>. Retrieved 11 October 2021, from.
- Gayle, George-Levi, Golan, Limor, Soytaş, Mehmet, 2018. Intergenerational mobility and the effects of parental education, time investment, and income on children educational attainment. *Fed. Reserv. Bank St. Louis Rev.* 100 (3), 281–295. <https://doi.org/10.20955/r.100.281-95>. Retrieved 11 October 2021, from.
- Goodman, Robert, Renfrew, D., Mullick, M., 2000. Predicting type of psychiatric disorder from strengths and Difficulties questionnaire (SDQ) scores in child mental health clinics in London and Dhaka. *Eur. Child Adolesc. Psychiatr.* 9 (2), 129–134.
- Goodman, Robert, Ford, Tamsin, Simmons, Helen, Gatward, Rebecca, Meltzer, Howart, 2003. Using the strengths and Difficulties questionnaire (SDQ) to screen for child psychiatric disorders in a community sample. *Int. Rev. Psychiatr.* 15 (1–2), 166–172.
- Goodman, Alissa, Joshi, Heather, Nasim, Bilal, Tyler, Claire, 2015. Social and Emotional Skills in Childhood and Their Long-Term Effects on Adult Life. Institute of Education, London, United Kingdom. Retrieved 28 October 2020, from: <https://www.nuffieldfoundation.org/news/active-policy-required-avoid-covid-19-crisis-exacerbating-inequalities>.
- Heckman, James J., 2012. The developmental origins of health. *Health Econ.* 21 (1), 24–29.
- Heckman, James J., García, Jorge Luís, 2017. Social policy: targeting programmes effectively. *Nat. Human Behav.* 1 (1), 1–2.
- Hendren, Nathaniel, Sprung-Keyser, Ben, 2020. A unified welfare analysis of government policies. *Q. J. Econ.* 135 (3), 1209–1318.
- Hills, John, 2017. Good Times, Bad Times: the Welfare Myth of Them and Us, Revised edition. Policy Press, Bristol, United Kingdom.
- Husereau, Don, Drummond, Michael, Augustovski, Federico, de Bekker-Grob, Esther, Briggs, Andrew H., Carswell, Chris, Caulley, Lisa, Chaiyakunapruk, Nathorn, Greenberg, Dan, Loder, Elizabeth, et al., 2022. Consolidated health economic evaluation reporting standards (CHEERS) 2022 explanation and elaboration: a report of the ISPOR CHEERS II good practices task force. *Value Health* 25 (1), 10–31.
- De Neve, Jan-Emmanuel, Clark, Andrew E., Krekel, Christian, Layard, Richard, O’Donnell, Gus, 2020. Taking a wellbeing years approach to policy choice. *Br. Med. J.* 371, m3853. <https://doi.org/10.1136/bmj.m3853>. Retrieved 11 October 2021, from.
- Layard, Richard, Clark, Andrew E., Cornaglia, Francesca, Powdthavee, Nattavudh, James, Vernoit, 2014. What predicts a successful life? A life-course model of well-being. *Econ. J.* 124 (580), F720–F738.
- Lee, Stephanie, Aos, Steve, Drake, Elizabeth, Pennucci, Annie, Miller, Marna, Anderson, Laurie, 2012. Return on Investment: Evidence-Based Options to Improve Statewide Outcomes. Washington State Institute for Public Policy, Olympia, Washington, pp. 673–716.
- Martin, Stephen, James Lomas, Claxton, Karl, 2020. Is an ounce of prevention worth a pound of cure? A cross-sectional study of the impact of English public health grant on mortality and morbidity. *BMJ Open* 10 (10), e036411.
- Masters, Rebecca, Anwar, Elspeth, Collins, Brendan, Cookson, Richard, Capewell, Simon, 2017. Return on investment of public health interventions: a systematic review. *J. Epidemiol. Community Health* 71 (8), 827–834.
- Miller, J.H., Page, S.E., 2007. *Complex Adaptive Systems: an Introduction to Computational Models of Social Life*. Princeton University Press.
- Mukuria, Clara, Connell, Janice, Jill Carlton, Peasgood, Tessa, Brazier, J., Scope, A., Clowes, M., Jones, K., 2018. Developing content for a new generic qaly measure: results from a qualitative literature review (E-Qaly Project). *Value Health* 21, S110.
- O’Donnell, Gus, Deaton, Angus, Durand, Martine, Halpern, David, Layard, Richard, 2014. Wellbeing and Policy. Legatum Institute, London, United Kingdom. Retrieved 24 January 2020, from: <https://li.com/wp-content/uploads/2019/03/commission-on-n-wellbeing-and-policy-report-march-2014-pdf.pdf>.
- O’Neill, Donal, McGilloway, Sinéad, Donnelly, Michael, Bywater, Tracey, Kelly, Paul, 2013. A cost-effectiveness analysis of the incredible years parenting programme in reducing childhood health inequalities. *Eur. J. Health Econ.* 14 (1), 85–94.
- Paull, Gillian, Xu, Xiaowei, 2017. Study of Early Education and Development (SEED): the Potential Value for Money of Early Education - Research Report. Department for Education, London, United Kingdom. Retrieved 24 January 2020, from: https://asset.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/627095/Frontier_SEED_VfM_Report.pdf.
- Richiardi, Matteo G., 2017. The future of agent-based modeling. *E. Econ. J.* 43 (2), 271–287.
- Scott, Stephen, Briskman, Jackie, O’Connor, Thomas G., 2014. Early prevention of antisocial personality: long-term follow-up of two randomized controlled trials comparing indicated and selective approaches. *Am. J. Psychiatr.* 171 (6), 649–657.
- Skarda, Ieva, Asaria, Miqdad, Cookson, Richard, 2021. LifeSim: a lifecourse dynamic microsimulation model of the Millennium birth cohort in England. *Int. J. Microsimul.* 14 (1), 2–42. <https://doi.org/10.34196/IJM.00228>. Retrieved 25 October 2021, from.
- HM Treasury, 2020. The Green Book: Appraisal and Evaluation in Central Government. Retrieved: <https://www.gov.uk/government/publications/the-green-book-appraisal-and-evaluation-in-central-government>. (Accessed 25 February 2022).
- HM Treasury, 2021. Green Book Supplementary Guidance: Wellbeing. Retrieved 25 February 2022, from: <https://www.gov.uk/government/publications/green-book-supplementary-guidance-wellbeing>.
- United States Congress Joint Committee on Taxation, 2019. Distributional Effects of Public Law, 115-97, JCX-10-19. Retrieved 27 March 2020, from: <https://www.jct.gov/publications.html?func=startdown&id=5173>.
- Van Aar, Jolien, Patty Leijten, Bram Orobio de Castro, Overbeek, Geertjan, 2017. Sustained, fade-out or sleeper effects? A systematic review and meta-analysis of parenting interventions for disruptive child behavior. *Clin. Psychol. Rev.* 51, 153–163.
- Washington State Institute for Public Policy, 2019. Benefit-Cost Results. Incredible Years Parent Training, Children’s Mental Health: Disruptive Behavior. Retrieved 25 February 2022, from: <http://www.wsipp.wa.gov/BenefitCost/ProgramPdf/158/Incredible-Years-Parent-Training>.
- Zhang, Xiange, 2018. Application of discrete event simulation in health care: a systematic review. *BMC Health Serv. Res.* 18 (1), 1–11.