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NEW EVIDENCE ON THE HECKMAN CURVE

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Abstract. The Heckman Curve characterizes the rate of return to public investments in human capital as rapidly diminishing with age. For the disadvantaged, it describes investments early in the life course as having significantly higher rates of return compared to later in life. This paper assesses the Heckman Curve using estimates of program benefit cost ratios from the Washington State Institute for Public Policy. We find no support for the claim that social policy programs targeted early in the life course have the largest benefit cost ratios, or that on average the benefits of adult programs are less than the cost of the intervention.

Keywords. Benefit cost analysis; Early intervention; Heckman curve

1. Introduction

A key finding of social science in recent decades has been the importance of early child development. Many studies have documented prenatal and early child environments as having important and long-term impacts on a range of outcomes including health and life expectancy (Felitti *et al.*, 1998; Poulton *et al.*, 2002; Centre on the Developing Child, 2010; Aizer *et al.*, 2016; Hoynes *et al.*, 2016), educational achievement (Duncan and Magnuson, 2013), employment and earnings (Almond and Currie, 2011; Caspi *et al.*, 2016) and youth and adult offending (Fergusson *et al.*, 2005).

A large body of research has documented how differences in maternal health, the quality of parenting, and family income play a critical role in child development (Almond and Currie, 2011). In addition, there is also evidence that early childhood education programs can have a profound impact on later life outcomes (Heckman *et al.*, 2013; Phillips *et al.*, 2017).

These findings have had a major influence on public policy as they suggest that early intervention in childhood can be an effective strategy to reduce the prevalence of later adult problems such as poverty, unemployment, offending and intergenerational disadvantage (OECD, 2009).

Central to the case to shift more public investment towards prenatal and early childhood has been James Heckman's research showing that early childhood intervention programs provide higher rates of return compared to remediation programs targeted at older ages. The widely cited Heckman Curve describes

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how the rate of return of human capital interventions declines rapidly with age, and interventions targeted at disadvantaged youth and adults often provide net benefits that are less than program costs.

This paper provides new empirical evidence relating to the Heckman Curve. We use a large dataset of program benefit cost ratios estimated by the Washington State Institute for Public Policy. Analysis of the dataset suggests that the Heckman Curve is not an accurate characterization of how the cost effectiveness of programs differ by age. The paper concludes by describing some of the limitations of our study, as well as some explanations and implications for the findings.

2. Background on the Heckman Curve

2.1 Description of the Heckman Curve

The Heckman Curve describes how the rate of return of human capital investments targeted at disadvantaged individuals declines with age. An early version was set out in a discussion paper about the changing US labour market in the 1990s. In the paper James Heckman argued that:

> *'We cannot afford to postpone investing in children until they become adults, nor can we wait until they reach school age - a time when it may be too late to intervene . . . . . . Skill remediation programs for adults with severe educational disadvantages are much less efficient compared to early intervention programs. So are training programs for more mature displaced workers. The available evidence clearly suggests that adults past a certain age and below a certain skill level obtain poor returns to skill investment' (Heckman,* 1999*, p. 48).*

A more formal description of the empirical relationship was published in Science in 2006. Heckman argued that:

> *'Early interventions targeted toward disadvantaged children have much higher returns than later interventions such as reduced pupil-teacher ratios, public job training, convict rehabilitation programs, tuition subsidies, or expenditure on police' (Heckman,* 2006*, p. 1902)*

Figure 1 reproduces what is now referred to as the Heckman Curve from his 2006 paper. Programs targeted to disadvantaged preschool age children are represented as having the highest rates of return. Rates of return for interventions targeted at older disadvantaged children, young people and adults are considerably lower. In addition, the rate of return for many school and postschool interventions is less than the opportunity cost of funds.

There are a number of important features of the relationship described in Figure 1.

First, investments are publicly subsidized interventions in human capital and skills. The definition of human capital and skills is expansive, and explicitly includes social and emotional competencies. The interventions that develop these skills are not solely delivered by education institutions, and include youth mentoring programs, job search assistance for the unemployed, and criminal justice interventions.

Second, the proposition about rates of return relate to only those investments targeting individuals from disadvantaged families.

Third, the curve describes the average rates of return for programs targeted at disadvantaged children as they age. At an individual program level, it would be expected that would be some variation around the average. This would mean that some early life course investments may not be cost effective, while some later investments might offer a good rate of return.

Fourth, the rates of return depicted are for the marginal participant given an existing distribution of investment in programs. Because the empirical relationship depends on the existing portfolio of investments, it might not apply in some time periods or countries.

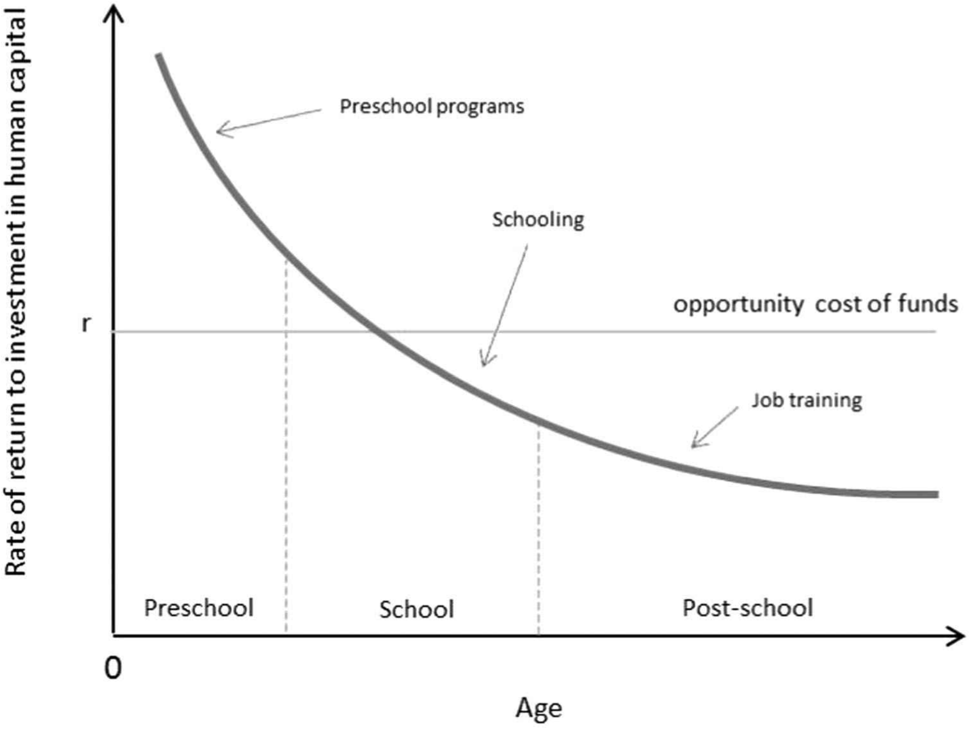

Figure 1. Rates of Return to Human Capital Investment in Disadvantaged Children.
Source: Heckman (2006).

Fifth, the figure depicts the social rate of return on investment. The costs and benefits of interventions accrue to taxpayers and other members of the community, as well as individuals who directly receive interventions.

Last, the return on investment metric relates to efficiency and does not incorporate any distributional or equity concerns. Heckman makes the point that investment in early intervention programs provides an example where the goals of economic efficiency and equity are not in conflict, whereas such a trade-off exists for many economically inefficient remediation programs targeted at young people and adults.

The Heckman Curve was originally described in terms of the 'internal rate of return' of the investment, but it can also be stated in terms of the more commonly estimated 'benefit cost ratio' metric which is used in this paper (see Appendix A for how these are related).

If described in terms of benefit cost ratios, the Heckman Curve suggests that on average early childhood investments have significantly higher benefit cost ratios than those targeted at older age groups, and in addition, investments targeted at older age groups have average benefit cost ratios that are lower than one (ie they are not cost-effective).

The Heckman Curve represents a summary of the empirical evidence about program rates of returns, but is also consistent with an underlying theory of human capital formation. Heckman argued that disadvantaged families invest less in their children. Early deficits in both cognitive and noncognitive skills become entrenched and difficult to address in later years because of the cumulative nature of human capital formation. Enriched early childhood education programs address early deficits, and because 'skills beget skills', early intervention can increase the productivity of later human capital investments (Heckman, 2006).

In subsequent work Heckman and colleagues have expanded this analysis to provide a comprehensive and general theory of skills. The essential elements are that:

- skills represent human capabilities that are able to generate benefits for the individual and society (Heckman and Mosso, 2014);
- skills are multiple in nature and cover not only intelligence, and noncognitive attributes (Cunha *et al.*, 2006), as well as technical skills, physical skills and also health;
- a major focus is noncognitive skills or behavioural attributes such as conscientiousness, openness to experience, extraversion, agreeableness and emotional stability, which are particularly influential on a range of life course outcomes (Heckman *et al.*, 2006);
- individuals, families and governments invest in the costly process of building skills (Heckman and Corbin, 2016);
- early skill formation provides a platform for further skill accumulation because childhood is a highly influential time for human development, and the skills acquired during this time reduce the cost of subsequent investments as a result of dynamic complementarities (Heckman, 2007);
- families play a critical role in early skill formation, and disadvantaged families invest less in their children, partly because of a lack of parenting skills, limited economic resources or credit constraints (Heckman, 2006; Cunha *et al.*, 2010; Heckman and Mosso, 2014).

2.2 Evidence Used to Derive the Heckman Curve

The Heckman Curve summarized the findings of a large empirical literature on the rates of return of programs. The summary drew on reviews of evidence by Heckman and colleagues in the areas of early childhood education, schooling, adolescent programs, tertiary education, and active labour market programs (Heckman *et al.*, 1999; Heckman, 2000; Cunha *et al.*, 2006).

These extensive reviews focused on well-designed studies of interventions that reported credible estimates of program impacts. Particular emphasis was given to studies with long-term follow-ups that provided evidence about the impacts of interventions many years into the future.

The early reviews of the evidence undertaken by Heckman and colleagues were ground-breaking summaries of an enormous range of research. They were also associated with papers that made a significant contribution to scientific knowledge on the estimation of causal impacts (Heckman, 1979; Heckman *et al.*, 1998), investment analysis (Heckman *et al.*, 2010), and a detailed reassessment of the impacts of model childhood education programs (Heckman *et al.*, 2013).

However, in retrospect the early reviews of the evidence lack many of features of modern meta-analysis. Documentation of the search strategy was sometimes vague, and information on how reviewers assessed each study is difficult to find. The reviews do not have tables of excluded and included studies, and there were no summary tables of program rates of return.

Across these early reviews there was a focus on program impacts. There was relatively less emphasis on rates of return, partly as a result of an absence of actual or comparable estimates (Heckman *et al.*, 1999; Cunha *et al.*, 2006). Program rates of return appear to have been summarized in a qualitative rather than quantitative manner, and as a result, the Heckman Curve is presented as a stylized pattern of rates of return without actual empirical estimates.

Recent work does, however, provide a more formal account of observed rates of return. In a paper published by the OECD, Heckman and colleagues set out evidence on the efficacy of interventions that target noncognitive skills, and within this there is a useful catalogue of program rates of return by age (Kautz *et al.*, 2014).

Overall, 27 different interventions were reviewed based on inclusion criteria relating to the quality of the study, having a long-term follow up, being widely adopted, or offering unique insights. Of the interventions reviewed, twelve had estimates of benefit cost ratios and are listed in Table 1.

Table 1. Benefit Cost Ratios by Age for Programs Reported in Kautz *et al.* (2014).

Age	Program	Age of recipients	Benefit cost ratio
Under 5 years	Nurse Family Partnership	<0	2.9
	Abecedarian Project	0	3.8
	Perry Preschool	3	7.1–12.2
	Chicago Child-Parent Center	3–4	10.8
5 years and above	LA's Best	5–6	0.9
	Seattle Social Development Project	6–7	3.1
	Big Brothers Big Sisters	10–16	1.0
	Empresários Pela Inclusão Social	13–15	0.9–3.0
	Quantum Opportunities Program	14–15	0.42
	National Guard ChalleNGe Program	16–18	2.66
	Jobs Corps	16–24	0.22
	Canadian Self Sufficiency Project	19+	2.67

Source: Kautz *et al.* (2014 p. 36).

The programs with benefit cost ratios range across the social policy spectrum from the well-known Nurse Family Partnership home visiting program for first-time at-risk mothers, to the Canadian Self Sufficiency project that provided a temporary earnings supplement for long-term recipients of income support. Both experimental and quasi-experimental studies are included in the sample, and the length of the follow-up periods range from 1 to 37 years.

The benefit cost ratios reported in Table 1 were sourced from studies that used a range of different methods for investment analysis, so some caution should be exercised in making strict comparisons. Nevertheless, consistent with the Heckman Curve, programs targeted to children under five have an average benefit cost ratio of around 6.8, while those targeted at older ages have an average benefit cost ratio of just under 1.6.

Because the sample is small the overall result is very dependent on the findings from the Perry Preschool program and the Abecedarian Project. Despite the long term-follow up periods, an exclusive reliance on only these studies is somewhat controversial in the early childhood education literature. There are many other high-quality intervention studies, including those related to the Head Start program, that provide rigorous evidence about impacts (Duncan and Magnuson, 2013; Bailey *et al.*, 2017; Phillips *et al.*, 2017). The older model programs were also small intensive academic prototypes that had not been scaled-up. In addition, because the control groups received very little other support, some care is needed before generalizing the findings to a modern context where there is more extensive investment in at-risk families.

Overall, the programs in the OECD report represent only a small sample of human capital interventions with well measured impacts and returns. As is evident in the following section, many rigorously studied and well-known interventions are not included in the analysis.

3. Data for This Study

This study uses a dataset of the benefit cost ratios for a large number of programs provided to us by the Washington State Institute for Public Policy.

The Washington State Institute for Public Policy has been reviewing evidence-based policies and programs since the mid-1990s. Reviews have covered programs across many sectors including child welfare, mental health, juvenile and adult justice, substance abuse, healthcare, higher education, and workforce development. Importantly for assessing the Heckman Curve, many of the programs have a human capital focus involving disadvantaged populations and cover a wide range of age groups.

The Washington State Institute for Public Policy dataset is well placed to provide evidence on the Heckman Curve for several reasons.

First, the Washington State Institute for Public Policy is nonpartisan and has a work program determined by elected officials and expert policy makers looking for advice on 'what-works' to address social policy issues in a cost-effective manner.

Second, program impacts are estimated using meta-analytic methods (described in more detail below).

Third, the Washington State Institute for Public Policy has developed a sophisticated set of procedures to calculate benefit cost ratios from estimates of program impacts and costs (Washington State Institute for Public Policy, 2018). Their methods have been extensively peer reviewed, most recently in collaboration with the Pew-MacArthur Results First Initiative (Dube and White, 2017). Findings have also been published in a range of peer-reviewed journals (Drake, 2012; Lee *et al.*, 2012; Kuklinski *et al.*, 2015). While there remain many conceptual and measurement challenges for assessing cost effectiveness of social programs, the Washington State Institute for Public Policy appears to be at the forefront of the development of rigorous methods for investment analysis (Karoly, 2012).

Fourth, the standardized approach to the estimation of benefit cost ratios means that the same modelling approach is used for different programs. Investment analysis of public policy programs is highly dependent on assumptions, and using the same methods is important in order to make 'apples-with-apples' comparisons (Vining and Weimer, 2010).

Fifth, the Washington State Institute for Public Policy methodology has explicit methods for modelling long-term impacts, and for measuring the uncertainty associated with the estimated costs and benefits of programs.

Last, the dataset is continually being developed and expanded, and is therefore able to draw on an expanding pool of rigorous impact evaluations and studies. Estimates derived from the most recent investment analysis is available on the Washington State Institute for Public Policy website (http://www.wsipp.wa.gov).

In what follows we describe in more detail how the Washington State Institute for Public Policy estimates program benefits and costs. Our discussion draws heavily on the Institute's published technical documentation (Washington State Institute for Public Policy, 2018).

A benefit cost ratio is the net present value of the impacts of an intervention expressed as a proportion of the net present value of the program cost. The Washington State Institute for Public Policy represents their implementation of this calculation in the following manner:

$$\textit{Benefit cost ratio} = \sum_{y=tage}^{N} \frac{Q_y \times P_y}{(1+Dis)^y} \Big/ \sum_{y=tage}^{N} \frac{C_y}{(1+Dis)^y}$$

where Q_y is a matrix of the quantity of outcomes in year y

P_y is a matrix of the unit prices of these outcomes in year y

C_y is the cost of the program in year y

Dis is the discount rate

$tage$ is the average age of recipients when first receiving the treatment

N is the number of years over which benefits and costs are evaluated.

A key part of the calculation is how a program impacts on the quantities of key outcomes (Q_y) such as child abuse and neglect, schooling, offending, employment, mental health disorders or mortality. These impacts are modelled as trajectories across multiple years, and in each period the return of the intervention is the value of these quantities multiplied by their unit price (P_y).

The Washington State Institute for Public Policy estimates program impacts in two different ways. 'Direct' impacts are estimated from a meta-analysis of intervention studies that measure the impacts of programs. 'Linked' impacts are estimated from a meta-analysis of causal studies that identify a causal relationship between outcomes measured in intervention studies and other important outcomes. For example, if studies of a particular intervention have only measured impacts on academic test scores, the existence of credible research showing a causal link between test scores and adult earnings is used to model the interventions impacts on subsequent lifetime earnings.

As part of the meta-analysis of intervention and causal studies there is a search of both the peer reviewed and wider literature. Effect sizes and standard errors are calculated for outcomes from studies that meet research design criteria. In some instances, effect sizes are adjusted using meta-regression to account for the quality of research design, as well as other dimensions including a researcher's prior involvement in creating the program. Effect sizes from causal studies may also be adjusted to account for differences between the study and the Washington State population.

The impact of a program on outcome quantities uses the estimated program effect size in relation to a base distribution of outcomes for the Washington State population. For example, the effect of a youth justice program on the number of crimes avoided reflects the overall estimated effect size of the program, and the estimated future distribution of offending for the untreated population in Washington State.

The long-term effects of programs are a key issue given that follow-up periods in many intervention studies are relatively short, and there is uncertainty about the persistence of effect sizes though time. Washington State Institute for Public Policy estimates changes in program effect sizes across time in the following manner. Where possible, the meta-analysis of a program creates summary effect sizes at two points after the intervention, and allows for some adjustments between the first and second estimate. When there are insufficient studies to estimate a second effect size, the analysis may use information from a wider program area to model how the effect size might change through time. Where this is not possible it is assumed that the effect size decays to zero for all post follow-up time periods.

The cost benefit model attaches a price per unit to the impacts of each intervention. For some of the outcomes such as mortality or the number of years of completed education, a key element of the price is how the outcome affects lifetime labor market earnings. Prices of outcomes are also based on direct costs to other people (eg criminal victimization), taxpayer burdens through the deadweight costs of taxation, and estimates of the statistical value of life net of earnings.

As part of the modelling, there are explicit rules to restrict double counting of related impacts, not all impacts are monetized, and estimates of outcome prices are benchmarked against other studies.

The costs of interventions are based on how much the program would cost if it was implemented in Washington State. Where appropriate capital costs are included and the time-profiles over which costs are incurred are also modelled. Importantly, it is the net cost of the intervention that is calculated. This is the cost of the intervention relative to the cost of any equivalent programs and services received by the comparison group. In a small number of cases the intervention is cheaper than the 'business as usual' comparison and the cost of the intervention represents a fiscal saving. A benefit cost ratio cannot be calculated in these cases.

The model uses discount rates of 2.0%, 3.5% and 5.0% to adjust all costs and benefits, and the time profile over which modelling occurs can be up to 100 years.

The expected costs and benefits of interventions are derived from a Monte Carlo simulation. The benefit cost model is run 10,000 times with key input parameters related to program effect sizes, linked effect sizes, and discount rates being randomly sampled from the probability distribution of the parameter. The simulation also produces a measure of investment risk for each estimate. This measure is the percentage of model simulations where the present value of the benefits of the program exceed the present value of the costs (in most situations this is the probability that the benefit cost ratio will be greater than one). When comparing two programs with the same benefit cost ratio, the program with the lower probability of achieving breakeven is a riskier investment.

In order to be more specific about methods, Appendix B provides an overview of the Washington State Institute for Public Policy analysis of the cost effectiveness of early childhood education funded by states and districts. This is then compared to the analysis of the benefits and costs of the Perry Preschool program undertaken by Heckman and colleagues (Heckman *et al.*, 2010). While the overall approaches to investment analysis are very similar, there are two important differences worth noting.

First, the Washington State Institute for Public Policy analysis has the advantage of being based on a meta-analysis of 14 studies while the analysis of Perry Preschool is based on a single study.

Second, the Washington State Institute for Public Policy is more dependent on assumptions because it makes more use of the modelling of lifetime impacts through 'linked impacts' (such as the link between high school graduation and adult earnings). The Heckman analysis also extrapolates 'direct impacts', but is less reliant on these values because of the longer window over which impacts are directly measured.

Although the Washington State Institute for Public Policy dataset is derived using rigorous methods, there are also some technical features of the data that impose some limitations on our analysis. The dataset does not have information on the variance associated with each benefit cost ratio estimate. In addition, there are a small number of programs where a benefit cost ratio cannot be calculated because of the way program costs are recorded. These issues and their implications for our analysis are discussed in a subsequent section.

4. Dataset and Results

4.1 Description of the Dataset

The data used for this study is from the Washington State Institute for Public Policy August 2017 update and contains information on 339 interventions. The full dataset is provided in an online appendix accompanying the paper.

Table 2 describes the broad characteristics of the programs within different samples of the dataset. Sample (a) contains all 339 programs. Sample (b) contains 314 programs which have benefit cost ratios recorded. Sample (c) is restricted to only programs which have a benefit cost ratio that is greater than zero. Sample (d) adds a further restriction related to outliers and includes programs where the benefit cost ratio is less than 100. Sample (e) is the same as (d) but restricted to programs in sectors that are close to those considered in the original formulation of the Heckman Curve.

The programs in the full dataset cover a wide range of different sectors. The programs also span the life course with 10% of the interventions in the overall sample targeted to children 5 years and under. Roughly 38% of the sample are interventions targeted at children and young people aged 6–15 years, and a smaller proportion (13%) are received by young people aged 16–24 years. Just over 39% of interventions in the sample are targeted at individuals 25 years of age or older.

Table 3 provides summary statistics on average benefit cost ratios for samples (b) through (e). On average across the sample of 314 programs with benefit cost ratios the interventions return $17.80 for every $1 invested. This average is influenced by a long tail of programs with large returns and the median benefit cost ratio is considerably smaller than the mean.

Table 3 also reports the average probability that the benefit cost ratio will be greater than unity across each of the samples. As mentioned, this is derived from the Monte Carlo simulation undertaken for each program and can be interpreted as the proportion of model runs where the program is calculated to break-even. Across the four samples this measure ranges from 0.65 to 0.77.

The dataset contains many programs with substantial benefit cost ratios. More than a quarter of the dataset is programs with benefit cost ratios larger than the upper bound estimate for the Perry Preschool listed in Table 1. This raises the question of whether the Washington State Institute for Public Policy

Table 2. Overview of the Washington State Institute for Public Policy Dataset: Number of Programs.

	Sample (a) Full dataset	Sample (b) Programs with benefit cost ratios	Sample (c) Programs with benefit cost ratios greater than zero	Sample (d) Programs with benefit cost ratios greater than zero and less than 100	Sample (e) Programs from sample (d) excluding the health sector
Program numbers by sector					
Child welfare	8	6	4	4	4
Child mental health	24	16	13	13	0
Pre-K to 12 education	50	50	44	41	41
Higher education	7	7	6	4	4
Juvenile justice	32	28	23	23	23
Adult justice	44	37	31	31	31
Public health and prevention	64	64	52	48	0
Adult mental health	25	24	20	19	0
Substance use disorder	39	37	29	29	0
Healthcare	36	35	29	29	0
Workforce development	10	10	7	7	7
Total programs	339	314	258	248	110
Program numbers by age of treatment group					
5 years and under	33	31	25	25	7
6–15 years	130	118	99	95	47
16–24 years	43	42	30	27	19
25 years and above	133	123	104	101	37
Total programs	339	314	258	248	110

Note: For some programs the dataset contains an estimate of the average age of both a primary and a secondary recipient (who is usually a child). For our analysis we allocate the program to the recipient for whom the benefits are the largest.
Source: Washington State Institute for Public Policy, August 2017 update.

Table 3. Overview of the Washington State Institute for Public Policy Dataset: Benefit Cost Ratio Statistics.

	Sample (b) Programs with benefit cost ratios	Sample (c) Programs with benefit cost ratios greater than zero	Sample (d) Programs with benefit cost ratios greater than zero and less than 100	Sample (e) Programs from sample (d) but excluding health sector
Median benefit cost ratio	3.9	6.2	5.8	5.7
75th percentile benefit cost ratio	13.5	16.5	14.8	13.5
Mean benefit cost ratio	17.8	23.6	12.7	11.6
Mean probability benefit cost ratio >1	0.65	0.73	0.73	0.77

Source: Washington State Institute for Public Policy, August 2017 update.

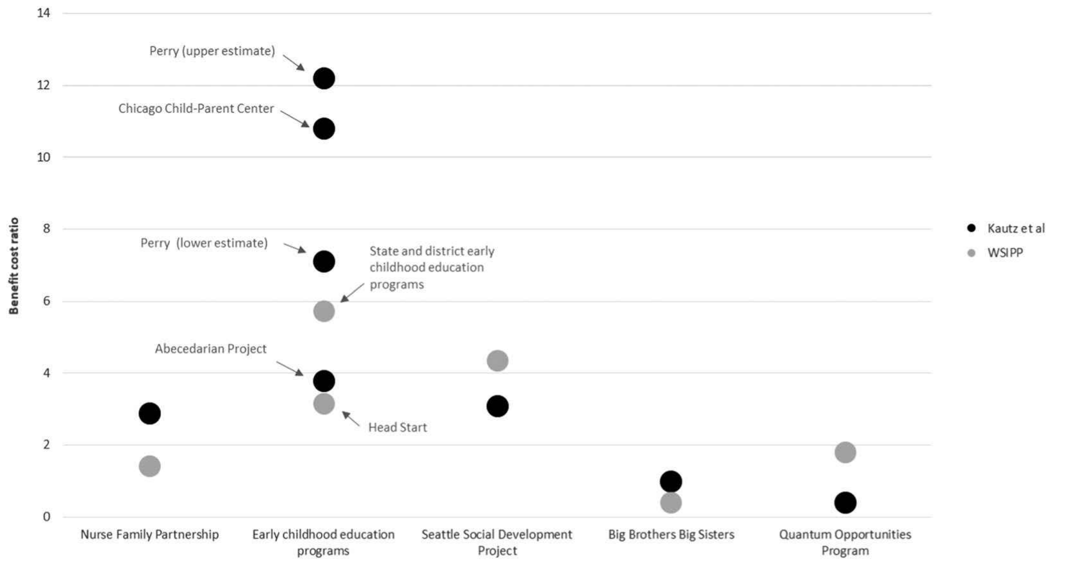

Figure 2. Comparisons of Benefit Cost Ratio Estimates for Selected Interventions (Kautz *et al.*, 2014 and Washington State Institute for Public Policy).

methodology produces estimates that are fundamentally different from those assembled by Heckman and colleagues.

Some insights into this question can be obtained by a comparison of the benefit cost ratios for programs that feature in both the Washington State and OECD report datasets. The Nurse Family Partnership, the Seattle Social Development Project, Big Brothers Big Sisters (available from the 2018 update of the Washington State data) and the Quantum Opportunities Program have estimates in both collections. For each of these programs the benefit cost ratios are broadly comparable, which appears to be partly the result of earlier Washington State estimates being used for the OECD report (Aos *et al.*, 2004).

Differences in the estimated benefit cost ratio for early childhood education programs can also be compared. The August 2017 dataset from Washington State Institute for Public Policy does not include estimates of the benefit cost ratios for the older Perry and Abecedarian interventions. They do however estimate a benefit cost ratio for Head Start (3.2), as well as early childhood education programs funded by states and districts (5.7). These are lower than the average of the Perry Preschool, Abecedarian and Chicago Child-Parent Centre programs reported in Table 1.

In terms of the large number of high benefit cost ratios interventions in the Washington State Institute for Public Policy dataset, one explanation is that the modelling of post-study impacts might be exaggerating some of the long-term benefits of programs. While this is clearly possible, it is not something that is apparent for the interventions shown in Figure 2.

An alternative explanation is that the Washington State Institute for Public Policy dataset contains a wider sample of programs that are cost-effective. Cognitive behavioural therapy provides an example of a class of programs that have high benefit cost ratios in a variety of settings. The evidence for these programs comes from many well conducted evaluations, and they mostly suggest reasonable impacts on different aspects of mental health and other outcomes.

Table 4. Characteristics of Programs with Low and High Benefit Cost Ratios (Sample (c)).

	Benefit cost ratio less than 16.5	Benefit cost ratio 16.5 or above
Mean benefit cost ratio	5.1	79.7
Costs	\$2,620	\$271
Taxpayer benefits	\$2,473	\$3,055
Nontaxpayer benefits	\$5,369	\$9,022
Total benefits	\$7,842	\$12,077
Mean probability benefit cost ratio >1	0.70	0.85
N	194	64

Note: Sample (c) are programs with benefit cost ratios greater than zero. Cut-off of 16.5 is 75th percentile of benefit cost ratios in the sample.
Source: Washington State Institute for Public Policy, August 2017 update.

Another related explanation is that the Washington State Institute for Public Policy dataset includes a number of low cost programs that are also effective. Because they are inexpensive, these programs only need modest impacts on valuable outcomes to generate a high benefit cost ratio. Examples of these types of interventions include peer tutoring in schools, the good behaviour game, and text message reminders for high school graduates.

Table 4 summarizes the characteristics of programs with benefit cost ratios greater than the 75th percentile for sample (c). On average the cost of the interventions from the upper quartile are only a tenth of those in rest of the sample. Despite their modest costs these interventions are estimated to produce sizeable benefits.

4.2 Analysis

Our analysis focuses on the estimated benefit cost ratios of interventions by the average age of the primary recipient. If the data is consistent with the Heckman Curve, then interventions received by very young children should have average benefit cost ratios that are larger than those targeted at older age groups. In addition, investments received by older age groups should have average benefit cost ratios that are less than unity.

Figure 3 plots average benefit cost ratios of programs for sample (d). There is a wide variation in estimated benefit cost ratio's by age, and there does not appear to be any clear relationship between the age of the treatment group and program cost effectiveness. It is hard to see any support for the Heckman Curve proposition that interventions targeted at children have the highest rates of return, or that those targeted at older age groups are on average poor investments.

Table 5 reports the average benefit cost ratios for interventions received by different age groups for each of the four samples. The Heckman Curve suggests that the benefit cost ratios of interventions targeted at the youngest age group should be higher than interventions received by older age groups. By way of contrast, across the different samples the average benefit cost ratio for interventions targeted at the youngest age group are *lower* than interventions targeted at older age groups. However, given the large standard errors these differences are mostly not significant at conventional levels.

Across all the samples there is no evidence for the hypothesis that interventions aimed at young children have higher average benefit cost ratios than older age groups. This includes sample (e) which removes programs from the health sector to approximate the original formulation of the Heckman Curve.

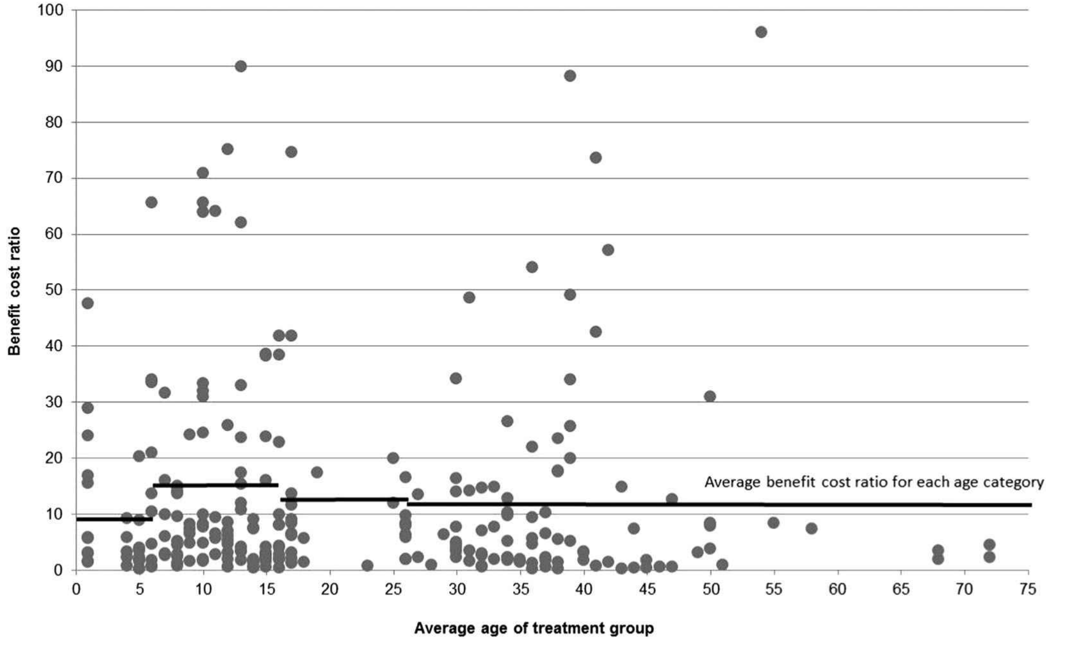

Figure 3. Benefit Cost Ratio's by Age for Programs from the Washington State Institute for Public Policy. *Note*: Sample (d) programs with benefit cost ratios greater than zero and less than 100 ($N = 248$). *Source*: Washington State Institute for Public Policy, August 2017 update.

The results are robust to different specifications including using the log of the dependent variable, as well as controlling for program costs and sector of intervention. The results are also robust to excluding low cost programs, programs in the upper quartile of returns, and programs targeted at people over 40 years of age.

Table 5 also shows that programs targeted at young people and adults can achieve average benefit cost ratios well above the cost of the program. In contrast to what is represented in the Heckman Curve, in all cases the 95% confidence interval for the benefit cost ratios for youth and adult interventions is well above unity.

Figure 4 shows the results for sample (d) and (e) graphically. As can be seen, there are large confidence intervals around each of the estimates. There is no evidence of a Heckman Curve relationship, even when health sector programs are excluded from the analysis.

The previous analysis is based on considering the Heckman Curve as a proposition about the rate of return of all programs that have positive benefits. However, it could be argued that the Heckman Curve refers to only those programs where the benefits of the program are larger than the costs. To assess the Heckman Curve from this perspective we further restricted samples (d) and (e) to programs where the benefit cost ratio was greater than unity, and where the modelled chance of this occurring was greater than 75%. As in the previous analysis, these samples contained many programs aimed at older age groups with substantial benefit cost ratios. There continued to be no evidence that early childhood interventions had the highest average benefit cost ratios.

Analysis of other measures of intervention returns for different age groups (set out in Appendix C) also provide no evidence for a Heckman Curve relationship.

Table 5. Average Benefit Cost Ratios for Programs Targeted at Different Age Groups.

Age group	Number of interventions	Mean benefit cost ratio	Standard error
Sample (b): Programs with benefit cost ratios			
5 years and under	31	**6.6**	2.0
6–15 years	118	**14.2**	3.4
16–24 years	42	**20.4**	8.4
25 years and above	123	**23.3**	8.6
Total	314	**17.8**	3.8
Sample (c): Programs with benefit cost ratios greater than zero			
5 years and under	25	**8.6**	2.3
6–15 years	99	**19.9**	3.2
16–24 years	30	**31.2**	11.1
25 years and above	104	**28.4**	10.1
Total	258	**23.6**	4.4
Sample (d): Programs with benefit cost ratios greater than zero and less than 100			
5 years and under	25	**8.6**	2.3
6–15 years	95	**14.7**	2.0
16–24 years	27	**12.8**	3.3
25 years and above	101	**11.9**	1.8
Total	248	**12.7**	1.1
Sample (e): Programs from sample (d) but excluding the health sector			
5 years and under	7	6.2	2.6
6–15 years	47	**15.8**	2.9
16–24 years	19	**12.8**	4.3
25 years and above	37	**6.6**	0.9
Total	110	**11.6**	1.5

Note: (1) Where the benefit cost ratio is in bold the difference from unity is statistically significant ($\alpha = 0.05$). (2) None of the estimates for programs targeted at children '5 years and under' are statistically significantly larger than any of the estimates for older age groups ($\alpha = 0.05$).
Source: Washington State Institute for Public Policy, August 2017 update.

4.3 Some Data Limitations

Ideally for the analysis presented above it would be useful to weight each benefit cost ratio by the variance of the estimate that is produced from the Washington State Institute for Public Policy modelling. This would then provide a more precise measure of the average return for each age group. Unfortunately, the data on the variance of the benefit cost ratio estimates for each program is not currently recorded each time the simulation is run. We investigated if it was possible to estimate the variance of each benefit cost ratio given that we know the investment risk statistic (the proportion of simulations where the benefit cost ratio was greater than unity), and assuming a modelling distribution. However, this was not feasible because of uncertainty about the precise shape of the skewed modelling distributions. This highlights a weakness in the current analysis which could usefully be addressed in future work.

Another important issue for the robustness of our results is the exclusion of programs which do not have benefit cost ratios. The difference between sample (a) and (b) is 25 programs where there is no benefit cost ratio calculated because the program costs the same or less than the counterfactual intervention. An example is a program called 'diversion of youth offenders from juvenile court system combined with the provision of community services'. In the August 2017 data this program was estimated to produce

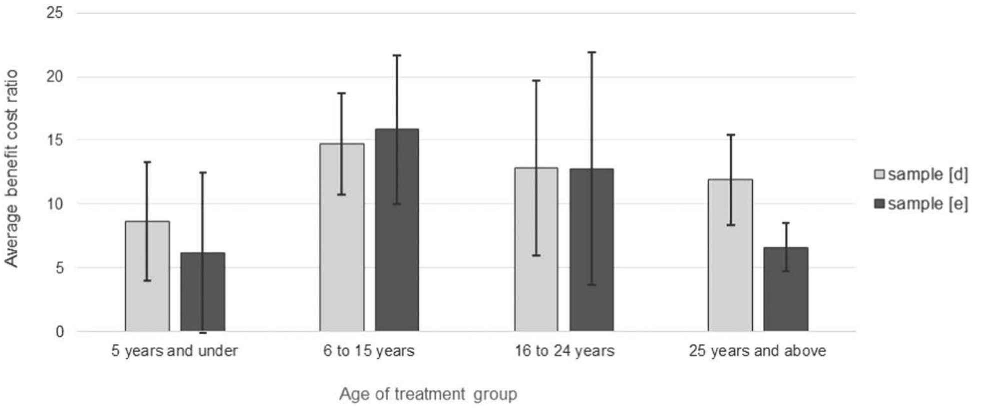

Figure 4. Average Benefit Cost Ratio's by Age for Samples (d) and (e).
Note: Sample (d) programs with benefit cost ratios greater than zero and less than 100 ($N = 248$). Sample (e) the same as (d) but excludes health sector programs ($N = 110$).
Source: Washington State Institute for Public Policy, August 2017 update.

benefits of $2,393. In addition, it was also estimated to cost around $573 less per person compared to the existing intervention which involves processing the young person through the juvenile court system. Overall the expected net benefits of this program were $2,966.

Like the diversion example, all but two of the excluded programs cost less than the status quo intervention and generate positive benefits. In some instances, the net benefits are reasonably large. Most of the programs are candidates for investment if the aim is to maximize the overall return of a portfolio of investments with a fixed budget. The issue for our analysis is that the exclusion of these high value programs may bias our results if many of them are targeted at young children.

Table 6 provides an overview of the excluded programs. Only two of the 25 programs are targeted at children 5 years of age and under, and in addition, the average net benefits of these early intervention programs are less than other age groups. Given this it would not be expected that the inclusion of the programs would change the findings from our analysis.

We also conducted a simulation to more formally assess how the inclusion of these programs might influence our conclusions. This involved the scenario of a decision maker optimizing their portfolio of investments under varying budget constraints. The decision maker aims to maximize the benefits from their spending and has no distributional preferences. In our simulation the decision maker can only invest in one unit of each program. As would be expected from the previous analysis of benefit cost ratios, these simulations show that an evidence-based decision maker will invest in programs targeted at people right across the age spectrum. In fact, interventions for children 5 years of age and under represent a relatively small share of funded programs, even when the decision maker has a very limited budget. Importantly, adding the 25 excluded programs to these simulations did not change the share of programs targeted at young children. This provides further assurance that the findings of our analysis are robust to the exclusions.

5. Discussion

The Washington State Institute for Public Policy dataset of benefit cost ratios provides information on a wide range of well researched social policy interventions. Estimates are based on a sophisticated and consistently applied methodology, and the dataset is regularly updated as more rigorous impact studies are reviewed.

Table 6. Interventions Excluded Because of Missing Benefit Cost Ratios.

Age group	Number of excluded interventions	As a percentage of programs in age category in full sample	Mean net benefits of programs
5 years and under	2	6.1	$2,996
6–15 years	12	9.2	$6,803
16–24 years	1	2.3	$77,515
25 years and above	10	7.5	$6,521
Total	25	7.4	$9,214

Source: Washington State Institute for Public Policy, August 2017 update.

The August 2017 update of the dataset does not show a Heckman Curve relationship between the benefit cost ratio of the intervention and the average age of recipients.

While many interventions targeted at young children generate high returns, the average benefit cost ratios for interventions targeted at young children are not higher than those targeting older age groups.

In addition, average benefit cost ratios of interventions targeted at older age groups show that many are cost effective. Examples include cognitive behavioural therapy for youth offenders, post-secondary and vocational education in prison, drug treatment during incarceration, case management for unemployment insurance claimants, and summer outreach programs and text messaging to encourage low income students to enrol in college.

While the Washington State Institute for Public Policy data suggests that a Heckman Curve does not exist, there are also reasons to be cautious about this finding. The large number of systematic reviews that underpin estimates of impacts do not always include the latest results for some interventions, and the number of interventions for which returns are calculated is still relatively small compared to what could be undertaken.

More generally, as occurs with all benefit cost analysis, estimates are sensitive to the assumptions about which outcomes are measured, how much they are valued, and how unmeasured long-term impacts are modelled. There is always the risk that the modelling of impacts outside of study follow-up periods creates a systematic bias that underestimates returns for child related interventions and overestimates the results for programs targeted at older ages. Such caveats suggest that it would be useful for this analysis to be conducted on similar datasets constructed using different assumptions.[1]

The main finding from the analysis presented here is somewhat puzzling in that it would seem reasonable to assume early interventions targeted at young children should be more cost effective than those targeted at older age groups. There is considerable evidence that early childhood is a critical stage of development, and there is ample evidence of enduring life course impacts from many interventions targeted at children.

We think the key to resolving this puzzle and understanding our results is to understand that the dynamics of human capital formation are only one of several factors that influence the cost effectiveness of social policy interventions. Overall the rate of return of any intervention depends on the cost of the program, its ability to impact on outcomes, the time profile of impacts, the value of these impacts, and the assumed discount rate.

Factors other than the cumulative nature of human capital development are often important. For example, some programs with only modest short-lived impacts can be highly cost effective if they are inexpensive to deliver.

Another related consideration is the extent to which an intervention is well targeted. Some interventions generate a high rate of return because they are only received by those who benefit. Other interventions may be less well targeted, and hence lead to spending on those who do not require help. A potential example of this might be interventions aimed at reducing youth offending. While early prevention programs may be effective at reducing offending, they are not necessarily more cost effective than later interventions if they require a large investment in those who are not at risk.

While it is often argued that an intervention in childhood has a longer period of time over which benefits can accumulate, another consideration is the proximity of the costs of the intervention to the time where there are the largest potential benefits. For example, the transition to adulthood is associated with an increase in mortality, injury, offending and unintended pregnancies. Youth interventions that aim to address these issues may potentially be more cost effective than early interventions because the cost of these programs is incurred later.

Another factor is that the technology or active ingredients of interventions differ, and it is not clear that those targeted at younger ages will always have more effective ingredients. Some adult interventions may be effective because they occur at a time or in a situation where people are highly motivated and responsive to change.

Lastly, and at a slightly deeper level, many human capital-based social policy interventions are responses to individuals experiencing partially random adverse events. This includes retraining after losing a job, rehabilitation after being seriously injured in an accident, or healthcare in response to a physical or mental illness. Prevention programs that build skills and competencies might be able to reduce the risk of adverse events, but there is no reason why they should always generate a higher return than human capital programs that deliver 'cures' or 'mitigation'.

6. Conclusion

The Washington State Institute for Public Policy estimates of the benefit cost ratios of many well-studied social policy programs do not show a Heckman Curve relationship.

Importantly, this finding does not imply that there should be less investment in early childhood programs. There are many early interventions that have large positive rates of return, and there are powerful equity reasons to invest in children, particularly in relation to equality of opportunity.

The Washington State Institute for Public Policy data suggests that early intervention can be cost effective, but in addition, later treatment and amelioration using evidence-based programs can also succeed. Rather than generalizing based on the age of intervention recipients, the key to identifying which interventions are cost-effective is to conduct a case-by-case assessment of individual programs using rigorous methods (Lee and Aos, 2011).

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Note

1. An example is recent analysis by Hendren and Sprung-Keyser (2019) who review 133 historical policy changes and programs where long-term impacts have been credibly identified. Using the slightly different metric of the marginal value of public funds they find that on average direct investments in health and education for low-income children and teenagers have the highest values. Policies targeted

at adults generally return lower values, although within each age group there is also quite a lot of variability. The authors argue that their results are not consistent with the Heckman proposition because average returns do not diminish rapidly with age, and there are many opportunities for high-return investments targeted at young people.

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Appendix A: The Internal Rate of Return and the Benefit Cost Ratio

The internal rate of return of a program is the maximum interest rate at which the present value of benefits equals the present value of costs of the intervention. It is the maximum interest rate (v) which solves:

$$\sum_{t=1}^{t=T} \frac{\left(Benefits_t\right)}{(1+v)^t} = \sum_{t=1}^{t=T} \frac{(Costs_t)}{(1+v)^t}$$

The benefit cost ratio is calculated for a given discount rate (r) and is the net present value of the benefits of the intervention as a proportion of the net present value of the costs of the specific costs of the investment. It can be expressed as

$$BCR = \frac{\sum_{t=1}^{t=T} \frac{\left(Benefits_t\right)}{(1+r)^t}}{\sum_{t=1}^{t=T} \frac{(Costs_t)}{(1+r)^t}}$$

If the rate of return of a program is equal to the discount rate then the benefit cost ratio is equal to 1. Where the rate of return is less than the discount rate then the benefit cost ratio is less than 1. If the rate of return is above the discount rate then the benefit cost ratio is greater than 1. For any specific investment the benefit cost ratio can be expressed as a function of the internal rate of return and the discount rate. However, there is no simple general formula because the internal rate of return depends on both the magnitude and timing of the costs and benefits. For an investment where investment costs are incurred at period 0 and benefits are incurred in only period 1 the relationship is

$$BCR = \frac{(1+v)}{(1+r)}$$

Appendix B: Comparison of Benefit Cost Ratio Analysis for Early Childhood Education

The table below summarizes the Washington State Institute for Public Policy analysis of the costs and benefits of early childhood education programs funded by states and districts. This is compared with the investment analysis undertaken by Heckman and colleagues relating to the HighScope Perry Preschool program (Heckman *et al.*, 2010).

Table B1. Comparison of Methods Used for the Benefit Cost Analysis of Early Childhood Education.

Method	Washington State Institute for Public Policy (2017)	Heckman *et al.* (2010)
Intervention	State and district early childhood education programs	The HighScope Perry Preschool Program
Impact data	Meta-analysis of 14 studies (mostly quasi-experimental)	Single randomized study with long-term follow up
Treatment	Pre-kindergarten programs funded by states or school districts that are universal or target low-income students (treatment *N* of 902 to 10,779 depending on outcome)	The program began at age three and lasted 2 years. Consisted of a 2.5-hour preschool program on weekdays during the school year. There were also weekly home visits by teachers (treatment *N* of 58)
Control	Control students could have received other preschool programs, subsidized or unsubsidized childcare, or Head Start	Minimal participation in other formal programs
Cost	$7,259 ($2017)	$17,759 ($2006)
Benefit cost ratio	5.7	7.1–12.2
Average age of treatment group	4	3
Average age at last follow up	Between 12 and 26 depending on impact	40
Discount rate	2, 3.5, 5	0, 3, 5, 7
Measurement of uncertainty	Yes	Yes
Values benefits for participants, taxpayers and others	Yes	Yes
Main benefits realized by program	Higher earnings, reduced crime, net costs of education	Higher earnings, reduced crime, lower welfare use, net cost of education

(*Continued*)

Table B1. *Continued.*

Method	Washington State Institute for Public Policy (2017)	Heckman *et al.* (2010)
Outcomes observed and valued	High school graduation, K–12 grade repetition, special education, higher education, criminal offending. Impacts on employment, earnings and public assistance for parents also valued	Participation in education, earnings and employment, criminal offending, welfare use
Outcomes observed but not directly valued	Test scores	Academic success, mortality
Key outcomes projected	Education impacts (test scores and high school graduation) are used to model lifetime earnings and health. Criminal offending is modelled after last follow up	Earnings, crime, welfare use after last follow up
Other key assumptions	Deadweight costs of taxation, Value of crime	Deadweight costs of taxation, Value of crime
Key differences	Meta-analysis, Shorter follow-ups, Earnings modelled from education impacts, Does not measure the subsequent welfare costs during adulthood, Includes impacts for parents	Small single study, Long-term follow-up, Earnings more directly measured although substantial imputation

Sources: Washington State Institute for Public Policy (2017) and Heckman *et al.* (2010).

Appendix C: Additional Measures of Intervention Returns by Age from the Washington State Institute for Public Policy Dataset

Table C1. Additional Investment Measures for Programs by Age of Main Recipients.

	Sample (a) All programs	Sample (b) Programs with benefit cost ratio	Sample (c) Programs with benefit cost ratio >0	Sample (d) Programs with benefit cost ratio >0 and <100	Sample (e) Programs from sample (d) excluding health sector
Median benefit cost ratio					
5 years and under	2.8	2.8	3.4	3.4	3.9
6–15 years	4.7	4.7	7.3	6.5	7.3
16–24 years	3.4	3.4	7.9	6.4	6.0
25 years and above	3.7	3.7	5.7	5.4	4.6
Total	3.9	3.9	6.2	5.8	5.7
Proportion with benefits exceeding costs					
5 years and under	73	71	88	88	86
6–15 years	78	76	91	91	96
16–24 years	67	67	93	93	95
25 years and above	75	74	88	87	92
Total	75	74	90	89	94
Mean benefits minus costs					
5 years and under	$3,106	$3,114	$5,043	$5,043	$9,065
6–15 years	$3,689	$3,373	$5,734	$5,526	$6,711
16–24 years	$7,835	$6,176	$10,087	$10,441	$14,413
25 years and above	$4,853	$4,718	$7,425	$6,727	$8,499
Total	$4,615	$4,249	$6,855	$6,502	$8,792

Note: Sample (a) contains 25 programs where a benefit cost ratio is not calculated and these are excluded from the calculation of the median.
Source: Washington State Institute for Public Policy, August 2017 update.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Supporting information