EFFECTS OF INEQUALITY, FAMILY INVESTMENT AND EARLY CHILDHOOD INTERVENTIONS ON CHILDREN COGNITIVE AND SOCIO-EMOTIONAL WELLBEING IN INDONESIA

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Background

Understanding inequality in children's health and development is important because effects of disadvantage early in life may contribute to health disparities throughout life. Evidence shows that children who live in poorer families tend to have poorer cognitive outcomes and higher risk of behavioural problems compared to their peers from non-poor families. In low and middle income countries, children from poor families are more likely to be exposed to a multitude of risk factors that compromise healthy child development including lack of access to safe drinking water and improved sanitation, lack of access to health and education services, as well as inadequate learning environment at home. Whilst parental investment in children's health and development often relies on resources that are available at home, effective interventions may protect children from negative consequences of living in poverty and increase investment in children's health and development.

Aims

The overall aim of this thesis is to investigate inequalities in cognitive function and socio-emotional well-being among Indonesian children, and how early childhood interventions might reduce these inequalities. The specific research questions are as follows:

1. What is the magnitude of socioeconomic inequality in Indonesian children's cognitive function in 2000 and 2007? What factors contribute to the inequality? Does

the inequality in children's cognitive functioning change between 2000 and 2007 and what factors contribute to the change in inequality?

2. What is the effect of household per capita expenditure on Indonesian children cognitive function and does a cash transfer intervention increase cognitive function scores?

3. What is the association of poverty at ages 0-7 and poverty at 7-14 with children's cognitive function at 7-14 years? What is the direct effect of poverty at 0-7 years on cognitive function at 7-14 years, and is this effect mediated through poverty at 7-14 and through school attendance and aspects of the child's home environment?

4. What is the relative and combined effect of different hypothetical interventions such as improving standard of living through provision of piped water and improved sanitation, maternal mental health and a parenting program on children's school readiness and socio-emotional wellbeing in Indonesia?

Methods

This thesis used data from the Indonesian Family Life Survey (IFLS) and the Early Childhood Education and Development (ECED) project. IFLS was used in studies 1-3, where the study participants consisted of two cohorts who were recruited for cognitive testing, comprising children aged 7-14 in 2000 (born between 1993 and 1986) and children aged 7-14 in 2007 (born between 2000 and 1993). In study 4, data from the ECED was used. Herein, the study participants included children aged 4 in 2009 and followed up at ages 5 and 8. This thesis used a range of statistical approaches to answer the aims of this thesis including the relative concentration index, decomposition of concentration index, Oaxaca-type decomposition of change, an inverse probability of treatment weight of a marginal structural model, conventional regression analysis, decomposition analysis (direct and indirect effects) and parametric g-formula. Multiple imputation analysis was also performed where applicable.

Results

In the first study, there were substantial reductions in inequality in children's cognitive function between 2000 and 2007, but the burden of poor cognitive function was still higher among the disadvantaged. In both 2000 and 2007, household per capita expenditure was the largest single contributor to inequality in children's cognitive function. However, improvements in maternal education, access to improved sanitation and household per capita expenditure were the main contributors to reductions in inequality in children's cognitive function from 2000 to 2007.

In study two, greater household per capita expenditure was associated with higher cognitive function but the effect size was small. Based on simulations of a hypothetical cash transfer intervention, an additional US$ 6-10/month of cash transfer for children from the poorest households in 2000 increased the mean cognitive function score by 6% but there was no overall effect of cash transfers at the total population level.

In the third study, being exposed to poverty was associated with poor cognitive function score at any age, however, there was no evidence that being exposed to poverty at 0-7 had a larger effect on cognitive function than poverty at 7-14 years. From decomposition analysis, poverty at 0-7 had a larger direct effect on children's cognitive function at 7-14 years than the effect of poverty at 0-7 that was mediated through poverty, school attendance and aspects of the child's home environment at 7-14 years. Moreover, the effect of poverty at 0-7 on cognitive function at 7-14 years was largely mediated through pathways involving child’s home environment, school attendance and poverty at 7-14 than the mediated effect through poverty at 7-14 alone.

From the final study, providing access to piped water as the main drinking water source, improved sanitation, maternal mental health and a parenting education program had positive effects on children’s school readiness and socio-emotional wellbeing in rural Indonesia. Intervention that combined multiple programs had a larger effect than any single intervention. In this study, a combination of provision of piped drinking water, improved sanitation, maternal mental health and a parenting education program is likely yield the largest effect, however, most of the effect was driven by provision of piped drinking water and improved sanitation.

Conclusions

This thesis provides some evidence to fill the knowledge gap on inequalities in children’s cognitive and socio-emotional wellbeing in Indonesia. It has also attempted to generate evidence that is relevant for policy intervention that may help to reduce these inequalities. Providing early childhood intervention that combined multiple programs is likely to have the largest effect. More importantly, the early childhood intervention in Indonesia should start with providing greater access to piped drinking water and improved sanitation.

Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university or other institution and affirms that to the best of my knowledge, the thesis contains no material previously published or written by another person, except where due reference is made in the text of thesis. In addition, I certify that no part of this work will, in the future be used in a submission for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Signed ....

Amelia Maika (Candidate)

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Publications contributing to this thesis

1. Maika A, Mittinty MN, Brinkman S, Harper S, Satriawan E, Lynch, J. Changes in Socioeconomic Inequality in Indonesian Children's Cognitive Function from 2000 to 2007: A Decomposition Analysis. PLOS ONE 2013 8(10): e78809. doi:10.1371/journal.pone.0078809
2. Maika A, Mittinty NM, Brinkman S, Lynch J. Effect on child cognitive function of increasing household expenditure in Indonesia: application of a marginal structural model and simulation of a cash transfer programme. Int. J. Epidemiology (2015) 44(1):218-228.
3. Maika A, Mittinty NM, Brinkman S, Lynch J. Associations of early and later childhood poverty with child cognitive function in Indonesia: Effect decomposition in the presence of exposure-induced mediator-outcome confounding. *American Journal of Epidemiology* (in press).

Conference presentation arising from this thesis

1. Maika A, Brinkman S, Pradhan M, Satriawan E, Adaptation of the Early Development Instrument in Indonesia, The 2012 Biennial Meeting, The International Society for the Study of Behavioural Development, 8th – 12th July 2012, Edmonton, Alberta, Canada.
2. Maika A, Mittinty, N Murthy, Brinkman S, Harper S, Satriawan E, Lynch J. Changes in Socioeconomic Inequality in Indonesian Children's Cognitive Function from 2000 to 2007: A Decomposition Analysis. The 7th Annual Faculty of Health Postgraduate Research Conference. University of Adelaide, 29th August 2013, Adelaide, Australia. Received the award for the winner from the School of Population Health.
3. Maika A, Mittinty N Murthy., Brinkman S., Harper S, Satriawan E, Lynch J. Changes in Socioeconomic Inequality in Indonesian Children's Cognitive Function from 2000 to 2007: A Decomposition Analysis. The 2013 State Population Health Conference, 26th October 2013, Adelaide, Australia. Received special mention for poster presentation.
4. Maika A, Mittinty N Murthy, Brinkman S, Lynch J. Effect Decomposition in the Presence of Exposure-Induced Mediator-Outcome Confounding : An Application for Estimating Effects of Early and Later Childhood Poverty on Child Cognitive Function in Indonesia. Young Statisticians Conference 2015, 5th – 6th February 2015, Adelaide, Australia.

5. Maika A, Mittinty N Murthy, Brinkman S, Lynch J. Effects of Maternal Mental Health on Child Cognitive and Behavioural Outcomes in Indonesia: An Application of a Marginal Structural Model. The Australian Development Census 2015 National Conference, 18th -20th February 2015, Glenelg, South Australia.

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Abbreviations

CCT	Conditional Cash Transfer
CDE	Controlled Direct Effect
DE	Direct Effect
ECED	Early Childhood Education and Development
GEE	General Estimating Equation
HICs	High Income Countries
IE	Indirect Effect
IFLS	Indonesian Family Life Survey
IPTW	Inverse Probability of Treatment Weights
IPW	Inverse Probability of Weights
LMICs	Lower and Middle Income Countries
MAR	Missing at Random
MCAR	Missing Completely at Random
MICE	Multiple Imputation by Chained Equation
MSM	Marginal Structural Model
NDE	Natural Direct Effect
NIE	Natural Direct Effect
NMAR	Not Missing Not at Random
OECD	Organization for Economic Cooperation and Development
PCE	Per Capita Expenditure
PKH	Program Keluarga Harapan
RCI	Relative Concentration Index
RCT	Randomized Controlled Trial
SD INPRES	Sekolah Dasar Instruksi Presiden (Presidential Instruction on Primary School program)
SW	Stabilized Weight
TCE	Total Causal Effect
UNICEF	United Nations Children’s Fund
WHO	World Health Organization

CHAPTER 1

Introduction

1.1. Introduction

Inequality in children's health and development outcomes has received international attention because they contribute to health disparities throughout life (1, 2). Evidence from both high income (HICs) and lower-middle income countries (LMICs) shows that children who live in poorer families have poorer health (3-5), poorer cognitive outcomes and higher risk of behavioural problems (6-8) compare to their peers from non-poor families. Being exposed to poverty in early childhood also has a long-term effect on various outcomes in adulthood. For example, children who are exposed to poverty tend to have less education (9), less earnings (10, 11), and poorer health (9, 12-14). Inequalities in children's health and development in LMICs are larger and more pronounced compared to HICs (15). This is because children from poor families in LMICs are more likely to be exposed to a multitude of risk factors that compromise healthy child development (16, 17) including lack of access to safe drinking water and improved sanitation, malnutrition, poor immunization, micronutrient deficiencies such as iodine and iron deficiencies, lack of access to health and education services, as well as inadequate learning environment at home (18, 19).

Many Indonesian children are exposed to poverty, poor housing conditions and lack of access to education services, which may affect their poor developmental outcomes. Recent statistics (20) suggest that 28.55 million (11%) of the Indonesian population lived below the poverty line in 2013 (equivalent to 308 826 *rupiah* or about US$ 25.21/month in the year 2013 exchange rates). In 2013, 61% of households used improved sanitation and less than half of households had access to either piped (11%), pumped (15%) or protected well (23%) as the main drinking water source, which also reflects the poor hygiene conditions in Indonesia. Inadequate access to improved sanitation and safe drinking water source is associated with poor growth and higher prevalence of diarrhoea, which is a leading contributor to under five mortality in Indonesia (21).

In terms of access to education services, many Indonesian children under 6 do not have access to an early childhood education and development (ECED) centre. Estimates suggest that only 18% of children aged 3-6 years participated in an ECED program in 2006 (22), and those that did mainly lived in urban areas and rich districts (23). In contrast, access to primary education (ages 7-12 years) is almost universal for both urban and rural, however, social inequalities in school enrolment widen after age 10 (24). Household financial resources (24, 25), distance to school and the cost of transportation (24) are common factors that contribute to inequality in school enrolment in Indonesia. In order to reduce inequality in school enrolment, the Indonesian government has implemented several programs including providing a community based ECED project throughout the country especially in rural areas (26) and provision of cash transfer for the poor families (23, 27).

Parental investment and benefits of early childhood interventions

Children's health and development outcomes partly rely on resources that are available at home and are invested in children (28). Children from lower income families tend to have poorer outcomes because their families may not have the resources to provide an adequate home environment that can support healthy child development including less stimulating activities at home and fewer visits to health checks. Children from poor families are also more likely to have mothers with mental health problems (29-31) and poor parenting behaviour (30). Parents from low income families and having poor mental health tend to be less nurturing and engaged with their children, which in turn affects poor development outcomes (6).

Evidence from HICs (32-35) and LMICs (19, 36, 37) indicates that effective interventions can protect children from negative consequences of living in poverty (36) and increase investment in children's health and development (1). Investing in early childhood has long-term benefits not only for individuals but also for the society and the country. Investing in early childhood improves cognitive ability, reduces the risk of behavioural problems, increases education attainment and earnings, reduces social problems such as delinquency and crimes in society, as well as increases government saving through higher tax revenue and reduced social welfare spending (35).

Among LMICs, effective early childhood interventions have been characterized by programs that targeted younger children and their families, had a mixed component of health, education and income support, and combined provision of high quality services with high intensity and longer duration (19, 36, 37). In HICs research in neuroscience (38) and economics (33) suggests that early childhood intervention yields better results than intervention in later childhood and is even more effective if it is followed up by later investment (39). Even when evidence for intervention effectiveness does exist, (19, 34, 36, 37) effective implementation of early childhood intervention is challenged by capacities in resourcing, targeting, and translating evidence-based policy into the actual programs and practices that directly touch poor children (40). For example, although there is a growing interest of the importance of ECED, financial resources for ECED programs are still limited. Whilst most countries spend less than 10% of their education budget for ECED programs (36), in Indonesia the allocation for preschool education was less than 1% of the national education budget (24). Funding from international organisations has provided support for the government to scale up intervention that could benefit the whole population (36, 41). Moreover, in LMICs interventions are often limited not only financially but also with the availability of supporting system in the community, and hence in some cases effective intervention in LMICs is more plausible when using community-based intervention by integrating the intervention into existing systems and staff to promote sustainability of the program (32, 42).

Previous studies about children's development outcomes in Indonesia

For the past decade, research about Indonesian children has largely focussed on traditional health outcomes. For example a recent systematic review by Schröders *et al* (21) identified 83 studies about inequities in children's health outcomes in Indonesia including immunisation and nutritional status, prevalence of diarrhoea and mortality. According to Schröders *et al* (21) determinants of inequity in children's health in Indonesia include place of residence, poor access to improved sanitation and clean piped drinking water, income, parental education, access and utilization of health care use and quality of health care system.

This thesis focuses on two child's development outcomes; cognitive and socio-emotional wellbeing. There is a great deal of empirical evidence showing that higher cognitive function is associated with better academic achievement (43, 44), physical and mental health (45-48), and economic outcomes such as occupational status, and earnings (49-52). Children's poor socio-emotional wellbeing are also associated with poorer academic achievement, poorer mental health at adolescence (42) and in adulthood (53).

Research examining children's cognitive and socio-emotional wellbeing in Indonesia is extremely limited. What evidence does exist comes from mostly small, cross sectional studies (54-57). In regards to socio-emotional wellbeing, current studies examining children's socio-emotional well-being in Indonesia often focus on children living in a specific environmental setting. For example, Tol *et al.*, (58) examined post-traumatic stress of children living in armed-conflict area in Poso, Indonesia, whilst Graham *et al.*, (59) and Jordan *et al.*, (60) investigated common mental health disorder (depression and anxiety) of children who were left behind by the migrating parents. Moreover, there are a couple of studies that examined posttraumatic stress of children living in the areas that were affected by natural disaster (61, 62).

There is also limited research examining the effects of early childhood interventions on children's cognitive and socio-emotional wellbeing in Indonesia. Recently, three randomized trials examined the effect of provision of micronutrient intervention for mothers (63), an educational media intervention for children (64) and school based psychosocial intervention (58) on Indonesian children's cognitive and emotional wellbeing. Although these trials provide valuable information regarding the effects of different early childhood interventions on children' cognitive and socio-emotional development, these trials only included one intervention component and had small sample sizes (ranging between 160 and 495).

This thesis provides some evidence to fill the knowledge gap on inequalities in children's cognitive and socio-emotional wellbeing in Indonesia using a large sample of children from two longitudinal studies. It also provides evidence about the type of early childhood interventions that may help to reduce the inequalities in children's development in Indonesia.

1.2. Thesis objective

The overall aim of this thesis is to investigate inequalities in cognitive function and socio-emotional well-being among Indonesian children, and how early childhood interventions might reduce these inequalities. The specific research questions are as follows

1. What is the magnitude of socioeconomic inequality in Indonesian children's cognitive function in 2000 and 2007? What factors contribute to the inequality? Does the inequality in children's cognitive functioning change between 2000 and 2007 and what factors contribute to the change in inequality?

2. What is the effect of household per capita expenditure on Indonesian children cognitive function and does a cash transfer intervention increase cognitive function scores?

3. What is the association of poverty at ages 0-7 and poverty at 7-14 with children's cognitive function at 7-14 years? What is the direct effect of poverty at 0-7 years on cognitive function at 7-14 years, and is this effect mediated through poverty at 7-14 and through school attendance and aspects of the child's home environment?

4. What are the relative and combined effects of different hypothetical interventions (e.g., provision of piped water and improved sanitation, maternal mental health, and parenting program) on children's school readiness and socio-emotional wellbeing in Indonesia?

1.3. Thesis outline

The remainder of the thesis is organised as follows. Chapter 2 describes the background context of Indonesian society and its development, followed by a literature review about factors that contribute to inequality in children's cognitive and socio-emotional wellbeing and provides the relevant interventions that may reduce inequality in children's cognitive and socio-emotional wellbeing. Chapter 3 describes the various data sources, measures, methodological and statistical approaches used to address each of the research questions. Chapter 4 addresses the first research question, which describes the magnitude of socioeconomic inequality in children's cognitive function in Indonesia, factors that contribute to the inequality and changes in the inequality between 2000 and 2007. Chapter 4 was published as a research article in a peer-reviewed journal (65).

Chapter 5 addresses the second research question, which discusses the effects of household expenditure on children's cognitive function and results from simulation of a hypothetical cash transfer intervention on children's cognitive function. Chapter 5 was also published in a peer-reviewed journal (66). Chapter 6 addresses the third research question, which presents the associations of early (at 0-7 years) and later childhood poverty (at 7-14 years) on cognitive function at 7-14 years and examines the mechanism through which early year's poverty could affect cognitive function at 7-14. Chapter 6 is accepted to be published in a peer-reviewed journal. Chapter 7 addresses the fourth research question, which describes the effects of various hypothetical interventions on children's school readiness and socio-emotional wellbeing in Indonesia. This chapter will be prepared for submission to a peer-reviewed journal after completion of the PhD.

Chapter 8 provides a summary from the overall thesis, synthesis of the findings, and agenda for future research.

CHAPTER 2

Literature Review

The structure of this chapter is as follows. Section 2.1 describes the background context of Indonesian society and related economic development. Section 2.2 presents a literature review about inequalities in children's cognitive and socio-emotional wellbeing. Section 2.3 presents relevant interventions that may reduce inequalities in children's cognitive and socio-emotional wellbeing, followed by a conclusion.

2.1. The Indonesian Context

Indonesia is a South East Asian nation with an estimated population of 248.8 million people (20). About half of the population live in Java Island and urban areas. Many Indonesians live in poverty. The first poverty rate was recorded in 1970, suggesting that 70 million (about 60%) of the population lived in poverty, placing Indonesia amongst the poorest countries in the world (67). Poverty rates have decreased substantially from 60% in 1970 to 11% in 1996 (Figure 1).

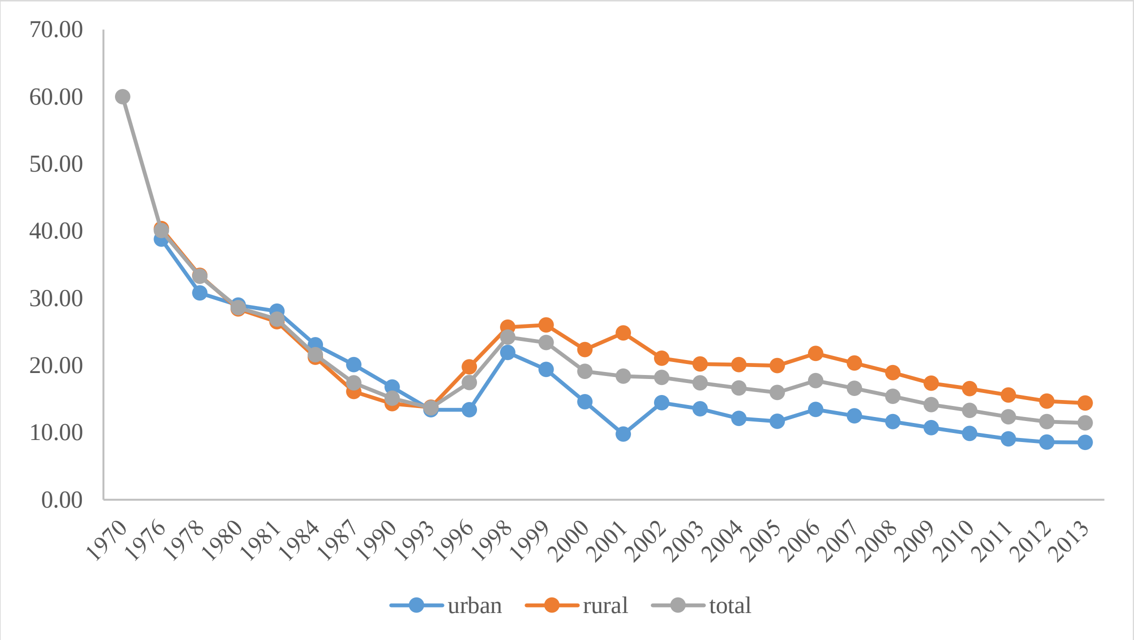

Figure 1. Poverty rates Indonesia 1970-2013 (Source: National Bureau Statistics Indonesia)

However, in 1997, Indonesia was hit by the Asian financial crisis (68). The *rupiah* devaluation to the US dollar resulted in millions of people losing their jobs, as roughly 2,000 companies having foreign debts went bankrupt. As a result, the poverty rate rose from 11% in 1996 to 19% in 2000. After the year 2000, the poverty rate decreased by less than 1% per year indicating no substantial progress in poverty reduction. Since 2010, economic growth has moved Indonesia from being among the poorest to a lower middle income country (LMIC) (23). According to a recent World Bank report (69) the national Gross Domestic Product (GDP) is expected to grow by 5.5% in 2015 indicating a moderate level of economic growth. In terms of macroeconomics, economic growth provides financial resources to improve living standards and reduce poverty (70). Recent statistics (20) suggest that 28.55 million (11%) of the Indonesian population lived below the poverty line in 2013 (equivalent to 308 826 *rupiah* or about US$ 25.21/month in the year 2013 exchange rates). In comparison with other provinces, Papua has the highest prevalence of poverty, which is more than triple the national average, whereas Jakarta, the capital city of Indonesia has the lowest poverty levels at 4% (20).

Figure 1 shows that poverty rates are higher in rural than in urban areas, suggesting that economic growth in Indonesia is not distributed equally across the country. Regional disparities are often characterized by geographical isolation, low resource base, harsh climate conditions, and lack of public services, transportation and infrastructure (71). These characteristics are mostly found in rural areas and provinces outside Java Island, especially in the Eastern part of Indonesia. Regional disparities are not only reflected in poverty rates as shown in Figure 1, but also in standards of living and access to education. The following section provides evidence regarding factors related to living standards and access to education in Indonesia.

2.1.1. Indonesian standards of living and access to education

Standards of living

In terms of living standards, this review only focuses on household access to electricity, sanitation and drinking water source. Currently, 93% of Indonesian households have access to electricity, but many of them live with a lack of access to improved sanitation and safe drinking water. Between 1993 and 2015, the proportion of households using improved sanitation has increased from 25% to 62% (Figure 2), however, it is estimated that 54 million of the population still practice open defecation, which placed the country as the second highest in the world for people defecate in the open (72). Of those people who use open defecation, 60% live in poverty.

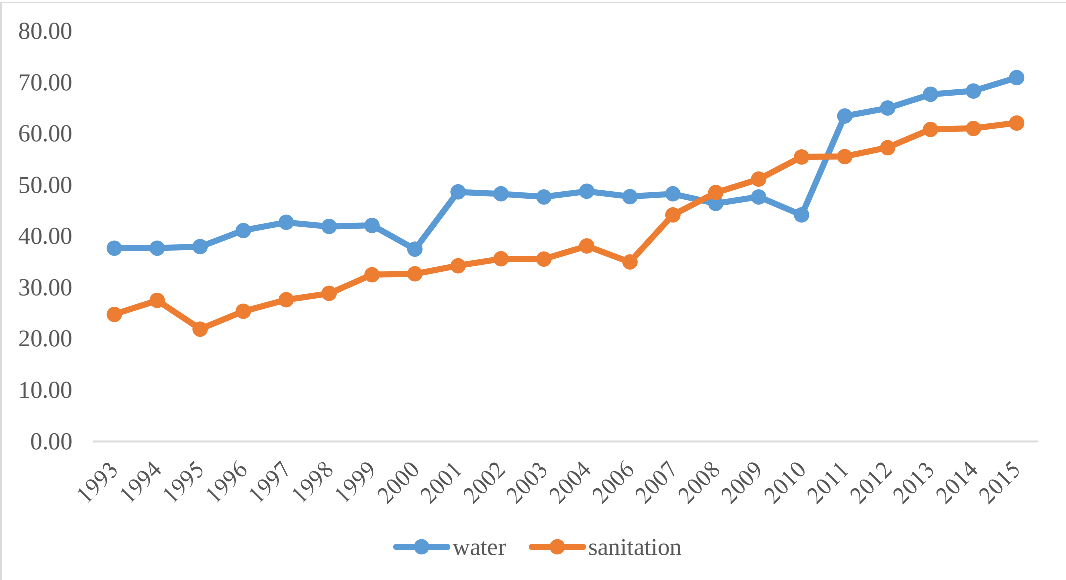

Figure 2. Proportion of households with improved sanitation and drinking water source, Indonesia 1993-2015 (Source: National Bureau Statistics Indonesia)

The proportion of households that used an improved drinking water source also increased from 38% in 1993 to 71% in 2015 (Figure 2). Herein, improved drinking water source includes piped, pumped well, protected well, spring water or rainwater where distance between the source and sewage system is more than 10 metres. In terms of drinking water sources, currently less than half of all households had access to either piped (11%), pumped (15%) or protected well (23%) as the main drinking water source. At the provincial level, the proportion of households that used piped water as their main drinking water source ranged from 20% in Bali to 4% in Papua (20).

Inadequate access to improved drinking water and sanitation is associated with poor growth and higher prevalence of diarrhoea, which is a leading contributor to under five mortality in Indonesia (21). National statistics suggest that 1 in 25 children under five dies before age 5 but estimates in the Eastern provinces is higher, suggesting that 1 for every 14 children under five dies in that region (73). Children in the poorest households are more than three times more likely to die during the first five years of life compared to the richest households.

Access to education

Regional disparities are also reflected in terms of access to education services. Overall, children from poorer households and who live in rural areas have lower access to education services compared to their peers from richer households, and those who live in urban areas. Many Indonesian children under 6 do not have access to early childhood education and development (ECED) services. Estimates suggest that only 18% of children aged 3-6 years participated in an ECED program in 2006 (22), and those that did mainly lived in urban areas and rich districts (23). Access to primary education (ages 7-12 years) is almost universal for both urban and rural, however, social inequalities in school enrolment widen after age 10 (24). For example, in 2010 of children aged 15, school enrolment rates in rural areas were 70% compared to 85% in urban areas. Children aged 13-15 years from the poorest families are four times more likely to drop out from school (72). Household financial resources (24, 25), distance to school and the cost of transportation(24) are common factors that contribute to inequality in school enrolment in Indonesia. Almost all primary education students live within four kilometres from a school and about 20% of junior secondary education students have to travel four or more kilometres to school. Distance to senior secondary education and higher education is even farther, which implies higher transportation costs. In 2010, the poorest income quintile spent about 205,000 rupiah/child (about US$26 using the year 2010 currency rate) for primary education, which is equivalent to a 15% of per capita household expenditure. The average cost for senior secondary education is about 1.2 million *rupiah*/child/year (about US$150) or equivalent to about 50% of per capita household expenditure (24). This is an enormous economic strain on most families, and maybe one reason why many children from poor families do not continue onto secondary education. Over the years, the Indonesian government has implemented several policies to improve universal access to education for its citizens (23, 24). Increasing access to education services also has been included as part of the national poverty reduction program. Some of these programs are presented in the following section.

2.1.2. Indonesian government policies to improve access to education

This section presents an overview of the government policy interventions aimed to improve access to education services in Indonesia including the school construction program, the ECED centre, and cash transfer programs.

The school construction program

The first program that aimed to improve access to education was the school construction program, also known as *SD INPRES (Sekolah Dasar Instruksi Presiden* – Presidential

Instruction for Primary School Program) (67). The school construction program was implemented in the 1970s, which aimed to improve access to primary education and to reduce poverty in the long run. Between 1973-1974 and 1978-1979, the Indonesian government built more than 61,000 primary schools across the country. On average two schools were built per 1000 children aged 5-14 years in 1971 (10), and more schools were built in the areas where there were higher proportions of school drop outs or lower participation rates in schooling. According to the World Bank, it was the fastest school construction on record (67). The school construction program successfully increased enrolment rates from 69% in 1973 to 83% in 1978. According to Duflo (10), the school construction program increased the average years of education by 0.12 to 0.19 years of education, and increased wages by 1.5 to 2.7% for each primary school constructed per 1000 children. Using evidence from the Indonesian Family Life Survey (IFLS), Pettersson (74) reported similar findings. He also found that children from lower socioeconomic position (SEP) and women benefitted more from the program than their peers from higher SEP families and men.

Early childhood Education and Development (ECED) program

As mentioned in section 2.1.1 many Indonesian children under 6 do not have access to an ECED centre. In the past decade, access to ECED services has been concentrated in urban and rich districts. In order to increase participation in the ECED services and improve children’s developmental potential and transition to more formal education, between 2006 and 2012 the Indonesian government launched a community-based ECED project throughout the country (26). The ECED program targeted about 738,000 children aged 0-6 years and their primary caregivers living in 3000 villages within 50 poor districts (26). A recent World Bank report (75) indicates that children living in the project area had a 7% higher chance to enrol in an ECED centre compared to those children living outside the project areas. The ECED project also had positive effects on children's school readiness and socio-emotional wellbeing, but no impact on nutritional status.

Cash transfer programs

As shown in section 2.1.1, household finances (24, 25) are a major contributor to inequality in school enrolment rates in Indonesia. The Indonesian government has rolled out several programs to provide financial assistance for poor families, including conditional (*Program Keluarga Harapan* PKH), and unconditional cash transfers (*Bantuan Langsung Tunai* BLT), scholarships for poor students (*Bantuan Siswa Miskin* BSM) (23), and recently the Indonesian Smart Card program (*Kartu Indonesia Pintar* KIP) (27). Of these programs, only the conditional cash transfer program PKH has both health and education components. The PKH program targeted poor households with pregnant and/or lactating women, children between 0-15 years, or children between 16-18 years, but who had not completed 9 years of basic education upon participation on local health and education services. The first pilot of the PKH program was conducted in 2007 and, targeted 300,000 poor households in 7 provinces (76). The targeted households received cash transfers ranging from 600,000 (US$ 21) to 2.2 million *rupiah* (US$ 232) per year, depending on the number of children in the household and children's age. Findings from the impact evaluation study of PKH (76) suggest that PKH households used the cash transfer to increase their spending in food, health and non-food expenditure, increase utilization in health services but not educational services.

In November 2014, the Indonesian government introduced a new cash transfer program, known as the Indonesian Smart Card program (*Kartu Indonesia Pintar* KIP). KIP provides cash transfers to poor families who have children between 7 and 18 years of age (27). The additional income from KIP should only be used for the purpose of children's education, for example to pay additional costs of education such as uniforms, reading materials, and the costs of transportation. Currently there is no study that has evaluated the effect of KIP on educational outcomes.

In summary, section 2.1 provides an overview of Indonesian society and related economic development. Indonesia continues to have significant economic growth, which has moved Indonesia from a lower to a middle-income country. However, the review of the literature suggests regional disparities in poverty rates, standards of living and access to education. People, who live in Java or in urban areas tend to have lower poverty rates, better standards of living and access to education services compared to the population who live outside Java or in rural areas. Several examples of policy interventions to improve access to education in Indonesia were presented.

2.2. Examining inequalities in children's cognitive and socio-emotional wellbeing

The aim of this thesis was to investigate inequalities in children's cognitive and socio-emotional wellbeing in Indonesia, and interventions that might reduce these inequalities. This review focuses on three factors that contribute to inequalities in children's cognitive and socio-emotional wellbeing including household socio-economic position (SEP), parental mental health and parenting styles. Figure 3 shows a conceptual model that represents the overall research framework. This graph shows that children's cognitive and socio-emotional wellbeing is affected by household SEP, maternal mental health and parenting styles. Household SEP may have a direct effect on children’s cognitive and socio-emotional wellbeing and an indirect effect mediated through parental mental health and parenting styles. Moreover, parental mental health may have a direct effect on children’s cognitive and socio-emotional wellbeing and indirect effect mediated through parenting styles confounded by household SEP. Finally, parenting has a direct effect on children’s cognitive and socio-emotional wellbeing, confounded by household SEP and parental mental health. Figure 3 also shows that whether a child lives in poorer SEP, has parents with poor mental health or poor parenting styles affects the likelihood of receiving intervention to improve household’s economic condition, parental mental health or parenting styles, and in turn improving children’s cognitive and socio-emotional wellbeing. Section 2.2 presents a review of the literature about the associations of household SEP, parental mental health and parenting styles with children’s cognitive and socio-emotional wellbeing.

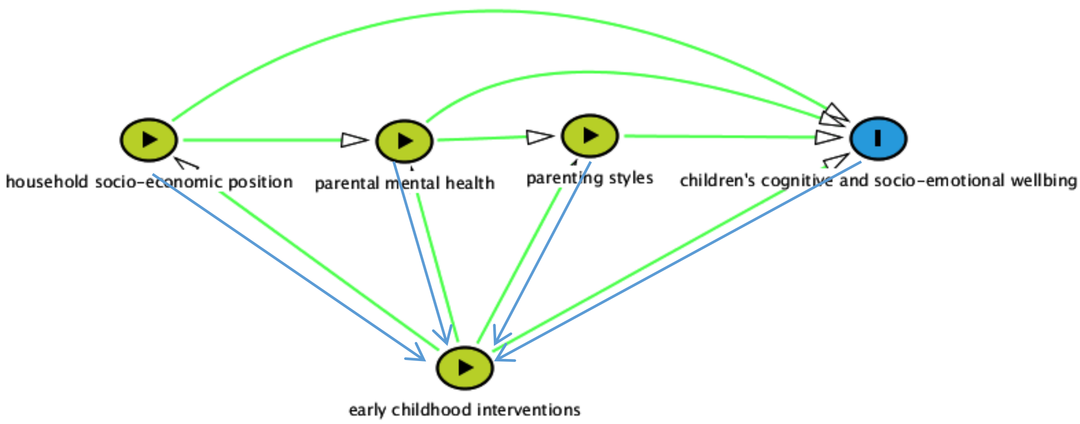

Figure 3. The conceptual model representing the overall research framework

2.2.1. Household socio-economic position

Extensive studies in high-income countries (HICs) and LMICs have examined the association of household SEP with children's cognitive and socio-emotional wellbeing. SEP is commonly used as an indicator of individual or family position based on their financial resources and/or social position in the society. There are various definitions and measures of SEP including income, expenditure, housing conditions, assets, education and occupation (77). Lower SEP is associated with lower household income or expenditure, lower parental education, and poor housing conditions, i.e. lack of access to improved sanitation and safe drinking water. Researchers have measured SEP in a number of ways, either as single or composite variables. The decision of which measure to be used in a study may rely on the context of the study and the availability of data (78-80). For example, 'income' is commonly used as a direct measure of SEP in HICs, however, in LMICs 'consumption expenditure' is preferable for both conceptual and practical reasons (81). In LMICs, many households are employed in the informal sector such as home production. In addition, many households in LMICs may have multiple sources of income, and as a result household income often fluctuates over time. Hence, use of consumption expenditure is preferred in LMICS partly because this measure is more stable than income.

In some studies, household 'standard of living' is used as a measure of SEP. This measure is useful especially when information about income or expenditure is not available (80). Household standards of living could be measured through housing conditions and household assets (82). Housing conditions may include access to drinking water supply, sanitation facilities, electricity, types of flooring, roof, wall and kitchen, cooking fuel and number of rooms in the house. Household assets may include owning a television, radio, refrigerator, vehicle and house tenure. Together these variables can be combined to provide a summary of standard of living or wealth index, which is generated using either a factor analysis or principal component analysis (80, 82).

Despite various ways to measure SEP, there is clear evidence indicating that children who live in higher SEP have better cognitive functioning (7, 83-89) and fewer socio-emotional problems (6-8, 90-92) compared to children from lower SEP. Results about the association of SEP with children's cognitive and socio-emotional wellbeing from HICs and LMICs are presented below.

Association of household SEP with children's cognitive and socio-emotional wellbeing in high income countries

Numerous studies in HICs have examined the association between household income, and children's cognitive and socio-emotional wellbeing (8, 86, 87, 92). Most studies show that higher income is associated with better cognitive function, however, the effect size is relatively small. For example, Dahl *et al.*, (86) used an instrumental variable method to estimate the association of income with children's language and math scores from an observational study in the United States (US). They found that for every US$ 1000/year increase in current income was associated with a 6% standard deviation (SD) units increase in language and math scores for children aged 8-14 years, and a larger effect was found among the lowest quartile income group (86). From a cohort study in the UK, the association of income with children's cognitive test scores ranged from 0.22 to 0.37 SD units for every £10,000 increase in the average annual family income at age 3 (8).

Studies that used a composite measure of SEP also showed similar patterns. Household income and assets were the largest contributors of inequality in reading and math assessment for children aged 3-17 years in the US (93), and associated with children's socio-emotional wellbeing in eleven European countries (90). A systematic review by Reiss *et al.,* (91) used evidence from cross sectional and longitudinal studies to examine the association of SEP (measured by household income and parental education) with internalising and externalising problems in children and adolescence. From this review, Reiss *et al.,* (91) showed that children from lower SEP were three times more likely to develop internalising and externalising problems compared to their peers from higher SEP. Reiss *et al.,* (91) also showed the association of SEP was stronger with externalising than with internalising problems, and was stronger in children aged 4-11 than in children aged 12-18 years.

Association of household SEP with children's cognitive and socio-emotional wellbeing in LMICs

Several studies from LMICs used the term 'household wealth' to define household standards of living. Wehby and McCarthy (88) used principal component analysis to generate a household wealth index based on housing conditions and assets in a sample of children in Argentina, Brazil, Chile and Ecuador. They examined the association of household wealth in the first two years of life with children's cognitive function (measured by Bayley Infant Neurodevelopmental Screener). Results showed that in all countries included in the study, children from higher wealth quintiles had higher cognitive scores after controlling for maternal age, education, and marital status, children's ethnicity and sex, and number of adults in the household. In Wehby and McCarthy's (88) study, the effect size of the association between household wealth and children's cognitive function was relatively small (ranged from 0.06 SD in Argentina to 0.15 SD in Ecuador). Another study that used data from community-randomized trials in India, Indonesia, Peru and Senegal (94) also showed similar results, suggesting that children from wealthier households had better cognitive function than their peers from poorer households. In this study (94), having a mother who completed 9 years of education or more was also associated with better cognitive function scores compared to those who had a mother who never attended formal education (effect size ranged between 0.26 and 0.48 of a SD score after controlling household wealth and other covariates).

Evidence from a nationally representative sample of poor children in poor communities In Madagascar suggested that household wealth and maternal education were associated with cognitive function and language development in children aged 3-6 years (89). In this study, children from the richest quintile group had a 0.72 SD higher receptive language (vocabulary) score compared to children from the poorest quintile, controlling for maternal education, residential area (urban-rural), household crowding (household size and number of rooms in the household), and children's sex, age and birth order. Furthermore the association of maternal education with children's receptive language score was smaller than household wealth. Children whose mothers had a secondary or higher education had a 0.39 SD higher receptive vocabulary score than children whose mothers had never received a formal education.

The following sections present evidence about the associations of parental mental health and parenting styles with children's cognitive and socio-emotional wellbeing.

2.2.2. Maternal mental health

Association of maternal mental health with children's cognitive and socio-emotional wellbeing in HICs

Studies about the associations of parental mental health and parenting with children's cognitive and socio-emotional wellbeing in HICs are well documented. Studies show children living in households with parents with poor mental health tend to have poorer cognitive and socio-emotional wellbeing (6, 7, 95-97). For example, evidence from the Millennium Cohort Study (MCS) in the UK suggested that poor maternal mental health at age 3 was associated with a 0.13 SD units increase in internalizing problems, and a 0.22 SD unit increase in externalizing problems (6). In this cohort, the association of maternal mental health with children's cognitive function was much smaller (-0.01 SD) than with socio-emotional wellbeing. A nationally representative sample in the US findings showed that the association of maternal depression with cognitive scores ranged from -0.18 to -0.42 SD for children age 13-50 months (7). Mothers who had mental health problems were more likely to have lower income, lower education, younger age, unmarried and unemployed, which are markers of economic and social disadvantage (7, 98-100).

Association of maternal mental health with children's cognitive and socio-emotional wellbeing in LMICs

Studies about the association of parental mental health with children's cognitive and socio-emotional wellbeing are often under-reported in LMICs. Women in LMICs are less likely to self-report having mental health problems and this is partly because their perception of mental health is shaped by cultural constraints such as stigma within the community (101). Although evidence from LMICs is more limited, findings from observational and RCT studies in LMICs also suggest that poor maternal mental health are associated with children's poor cognitive and socio-emotional wellbeing (102-104).

2.2.3. Parenting styles

Association of parenting styles with children's cognitive and socio-emotional wellbeing in HICs

In terms of parenting styles, positive parenting was associated with improved child temperament, lowered behavioral problems or disruptive behavior, better social emotional competence and higher language scores (8, 30). Findings from the UK showed that among children aged 3-5 years, warm parenting was associated with a 0.06 SD units increase in cognitive scores and a 0.15 SD units decrease in externalizing behavior problems, whereas punitive parenting was associated with a 0.08 SD units decreased cognitive scores (30).

Associations of parenting styles with children's cognitive and socio-emotional wellbeing in LMICs

Cultural variations in parental styles were also found in Bornstein, *et al.*, (105) study, conducted in nine countries i.e. China, Colombia, Italy, Jordan, The Philippines, Kenya, Sweden, Thailand and the US. This study found that parents from Kenya, Colombia and the Philippines were more likely to have authoritarian attitudes, whereas parents from the US, Sweden, Thailand, China and Jordan were more likely to have progressive attitudes even after controlling for parent's age, education and potential reporting bias. In terms of the characteristics, authoritarian parents demanded children to be respectful and obedient towards parents, whereas progressive parents encouraged children to think independently, and to speak their minds. A survey of 273 Indonesian parents of children aged 2-12 years reported a positive correlation between poor parenting and children's emotional and behavioral problems (106). In this study, parents who reported low levels of children's emotional and behavioral problems not only tend to have better parenting but also greater self-efficacy and less mental health problem than parents who reported high levels of children's emotional and behavioral problems.

Long term effects of household SEP, parental mental health and parenting

Longitudinal studies have showed long term effects of being exposed to poverty, having parents with poor mental health, and poor parenting ability. Children exposed to poverty in the first year of life tend to have poor cognitive (83, 107) and socio-emotional problems (107, 108) at later childhood and adolescence, and those who were exposed to longer periods of poverty had poorer outcomes compared to the children who only experienced poverty at one point in time (107). Evidence showed parental mental health (measured through depression) in the first year of life was associated with poorer children's behavioural problems at age under five (109, 110), at preschool (97) and increased the risk of depression at age 16 (111). Moreover, low maternal warmth was associated with more socio-emotional problems at younger ages and at adolescence (112, 113).

2.2.4. The relations between household SEP, parental mental health, parenting and children's cognitive and socio-emotional wellbeing

This review of the literature demonstrates consistent findings from both HIC and LMICs that children from lower SEP families tend to have poorer cognitive and socio-emotional wellbeing compared to their peers living in families from higher SEP. Household SEP such as income represents financial resources that are available in the family, and the extent to which these resources are invested in children's development (28). As outline in section 2.1.1 poor financial resources limit parental investment on children's education in Indonesia. Children from lower income families tend to have poorer development outcomes because their families were less likely to engage in cognitive stimulating activities and had fewer visits to health checks (29, 30, 92).

The relations between poverty, parental mental health and parenting are well documented, although most evidence comes from HICs. Evidence from a systematic review and cohort studies (6, 8, 30, 114, 115) suggest that the association of SEP with children's cognitive and socio-emotional wellbeing was potentially mediated by parental mental health and parenting styles. A cohort study in the UK found a direct effect of income on cognitive ability and socio-emotional wellbeing at age 9 months, 3 years and 5 years, and an indirect effect mediated through parental stress (8). Among mothers, higher income and higher education are associated with positive psychological functioning because educated mothers usually have greater self-esteem and optimism, and therefore show fewer symptoms of depression (116). In contrast, low income may affect emotional distress in parents, and reduce their capability to interact and to build healthy relationships with children (117). Parents from low income families who had poor mental health tended to be less nurturing and engaged with their children, which in turn affects poor development in children (6).

In summary, section 2.2 shows a great deal of research pointing to the importance of household and parental characteristics, parental mental health, and parenting skills on children's cognitive and socio-emotional wellbeing. The following section presents evidence from relevant policy interventions that could reduce inequalities in children's cognitive and socio-emotional wellbeing and strategies for effective implementation of these interventions.

2.3. Early childhood interventions and strategies for effective implementation of intervention

Evidence from HICs (32-35) and LMICs (19, 36, 37) indicates that effective interventions can protect children from negative consequences of living in poverty (36) and increase investment in children's health and development (1). The final section of this chapter presents several examples from relevant early childhood interventions that might reduce inequalities in children's cognitive and socio-emotional wellbeing. This review focuses on interventions that aim to enhance family investment in children, maternal mental health and parenting skills, followed by evidence about effective interventions.

2.3.1. Income supports for poor families

There is clear evidence that children from poor income families tend to have poorer cognitive ability, and higher risk of behavioural problems compared to their peers from higher income families. One of the strategies to support parental investment in children is through providing financial intervention to poor families. In HICs, financial intervention could be in the form of direct cash payments or tax benefits. A systematic review by Lucas *et al.,* (118) used evidence from RCTs and quasi-randomised trials to examine the effect of a financial intervention (through direct cash payments or tax benefit) for poor families in HICs on children's health, socio-emotional and educational outcomes. Despite strong evidence of the association between family income and children's health, socio-emotional and educational outcomes, they could not find evidence of the effect of financial interventions on the overall outcomes. Moreover, Lucas *et al.,* (118) argued that on the basis of current evidence, they could not show whether providing financial interventions are effective to reduce inequalities in children’s development outcomes in HICs.

In LMICs, providing financial intervention through conditional cash transfer (CCT) programs is widely used to help parental investment in children’s health and education, and reduce poverty in the long run (119). In general, CCT target poor households with pregnant or lactating women, and children aged 0-18 years. In CCT program, the money was transferred to households conditional upon their compliance with regular visits to health clinics, and attendance in primary or secondary school depending on the child’s age.

Evidence from the CCT program in Mexico, *Oportunidades,* suggested that children who received CCT had better nutritional status, better motor skills, higher cognitive scores, and lower socio-emotional problems (120). A study by Fernald *et al.*, (121) examined long terms effects of the *Oportunidades* on various child outcomes and showed that this program continue to have a positive effects on children’s health, cognitive and socio-emotional wellbeing even after ten years of its implementation.

Evidence from various cash transfer program in LMICs showed that cash transfer intervention had improved children’s health, cognitive functioning, schooling and socio-emotional wellbeing (37, 76, 120-124) but the effect size was small. For example, Paxson and Schady (125) examined the effect of cash transfer on children’s cognitive and socio-emotional wellbeing in Ecuador. In Ecuador, the average effect size of cash transfer program on children’s cognitive and socio-emotional wellbeing was about 5% of a SD score for an additional $15 of cash transfer (an equivalent to a 10% increase in household expenditure for the average eligible households). Another example is from Nores and Barnett (37) who conducted a meta-analysis on the benefits of early childhood interventions in LMICs particularly studies that used quasi-experimental or random assignment. In their meta-analysis, Nores and Barnett (37) reported the average Cohen *d* effect size of cash transfer programs on children's cognitive function ranged between 0.08 and 0.30, whereas the effect of cash transfer on socio-emotional wellbeing ranged between 0.10 and 0.39.

2.3.2. Improving household standards of living

As shown in section 2.2.1 housing conditions are commonly used as an indicator of household standards of living in LMICs. Many poor children in LMICs including Indonesia are exposed to poor housing conditions including lack of access to clean water and improved sanitation, which effects their health and development (18, 19, 21). Children living in poor housing conditions tend to have poorer cognitive function (88, 94), less likely to be able to read paragraphs (126) and lower levels of education (127) compared to their peers who live in better housing conditions. There is a growing recognition by international organisations that improving daily living conditions is one of the key recommendations to reduce inequalities in children's healthy development (1, 2, 128). One of the strategies to improve housing conditions is through provision of clean water and sanitation intervention for the poorest population.

Nowadays, providing water and sanitation interventions could be more relevant for the poorest population living in LMICs than for those living in HICs. However, the benefits of water and sanitation intervention in HICs have been recorded since the early 19th century. For example, two studies from the US showed that water and sanitation intervention between 1880 and 1915 contributed to a 35% reduction in infant mortality rate (129), whereas provision of public water and sewage system between 1900 and 1940 reduced mortality by 20%.

Cochrane Database of Systematic Reviews showed extensive evidence about the benefits of water and sanitation intervention on children's health including better nutritional status (130) and a reduction in diarrhoea (131) but little is known about the effect of this intervention on children's cognitive and socio-emotional wellbeing. Recent evidence from the Total Sanitation Campaign (TSC) in rural India suggested that every improved sanitation built in the community at age 1 was associated with a 0.75 SD increased in the mean literacy scores at age 6 and similar effect size for the math score (126).

The effect of water and sanitation interventions on children's cognitive function is potentially mediated through children's health status. Poor sanitation and hygiene is associated with higher prevalence of diarrhoea and infectious diseases, which links to the children's nutritional status, and in turn affects their poor cognitive functioning and reduced years of schooling (17, 18). Studies showed providing water and sanitation interventions promoted better overall health, eliminated diarrhoea and typhoid, improved immune system function to fight disease due to poor sanitation (130-132). Moreover, providing water and sanitation in the household may also reduce stress (132) and less time to travel to get water or use communal sanitation facilities (133).

2.3.3. Maternal mental health and parenting interventions

As outlined in section 2.2.4 evidence shows that poverty is often associated with poor mental health status. Using data from RCT, non-randomized intervention and cohort studies in LMICs Lundt, *et al.,* (134) conducted two systematic reviews to examined the effect of poverty alleviation interventions on individual and family or caregiver mental health status and vice versa. In the first review they identified poverty alleviation programs that focused on providing financial support including cash transfer, microfinance, loans, social insurance, debt management and financial services. Results show that only interventions to provide cash transfer and accumulation of assets in the family had a greater effect to reduce mental health problems compared to other financial interventions. The second part of the systematic review examined the effect of mental health interventions on economic outcomes such as employment status. In the second review, they identified a wide range of mental health interventions including personal, community-based rehabilitation program, preventive program, medication and some of their combination. Results show that all mental health interventions were associated with improved household economic conditions.

Based on a systematic review of evidence from RCT and observational studies (135) mental health interventions for parents also had benefits for children. Parents who received mental health intervention had fewer children with or suffering from internalising and externalising problems and learning difficulties (135). Moreover, evidence from systematic reviews suggests that parenting interventions in HICs and LMICS have several benefits for both families and their children including reduced family stress and maternal ill health (136), and improved women’s perception for existing social support (137), reduced harsh or abusive parenting and increased parenting practices (138-140), improved home learning environment (137), more visits to library (32), improved children’s overall health, higher immunization rates, better infant feeding patterns, better fine motor skills and cognitive functioning (32, 140), and better socio-emotional wellbeing (140).

2.3.4. Strategies for effective implementation of interventions

Timing for intervention

A review of the literature showed that the association of household SEP with children's cognitive and socio-emotional wellbeing are stronger in younger children (37, 114, 141, 142), suggesting that early childhood interventions may have greater effect than intervention in later childhood (19, 37). In HICs research in neuroscience (38) and economics (33) support the argument that early childhood intervention yields better results than intervention in later childhood. In terms of cost-effectiveness, Doyle *et al.*, (33) provide a summary of benefit for investing in early childhood based on the rates of return in human capital investment (Figure 4). As shown in figure 4, assuming the costs of interventions are held constant across all ages, early years interventions would yield the highest rates of return. Rates of return can be defined as economic benefits in the form of individual's earnings, higher education, better physical and mental health, whereas at community level the rates of return of early intervention may include higher government savings and revenues from taxes, as well as reduce crime and delinquency (33, 35). In terms of benefit-cost ratios, an example from a meta-analysis of early childhood interventions in the US estimated that using a 3% of annual discount rate, every dollar invested in children had benefit of about USD 1.27 to USD 17.7 for society (35). The largest benefit was associated with programs that had long term follow up (35) and followed by late investment (39).

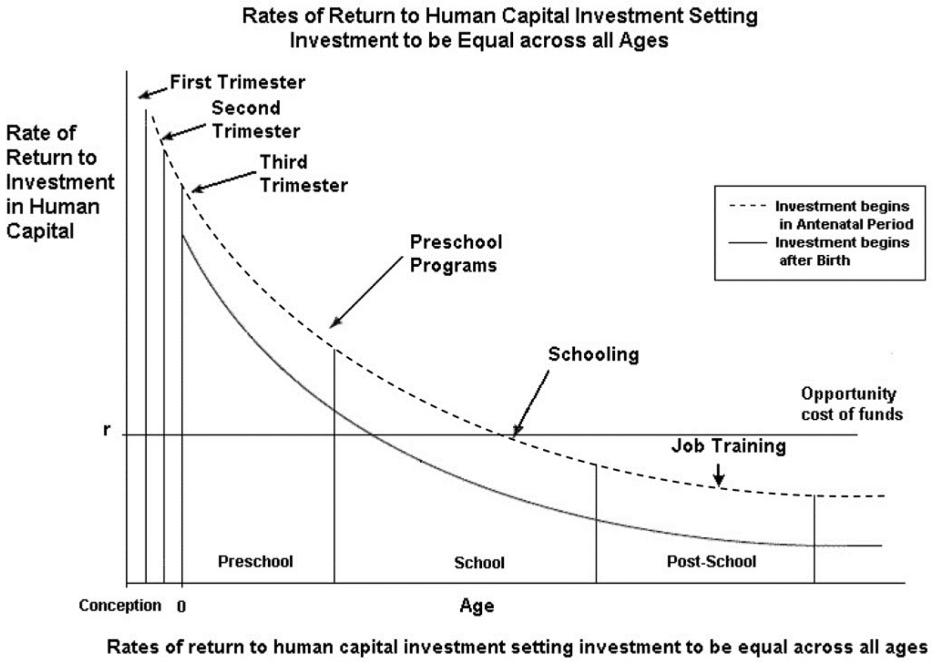

Figure 4. Rates of return to human capital investment (Source; Doyle et al. 2000)

Coverage of intervention

Effectiveness of early childhood intervention could also be influenced by the interventional approaches and coverage of the program. A universal approach may reduce inequalities in early childhood development by providing equal access to all social groups in a defined population (1). A meta-analysis in HICs and LMICs suggested that provision of universal interventions on education had greater effect for improving children's cognitive outcome than targeted interventions (37). Although universal intervention is costly, some would argue that the benefit is greater than the cost (32, 143).

In contrast, targeted interventions were more effective to improve children's socio-emotional wellbeing (37), maternal mental health (144) and parenting skills (137, 139, 140). Evidence from RCTs about parenting interventions in HICs suggested that an intervention targeted young and unmarried mothers from low socioeconomic position is the most effective to improve parenting skills and in turn affect healthier children's developmental outcomes (137, 139, 140). Despite the advantage, targeted intervention may limit participation and create stigma among people who were targeted for an intervention (32). Universal approaches may be costly but reach a much larger population and remove stigma associated with targeted programs (32, 143).

Evidence from HICs and LMICs also showed that provision of intervention that had a mixed component early childhood program may yield greater benefit to improve children's cognitive function than a single intervention. For example, in Nores and Barnett meta-analysis of quasi-experiments and RCTs (37) the average effect size of cash transfer programs on children's cognition was 0.17 (SD 0.06), whereas the average effect size of intervention that combined cash transfer, nutrition and an educational program was 0.35 (SD 0.22). Finally, evidence about effective implementation of parenting intervention is also found in HICs and LMICs. Studies showed that the most effective parenting intervention was characterized by a program that combined home visits, clinic care and educational program for both parents and children, workshops or public health campaign or mass media education and (32, 137, 140, 145), and focused on specific behavioural change including promoting positive mother-child relationships (32, 36, 140).

2.4. Conclusions

There is evidence to show that inequalities in children's cognitive and socio-emotional wellbeing are influenced by a range of household and parental characteristics including household SEP, parental mental health status and parenting styles. Interventions that provide support for family investment in children, improve housing conditions, enhance maternal mental health and parenting skills may improve children's cognitive and socio-emotional wellbeing. In order to have greater benefit, the intervention should be conducted at early ages (e.g. under seven) and have multiple components of intervention such as cash transfer, nutrition and an educational program.

This research will seek to identify the magnitude of, and contributors to socioeconomic inequality experienced by children in Indonesia. We then investigate the mediating effect of early vs late poverty on cognitive function, and the simulated effect of different types of interventions designed to improve cognitive function and socio-emotional wellbeing. These studies extend previous work by providing context specific evidence that can contribute to the implementation of evidence based interventions, to improve child health and development in Indonesia.

CHAPTER 3

Methods

The overall aim of this thesis is to investigate inequalities in cognitive function and socio-emotional well-being among Indonesian children, and how early childhood interventions might reduce these inequalities. Four studies were conducted to address this overall aim. This chapter provides an overview of data used in this thesis, the measures, the methodological and the statistical approaches in each study including how to address the uncertainties due to missing data and unmeasured confounding.

3.1. Data sources

3.1.1. The Indonesian Family Life Survey

The first data source used in this thesis was the Indonesian Family Life Survey (IFLS). IFLS is an ongoing longitudinal survey, which was first conducted in 1993 and subsequently in 1997, 2000 and 2007 (146-149). In 1993, 13 of the 27 provinces were selected purposively due to logistical reasons but to still maximize representation of the population, and capture the cultural and socioeconomic diversity. These provinces spread across Indonesia including the islands of Sumatera, Java, Bali, West Nusa Tenggara, Kalimantan and Sulawesi (Figure 5). The sampling scheme was stratified on provinces and urban rural areas, where within each province the enumeration area was selected randomly. In IFLS1 over 7000 households and 22,000 individuals were interviewed. This sample was considered to be representative of 83% of the Indonesian population (146). In the most current data collection (IFLS4), over 13,000 households and 44,000 individuals were interviewed.

Figure 5. The Indonesian Family Life Survey enumeration areas

IFLS had relatively high re-contact rates in the follow up survey (94%, 95% and 94% for IFLS2, 3, and 4 respectively) (149). In IFLS, respondents who moved from the enumeration area or from the original household were tracked as long as they lived within or close to the sampling areas and still be cost effective. IFLS provided extensive information about socioeconomic, behaviour and health related outcomes at household and individual levels, as well as information about public facilities at the community level. IFLS data and documentation are available for public and can be downloaded from the RAND website (http://www.rand.org/labor/FLS/IFLS.html).

In this thesis IFLS was used in studies 1-3. This thesis used information that was collected at the individual and household levels. In study 1, the study participants consisted of two cohorts who were recruited for cognitive testing, comprising children aged 7-14 in 2000 (born between 1993 and 1986) and children aged 7-14 in 2007 (born between 2000 and 1993). In study 2, the participants consisted of children aged 7-14 in 2000 who were contacted for cognitive testing in 2000 (cohort 1) and followed in 2007. Lastly, in study 3, the participant included children aged 7-14 who were recruited for cognitive testing in 2007 (cohort 2).

3.1.2. The Early Childhood Education and Development (ECED)

The ECED data was used in study 4, which investigated the relative and combined effect of different hypothetical interventions on children's school readiness and socio-emotional wellbeing. Study 4 used information that was collected at the individual (children and caregiver) as well as household levels and was analysed as a cohort study of children aged 4 in 2009 and followed up at ages 5 and 8.

Background to ECED Study

There is a growing awareness about the importance of early childhood education and development (ECED) programs in Indonesia (150), however, access to ECED services remains very low and are more concentrated in urban areas and rich districts. Estimates from the World Development Indicators 2006 suggest that the total ECED participation rate among children ages 3-6 years in Indonesia was 18%, which is lower than the global average in low income countries (27%) (22). To provide greater access to ECED services in the country, between 2006 and 2012 the Indonesian government through the Ministry of National Education and Culture (formerly the Ministry of National Education MoNE) implemented a community based ECED project, which aimed to improve children's development and readiness for transition to formal education (26).

This project was financed through multiple sources including the World Bank, the government of the Netherlands and the Indonesian government with a total cost of US$ 127.7 million. The ECED project targeted about 738,000 children ages 0-6 years and their primary caregivers living in 3000 villages within 50 poor districts that were selected based on low participation rates in ECED services, high poverty rates, and commitment to developing, managing and financing the ECED project in their area. Within each district, 60 villages were selected based on high numbers of children aged

0-6 years, had high poverty rates and had shown interest in the ECED project. In each district, the project was implemented in three waves with 20 new villages receiving the program per implementation wave, each nine months apart.

The Indonesian government also received technical support from the World Bank to conduct a cluster randomized controlled trial (RCT) to evaluate the impact of the ECED project on children's developmental outcomes and factors that contribute to the effectiveness of the program (26). The RCT also aimed to increase awareness and generate discussion among policy makers and the general public about the importance of ECED and effective implementation to improve ECED programs. Evidence from this project may then be used to scale up the coverage of ECED services for poor children in Indonesia (26). After the implementation of the ECED project, in late 2013 the Indonesian government initiated a national program "*Satu Desa Satu PAUD*" (one village one ECED centre) to provide greater access to ECED services especially in rural areas. This could be evidence that scaling up ECED interventions in the country is already in progress.

For the RCT, the Indonesian government selected 10 out of 50 districts based on their willingness to randomize villages into the implementation waves and still represent geographic diversity. The randomization did not take place at the district level because many districts had already allocated villages to a particular wave. Prior to the first data collection in 2009, one district was dropped from the study due to non-compliance. The final sample in the RCT consisted of 310 villages in 9 districts including Sarolangun, North Bengkulu, East Lampung, Majalengka, Rembang, Kulon Progo, Sidenreng Rappang (Sidrap), Ketapang and Middle Lombok (Figure 6).

Figure 6. The Early Childhood Education and Development enumeration areas

The ECED study comprised cohorts aged 1 and 4 in 2009 with follow up in 2010 and 2013. Additionally, the study also collected information at the household and community levels. At the follow up in 2010, 99% of children were successfully recontacted. The reason the ECED project had high recontact rates was partly because children who moved to another village were tracked as long as they lived within the study sample (26). For this thesis, access to ECED data was obtained through the World Bank.

3.2. Measures

The following section describes the various measures used in the thesis.

3.2.1. Outcomes

Raven Progressive Matrices – Cognitive Ability

The Raven’s Progressive Matrices (RPM) was used as a measure of cognitive function or general intelligence (151). The RPM was available in IFLS collected from children aged 7-14 in 2000 and aged 7-14 in 2007. Children who took the test in 2000 were interviewed again in 2007 when they were 14-22 years. In IFLS, the questions were reduced in number due to logistical constraints. The test comprised 12 shapes with a missing part where children selected the correct part to complete the shape (Figure 7). Each correct answer was coded 1 or 0 otherwise and scores combined as the total raw scores. The total raw scores increased with age and had skewed distributions towards the left tail. The total raw scores were then transformed into an age-specific z-score. Because the total scores were skewed, the mean and the variance of score distributions were calculated by taking into account the range, median and the sample size using the formula from Hozo, *et al.,* (152) and used the estimated mean and standard deviation to create an age specific z-score. The RPM was used as the cognitive function outcome in studies 1-3.

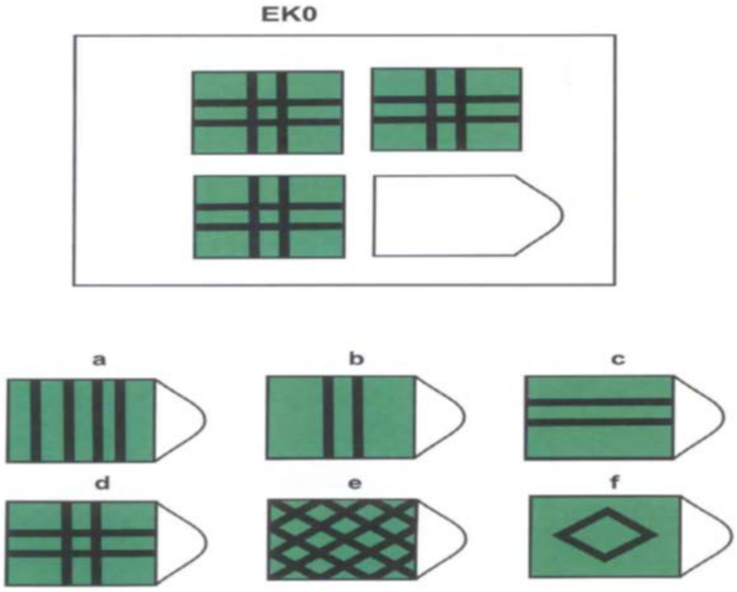

Figure 7. Example of item in Raven Progressive Matrices as appeared in IFLS questionnaire

Early Development Instrument (EDI)

The Early Development Instrument (EDI) was used as a measure of school readiness and comprised five major developmental domains including physical health and well-being, social competence, emotional maturity, language and cognitive development, as well as communication skills and general knowledge (153, 154). For each domain the score ranged from 0 to 10, where a higher score indicated better outcomes. A child whose score was in the lowest 10% in each domain was classified as developmentally vulnerable in that specific domain (coded as 1 or 0 otherwise). The scores were summed to define whether a child was developmentally vulnerable in one or more domains (coded as 1 or 0 otherwise). The EDI was available in ECED collected on children aged 4 in 2009 and follow up at ages 5 and 8.

Strengths and Difficulties Questionnaire (SDQ)

The Strengths and Difficulties Questionnaire (SDQ) was used as a measure of children's socio-emotional wellbeing (155). The SDQ comprises five subscales including emotional symptoms, conduct problems, hyperactivity/inattention, peer relation problem and prosocial behaviour. For each subscale the score ranged from 0 to 10. With the exception of prosocial behavior, higher scores in emotional symptoms, conduct problems, hyperactivity/inattention and peer problems indicated poorer behavioural outcomes. The scores of emotional and peer problems subscales were combined to define internalising behaviour, whereas the scores of conduct problems and hyperactivity/inattention subscales were combined to define externalising behaviour. According to Goodman, *et al.*, (156) use of internalising and externalising problems subscales is more appropriate in epidemiological studies and to define children's behavioural problems in low risk populations. The SDQ was available in ECED collected on children aged 4 and follow up at ages 5 and 8.

Both the EDI and the SDQ were used as the outcomes in study 4. This analysis only used the EDI and the SDQ that were measured at age 8 based on caregiver's report.

3.2.2. Exposures

Household expenditures

Household per capita expenditure (PCE) was used as an indicator of relative socioeconomic position and resources for parental investment in children. Information about household PCE was only available in IFLS. Household PCE was constructed by summing the monthly total household food and non-food expenditures divided by the number of household members (157). This variable was used in continuous form, where higher PCE indicated higher socioeconomic position and the potential for more financial resources invested in children. This thesis used information about household PCE that was collected in 2000 and 2007. Household PCE collected in 2000 and 2007 was used as the exposure in studies 1 and 2. Additionally, a new variable was constructed to define poverty status based on the distribution of household PCE in the population. Following the World Bank and WHO proposition, the poorest 40% of the population was considered as in “poverty” for the purpose of determining access to universal health coverage (158). Herein, poor households were defined as those living in the bottom 40% of PCE (coded as 1 or 0 otherwise). Poverty status was used to identify the target population for cash transfer intervention (study 2) and children who lived in poverty (study 3). Moreover, in study 3, poverty status in 2000 (children ages 0-7 years) was defined as the exposure and poverty status in 2007 (children ages 7-14 years) was defined as the mediator.

In study 4, three exposures that affect children’s school readiness and socio-emotional wellbeing were identified based on the literature review in chapter 2, the availability of data in the ECED study and feasibility of intervention. These exposures included household standards of living (126, 129), maternal mental health (6, 145) and parenting styles (32, 36, 138, 140, 159).

Household standards of living

Household standards of living is commonly used as a measure of economic status and is useful especially when information about income or consumption expenditure is not available in the data (80). Herein, a household standard of living was measured using two indicators including access to improved drinking water source and sanitation. Access to improved drinking water source was measured through whether the child lived in a household that used piped water as the main drinking water source (coded as 1 and 0 otherwise), whereas access to improved sanitation was measured through whether the child lived in a household that owned a private toilet connected to septic tank (coded as 1 and 0 otherwise).

Maternal mental health intervention

Maternal mental health was measured using Kessler 10 (K10) (160), which is a self-reported questionnaire that was designed to measure non-specific psychological distress. K10 comprises 10 items of feelings of anxiety and depression in the past four weeks and their frequency. Each response item was reported on a 3-point scale where the score ranges from 1 “never”, 3”sometimes” and 5”often”. All the 10 items were combined to generate a total mental health score, where higher score is associated with poorer mental health (scores ranging 10-50).

Parenting styles

Parenting styles was measured using 24 items describing parent-child relationships such as warmth, consistency and hostility. This measure was adapted from the Longitudinal Study of Australian Children (LSAC) study (161). For each item, the response was reported on a 5-point scale, which ranges from never to always. All 23 items were combined to generate a total parenting score, where higher score indicated better parenting styles. This variable was used in continuous form (scores ranging 23-115).

3.2.3. Covariates

A series of covariates were selected *a priori* as potential confounding based on the literature review in chapter 2.

Child characteristics

Child characteristics included age, gender, and education (30, 56, 151). Age was reported in years and was used in continuous form. Gender was coded as 1 for male and 0 for female. Child's education was measured using two indicators. For children aged 7-14, education was measured as whether the child was currently attending school. For those children who were interviewed at follow up (aged 14-22), education was measured as whether the child completed at least 8 years of education.

Parent characteristics

Parent characteristics were measured separately for mother and father including education (30, 83, 90, 162, 163), employment status (164) and mental health (6, 95, 141, 165). In IFLS, education was measured as the highest level of education attended, (categorized as none, primary school, junior high school, senior high school and diploma/university degree). In ECED, education was measured as the highest education completed (categorized as none or not completed primary school, primary school, junior high school, senior high school and diploma/university). Employment status was measured as whether parent was working in the past week.

Mental health was also measured in IFLS3 and 4. In IFLS3, the measure consisted of eight items of feelings experienced in the past 4 weeks, with responses in three categories ranging from never to often. In IFLS4, the measure was adapted from the shorter version of the Centre for Epidemiological Studies-Depression scales (CES-D) (166) consisting of

10 items of symptoms or feelings experienced in the past week, with responses in five categories ranging from not at all, rarely (<=1 day), some days (1–2 days), occasionally (3–4 days) and most of the time (5–7 days). For both measures, each item was scored from 0 to 3 and summed as the total mental health score separately for 2000 (scores ranging 0–24) and 2007 (scores ranging 0–30) (167-169). The variable was used in continuous form, where a higher score indicated poorer mental health. Last, maternal age (30, 83, 108) was reported in years and used in continuous form.

Household characteristics

Household characteristics included household size (continuous) (30), the number of self-reported economic hardships experienced by household (continuous) (102), residential area (categorized as urban or rural and Java/Bali or otherwise) (30), housing conditions and assets (23, 88, 126, 162, 163). Housing conditions were measured as whether the household had electricity, used piped or pumped well as the main drinking water source, and improved sanitation (defined as a toilet that was connected to a septic tank).

In study 4, factor analysis (170, 171) was used to construct a standard of living index based on housing conditions and household assets. Housing conditions included whether the household had electricity, separate kitchen, used non-earth floor, and type of cooking fuel (used wood, kerosene or gas/electricity). Household assets included whether the household had telephone, radio, television, refrigerator, bike, motorcycle and car. The standards of living index was estimated as the sum of the variables weighted by the elements of the first eigenvector, which was the first linear combination of the variables. The total score was then classified into quintiles, which ranged from the poorest (quintile 1) to the richest (quintile 5).

3.3. Methodological Approach and Statistical Analysis

The following section describes the various methodological and statistical approaches used in the four studies presented in the thesis. This section also discusses methods used to address missing data and unmeasured confounding.

3.3.1. Study 1: measuring inequality in children's cognitive function

Study 1 aimed to address the following questions, (1) what is the magnitude of socioeconomic inequality among Indonesian children's cognitive function in 2000 and 2007; (2) what factors contribute to the inequality; (3) does the inequality in children's cognitive function change between 2000 and 2007 and what factors contribute to the change in inequality? In study 1, measuring inequality in socioeconomic position is of more interest because it has a broader concept than poverty. Poverty is defined by comparing individual's income or expenditure with some defined threshold in the population. For example, individuals whose expenditure is below a certain poverty line are classified as being poor. In contrast, inequality focuses on the distribution of expenditure across the whole population (from the poorest to the riches) rather than only focus on the poor (71).

In study 1, data from IFLS was used. The study participants were children aged 7-14 in 2000 and aged 7-14 in 2007. The Relative Concentration Index (RCI) (81, 172, 173) was used to estimate the magnitude of relative socioeconomic inequality in child's cognitive function. This method has advantages; first the RCI estimates the magnitude of inequality across all levels of socioeconomic position in the population (from the poorest to the richest) rather than compares inequality between two groups, e.g., poor versus non-poor. Second, the RCI can be decomposed into factors that contribute to the inequality.

Concentration curve

The RCI is derived from a concentration curve, which gives a graphical illustration of the magnitude of inequality (Figure 8). The concentration curve is drawn by comparing the cumulative percent of people ranked by their relative socioeconomic position for example income or expenditure (*x*-axis) from the poorest (left hand side) to the richest (right hand side), against the cumulative percent of the outcome *Y* (*y*-axis) – in this case children's cognitive function. The diagonal line is defined as the line of equality.

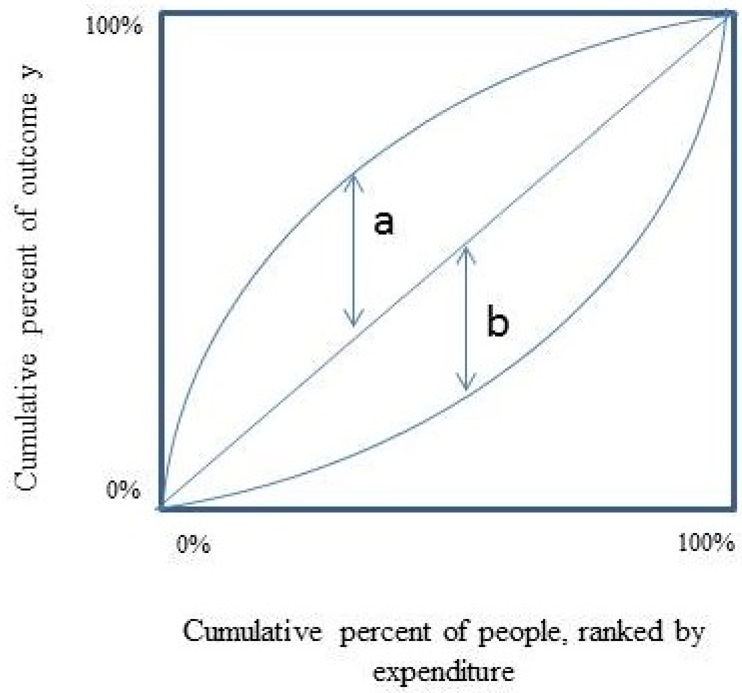

Figure 8. Concentration curve

The upper (a) and lower (b) curve indicates that inequality exists in the population. Equality exists when the outcome *Y* is distributed proportionately across the socioeconomic groups, for example when ranked by household expenditure 20 percent of children with lower outcome scores live in the poorest 20th percent of households. In contrast, inequality exists when there is a disproportionate distribution of people with lower or higher scores across socioeconomic groups, for example, where 35 percent of children with poorer cognitive function scores live among the poorest 20% of household PCE. The magnitude of inequality is shown as the distance between the line of equality (the diagonal) and the curve (a or b). The farther the curve is from the line of equality, the bigger the magnitude of inequality. If the outcome variable indicates a poor outcome, for example malnutrition, then the inequality is shown by the curve that lies above the diagonal line (curve a in Figure 8) indicating higher malnutrition rates are concentrated among the poorer socioeconomic groups. On the other hand, if the outcome variable indicates a positive outcome, for example cognitive function scores then the curve lies below the diagonal (curve b) indicating children with poorer cognitive function scores are concentrated among the poorer socioeconomic groups.

The Relative Concentration Index

The RCI was used to estimate the magnitude of inequality, and is defined as twice the area between the line of equality and the curve. A value of zero in the RCI indicates there is no inequality. The RCI values are commonly bounded between -1 and +1, however, if the outcome is a dichotomous, the bounds depend on the mean of the outcome ($\mu - 1$ for the lower and $1 - \mu$ for the upper bound) (174). If the outcome variable takes negative as well as positive values, the RCI is not bounded. The RCI (172) can be defined as

Equation 1. Relative Concentration Index

$$RCI = \frac{2}{n\mu}\sum_{i=1}^{n} y_i R_i - 1$$

Where μ is the mean of the outcome y (cognitive function score), and R_i is the relative rank of the *ith* person in the socioeconomic distribution (household PCE). Delta method was used to estimate the standard error, followed by the 95% confidence interval (CI) estimation (81).

Decomposition of the RCI

The RCI can be decomposed into factors that contribute to the inequality. Suppose that the outcome Y is a continuous score with a set of k contributors (x_1, …x_k), then equation 2 shows the statistical model to estimate the association between a set of k contributors and outcome Y including child's gender, current's school attendance, parental education, employment status, mental health scores, housing conditions (access to improved drinking water, improved sanitation, and electricity) and residential areas (living in urban or rural areas, and Java/Bali or otherwise).

Equation 2. Linear regression model

$$Y_i = \alpha + \sum_{k} \beta_k x_{ik} + \varepsilon_i$$

Let β_k equal the coefficients of k contributors and ε_i is an error term, obtained from equation 2, and then for decomposition analysis the RCI is estimated as the sum of relative concentration index of the contributors weighted by the elasticity (η_k) of y with respect to each contributor (equation 3).

Equation 3. Decomposition of the concentration index

$$RCI = \sum_k \eta_k C_k + GC_\varepsilon / \mu$$

$$\text{Where } \eta_k = \frac{\beta_k \bar{x}_k}{\mu}$$

Where β_k is the estimated coefficient of k^{th} contributor, $\bar{x}_k$ is the mean of k^{th} contributor, μ is the mean of outcome y, C_k is the concentration index for each of the k^{th} contributor and GC_ε is the generalized concentration index for the error term. In other words, GC_ε is the unexplained residual or unknown contributors to the concentration index. For each k^{th} contributor, decomposition of the RCI provides information on the magnitude of the association between k^{th} contributor and the outcome, the elasticity, the RCI, its contribution and the percent contribution to the overall inequality. Elasticity (η_k) is a unit free measure of “responsiveness” of change in y as a response to the change in the k^{th} contributor. In order to have a large contribution to the total inequality, a factor should have either large elasticity or large relative concentration index (C_k) or both. For decomposition of RCI, the 95% CI was estimated using Gibb’s re-sampling method of Markov Chain Monte Carlo (MCMC) simulation (175). This was chosen over bootstrap methods because it allows use of the survey weights without requiring any additional computational complexity. The 95% confidence interval was calculated using the equal tail method, where the interval runs from 2.5th percentile and 97.5th percentile of the posterior distributions (176).

Oaxaca-type decomposition

Oaxaca-type decomposition was used to decompose factors contributing to the change in inequality (81, 177). As in equation 4, the Oaxaca-type decomposition is defined as

Equation 4. Oaxaca-type decomposition of change

$$\Delta C = \sum_k \eta_{kt}(C_{kt} - C_{kt-1}) + \sum_k C_{kt-1}(\eta_{kt} - \eta_{kt-1}) + \Delta(GC_{\varepsilon t} / \mu_t)$$

Where η_{kt} and η_{kt-1} is the elasticity of k^{th} contributor at time *t* and *t-1* respectively, C_{kt} and C_{kt-1} is the concentration index of k^{th} contributor at time *t* and *t-1*, respectively, $GC_{\varepsilon k}$ is the concentration index for the error term at time *t* and μ_t is the mean of *y* at time *t*.

Missing data

Missing data is common in observational studies. In longitudinal studies, missing data could be in the form of attrition or loss to follow up, and non-response to an item where an individual cannot be contacted during data collection, refusal and for other unknown reasons. One of the methods to address the problem with missing values is multiple imputation (178). In study 1, Multiple Imputation by Chained Equation (MICE) procedure was performed to minimize bias due to attrition and missing responses to questions under the assumption that the imputed data were missing at random (179, 180).

The steps in conducting multiple imputation are as follows.

- First, generate *m* complete dataset using a specified imputation model. This process is conducted by running a series of sequential regression models for each variable with missing data conditional upon other variables in the data. Each variable is modelled according to its distribution, for example logistic regression was used to model binary variables, linear regression was used to model continuous variables and multinomial logistic regression was used to model categorical variables. The process was repeated fifty times (cycles) to generate one imputed data set. Van Buuren defined this process as regression switching (180). In the analysis, a total of twenty imputed datasets was generated using fifty cycles of regression switching.
- Second, perform analysis in each separate *m* dataset.
- Finally, combine and analyse the result from imputed dataset using Rubin's rule (181).

An extension of this method of imputation is known as 'multiple imputation then deletion' (MID) of the imputed outcome. This method was introduced Von Hippel (182), who argued that using imputed outcomes will not provide additional information to the imputation model and may bring noises to the estimates. For that reason, imputed outcomes should not be included in the final analysis. Subsequent to our first study being published this approach has been questioned in statistical literature (183).

In study 1, both MICE and MID were used for estimating the RCI. However, for both decomposition analyses, analysis was restricted to the complete case sample. This is because there is no current method available to combine estimates from decomposition analysis using Rubin's rule. Findings from study 1 are presented in chapter 4.

3.3.2. Studies 2-4: using observational longitudinal data to aid causal interpretation

This thesis used data from longitudinal observational studies wherein data were collected at multiple time points. This thesis took advantage of having repeated measures in the data in a number of ways. First, the change in inequality in children's cognitive function between 2000 and 2007 (study 1) was estimated. Second, the cumulative effect of time varying exposures (study 2) was estimated. Third, the effect of time specific exposure (study 2 and 3) and finally, the effect of hypothetical interventions at ages 4, 5, and 8 on children's school readiness and socio-emotional wellbeing at age 8 (study 4) was estimated. The following section provides graphical illustrations of data structures commonly presented in longitudinal studies.

Directed Acyclic Graphs (DAGs)

Directed acyclic graphs (DAGs) provide graphical representations of data structure and show the hypothesized causal relationships between variables of interest (184, 185). All causal diagrams presented in this thesis were drawn using DAGitty 2.0, a computer based program recently developed by Textor *et al.*, (186), for drawing and analysing causal diagrams. This section starts with a simple DAG followed by more complex data structures, which may affect the statistical methods used in the analysis.

Figure 5 is an example of a causal diagram, which represents the association between confounder, exposure and outcome in longitudinal studies. Let t be the time variable representing the period of data collection, C be the confounder, X be the exposure and Y be the outcome. This implies that each variable C, X and Y in figure 5 is measured at a different time point. Suppose that the parameter of interest is exposure X measured at t_1 and the causal effect to be estimated is the effect of X on an outcome Y measured at t_2, wherein variable C at t_0 confounds the association between X and Y. Conventional regression analysis is one of the methods commonly use to estimate this association. In conventional regression, the outcome is regressed on the exposure adjusting for all other covariates in the model (C). Figure 9 shows a simple version of a causal diagram which is commonly found in longitudinal studies. The following section will explain how the causal graph can be extended for more complex longitudinal analysis.

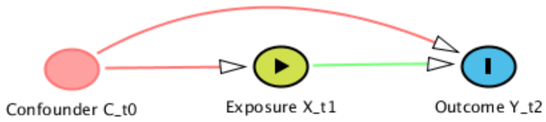

Figure 9. Causal diagram representing the association between confounder, exposure and outcome, where each variable is measured at a different time point

Time varying exposure

In longitudinal studies data are collected at multiple time points, which brings both potential advantages and complexities to the analysis. For simplicity, suppose that both exposure and outcome are measured at two time points then the causal diagram in figure 9 can be extended as follow.

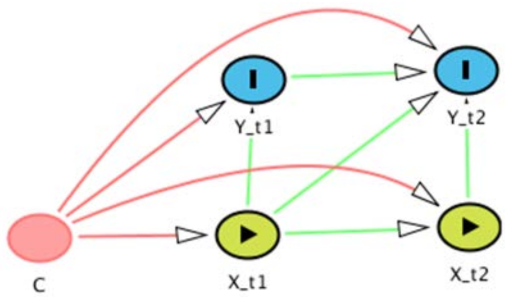

Figure 10. Causal diagram representing the association between confounder, time-varying exposure and outcome

Figure 10 shows that both exposures and outcomes are time varying, where covariate *C* is the confounder. Suppose that the parameters of interest are $X_{\_t1}$ and $X_{\_t2}$, then conventional regression analysis, such as generalized equation estimation (GEE), might be used to estimate the effect of *X* on *Y*. In a scenario where all information about time varying confounding (L_t) is also collected in the study, then the data structure in figure 10 can be extended as follows.

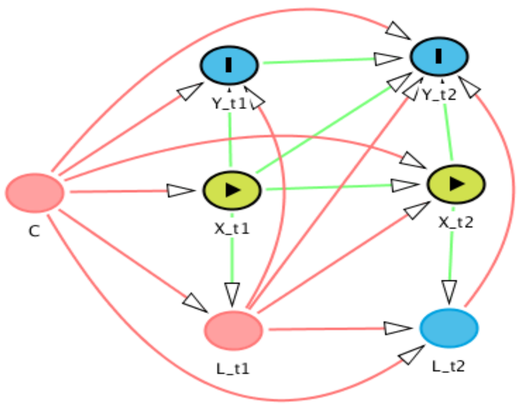

Figure 11. Causal diagram representing the association between time-varying exposure, confounding and outcome

Figure 11 shows that the data structure is now more complex with the need to account for all time varying confounding, exposures and outcomes. Figure 12 has the same data structure as Figure 11 with an additional black circle to indicate the parameter of interest in the analysis. A caveat in using conventional regression to estimate the effect of time varying exposures on outcome in longitudinal studies is when the covariate that was affected by prior exposure also predicts the subsequent exposure and outcome (187-190). Herein, covariate L is considered as time dependent (or time varying) confounding because it affects subsequent exposure ($X_{\_t2}$) and outcome ($Y_{\_t2}$). In the presence of time varying confounding, conventional regression analysis would introduce bias whether or not L is adjusted in the model. Intuitively, L should be included in the analysis because it confounds the association between the exposure and the outcome, however, adjusting $L_{\_t1}$ would block the path from exposure ($X_{\_t1}$) to outcome ($Y_{\_t2}$) and opens the potential backdoor path other than $X_{\_t1}$ - $L_{\_t1}$ - $Y_{\_t2}$. In this case, using conventional regression adjusting for time-varying confounding may lead to "collider stratification bias" and does not have a clear causal interpretation (184, 191).

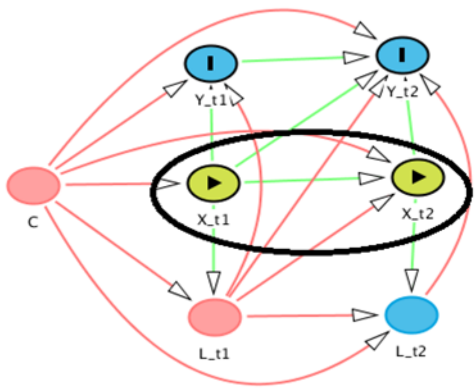

Figure 12. Causal diagram for estimating the cumulative effect of exposure (X_{t1} and X_{t2}) in the presence of time-varying confounding and outcome

Methods that can be used to aid causal interpretation from complex longitudinal observational studies include g-formula (187, 188, 192), g-estimation of the structural nested models (SNMs) (189) and marginal structural models (MSMs) (189, 190, 193, 194). These are collectively known as “g-methods” or the generalization of standardization for time varying exposures and confounders. The g-formula can be used to estimate the potential outcome of *Y* by simulating the joint distributions of exposure *X*, confounding *L* and outcome *Y*. Whilst g-estimation of the structural nested model also uses simulation models of *X*, *L* and *Y*, the potential outcome is estimated under the assumption that the effect of exposure varies for different levels of confounding, in other words there is effect measure modification by *L*. Finally, MSMs use the inverse probability of treatment weight to control the potential bias due to confounding *L*. In this thesis, study 2 has the same data structure with figures 11 and 12, which aimed to estimate the effect of household expenditure and cash transfer intervention on children’s cognitive function. In study 2, the effect of cumulative time varying exposures (household expenditure and cash transfer) were estimated using MSMs. Details about the statistical analysis in study 2 will be discussed in section 3.3.3.

Time specific exposure

The previous section shows how to take advantage of having repeated measures to estimate the effect of time varying exposures on outcome in the analysis. This section explains another way of using repeated measure by partitioning the effect of exposure into several potential pathways, which can be illustrated in the following graphs.

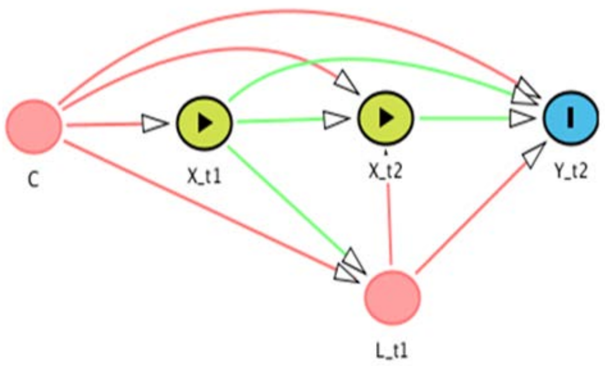

Figure 13. Causal diagram representing the association between confounder, time-varying exposure, mediator-outcome confounder and outcome

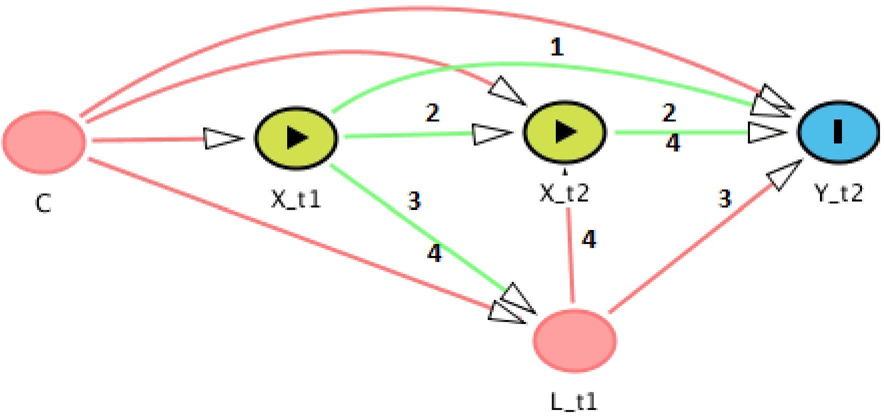

Figure 14 Causal diagram representing potential pathways between exposure and outcome in effect decomposition analysis.

Suppose that the exposures are measured at two time points and the outcome is measured at the end of the study, then the relations between the exposures, covariates and outcome can be presented in Figure 13. Herein, the exposure at time 2 ($X_{\_t2}$) can be defined as the mediator because it is in the pathway between $X_{\_t1}$ and outcome $Y_{\_t2}$. In addition, the covariate $L_{\_t1}$ is a confounder of $X_{\_t2}$ and $Y_{\_t2}$, which is also affected by the past exposure ($X_{\_t1}$). In other words, $L_{\_t1}$ is an exposure-induced mediator-outcome confounder. Suppose that the parameter of interest is the exposure at time 1 ($X_{\_t1}$) then there are at least four potential pathways that can be identified to estimate the causal effect of $X_{\_t1}$ on Y (Figure 14).

The first potential pathway is to estimate the direct effect of exposure on outcome (pathway 1 $X_{\_t1} \rightarrow Y_{\_t2}$). Second, to estimate the indirect effect of exposure on outcome mediated through the second exposure (pathway 2 $X_{\_t1} \rightarrow X_{\_t2} \rightarrow Y_{\_t2}$). Third, to estimate the indirect effect of exposure on outcome mediated through covariate L (pathway 3

$X_{\_t1}$→$L_{\_t1}$→$Y_{\_t2}$), and finally to estimate the indirect effect of exposure at time 1 on outcome mediated through covariate *L* and exposure at time 2 (pathway 4 $X_{\_t1}$→L_t_1→$X_{\_t2}$→$Y_{\_t2}$).

To estimate the effect of exposure on outcome by adjusting for covariates using conventional mediation analysis, such as Baron and Kenny (195) would yield bias in the effect estimation and may fail to have causal interpretation (196, 197). In conventional mediation analysis, direct and indirect effects of exposure on outcome were estimated from a sequential regression analysis. In the first model, the outcome was regressed on exposure adjusting for covariates. The coefficient of the exposure in model 1 was defined as the direct effect. In the second model, the outcome was regressed on exposure adjusted for covariates and the mediator. The difference between the coefficients of the exposure in the first and second models was then defined as the indirect effect of the exposure through the mediator. However, as shown in figure 14 in conventional regression adjusting the mediator $X_{\_t2}$ would open the backdoor path from $X_{\_t1}$→$L_{\_t1}$→$Y_{\_t2}$ (pathway 3) in addition to $X_{\_t1}$→$X_{\_t2}$→$Y_{\_t2}$ (pathway 2). On the other hand, because $L_{\_t1}$ is affected by $X_{\_t1}$ then adjusting $L_{\_t1}$ would block the backdoor path from $X_{\_t1}$→$L_{\_t1}$→$Y_{\_t2}$ (pathway 3).In these situation, conventional regression results in “collider stratification bias” (184). In other words, L_{t1} can be defined as an exposure-induced mediator-outcome confounder.

Under a potential outcome approach, effect of exposure on outcome can be decomposed into direct and indirect effects under the following assumptions

1. the effect of *X* on *Y* is unconfounded given C, $(Y_x \coprod X, C)$

2. the effect of *M* on *Y* is unconfounded given *X*, *C* $(Y_{x,m} \coprod M \mid X, C)$

3. the effect of *X* on *M* is unconfounded given *C* $(M_x \coprod X, C)$

4. there is no exposure-induced mediator-outcome confounding $(Y_{x,m} \coprod M_{x^*} C)$

In the presence of mediator-outcome confounding that is affected by exposure, methods to estimate the causal effect of exposure on outcome without introducing bias in the effect estimation include MSM (194) and g-computation (187, 188). In so-called "causal mediation analysis", MSM is used to estimate the controlled direct effect (CDE) of exposure on outcome (198). MSM provides robust estimation for the effect of exposure on outcome by controlling the mediator and mediator-outcome confounding properly through inverse probability of weighting and is useful when the substantive interest is only the CDE of exposure on outcome. However, MSM cannot be used for effect decomposition (197). Estimation of CDE only requires the first two assumptions;(1) the effect of *X* on *Y* is unconfounded given *C*, and (2) the effect of *M* on *Y* is unconfounded given *X*, *C*. In other words, there are no unmeasured confounding of the association between exposure and outcome, and there are no unmeasured confounding of the association between mediator and outcome.

G-computation is useful for decomposing the total effect of exposure into direct and indirect effects. However, because the estimation of g-computation is conducted under sequential non-parametric models there is potential risk of bias if there is misspecification of the link function (i.e., *X*-*Y* link) in the working models (for example by not including a product term in the model when there is an interaction between the exposure and mediator) (199). In addition, although g-computation controls the potential bias due to exposure-induced mediator-outcome confounder *L*, this method can only be used to partition the effect mediated through mediator *M* but not through *L*. The most recent effect decomposition analysis was introduced by Vanderweele, Vansteelandt and Robins (VVR) (200) in 2014, which include joint mediators, path specific and interventional analogues approaches. This thesis used the VVR approach in study 3.

In this thesis, study 3 used a similar causal graph as Figure 13, which aimed to estimate the direct effect of poverty at 0-7 years on cognitive function at 7-14 years and whether the effect is mediated through poverty at 7-14 and school attendance/home environment. Details about the statistical analysis used in study 3 will be explained in section 3.3.4.

Potential outcome or counterfactual framework

This thesis aimed to estimate the causal associations between exposure and outcome from observational studies via the potential outcome (counterfactual) framework. Use of a potential outcome framework in observational studies is intended to mimic a randomized control trial where the individuals are assigned to a potential intervention. The idea of potential outcomes in observational studies is that each subject in a population of interest could experience different types of exposure even though she/he only has one observed outcome at any time point. The potential outcome or counterfactual can be defined as the expected outcome an individual would have had, contrary to fact, that the same individual had the observed exposure (201). Suppose that the exposure is binary, i.e. whether a child is poor or not poor, then for a subject who is poor his potential outcome can be defined as what would happen if the same subject is not poor and vice versa.

Formally, let *x* be the value of the observed exposure and *x** be the alternative exposure, then the causal effect is estimated as the difference between the outcome under the observed value and the counterfactual value $(Y_{ix} - Y_{ix*})$ Since each subject can only have one observed value, this implies that causal effect cannot be directly estimated from the data. Estimation of a causal effect under the potential outcome framework depends on several assumptions, and proper analytical methods that can provide unbiased estimation to move closer towards causal interpretation.

Under a potential outcome framework, estimation of causal effects in observational studies is dependent on the following assumptions (189, 201)

1. **Consistency**, which means the individual's potential outcome depends only on his/her own exposure history and was not influenced by treatment applied to other individuals. Rubin (202) defined this assumption as the stable unit treatment value assumption (SUTVA).
2. **Conditional exchangeability**, which means that the mean of outcome *Y* given exposure is independent of the individual's exposure given covariates. In other words, conditional exchangeability assumes there is no unmeasured confounding.
3. **Positivity**, which means both exposed and unexposed individuals are present at every level of any confounders. In other words, the exposure is not deterministically assigned within any levels of covariates. i.e., probability of exposure does not equal one or zero. Probability of exposure in a standard RCT is 0.5.

Although estimation of causal effects may be plausible, the assumptions on which it is based are not guaranteed by design and cannot be tested in observational studies (189).

In a randomized experiment, the causal effect can be estimated directly from the data as the difference in the outcome between the treatment and control group. In contrast, in observational studies the causal effect cannot be directly estimated because the studies were not designed to estimate the causal association between the exposure and outcome. Hence *a priori* knowledge about the association between the exposure and outcome is important to determine their causal relations (203). Proper understanding about the association between the exposure and outcome would be useful to generate well-defined interventions (204).

As mentioned earlier, under a potential outcome (counterfactual) framework, methods that can be used to assess causality from complex longitudinal observational studies include g-formula (187, 188, 192), g-estimation of the structural nested models (SNMs) (189) and marginal structural models (MSMs) (189, 190, 193, 194).

3.3.3. Study 2: estimating the effect of household expenditure and cash transfer intervention on children's cognitive function

Study 2 aimed to address the following questions, (1) what is the effect of household PCE on Indonesian children's cognitive function; and (2) does a cash transfer intervention increase cognitive function scores? Assuming there is no unmeasured confounding of all the associations between *C, X, L, Y* Figure 15 shows the hypothesized causal diagram for study 2, representing associations between confounders, household PCE and children's cognitive function.

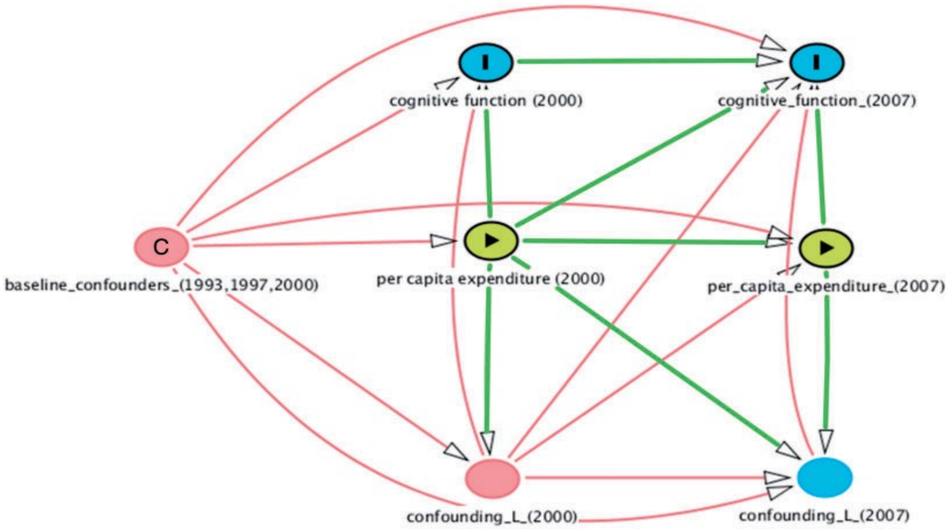

Figure 15. Direct acyclic graph (DAG) representing the hypothesized causal structure in estimating the effect of household per capita expenditure on cognitive function.

Exposure: household per capita expenditure. Outcome: cognitive function z-score. Ancestor of exposure and outcome (baseline confounders measured in 1993, 1997 and 2000): caregiver's age, education, employment status, household size, economic hardship, household had electricity, used piped or pumped well as the main drinking water source, owned toilet with septic tank, and residential area. Ancestor of exposure and outcome (confounding *L* measured in 2000): attending school and caregiver's mental health. Ancestor of outcome (confounding *L* measured in 2007): completed at least 8 years of education and caregiver's mental health. Causal path. Biasing path.

In study 2, MSMs (189, 190, 193, 194) were used to estimate of the effect of household PCE and cash transfer intervention on children's cognitive function. MSMs used the Inverse Probability of Treatment Weights (IPTW) to control potential bias due to time-varying confounding. In MSMs, each subject is weighted by their subject-specific IPTW to create pseudo-populations. In pseudo populations, the effect of time varying confounding *L* is removed by including *L* into the weight rather than conditioning on *L* in the statistical model. Hence, if all underlying assumptions (as described above on page 27) hold, and there is no effect of confounding, the mean potential outcome in the pseudo-population equals the mean potential outcome in the actual population.

Steps for estimation of the weights are as follows:

1. Generate the time-specific stabilized weight.

Let X_{it} be the exposure for individual *i* at time *t*, $\overline{X}$ and $\overline{L}$ be the history of exposure and time varying confounding, respectively then the construction of the stabilized weight for each individual *i* at time *t* (SW_{it}) defined as (194)

Equation 5. Stabilized weight

$$SW_{it} = \prod_{t=0}^{T} \frac{f(X_{it} \mid \overline{X}_{it-1})}{f(X_{it} \mid \overline{X}_{it-1,} \overline{L}_{it-1,} C)}$$

Where each factor in numerator in equation 5 is the probability density function that the subject received his/her observed exposure conditional on her/his past exposure, and the denominator is the probability density function that the subject received her/his exposure given his/her past exposure and covariates, which include both time varying confounding and baseline confounder.

Another approach of weight creation is using non-stabilized weight. In contrast with stabilized weight, the numerator of non-stabilized weight is not estimated from the observed value of exposure at each time point given the past exposure but replaced by the value of 1, whereas the denominator of non-stabilized weight is estimated similar to denominator in stabilized weight (the probability of density function that a subject received his/her exposure given past exposure and covariates). Use of stabilized weight is preferable over non-stabilized weight because the former has smaller variance, narrower confidence interval and better coverage rates than the later (194). For each time point, the mean of the weight is expected to be one because the size of the pseudo population equals the study population and has a small range suggesting positivity or there is no misspecification of the weight model (205). To reduce potential bias if the weight model is miss-specified, weights with large variance or extreme values were truncated at the 1^{st} and 99^{th} percentile or at the 5^{th} and 95^{th} percentile.

In the analysis, the stabilized weight is defined as

Equation 6. Stabilized weight for the exposure in 2000

$$SW_{i2000} = \frac{f(X_{i2000})}{f(X_{i2000} \mid \overline{C}_i)}$$

Equation 7. Stabilized weight for the exposure in 2007

$$SW_{i2007} = \frac{f(X_{i2007} \mid X_{i2000})}{f(X_{i2007} \mid X_{i2000}, \overline{C}_i, \overline{L}_i)}$$

Equations 6 and 7 show the stabilized weight for the exposure in 2000 (SW_{i2000}) and 2007 (SW_{i2007}), respectively. The numerator in equation 6 is the marginal density of the exposure (household PCE) in 2000 (X_{i2000}), and the denominator is the conditional density function of X_{i2000} given the history of confounders ($\overline{C}_i$) up to 2000 including caregiver and household characteristics. The numerator in equation 7 is the conditional density function of the exposure in 2007 (X_{i2007}) given X_{i2000}, and the denominator is the density function of X_{2007} given X_{2000}, history of confounders ($\overline{C}_i$), and time varying confounders ($\overline{L}_i$) which includes the child attending school and their caregiver's mental health in 2000, and the child's completion of at least 8 years of education and their caregiver's mental health in 2007.

2. Generate IPTW for the marginal structural mean model

IPTW was estimated as the product of time-specific *SW* (equation 8), which is defined as

Equation 8. The inverse probability of treatment weighting

$$IPTW = SW_{2000} \times SW_{2007}$$

In study 2, the MSM was estimated using generalized estimating equations (GEE) with an independent working correlations matrix (206, 207), defined as

Equation 9. Marginal Structural Mean Model

$$E(\overline{Y}_{it} \mid cum_{xit}) = \beta_0 + \beta_1 cum_{xit}$$

Where $\overline{Y}_{it}$ is the expected mean potential outcome of cognitive function z-score given the observed cumulative household PCE over two time points (cum_{xit}) weighted by the individual's subject specific weight (IPTW).

Sensitivity analysis for unmeasured confounding

Causal analysis in observational studies is conducted under the assumption of no unmeasured confounding. Although this assumption cannot be tested, unmeasured confounding may lead to bias in effect estimation. To address this issue, Robins (190) argued that conducting sensitivity analysis is important to quantify how effect estimation may vary as a function of the magnitude of unmeasured confounding.

In study 2, sensitivity analysis was conducted to estimate bias in the causal effect of household PCE on cognitive function due to unmeasured confounding of the exposure (*U*). In sensitivity analysis, *U* was defined as a binary variable and it was assumed that the association between *U* and cognitive function did not vary across levels of household PCE i.e., no effect measure modification of *U* and *X*. Following VanderWeele and Arah (208), the sensitivity parameter δ was defined as the effect of *U* on cognitive function (*U*-*Y*) and the sensitivity parameter γ was defined as the prevalence of *U* for given level of *X* (household PCE). These two quantities define the strength of potential confounding by U of the X-Y association. Equation 10 shows formula for sensitivity analysis, where the magnitude of potential bias (d_{x+}) in the estimated X-Y association was estimated as the product of δ and γ.

Equation 10 Formula for sensitivity analysis

$$d_{x+} = \delta\gamma$$

where

$$\delta = \{P(U = 1) \mid x, c) - P(U = 0) \mid x, c)\}$$

$$\gamma = \mathrm{E}(Y \mid x, c, U = 1) - \mathrm{E}(Y \mid x, c, U = 0)$$

Equation 10 also shows the effect of U on cognitive function Y (δ) was estimated as the difference between the probability of U given the exposure and covariates, whereas the prevalence of U (γ) was estimated as the difference in cognitive function Y given exposure, covariates and U. The magnitude of potential bias (d_{x+}) was then estimated over several simulations of plausible levels of δ and γ.

Missing data

Similar to study 1, in study 2 the Multiple Imputation by Chained Equation (MICE) procedure was performed to minimize bias due to attrition and missing responses to questions under the assumption that the imputed data were missing at random (179, 180). In this study, a total of twenty imputed datasets was generated using fifty cycles of regression switching. Rubin's rule (181) was used to combine and analyse imputed datasets. In addition, the method of multiple imputation then deletion of the imputed outcome (MID) as derived by Von Hippel (182) was also performed as part of the sensitivity analysis.

Findings from study 2 are presented in chapter 5.

3.3.4. Study 3: estimating the associations of early and later childhood poverty on children's cognitive function

Study 3 aimed to address the following questions, (1) what is the effect of poverty at 0-7 and poverty at 7-14 years on cognitive function at 7-14 years; (2) what is the direct effect of poverty at 0-7 on cognitive function at 7-14 years, and (3) is this effect mediated through poverty at 7-14 and through school attendance and aspects of the child's home environment, children's living conditions and school attendance? This study was motivated to better estimate the optimal timing for intervention and the mechanism by which poverty earlier in life at 0-7 could affect cognitive function at 7-14 years.

Figure 16 shows the causal diagram for estimating the effect of poverty at 0-7 on cognitive function at 7-14. The hypothetical structure of the DAG suggests that household poverty at 0-7 (exposure, reflecting household expenditure on children) would affect both household poverty at 7-14 years (mediator), children's living conditions and the opportunity to attend school at ages 7-14 (exposure induced time-varying confounder of the mediator-outcome association), which subsequently would affect both family expenditure on children and their cognitive function at 7-14. In Indonesia, social inequalities in school enrolment widen after age 10, likely due to costs of schooling (209) The cost burden of education is higher among the poor and those living in rural areas. For example, in 2010 about 44% of students who dropped-out of school at ages 13-15 years were from the poorest quintile of households. Among this group, the average cost of education is about 500,000 *rupiah*/child/year (about US$59), representing about a quarter of annual household expenditure.

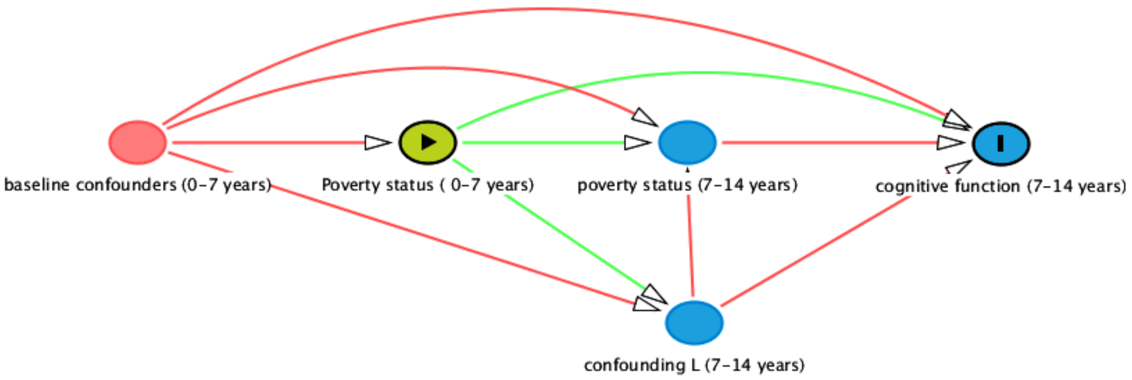

Figure 16. Directed Acyclic Graph representing the associations between baseline confounders, poverty at 0-7 and poverty at 7-14 years, poor home environment not attending school at 7-14, and cognitive function at 7-14

Legend

Ancestor of exposure *and* outcome (baseline confounders measured at 0-7 years): caregiver's age, education, employment status, household size, economic hardship, household had electricity, used piped or pumped well as the main drinking water source, improved sanitation and residential area. Exposure: poverty status at 0-7 years. Ancestor of outcome (mediator): poverty status at 7-14 years. Ancestor of outcome (exposure-induced mediator-outcome confounders): latent variable (child is attending school, caregiver's employment status, household had electricity, used piped or pumped well as the main drinking water source, improved sanitation, house tenure, types of cooking fuel, had television and residential area). Outcome: cognitive function z-score at 7-14 years. Causal path. Biasing path

Assuming there is no unmeasured confounding of all the associations of *C*, *X*, *L*, *M* and *Y*, the DAG in Figure 16 shows exposure *X* (poverty at 0-7) has a direct effect on outcome *Y* (cognitive function score at 7-14). The path from *X* to *Y* is potentially mediated through poverty at 7-14 (*M*). In addition children's living conditions and school attendance (*L)* is a potential mediator-outcome confounder, which is also affected by the exposure.

Conventional regression analysis

Conventional regression analysis was used to answer the first objective, which examined the associations of early poverty (at 0-7) and later childhood poverty (at 7-14 years) with cognitive function at 7-14 years. Herein, equation 11 shows the regression model estimating the association of poverty at 0-7 (*X*) with cognitive function adjusting for baseline confounders (*C*). Equation 12 shows the regression model estimating the association of poverty at 7-14 (*M*) adjusting for all covariates including poverty at 0-7 (*X*), baseline confounders (*C*) and schooling/home environment (*L*).

Equation 11. Model for estimating the association of poverty at 0-7 with cognitive function at 7-14 years

$$E(Y \mid X, C) = \beta_0 + \beta_1 X + \beta_2 C$$

Equation 12. Model for estimating the association of poverty at 7-14 with cognitive function at 7-14 years

$$E(Y \mid M, X, C, L) = \beta_0 + \beta_1 M + \beta_2 X + \beta_3 C + \beta_4 L$$

Decomposition Analysis

To estimate the effect of poverty at 0-7 years on cognitive function by adjusting for covariates using conventional mediation analysis, such as Baron and Kenny (195) would yield bias in the effect estimation and may lack causal interpretation (196, 197).

Limitations of using conventional mediation analysis were explained in section 3.3.2. Briefly, in the presence of exposure induced mediator outcome confounder (*L*) in conventional regression adjusting *M* would open the backdoor path from $X \rightarrow L \rightarrow Y$ in addition to $X \rightarrow M \rightarrow Y$. On the other hand, because *L* is affected by *X* then adjusting *L* would block the backdoor path from $X \rightarrow L \rightarrow Y$, however, not adjusting *L* would generate bias in estimates because it confounds the association of *M* with *Y*. In this situation, conventional regression would result in "collider stratification bias" (184).

Estimation of effect decomposition requires the following assumptions

1. the effect of *X* on *Y* is unconfounded given C, $(Y_x \coprod X, C)$
2. the effect of *M* on *Y* is unconfounded given X, C $(Y_{x,m} \coprod M \mid X, C)$
3. the effect of *X* on *M* is unconfounded given C $(M_x \coprod X, C)$
4. there is no exposure-induced mediator-outcome confounding $(Y_{x,m} \coprod M_{x^*} C)$

The fourth assumption is known as the "cross-world independence assumption" (210). There have been criticisms concerning estimation of direct and indirect effects that involve the cross-world independence assumption (211). Cross-world independence assumes that the joint effect of the observed exposure and the mediator on the outcome is independent of the effect of the mediator under the counterfactual exposure ($X=x^*$) given *C*, which implies that each individual has both observed and counterfactual exposures. Avin *et al.,* (210) showed that estimation of direct and indirect effects that involve the cross world assumption is unidentifiable even when the exposure-induced mediator-outcome confounder is observed in the data. Furthermore, Naimi *et al.,* (211) argued that the estimation of direct and indirect effects that involves a cross-world independence assumption involves a logical inconsistency in the two states required for its calculation and so has no sensible real world interpretation but is rather a product of purely mathematical formulations.

Under a potential outcome approach (212, 213) the total causal effect (TCE), the natural direct (NDE), indirect effect (NIE) and the controlled direct effect (CDE) are defined as follows.

Equation 13. Total Causal Effect

$$TCE = E[Y_{x,M(x)} - Y_{x^*,M(x^*)}]$$

Equation 13 shows the TCE is the expected potential outcome (child cognitive function z-score) in children exposed to poverty at 0-7 (X=x) and the mediator (poverty at 7-14, $M(x)$) is set at the level it would be among those who were exposed to poverty at age 0-7, *minus*, the expected potential outcome in children not exposed to poverty at 0-7, and the mediator is set at the level it would be among those who were unexposed to poverty at 0-7 (M(x*)).

Equation 14. Natural Direct Effect

$$NDE = E[Y_{x,M(x^*)} - Y_{x^*,M(x^*)}]$$

In equation 14, the NDE is the expected potential outcome in children exposed to poverty at 0-7 (X=x) and the mediator is set at the level it would be among those who were not exposed to poverty at 0-7 (M(x*)), *minus*, the expected outcome in the unexposed to poverty at 0-7, and the mediator is set at the level it would be among those who were unexposed to poverty at 0-7 (M(x*)). Intuitively, the NDE estimates the effect of poverty at 0-7 on cognitive function through pathways that do not involve poverty at 7-14 years.

Equation 15. Natural Indirect Effect

$$NIE = E[Y_{x,M(x)} - Y_{x,M(x^*)}]$$

In equation 15, the NIE is the expected potential outcome in children exposed to poverty at 0-7 and the mediator is set at the level it would be among those who were exposed to poverty at 0-7 ($M(x)$) *minus* the expected potential outcome in children exposed to poverty at 0-7 and the mediator is set at the level it would be among those who were unexposed to poverty at 0-7 ($M(x^*)$). This algebra invokes the cross-world assumption because NIE requires the mediator to simultaneously take on values under $X=x$ and $X=x^*$ i.e., M cannot take on its value under x and x^* simultaneously and so is logically inconsistent and requires X to exist in two worlds to observe the NIE (211). Nevertheless, intuitively, the NIE estimates the effect of poverty at 0-7 on cognitive function through poverty at 7-14 years.

Equation 16. Controlled Direct Effect

$$CDE = E[Y_{x,M=m} - Y_{x^*,M=m}]$$

In equation 16, CDE is the difference in the expected potential outcome between children who were exposed ($X=x$) and not exposed to poverty at 0-7 ($X=x^*$) with the mediator set at some level $M=m$ for all individuals in the population. This approach is used in MSM and effectively blocks any variation in M by setting it to some plausible level m. It shows why MSMs cannot be used to decompose direct and indirect effects because *M* is essentially blocked at one level for all individuals and so cannot vary across *X* or *Y*.

The VanderWeele, Vanstelandt and Robins (2014) approach to effect decomposition

The most recent approach to effect decomposition is derived by Vanderweele, Vansteelandt and Robins (hereafter VVR) (200). VVR introduced three approaches to effect decomposition that partially overcome the identification limitations due to exposure induced mediator-outcome confounding. The three VVR approaches to effect decomposition do not estimate the “natural” direct and indirect effects but they provide insight into mediation and pathways when exposure induced mediator-outcome confounding exists. This included a) the joint mediators, b) the path specific and c) the interventional analogue approaches.

a) Joint mediators

In the joint mediators approach, the direct effect (*X*→*Y)* is defined as the effect of poverty at 0-7 (*X*) that is not through poverty at 7-14 (*M)* or schooling/home environment *L*. The indirect effect is defined as the effect of *X* that is mediated through *M* or *L* or both. Under the joint mediator approach, *M* and *L* are considered as joint mediators, the fourth assumption is modified as $Y_{xlm} \amalg (L_{x^*}, M_{x^*}) | C$ and is effectively satisfied. In other words in Figure 16 there is no effect of exposure *X* that confounds the relationship between the joint mediator (*L*, *M*). This approach is useful if partitioning the indirect effect of *X* through *M* or *L* was not of interest so that both poverty at 7-14

(*M*) and schooling/home environment (*L*) were assumed to be equally important as mechanisms by which poverty at 0-7 (*X*) affects cognitive function at 7-14 (*Y*).

Let *X* be the exposure (poverty at 0-7 years), where $X=x$ is defined as exposure set to the child being poor and $X=x^*$ is defined as the exposure being set to child not being poor at 0-7. Let *M* be the mediator (poverty at 7-14 years), where M_{x^*} is defined as the value of observed poverty status at 7-14 years and poverty at 0-7 is set to being not poor. Let L_{x^*} be defined as the value of observed mediator-outcome confounder (home environment/schooling) and poverty at 0-7 is set to being not poor. Equation 17 shows formula for estimating the direct effect (*DE*) in joint mediators approach.

Equation 17. Estimation of direct effect for the joint mediator approach

$$DE_{X\rightarrow Y} = E[Y_{xLx^*Mx^*} - Y_{x^*Lx^*Mx^*}] = \sum\nolimits_{c,l,m} E\{[Y \mid x,l,m,c] - E[Y \mid x^*,l,m,c]\}P(l,m \mid x^*,c)P(c)$$

In this approach, the DE is the sum of the products of three statistical models. The first model $E[Y \mid x,l,m,c] - E[Y \mid x^*,l,m,c]$ estimates the difference between two potential outcomes, (1) the expected cognitive function z-score *Y* given the child is poor at 0-7 (*X=x*), home environment/schooling (*L*), poverty at 7-14 (*M*) and baseline confounders *C* (caregiver's age, education, employment status, household size, economic hardship, household had electricity, used piped or pumped well as the main drinking water source, improved sanitation and residential area); *minus* (2) the expected cognitive function z-score given the child is not poor at 0-7(*X=x**), home environment/schooling, poverty at 7-14 and confounders. The second part of the model $P(l,m \mid x^*,c)$ estimates the joint probabilities that the child is living in poor home environment (*L*) and poverty at 7-14 given the child is not poor at 0-7 (*X*=*x**), and *C*. The final statistical model $P(c)$ estimates the probability of confounders.

Equation 18 shows the formula for estimating the indirect effect (IE) in joint mediators approach.

Equation 18. Estimation for the indirect effect for the joint mediator approach

$$IE_{X\rightarrow M\rightarrow Y} = E[Y_{xLxMx} - Y_{xLx^*Mx^*}] = \sum\nolimits_{c,l,m} E[Y \mid x,l,m,c]\{P(l,m \mid x,c) - P(l,m \mid x^*,c)\}P(c)$$

In equation 18, the joint mediators approach estimates the indirect effect (IE) as the sum of the product of three statistical models. The first model $E[Y \mid x,l,m,c]$ estimates the expected cognitive function z-score *Y* given the child is poor at 0-7 (*X*=*x*), home environment/schooling, poverty at 7-14 and confounders. The second part of the model $P(l,m \mid x,c) - P(l,m \mid x^*,c)$ estimates the difference between two joint probabilities; (1) the joint probability of the child is living in poor home environment/schooling (*L*) and poverty at 7-14 (*M*) given the child is poor at 0-7 *(X=x)* and *C, minus* (2) the joint probability of *L* and *M* given the child is not poor at 0-7 (*X*=*x**) and *C*. The final model $P(c)$ estimates the probability of confounders.

In the VVR method, effect decomposition was estimated using a combination of sequential simulations of parametric models for *Y*, *X*, *M*, and *L* and inverse-probability of weighting for probabilities of *X*, *M* and *L*. Combination of sequential simulations and weighting may overcome the issue of model compatibility (214). In study 3, effect decomposition was estimated under the assumption of no interaction between the exposure and the mediator. Assuming the parametric models for *Y*, *X*, *M* and *L* are correctly specified, the simulation was run under restricted models by not included the interaction terms of *X* and *M* in the simulation model. However, if there is in fact an interaction between *X* and *M* then estimates of direct and indirect effects could be biased because the model was misspecified. The weighting and duplication of the exposure method allows for estimation of the effect of exposure on outcome that was partly through the mediator and sequentially through the change in mediator under specified exposure level without adding interaction terms in the model.

In VVR, the sequential simulation was started by generated duplicates of the exposure data and added variables that represent counterfactual of the exposure. For example, in joint mediators approach, two copies of the data were generated and a variable of exposure X^* was added to each of the new data set. Herein, in the first replicate the value of X^* was set to 0 and in the second replicate the value of X^* was set to 1. Intuitively, in each replicate a child will have one observed value of the exposure (X) and one counterfactual value of the exposure (X^*). Both data were then combined to generate person specific weight.

The construction of the weight for the joint mediators approach is as follow.

Equation 19. Weight for the joint mediator approach

$$W_1 = \frac{P(l \mid x^*, c)P(m \mid l, x^*, c)}{P(x \mid c)P(l \mid x, c)P(m \mid l, x, c)}$$

In equation 19, the numerator is the product of two statistical models; (1) the probability of schooling/home environment (L) given poverty at 0-7 is set to x^* and C, and the probability of poverty at 7-14 (M) given schooling/home environment, poverty at 0-7 is set to x^* and C. The denominator is the product of three statistical models; (1) the probability of the observed poverty 0-7 (X=x) given C; (2) the probability of schooling/home environment given the observed poverty at 0-7 and C; and (3) the probability of poverty at 7-14 given schooling/home environment, the observed poverty at 0-7, and C.

Effect decomposition was then estimated using a weighted regression. To estimate the direct effect, the cognitive function Y was regressed on the observed X among $X^*=0$. Of those children who were poor at 0-7 years (X=1), a weighted regression of Y on X^* was used to estimate the indirect effect of poverty at 0-7 years that was mediated through poverty at 7-14 or home environment/schooling or both.

b) Path specific

Assuming that the above four assumptions of unmeasured confounding (1-4) hold, the identifiable path specific effects (210) are $X \rightarrow Y$, $X \rightarrow LY$, $X \rightarrow M \rightarrow Y$. The path specific approach is more relevant if the substantive question is to estimate the relative importance of specific pathways by partitioning the indirect effects of poverty at 0-7 through poverty at 7-14 ($X \rightarrow M \rightarrow Y$) and through pathways that involve schooling/home environment at 7-14 ($X \rightarrow LY$), which is the combination of $X \rightarrow L \rightarrow M \rightarrow Y$ and $X \rightarrow L \rightarrow Y$. Thus the path specific approach can be used to estimate whether the effect of poverty at 0-7 is largely mediated through poverty at 7-14 (M) only or through schooling/home environment (L).

Similar to the joint mediators approach, the path specific effect defines *DE* as the effect of exposure on outcome that is not through *M* or *L* (See equation 17 above). In the path specific approach, the indirect effect of poverty at 0-7 through poverty at 7-14 ($X \rightarrow M \rightarrow Y$) defined as

Equation 20. Estimation for the indirect effect through mediator in the path specific approach

$$IE_{X \rightarrow M \rightarrow Y} = \sum_{c,l,m} E[Y \mid x, l, m, c]\{P(m \mid x, l, c) - P(m \mid x^*, l, c)\}P(l \mid x^*, c)P(c)$$

In equation 20, $IE_{X \rightarrow M \rightarrow Y}$ is estimated as the sum of the product of four statistical models. The first model $E[Y \mid x, l, m, c]$ estimates the expected cognitive function z-score given the child is poor at 0-7, home environment/schooling, poverty at 7-14 and confounders. The second part of the model $P(m \mid x, l, c) - P(m \mid x^*, l, c)$ estimates the difference between two probabilities; (1) the probability of poverty at 7-14 given the child is poor at 0-7, home environment/schooling and confounders, *minus*, (2) the probability of poverty at 7-14 given the child is not poor at 7-14, home environment/schooling and confounders. The third part of the model $P(l \mid x^*, c)$ estimates the probability of living in poor home environment/schooling given the child is not poor at 0-7 and confounders. The fourth part of the model $P(c)$ estimates the probability of confounders.

Equation 21 shows the indirect effect of poverty at 0-7 that involving pathway through home environment/schooling $X \rightarrow LY$ defined as

Equation 21. Estimation of the indirect effect mediated through confounding L in the path specific approach

$$IE_{X \to LY} = \sum\nolimits_{c,l,m} E(Y \mid x,l,m,c)P(m \mid x,l,c)\{P(l \mid x,c) - P(l \mid x^{*},c)\}P(c)$$

In equation 21, the *IE* is estimated as the sum of the product of four statistical models. The first model $E(Y \mid x, l, m, c)$ estimates the expected potential cognitive function z-score given the child is not poor at 0-7, home environment/schooling, poverty at 7-14 and confounders. The second part of the model $P(m \mid x, l, c)$ estimates the probability of poverty at 7-14 given the child is not poor at 0-7, home environment/schooling and confounders. The third part of the model $P(l \mid x, c) - P(x^{*}, c)$ estimate the difference between two probability models; (1) the probability of the child is living in poor home environment/schooling given the child is poor at 0-7 and covariates, *minus*, (2) the probability of the child is living in poor home environment/schooling given the child is not poor at 0-7 and confounders. The fourth part of the model $P(c)$ estimates the probability of confounders.

For path specific effect, three copies of the data were generated and two variables X^{*} and X^{**} were added to each data set. In the first replicate of data, both variables X^{*} and X^{**} were set to the same value of observed exposure X ($X^{*}=x$ and $X^{**}=x$). In the second replicate of data, variable X^{*} was set to 1-x and X^{**} was set to the observed exposure. Lastly, in the third replicate of data variable X^{*} is set to 1 and X^{**} is set to 1-x. The copies of the data set were merged to generate a person specific weight for the path specific effect (equation 22).

The construction of the weight for the identifiable path specific effects is as follows.

Equation 22. Weight for the path specific approach

$$W_2 = \frac{P(l \mid x^*, c)P(m \mid l, x^{**}, c)}{P(x \mid c)P(l \mid x, c)P(m \mid l, x, c)}$$

In equation 22, the numerator is the product of two statistical models; (1) the probability of schooling/home environment (*L*) given poverty at 0-7 is set to *x** and *C*, and (2) the probability of poverty at 7-14 given poverty at 0-7 is set to *x*** and *C*. The denominator is the product of three statistical models; (1) the probability of poverty at 0-7 given *C;* (2) the probability of schooling/home environment given the observed poverty at 0-7 (*X*=*x*) and *C;* and (3) the probability of poverty at 7-14 years given schooling/home environment, the observed poverty at 0-7 and *C*. Herein, *x** represents potential outcome for the *X*→*LY* path, whereas *x*** represents potential outcome for the *X*→*M*→ *Y* path.

In the path specific effect, a weighted regression of *Y* on the observed *X (X=x)* was used to estimate the direct effect of poverty at 0-7 on cognitive function among those who were not poor at 0-7 years in both in the replicate data set (*X**=0 and *X***=0). Estimates of the indirect effect of poverty at 0-7 mediated through poverty at 7-14 (M) years was calculated from a weighted regression of *Y* on *X*** among those who were observed being poor at 0-7 but not poor on the counterfactual exposure in the replicate data (*X**=1).

A weighted regression of *Y* on *X** was used to estimate the indirect effect of poverty at 0-7 on cognitive function that was mediated through home environment/schooling L and poverty at 7-14. Herein, the weighted regression was estimated among those who were poor at 0-7 in both observed and replicate data (X=1 and X^{**}=1). Although the VVR can be used to estimate the indirect effect of exposure that was through L and M ($X \rightarrow LY$), the current method cannot be used to estimate the indirect effect of X that was only mediated through L alone *(*$X \rightarrow L \rightarrow Y$*).*

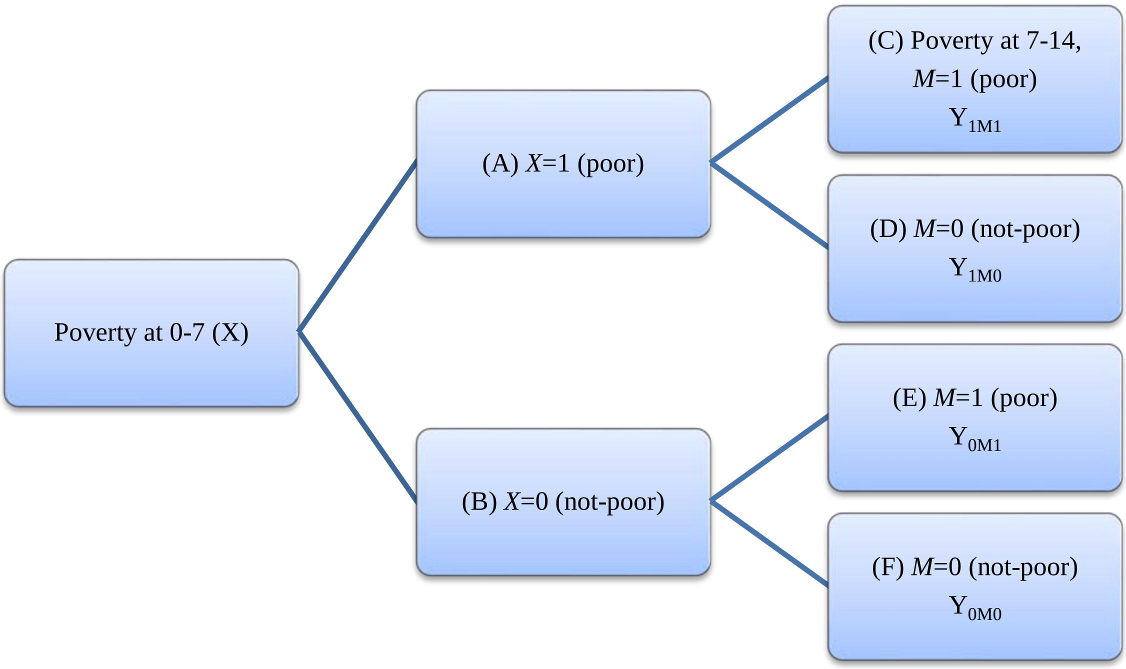

Figure 17 Sequential randomization in the intervention analogue approach.

c) Intervention Analogue

Effect decomposition carried out under the intervention analogue approach is similar to a sequential randomized trial (Figure 17) (185, 212, 215). The randomized intervention analogue of the natural direct effect is defined as the difference in potential outcome between children who were exposed and not exposed to poverty at 0-7, where in both cases the value of the mediator (poverty at 7-14) was randomly drawn from the distribution of the mediators amongst children who were not exposed to poverty at 0-7 (Y_{1m0}-Y_{0m0}).

The randomized intervention analogue of the indirect effect is defined as the difference in potential outcome in children who were exposed to poverty at 0-7 where the value of the mediator was first randomly drawn from the distribution of the mediator amongst children who were exposed to poverty at 0-7 ((Y_{1M1}) in Figure 17) and then the value of the mediator was randomly drawn from the distribution of mediator amongst children who were not exposed to poverty at 0-7 ((Y_{1M0}) in Figure 17), thus simulating an RCT of the mediator (poverty at 7-14). Subtraction of these two quantities estimates the intervention analogue of the indirect effect (See equation 24). Thus effect decomposition conducted as an analogue of sequential randomization of the mediator, requires only the first three assumptions.

In the third approach, effect decomposition is estimated as the difference between two potential outcomes where the value of the mediator (poverty at 7-14) is randomly drawn from the distribution of exposure level (poverty at 0-7). Equation 23 shows the estimation of *DE* in the intervention analogue approach.

Equation 23. Estimation of the direct effect in the intervention analogue approach

$$DE_{X \to Y} = E(Y_{xG_{x|c}}) - E(Y_{x^*G_{x^*|c}})$$
$$= \sum_{c,l,m} \{E(Y \mid x,l,m,c)P(l \mid x,c) - E(Y \mid x^*,l,m,c)P(l \mid x^*,c)\} \times P(m \mid x^*,c)P(c)$$

In equation 23, the *DE* is the expected cognitive function z-score in children exposed to poverty at 0-7 (*X=x)* when the value of the mediator (poverty at 7-14) is randomly drawn from children exposed to poverty at 0-7 ($G_{x|c}$) given covariates, *minus,* the expected potential outcome in children not exposed to poverty at 0-7 ($X=x^*$) when the value of mediator is randomly drawn from children not exposed to poverty at 0-7 ($G_{x^*|c}$) given covariates.

Equation 24. Estimation of the indirect effect in the intervention analogue approach

$$
\begin{aligned}
IE_{X\to G\to Y} &= E(Y_{xG_{x|c}}) - E(Y_{xG_{x^*|c}}) \\
&= \sum\nolimits_{c,l,m} E(Y \mid x,l,m,c)P(l \mid x,c)\{P(m \mid x,c) - P(m \mid x^*,c)\}P(c)
\end{aligned}
$$

In equation 24, the *IE* is the expected potential outcome in children exposed to poverty at 0-7 ($X=x$) with the value of the mediator (poverty at 7-14) randomly drawn from children exposed to poverty at 0-7 (G_x) given covariates, *minus*, the expected potential outcome in children exposed to poverty at 0-7 when the value of the mediator was drawn from children who were not exposed to poverty at 0-7 (G_{x^*}) given covariates.

For the interventional analogue approach, two copies of the data were generated and a variable *X* was added in each replicate of the data set. Herein, in the first replicate the value of *X* was set to 0 (not poor at 0-7) and in the second replicate the value of *X* was set to 1 (poor at 0-7). Similar to other approaches, both replicates of the data set were then merged to generate person specific weight.

The construction of the weight for the intervention analogue approach is as follow.

Equation 25. Weight for the intervention analogue approach

$$W_3 = \frac{\sum_l P(m \mid l, x^*, c) P(l \mid x^*, c)}{P(x \mid c) P(m \mid l, x, c)}$$

In equation 25, the numerator is the sum of the product of two statistical models; (1) the probability of poverty at 7-14 (*M*) given schooling/home environment/, poverty at 0-7 is set to *x** and *C*, and (2) the probability of schooling/home environment/ given poverty at 0-7 is set to *x** and *C*. The denominator is the product of two statistical models; (1) the probability of poverty 0-7 years given *C*, and (2) the probability of poverty at 7-14 given schooling/home environment, the observed poverty at 0-7 years, and *C*.

To estimate the direct effect in the interventional analogue approach, the cognitive function *Y* was regressed on the observed *X* among children who were not poor at 0-7 (*X=0),* whereas of those children who were poor at 0-7 years (*X*=1), a weighted regression of *Y* on *X* was used to estimate the indirect effect of poverty at 0-7 years that was mediated through poverty at 7-14.

The 95% CI was estimated based on a bootstrap of 1000 resamples. Analyses using the VVR approach were conducted in SAS 9.4 (SAS Institute, Cary, North Carolina).

Complete case analysis

The analysis in study 3 was restricted to complete cases (178). Complete case analysis was conducted by deleting observations that had missing information in any variables of interest (confounder, exposure, mediator and outcome). Using complete case analysis has several well-known limitations including reduction of the sample size, loss of precision and potential bias in the estimates if the missing mechanism is not missing completely at random (MCAR), suggesting that the missing data is not related to any variables in the dataset (178, 181, 216). The reason analysis in study 3 was restricted to complete cases was because there is no current method available to combine estimates from VVR approach to effect decomposition using Rubin's rule.

Sensitivity analysis for potential unmeasured confounding

Potential bias in effect estimation is still plausible if there is potential unmeasured confounding. Sensitivity analysis method (217) was used to estimate bias in effect decomposition due to unmeasured mediator-outcome confounding. The sensitivity analysis that was developed by Vander Weele and Chiba was conducted as a non-parametric approach, which can be applied for any effect decomposition method including the method that has an exposure-induced mediator-outcome confounding.

Findings from study 3 are presented in chapter 6.

3.3.5. Study 4: estimating the effect of hypothetical interventions on children's school readiness and socio-emotional wellbeing

Study 4 aimed to investigate the relative and combined effects of different hypothetical interventions on children's school readiness and socio-emotional wellbeing at age 8. Assuming there is no unmeasured confounder; Figure 18 shows a DAG representing the associations between baseline confounders at age 4, exposure *X* and covariates *L*. In this DAG, both exposure *X* and confounding *L* are time-varying because they were measured at ages 4, 5 and 8. As outline in section 3.2, children's school readiness was measured using the Early Development Instrument (EDI), whereas socio-emotional wellbeing were measured using SDQ internalising and externalising behaviour scores. Moreover, four variables were identified as the exposure in study 4 including whether a child lived in a household that used piped water as the main drinking water source, improved sanitation, maternal mental health and parenting styles.

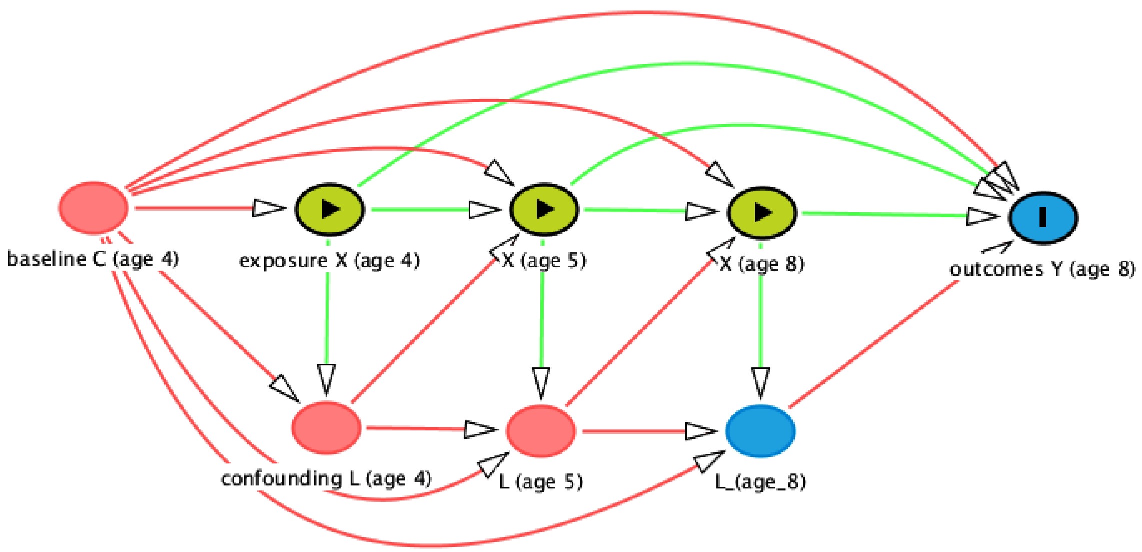

Figure 18. Causal diagram for estimating the effect of hypothetical intervention on children's school readiness and socio-emotional wellbeing at age 8.

Under a potential outcome approach, study 4 aimed to estimate (1) the risk of being vulnerable in one or more EDI domains; (2) the risk of being vulnerable in each of the school readiness domains (EDI) and (3) the mean of internalising and externalising behaviour scores at age 8 that would have been observed under each of the following specified hypothetical intervention scenario.

Scenario 1 Improving household standards of living

In LMICs, household standards of living is commonly used as an indicator of poverty particularly when information about income or expenditure is not available in the data (80, 82). Evidence suggests that children living in poor housing conditions tend to have poorer cognitive function (88, 94), less likely to be able to read paragraphs (126) and lower levels of education (127) compared to their peers who live in a better housing condition. Improving daily living conditions is one of the key recommendations to reduce inequalities in children's healthy development (1, 2, 128).

Scenario 1 has two components of intervention including provision of piped water as the main drinking water source and improved sanitation. Studies show a combination of improved water and sanitation intervention would generate a greater effect than a single intervention (129, 218), hence in scenario 1 provision of piped water and improved sanitation were considered as a joint intervention. Hypothetically, provision of piped water as the main drinking water source and improved sanitation would enhance housing conditions and in turn would have positive effect on children's school readiness and socio-emotional wellbeing. Under scenario 1, all children would have access to piped water and improved sanitation.

Scenario 2 Maternal mental health intervention

Poor maternal mental health is one of the risk factors that associated with children's poor cognitive and socio-emotional wellbeing (6, 95, 109-111). A systematic review that used evidence from RCTs and observational studies (135) suggest that mental health intervention for mothers had benefit for both mothers and their children, i.e. mothers who received mental health intervention had fewer children's internalising and externalising problems and learning difficulties. In terms of coverage of intervention, there was no evidence that a universal program of mental health intervention had a greater effect compare to targeted interventions (144). In terms of the prevalence of the population with mental health problems, a study by Bahar *et al.,* (219) reported that 20% of 1670 adults in Indonesia were classified as having mental health problems (measured by General Health Questionnaire). Patel and Kleinman (220) systematically reviewed evidence of the association between poverty and common mental health disorder in LMICs. They reported that the median prevalence rates of common mental disorder in LMICs ranged between 20% and 30%.

Hence, under scenario 2, a mother whose score was in the highest 20% of the K10 score was targeted for mental health intervention (score 17 or above from the observed data). Hypothetically, the targeted mothers received mental health intervention in the form of community based intervention to promote good mental health, which is commonly conducted in LMICs in the setting where access to mental health services are limited (32, 42). In LMICs, intervention programs were often integrated into existing services in the community. In this study setting, this typical mental health intervention is plausible to be implemented by integrating mental health intervention as part of services provided by community-based ECED center.

Scenario 3 Parenting intervention

Poverty and poor maternal mental health is also associated with poor parenting behaviour (30), which in turn affects poor cognitive and socio-emotional (6, 8, 30, 221). A great deal of evidence suggests that parenting interventions benefits both parents and children. Parenting intervention reduce harsh or abusive parenting and increase parenting practices (138, 139, 222), reduce family stress and maternal ill health (223), improve the home learning environment (137), improve children's overall health, better fine motor skills and cognitive functioning (32, 222), and socio-emotional wellbeing (222). In scenario 3, hypothetically mothers received parenting intervention in a form of a parenting education program to improve caregiving behaviour (parent-child relationship), which is shown as an effective intervention in LMICs (36, 138, 222). The parenting intervention in LMICs (32) was relatively low cost because they often combined this with other programs such as food supplementation and was integrated into the existing program (222) .

In scenario 3, a mother whose score was in the lowest 20% of the total parenting scores was targeted for intervention (scores 75 or lower based on the observed data). Hypothetically, mothers who received parenting interventions improved their relationships with the child and this may reduce harsh or abusive parenting, which in turn will improve children's school readiness and socio-emotional wellbeing (32, 36, 222). Similar to scenario 2, this parenting education program is likely to be implemented in Indonesia by using the community-based ECED center to promote positive parenting behavior.

Scenario 4 Joint intervention of maternal mental health and parenting education program

Nores and Barnett (37) conducted a meta-analysis on the benefits of early childhood interventions in LMICs and found interventions that combined several programs had a greater benefits than single intervention. This study was also interested to estimate the joint effects of maternal mental health and parenting education program interventions on children's school readiness and socio-emotional wellbeing.

Scenario 5 Joint intervention of improving standards of living, maternal mental health and parenting program

Under scenario 5, this study examined the joint effects of interventions on providing piped water as the main drinking water source, improved sanitation, maternal mental health and parenting education program (scenario 1-3 above). This is an example of intervention that has components of progressive universalism (40) where all children would have access to a decent standard of living and more support is provided for children's whose mothers need mental health and parenting interventions.

Statistical analysis

Notation

Let t be the time variable where t_0, t_1 and t_2 is defined as the time when data was collected (ages 4, 5 and 8, respectively). Let Y_2 be the outcome (school readiness and socio-emotional wellbeing) that was measured at age 8. Let $d=(d_1, d_2, d_3, d_4, d_5)$ be the intervention scenario (regime). Let f_d be the density function under a particular intervention d. Let $X=(X_1, X_2, X_3, X_4)$ be the exposure, where X_1 is defined as used piped water as the main drinking water source, X_2 defined as used improved sanitation,

X_3 defined as maternal mental health score, and X_4 defined as parenting scores. Let x_t^* is the observed value of exposure under no intervention at time *t*. Let x_t be the value of exposure under intervention *d* at time *t*. Let $L=(L_1, L_2, L_3, L_4)$ be confounding, where L_1 defined as used piped water as the main drinking water source, L_2 defined as used improved sanitation, L_3 defined as maternal mental health score, and L_4 defined as parenting scores. Let l_t be the value of confounding at time *t*. Let variables with over bars $\left(\bar{x}_t, \bar{x}_t^*, \bar{l}_t\right)$ represent the history of the intervention, observed exposure and covariates up to time *t*, respectively. Let $\bar{c}$ be a vector of baseline confounders measured at time 0 (age 4) including maternal age and education, household size, the number of self-reported economic hardships in the past year, standard of living index and whether the child is living in a village that receive the ECED program or otherwise.

Study 4 used observational longitudinal data where both exposure and confounding were measured at multiple time points (ages 4, 5, and 8). As shown in section 3.3.2, methods that can be used to aid causal interpretation from complex longitudinal observational studies include g-formula (187, 188, 192), g-estimation of the structural nested models (SNMs) (189) and marginal structural models (MSMs) (189, 190, 193, 194). MSMs use the inverse probability of treatment weight to control the potential bias due to confounding *L*. G-estimation of the structural nested model uses simulation models of *X*, *L* and *Y*, to estimate the potential outcome under the assumption that the effect of exposure varies for different levels of confounding *L*. Finally, the g-formula can be used to estimate the potential outcome of *Y* by simulating the joint distributions of exposure *X*, confounding *L* and outcome *Y* (equation 26).

G-formula

The earlier version of g-formula was derived by Robins (187, 188) to estimate the effect of time-varying exposure in the presence of time-varying confounding through standardization modelling. The original g-formula is a nonparametric method because the estimation did not require a *priori* restrictions on the value of the effect estimates.

Equation 26. Statistical model for g-formula

$$f_{obs} = f(Y \mid \overline{X}_{t,} \overline{L}_t) \times \prod_{t=0}^{T} f(\bar{l}_t \mid \bar{l}_{t-1}, \bar{x}_{t-1}) \times \prod_{t=0}^{T} f(x_t \mid \bar{x}_{t-1}, \bar{l}_t)$$

Equation 26 shows that g-formula estimates the potential outcome of *Y* under a joint density of conditional probabilities of the observed exposure *X*, confounder *L* and *Y* at time *t* given the history of the observed *X* and *L*. G-formula is useful to estimate the effect of time varying exposure in the presence of time varying confounders that are also affected by the past exposure. However, in the case where data has many confounders (high dimensional data), g-formula can only be estimated under parametric modelling assumptions and uses a Monte Carlo simulation to estimate the sum over all histories of covariates (224). Moreover, the earlier version of g-formula cannot be used to estimate the potential outcome of *Y* under joint interventions of multiple exposures. To estimate the relative effect of specified hypothetical interventions on children's school readiness and socio-emotional wellbeing, this study used an extended version of g-formula, which also known as parametric g formula (224-226).

Parametric g formula

Parametric g-formula (224-226) is the extended version of nonparametric g-formula (187, 188). This method was firstly introduced by Robins, Hernan and Siebert (224) for estimation of the potential outcome under several types of hypothetical interventions (regimes). By definition, intervention (treatment regime) can be in the form of single (intervention on one risk factor) or joint interventions (intervention on multiple risk factors), and static or dynamic interventions. An intervention is defined as “static deterministic” if the assignment of intervention did not depend on the past treatment or covariates. This approach is also known as non-dynamic intervention because all subject receive the same value of intervention irrespective of the past exposure or covariates. In contrast, intervention where assignment was based on past treatment or covariates is classified as “dynamic intervention”.

The steps in parametric g-formula are as follows.

Step 1. Parametric modelling

Specify four parametric models of each covariate *L=l* in the following order; whether a child was exposed to pumped water as the main drinking water source (l_1), improved sanitation (l_2), maternal mental health (l_3) and parenting scores (l_4).

In Model 1, $\Pr(l_{1t} \mid l_{it-1}, l_{2t,} l_{2t-1}, \bar{l}_{3t-1}, \bar{l}_{4t-1}, \bar{c})$ logistic regression was used to estimate the conditional probability of the child exposed to piped water as the main drinking water source at time *t* $(L_{1t} = l_{it})$ given whether the child used piped water in the past, the history of other covariates up to time *t-1* $\bar{L}_t$ (improved sanitation, maternal mental health and parenting scores) and baseline confounders *C*.

In Model 2, $\Pr(l_{2t} \mid l_{2t-1}, l_{1t}, l_{1t-1}, \bar{l}_{3t-1}, \bar{l}_{4t-1}, \bar{c})$ logistic regression was used to estimate the conditional probability of the child exposed to improved sanitation at time *t* $(L_{2t} = l_{2t})$ given whether the child used improved sanitation in the past, the history other covariates up to time *t-1* (used piped water as the main drinking water source, maternal mental health and parenting scores) and baseline *C*.

In Model 3, $E(l_{3t} \mid \bar{l}_{3t-1}, l_{1t}, l_{1t-1}, l_{2t}, l_{2t-1}, \bar{l}_{4t-1}, \bar{c})$ linear regression was used to estimate the conditional density function of maternal mental health scores at time *t* $(L_{3t} = l_{3t})$ given the cumulative mean of maternal mental health score in the past, the history of other covariates up to time *t-1* (whether a children used piped water, improved sanitation and parenting score) and baseline *C*.

In Model 4, $E(l_{4t} \mid \bar{l}_{4t-1}, l_{1t}, l_{1t-1}, l_{2t}, l_{2t-1}, \bar{l}_{3t-1}, \bar{c})$ linear regression was used to estimate the conditional density function of parenting score at time *t* $(L_{4t} = l_{4t})$ given the cumulative mean of parenting score in the past, the history of other covariates up to time *t-1* (whether a child used piped water as the main drinking water source, improved sanitation and maternal mental health score) and baseline *C*.

Fit a model for each outcome

Model $\Pr[Y_{it+1} \mid \bar{x}_t, \bar{l}_t, \bar{c}]$ used logistic regression to estimate the risk of being vulnerable in each EDI domain (or vulnerable in one or more EDI domains) at age 8 given the history of exposure, confounding and baseline *C*.

Model $E\left[Y_{t+1} \mid \bar{x}_t, \bar{l}_t, \bar{c}\right]$ used linear regression to estimate the expectation of internalising (or externalising) score at age 8 given the history of exposure, confounding and baseline *C*.

Step 2. Monte Carlo simulation

For each time *t* generate the intervention *d* value for each covariate, “provide piped water as the main drinking water source and improved sanitation” (scenario 1); “set maternal mental health score to a maximum value of 17” (scenario 2); and “set parenting score to a minimum value of 75” (scenario 3). Monte Carlo simulation with a full sample samples (n=2906 for the EDI and n=2955 for the SDQ) was conducted to estimate parametric models in step 1 and was used to estimate the outcome under each intervention.

Step 3. Estimation of the outcome under each intervention

Under the assumption of conditional exchangeability, positivity and consistency, parametric g-formula was used to estimate the potential outcome under each hypothetical intervention above, defined as

Equation 27. Parametric g-formula

$$\sum_{t=0}^{T}\sum_{\bar{x}_t}\sum_{\bar{x}_t^*}\sum_{\bar{l}_t}\Pr\left[Y_{t+1} \mid \bar{x}_t, \bar{l}_t, \bar{c}\right]$$
$$\times f_d\left(x_t \mid \bar{l}_t, x^*, \bar{x}_{t-1}, \bar{c}\right)$$
$$\times f\left(l_t \mid \bar{l}_{t-1}, \bar{x}_{t-1}, \bar{c}\right)$$
$$f\left(x_t^* \mid \bar{l}_t, \bar{x}_{t-1}, \bar{c}\right)$$

For school readiness outcomes, the model in equation 27 can be defined as the risk of being vulnerable in each EDI domain (or vulnerable in one or more domains) given the history of specified intervention *d*, covariates and observed exposure under no intervention. For socio-emotional wellbeing, the model can be replaced by

$E\left[Y_{t+1} \mid \bar{x}_t, \bar{l}_t, \bar{c}\right]$ defined as the expectation of internalising (or externalising) behaviour scores given the history of specified intervention *d*, covariates and observed exposure under no intervention.

This process (steps 1-3) was repeated sequentially for each scenario and for each different outcome. The 95% CI was estimated based on a bootstrap of 1000 resamples. Analysis of parametric g formula was conducted in SAS 9.4 (SAS Institute, Cary, North Carolina). The algorithm for parametric g-formula was adapted from SAS macro program version June 2015 that is available from www.hsph.harvard.edu/causal/software.

Complete case analysis

Analysis in study 4 was also restricted to complete cases (178) because of there is no current method available to combine estimates from parametric g-formula using Rubin's rule.

Findings from study 4 are presented in chapter 7.

CHAPTER 4

Changes in Socioeconomic Inequality in Indonesian Children's Cognitive Function From 2000 to 2007:

A Decomposition Analysis

4.1. Preface

This chapter contains the first study of the thesis, which examined the magnitude of socioeconomic inequality in Indonesian children's cognitive function in 2000 and 2007, factors contribute to the inequality, whether the inequality in children's cognitive functioning change between 2000 and 2007 and factors contribute to the change in inequality. This chapter has been published in PLOS One.

4.2. Statement of authorship

Maika A, Mittinty MN, Brinkman S, Harper S, Satriawan E, Lynch, J.

Changes in Socioeconomic Inequality in Indonesian Children's Cognitive Function from 2000 to 2007: A Decomposition Analysis. PLoS ONE 2013 8(10): e78809

By signing below, the authors declare that they give consent for this paper to be presented by Amelia Maika towards examination for the Doctor of Philosophy.

Amelia Maika (Candidate)

Designed the study, performed the analyses, interpreted the results and drafted the manuscript.

Signed: Date: 11/11/2015

Murthy Mittinty

Contributed to the design of the study and interpretation of the results, and reviewed the manuscript. I give consent for Amelia Maika to present this paper towards examination for the Doctor of Philosophy.

Signed: Date: 3/11/2015

Sally Brinkman

Contributed to the design of the study and interpretation of the results, and reviewed the manuscript. I give consent for Amelia Maika to present this paper towards examination for the Doctor of Philosophy.

Signed: Date: 29/10/2015

Sam Harper

Contributed to the interpretation of the results and reviewed the manuscript. I give consent for Amelia Maika to present this paper towards examination for the Doctor of Philosophy.

Signed: Date: 2/11/2015

Elan Satriawan

Contributed to the interpretation of the results and reviewed the manuscript. I give consent for Amelia Maika to present this paper towards examination for the Doctor of Philosophy.

Signed: Date: 31/10/2015

John Lynch

Contributed to the design of the study and interpretation of the results, and reviewed the manuscript. I give consent for Amelia Maika to present this paper towards examination for the Doctor of Philosophy.

Signed: Date: 3/11/15

4.3. Abstract

Background

Measuring social inequalities in health is common, however, research examining inequalities in child cognitive function is more limited. We investigated household expenditure-related inequality in children's cognitive function in Indonesia in 2000 and 2007, the contributors to inequality in both time periods, and changes in the contributors to cognitive function inequalities between the periods.

Methods

Data from the 2000 and 2007 round of the Indonesian Family Life Survey (IFLS) were used. Study participants were children aged 7-14 years (n=6179 and n=6680 in 2000 and 2007, respectively). The relative concentration index (RCI) was used to measure the magnitude of inequality. Contribution of various contributors to inequality was estimated by decomposing the concentration index in 2000 and 2007. Oaxaca-type decomposition was used to estimate changes in contributors to inequality between 2000 and 2007.

Results

Expenditure inequality decreased by 45% from an RCI=0.29 (95% CI 0.22 to 0.36) in 2000 to 0.16 (95% CI 0.13 to 0.20) in 2007 but the burden of poorer cognitive function was higher among the disadvantaged in both years. The largest contributors to inequality in child cognitive function were inequalities in per capita expenditure, use of improved sanitation and maternal high school attendance. Changes in maternal high school participation (27%), use of improved sanitation (25%) and per capita

expenditures (18%) were largely responsible for the decreasing inequality in children's cognitive function between 2000 and 2007.

Conclusions

Government policy to increase basic education coverage for women along with economic growth may have influenced gains in children's cognitive function and reductions in inequalities in Indonesia.

4.4. Introduction

In 1970 Indonesia was among the poorest countries in the world with 60% of the population living in absolute poverty (67). In the decade from 2003, the poverty rate in Indonesia decreased from 17% to 12% and economic growth in the past decade has moved Indonesia from a low to a middle-income country (227). Despite this overall progress, regional and socioeconomic disparities within the country are still evident, driven by inequalities in economic, infrastructure and human resources (228, 229). For example, the mean years of schooling for the household head in poor families was 5 compared to 8 years for non-poor families (229). Fewer than half of the households in 2011 had access to safe drinking water and only about 56% had access to a latrine connected to septic tank or a composting toilet (230).

Measuring inequalities in health related outcomes is relatively common (177, 231, 232), but research examining inequalities in children's development is more limited. Children under five living in poorer socioeconomic circumstances in low and middle income countries are often exposed to a multitude of risk factors such as poverty, malnutrition, poor housing conditions and sanitation that influence their opportunities for healthy child development (16, 17). There is growing interest in the influences of children's health, learning and well-being, on their later school readiness, academic achievement and labor force participation (51). Cognitive function is an important aspect of healthy child development as it has both short and longer terms effects. Higher cognitive function is associated with better academic achievement (43, 44) physical and mental health (45, 46, 233) and in the long-term economic outcomes such as higher occupational status, earnings and may influence national economic performance (49, 50). Early life social disadvantage has been associated with poorer cognitive outcomes and neurodevelopment in richer and poorer countries (6-8, 88, 89, 234). Among school aged children, inequality in early life socioeconomic circumstances also contributes to inequality in children's cognitive outcomes as measured through literacy (93, 235) and math scores (93, 236).

The aim of the current study was to quantify household expenditure-related inequality in Indonesian children's cognitive function in 2000 and 2007. We also investigated the contributions of child, parental and household characteristics to inequality in both periods and changes in contributions to children's cognitive function inequalities between 2000 and 2007.

4.5. Methods

Ethics statement

This research has been approved by Human Research Ethics Committee the University of Adelaide.

Data

We used data from the 2000 and 2007 round of the Indonesia Family Life Survey (IFLS), which is an ongoing longitudinal survey in Indonesia. IFLS was conducted in 1993, 1997, 2000 and 2007. IFLS provided extensive information about socioeconomic, behavior and health related outcomes at household and individual levels, as well as information about public facilities at the community level. IFLS used multi-stage sampling. Stratified sampling was used to select province, which covers 13 out of 27 provinces in 1993. Random sampling was used to select households within these provinces. The sample of households represented 83% of the Indonesian population living in the 13 provinces in 1993 (146). In this study, we used data from the third (2000) and fourth (2007) round of the IFLS (148, 149). We selected participants aged 7 to 14 years who were interviewed for cognitive assessment in 2000 (n=6179) and aged 7 to 14 in 2007 (n=6680). The response rate for this cognitive test was 96% for each year. The data was analyzed as a repeated cross sectional study and was weighted using cross-sectional person sampling weights provided in the IFLS datasets for 2000 and 2007.

Cognitive function

Cognitive function was measured using a subset from the Raven's Progressive Matrices, comprising 12 shapes with a missing part where children selected the correct part to complete the shape (151). Each correct answer was coded 1 or 0 otherwise and scores combined as the total raw score. The distributions of the total raw scores were skewed towards the left tail at all ages, and as expected also increased with age. Because scores were highly skewed, we calculated the mean and the variance by taking into account the range, median and the sample size using the formula from Hozo, *et al.,* (152) and used the estimated mean and standard deviation to create an age specific z-score.

Per capita expenditure

We used the log of per capita expenditure which was constructed from the monthly total household expenditures divided by the number of household members (157).

Covariates

A range of child, parental and household characteristics was selected *a priori* as contributors to inequality in children's cognitive function. Children's characteristics included gender and whether the child was currently attending school (151, 237, 238). Parental characteristics were measured separately for father and mother including education, employment and mental health (6-8, 162, 239). Parental education was measured as the highest level of education attended and was recoded in three categories, none or primary, high school, or university. Parental primary employment was defined whether parents were working in the past week, categorized as "yes" and "no". Parental mental health was measured using the short version of the Centre for Epidemiology Studies Depression Scale (CES-D) (166). For this study we used mental health as a continuous variable from total scores of the CES-D measure, where higher score is associated with poorer mental health symptoms. Household characteristics included whether the household had electricity, used an improved drinking water source (defined as piped water, electric or hand pumps boreholes and bottled water) and improved sanitation (defined as toilet with septic tank) (162, 240, 241). Residential area included whether the household was in a rural area and province of residence, categorized as Java Bali or otherwise.

Missing data

In 2000, of the 6179 children, 2023 children had missing data in one or more variables of interest (exposure, outcome or covariate) leaving 4156 children with complete information. In 2007, of the 6680 children, 2389 children had missing data in one or more variable of interest and 4291 children had complete information. We performed Multiple Imputation by Chained Equation (MICE) procedure in STATA to impute all the missing variables under the assumption that the data are missing at random (181). We generated a total of twenty imputed datasets using fifty cycles of regression switching. Children who do not have either one or both parents, due to death or were not residing in the same household were excluded from the imputation analysis. Imputations were conducted for each study year separately. Multiple imputation was only used for the estimation of the RCI not in the decomposition. That is because there are currently no methods for combining the estimates in the decomposition part of the analysis.

Analysis

The magnitude of the inequality in children's cognitive function

The concentration curve is a graphical illustration of the magnitude of the inequality in children's cognitive function. The relative concentration curve can be drawn by plotting the cumulative share of the population ranked by the log of per capita expenditures (starting from the lowest to the highest) on the x-axis, against the cumulative share of cognitive function z-score on the *y*-axis. We used the relative concentration index (RCI) to calculate the magnitude of the inequality, defined as twice the area between the curve and the line of equality (172, 177). The RCI can be written as

Equation 1. Relative Concentration Index

$$RCI = \frac{2}{n\mu}\sum_{i=1}^{n} y_i R_i - 1$$

where μ is the mean of cognitive function z-score (y), R_i is the relative rank of the ith individual in the per capita expenditures distribution. The RCI normally takes value -1 to 1 with a value of zero indicating no inequality. However, the value is not bounded when the y takes negative and positive values (81). In our study, y is a positive outcome (higher score is associated with a better cognitive function), so positive values of concentration index indicate children with higher cognitive function are concentrated among the non-poor and vice versa. We applied the Delta method to estimate the standard errors (SE) of the RCI (81) and then used the estimated SE to calculate confidence interval. For imputed data we estimate RCI and SE in each of the twenty datasets and then use Rubin's rules for combining these results (181).

Decomposition of contributors to inequality in children's cognitive function

We used decomposition analysis to estimate contributions to inequality in children's cognitive function for each year (81, 177) In decomposition analysis a set of k contributors (x_k) is regressed on continuous y in a linear regression model (Equation 2), where β_k are the coefficients and ε_i is an error term.

Equation 2. Linear regression model

$$Y_i = \alpha + \sum_k \beta_k X_{ik} + \varepsilon_i$$

Given the relationship between y_i *and* x_{ik} in Equation 2, the RCI is estimated as the sum of the relative concentration index of the determinants weighted by the elasticity (η_k) of *y* with respect to each determinant. The formula can be written as

Equation 3. Decomposition of the concentration index

$$RCI = \sum_k \eta_k C_k + GC_\varepsilon / \mu$$

$$\eta_k = \frac{\beta_k \overline{X}_k}{\mu}$$

where β_k is the estimated coefficient of k contributor, $\overline{x}_k$ is the mean of *k*, μ is the mean of *y*, C_k is the relative concentration index for *k* contributor, and GC_ε is the generalized concentration index for the error term. The contribution of each factor is a function of the elasticity of cognitive function with respect to the particular contributor and the degree of per capita expenditures-related inequality**.** Therefore, in order to have a large contribution to the total inequality, a factor should have either large elasticity or large relative concentration index (C_k) or both.

For estimating the uncertainty in the decomposition we used Markov chain Monte Carlo (MCMC) simulation method (175). This was chosen over bootstrap methods because it allows use of the survey weights without requiring any additional computational complexity. In MCMC we used the Gibbs re-sampling method. The 95%

confidence interval was calculated using the equal tail method. The equal tail interval runs from 2.5th percentile and 97.5th percentile of the posterior distributions (176). The decomposition analysis is limited to complete case because the methodology for estimating the SE of percent contribution of each determinant is not yet available, which in-turn limits the use of Rubin's rule for combining the imputed data.

Decomposition of changes in the inequality in children's cognitive function

We also examined changes in per capita expenditure inequality in cognitive function between 2000 and 2007. We used the Oaxaca-type decomposition to measure changes in inequality in the contributors to cognitive function inequality and changes in the elasticity of cognitive function with respect to these contributors (81, 177). The formula can be written as

Equation 4. Oaxaca-type decomposition of change

$$\Delta C = \sum_k \eta_{kt}(C_{kt} - C_{kt-1}) + \sum_k C_{kt-1}(\eta_{kt} - \eta_{kt-1}) + \Delta(GC_{\varepsilon t} / \mu_t)$$

where η_{kt} is the elasticity of k contributor at time t and C_{kt} is the relative concentration index of k at time t. Similar to decomposition analysis, the decomposition of change is also restricted to complete case.

Table 1. Summary statistics for cognitive function and its contributors using complete case analysis, 2000 and 2007

	2000 n=4156	2007 n=4291
	% or Mean (SD)	% or Mean (SD)
Outcome		
cognitive function (z-score)	0.24 (0.79)	0.34 (0.66)
Children characteristics		
Age	10.5 (2.28)	10.2 (2.31)
Gender		
Male	51	52
Female	49	48
Primary activity		
-attending school	91	95
Parental characteristics		
Father education		
- none or primary	60	45
- high school	32	44
-university	8	11
Mother education		
-none or primary	69	50
-high school	26	42
-university	5	7
Father primary activity		
-working	93	95
-others	7	5

Table 1. Continued

	2000 n=4156	2007 n=4291
	% or Mean (SD)	% or Mean (SD)
Mother education		
-none or primary	69	50
-high school	26	42
-university	5	7
Father primary activity		
-working	93	95
-others	7	5
Mother primary activity		
-working	53	49
-others	47	51
Mental health		
-Father	2.03 (2.98)	3.29 (3.18)
-Mother	2.56 (3.50)	3.53 (3.48)
Household characteristics		
Residential area		
-Living in rural	57	49
-Living in urban	43	51
-Living in Java or Bali	58	59
-Living in outside Java or Bali	42	41
Log per capita expenditures	11.93 (0.70)	12.82 (0.65)
Has electricity	89	96
Improved drinking water	51	55
Improved sanitation	44	64

4.6. Results

Table 1 shows the summary statistics of cognitive function and its contributors. The average child cognitive function z-score increased from 0.24 (SD 0.79) in 2000 to 0.34 (SD 0.66) in 2007. Of the 4156 children in 2000, 51% were males and 91% of them were still attending school. In 2007, of the 4251 children 95% were still attending school. In terms of parental education, the mothers had lower education than the fathers in both years. In 2000, 69% of mothers had no or primary education, whereas in 2007 this had dropped to 50%. There was also improvement in fathers' education, 60% of fathers had no or primary education in 2000 down to 45% in 2007. The average log per capita expenditures was 11.93 *rupiah* (SD 0.70) in 2000 and 12.82 *rupiah* (SD 0.65) in 2007, which is equivalent to an increase from approximately 16 to 37 USD per month. In 2000, the proportion of households that had electricity was 89%, used an improved drinking water source was 51% and used improved sanitation was 44%, whereas in 2007, the proportion was 96%, 55% and 64%, respectively.

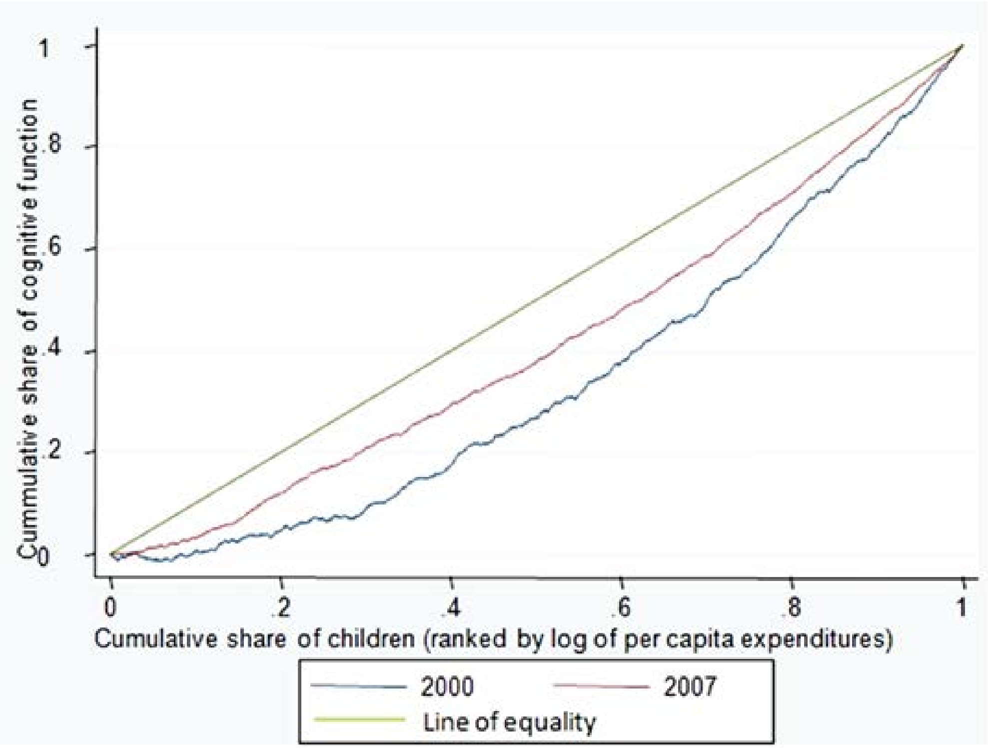

Figure 19. Relative concentration curve for inequality in children's cognitive function using complete cases analysis, Indonesia 2000 and 2007

The relative concentration curves for inequality in children's cognitive function in 2000 and 2007 based on complete case analysis are shown in Figure 19. Using complete case analysis, the RCI in 2000 was 0.29 (95% CI 0.22-0.36) and was 0.16 (95% CI 0.13-0.20) in 2007, showing the burden of poorer cognitive function was higher among the disadvantaged in both years.

Table 2. Comparison between complete cases and multiple imputation

	2000		2007	
	Sample N=6179	RCI (95% CI)	Sample N=6680	RCI (95% CI)
Complete case	4156	0.29 (0.22-0.36)	4291	0.16 (0.13-0.20)
Multiple imputation	5079	0.32 (0.24-0.41)	5560	0.20 (0.15-0.25)

Table 2 shows the comparison of RCI and their confidence interval for 2000 and 2007 between complete case analysis and multiple imputation analysis. The magnitude of the RCI from multiple imputation analysis were 0.3 and 0.4 higher than using complete case analysis, for 2000 and 2007 respectively,

Table 3. Decomposition of inequality in children's cognitive function ranked by contribution in 2000

Contributors	2000					
	β	Elasticity	concentration index	contribution	95% CI lower	95% CI upper
Log per capita expenditures	0.08	3.38	0.03	37%	19%	55%
Use improved sanitation	0.14	0.21	0.26	18%	11%	26%
Mother attended high school	0.18	0.16	0.33	18%	11%	24%
Father attended university	0.12	0.03	0.67	7%	0%	14%
Mother attended university	0.17	0.03	0.69	7%	1%	12%
Has electricity	0.20	0.65	0.03	6%	4%	9%
Living in rural	-0.07	-0.16	-0.10	6%	2%	9%
Child is attending school	0.17	0.56	0.02	3%	2%	5%
Living in Java/Bali	0.13	0.37	0.02	3%	1%	4%
Father's mental health scores	-0.01	-0.04	-0.06	1%	0%	2%
Mother's mental health scores	-0.01	-0.06	-0.03	1%	2%	9%
Father attended high school	0.00	0.00	0.20	0%	-4%	5%
Father is working	0.04	0.13	0.01	0%	0%	1%
Mother is working	0.01	0.02	0.01	0%	0%	0%
Use improved drinking water	0.00	0.00	0.16	0%	-5%	5%
Child is male	0.10	0.19	-0.02	-1%	-2%	-1%
Residual		0.00	0.00	-5%		

Table 3. Continued

Contributors	2007					
	β	elasticity	concentration index	contribution	95% CI lower	95% CI upper
Log per capita expenditures	0.10	3.09	0.03	52%	33%	70%
Use improved sanitation	0.09	0.14	0.13	12%	6%	18%
Mother attended high school	0.10	0.09	0.16	9%	4%	13%
Father attended university	0.10	0.02	0.57	9%	2%	15%
Mother attended university	0.07	0.01	0.64	5%	-2%	11%
Has electricity	0.25	0.60	0.01	5%	3%	70%
Living in rural	-0.03	-0.05	-0.09	3%	-1%	7%
Child is attending school	0.09	0.22	0.02	2%	0%	4%
Living in Java/Bali	0.14	0.29	0.00	0%	0%	0%
Father's mental health scores	-0.01	-0.05	-0.03	1%	0%	2%
Mother's mental health scores	0.00	-0.03	-0.03	1%	0%	2%
Father attended high school	0.04	0.04	0.11	3%	0%	6%
Father is working	-0.13	-0.31	0.01	-2%	-3%	-1%
Mother is working	0.05	0.07	0.07	3%	1%	5%
Use improved drinking water	0.04	0.05	0.09	3%	0%	6%
Child is male	0.05	0.06	-0.01	0%	-1%	0%
Residual		0.00	0.00	-3%		

Table 3 shows the decomposition of the inequality in cognitive function for 2000 and 2007 ranked by the contribution in 2000. The β coefficient shows the association between cognitive function and each contributor. Being male, still attending school, living with a parent who had higher education, and living in Java-Bali were all associated with higher cognitive function scores. Whereas higher parental mental health score and living in a rural area are associated with a lower cognitive function score. The elasticity shows how sensitive cognitive function is to each contributor. The largest elasticity was the log of per capita expenditure (3.38 in 2000 and 3.09 in 2007). The concentration index shows the magnitude of inequality in cognitive function with respect to each contributor. The concentration indices for parental education were all positive, indicating parents with higher education were more concentrated among the higher economic groups. For example, in 2000 the concentration index for the father's university attendance was 0.67 and was 0.69 for mothers. The concentration indices for parental mental health were negative, indicating that parents with higher mental health scores were more concentrated among the higher economic groups.

The largest contribution to inequality in cognitive function was inequality in per capita expenditures, accounting for 37% and 52% of the total inequality in 2000 and 2007, respectively. Inequality in using improved sanitation accounted for 18% (in 2000) and 12% (in 2007) of the total inequality in children's cognitive function. As an important determinant of child cognitive function, parental education disproportionately contributed to the total inequality with maternal high school attendance having the largest contribution in 2000 (18%) and having equal contribution with fathers' university attendance in 2007 (9%). Although residential location made a very small contribution to the total inequality, children residing in rural areas or outside Java-Bali had poorer cognitive function compared to their urban peers or those children residing in Java-Bali.

Table 4. Oaxaca-type decomposition for change in children's cognitive function inequality, 2000 and 2007

Contributors	change in inequality	change in elasticity	total	%
Mother attended high school	-0.02	-0.02	-0.04	27%
Use improved sanitation	-0.02	-0.02	-0.03	25%
Log per capita expenditures	-0.02	-0.01	-0.02	18%
Living in rural	0.00	-0.01	-0.01	8%
Mother attended university	0.00	-0.01	-0.01	8%
Has electricity	-0.01	0.00	-0.01	7%
Father attended university	0.00	-0.01	-0.01	5%
Living in Java/Bali	-0.01	0.00	-0.01	5%
Child is attending school	0.00	-0.01	-0.01	4%
Father is working	0.00	0.00	0.00	3%
Father's mental health scores	0.00	0.00	0.00	1%
Mother's mental health scores	0.00	0.00	0.00	0%
Residual	0.00	0.00	0.00	0%
Father attended high school	0.00	0.01	0.00	-2%
Child is male	0.00	0.00	0.00	-3%
Mother is working	0.00	0.00	0.00	-3%
Use improved drinking water	0.00	0.01	0.00	-3%
Total	-0.07	-0.07	-0.14	100%

There was 0.13 (45%) decrease in inequality in children’s cognitive function between 2000 and 2007. Table 4 shows the decomposition for change in inequality in children’s cognitive function. The first column shows changes in the magnitude of inequality in the contributors and the second column shows changes in the elasticity of the cognitive function with respect to these contributors. The total change for each determinant and the percent change are presented in the last two columns. Overall, changing inequalities and changing elasticities contributed equally to the reduction in inequality in cognitive function. Although inequality in per capita expenditures accounted for the largest contribution to the total inequality for each year, it only contributed 18% to decreasing inequality. Changes in maternal participation in high school (27%), use of improved sanitation (25%) and increases in per capita expenditures were largely responsible for changes in inequality in children's cognitive function.

4.7. Discussion

Inequality in Indonesian children's cognitive function favored more advantaged households in both 2000 and 2007. However, children aged 7-14 years in 2007 had higher cognitive scores than the cohort of 7-14 year olds in 2000. Importantly, although pro-rich inequality remains, inequality in cognitive function decreased by 45% between 2000 and 2007. Inequalities in per capita expenditures, maternal high school attendance and use of improved sanitation were the largest contributors to inequality for each year, suggesting that the change in cognitive function is most sensitive to these three important determinants. Children living in households with higher per capita expenditures, having a mother with high school education and using improved sanitation were more concentrated among the higher economic groups. Between 2000 and 2007, inequality in the social distribution of children with mothers who attended high school and used improved sanitation decreased. In these data, these were the main contributors to reduction in inequalities in children's cognitive function. Our findings are consistent with the recent Program for International Student

Assessment's (PISA) results, indicating Indonesia was among the small number of countries where the level of socioeconomic inequality decreased and the average student's performance improved between 2000 and 2009 (242).

The decomposition analysis presented here is descriptive rather than causal, partly because we are limited by the factors included in the ILFS survey to examine as contributors. To triangulate our findings, we examined the national statistics on school participation, population with access to improved sanitation and GDP growth (243) as well as policy trends that may shed light on what we found to be the three largest contributors to reduction in cognitive function inequality. Statistics on trends in school participation show that between 1971 and 2010 both primary and secondary school enrolments have increased, with a substantial increase between 1971 and 1987 for primary school and between 1978 and 1987 for secondary school enrolment (Figure 20).

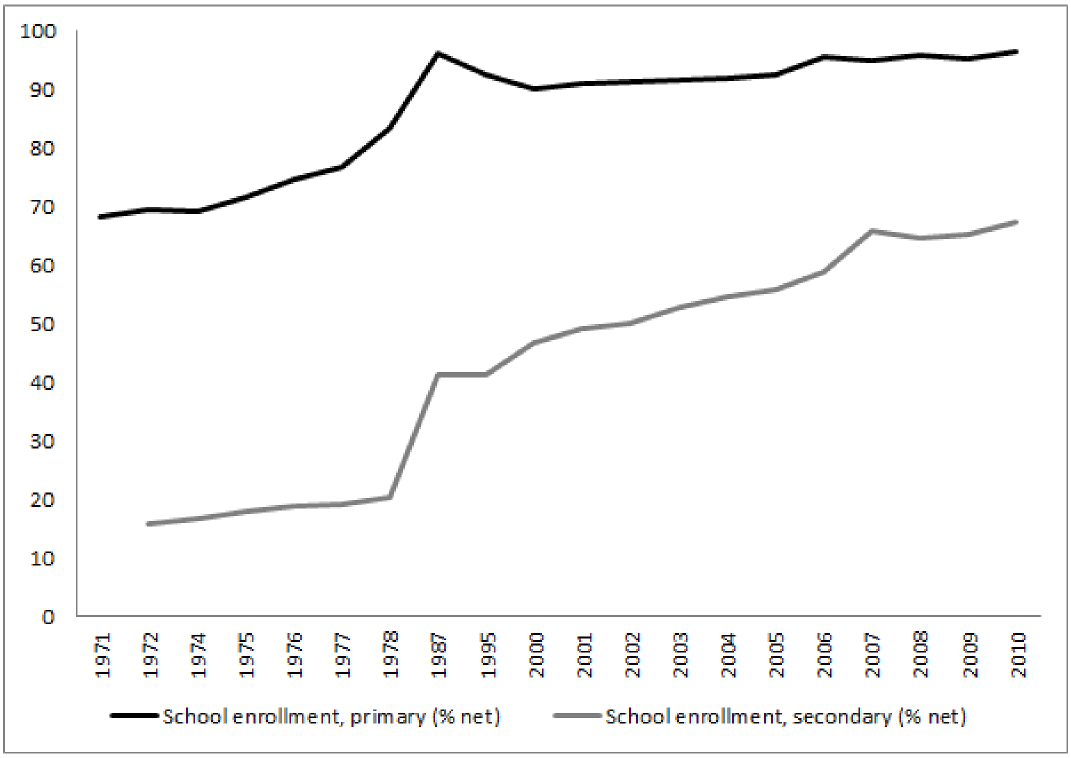

Figure 20. Trends in school enrolment, Indonesia 1971-2010

One possible explanation is related to government policy to provide universal access to basic education through the school construction program in 1973-1979 and the elimination of primary school fees in 1978 (67). Through the Presidential Instruction for Primary School program (*SD Inpres*), the government doubled the number of primary schools by building more than 61,000 new primary schools between 1973 and 1979. The number of schools constructed in each district was proportional to the number of primary school aged children not enrolled in schools in 1972 (10). *SD Inpres* was not only the largest school construction program in the country's history, but also the fastest increase in school provision in the world (67). A study by Duflo (10) suggested that this program had more impact on the cohort aged 7 or younger in 1974 but not the cohort born in 1962 or before. The same study also found this program had more impact in poor provinces and increased the probability of completing primary school by 12% among the affected children.

Using data from the IFLS 2000, Petterson (244) found that women and students from low socioeconomic groups received more benefits from the school construction program in Indonesia. Following that program, in 1984 the government passed the first law of compulsory basic education (*Wajib Belajar*), where every child aged 7-12 had to attend six years basic education.

Our results show that reduction in the inequality in maternal high school attendance made the largest contribution to decreasing inequality in children's cognitive function between 2000 and 2007. This is consistent with the evidence from developing countries that shows increasing school availability at the local level has greater benefit for educational achievement in females although the Indonesian program was not specifically targeting girls (245). In our study, the mean age of mothers was 37 (SD 6.61 for 2000 and 6.58 for 2007). With the assumption that the cohort born after 1962 received more benefit from the school construction program, we estimated 85% of the mothers in 2007 were among the cohort who were more likely to benefit from the school construction program and the laws making six years basic education compulsory, compared to 55% of the mothers in 2000. In addition to change in inequality in maternal high school attendance, reduction in cognitive function inequality was also sensitive to change in household access to improved sanitation and change in per capita expenditures. Figure 21 shows steadily increasing trends in the proportion of the population with access to improved sanitation and improvements in the average GDP in 2000 and 2011.

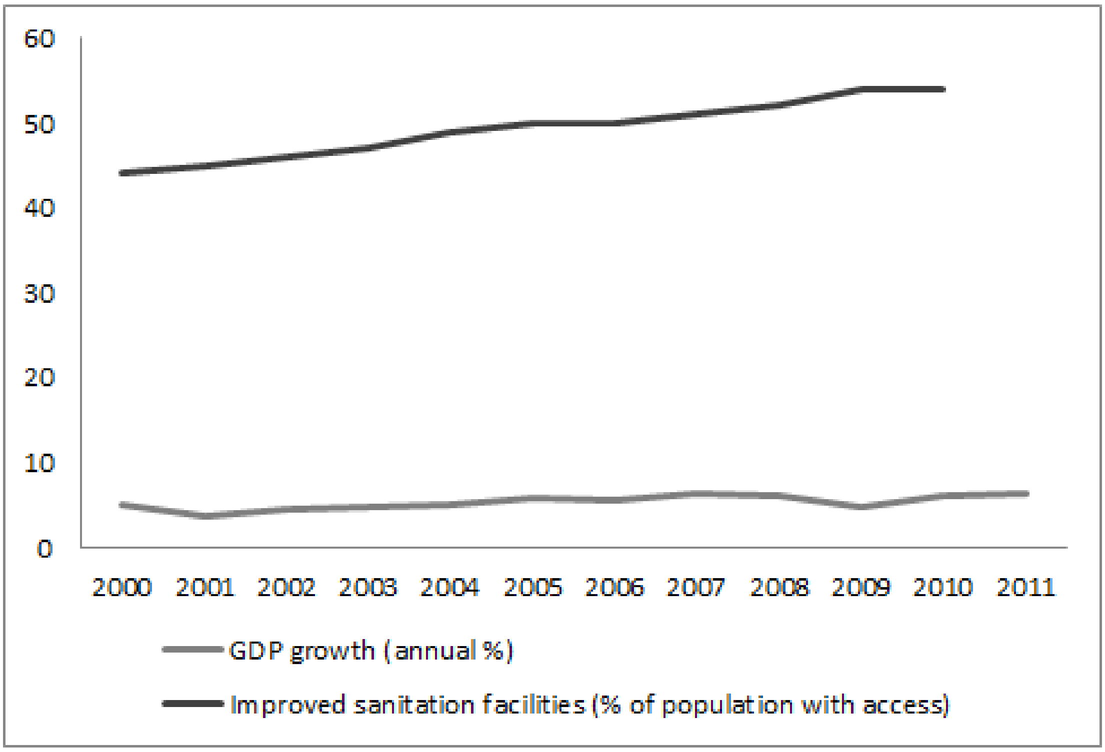

Figure 21. Trends in GDP growth and improved sanitation facilities, Indonesia 2000-2011

A great deal of evidence shows that increasing pro-equity public service coverage including health and education programs could help reduce health related inequalities at the population level (246-248). A systematic review by Gakidou, *et al.*, (249) found increases in women's educational attainment reduced gender gaps in education and contributed about 51% to decreasing under five mortality in 175 countries between 1970-2009. Evidence from Japan shows universal access to primary education in the early 1900s increased primary school attendance and reduced gender inequality in education, which in the longer term also had benefits on population health through reduction of infant mortality and increased life expectancy (250). Qualitatively similar processes resulting in reductions in infant mortality on increasing life expectancy has also been demonstrated in South Korea (245).

The limitations of this study include that it is a descriptive analysis of cross sectional data in 2000 and 2007. Estimates of the magnitude and contribution to inequality calculated in these data are based on the socioeconomic measure used - in this case, per capita household expenditure. Other indicators of socioeconomic inequality may yield different estimates, especially for the contributions (81, 251). Results from the decomposition analysis are sensitive to which determinants are selected for inclusion in the model. Remaining cognizant that our findings cannot be considered causal, we argue that pro-equity government policy and investment in education, particularly for women, improved sanitation and to a lesser extent economic growth are plausible important contributors to overall improvements and decreased inequalities in children's cognitive function in Indonesia.

CHAPTER 5

Effect on Child Cognitive Function of Increasing Household Expenditure in Indonesia: Application of a Marginal Structural Model and Simulation of a Cash Transfer Programme

5.1. Preface

As outlined in chapter 4, findings from study one suggested that the burden of poor cognitive function was higher among the disadvantages. In both 2000 and 2007, household per capita expenditure was the largest single contributor to inequality in children's cognitive function. This chapter presents the second aim of this thesis, which examined the effects of household per capita expenditure on children's cognitive function and whether a cash transfer intervention increased cognitive function scores. In study two, the effects of household expenditure and cash transfer intervention were estimated using an inverse probability of treatment weight in a marginal structural model. Under a potential outcome approach, marginal structural models provide robust estimates for better causal interpretation. Simulations of hypothetical cash transfer interventions were modelled using the Indonesian conditional cash transfer program (*Program Keluarga Harapan* PKH). Findings from this study provide evidence whether cash transfer intervention could be used as an effective intervention to improve children's cognitive function in Indonesia.

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5.2. Statement of authorship

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By signing below, the authors declare that they give consent for this paper to be presented by Amelia Maika towards examination for the Doctor of Philosophy.

Amelia Maika (Candidate)

Designed the study, performed the analyses, interpreted the results and drafted the manuscript.

Signed: Date: 11/11/2015

Murthy Mittinty

Contributed to the design of the study and interpretation of the results, and reviewed the manuscript. I give consent for Amelia Maika to present this paper towards examination for the Doctor of Philosophy.

Signed: Date: 3/11/2015

Sally Brinkman

Contributed to the design of the study and interpretation of the results, and reviewed the manuscript. I give consent for Amelia Maika to present this paper towards examination for the Doctor of Philosophy.

Signed: Date: 29/10/2015

John Lynch

Contributed to the design of the study and interpretation of the results, and reviewed the manuscript. I give consent for Amelia Maika to present this paper towards examination for the Doctor of Philosophy.

Signed: Date: ....3/11/15............

5.3. Abstract

Background

Parental investments in children are an important determinant of human capability formation. We investigated the causal effect of household expenditure on Indonesian children's cognitive function between 2000 and 2007. We also investigated the effect of change in mean cognitive function from a simulation of a hypothetical cash transfer intervention.

Methods

A longitudinal analysis using data from the Indonesian Family Life Survey (IFLS) was conducted using 6136 children aged 7 to 14 years in 2000 and still alive in 2007. We used the inverse probability of treatment weighting of a marginal structural model to estimate the causal effect of household expenditure on children's cognitive function.

Results

Cumulative household expenditure was positively associated with cognitive function z-score. From the marginal structural model, a 74534 *rupiah*/month (about US$9) increase in household expenditure resulted in a 0.03 increase in cognitive function z-score (β=0.32, 95% CI 0.30 – 0.35). Based on our simulations, among children in the poorest households in 2000, an additional about US$6-10 of cash transfer resulted in a 0.01 unit increase cognitive function z-score, equivalent to about 6% increase from the mean z-score prior to cash transfer. In contrast, children in the poorest household in 2007 did not benefit from an additional about US$10 cash transfer. We found no overall effect of cash transfers at the total population level.

Conclusion

Greater household expenditure had a small causal effect on children's cognitive function. Although cash transfer interventions had a positive effect for poor children, this effect was quite small. Multi-faceted interventions that combine nutrition, cash transfer, improved living conditions and women's education are required to benefit children's cognitive development in Indonesia.

Key Messages

- Household expenditure is weakly associated with higher cognitive function
- From our hypothetical intervention, small cash transfers (e.g. US$6-10/months) for the poorest households had a very small effect in improving child cognitive function but no overall effect at the population level.
- Multi-faceted interventions that combine nutrition, cash transfer, improved living conditions and women's education are required to benefit children's cognitive development in Indonesia.

5.4. Introduction

Parental investments in children are an important determinant of human capability formation. These investments include economic, learning, social, cultural and behavioural resources that help create the early life supports for the accumulation of capabilities over the life course. Parental investments rely on the resources in the household that can be deployed, and transferred to their children (28). The unequal distribution of resources in society limits people's freedom to fully function and may lead to capability deprivation (252). The Commission on Social Determinants of Health's indicated that investing in early childhood interventions was a major driver of improving health disparities over the life course (1). Even when evidence for intervention effectiveness does exist (34, 37), effective implementation of early childhood intervention is challenged by capacities in resourcing, targeting, and translating evidence-based policy into practice (40).

Conditional Cash Transfer (CCT) programs are a welfare strategy generally aimed at families to alleviate poverty through conditional actions. In relation to children, the cash transfers are commonly conditional on immunization and/or primary school enrolment. Such CCT programs have been widely used in developing countries, including Indonesia. CCT programs combine redistribution of resources to poor households and have been shown to promote greater investment in human capital of children, which is expected to, in turn reduce long-term poverty (119). Evidence from Mexico's CCT program, *Opportunidades* suggests that CCT had both short and long-term positive effects on children's cognitive function (120, 121). The CCT program in Indonesia, *Program Keluarga Harapan,* successfully increased food consumption expenditure, especially high protein food and increased participation in local health services but had little effect on education services (76).

Our recent study (65) found that among Indonesian children aged 7-14 years, the burden of poorer cognitive function was higher among disadvantaged groups. This inequality, however, reduced markedly between 2000 and 2007. Decreasing inequality in children's cognitive function was mainly driven by changes in maternal education, use of improved sanitation and household per capita expenditure. Decomposition of the inequality showed that household expenditure was the largest single contributor to socioeconomic inequality in 2000 and 2007 (65). The aim of the current study was to estimate the causal effect of household expenditure on Indonesian children's cognitive function between 2000 and 2007, and then simulate the effect of a hypothetical CCT on change in cognitive function after a plausible intervention.

5.5 Methods

Data

We used data from four waves of the Indonesian Family Life Survey (IFLS). IFLS is an ongoing longitudinal survey in Indonesia, which was first conducted in 1993 and subsequently in 1997, 2000 and 2007 (146-149). The IFLS sample is considered to be representative of 83% of the whole Indonesian population. The sample was collected from households in 13 of the 27 provinces in Indonesia in 1993,and specific details of the sampling methodology are detailed elsewhere (146). During follow-up, the IFLS tracked not only individuals who resided in the original household in 1993, but also individuals who had moved out from the original household but still live within the IFLS provinces. For our study, we selected children aged 7 to 14 years in 2000 and still alive at the follow up in 2007 (n=6136) (Figure 22). Of 44 children who were reported dead at follow up, we found no difference in cognitive function score at baseline between these children and those who are still alive in 2007 (data not shown).

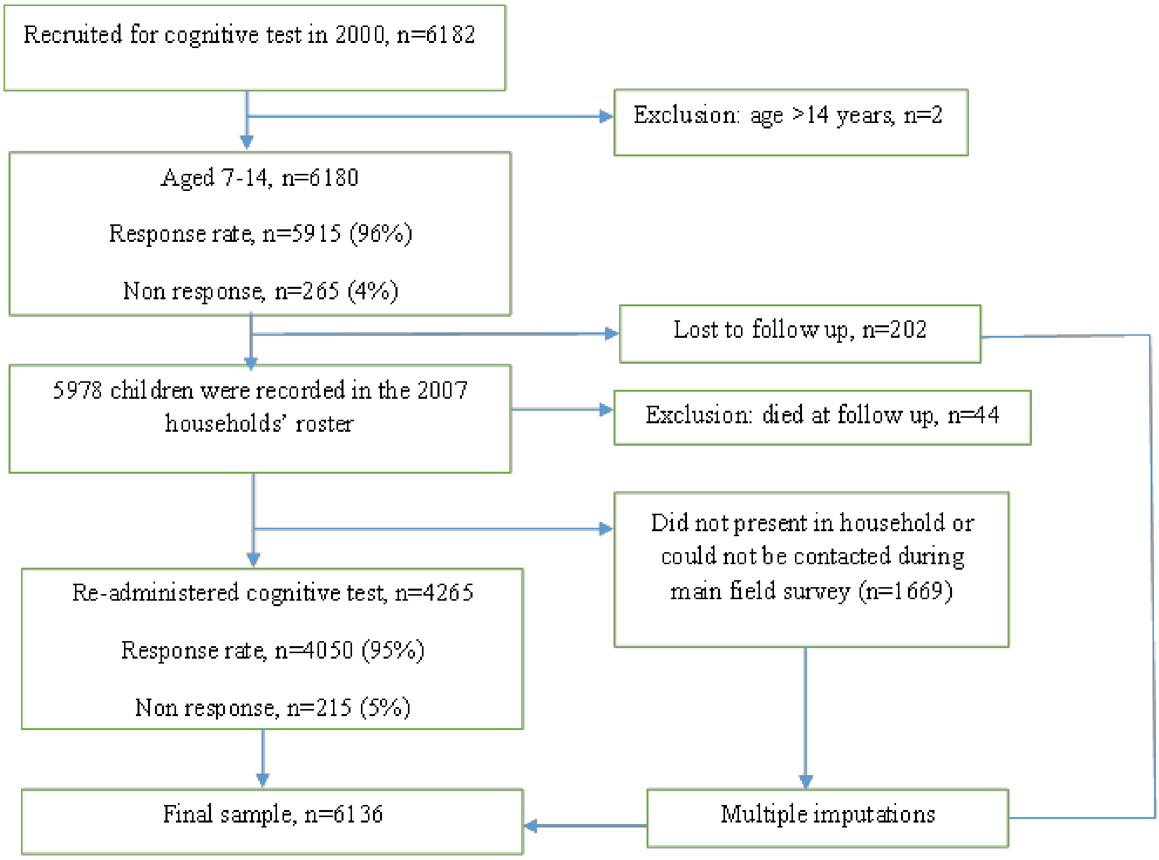

Figure 22. Flow chart of sample selection

Child cognitive function

Cognitive function was measured in 2000 and 2007 using a subset from Raven's Progressive Matrices that was originally designed to measure general intelligence (151). In the IFLS, the questions were reduced in number due to logistical constraints. The test comprised 12 shapes with a missing part where children selected the correct part to complete the shape. Each correct answer was coded 1 or 0 otherwise and scores combined as the total raw score. The total raw score increased with age and had skewed distributions towards the left tail. The total raw scores were then transformed into an age-specific z-score. Because the total scores were skewed, we calculated the mean and the variance of score distributions by taking into account the range, median and the sample size using the formula from Hozo, *et al.*, (152) and used the estimated mean and standard deviation to create an age specific z-score (65).

Household Expenditure

We used the log of household per capita expenditure (PCE) constructed from the monthly total household expenditures divided by the number of household members.(157) The cumulative household PCE was constructed by summing PCE in 2000 and 2007. The PCE was reported in Indonesian *rupiah* value. To aid interpretation we also report PCE in US dollar (US$) at the year 2000 exchange rates (1 US$=8422 *rupiah*).

Confounding

A series of child, caregiver and household characteristics measured variously in 1993, 1997, 2000 and 2007 was selected *a priori* based on the directed acyclic graph (DAG) in Fig.2 as representing baseline and time-varying confounding of the associations between household PCE and child cognitive function in 2000 and 2007. Child characteristics included age (continuous), whether the child was attending school in 2000 and had completed at least 8 years of education by 2007. Caregiver characteristics included maternal age (continuous), the highest level of education attended (categorized as none, primary school, junior high school, senior high school and diploma/university), whether the mother was working in the past week, and self-reported mental health. All information about caregiver characteristics was measured in 1993, 1997 and 2000 except for mental health. Maternal self-reported mental health was measured in 2000 and 2007. The measure in 2000 consisted of eight items of feelings experienced in the past four weeks with response in three categories ranging from never to often. In 2007, the measure was adapted from the shorter version of Centre for Epidemiological Studies-Depression scales (CES-D) (166) consisting of 10 items of symptoms or feelings experienced in the past week with response in five categories ranging from not at all, rarely (<=1 day), some days (1-2 days), occasionally (3-4 days) and most of the time (5-7 days). For both measures, each item was scored ranging from 0 to 3 and summed as the total mental health score separately for 2000 (scores ranging 0-24) and 2007 (scores ranging 0-30). In the analysis, we used the total mental health score where a higher score indicated poorer mental health.

In 1993, 96% of caregivers were the mothers and the proportion slightly decreased in 1997 and 2000 (92% and 90%, respectively). For each survey round, if a mother was not present in the household, either because she was living elsewhere or was reported dead, other family members who took the role as the child's main caregiver provided information. However, information about caregiver was only collected for children under 15 years of age. In 2007, 5626 (92%) children were between 15 and 22 years of age. Of these, 1116 (20%) children in the sample did not have associated information on their mothers. In this circumstance caregiver's mental health was replaced by the father, but when both parents were not present; this information was replaced by the household head.

Household characteristics include household size (continuous), the number of economic hardships experienced in the past five years (continuous), whether the household had electricity, used piped water or a pumped well as the main drinking water source, owned a toilet connected to septic tank, and place of residence (categorized as urban or rural). All information about household characteristics was measured in 1993, 1997 and 2000, except for economic hardship. We used information about economic hardship collected in 1993 and 2000.

Missing data

Of the children in the IFLS who were administered the cognitive test, the response rate was 96% and 95% in 2000 and 2007, respectively. The proportion of children with missing information on the exposure was 0.7% in 2000 and 7% in 2007. Of the 6136 children, only 5305 (86%) were recorded as a member of the original household in 1993, whereas 831 children were recorded as either a new member of the original household or a member of the split off households who were included in 1997 and 2000 survey. As such, data related to all confounders in 1993 were not available for 831 (14%) children. Additionally, 1669 children were either not present in household or could not be contacted during the main field survey in 2007. To minimize bias due to attrition and missing responses to questions, we performed the Multiple Imputation by Chained Equation (MICE) procedure in STATA under the assumption that the imputed data were missing at random (179, 180). We generated twenty imputed datasets using fifty cycles of regression switching. We used Rubin's rule to combine and analyse imputed datasets (181). We used all imputed outcomes in our analysis. As a sensitivity analysis, we conducted the method of multiple imputation then deletion of outcomes as described by von Hippel (182) and the results did not change.

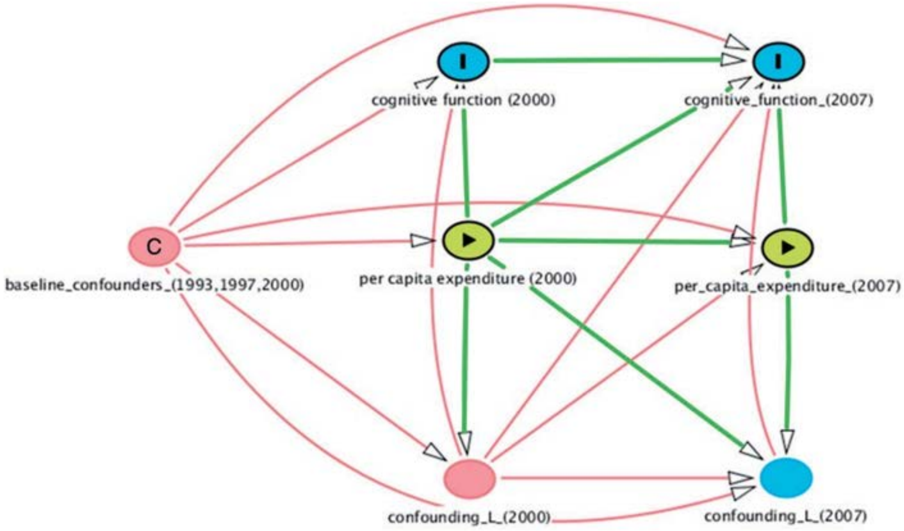

Figure 23. Direct acyclic graph (DAG) representing the relations between confounders, household per capita expenditure and child cognitive function

Exposure: household per capita expenditure. Outcome: cognitive function z-score. Ancestor of exposure and outcome (baseline confounders measured in 1993, 1997 and 2000): caregiver's age, education, employment status, household size, economic hardship, household had electricity, used piped or pumped well as the main drinking water source, owned toilet with septic tank, and residential area. Ancestor of exposure and outcome (confounding *L* measured in 2000): attending school and caregiver's mental health. Ancestor of outcome (confounding *L* measured in 2007): completed at least 8 years of education and caregiver's mental health. Causal path. Biasing path.

Analysis

We used observational data to investigate a potential causal link between household PCE and children's cognitive function. For this analysis we used the inverse probability of treatment weighting (IPTW) of a marginal structural model (MSM) based on the assumptions of consistency, no unmeasured confounders (exchangeability) and positivity (189, 194). Under the assumption of no unmeasured confounders, the causal DAG (184) shown in figure 23 presents the association between confounders, exposure and outcome. This causal graph was drawn using DAGitty program version 2.0 (186). Both the exposure and the outcome were measured at two time points (2000 and 2007), whereas a series of baseline confounders were measured in 1993, 1997 and 2000. The confounders included - caregiver's age, education, employment status, household size, economic hardship, housing conditions (access to electricity, the main drinking water source and type of toilet) and place of residence. The use of confounding information measured at three survey rounds allowed for the situations where a child was raised by a different caregiver, or lived in different housing environments over the course of the study period. This model specification may also help to reduce measurement error by having multiple indicators over time. In the DAG, the child's current schooling and caregiver's mental health in 2000 were included because they indicate the presence of time varying confounding so that given past household PCE, current schooling and maternal mental health predict subsequent exposure and outcome. In addition, the DAG reflects the proposition that a child's current schooling affects completion of at least eight years of education and also affects cognitive function in 2007. Similarly, caregiver's mental health in 2000 affects mental health and in turn affects child's cognitive function in 2007.

In the presence of time varying confounding, the use of conventional regression lacks a causal interpretation and may introduce collider stratification bias (184, 191). Therefore in this study, we use a MSM to estimate the causal effect of household PCE on children's cognitive function.

Construction of the Inverse Probability of Treatment Weighting (IPTW)

We used the inverse probability of treatment weighting (IPTW) to adjust for confounding in the marginal structural model (194). The weighting method creates a pseudo population, based on the child's potential exposure at each time point. The weight was estimated based on the probability of an individual having the observed exposure given their covariates. Because the exposure variable was in continuous form, we used stabilized weight (SW) to reduce large variance in the weight (194, 205). The weight was calculated separately for 2000 and 2007, which can be defined as follow;

Equation 6. Stabilized weight for the exposure in 2000

$$SW_{i2000} = \frac{f(X_{i2000})}{f(X_{i2000} \mid \overline{C}_i)}$$

Equation 7 Stabilized weight for the exposure in 2007

$$SW_{i2007} = \frac{f(X_{i2007} \mid X_{i2000})}{f(X_{i2007} \mid X_{i2000}, \overline{C}_i, \overline{L}_i)}$$

where the numerator in equation 6 is the marginal density of the exposure in 2000 (X_{i2000}), and the denominator is the conditional density function of X_{i2000} given the history of confounders ($\overline{C}_i$) up to 2000 including caregiver and household characteristics. The numerator in equation 7 is the conditional density function of the exposure in 2007 (X_{i2007}) given X_{i2000}, and the denominator is the density function of X_{2007} given X_{2000}, history of confounders ($\overline{C}_i$), and time varying confounders ($\overline{L}_i$) which includes the child attending school and their caregiver's mental health in 2000, and the child's completion of at least 8 years of education and their caregiver's mental health in 2007. The mean weight was expected to be around one, suggesting no misspecification of the weight model (nonpositivity) (205). To test whether there is a bias in our causal estimation due to nonpositivity, we truncated the weight at the 1st and the 99th percentile as well as at the 5th and the 95th percentile of the weight distributions (205).

The last step was the creation of the final weight;

Equation 8. The inverse probability of treatment weights

$$IPTW = SW_{2000} \times SW_{2007}$$

Marginal structural mean model

Since we have repeated measures on both the exposure and the outcome, we used the generalized estimating equations model (GEE) (253) to estimate the effect of household PCE on cognitive function. We specified an independent working correlation structure and calculated the 95% confidence interval (CI) using robust variance estimator. Use of the independent correlation structure is preferable in the GEE when using IPTW because although there is potential that the working correlation structure is miss-specified the independent correlation structure still gives consistent estimation (206, 207). All analyses were conducted using STATA 13 (254).

The marginal structural mean model can be defined as

Equation 9. Marginal Structural Mean Model

$$E(\overline{Y}_{it} \mid cum_{xit}) = \beta_0 + \beta_1 cum_{xit}$$

Where $\overline{Y}_{it}$ is the expected mean potential outcome of cognitive function z-score given the observed cumulative household PCE (cum_{xit}). We present three types of GEE models. The first model is the standard (unadjusted) regression GEE model estimating the effect of cumulative household PCE on cognitive function. The second model estimated the effect of cumulative household PCE on cognitive function using standard regression adjusted covariates. Finally, we present the GEE from a MSM estimating the causal effect of cumulative household PCE on cognitive function, accounting for confounding by the IPTW.

Hypothetical intervention on household PCE

We used the Indonesian CCT program, *Program Keluarga Harapan* (PKH or Hopeful Families Program), as a hypothetical intervention to estimate the effect of change in household PCE on mean cognitive function after a plausible cash transfer intervention. The PKH provided cash transfer to very poor households with children ages 0-6 years conditional on their participation in the local health service to ensure the child was fully immunized, took Vitamin A capsules a minimum of twice a year, and attended growth monitoring check-ups. The PKH also provided cash transfer to very poor households with children ages 6-15 conditional on enrolment in school and ensured attendance for minimum of 85% of school days. Lastly, PKH provided cash transfer to very poor households with children ages 16-18 years but who had not completed 9 years of basic education conditional on their school enrolment to finish a full 9 years of education. In PKH, the money was transferred quarterly. The compliance of conditions were monitored and verified through health and education service providers report. Non-compliance of these conditions would result in a warning, 10% discount of benefit and even discontinuity of the cash transfer (76).

For this study, we modelled the hypothetical intervention on the PKH education program, which targeted very poor household with children ages 6-15 years and ages 16-18 years but who had not completed 9 years of education. This program provided a fixed amount of 200,000 *rupiah*/household/year and an additional of 400,000 *rupiah*/year for each child aged 6-12 years and 800,000 *rupiah*/year for each child aged 13-15 years (255). Based on results from a World Bank report, the first batch of PKH beneficiaries in 2007, increased their average household per capita income by 19000 *rupiah*/month (about $2) or by 10% compared to prior to the program (76). At the national level, the transfer was equivalent to about 5% of the average PCE in 2007 (353421 *rupiah* or about US$42/month) (256).

Our simulated intervention focused on the poorest 40% of the population, which is similar to the target group that was proposed by the World Bank and WHO for the equity goal in universal health coverage (158). Herein, the poorest household were defined as those having children living in the bottom 40% of PCE. We simulated the intervention in both 2000 and 2007 to examine whether a CCT at ages 7-14 had a larger effect than in adolescence at ages 14-18 years.(39) In step one, we targeted the poorest households in 2000 who had children aged 7-14 years. Of the total population, 2456 (40%) children were eligible to receive a CCT in 2000. In 2000, all eligible children received 200,000 rupiah/year. In addition, each child aged 7-12 received 400*,000 rupiah*/year and each child aged 13-14 received 800,000 rupiah/year. Assuming this money was transferred monthly, each child aged 7-12 received 50000 *rupiah/*month (about US$6) whereas each child aged 13-14 received about 83333 *rupiah/*month (about

US$10). In step two, we targeted the poorest households in 2007 and who had children aged 14-15 years as well those who had children aged 16-18 but who had not completed 9 years of education. Of the total population, 961 (16%) children were eligible to receive a CCT in 2007. In 2007, each eligible child received 200,000 rupiah/year and an additional 800,000 *rupiah*/year. Similar to step one, assuming this money was transferred monthly each child received 83333 *rupiah*/month (about US$10). Our hypothetical intervention assumed that all the increased income from the CCT was invested in the child's education.

Sensitivity analysis for unmeasured confounding

We conducted sensitivity analysis to estimate bias in the causal effect of household PCE on cognitive function due to unmeasured confounding (*U*). In sensitivity analysis, we defined *U* as a binary variable and assumed that the association between *U* and cognitive function did not vary across levels of household PCE. Following VanderWeele and Arah (208), we defined the sensitivity parameter δ as the effect of *U* on cognitive function and the sensitivity parameter γ as the prevalence of *U*. The magnitude of bias d_{x+} was then estimated as the product of δ and γ.

Table 5. Characteristics of study participants, IFLS 1993, 1997, 2000 and 2007

	1993	1997	2000	2007
Outcome				
Cognitive function z-score, median (IQR)			0.41 (-0.29 – 0.82)	0.53 (0.10 – 0.83)
Exposure				
Log of per capita expenditure/month (PCE), mean (SD)			11.91 (0.71)	12.94 (0.70)
-PCE in *rupiah*, median (IQR)			142231 (91831 – 227202)	394682 (254286 – 644316)
-PCE in US$ (1US$=8422 *rupiah*), median (IQR)			17 (11 -27)	47 (30 – 77)
Log of cumulative PCE, mean (SD)				13.29 (0.65)
-cumulative PCE in *rupiah*, median (IQR)				560852 (374714 – 887050)
-cumulative PCE in US$, median (IQR)				67 (44 – 105)
Covariates				
Children's characteristics				
Gender: male, n (%)			3129 (51)	
Age, mean (SD)	3.76 (2.33)	7.71 (2.29)	10.53 (2.30)	17.89 (2.36)
Currently attending school, n (%)			5461 (89)	
Completed at least 8 years education, n (%)				4503 (73)
Caregiver's characteristics				
Caregiver's age, median (IQR)	31 (23 – 39)	35 (26 – 45)	37 (33 – 42)	
Highest education attended, n (%)				
-None	2270 (37)	1391 (23)	858 (14)	
-Primary (grade 1-6)	2635 (43)	3009 (49)	3434 (56)	
-Junior high school (grade 7-9)	533 (9)	806 (13)	761 (12)	
-Senior high school (grade 10-12)	544 (9)	723 (12)	805 (13)	
-Diploma/university	154 (2)	207 (3)	278 (5)	

Table 5. Continued

	1993	1997	2000	2007
Caregiver’s characteristics				
Working in the past week, n (%)	1901 (31)	3319 (54)	3472 (56)	
Mental health scores, median (IQR)			2 (0 – 7)	
Mental health scores (CES-D), median (IQR)				3 (1 – 5)
Household’s characteristics				
Household size, mean (SD)	5.93 (2.21)	5.76 (2.04)	5.59 (1.93)	
The number of economic hardship in the past five years, mean (SD)	0.43 (0.70)		0.46 (0.71)	
Had electricity, n (%)	3970 (65)	5043 (82)	5412 (88)	
Drinking water source: piped or pump well, n (%)	1984 (32)	2623 (43)	3037 (50)	
Owned toilet with septic tank, n (%)	1652 (27)	2426 (39)	2611 (43)	
Place of residence: urban, n (%)	2576 (42)	2516 (41)	2540 (41)	

5.6 Results

Table 5 shows the characteristics of study participants in all survey rounds based on multiple imputed data. The median of cognitive function z-score was 0.41 (interquartile range IQR -0.29 to 0.82) in 2000 and was 0.53 (IQR 0.10 to 0.83) in 2007, suggesting improvement. In the same period, the mean of log PCE also increased from 11.91 (SD 0.71) to 12.94 (SD 0.70) equivalent to 49985 rupiah/month/year (about $6), slightly higher than the national average (Figure 24).

The median age of caregiver in 1993 was 31 years (IQR 23 – 39). In terms of education, we found a small number of caregivers improved their education, for example the proportion of caregivers with a diploma or attended university increased from 2% in 1993 to 3% in 1997 and 5% in 2000. Among mothers who were found in the follow up, we found some discordance in the level of education reported. To test whether bias in reporting education was affecting the estimates of our MSM, we conducted sub-group analysis for children whose caregiver reporting was consistent and the result showed no substantial difference. We also tested whether using education as a continuous instead of a categorical variable changed the estimate and the result suggested no substantial difference.

The proportion of caregivers who reported working in the past week increased substantially from 31% in 1993 to 51% in 1997 and steadily increased to 56% in 2000. The substantial increase found between 1993 and 1997 might be influenced by the economic crisis that hit Indonesia in 1997 forcing more women to participate in the labour force (257). The median mental health score was 2 (IQR 0 – 7) and 3 (IQR 1 – 5) in 2000 and 2007, respectively.

At the household level, the proportion of children who had access to electricity, drinking water from piped water or a pumped well and improved sanitation increased over the years.

However in 2000, about half of the children still did not have access to piped or pumped water as their main drinking source and only 43% had access to improved sanitation.

Table 6. Estimates for the stabilized weight and the inverse probability of treatment weighting (IPTW)

	Mean (SD)	1st and 99th percentile	5th and 95th percentile
Stabilized weight for 2000(SW_{2000})	1.52 (0.79)	0.39 – 4.29	0.57 – 2.98
Stabilized weight for 2007 (SW_{2007})	1.18 (0.39)	0.49 – 2.44	0.64 – 1.90
IPTW	1.85 (1.22)		
IPTW was truncated at the 1st and 99th percentile	1.83 (1.11)		
IPTW was truncated at the 5thand 95thpercentile	1.79 (0.92)		

Table 7. Estimates for the effect of per capita expenditure on children's cognitive function (n=6136)

		Estimate	SE	95% CI	
Standard GEE regression					
model 1	$E(\overline{Y}_{it} \mid cum_{xit})$	0.27	0.01	0.25	0.30
model 2	$E(\overline{Y}_{it} \mid cum_{xit}, \overline{C}_i, \overline{L}_i, \mathrm{cov})$	0.11	0.02	0.08	0.14
Marginal structural model					
Model 3	$E(\overline{Y}_{it} \mid cum_{xit}[pw = iptw])$	0.32	0.01	0.30	0.35

Model 1 only included cumulative household PCE.

Model 2 included cumulative household PCE adjusted for caregiver's age, education, employment status, mental health scores (2000 and 2007), household had electricity, used piped or pump well as drinking water source, owned toilet connected to septic tank, residential area (urban or rural), household size, the number of economic hardship experienced in the past five years (1993 and 2000), whether child was attending school in 2000, and completed at least 8 years of education in 2007. All variables were measured in 1993, 1997 and 2000 unless otherwise specified.

Model 3 included cumulative household PCE weighted by IPTW.

Table 6 shows estimates for the stabilized weight and the IPTW. The mean stabilized weight was 1.58 (SD 0.79) for 2000 and was 1.18 (SD 0.39) for 2007.

Table 7 shows estimates for the effect of cumulative household PCE on cognitive function from standard GEE models (top panel) and a MSM (lower panel). Cumulative household PCE was associated with an increase in the cognitive function z-score. From the standard unadjusted model, for every 10% increase in household PCE (74534 *rupiah*/month or US$9) there was an associated 0.27 x ln(1.10) = 0.02 unit increase in the cognitive function z-score or 0.09 unit increase in raw score. From the second adjusted regression model, a 74534 rupiah (US$9) increase in cumulative household PCE was associated with 0.11 x ln(1.10) = 0.01 unit increase cognitive function z-score or 0.04 unit increase in raw score after conventionally adjusting for all covariates in the analysis. From the MSM, a 74534 rupiah (US$9) increase in cumulative household PCE was associated with 0.32 x ln(1.10) = 0.03 unit increase cognitive function z-score or 0.11 unit increase in raw score. Use of truncation weights did not substantially change the result.

Application of a Hypothetical CCT Intervention

Of 2458 children aged 7-14 from the poorest households in 2000, the average household PCE in that year was 81190 *rupiah/*month (US$10). An additional 50000 (about US$6) or 83333 *rupiah/*month (about US$10) of CCT depending on the child's age increased the average household PCE by about 70%. This cash transfer increased the average cognitive function score z-score from 0.18 (95% CI 0.17 – 0.20) to 0.19 (95% CI 0.18 – 0.21). Of the 961 children from the poorest households in 2007 aged 14-15 or aged 16-18 but who had not completed 9 years of education, the average household PCE in that year was 219847 *rupiah/*month (US$26) and the average cognitive function z-score was 0.17 (95% CI 0.16 – 0.19). An additional 83333 *rupiah/*month (about US$10) of CCT, representing about 38%

increase in household PCE, had no effect on cognitive function z-score. Moreover, we found no effect of CCT for the total population under these two scenarios.

Table 8. Results of the sensitivity analysis

δ[a]	γ[b]	d_{a+}[c]
-0.05	0.20	-0.01
-0.05	0.40	-0.02
-0.05	0.60	-0.03
-0.05	0.80	-0.04
-0.05	1.00	-0.05
0.31	0.20	0.06
0.31	0.40	0.12
0.31	0.60	0.19
0.31	0.80	0.25
0.31	1.00	0.31
1.43	0.20	0.29
1.43	0.40	0.57
1.43	0.60	0.86
1.43	0.80	1.14
1.43	1.00	1.43

[a] sensitivity parameter δ is the effect of unmeasured confounder (*U*) .

[b] sensitivity parameter γ is the prevalence of *U*.

[c] d_{a+} is the magnitude of bias, which is a product of δ and γ.

Sensitivity analysis

Table 8 presents results of the sensitivity analysis for unmeasured confounding. Our findings suggest that the unmeasured confounder could eliminate the effect of household PCE on cognitive function if the effect size of *U* was 1.43 and the prevalence of U was 0.40 or higher, where *U* is an early childhood intervention, it seems possible to have the unmeasured confounder with an effect size of 1.43. According to a meta-analysis by Nores and Barnett (37), the average effect size found across early childhood interventions on cognitive function was 0.31 (SD 0.20, minimum -0.05, maximum 1.43). However, to have prevalence of U ≥ 0.40 makes it implausible to have U that can eliminate the effect of household PCE on cognitive function.

5.7. Discussion

Our results suggest that cumulative household expenditure has a small causal effect on cognitive function in Indonesian children aged 7-14 and 14-22 in 2000 and 2007. Our findings are consistent with evidence suggesting CCT programs have a positive but small effect on children's cognitive function (120, 121). From our hypothetical intervention, a CCT involving increased household expenditure of 50000 (about US$6) to 83333 *rupiah*/month (about US$10) in 2000 increased the average cognitive function score by 0.01 SD; a small effect size by traditional metrics. This represents about 6% increase from the average cognitive function z-score prior to cash transfer. We also found that a CCT in 2000 had a larger effect than a CCT in 2007, possibly because a CCT in 2000 had a larger contribution to the average household PCE (70% vs 38%) and higher levels of coverage of children in the population (40% vs 16%). According to the World Bank, one of the reasons PKH had a small effect on participation in education services such as enrolment rates and transitions to higher grades, was partly because the cash transfer was too small to benefit the target children (76). For example, to send a student to secondary school in Indonesia costs on average 2.8 million *rupiah*/year for education (equivalent to about $US28/month), which represents about 30% of the total household expenditure for those living in the poorest quintile of households.

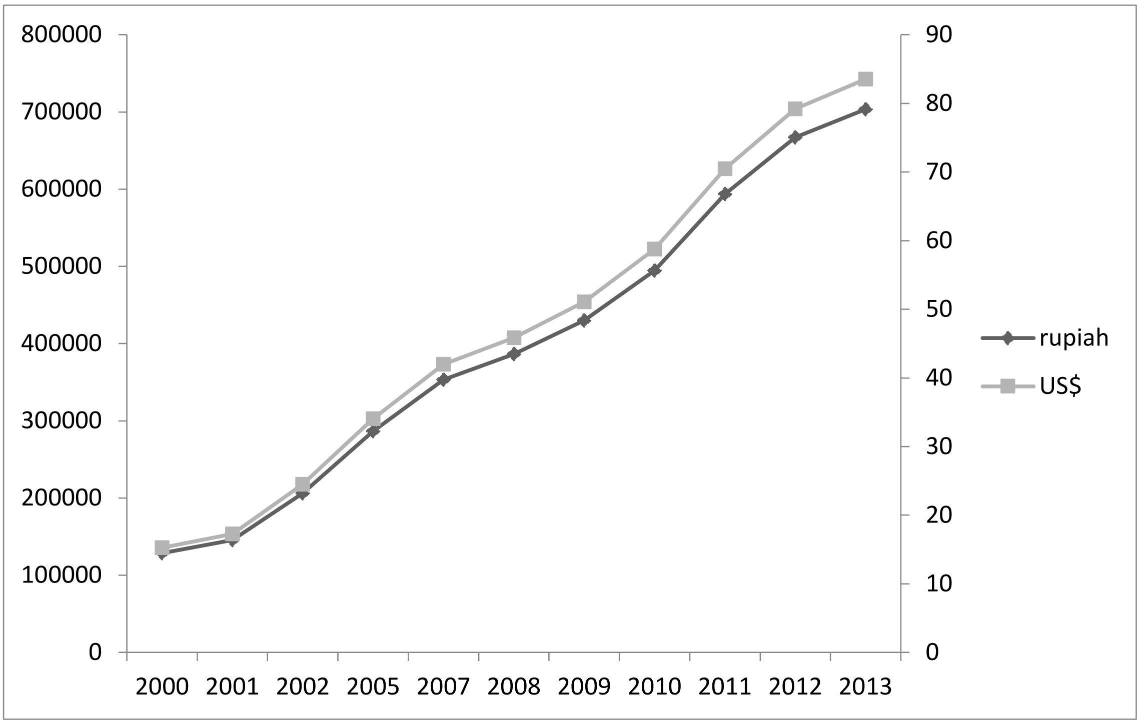

Figure 24 National statistics on average monthly per capita expenditure, Indonesia 2000-2013

Source: Statistics Indonesia, Trends of selected socio economic indicators of Indonesia. Data for 2002-2013 are available at http://www.bps.go.id/eng/aboutus.php?65tahun=1 (accessed 18 May 2014).

Given the effect size of hypothetical cash transfer in this study, a cash transfer would need to be much larger than those used to have a substantial impact on children's cognitive function. Under our first scenario, the estimated amount of cash transfer to shift the average cognitive function score of the poorest children in 2000 to the average population score is about 825356 *rupiah*/child/month (about US$98). The national statistics show that the average annual growth of PCE between 2000 and 2013 has been about US$5/month (Figure 24). At current levels of national growth in PCE, assuming that household expenditure remains consistent across groups and assuming that the remainder of the population stay at current levels of cognitive ability then it will take 20 years to reduce cognitive inequality between children in the bottom 40% of households and the reminder of the population. However, since it is unlikely that expenditure growth is equally distributed across the population, it may take longer for the poorest children to increase their cognitive score to the average level. For this reason investment in child human capital through cash transfer alone could be very expensive. It is important to find other types of intervention programs that may be more efficient in closing the inequality in children's cognitive function. Our recent study found that in addition to household PCE, the largest contributors to inequality in Indonesian children's cognitive function include access to improved sanitation and maternal education (65). Numerous studies suggest that early intervention programs that have an educational component for children, caregivers or both, have a positive effect on various cognitive development outcomes in both low and middle income countries (19) as well as in high income countries (258).

Another potential intervention that benefits child cognitive function are nutrition programs, which may involve nutrition supplementation and nutrition education. Evidence from Nores and Barnett (37) suggest that nutrition interventions had a larger effect on child cognitive function than cash transfer programs (mean effect size was 0.26, SD 0.16 for nutrition, and was 0.17, SD 0.06, for cash transfer). They also found provision of an integrated early childhood program may yield greater benefit than a single intervention. However, a recent systematic review by Grantham-McGregor, *et al.*, (259) failed to find any evaluations of programs delivered at scale in which the effects of integrating psychosocial stimulation into health and nutrition services on children's growth and development were assessed. They argued that this is an urgent need. An integrated intervention program that combined provision of nutrition, cash transfer, improved living conditions and educational components especially for young women may yield a greater effect on improving the Indonesian children's cognitive function. To a large extent, such an integrated intervention program could also become part of a strategic plan to promote a better understanding of the social determinants of health and improving health equity in Indonesia (1).

Our study is subject to limitations. First, our measure of cognitive function was limited to data that were available in the IFLS, which might not be the best measure to capture the true cognitive ability of Indonesian children. Second, our findings should be interpreted with care. Use of standard regression models to estimate the effect of household PCE does not generally have a causal interpretation and may yield biased effect estimates. The first GEE model presented a crude association between household PCE on cognitive function, assuming there were no other factors that potentially confounded this association. Although the second model included all potential measured confounders, use of standard regression could not control the potential bias in the presence of time varying confounding. Therefore our use of the MSM presents a more robust estimation with causal interpretation. However, estimates for our causal inferences are only true under the assumption of consistency, exchangeability and positivity, which are not guaranteed by design when using observational data (189, 260). Third, it is plausible that there are variables that confound the relationship between household PCE and cognitive function but were not included in the analysis. To address the issue of potential bias in effect estimation due to unmeasured confounding, we conducted the sensitivity analysis. Fourth, our estimates assume that financial investment in children's capability are drawn from their household's expenditure. In our hypothetical CCT we assume that targeted families would spend their CCT funds on their children's education. When considering these two assumptions together, it is important to point out that the effect sizes could indeed be different if increases in household income were not invested in their children's education (as we have assumed with the CCT).

In summary, household expenditure had a small positive effect on children's cognitive function. Although a hypothetical cash transfer intervention had a positive effect on children's cognitive function, the effect was very small. Interventions that combine cash transfer, improved living conditions and educational opportunities especially for young women may have greater benefit for the future of children's cognitive development in Indonesia.

CHAPTER 6

Associations of Early and Later Childhood Poverty with Child Cognitive Function in Indonesia: Effect Decomposition in the Presence of Exposure-Induced Mediator-Outcome Confounding

6.1. Preface

As shown in chapter five, greater household per capita expenditure was associated with higher cognitive function score but the effect size was small. Based on simulations of a hypothetical cash transfer intervention, an additional US$ 6-10/month of cash transfer for children from the poorest households in 2000 increased the mean cognitive function score by 6% but there was no overall effect of cash transfers at the total population level. This chapter presents the third study of this thesis, which investigated the associations of poverty at ages 0-7 and poverty at 7-14 on children's cognitive function at 7-14 years. Using decomposition analysis, this study also examined the direct and indirect effects of poverty at 0-7 years on cognitive function at 7-14 years mediated through poverty at 7-14 and school attendance and aspects of the child's home environment. This study was motivated to better estimate the optimal timing for intervention and the mechanism by which poverty earlier in life at 0-7 could affect cognitive function at 7-14 years.

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6.2. Abstract

The amount of family financial resources available in early-life influences child health and development. Using data from the Indonesian Family Life Survey 2000 and 2007, we estimated the effects of early-life poverty (at 0-7 years) and poverty in later childhood (7-14 years) on cognitive function at 7-14. Our analysis provides little support for the idea that an early intervention to support household income has a larger effect than intervention later in childhood, both seem equally important. We also decomposed the effect of poverty at 0-7 into direct and indirect effects mediated through poverty and schooling/home environment at 7-14. For decomposing the effects we used three approaches; joint mediators, path specific and intervention analogue. Being exposed to poverty under 7 had a larger direct effect on child cognitive function at 7-14 (i.e. joint mediator β = -0.07, 95% confidence interval: -0.12, -0.02) than the indirect effects mediated through later poverty at 7-14 (β = -0.01, 95% confidence interval: -0.04, 0.01) and school attendance/home environment at 7-14. However, the effect of poverty on cognitive function was small. Providing a comprehensive early childhood development intervention that combines cash transfer, enhanced nutrition and education may yield greater benefit on cognitive functioning of Indonesian children than income transfer alone.

Keywords: poverty, cognitive function, Indonesia, potential outcome, effect decomposition

6.3. Introduction

Greater family financial resources are one of the key factors enabling parental investment in health and development of children. Extensive evidence shows that children of families with fewer financial resources have poorer cognitive function at young ages (6, 8, 261) and in middle childhood (85). In low and middle-income countries fewer financial resources may contribute directly to poor child outcomes through poor housing conditions, limited access to health care, nutrition and schooling costs (18, 19, 28). Evidence from Indonesia shows that during the financial crisis in 1997-1998, average household expenditure on children's education decreased, and poorer households protected the education of their older children at the expense of younger children (25). While a recent World Bank report (209) shows near universal enrolment rates for primary school in Indonesia, social inequalities in school enrolment widen after age 10, likely due to costs of schooling. The cost burden of education is higher among the poor and those living in rural areas. In 2010 about 44% of students who dropped-out of school at ages 13-15 years were from the poorest quintile of households. Among this group, the average cost of education is about 500,000 *rupiah*/child/year (about US$59), representing about a quarter of annual household expenditure. Financial incentive programs such as conditional cash transfers are widely used in LMIC, including Indonesia, to help poor families invest in children's human capability formation (23, 119).

We previously examined changes in socioeconomic inequality in Indonesian children's cognitive function in 2000 and 2007 (65). Decomposing the relative concentration index showed that household expenditure was the largest single contributor to inequality in Indonesian children's cognitive function (65). In this study we used household expenditure as a measure of poverty. This is consistent with many international studies that favour expenditure measures over income as indicators of economic resources that convert household economic inputs into health and development enhancing investments (262). The aim of the current study was twofold. First, we examined the association of early poverty, measured as being in the poorest 40% of household expenditure at 0-7 years and later childhood poverty (at 7-14) with cognitive function. This is important for understanding the optimal timing for intervention. Second, we decomposed the direct and indirect effects of poverty at 0-7 on cognitive function at 7-14 years. Estimation of direct and indirect effects is of policy interest for better understanding the mechanisms by which early-life poverty could affect cognitive function at 7-14.

Conventional mediation and effect decomposition analysis (195) has been used to estimate natural direct and indirect effects but extensive argument has shown these conventional methods often generate biased estimates and lack causal interpretation (196, 197). Decomposing natural direct and indirect effects requires satisfying four assumptions;

1. effect of exposure *X* on outcome *Y* is unconfounded given covariates *C*,
2. effect of *M* on *Y* is unconfounded given *X*, *C*,
3. effect of *X* on *M* is unconfounded given *C*, and
4. there is no exposure-induced mediator-outcome confounding (*L*), $(Y_{xm} \coprod M_{X*} | C)$.

The fourth assumption can be stated as the joint effect of the observed exposure and the mediator on the outcome is independent of the effect of the mediator under the counterfactual exposure (*X=x**) given C, $(Y_{xm} \coprod M_{X*} | C)$. This is known as the 'cross-world' independence assumption. There have been criticisms concerning estimation of direct and indirect effects that involve the cross-world independence assumption. Avin, *et al*.,(210) showed that estimation of direct and indirect effects that involve the cross-world assumption is unidentifiable even when the exposure-induced mediator-outcome-confounding is observed. Furthermore, Naimi, *et al*.,(211) argued that the estimation of natural direct and indirect effects that involves a cross-world independence assumption has no real world interpretation but is rather a product of purely mathematical formulations that cannot be observed or estimated from any randomised controlled trial.

In this paper we have utilised recently developed methods by VanderWeele, Vansteelandt, and Robins (hereafter VVR) (200) for effect decomposition, that partially overcome the identification limitations due to exposure-induced mediator-outcome confounding. The three VVR approaches to effect decomposition do not estimate the "natural" direct and indirect effects but they provide insight into mediation and pathways when exposure-induced mediator-outcome confounding exists. In this study we hypothesized that household poverty at 0-7 (exposure, reflecting household expenditure on children) would affect both household poverty at 7-14 (mediator), children's living conditions and the opportunity to attend school at ages 7-14 (exposure-induced mediator-outcome confounding), which subsequently would affect both family expenditure on children and their cognitive function at 7-14.

6.4. Materials and Methods

Study population

Our analysis uses data from the 2000 and 2007 waves of the Indonesian Family Life Survey (IFLS) (148, 149). IFLS is an ongoing longitudinal survey conducted in 1993, 1997, 2000 and 2007. A random sample was collected from households spread across

13 of the 27 provinces on the islands of Java, Kalimantan, Sulawesi, West Nusa Tenggara, Bali, and Sumatra in 1993. Together these provinces contain 83% of the Indonesian population (146). Our analysis used 6680 children aged between 7 and 14 years who were contacted for cognitive tests in 2007 (Figure 25). Of these, 6400 children (96%) participated in the test, with 280 children not responding (119 refusals, 56 unavailable and 75 others). The youngest children in this cohort were aged less than 1 year in 2000. These children then turned 7 in 2007 so there are 7 year olds in both 2000 and 2007. Distributions of variables in the complete case sample are consistent with the response sample (Web Table 1). Despite the importance of multiple imputation for missing data, given the technical complexity of the decomposition methods used in this paper the analysis is restricted to complete cases (*n*=4,245).

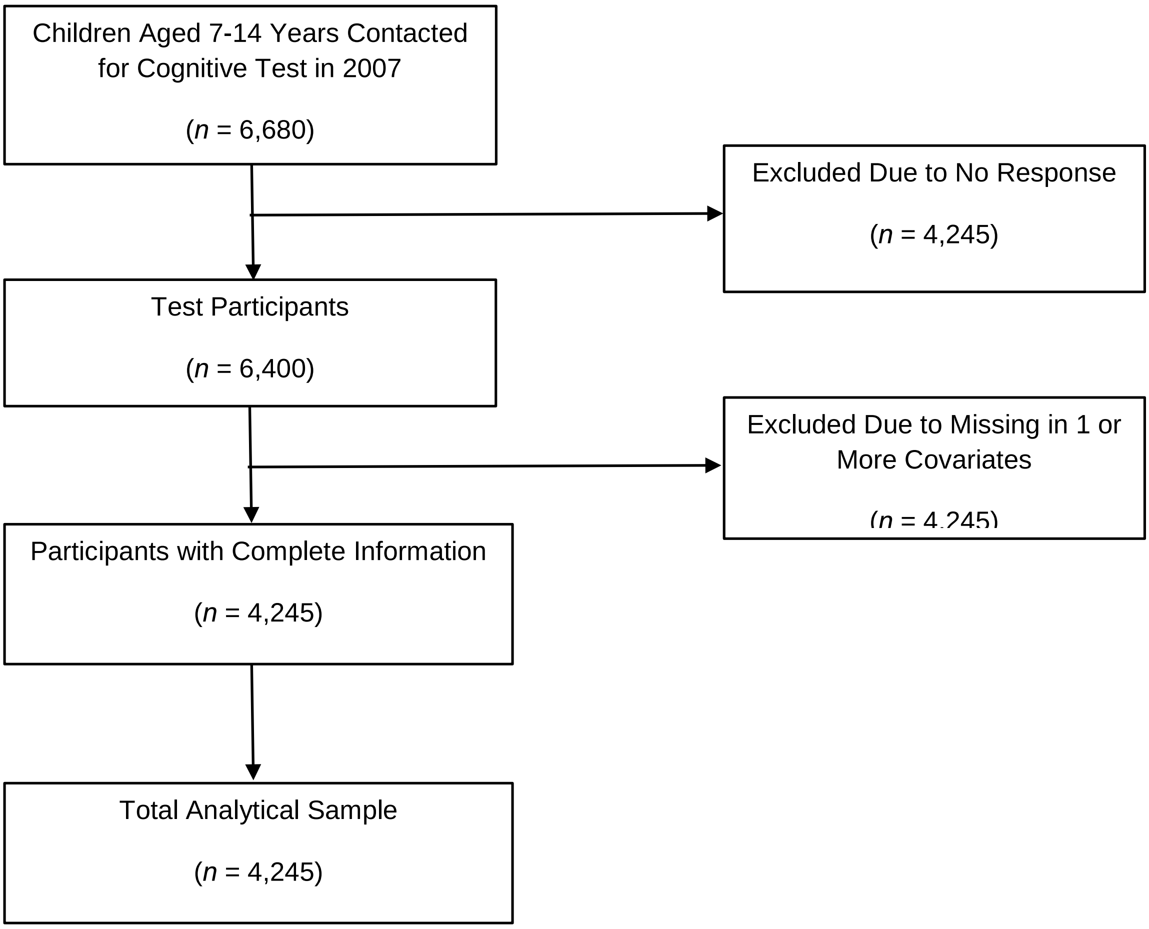


Figure 25 Sample selection from the Indonesian Family Life Survey, 2000 and 2007

Cognitive function

Cognitive function was measured using a subset from the Raven's Progressive Matrices (151). The test comprises 12 shapes with a missing part where children selected the correct part to complete the shape. Each correct answer was coded 1 or 0 and combined as the total raw score. The total raw score increased with age as expected and had skewed distributions towards the left tail. We generated an age-specific z-score and used this variable in continuous form where a higher score is associated with better outcome (65).

Poverty

Household per capita expenditure (PCE) was used as an indicator of poverty. PCE was constructed from the monthly total household expenditures divided by the number of household members (157). The PCE was reported in Indonesian *rupiah* value. To aid interpretation we also report PCE in US dollars in 2000 exchange rates (1 US$=8422 *rupiah*). We reported association of PCE in 2000 with cognitive function in Web Table 2 and association of PCE in 2007 with cognitive function in Web Table 3. The World Bank and WHO (158) have proposed that the poorest 40% of the population be considered as in 'poverty' for the purposes of determining access to universal health coverage. We defined poor households as those living in the bottom 40% of PCE (about US$14/month or less for 2000 and about US$36/month or less for 2007). We considered poverty at 0-7 years as the main exposure and poverty at 7-14 years as the mediator.

Confounding

A series of child's (151), maternal (162-164), and household characteristics (88, 126, 162, 263) were selected *a priori* as potentially confounding associations between poverty and cognitive function at 0-7 and as time-varying covariates at 7-14. Child's characteristics included age (continuous) and whether they currently attended school. Maternal characteristics included age (continuous), the highest level of education attended (categorized as none, primary school, junior high school, senior high school and diploma/university degree), and whether the mother was working in the past week.

Household characteristics included household size (continuous), the number of self-reported economic hardships in the past five years (continuous), whether the household had electricity, used piped or pumped well water as the main drinking source, improved sanitation (defined as owned a toilet that was connected to a septic tank) and place of residence as urban or rural. We defined maternal age, education and employment status and household characteristics that were measured in 2000 as potential baseline confounders. We defined child's current schooling, maternal employment status and the household characteristics that were measured in 2007 as intermediate confounding (L) affected by the exposure. In 2007, household characteristics included whether household had electricity, used piped or pumped well water, improved sanitation, place of residence, types of cooking fuel, house tenure and had television. We used factor analysis (170, 171) to construct a home environment score based on the variables included in L. We defined poor home environment as those having the lowest 40% of the total home environment score.

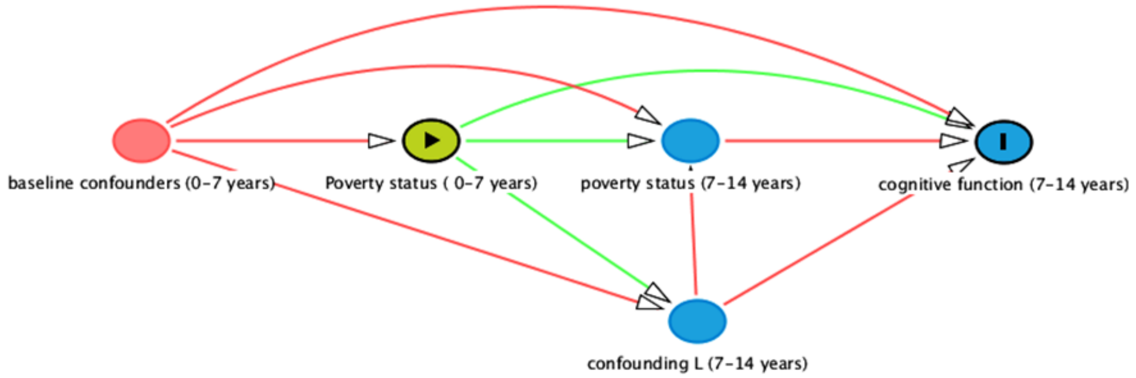


Figure 26 DAG Directed Acyclic Graph representing the associations of baseline confounders, poverty at 0-7 and poverty at 7-14 years, poor home environment/not attending school at 7-14, and cognitive function at 7-14.

Legend

Ancestor of exposure *and* outcome (baseline confounders measured at 0-7 years): caregiver's age, education, employment status, household size, economic hardship, household had electricity, used piped or pumped well as the main drinking water source, improved sanitation and residential area. Exposure: poverty status at 0-7 years. Ancestor of outcome (mediator): poverty status at 7-14 years. Ancestor of outcome (exposure-induced mediator-outcome confounders): latent variable (child is attending school, caregiver's employment status, household had electricity, used piped or pumped well as the main drinking water source, improved sanitation, house tenure, types of cooking fuel, had television and residential area). Outcome: cognitive function z-score at 7-14 years. Causal path. Biasing path

Statistical analysis

DAGitty 2.0 (186) was used to draw a Directed Acyclic Graph (DAG) (184) representing the association between confounders, exposure, mediator, and outcome (Figure 26). Assuming there is no unmeasured confounding, the directed acyclic graph shows poverty at 0-7 years (X) has a direct effect on cognitive function at aged 7-14 (Y). The path from X to Y is potentially mediated by poverty at 7-14 (M). In addition schooling/home environment (L) is a mediator-outcome confounder, which is also affected by the exposure opening a potential path from $X \rightarrow L \rightarrow Y$ in addition to

$X \rightarrow M \rightarrow Y$. We described the magnitude of associations along all paths between *X, M, L* and *Y* using regression analysis (Web Table 4).

We examined the association of poverty at 0-7 and poverty at 7-14 with cognitive function at 7-14 using conventional regression analysis (Web Appendix 1). Figure 26 shows there is mediator-outcome confounding (schooling/home environment) induced by the exposure. In this case, we hypothesized that the extent of financial resources available at ages 0-7 could plausibly influence whether a child was attending school and living in poor home environment at age 7-14. Because of this intermediate confounding, we used the method for effect decomposition derived by VVR (200) who introduced three approaches for effect decomposition in the presence of exposure-induced mediator-outcome confounding. These are a) joint mediators, b) path-specific, and c) intervention analogue.

a) Joint mediators

In the joint mediators approach, the direct effect ($X \rightarrow Y$) is defined as the effect of poverty at 0-7 (*X*) that is not through poverty at 7-14 (*M*) or schooling/home environment (*L*). The indirect effect is defined as the effect of *X* that is mediated through *M* or *L* or both. Under the joint mediator approach, where *M* and *L* are considered as joint mediators, the fourth assumption is modified as $Y_{xlm} \coprod (L_{x*} M_{x*}) \mid C$ and is effectively satisfied. In other words in Figure 26 there is no effect of exposure that confounds the relationship between the joint mediator (*L*, *M*). This approach is useful if partitioning the indirect effect of *X* through *M* or *L* was not of interest so that both poverty at 7-14 and schooling/home environment were assumed to be equally important as mechanisms by which poverty at 0-7 affects cognitive function at 7-14 (*Y*).

b) Path specific

Assuming that the above four assumptions of unmeasured confounding (1-4) hold, the identifiable path specific effects (210) are *X→Y, X→LY, X→M→Y*. The path specific approach is more relevant if the substantive question is to estimate the relative importance of specific pathways by partitioning the indirect effects of poverty at 0-7 through poverty at 7-14 (*X→M→Y)* and through pathways that involving schooling/home environment at 7-14 (*X→LY)*, which is the combination of *X→L→M→Y* and *X→L→Y*. Thus the path specific approach can be used to estimate whether the effect of poverty at 0-7 is largely mediated through poverty at 7-14 only or through schooling/home environment.

c) Intervention Analogue

Effect decomposition carried out under the intervention analogue approach is similar to a sequential randomized trial (Web Figure 1) (185, 212, 215). The randomized intervention analogue of the direct effect is defined as the difference in potential outcome between children who were exposed and not exposed to poverty at 0-7, where in both cases the value of the mediator (poverty at 7-14) was randomly drawn from the distribution of the mediators amongst children who were not exposed to poverty at 0-7. The randomized intervention analogue of the indirect effect is defined as the difference in potential outcome in children who were exposed to poverty at 0-7 where the value of the mediator was first randomly drawn from the distribution of the mediator amongst children who were exposed to poverty at 0-7 (Y_{1M1}) and then the value of the mediator was randomly drawn from the distribution of mediator amongst children who were not exposed to poverty at 0-7 (Y_{1M0}), thus simulating an RCT of the mediator. Subtraction of these two quantities estimates the intervention analogue of the indirect effect (See equation e11). Thus effect decomposition conducted as an analogue of sequential randomization of the mediator, requires only the first three assumptions.

In the VVR approach, effect decomposition was estimated using inverse-probability weights. Analyses using the VVR approach were conducted in SAS 9.1 (SAS Institute, Cary, North Carolina). We presented details about formula for estimating effect decomposition in Web Appendix 2, the VVR methods in Web Appendix 3, construction of the weights in Web Appendix 4 and the SAS code in Web Appendix 5. Despite its documented limitations, for comparative purposes, we estimated effect decomposition using conventional sequential regression analysis (Web Appendix 6) and presented the results in Web Table 5.

Table 9. Characteristics of study participants, IFLS 2000 and 2007, *n*=4,245

Variables	2000				2007			
	No.	%	Median (IQR)	Mean (SD)	No.	%	Median (IQR)	Mean (SD)
Outcome								
Cognitive function z-score							0.53 (-0.07 - 0.83)	
Exposure and mediator								
Child is poor	1,698	40			1,698	40		
Household per capita expenditure per month (PCE), *Rupiah*								
-the poor			83,273 (65,112 – 99,362)				214,376 (171,561 – 258,117)	
-the non-poor			200,644 (150,156 – 280,083)				500,119 (382,821 – 713,208)	
Household PCE per month, US$ (1 US$=8422 *rupiah*)								
-the poor			10 (8 – 12)				25 (20 – 31)	
-the non-poor			24 (18 – 33)				59 (45 – 85)	
Covariates								
Child's characteristics								
Child is male					2,177	51		
Age				3.24 (2.24)				10.60 (2.22)
Attending school					4,008	94		
Caregiver's characteristics								
Age			30 (25 - 35)					

Abbreviations: IFLS, Indonesian Family Life Survey; IQR, inter quartile range; PCE, per capita expenditure; SD, standard deviation.

Table 9. Continued

Variables	2000				2007			
	No.	%	Median (IQR)	Mean (SD)	No.	%	Median (IQR)	Mean (SD)
Highest education attended								
None	259	6						
Primary school (Grade 1-6)	2,038	48						
Junior high school (Grade 7-9)	776	18						
Senior high school (Grade 10-12)	935	22						
Diploma/university	237	6						
Working in the past week	1,750	41			1,784	42		
Household characteristics								
Household size				5.41 (2.06)				
Economic hardship experience in the past 5 years				0.45 (0.72)				
Had electricity	3,787	89			4,091	96		
Used piped or pumped well as the main drinking water source	2,169	51			2,345	55		
Improved sanitation	1,875	44			2,668	63		
Residential area								
-urban	1,877	44			2,094	49		
-Java/Bali					2,557	60		
Type of cooking fuel								
-gas/electricity					738	17		
-kerosene					1,800	43		
-wood/coal					1,707	40		
Had television					3,412	80		
House tenure: own house					3,406	80		

6.5. Results

Table 9 shows the characteristics of study participants using the complete-case sample. The median age-specific cognitive function z-score was 0.53 (interquartile range IQR -0.07 – 0.83). Between 2000 and 2007, the median PCE among the poor households increased from 83,273 *rupiah* /month (about US$10) to 21,4376 *rupiah*/month (about US$25). Although this indicates overall improvement, the gap in PCE between the poor and non-poor during this time period increased. About half (48%) of the children lived with a mother with only primary school education. Overall, the household living conditions improved from 2000 to 2007, however, only 55% of children had access to piped and pumped well as the main drinking water source and 63% used improved sanitation in 2007.

Table 10. The associations of poverty at 0-7 and poverty at 7-14 years with cognitive function at 7-14 years, IFLS 2000 and 2007, *n*=4,245

Model	β	95% CI
The effect of poverty at 0-7 years[a]	-0.08	-0.13, -0.03
The effect of poverty at 7-14 years[b]	-0.07	-0.11, -0.02

Abbreviations: CI, confidence interval; IFLS, Indonesian Family Life Survey.

[a] Model included the effect of poverty at 0-7 adjusted for baseline confounders.

[b] Model included the effect of poverty at 7-14 adjusted for poverty at 0-7, baseline confounders and schooling/home environment.

Table 10 shows results from conventional regression where the association of poverty at 0-7 with cognitive function was -0.08 (95% confidence interval (CI): -0.13, -0.03) after accounting for baseline confounders. The association of poverty at 7-14 was -0.07 (95% CI: -0.11, -0.02) after adjusting for poverty at 0-7, baseline and time-varying confounding

Table 11. Decomposition of the effect of poverty status at 0-7 years on cognitive function at 7-14 years from VVR analysis, IFLS 2000 and 2007, *n*=4,245

Model	The direct effect of poverty at 0-7[a]	95% CI	The indirect effect through poverty at 7-14	95% CI	The indirect effect through home environment	95% CI
Approach 1: Joint Mediators	-0.07	-0.12, -0.02	-0.01[b]	-0.04, 0.01		
Approach 2: Path Specific	-0.07	-0.12, -0.02	-0.003[c]	-0.03, 0.02	-0.01[d]	-0.02, -0.0004
Approach 3: Intervention Analogue	-0.08	-0.13, -0.03	-0.003[e]	-0.03, 0.02		

Abbreviation: CI, confidence interval; IFLS, Indonesian Family Life Survey.

[a] The effect of poverty at 0-7 years on cognitive function at 7-14 years (X→Y).

[b] The effect of poverty at 0-7 years on cognitive function at 7-14 years through poverty at 7-14 (X→M→Y) or home environment/schooling (X→L→Y) or both.

[c,e] The effect of poverty at 0-7 on cognitive function at 7-14 years mediated through poverty at 7-14 years (X→*M*→*Y*).

[d] The effect of poverty at 0-7 on cognitive function at 7-14 years mediated home environment/schooling (X→L→Y), as well as through home environment/schooling and poverty at 7-14 years (X→L→M→Y).

Table 11 shows the estimates for the effect decomposition of poverty at 0-7 on cognitive function at 7-14 years. The joint mediator approach showed the direct effect of poverty at 0-7 on cognitive function was -0.07 (95% CI: -0.12, - 0.02), which is similar with the estimate from the path specific effect. The direct effect of poverty at 0-7 from the intervention analogue approach was slightly higher (β = -0.08, 95% CI: -0.13, -0.03). The indirect effect of poverty at 0-7 mediated through poverty at 7-14 for the joint mediator approach was -0.01 (95% CI: -0.04, 0.01). We used McKinnon *et al* (264) method to estimate CI for the ratio mediated effect. This suggests 18% (95% CI 7, 29) of the total effect was mediated indirectly. From both path specific effect and intervention analogue, the indirect effect of poverty at 0-7 mediated through poverty at 7-14 was smaller (β = -0.003, 95% CI: -0.03, 0.02). Furthermore, the path specific approach showed the effect of poverty at 0-7 mediated through schooling/home environment was -0.01 (95% CI: -0.02, -0.0004).

For comparison, Web Table 5 shows results from a conventional sequential regression analysis where the direct effect of poverty at 0-7 on cognitive function was -0.08 (95% CI: -0.13,-0.03). After further adjustment for poverty and schooling/home environment at 7-14, the direct effect was -0.05 (95% CI: -0.10, -0.002). The change in the coefficient for the direct effect ((-0.03)/(-0.08)=0.37) showed that 37% the effect of poverty at 0-7 on cognitive function was explained by *M* and *L*.

6.6. Discussion

Our goal was to obtain an estimate of the optimal timing for a potential poverty alleviating financial intervention, and the mechanisms by which poverty in early-life at 0-7 years could affect cognitive function at 7-14. From conventional regression, the effect of early-life poverty was similar to the effect of poverty in later childhood. From effect decomposition, we found that poverty at 0-7 had a bigger direct effect on cognitive function than via its mediated effect through poverty at 7-14. Moreover, the mediated effect of poverty at 0-7 years was stronger through pathways that involving schooling/home environment and poverty at 7-14 than through poverty at age 7-14 alone.

Although conventional mediation analysis (195) can be used to estimate direct and indirect effects, this method may generate biased estimates, especially for indirect effects in the presence of exposure-induced mediator outcome confounding (196, 197). In terms of the magnitude of the effect, conventional regression may yield similar estimates for the direct effect of poverty at 0-7 with the VVR approach, however, conventional regression does not deal properly with time-varying confounding and mediation. Results of the ‘mediated effect’ from conventional regression suggest 37% of the total effect is mediated (95% CI 36, 38) compared to 18% (95% CI 7, 29) from the VVR approach. Thus, conventional regression over-estimates the amount of mediation by a factor of two compared to the VVR method.

Our findings have several implications. First, our findings are qualitatively consistent with other studies suggesting that children exposed to poverty from birth to 14 years have lower cognitive function (85, 265). Second, and contrary to our *a priori* expectations, our findings provide little support for the idea that an early intervention to support household income has a larger effect than intervention later in childhood, both seem equally important (33, 266). Third, the direct effect of poverty at 0-7 on cognitive function at 7-14 was small. In this study a US$14 difference in the median household expenditure between the poor and the non-poor was associated with a 0.07 unit lower cognitive function z-score. Small effects were also reported by Paxson and Schady

(125), suggesting that a $15 cash transfer intervention was associated with a 5% SD increase in cognitive score among children under 7 in Ecuador. The estimated effect size in our study is about half that reported in a recent systematic review and meta-analysis of experimental and quasi-experimental evaluations of early childhood interventions in low and middle=income countries (37) which found cash transfer programs had a mean effect size 0.17 (SD 0.06) on cognitive ability. Our study thus adds to evidence about the financial costs of cash-transfer interventions and the likely effects on improving cognitive function in children, which may in turn have flow on effects on individual earnings and economic growth (267, 268). In our data, the mechanism by which poverty under 7 affects cognitive function is largely mediated through schooling/home environment and subsequent childhood poverty (ages 7-14) than mediated through poverty at 7-14 alone, which supports the argument that family financial resources contribute to children's development outcomes through direct parental investments of time and attention, and through expenditure on their skills, health, and education (28).

Use of effect decomposition provides estimates for direct and indirect effects by controlling confounding appropriately even in the presence of exposure-induced mediator-outcome confounding. We present three approaches to effect decomposition in the presence of exposure-induced mediator-outcome confounding (L). Although our estimates show similar results, each method can be applied in different contexts. If there is L, the joint mediators approach does not violate the fourth assumption because both the mediator and the mediator-outcome confounder were considered as joint mediators. The path specific approach is useful to partition the indirect effect of exposure on outcome, which is mediated through confounding L in addition to the pathway involving the mediator. Finally, in the intervention analogue approach, effect decomposition is estimated as an analogue of a sequentially randomized mediator based on the exposure level, which effectively removes *L*.

We are fully aware that there are other potential mechanisms by which poverty at 0-7 years could affect cognitive function at 7-14 years including but not limited to access to health care, nutrition, cognitive stimulating environment, parental stress and parenting practices but we did not have such measures in the IFLS data (269, 270). To estimate potential bias due to unmeasured mediator-outcome confounding (*U*), we conducted sensitivity analysis (Web Appendix 7). We found the effect of *U* would be small to explain away the direct effect of poverty at 0-7 on cognitive function (Web Table 6).

In summary, exposure to poverty at 0-7 had similar effects on child cognitive function at 7-14 as child poverty at 7-14. Despite the small effect size, cash-transfer intervention may improve children's cognitive function.

6.7. Chapter 6 Appendices

6.7.1. Web Table 1. Characteristics of study participants from response sample in each IFLS survey 2000 and 2007, *n*=6,680

Variables	2000					2007				
	Response sample	No.	%	Median (IQR)	Mean (SD)	Respons e sample	No.	%	Median (IQR)	Mean (SD)
Outcome										
Cognitive function z-score						6,247			0.53 (-0.08 - 0.83)	
Exposure and mediator										
Household per capita expenditure per month (PCE), *Rupiah*	5,571			140,253 (92,019 – 223,942)		6,510			351,408 (231,881 - 545,340)	
-the poor	2,229			83,490 (65,154 – 100,229)		2,604			209,875 (166,700 - 253,713)	
-the non-poor	3,342			202,459 (152,642 – 287,258)		3,906			493,752 (377,815 - 713,920)	
Household PCE per month, US$ (1 US$=8422 *rupiah*)	5,571					6,510				
-the poor	2,229			8 (12 - 17)		2,604			25 (20 – 30)	
-the non-poor	3,342			21 (14 - 32)		3,906			45 (30 – 85)	
Covariates										
Child's characteristics										
Child is male	5,595	2,879	51			6,680	3,431	51		
Age, mean (SD)	5,595				3.22 (2.24)	6,680				10.31 (2.32)
Attending school						6,678	6,220	93		

Web Table 1. Continued

Variables	2000					2007				
	Response sample	No.	%	Median (IQR)	Mean (SD)	Response sample	No.	%	Median (IQR)	Mean (SD)
Caregiver's characteristics										
Age, median (IQR)	5,578			30 (25 – 35)						
Highest education attended	5,563									
None		364	7							
Primary school (Grade 1-6)		2,620	47							
Junior high school (Grade 7-9)		1,016	18							
Senior high school (Grade 10-12)		1,241	22							
Diploma/university		322	6							
Working in the past week	5,543	2,300	41			5,427	2,270	42		
Household characteristics										
Household size, mean (SD)	5,589		89		5.41 (2.06)					
Economic hardship experience in the past 5 years, mean (SD)	5,588		51		0.45 (0.71)					
Had electricity	5,588	4,981	44			6,659	6,391	96		
Used piped or pumped well as the main drinking water source	5,588	2,852				6,659	3,653	55		
Improved sanitation	5,588	2,482	44			6,659	4,163	63		

Web Table 1. Continued

Variables	2000					2007				
	Response sample	No.	%	Median (IQR)	Mean (SD)	Response sample	No.	%	Median (IQR)	Mean (SD)
-urban	5,595	2,462	47			6,666	3,302	50		
-Java/Bali						6,666	3,894	58		
Type of cooking fuel						6,634				
-gas/electricity							1,197	18		
-kerosene							2,779	42		
-wood/coal							2,658	40		
Had television						6,633	5,276	80		
House tenure: own house						6,659	5,244	79		

Abbreviations: IFLS, Indonesian Family Life Survey; IQR, inter quartile range; PCE, per capita expenditure; SD, standard deviation.

6.7.2. Web Table 2. Estimates of the association between household per capita expenditure at 0-7 and cognitive function at 7-14 years. IFLS 2000 and 2007, complete cases, *n*=4,245

Decile	US$	*β*	95% CI	
1	≤ 7.73	*ref*		
2	7.74 – 9.89	0.07	-0.03	0.16
3	9.90 – 11.80	0.06	-0.03	0.15
4	11.81 – 13.87	0.06	-0.03	0.15
5	13.89 – 16.54	0.14	0.04	0.23
6	16.55 – 19.50	0.18	0.09	0.28
7	19.51 – 23.82	0.20	0.11	0.29
8	23.83 – 28.86	0.24	0.14	0.33
9	28.93 – 41.49	0.31	0.22	0.40
10	≥ 42	0.40	0.31	0.49

6.7.3. Web Table 3. Estimates of the association between household per capita expenditure at 7-14 and cognitive function at 7-14 years. IFLS 2000 and 2007, complete cases, *n*=4,245

Decile	US$	*B*	95% CI	
1	≤ 20.37	*Ref*		
2	20.42 – 25.45	0.14	0.05	0.23
3	25.46 – 30.65	0.16	0.07	0.25
4	30.65 – 35.92	0.19	0.09	0.28
5	35.93 – 42.20	0.20	0.11	0.30
6	42.27 – 49.34	0.22	0.13	0.31
7	49.37 – 59.38	0.31	0.22	0.40
8	59.46 – 72.57	0.34	0.24	0.43
9	72.63 – 101.72	0.40	0.31	0.49
10	≥ 102	0.49	0.40	0.58

6.7.4. Web Table 4. Crude associations between poverty at 0-7 years (*X*), poverty at 7-14 years (*M*), schooling/home environment (*L*) and cognitive function at 7-14 years (*Y*), IFLS 2000 and 2007, complete cases, *n*=4245.

Model	OR	β	95% Confidence Interval	
Pr (M|X)	5.51		4.81	6.30
Pr (L|X)	4.20		3.69	4.79
Pr (M|L)	4.73		4.14	5.39
E (Y|X)		-0.20	-0.24	-0.15
E (Y|M)		-0.21	-0.25	-0.16
E (Y|L)		-0.24	-0.28	-0.19

Abbreviations: IFLS, Indonesian Family Life Survey; OR, odds ratio.

6.7.5. Web Appendix 1

THE ASSOCIATIONS OF EARLY (AT 0-7 YEARS) AND LATER CHILDHOOD POVERTY (AT 7-14 YEARS) WITH COGNITIVE FUNCTION AT 7-14 YEARS

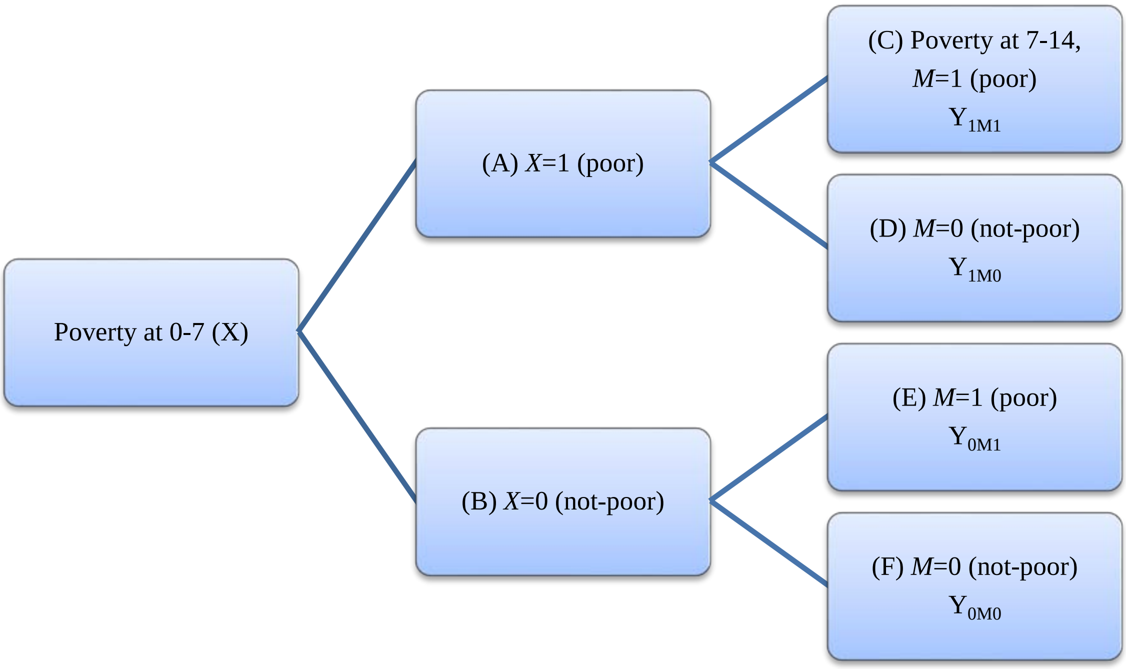
We used conventional regression analysis to examine the associations of early poverty (at 0-7) and later childhood poverty (at 7-14 years) with cognitive function at 7-14 years. Herein, equation e1 shows the regression model estimated the association of poverty at 0-7 (*X*) with cognitive function adjusting for baseline confounders (*C*). Equation e2 shows the regression model estimated the association of poverty at 7-14 (*M*) adjusting for all covariates including poverty at 0-7 (*X*), baseline confounders (*C*) and schooling/home environment (*L*).

$$E(Y \mid X, C) = \beta_0 + \beta_1 X + \beta_2 C \quad \text{(e1)}$$

$$E(Y \mid X, X, C, L) = \beta_0 + \beta_1 M + \beta_2 X + \beta_3 C + \beta_4 L \quad \text{(e2)}$$

6.7.6. Web Figure 1

Web Figure 1. Sequential randomization in the intervention analogue approach



6.7.7. Web Appendix 2

EFFECT DECOMPOSITION UNDER POTENTIAL OUTCOME APPROACH

In general, a potential outcome approach (212, 213) decomposes the total causal effect (TCE), into the natural direct (NDE) and indirect effects (NIE). In this study, effect decomposition can be defined as

$$TCE = E[Y_{x,M(x)} - Y_{x^*,M(x^*)}] \tag{e3}$$

$$NDE = E[Y_{x,M(x^*)} - Y_{x^*,M(x^*)}] \tag{e4}$$

$$NIE = E[Y_{x,M(x)} - Y_{x,M(x^*)}] \tag{e5}$$

In equation e3 TCE is the expected potential outcome (child cognitive function z-score) in children exposed to poverty at 0-7 (X=x) and the mediator (poverty at 7-14, $M(x)$) is set at the level it would be among those who were exposed to poverty at age 0-7, *minus*, the expected potential outcome in children not exposed to poverty at 0-7, and the mediator is set at the level it would be among those who were unexposed to poverty at 0-7 (M(x*)). In equation e4, the NDE is the expected potential outcome in children exposed to poverty at 0-7 (X=x) and the mediator is set at the level it would be among those who were not exposed to poverty at 0-7 (M(x*)), *minus*, the expected outcome in the unexposed and the mediator is set at the level it would be among those who were unexposed to poverty at 0-7 (M(x*)). Intuitively, the NDE estimates the effect of poverty at 0-7 on cognitive function through pathways that do not involve poverty at 7-14 years. In equation e5, the NIE is the potential outcome in children exposed to poverty at 0-7 when the mediator is set at the level it would be among those who were exposed to poverty at 0-7 (M(x)) *minus* the potential outcome in children exposed to poverty at 0-7 and the mediator is set at the level it would be among those who were unexposed to poverty at 0-7 ($M(x^*)$). This algebra invokes the cross-world assumption because NIE requires the mediator to simultaneously take on values under X=x and X=x^* i.e., M cannot take on its value under x and x^* simultaneously (211). Nevertheless, intuitively, the NIE estimates the effect of poverty at 0-7 on cognitive function through poverty at 7-14 years.

6.7.8. Web Appendix 3

FORMULA FOR EFFECT DECOMPOSITION IN VVR METHODS

a) Joint Mediators Approach

Let *X* be the exposure (poverty at 0-7 years), where *X*=*x* is defined as exposure set to the child being poor and *X*=*x** is defined as the exposure being set to child not being poor at 0-7. Equation e1 shows formula for estimating the direct effect (*DE*) in joint mediators approach.

$$DE_{X \to Y} = \sum_{c,l,m} E\{[Y \mid x, l, m, c] - E[Y \mid x^*, l, m, c]\} P(l, m \mid x^*, c) P(c) \qquad \text{(e6)}$$

In this approach, the DE is the sum of the products of three statistical models. The first model $E[Y \mid x, l, m, c] - E[Y \mid x^*, l, m, c]$ estimates the difference between two potential outcomes, (1) the expected cognitive function z-score *Y* given the child is poor at 0-7 (*X=x),* home environment/schooling (*L*), poverty at 7-14 (*M*) and baseline confounders *C* (caregiver's age, education, employment status, household size, economic hardship, household had electricity, used piped or pumped well as the main drinking water source, improved sanitation and residential area); *minus* (2) the expected cognitive function z-score given the child is not poor at 0-7*(X=x*),* home environment/schooling, poverty at 7-14 and confounders. The second part of the model $P(l, m \mid x^*, c)$ estimates the joint probabilities that the child is living in poor home environment (*L*) and poverty at 7-14 given the child is not exposed (*X*=*x**), in our case not poor at 0-7 and C. The final statistical model $P(c)$ estimates the probability of confounders.

Equation e7 shows the formula for estimating the indirect effect (IE) in joint mediators approach.

$$IE_{X \to M \to Y} = \sum_{c,l,m} E[Y \mid x, l, m, c]\{P(l, m \mid x, c) - P(l, m \mid x^*, c)\}P(c) \tag{e7}$$

In equation e7, the joint mediators approach estimates the indirect effect (IE) as the sum of the product of three statistical models. The first model $E[Y \mid x, l, m, c]$ estimates the expected cognitive function z-score *Y* given the child is poor at 0-7 (*X*=*x*), home environment/schooling, poverty at 7-14 and confounders. The second part of the model $P(l, m \mid x, c) - P(l, m \mid x^*, c)$ estimates the difference between two joint probabilities; (1) the joint probability of the child is living in poor home environment/schooling (*L*) and poverty at 7-14 (*M*) given the child is not poor at 0-7 and *C*, *minus* (2) the joint probability of *L* and *M* given the child is not poor at 0-7 (*X*=*x**) and *C*. The final model $P(c)$ estimates the probability of confounders.

b) Path Specific Approach

Similar to the joint mediators approach, the path specific effect defines *DE* as the effect of exposure on outcome that is not through *M* or *L*. In the path specific approach, the indirect effect of poverty at 0-7 through poverty at 7-14 ($X \to M \to Y$) defined as

$$IE_{X \to M \to Y} = \sum_{c,l,m} E[Y \mid x, l, m, c]\{P(m \mid x, l, c) - P(m \mid x^*, l, c)\}P(l \mid x^*, c)P(c) \tag{e8}$$

In equation e8, $IE_{X \to M \to Y}$ is estimated as the sum of the product of four statistical models. The first model $E(Y \mid x,l,m,c)$ estimates the expected cognitive function z-score given the child is poor at 0-7, home environment/schooling, poverty at 7-14 and confounders. The second part of the model $P(m \mid x,l,c) - P(m \mid x^*,l,c)$ estimates the difference between two probabilities; (1) the probability of poverty at 7-14 given the child is poor at 0-7, home environment/schooling and confounders, *minus*, (2) the probability of poverty at 7-14 given the child is not poor at 7-14, home environment/schooling and confounders. The third part of the model $P(l \mid x^*,c)$ estimates the probability of living in poor home environment/schooling given the child is not poor at 0-7 and confounders. The fourth part of the model $P(c)$ estimates the probability of confounders.

Equation e9 shows the indirect effect of poverty at 0-7 that involving pathway through home environment/schooling X→*LY* defined as

$$IE_{X \to LY} = \sum\nolimits_{c,l,m} E(Y \mid x,l,m,c) P(m \mid x,l,c) \{P(l \mid x,c) - P(l \mid x^*,c)\} P(c) \qquad \text{(e9)}$$

In equation e9, the *IE* is estimated as the sum of the product of four statistical models. The first model $E(Y \mid x,l,m,c)$ estimates the expected potential cognitive function z-score given the child is not poor at 0-7, home environment/schooling, poverty at 7-14 and confounders. The second part of the model $P(m \mid x,l,c)$ estimates the probability of poverty at 7-14 given the child is not poor at 0-7, home environment/schooling and confounders. The third part of the model $P(l \mid x,c) - P(x^*,c)$ estimate the difference between two probability models; (1) the probability of the child is living in poor home environment/schooling given the child is poor at 0-7 and covariates, *minus*, (2) the probability of the child is living in poor home environment/schooling given the child is not poor at 0-7 and confounders. The fourth part of the model $P(c)$ estimates the probability of confounders.

c) Intervention Analogue Approach

In the third approach, effect decomposition is estimated as the difference between two potential outcomes where the value of the mediator (poverty at 7-14) is randomly drawn from the distribution of exposure level (poverty at 0-7). Equation e10 shows the estimation of *DE* in the intervention analogue approach.

$$DE_{X \to Y} = E(Y_{xG_{x|c}}) - E(Y_{x^*G_{x^*|c}}) \qquad \text{(e10)}$$
$$= \sum_{c,l,m} \{E(Y \mid x,l,m,c)P(l \mid x,c) - E(Y \mid x^*,l,m,c)P(l \mid x^*,c)\} \times P(m \mid x^*,c)P(c)$$

In equation e10, the *DE* is the expected cognitive function z-score in children exposed to poverty at 0-7 (*X=x)* when the value of the mediator (poverty at 7-14) is randomly drawn from children exposed to poverty at 0-7 ($G_{x|c}$) given covariates, *minus*, the expected potential outcome in children not exposed to poverty at 0-7 ($X=x^*$) when the value of mediator is randomly drawn from children not exposed to poverty at 0-7 ($G_{x^*|c}$) given covariates.

$$IE_{X \to G \to Y} = E(Y_{xG_{x|c}}) - E(Y_{xG_{x^*|c}}) \qquad \text{(e11)}$$
$$= \sum_{c,l,m} E(Y \mid x,l,m,c) P(l \mid x,c) \{P(m \mid x,c) - P(m \mid x^*,c)\} P(c)$$

In equation e11, the *IE* is the expected potential outcome in children exposed to poverty at 0-7 ($X=x$) with the value of the mediator randomly drawn from children exposed to poverty at 0-7 (G_x) given covariates, *minus*, the expected potential outcome in children exposed to poverty at 0-7 when the value of the mediator was drawn from children who were not exposed to poverty at 0-7 (G_{x^*}) given covariates.

6.7.9. Web Appendix 4

FORMULA FOR THE INVERSE PROBABILITY OF WEIGHTS IN VVR METHODS

The construction of the weight for the joint mediators approach is as follow.

$$W_1 = \frac{P(l \mid x^*, c) P(m \mid l, x^*, c)}{P(x \mid c) P(l \mid x, c) P(m \mid l, x, c)} \qquad \text{(e12)}$$

In equation e12, the numerator is the product of two statistical models; (1) the probability of schooling/home environment (*L*) given poverty at 0-7 is set to *x** and *C*, and the probability of poverty at 7-14 (*M*) given schooling/home environment, poverty at 0-7 is set to *x** and *C*. The denominator is the product of three statistical models; (1) the probability of the observed poverty 0-7 (*X=x*) given *C;* (2) the probability of schooling/home environment given the observed poverty at 0-7 and *C;* and (3) the probability of poverty at 7-14 given schooling/home environment, the observed poverty at 0-7, and *C*.

The construction of the weight for the identifiable path specific effects is as follows.

$$W_2 = \frac{P(l \mid x^*, c) P(m \mid l, x^{**}, c)}{P(x \mid c) P(l \mid x, c) P(m \mid l, x, c)} \qquad \text{(e13)}$$

In equation e13, the numerator is the product of two statistical models; (1) the probability of schooling/home environment (*L*) given poverty at 0-7 is set to *x** and *C*, and (2) the probability of poverty at 7-14 given poverty at 0-7 is set to *x*** and *C*. The denominator is the product of three statistical models; (1) the probability of poverty at

0-7 given *C;* (2) the probability of schooling/home environment given the observed poverty at 0-7 (X=x) and *C;* and (3) the probability of poverty at 7-14 years given schooling/home environment, the observed poverty at 0-7 and *C*. Herein, x* represents potential outcome for the $X \rightarrow LY$ path, whereas x** represents potential outcome for the $X \rightarrow M \rightarrow Y$ path.

The construction of the weight for the intervention analogue approach is as follow.

$$W_3 = \frac{\sum_l P(m \mid l, x^*, c) P(l \mid x^*, c)}{P(x \mid c) P(m \mid l, x, c)} \qquad \text{(e14)}$$

In equation e14, the numerator is the sum of the product of two statistical models; (1) the probability of poverty at 7-14 (*M*) given schooling/home environment/, poverty at 0-7 is set to x* and *C*, and (2) the probability of schooling/home environment/ given poverty at 0-7 is set to x* and *C*. The denominator is the product of two statistical models; (1) the probability of poverty 0-7 years given *C*, and (2) the probability of poverty at 7-14 given schooling/home environment, the observed poverty at 0-7 years, and *C*.

We estimated the 95% CI based on a bootstrap of 1000 resamples.

6.7.10. Web Appendix 5

SAS CODE FOR EFFECT DECOMPOSITION IN THE PRESENCE OF

EXPOSURE-INDUCED MEDIATOR-OUTCOME CONFOUNDER

```
/* Definition of terms

Y= outcome (cognitive function at 7-14 years).

X= exposure (poverty status at 0-7 years).

M=mediator (poverty status at 7-14 years).

L= exposure-induced mediator-outcome confounder (home
environment/schooling at 7-14).

C1-C9=baseline confounders (caregiver’s age, education, employment
status, household size, economic hardship, household had electricity,
used piped or pumped well as the main drinking water source, improved
sanitation and residential area).

*/

/*Prepare the data and create duplicates of the data set

For approach 1 and 3, generate two copies of the data and add variable
X=0 for the first replicate and X=1 for the second replicate.

For approach 2, generate three copies of the data set and add two
variables X* and X**. In the first replicate X*=X**=the observed x. In
the second replicate, X*=1-x and X**=the observed x. In the third
replicate X*=1 and X**=1-x. */

proc surveyselect data=mydata out=mydatab seed=3022 method=urs
samprate=1 outhits rep=1000 noprint; run;

data mydata0; set mydatab; x = 0; by Replicate; output; run;

data mydata1; set mydatab; x = 1; by Replicate; output; run;

proc logistic data = mydatab noprint;

model x = c1 c2 c3 c4 c5 c6 c7 c8 c9; by Replicate; score data =
mydatab out = preda; run;

data preda; set preda; pa1 = P_1; by Replicate; run;

proc logistic data = mydatab noprint; model l = x c1 c2 c3 c4 c5 c6 c7
c8 c9; by Replicate; score data = mydata1 out = predl1;

score data = mydata0 out = predl0; run;

data predl1; set predl1; pl1 = P_1; by Replicate; run;

data predl0; set predl0; pl10 = P_1; by Replicate; run;

data mydata00; set mydatab; x = 0; l = 0; by Replicate; output; run;
```

```
data mydata10; set mydatab; x = 1; l = 0; by Replicate; output; run;

data mydata01; set mydatab; x = 0; l = 1; by Replicate; output; run;

data mydata11; set mydatab; x = 1; l = 1; by Replicate; output; run;

proc logistic data = mydatab noprint; model m = x l c1 c2 c3 c4 c5 c6
c7 c8 c9; by Replicate;

score data = mydata1 out = predm1;

score data = mydata0 out = predm0;

score data = mydata00 out = predm00;

score data = mydata01 out = predm01;

score data = mydata10 out = predm10;

score data = mydata11 out = predm11;

run;

data predm1; set predm1; pm1 = P_1; by Replicate; run;

data predm0; set predm0; pm10 = P_1; by Replicate; run;

data predm00; set predm00; pm100 = P_1; by Replicate; run;

data predm10; set predm10; pm110 = P_1; by Replicate; run;

data predm01; set predm01; pm101 = P_1; by Replicate; run;

data predm11; set predm11; pm111 = P_1; by Replicate; run;

data mydataw;

merge preda predl1 predl0 predm1 predm0 predm00 predm01 predm10
predm11 mydatab; by Replicate; run;


*/This part will generate the weight for the joint mediator approach
*/

data mydatanew; set mydataw; xstar = x; w1 = x/pa1+(1-x)/(1-pa1);
output; xstar = 1-x;

if x = 0 then w1 = (1/(1-pa1))*(l*pl1/pl10+(1-l)*(1-pl1)/(1-pl10))

*((1-m)*(1-pm1)/(1-pm10) + m*pm1/pm10);

if x = 1 then w1 = (1/pa1)*((l*pl10/pl1+(1-l)*(1-pl10)/(1-pl1))

*((1-m)*(1-pm10)/(1-pm1) + m*pm10/pm1));

by Replicate; output; run;


*/This part will generate the weight for the intervention analogue */

data mydatanew; set mydatanew;
```

```
if (x = 0) & (xstar = 0) & (m = 1) then

w3 = (1/(1-pa1))*(pm100*(1-pl10)+pm101*pl10)/pm10;

if (x = 0) & (xstar = 0) & (m = 0) then

w3 = (1/(1-pa1))*((1-pm100)*(1-pl10)+(1-pm101)*pl10)/(1-pm10);

if (x = 0) & (xstar = 1) & (m = 1) then

w3 = (1/(1-pa1))*(pm110*(1-pl1)+pm111*pl1)/pm10;

if (x = 0) & (xstar = 1) & (m = 0) then

w3 = (1/(1-pa1))*((1-pm110)*(1-pl1)+(1-pm111)*pl1)/(1-pm10);

if (x = 1) & (xstar = 0) & (m = 1) then

w3 = (1/pa1)*(pm100*(1-pl10)+pm101*pl10)/pm1;

if (x = 1) & (xstar = 0) & (m = 0) then

w3 = (1/pa1)*((1-pm100)*(1-pl10)+(1-pm101)*pl10)/(1-pm1);

if (x = 1) & (xstar = 1) & (m = 1) then

w3 = (1/pa1)*(pm110*(1-pl1)+pm111*pl1)/pm1;

if (x = 1) & (xstar = 1) & (m = 0) then

w3 = (1/pa1)*((1-pm110)*(1-pl1)+(1-pm111)*pl1)/(1-pm1);

by Replicate; run;


*/Estimation of effect decomposition under the joint mediator
approach*/

proc reg data = mydatanew outest=estw1x noprint;

where xstar = 0; model y = x; weight w1; by Replicate; run;

proc reg data = mydatanew outest=estw1xs noprint; where x = 1; model y
= xstar; weight w1; by Replicate;

run;

data estfw1; merge estw1x estw1xs; by Replicate; run;

proc univariate data=estfw1; var x xstar;

output out=cilw1 pctlpts=2.5, 50, 97.5 pctlpre=x xstar;

run;


*/Estimation of effect decomposition under the intervention analogue
*/

proc reg data = mydatanew outest=estw3x noprint;

where xstar = 0; model y = x; weight w3; by Replicate; run;
```

```
proc reg data = mydatanew outest=estw3xs noprint; where x = 1; model y
= xstar; weight w3; by Replicate;

run;

data estfw3; merge estw3x estw3xs; by Replicate; run;

proc univariate data=estfw3; var x xstar;

output out=cilw3 pctlpts=2.5, 50, 97.5 pctlpre=x xstar;

run;


*/This part will generate the weight for the path specific effect */

data mydatanew2; set mydataw;

xstar = x; xstarstar = x; w2 = x/pa1+(1-x)/(1-pa1); output;

xstar = 1-x; xstarstar = x;

w2 = (x/pa1)*(l*pl10/pl1+(1-l)*(1-pl10)/(1-pl1)) +

((1-x)/(1-pa1))*(l*pl1/pl10+(1-l)*(1-pl1)/(1-pl10)); output;

xstar = 1-x; xstarstar = 1-x;

w2 = (x/pa1)*(l*(pl10/pl1)*(m*(pm101/pm111)+(1-m)*(1-pm101)/(1-pm111))

+(1-l)*((1-pl10)/(1-pl1))*(m*(pm100/pm110)+(1-m)*(1-pm100)/(1-pm110)))

+((1-x)/(1-pa1))*(l*(pl1/pl10)*(m*(pm111/pm101)+(1-m)*(1-pm111)/(1-
pm101))

+(1-l)*((1-pl1)/(1-pl10))*(m*(pm110/pm100)+(1-m)*(1-pm110)/(1-
pm100))); output; by Replicate; run;


*/Estimation of effect decomposition under the path specific effect */

proc reg data = mydatanew2 outest=est noprint;

where (xstar = 0) & (xstarstar = 0); model y = x; weight w2; by
Replicate; run;

proc reg data = mydatanew2 outest=est2 noprint;

where (x = 1) & (xstarstar = 1); model y = xstar; weight w2; by
Replicate; run;

proc reg data = mydatanew2 outest=est3 noprint;

where (x = 1) & (xstar = 0); model y = xstarstar; weight w2; by
Replicate; run;

data estf; merge est est2 est3; by Replicate; run;

proc univariate data=estf; var x xstar xstarstar;

output out=cilw2 pctlpts=2.5, 50, 97.5 pctlpre=x xstar xstarstar;
```

```
run;
```

6.7.11. Web Appendix 6.

DECOMPOSITION OF THE EFFECT OF POVERTY AT 0-7 AND POVERTY AT 7-14 YEARS FROM CONVENTIONAL SEQUENTIAL REGRESSION ANALYSIS

For comparative purpose, we conducted a conventional sequential regression analysis to estimate the effect of poverty at 0-7 and at 7-14 on children's cognitive function. Web Table 5 presents estimates for the association of poverty at 0-7 with cognitive function from a sequential regression analysis. In this table, the coefficient α_1 in model 1 can be interpreted as a direct effect, whereas the difference between α_1 and ϕ_1 represents an indirect effect by controlling for *M* (poverty 7-14) and *L* (poor home environment and school attendance 7-14). The adjusted (model 1) effect of poverty at 0-7 on cognitive function was -0.08 z-score units of cognitive ability, and the adjusted effect (model 3) was (-0.08)-(-0.05) = -0.03 in cognitive function z-score. Thus the proportion "explained" was ((-0.03)/(-0.08))*100 = 38%. This can be interpreted as 38% of the effect of poverty at 0-7 was "mediated" through poverty and poor home environment and school attendance at 7-14 years of age.

6.7.12. Web Table 5. Estimates for the association of poverty at 0-7 with cognitive function at 7-14 from conventional regression analysis, IFLS 2000 and 2007, complete cases, *n*=4,245

		Coefficient of the exposure	95% CI	
Model 1	$E(Y \mid X, C) = \alpha_0 + \alpha_1 X + \alpha_2 C$	-0.08	-0.13	-0.033
Model 2	$E(Y \mid X, C, M) = \beta_0 + \beta_1 X + \beta_2 C + \beta_3 M$	-0.06	-0.11	-0.009
Model 3	$E(Y \mid X, C, M, L) = \phi_0 + \phi_1 X + \phi_2 C + \phi_3 M + \phi_4 L$	-0.05	-0.10	-0.002

Model 1 included poverty at 0-7 years (*X*) and baseline confounders (*C*)

Model 2 included model 1 and poverty at 7-14 years (*M*)

Model 3 included model 2 and home environment/schooling at 7-14 years (*L*)

6.7.13. Web Appendix 7.

SENSITIVITY ANALYSIS DUE TO UNMEASURED MEDIATOR-OUTCOME CONFOUNDING

We used sensitivity analysis method that was developed by Vander Weele and Chiba (217) to estimate bias in effect decomposition due to unmeasured mediator-outcome confounding. The sensitivity analysis was conducted as a non-parametric approach, which can be applied for any effect decomposition method including the method that has an exposure-induced mediator-outcome confounding.

The steps for conducting the sensitivity analysis are as follows.

Step 1. We defined sensitivity analysis parameter

Let γ_{mc} be the sensitivity analysis parameter for each level of poverty at 7-14 years (M=m), then

$$\gamma_{0c} = E[Y_{10} \mid X = 1, M = 0, c] - E[Y_{10} \mid X = 0, M = 0, c] \qquad \text{(e15)}$$

$$\gamma_{1c} = E[Y_{11} \mid X = 1, M = 1, c] - E[Y_{11} \mid X = 0, M = 1, c] \qquad \text{(e16)}$$

the sensitivity analysis parameter γ_{0c} was defined as the difference in the expected cognitive function z-score in children who were exposed to poverty at 0-7 (*X=1*) but were not exposed to poverty at 7-14 years (*M=0*), *versus*, those who were not exposed to poverty at 0-7 (*X=0)* and at 7-14 years *(M=0)* given covariates *C* (equation e15), whereas the sensitivity analysis parameter γ_{1c} was defined as the difference in cognitive function z-score in children who were exposed to poverty at 0-7 (*X=1*) and at 7-14 years (*M=1*), *versus*, those who were not exposed to poverty at 0-7 (*X=0*) but were exposed to poverty at 7-14 years (*M=1*) given *C* (equation e16). Under the assumption that *Y* is not misclassified, and the level of *X* and *M* are fixed, the difference in cognitive function score could be due to unmeasured mediator-outcome confounding.

Step 2.We estimated the probabilities of the mediator in the control group

Under the assumption that there was no measurement error in *M* and *C*, we used the observed data to estimate the probability of poverty status at 7-14 years given the child was not exposed to poverty at 0-7 years and *C*, $P(m \mid X = 0, c)$.

Step 3. We estimated the bias factor Γ_c

$$\begin{aligned}\Gamma_c &= \sum_m \gamma_{mc} P(m \mid X = 0, c) \\ &= [P(m_0 \mid X = 0, c)(\gamma_{0c})] + [P(m_1 \mid X = 0, c)(\gamma_{1c})]\end{aligned} \quad \text{(e17)}$$

As shown in equation e17, the bias factor Γ_c was estimated as the sum of the product of sensitivity parameter values and the probability of the mediator in the control group.

Step 4. We obtained the corrected estimates for the direct and indirect effects

Let Γ_c be the bias factor for direct effect and $-\Gamma_c$ be the bias factor for the indirect effect, then

$$B_c^{DE} = DE - \Gamma_c \quad \text{(e18)}$$

$$B_c^{IE} = IE - (-\Gamma_c) \quad \text{(e19)}$$

the corrected estimates for direct and indirect effects were obtained as the difference between estimates of direct and indirect effects, and the bias factor, respectively (equations e18-e19).

Results of the sensitivity analysis are presented in Web table 6. As illustration, we specified the values of sensitivity parameters at 0.03, 0.07, 0.10 and 0.14, representing about 5%, 10%, 15% and 20% SD of cognitive function z-score, respectively. We used estimates of direct and indirect effects of poverty at 0-7 from the VVR joint mediators approach. Under different values of specified sensitivity parameters, we found that the sensitivity analysis values and the bias factor would be small to explain away the direct effect of poverty at 0-7 on cognitive function at 7-14 years (scenario 12). This also implies that the magnitude of the effect of unmeasured mediator-outcome confounding is relatively small to eliminate the effect of exposure on outcome.

6.7.14. Web Table 6. Results of the sensitivity analysis. IFLS 2000 and 2007, complete cases, *n*=4,245

	γ_{0c} [a]	γ_{1c} [b]	$P(m_0 \mid X=0,c)^c$	$P(m_1 \mid X=0,c)^d$	DE[e]	IE[f]	$\Gamma_c{}^g$	$-\Gamma_c{}^h$	$DE-\Gamma_c{}^i$	$IE-(-\Gamma_c)^j$
1	-0.03	-0.07	0.76	0.24	-0.07	-0.01	-0.04	0.04	-0.03	-0.05
2	-0.03	-0.10	0.76	0.24	-0.07	-0.01	-0.05	0.05	-0.02	-0.06
3	-0.07	-0.03	0.76	0.24	-0.07	-0.01	-0.06	0.06	-0.01	-0.07
4	-0.03	-0.14	0.76	0.24	-0.07	-0.01	-0.06	0.06	-0.01	-0.07
5	-0.07	-0.07	0.76	0.24	-0.07	-0.01	-0.07	0.07	0.00	-0.08
6	0.03	0.10	0.76	0.24	-0.07	-0.01	0.05	-0.05	-0.12	0.04
7	0.07	0.03	0.76	0.24	-0.07	-0.01	0.06	-0.06	-0.13	0.05
8	0.03	0.14	0.76	0.24	-0.07	-0.01	0.06	-0.06	-0.13	0.05
9	0.07	0.10	0.76	0.24	-0.07	-0.01	0.08	-0.08	-0.15	0.07
10	0.10	0.03	0.76	0.24	-0.07	-0.01	0.08	-0.08	-0.15	0.07
11	0.07	0.14	0.76	0.24	-0.07	-0.01	0.09	-0.09	-0.16	0.08
12	0.10	0.07	0.76	0.24	-0.07	-0.01	0.09	-0.09	-0.16	0.08

[a] sensitivity parameter γ_{0c} is the difference in cognitive function z-score between two subgroups, where the first group is children who were poor at 0-7 (*X*=1) but not poor at 7-14 years (*M*=0), and second those who were not poor both at 0-7 (*X*=0) and at 7-14 (*M*=0) given covariates. [b] sensitivity parameter γ_{1c} is the difference in cognitive function z-score between two subgroups, where the first group is children who were poor both at 0-7 (*X*=1) and at 7-14 (M=1), and second those who were not poor at 0-7 (*X*=0) but poor at 7-14 (*M*=1) given covariates. [c-d] the probability of poverty status at 7-14 years in the control group. [e-f] estimates for the natural direct and indirect effects of poverty status at 0-7 years on cognitive function, respectively. [g-h] bias factor for DE and IE, respectively. [i-j] the corrected estimate for DE and IE, respectively.

CHAPTER 7

Effects of Hypothetical Interventions on Children's School Readiness and Socio-emotional wellbeing in Rural Indonesia: Application of Parametric G-Formula

7.1. Preface

This chapter contains the final study of this thesis, which investigated the relative and combined effects of different hypothetical interventions on children's school readiness and socio-emotional wellbeing in rural Indonesia. As outline in chapter 4, findings from study 1 suggested that household per capita expenditure was the largest contributor to inequality in children's cognitive function in 2000 and 2007. Between 2000 and 2007, substantial reductions in inequality in children's cognitive function were mainly driven by improvements in maternal education, access to improved sanitation and household per capita expenditure. In study 2, the effects of household per capita expenditure and cash transfer intervention on children's cognitive function were examined (chapter 5). Findings from study 2 suggested that a cash transfer intervention for the poorest households in 2000 increased children's cognitive function score by 6% but there was no overall effect of cash transfers at the population level because the cash transfer was too small to benefit the target children. This implies that providing cash transfer alone is not effective in improving children's cognitive function at the population level. Hence, the current study aimed to examine the relative and combined strategies of interventions that potentially could improve children's development outcomes in rural Indonesia.

7.2. Introduction

Since 2010, economic growth has moved Indonesia from being among the poorest to a lower middle income country (23). Despite this progress, many Indonesian households still live in poor standards of living. The current national statistics suggest that only 11% of the Indonesian population used piped water as the main drinking water source and 70% had private toilet (271). In low and middle income countries (LMICs) inadequate access to water and sanitation is associated with poverty, increased maternal poor mental health and poor parenting behaviour (16, 17), which in turn may affect children's cognitive and socio-emotional wellbeing (6, 8, 30, 221). Evidence from LMICs also suggests that children living in poor housing conditions tend to have poorer cognitive function (88, 272), and are less likely to be able to read paragraphs (126) and have lower levels of education (127) compared to children who live in better housing conditions. Evidence from a range of studies also shows that effective interventions can protect children from multiple negative consequences of living in poverty (36), improve maternal mental health (145) and parenting behaviour (138, 140).

Our recent study examined the effect of a hypothetical cash transfer intervention on children's cognitive function (66). Based on simulations of a plausible hypothetical cash transfer intervention, we found that a US$ 6-10/month of cash transfer for children from the poorest 40% of household expenditure increased the mean cognitive function score by 6% but there was no overall effect of cash transfers at the total population level because the cash transfer was too small to benefit the target children. Given the small effect size of cash transfer intervention in our previous study, a stand-alone cash transfer would need to be much larger to have a substantial impact on children's cognitive function (66). This implies that providing cash transfer alone is not an effective intervention to improve children's cognitive function in Indonesia. Moreover, evidence from systematic review and meta-analysis (37, 259) that examined effectiveness implementation of early childhood interventions suggested that an intervention that combined multiple programs may yield greater effect than single intervention.

The current study examined the relative and combined effects of a range of hypothetical interventions at ages 4, 5 and 8 years on a holistic measure of children's school readiness and socio-emotional wellbeing at age 8 among children living in rural Indonesia. In this study, we focused on interventions that provide piped water as the main drinking water source and improved sanitation (126, 129), improve maternal mental health (6, 141, 145, 165) and parenting behaviour (32, 36, 138, 140).

7.3. Methods

Data

We used data from a pragmatic clustered randomized controlled trial (RCT) evaluating the impact of community-based Early Childhood Education and Development (ECED) intervention in rural communities in Indonesia (26). In this study, we used information about whether or not a village was randomized to receive an ECED project as a baseline confounder. The ECED project was implemented by the Indonesian government, which aimed to provide greater access to ECED services in the community and improve children's development and readiness for transition to formal education (26). The ECED project targeted about 738,000 children ages 0-6 years and their primary caregivers living in 3000 villages within 50 poor districts. These districts were selected based on low participation rates in ECED services, high poverty rates, and commitment to developing, managing and financing the ECED project in their area. Within each district, 60 villages were selected based on high numbers of children aged 0-6 years, high poverty rates and had shown interest in the ECED project.

The RCT was conducted in 310 villages in 9 districts including Sarolangun, North Bengkulu, East Lampung, Majalengka, Rembang, Kulon Progo, Sidenreng Rappang (Sidrap), Ketapang and Middle Lombok. The first data collection was conducted in 2009 and subsequently in 2010 and 2013. The ECED study comprised cohorts aged 1 (n=3118) and 4 (n=3251) in 2009 with follow up in 2010 and 2013. In this study, we selected participants aged 4 in 2009 and followed up at ages 5 and 8 who had complete information about variables of interest (Figure 27).

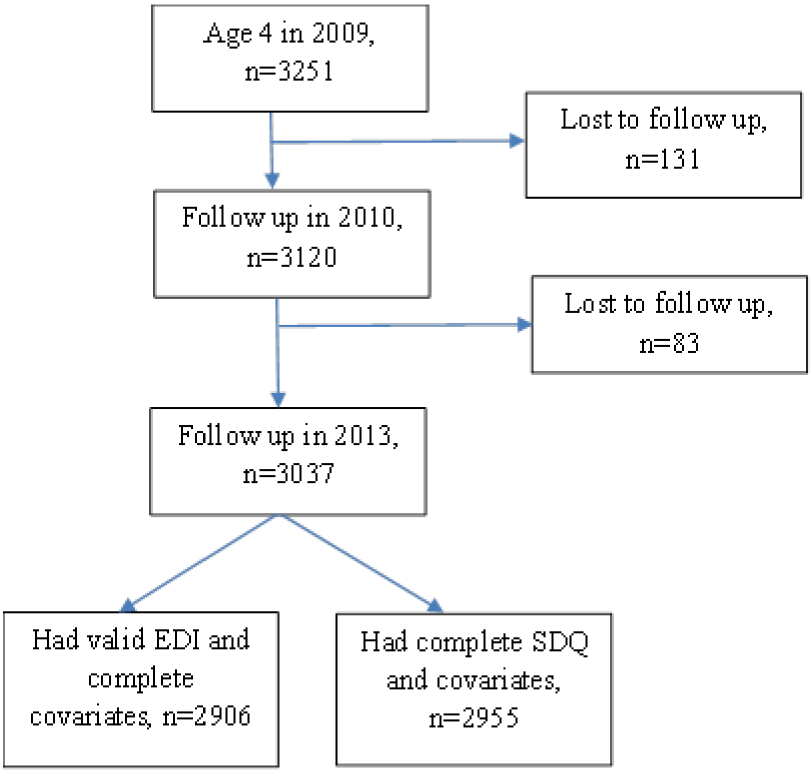


Figure 27 Flow of study participants, children aged 4 in 2009 follow up aged 5 in 2010 and aged 8 in 2013

Measures

Outcome

School readiness

The Early Development Instrument (EDI) is a holistic measure of child development at school entry that comprises that five major developmental domains including physical health and well-being, social competence, emotional maturity, language and cognitive development, as well as communication skills and general knowledge (153, 154). For each domain the score ranged from 0 to 10, where a higher score indicated better outcomes. According to standard practice, a child whose score was in the lowest 10% in each domain was classified as developmentally vulnerable in that specific domain (coded as 1 or 0 otherwise) (154). The scores were summed to define whether a child was developmentally vulnerable in one or more domains (coded as 1 or 0 otherwise). We used the classification of being vulnerable in one or more domains as the primary outcome, which is consistent with its use in national population survey (273, 274).

Socio-emotional wellbeing

The second main outcome used the Strengths and Difficulties Questionnaire (SDQ) as a measure of children's socio-emotional wellbeing (155). The SDQ comprises five subscales including emotional symptoms, conduct problems, hyperactivity/inattention, peer relation problem and prosocial behaviour. For each subscale the score ranged from 0 to 10. With the exception of prosocial behavior sub-scale, higher scores are associated with poorer behavioural outcomes. Consistent with standard practice, the scores of emotional and peer problems subscales were combined to define internalising behaviour, whereas the scores of conduct problems and hyperactivity/inattention subscales were combined to define externalising behaviour (156). In the analysis both internalising and externalising behaviour problems were used as continuous scores.

Exposure

Household standards of living

Household standards of living were measured using two indicators. First, whether the child lived in a household that used piped water as the main drinking water source (coded as 1 and 0 otherwise). Second, whether the child lived in a household that used improved sanitation, defined as owned a toilet that was connected to a septic tank (coded as 1 and 0 otherwise).

Maternal mental health

Maternal mental health was measured using Kessler 10 (K10) (160), which is a self-reported questionnaire that was designed to measure non-specific psychological distress. K10 comprises 10 items of feelings of anxiety and depression in the past four weeks and their frequency. Each response item was reported on a 3-point scale where the score ranged from 1 “never”, 3”sometimes” and 5”often”. All the 10 items were combined to generate a total mental health score, where higher score is associated with poorer mental health (scores ranging 10-50).

Parenting styles

Parenting style was measured using 24 items describing parent-child relationships such as warmth, consistency and hostility. This measure was adapted from the Longitudinal Study of Australian Children (LSAC) study (161). For each item, the response was reported on a 5-point scale, which ranged from never to always. All 23 items were combined to generate a total parenting score, where higher score indicated better parenting styles. This variable was treated as a continuous variable (scores ranging 23-115).

Covariates

A series of covariates were selected *a priori* as baseline confounders (C) that were measured at age 4 including maternal age (83, 108) and education (83, 90, 162, 163). Maternal age was measured in years and used as continuous variable. Maternal education was measured as the highest education completed (categorized as none or not completed primary school, primary school, junior high school, senior high school and diploma/university). Household characteristics include household size (continuous) (30), the number of self-reported economic hardships experienced by household (continuous) (102), housing conditions and assets (23, 88, 126, 162) and whether the child is living in a village that receive the ECED program or otherwise.

Factor analysis (170, 171) was used to construct a standard of living index based on housing conditions and household assets at aged 4. Housing conditions include whether the household had electricity, separate kitchen, used non-earth floor, and type of cooking fuel (used wood, kerosene or gas/electricity). Household assets include whether the household had telephone, radio, television, refrigerator, bike, motorcycle and car. The standards of living index was estimated as the weighted sum of the scores on these variables, where the weights are the eigen values. The latent variable/factor score was then classified into quintiles, which ranged from the poorest (quintile 1) to the richest (quintile 5).

Statistical analysis

Assuming there is no unmeasured confounding, Figure 18 shows a Directed Acyclic Graph (DAG) representing the associations between baseline confounders (C), exposure *X* and covariates *L* on children's school readiness and socio-emotional wellbeing at age 8.

In this DAG, both exposure X and confounding *L* are time-varying because they were measured at ages 4, 5 and 8, whereas a series of baseline confounders (maternal age, education, economic hardships, whether a child is living in the ECED program and household standards of living) were measured at aged 4.

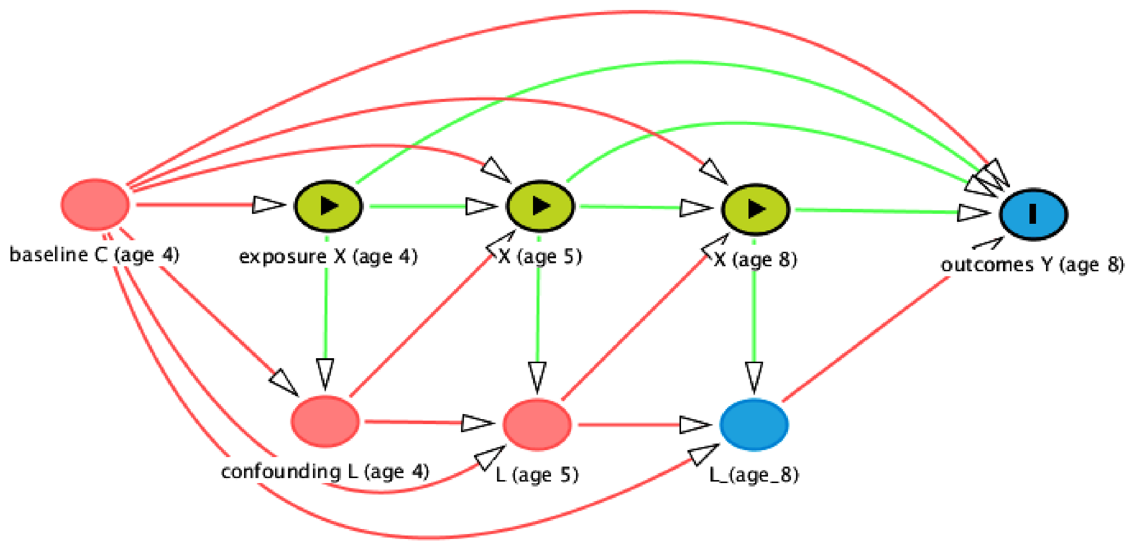


Figure 28. Causal diagram for estimating the effects of hypothetical interventions on children's school readiness and socio-emotional wellbeing

We examined the relative and combined effects of different interventions at ages 4, 5, and 8 on children's school readiness and socio-emotional wellbeing at age 8 under the following hypothetical intervention scenario.

Scenario 1. Improving household standards of living

Scenario 1 has two components of intervention provision of piped water as the main drinking water source and improved sanitation. Studies show a combination of improved water and sanitation intervention would generate a greater effect than a single intervention (129, 218), hence in scenario 1 provision of piped water and improved sanitation were considered as a joint intervention. Hypothetically, provision of piped water as the main drinking water source and improved sanitation would enhance housing conditions and in turn would have positive effect on children's school readiness and socio-emotional wellbeing. Under scenario 1, all children would have access to piped water and improved sanitation.

Scenario 2. Maternal mental health intervention

In scenario 2, we generated a hypothetical community-based mental health intervention to promote good mental health, which is commonly conducted in LMICs in the setting where accesses to mental health services are limited (32, 42). In this scenario, a mother whose score was in the highest 20% of the K10 score was targeted for mental health intervention (score 17 or above from the observed data). The 20% cut off for our intervention coverage was based on the prevalence of common mental health disorder in Indonesia (219) and in LMICs (220). Hypothetically, mental health intervention for mothers had benefit both mothers and their children (145).

Scenario 3. Parenting intervention

In scenario 3, we generated a hypothetical parenting education program to improve caregiving behaviour, which has been shown as an effective parenting intervention in LMICs (36, 138, 140). Under this scenario, a mother whose score was in the lowest

20% of the total parenting scores was targeted for intervention (scores 75 or lower based on the observed data). Hypothetically, mothers who received parenting interventions improve their relationships with the child and this may reduce harsh or abusive parenting, which in turn will improve children's school readiness and socio-emotional wellbeing (32, 36, 140).

Scenarios 4-5. Joint interventions

A great deal of evidence shows that interventions that combined several programs had greater benefits than a single intervention (37, 259), hence under scenario 4 and 5, we generated hypothetical intervention that combined multiple programs. In scenario 4, we estimated the joint effects of intervention that combined maternal mental health and a parenting education program (scenario 2 and 3). In scenario 5, we estimated the joint effects of all interventions from scenarios 1-3 above that combined provision of piped water as the main drinking water source, improved sanitation, maternal mental health and parenting education program.

Using a potential outcome approach, we estimated the risk of being vulnerable in one or more EDI domains and the average of internalising and externalising behaviour scores (SDQ) at age 8 that would have been observed under each of the specified hypothetical interventions at ages 4, 5 and 8. In the presence of time-varying exposure and confounding, use of conventional regression may yield bias in effect estimation (187-190). Methods that can be used to assess causality from complex longitudinal observational studies include g-formula, g-estimation of the structural nested models (SNMs) and marginal structural models (MSMs) (189).

We used parametric g-formula (224-226) for estimating the potential outcome under the specified hypothetical interventions. Parametric g-formula (59-61) is the extended version of nonparametric g-formula (55, 56). The earlier version of g-formula is useful to estimate the effect of time-varying exposure in the presence of time-varying confounding through standardization modelling. The original g-formula is a nonparametric method because the estimation did not require a *priori* specification of distributions to link restrictions on the value of the effect estimates. Estimates from g-formula were based on the joint distributions of the observed exposure X, confounding L and outcome Y in the population. However, in the case where data has many confounders (high dimensional data), g-formula can only be estimated under parametric modelling assumptions and uses a Monte Carlo simulation to estimate the sum over all histories of covariates.

Notation

Let t be the time variable where t_0, t_1 and t_2 is defined as the time when data was collected (ages 4, 5 and 8, respectively). Let $Y2$ be the outcome (school readiness and socio-emotional wellbeing) that was measured at age 8. Let $d=(d_1, d_2, d_3, d_4, d_5)$ be the different intervention scenarios . Let f_d be the density function under a particular intervention d. Let $X=(X_1, X_2, X_3, X_4)$ be the exposure, where X_1 is defined as used piped water as the main drinking water source, X_2 defined as used improved sanitation, X_3 defined as maternal mental health score, and X_4 defined as parenting scores. Let x_t^* is the observed value of exposure under no intervention at time t. Let x_t be the value of exposure under intervention d at time t. Let $L=(L_1, L_2, L_3, L_4)$ be confounding, where L_1

defined as used piped water as the main drinking water source, L_2 defined as used improved sanitation, L_3 defined as maternal mental health score, and L_4 defined as parenting scores. Herein, when X_1 is defined as piped water then other covariates (improved sanitation, maternal mental health and parenting) are used as confounding L (L_2, L_3, L_4), which implies that there are multiple Xs and Ls.

Let l_t be the value of confounding at time *t*. Let variables with over bars $\left(\bar{x}_t, \bar{x}_t^*, \bar{l}_t\right)$ represent the history of the intervention, observed exposure and covariates up to time *t*, respectively. Let $\bar{c}$ be a vector of baseline confounders measured at time 0 (age 4) including maternal age and education, household size, the number of self-reported economic hardships in the past year, standard of living index and whether the child is living in a village that receive the ECED program or otherwise.

The steps in parametric g-formula are as follows.

Step 1. Parametric modelling

We specified four parametric models of each covariate in the following order; whether a child was exposed to pumped water as the main drinking water source, improved sanitation, maternal mental health and parenting scores.

In Model 1, $\Pr(l_{1t} \mid l_{it-1}, l_{2t,} l_{2t-1}, \bar{l}_{3t-1}, \bar{l}_{4t-1}, \bar{c})$ logistic regression was used to estimate the conditional probability of the child exposed to piped water as the main drinking water source at time *t* $(L_{1t} = l_{it})$ given whether the child used piped water in the past, the history of other covariates up to time *t-1* $\bar{L}_t$ (improved sanitation, maternal mental health and parenting scores) and baseline confounders *C*.

In Model 2, $\Pr(l_{2t} \mid l_{2t-1}, l_{1t}, l_{1t-1}, \bar{l}_{3t-1}, \bar{l}_{4t-1}, \bar{c})$ logistic regression was used to estimate the conditional probability of the child exposed to improved sanitation at time t $(L_{2t} = l_{2t})$ given whether the child used improved sanitation in the past, the history other covariates up to time *t-1* (used piped water as the main drinking water source, maternal mental health and parenting scores) and baseline *C*.

In Model 3, $E(l_{3t} \mid \bar{l}_{3t-1}, l_{1t}, l_{1t-1}, l_{2t}, l_{2t-1}, \bar{l}_{4t-1}, \bar{c})$ linear regression was used to estimate the conditional density function of maternal mental health scores at time t $(L_{3t} = l_{3t})$ given the cumulative mean of maternal mental health score in the past, the history of other covariates up to time *t-1* (whether a children used piped water, improved sanitation and parenting score) and baseline *C*.

In Model 4, $E(l_{4t} \mid \bar{l}_{4t-1}, l_{1t}, l_{1t-1}, l_{2t}, l_{2t-1}, \bar{l}_{3t-1}, \bar{c})$ linear regression was also used to estimate the conditional density function of parenting score at time t $(L_{4t} = l_{4t})$ given the cumulative mean of parenting score in the past, the history of other covariates up to time *t-1* (whether a child used piped water as the main drinking water source, improved sanitation and maternal mental health score) and baseline *C*.

Fit a model for each outcome

Model $\Pr[Y_{it+1} \mid \bar{x}_t, \bar{l}_t, \bar{c}]$ used logistic regression to estimate the risk of being vulnerable in one or more EDI domains) at age 8 given the history of exposure, confounding and baseline *C*.

Model $E\left[Y_{t+1} \mid \bar{x}_t, \bar{l}_t, \bar{c}\right]$ used linear regression to estimate the expectation of internalising (or externalising) score at age 8 given the history of exposure, confounding and baseline *C*.

Step 2. Monte Carlo simulation

For each time *t* generate the intervention value for each covariate, "provide piped water as the main drinking water source and improved sanitation" (scenario 1); "set maternal mental health score to a maximum value of 17" (scenario 2); and "set parenting score to a minimum value of 75" (scenario 3). Monte Carlo simulation with a full sample samples (n=2906 for the EDI and n=2955 for the SDQ) was conducted to estimate parametric models in step 1 and was used to estimate the outcome under each intervention. The 95% CI was estimated based on a bootstrap of 1000 re-samples.

Step 3. Estimation of the outcome under each intervention

The statistical model for parametric g formula is defined as

Equation 26 Parametric g-formula

$$\sum_{t=0}^{T}\sum_{\bar{x}_t}\sum_{\bar{x}_t^*}\sum_{\bar{l}_t}\Pr\left[Y_{t+1} \mid \bar{x}_t, \bar{l}_t, \bar{c}\right]$$
$$\times f_d\left(x_t \mid \bar{l}_t, x^*, \bar{x}_{t-1}, \bar{c}\right)$$
$$\times f\left(l_t \mid \bar{l}_{t-1}, \bar{x}_{t-1}, \bar{c}\right)$$
$$f\left(x_t^* \mid \bar{l}_t, \bar{x}_{t-1}, \bar{c}\right)$$

For school readiness outcomes the model in equation 26 can be defined as the risk of being vulnerable in vulnerable in one or more domains given the history of specified intervention *d*, covariates and observed exposure under no intervention. For socio-emotional wellbeing, the model can be replaced by $E\left[Y_{t+1} \mid \bar{x}_t, \bar{l}_t, \bar{c}\right]$ defined as the expectation of internalising (or externalising) behaviour scores given the history of specified intervention *d*, covariates and observed exposure under no intervention.

Under the assumption of conditional exchangeability, positivity and consistency, parametric g-formula (224-226) was estimated as a weighted sum of the outcome (i.e. the risk of being vulnerable in EDI or the mean of internalising behaviour scores) conditional on the specified intervention, time varying exposure and covariates. Analysis of parametric g formula was conducted in SAS 9.4 (SAS Institute, Cary, North Carolina).

Complete case analysis

Currently there is no method available for estimating parametric g-formula using multiple imputed data. Due to complexity of the method used in this study, analysis was restricted to complete cases (178).

7.4. Results

Table 12 shows the characteristics of study participants. Of the 2906 children with complete EDI and covariates, 37% of children were classified as vulnerable in one or more EDI domains. In terms of specific domains, 28% of children were classified as vulnerable in the emotional maturity domain and in contrast only 2% of children were classified as vulnerable in the language and cognitive development and another 1% of children were classified as vulnerable in the communication skills and general knowledge domain. Whilst EDI was originally designed for children ages 4-7 years (154), our analysis was conducted using information that was collected on children's at age 8. This could be the reason there were very few children being classified as vulnerable in some of the EDI domains. Most of early childhood interventions had multiple outcomes (37, 259), hence we used the classification of being vulnerable in one or more EDI domains, children's internalising and externalising behaviour scores as the primary outcomes. Of the 2955 children with complete SDQ and covariates, the mean of internalising behaviour scores was 6.16 (SD 3.06) and externalising behaviour scores was 7.77 (SD 2.66).

The proportion of households that used piped water as the main drinking water source increased from 7% in 2009 to 11% in 2013, which is similar to the national average (271). The proportion of households that used improved sanitation also increased from 44% in 2009 to 61% in 2013, but it is slightly lower than the national average (70%). In 2009, the median maternal mental health score was 14 (inter quartile range IQR 12 -16) and the mean parenting score was 0.42 (SD 7.19). Both estimates did not change substantially at follow up. Finally, about half of the children lived with caregiver who either had none or completed primary school (18% and 38% respectively).

Table 12. Characteristics of study participants, ECED 2009, 2010 and 2013

	Complete case EDI (n=2906)			Complete case SDQ (n=2955)		
	2009	2010	2013	2009	2010	2013
Child is male, n (%)			1454 (50)			1479 (50)
Age, mean (SD)	4 (0.04)	5.23 (0.42)	7.81 (0.39)	4 (0.04)	5.24 (0.42)	7.83 (0.42)
Outcomes						
Early Development Instrument (EDI), n (%)						
-Vulnerable in 1 or more domains			1074 (37)			
EDI domains						
-Vulnerable in physical health and wellbeing			230 (8)			
-Vulnerable in social competence			233 (8)			
-Vulnerable in emotional maturity			826 (28)			
-Vulnerable in language & cognitive development			72 (2)			
-Vulnerable in communication skills and general knowledge			30 (1)			
Strengths and Difficulties Questionnaire (SDQ)						
-Internalising behaviour scores, mean (SD)						6.16 (3.06)
-Externalising behaviour scores, mean (SD)						7.77 (2.66)

Table 12. Continued

	Complete case EDI (n=2906)			Complete case SDQ (n=2955)		
	2009	2010	2013	2009	2010	2013
Exposures						
Main drinking water source						
-piped water	197 (7)	222 (8)	310 (11)	203 (7)	224 (8)	314 (11)
-pump well	433 (15)	634 (22)	716 (24)	435 (15)	642 (22)	729 (24)
-well	1666 (57)	1383 (47)	1196 (41)	1694 (57)	1402 (47)	1211 (41)
-springs	368 (13)	398 (14)	314 (11)	375 (13)	406 (14)	320 (11)
-others	242 (8)	269 (9)	370 (13)	248 (8)	281 (9)	381 (13)
Household had improved sanitation	1271 (44)	1422 (49)	1780 (61)	1291 (44)	1441 (49)	1807 (61)
Caregiver mental health scores (K10) (range 10-50), median (IQR)	14 (12 – 16)	14 (12 – 17)	14 (12 – 17)	14 (12 – 16)	14 (12 – 17)	14 (12 – 17)
Total parenting scores (range 23-120), mean (SD)	80.42 (7.19)	79.73 (7.06)	80.56 (7.28)	80.39 (7.19)	79.73 (7.09)	80.55 (7.27)
Covariates						
Village receive ECED project	2092 (72)			2122 (72)		
Caregiver characteristics						
Age, median (IQR)	30 (26 - 36)			30 (26 - 36)		
Education, n (%)						
-None/not completed primary school	534 (18)			550 (18)		
-Primary school (grade 1-6)	1099 (38)			1118 (38)		
-Junior high school (grade 7-9)	663 (23)			673 (23)		
-Senior high school (grade 10-12)	491 (17)			494 (17)		
-Diploma/university	119 (4)			120 (4)		

Table 12. Continued

	Complete case EDI (n=2906)			Complete case SDQ (n=2955)		
	2009	2010	2013	2009	2010	2013
Household characteristics						
Number of economic disturbances, mean (SD)	0.48 (0.72)			0.48 (0.72)		
Household size, mean (SD)	4.66 (1.51)			4.66 (1.51)		
Non-earth floor, n (%)	2574 (89)			2623 (89)		
Electricity, n (%)	2676 (92)			2719 (92)		
Separate kitchen, n (%)	2752 (95)			2798 (95)		
Cooking fuel, n (%)						
-Wood	2131 (73)			2167 (73)		
-Kerosene	401 (14)			409 (14)		
-Gas/electricity	374 (13)			379 (13)		
Assets, n (%)						
-Telephone	1629 (56)			1651 (56)		
-Radio	1207 (42)			1233 (42)		
-Television	2110 (73)			2144 (73)		
-Refrigerator	587 (20)			594 (20)		
-Bike	1433 (49)			1458 (49)		
-Motor	1597 (55)			1628 (55)		
-Car	159 (5)			161 (5)		

Table 13 shows the estimated risk of being vulnerable in one or more EDI domains under the specified hypothetical interventions. The estimated risk under no intervention was 37.62% (95% CI 35.61, 39.35). Under scenario 1, if all children were exposed to piped water as the main drinking water source and improved sanitation, the risk was 28.90% (95% CI 23.77, 33.98). This implies that intervention that provide piped water and improved sanitation reduced the risk of being vulnerable in one or more domains by 23% (8.71/37.62=0.23) compared to no intervention. Providing a hypothetical maternal mental health intervention (scenario 2) reduced the risk by 6%, whereas a parenting education program (scenario 3) reduced the risk by 8%. Under scenario 4, we found a 14% reduction in the risk of being vulnerable in one or more domains if all mothers who had the poorest 20% of mental health scores and the poorest 20% of parenting scores received intervention to improve their mental health and parenting behaviour compared to no intervention. Under scenario 5, intervention that combined provision of piped water, improved sanitation, maternal mental health intervention and parenting education program had the largest effect on reducing the risk of being vulnerable in one or more domains (36%).

We also present the estimated risk of being vulnerable in each of the EDI domains under the hypothetical interventions as our secondary outcome (Table 14). Overall, table 3 shows combined interventions (scenario 4 and 5) had the largest positive effect on reducing the risk of being vulnerable in the physical health and wellbeing, social competence and emotional maturity domains. Providing piped water and improved sanitation reduced the risk of being vulnerable in emotional maturity by 20% but there is no evidence of the effect on other domains.

Table 13. Estimates for the risk of being vulnerable in one or more domains under different hypothetical interventions (complete case EDI, *n*=2906)

Intervention[a]	Risk[b],%	95% CI		Risk difference[c], %	95% CI		% reduction
Natural course	37.62	35.61	39.35	0	0	0	
S1 Water and sanitation	28.90	23.77	33.98	-8.71	-13.57	-3.77	23
S2. Mental health	35.25	33.17	36.92	-2.37	-3.32	-1.73	6
S3. Parenting	34.64	33.05	36.84	-2.98	-3.18	-1.86	8
S4.S2 + S3	32.49	30.79	34.45	-5.12	-5.71	-4.11	14
S5.S1 + S2 + S3	24.26	19.65	29.17	-13.36	-17.67	-8.39	36

[a] natural course (no intervention); scenario 1 (provide piped water as the main drinking water source and improved sanitation); scenario 2 (20% of mothers with the highest K10 score received maternal mental health intervention); scenario 3 (20% of mothers with the lowest parenting scores received parenting education program); scenario 4 (joint intervention 2 and 3); scenario 5 (joint intervention 1-3). [b] Estimated risk under the specified hypothetical intervention. [c] Estimated risk after intervention (defined as the difference between the risk under natural course and the risk under specified intervention).

Table 14. Estimates for the risk of being vulnerable in each EDI domain under different hypothetical intervention scenarios (complete case EDI, *n*=2906)

Intervention[a]	Risk[b], %	95% CI		Risk difference[c], %	95% CI		% reduction
			physical health and wellbeing				
Natural course	7.96	7.03	9.02	0	0	0	
S1. Water and sanitation	6.65	4.15	9.65	-1.31	-3.83	1.59	16
S2. Mental health	6.77	5.83	7.66	-1.19	-1.72	-0.85	15
S3. Parenting	7.42	6.55	8.55	-0.54	-0.84	-0.14	7
S4.S2 + S3	6.38	5.49	7.30	-1.58	-2.09	-1.20	20
S5.S1 + S2 + S3	5.44	3.31	8.03	-2.53	-4.73	-0.18	32
			Social competence				
Natural course	8.09	7.08	9.02	0	0	0	
S1. Water and sanitation	7.29	4.46	10.30	-0.80	-3.55	2.31	10
S2. Mental health	7.68	6.65	8.64	-0.41	-0.75	-0.01	5
S3. Parenting	6.76	5.95	7.80	-1.33	-1.62	-0.83	16
S4.S2 + S3	6.58	5.64	7.48	-1.51	-1.93	-1.06	19
S5.S1 + S2 + S3	5.79	3.55	8.59	-2.30	-4.48	0.43	28

Table 14.continued

Intervention[a]	Risk[b], %	95% CI		Risk difference[c] ,%	95% CI		% reduction
			Emotional maturity				
Natural course	28.96	27.09	30.61	0	0	0	
S1. Water and sanitation	23.07	18.41	28.22	-5.90	-10.39	-1.02	20
S2. Mental health	26.49	24.53	28.03	-2.47	-3.40	-1.87	9
S3. Parenting	26.27	24.86	28.37	-2.69	-2.95	-1.64	9
S4.S2 + S3	24.08	22.56	25.86	-4.88	-5.49	-3.90	17
S5.S1 + S2 + S3	18.83	14.84	23.67	-10.14	-13.98	-5.39	35
			Language and cognitive development				
Natural course	2.48	1.96	3.03	0			
S1. Water and sanitation	2.00	0.67	3.64	-0.48	-1.78	1.09	19
S2. Mental health	2.20	1.70	2.77	-0.28	-0.52	-0.02	11
S3. Parenting	2.18	1.66	2.79	-0.30	-0.58	-0.03	12
S4.S2 + S3	2.01	1.50	2.55	-0.48	-0.82	-0.19	19
S5.S1 + S2 + S3	1.61	0.51	3.08	-0.87	-1.93	0.56	35

Table 14.continued

Intervention[a]	Risk[b], %	95% CI		Risk difference[c] ,%	95% CI		% reduction
Communication skills and general knowledge							
Natural course	1.03	0.68	1.42	0	0	0	
S1. Water and sanitation	0.94	0.00	2.16	-0.09	-1.01	0.96	9
S2. Mental health	0.88	0.54	1.26	-0.15	-0.33	0.01	15
S3. Parenting	1.00	0.65	1.41	-0.03	-0.19	0.08	3
S4.S2 + S3	0.86	0.51	1.26	-0.16	-0.36	0.86	16
S5.S1 + S2 + S3	0.81	0.00	1.85	-0.22	-1.03	0.71	21

[a] natural course (no intervention); scenario 1 (provide piped water as the main drinking water source and improved sanitation); scenario 2 (20% of mothers with the highest K10 score received maternal mental health intervention); scenario 3 (20% of mothers with the lowest parenting scores received parenting education program); scenario 4 (joint intervention 2 and 3); scenario 5 (joint intervention 1-3). [b] Estimated risk under the specified hypothetical intervention. [c] Estimated risk after intervention (defined as the difference between the risk under natural course and the risk under specified intervention).

Table 15 shows the estimated mean of internalising and externalising behaviour scores (SDQ) under the specified hypothetical interventions. For internalising behaviour, the estimated mean under no intervention was 6.23 (95% CI 6.12, 6.35). Intervention that combined provision of piped water, improved sanitation, mental health intervention and a parenting education program (scenario 5) had the largest effect on reducing the mean of internalising behaviour scores. Under this scenario, the estimated mean of internalising behaviour score was 5.42 (95% CI 5.11, 5.75), which equals a 13% (0.81/6.23=0.13) reduction on the mean score compared to no intervention. In contrast, a parenting education program had the smallest effect on reducing the internalising behaviour score (mean difference -0.09, 95% CI -0.13, -0.04).

For externalising behaviour, the estimated mean under no intervention was 7.81 (95% 7.71, 7.91). We found a 4% (0.34/7.81=0.04) reduction on the mean score under scenario 5, which is somewhat similar (due to rounding) with the proportion of reduction in the mean score under scenario 4. This may suggests that scenario 4 and 5 are equally important to reduce children's externalising problems. Examining cost effectiveness of intervention is beyond the scope of this study, however, based on the number of intervention components, scenario 4 may be more cost effective than scenario 5. Last, maternal mental health intervention had the smallest effect on reducing the mean of externalising behaviour score (0.11/7.81=0.01).

Table 15. Estimates for the mean of internalising and externalising behaviour scores under different hypothetical interventions (complete case SDQ, *n*=2955)

Intervention[a]	Mean[b]	95% CI		Mean difference[c]	95% CI		% reduction
			Internalising behaviour scores				
Natural course	6.23	6.12	6.35	0	0	0	
S1. Water and sanitation	5.72	5.41	6.05	-0.51	-0.82	-0.17	8
S2. Mental health	5.97	5.85	6.08	-0.26	-0.31	-0.22	4
S3. Parenting	6.13	6.03	6.26	-0.09	-0.13	-0.04	1
S4.S2 + S3	5.89	5.78	5.99	-0.34	-0.39	-0.29	5
S5.S1 + S2 + S3	5.42	5.11	5.75	-0.81	-1.12	-0.48	13
			Externalising behaviour scores				
Natural course	7.81	7.71	7.91	0	0	0	
S1. Water and sanitation	7.75	7.47	8.03	-0.06	-0.33	0.22	1
S2. Mental health	7.71	7.59	7.78	-0.11	-0.17	-0.08	1
S3. Parenting	7.64	7.54	7.74	-0.18	-0.21	-0.13	2
S4.S2 + S3	7.53	7.42	7.63	-0.29	-0.33	-0.24	4
S5.S1 + S2 + S3	7.48	7.19	7.75	-0.34	-0.60	-0.07	4

[a] natural course (no intervention); scenario 1 (provide piped water as the main drinking water source and improved sanitation); scenario 2 (20% of mothers with the highest K10 score received maternal mental health intervention); scenario 3 (20% of mothers with the lowest parenting scores received parenting education program); scenario 4 (joint intervention 2 and 3); scenario 5 (joint intervention 1-3). [b] Estimated mean outcome under the specified hypothetical

intervention. [c] Estimated mean outcome after intervention (defined as the difference between the mean under natural course and the mean under specified intervention).

7.5. Discussion

We investigated the relative and combined effects of a range of hypothetical interventions on children's school readiness and socio-emotional wellbeing in rural Indonesia. In this study, we defined five hypothetical scenarios of intervention including provision of piped water as the main drinking water source, improved sanitation, maternal mental health intervention, a parenting education program and their combination.

Effects on Overall Child Development

Not surprisingly, combined interventions had the largest positive effects on both primary outcomes. For instance scenario 5 shows that provision of piped water, improved sanitation, maternal mental health and a parenting education program reduced the risk of being vulnerable in one or more EDI domains by 36%. In contrast, we estimated a 6% reduction on the risk of being vulnerable in one or more EDI domains if intervention only focused on mothers who had mental health problems. Based on our hypothetical interventions, our findings support evidence that shows interventions that combined multiple programs had a greater effect on children's development outcomes compared to single intervention (37, 259).

Interestingly, we found that the joint effects of combined interventions (scenario 5) on children's school readiness was largely driven by provision of piped water and improved sanitation. Herein, providing piped water and improved sanitation reduced the risk of being vulnerable in one or more EDI domains by 23%, but they contribute to a 63% (23/36=0.63) of the total reduction on the risk of being vulnerable in one or more EDI domains if all interventions were combined. This adds to the evidence that providing piped water and improved sanitation for rural households had positive effect on different aspect of child's development outcome other than health (130, 131) and cognitive ability (126). In rural Indonesia, inadequate access to improved sanitation and safe drinking water is associated with poor growth and higher prevalence of diarrhoea, which is a leading contributor to under five mortality in Indonesia (21). Diarrhoeal disease is also linked to malnutrition and leads to poor cognitive function among Indonesian children (56, 57). The burden of inadequate access to safe water and sanitation is higher among children and women. Many Indonesian people who do not have access to improved drinking water source and sanitation facilities have to walk long distance to get water or use communal sanitation facilities (133). This implies that mothers may have less time spent providing adequate care and attention for children.

Effects on Socio-emotional Development

In terms of socio-emotional wellbeing, combined interventions also had the largest positive effects on children's socio-emotional wellbeing, however, the percentage of reduction on the average score is larger for the internalising (13%) than for the externalising behaviour scores (4%). Our findings support evidence from RCTs and observational studies (140, 145), suggesting that mental health intervention for mothers had positive effect on children's internalising and externalising behaviour problems. Moreover, a combination of maternal mental health and parenting education intervention also reduced the average externalising behaviour score by 4%, which supports evidence about the benefits of maternal mental health intervention and parenting education program on socio-emotional wellbeing (32, 36, 140, 145).

In terms of coverage of intervention, we used various approaches to intervention. For example, both maternal mental health and parenting interventions targeted specific group of mothers in the population, defined as mothers who had the poorest 20% of mental health score or the poorest 20% of parenting score or both. Targeted intervention was chosen over a universal program because there was no evidence that universal maternal mental health intervention had a greater effect compare to targeted interventions (144). However, targeted intervention have some limitations, for example the target mothers can be stigmatizing for being classified as having poor mental health or poor parenting (15, 42). We found intervention that has components of progressive universalism (40) yields the greatest effect on improving children's school readiness and socio-emotional wellbeing. In this case, the greatest reduction on the risk of being vulnerable in school readiness or poor socio-emotional wellbeing occur if all children have access to piped water and improved sanitation and more support is provided for children's whose mothers need mental health and parenting interventions.

All specified intervention in this study had potential to be implemented in Indonesia, however, one of the challenges for effective implementation of intervention may related to the government capacities to provide resources in communities (40). In Indonesia, improving access to sanitation has received increasing attention from the government. The Indonesian government has put additional resources to finance sanitation programs but the allocation for sanitation remains insubstantial representing about 0.03% of the annual government budget (275). Studies in the US recorded evidence from the early 19th century about the contribution of providing public safe water and sewerage system interventions on reduction of mortality among the US population (129, 132). With a growing evidence of the benefits of having access to piped water as the main drinking water source and improved sanitation on child's health and development outcomes, the Indonesian government may need to invest more resources for providing improved sanitation.

Limitations

Findings from this analysis need to be interpreted with care. First, we used parametric g-formula (224-226) to estimate the relative effects of a range of interventions on children's school readiness and socio-emotional wellbeing in rural Indonesia from observational data. Parametric g-formula is a robust method to estimate the effects of multiple interventions on outcome when using observational data in the presence of time varying exposure and confounding. Our estimates are made under the assumptions of consistency, conditional exchangeability, and positivity (no misspecification in the model). Although estimation of causal effects may be plausible, the assumptions on which it is based are not guaranteed by design and cannot be tested in observational studies (189). Therefore, although the method can provide a robust estimate, it cannot guarantee causal interpretation. In order to support our analysis, we specified our hypothetical interventions based on *a priori* knowledge about the associations between housing conditions, maternal mental health, parenting behaviour and children's development. Proper understanding about the association between our specified exposure and outcome are important to generate well-defined interventions (204).

Second, this analysis did not taken into account measurement error in the data. We used the EDI as a measure of children's school readiness, which is originally designed for children ages 4-7 years (154). In this study, we used the EDI that was collected on children at age 8, which may not reflect the true school readiness outcome.

In summary, providing access to piped water as the main drinking water source, improved sanitation, maternal mental health and a parenting education program had positive effect on children's school readiness and socio-emotional wellbeing in rural Indonesia. The effect of interventions on school readiness outcome ranged between 6%

and 36%, whereas the effect on socio-emotional wellbeing ranged between 1% and 13%. Intervention that combined multiple programs had a larger effect than any single intervention. For example, provision of piped water, improved sanitation, maternal mental health and a parenting education program reduced the risk of being vulnerable in one or more EDI domains by 36%. In contrast, we estimated a 6% reduction on the risk of being vulnerable in one or more EDI domains if intervention only focused on mothers who had mental health problems. In this study, a combination of provision of piped drinking water, improved sanitation, maternal mental health and a parenting education program is likely yield the largest effect, however, most of the effect was driven by provision of piped drinking water and improved sanitation. This is perhaps understandable given the population was largely rural. Providing early childhood intervention that combined multiple programs may improve children’s school readiness and socio-emotional wellbeing in rural Indonesia but more importantly the intervention should start with providing greater access to piped drinking water and improved sanitation.

CHAPTER 8

Discussion and Conclusion

This thesis investigated inequalities in children's cognitive and socio-emotional wellbeing in Indonesia, and interventions that might reduce these inequalities. Studies arising from this thesis add to the limited evidence about children's development in Indonesia, which to date is still limited. This final chapter provides a synthesis of the findings, limitations of the studies and potential future research.

8.1. Synthesis of the findings

Inequality in children's cognitive function in Indonesia

The first study of this thesis investigated the magnitude of socioeconomic inequality among Indonesian children's cognitive function in 2000 and 2007, and factors that contribute to the inequality. It also examined whether the inequality in children's cognitive function changed between 2000 and 2007, and the factors contributing to the change in the inequality. Using data from the Indonesian Family Life Survey (IFLS), the results showed that the burden of poor cognitive function was higher among the disadvantaged. From the decomposition analysis, we found that household per capita expenditure was the largest single contributor of inequality in children's cognitive function in both 2000 and in 2007. We also found substantial reductions in the inequality in children's cognitive function, which was largely driven by changes in maternal high school attendance, access to improved sanitation and household per capita expenditure. As discussed in chapter 4, one possible explanation for maternal education being the largest contributor of decreasing inequality in children's cognitive function between 2000 and 2007 was related to the Indonesian government policy of school construction in the 1970s. The school construction program was the first national program, which aimed to provide universal access to primary education in Indonesia. Previous studies showed the school construction program had successfully increased school enrolment in Indonesia, where women and students from low socioeconomic groups received more benefits from this program (10, 244). This is consistent with the evidence from low and middle income countries (LMICs) that shows increasing school availability at the local level has greater benefit for educational achievement in females, although the Indonesian program was not specifically targeting girls (245).

As also shown in chapter 4, whilst maternal education was the largest contributor to the change in inequality in children's cognitive function between 2000 and 2007, however, household per capita expenditure was the largest contributor of inequality in children's cognitive function in both 2000 and 2007, which led us to investigate the effect of household per capita expenditure on children's cognitive function. Moreover, we simulated a hypothetical cash transfer intervention, and estimated the change in cognitive function after a plausible cash intervention.

Cash transfer intervention for the poorest households increased cognitive function score by 6% but no overall effect for the population

Whilst study 1 was conducted as a descriptive analysis, in study 2 we used a more complex analytical approach to determine the effect of household per capita expenditure and whether cash transfer intervention could increase cognitive function score. This is partly because of the complexity of the data structure as shown in our causal DAG (Figure 13 chapter 5), indicating the presence of time varying exposure and confounding. Hence, a potential outcome approach was used in this thesis to aid causal interpretation while using observational data. In this thesis the potential outcome approach was used in studies 2-4. However, this method has limitations. Under a potential outcome approach, our estimates were made under the assumptions of consistency, conditional exchangeability, and positivity. None of these assumptions are guaranteed by design nor can they be tested in observational studies. In study 2, we used an inverse probability of treatment weight of a marginal structural model (MSM), which allowed us to better handle the potential bias in our effect estimation due to time varying confounding.

As presented in chapter 5, consistent with studies from high income (HICs) and LMICs, we found that greater household per capita expenditure was associated with higher cognitive function scores, but the effect size was small. Based on simulations of a hypothetical cash transfer intervention, an additional US$ 6-10/month of cash transfer for children from the poorest households in 2000 increased the mean cognitive function score by 6%, however, there was no overall effect of cash transfers at the total population level because the cash transfer was too small to benefit the target children. This implies that a cash transfer would need to be much larger to have a substantial impact on children’s cognitive function.

The first study of thesis showed while household per capita expenditure was an important factor that influenced children’s cognitive function in Indonesia, in study 2 there was little evidence of the benefit of a plausible cash transfer intervention on increasing children’s cognitive function. This finding is very relevant to the Indonesian context. In the past decade, the Indonesian government has implemented various cash transfer programs for poor families. Findings from this thesis suggest that providing cash transfers may not be an effective intervention to improve children’s cognitive function in Indonesia.

Study 2 examined the effect of household per capita expenditure as a cumulative exposure on children’s cognitive function, whereas in study 3, the effect of household per capita expenditure at different time points was examined. In study 3, household per capita expenditure was used as a binary rather than a continuous variable to define whether a child was classified as being poor or non-poor based on distribution of household per capita expenditure in the population.

Little evidence for a larger effect from earlier intervention, and poverty at 0-7 had a larger direct effect on cognitive function than the mediated effect through schooling, the home environment and poverty at 7-14

The third study of this thesis investigated the effects of poverty at 0-7 and at 7-14 on children's cognitive function at 7-14 years. Ideally, it would allow us to obtain an estimate for the optimal timing for a potential poverty alleviating financial intervention. However, use of conventional regression analysis to obtain this estimate has limitation because it does not allow us to handle confounding properly. In study 3, we also examined the direct effect of poverty at 0-7 on cognitive function at 7-14 years, and whether this effect was mediated through poverty at 7-14, and through school attendance, and aspects of the child's home environment. Use of effect decomposition analysis allowed us to examine the mechanism by which poverty in early-life at 0-7 years could affect cognitive function at 7-14 years.

Consistent with other studies from both HICs and LMICs, the results showed that being exposed to poverty was associated with poor cognitive function score at any time period; however, there was no evidence that being exposed to poverty at 0-7 had a larger effect than being exposed to poverty at 7-14 years. From the decomposition analysis, we found that poverty at 0-7 years had a bigger direct effect on cognitive function than via its mediated effect through poverty at 7-14. Moreover, the mediated effect of poverty at 0-7 years was stronger through pathways that involved schooling/home environment and poverty at 7-14 than through poverty at age 7-14 alone.

In this study, the magnitude of the direct effect of poverty at 0-7 years was small, implying that policies providing stand-alone income interventions for poor families may not be sufficient to achieve intended changes in children's cognitive function (chapter 6). A study that examined the effect of early childhood interventions on various aspects of children's development (37) found that provision of a comprehensive early childhood program had a greater effect than any single intervention. Hence, it is necessary to examine the combined strategies of interventions that potentially improve children's development in Indonesia.

Combined interventions had the largest effect on reducing poor developmental outcomes

The final study of this thesis investigated the relative and combined effects of different hypothetical interventions on children's school readiness and socio-emotional wellbeing. This study was motivated by the results from studies 2-3, suggesting that cash transfer a lone intervention may not be an effective strategy to improve children's cognitive function in Indonesia. Using data from the ECED project, this final study identified four components of interventions and generated five hypothetical interventions including provision of piped water as the main drinking water source, improved sanitation, maternal mental health, parenting education program and a combination of these programs. The analysis was conducted using parametric g-formula, which allowed us to estimate the effects of multiple interventions from a complex data structure (high dimensional data).

In general, most of the specified interventions had a positive effect on children's school readiness and socio-emotional wellbeing, however, the relative effect of each intervention may not be equally important. Our findings support evidence suggesting that combined multiple programs had a greater effect on children's cognitive and socio-emotional wellbeing compared to single intervention. For example, provision of piped water, improved sanitation, maternal mental health and a parenting education program reduced the risk of being vulnerable in one or more EDI domains by 36%. In contrast, we estimated a 6% reduction on the risk of being vulnerable in one or more EDI domains if intervention only focused on mothers who had mental health problems. In this study, a combination of provision of piped drinking water, improved sanitation, maternal mental health and a parenting education program showed the largest effect on children's school readiness and socio-emotional wellbeing, however, most of the effect was driven by provision of piped drinking water and improved sanitation. This is perhaps understandable given the population was largely rural.

Again, this thesis is very relevant to the Indonesian context. Despite growing commitment from the Indonesian government to increase population access to improved sanitation, the financial resources that have been invested in the sanitation program remain insignificant. With growing evidence of the benefits of having access to piped water as the main drinking water source and improved sanitation on children's health and development, the Indonesian government may need to invest more resources for sanitation. Furthermore, providing early childhood interventions that combine multiple programs may also improve children's school readiness and socio-emotional wellbeing, but more importantly any intervention should start with providing greater access to piped drinking water and improved sanitation.

8.2. Limitations and future research

The limitations of each study were discussed in the relevant chapters. This section discusses the limitations of this thesis in general and potential future research.

Data source

This thesis used data from two sources, the Indonesian Family Life Survey (IFLS) and the early Childhood Education and Development (ECED) project. From the first data source, IFLS 1-4 was used to address research aims in studies 1-3. IFLS 1-4 were conducted in 13 out of 27 provinces in Indonesia including the islands of Sumatera, Java, Bali, West Nusa Tenggara, Kalimantan and Sulawesi (Figure 29) (146). These provinces are mainly located in the Western and Central part of Indonesia and were selected purposively due to logistical reasons, but to still maximize representation of the population, and capture the cultural and socioeconomic diversity. The sample in IFLS 1-4 was considered to be representative of 83% of the Indonesian population, but they did not have information about the population living in the Eastern provinces of Indonesia. Only recently the IFLS-East was conducted in 2012 to capture the characteristics of the population living in the Eastern provinces including East Kalimantan, East Nusa Tenggara, Maluku, Southeast Sulawesi, Papua and West Papua (Figure 30) (276). The IFLS-East data was released for public access in 2014. The new IFLS data could be used for future research to examine the characteristics of families and children's outcomes from the Eastern provinces of Indonesia.

Figure 29. IFLS 1-4 Enumeration areas

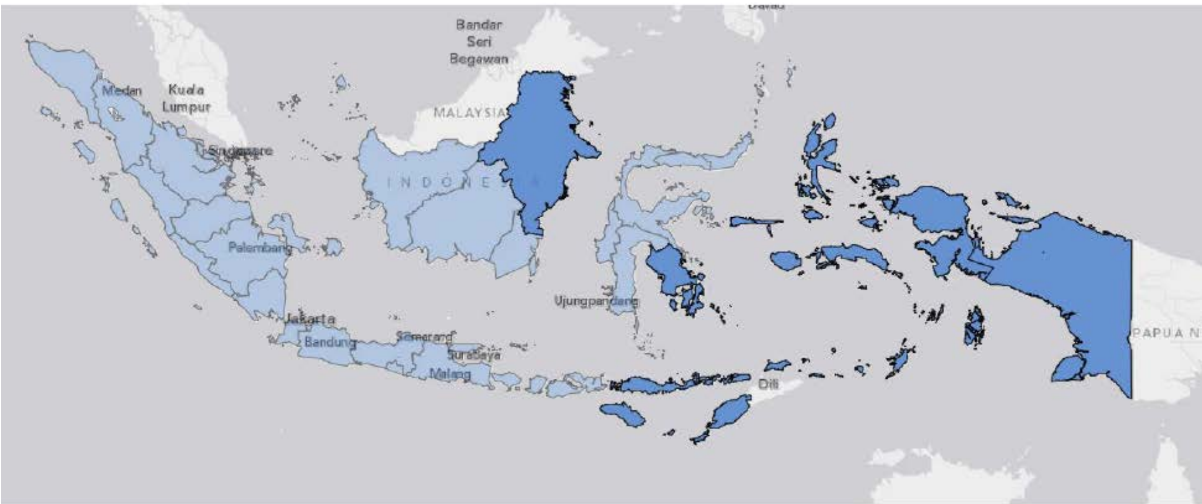


Figure 30. IFLS-East enumeration areas

From the second data source, the ECED data was used in study 4. The ECED data collected baseline information for children aged 1 and 4 in 2009 and followed up in 2010 (aged 2 and 4) and 2013 (aged 6 and 8). However, this thesis only used information that was collected for children aged 4 in 2009 and followed up at ages 5 and 8. This is because our outcome of interest (school readiness and socio-emotional wellbeing) was firstly collected on children at aged 4 in 2009. Further research could be conducted using information from the younger cohort.

Aspect of child's development

Whilst most previous research about Indonesian children has focused on health related outcomes, this thesis examined two understudied aspects of children's development, cognitive ability (studies 1-3) and socio-emotional wellbeing (study 4). In addition, a small component of this thesis examined children's school readiness as a measure of overall development (study 4). Both IFLS and ECED data contain extensive information at the individual, household and community level. This thesis only utilized data that was collected at individual and household level. Further research could examine other aspects of child's health and development, and the extent to which community characteristics may influence children's development outcomes in Indonesia.

Early childhood interventions

This thesis examined the effects of various hypothetical interventions that may improve children's cognitive and socio-emotional wellbeing in Indonesia. These interventions were selected based on relevance with the study, availability of data, and potential for implementation in the Indonesian context. In this thesis, the hypothetical interventions included provision of cash transfer (study 2), piped water as the main drinking water source, improved sanitation, maternal mental health and a parenting education program (study 4). Although most of the interventions had a positive effect on children's development, the effect size of these interventions was small to modest. Hence, further research is required to examine other interventions that potentially yield larger effects on improving children's health and development in Indonesia.

Statistical analysis

This thesis used various methodological and statistical approaches in the analysis, which were challenging and time consuming. For example, this thesis did not take into account potential bias due to measurement error or misclassification of using binary rather than a continuous variable. Particularly in study 2 and 4, this thesis did not examine the effect of censoring on the effect estimation, which could be conducted as part of a sensitivity analysis. These are all the potential areas for future research.

8.3. Concluding remarks

This thesis presents a rigorous and comprehensive analysis about inequalities in Indonesian children's cognitive and socio-emotional wellbeing, and potential early childhood interventions that may reduce these inequalities. Whilst most previous research about Indonesian children has focused on health related outcomes, this thesis has filled a significant gap in knowledge about the effect of inequalities on children's cognitive and socio-emotional development in Indonesia. This thesis has used the best available methodological and statistical approaches to provide robust estimates.

This thesis began with a discussion about inequality in children's cognitive function and identifying factors that contribute to the inequality as well as to the change in inequality in children's cognitive function. These findings were then followed by examining the effect of poverty on inequality in children's cognitive function and the mechanism by which early years exposure affects cognitive function at later childhood. Finally, various potential interventions were examined to find the most effective strategy to improve children's cognitive and socio-emotional wellbeing in Indonesia. These results could inform the Indonesian government policy to enhance children's health and development and to reduce these inequalities in the long term.

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APPENDIX

Published Papers

1. Maika A, Mittinty MN, Brinkman S, Harper S, Satriawan E, Lynch, J. Changes in Socioeconomic Inequality in Indonesian Children's Cognitive Function from 2000 to 2007: A Decomposition Analysis. *PLOS ONE* 2013 8(10): e78809. doi:10.1371/journal.pone.0078809

2. Maika A, Mittinty NM, Brinkman S, Lynch J. Effect on child cognitive function of increasing household expenditure in Indonesia: application of a marginal structural model and simulation of a cash transfer programme. *Int. J. Epidemiology* (2015) 44(1):218-228.

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Changes in Socioeconomic Inequality in Indonesian Children's Cognitive Function from 2000 to 2007: A Decomposition Analysis

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Abstract

Background: Measuring social inequalities in health is common; however, research examining inequalities in child cognitive function is more limited. We investigated household expenditure-related inequality in children's cognitive function in Indonesia in 2000 and 2007, the contributors to inequality in both time periods, and changes in the contributors to cognitive function inequalities between the periods.

Methods: Data from the 2000 and 2007 round of the Indonesian Family Life Survey (IFLS) were used. Study participants were children aged 7–14 years (n = 6179 and n = 6680 in 2000 and 2007, respectively). The relative concentration index (RCI) was used to measure the magnitude of inequality. Contribution of various contributors to inequality was estimated by decomposing the concentration index in 2000 and 2007. Oaxaca-type decomposition was used to estimate changes in contributors to inequality between 2000 and 2007.

Results: Expenditure inequality decreased by 45% from an RCI = 0.29 (95% CI 0.22 to 0.36) in 2000 to 0.16 (95% CI 0.13 to 0.20) in 2007 but the burden of poorer cognitive function was higher among the disadvantaged in both years. The largest contributors to inequality in child cognitive function were inequalities in per capita expenditure, use of improved sanitation and maternal high school attendance. Changes in maternal high school participation (27%), use of improved sanitation (25%) and per capita expenditures (18%) were largely responsible for the decreasing inequality in children's cognitive function between 2000 and 2007.

Conclusions: Government policy to increase basic education coverage for women along with economic growth may have influenced gains in children's cognitive function and reductions in inequalities in Indonesia.

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Introduction

In 1970 Indonesia was among the poorest countries in the world with 60% of the population living in absolute poverty [1]. In the decade from 2003, the poverty rate in Indonesia decreased from 17% to 12% and economic growth in the past decade has moved Indonesia from a low to a middle-income country [2]. Despite this overall progress, regional and socioeconomic disparities within the country are still evident, driven by inequalities in economic, infrastructure and human resources [3,4]. For example, the mean years of schooling for the household head in poor families was 5 compared to 8 years for non-poor families [4]. Fewer than half of the households in 2011 had access to safe drinking water and only about 56% had access to a latrine connected to septic tank or a composting toilet [5].

Measuring inequalities in health related outcomes is relatively common [6–8], but research examining inequalities in children's development is more limited. Children under five living in poorer socioeconomic circumstances in low and middle income countries are often exposed to a multitude of risk factors such as poverty, malnutrition, poor housing conditions and sanitation that influence their opportunities for healthy child development [9,10]. There is growing interest in the influences of children's health, learning and well-being, on their later school readiness, academic achievement and labor force participation [11]. Cognitive function is an important aspect of healthy child development as it has both short and longer terms effects. Higher cognitive function is associated with better academic achievement [12,13] physical and mental health [14–16] and in the long-term economic outcomes such as higher occupational status, earnings and may influence

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