Human Capital Outcomes for Children:

The Impact of School Subsidies and Natural Disasters

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by

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Abstract

This thesis contains a series of related studies about the human capital outcomes of children as consequences of school subsidy reform and natural disasters. All the studies in this thesis rely on the Indonesia Family Life Survey data 2000 and 2007. The first study is an evaluation of the impact of the school operational assistance program (BOS) on child test scores. This study uses three different methods: Ordinary Least Square (OLS), Instrumental Variable (IV) and Propensity Score Matching (PSM) estimation. OLS is used as conventional method and estimates the effect of school subsidy on average by assuming that BOS is exogenous, while IV estimation is used to deal with endogeneity of BOS and also correct for selection bias based on unobservable characteristics. PSM is used to estimate the average treatment effect in the absence of selection on unobserved characteristics. The results confirm that the BOS can increase student performance. Paradoxically it does not help very poor students, yet it helps less poor students.

The second study is an examination of the impact of natural disasters on child test scores and child health. Arguably natural disasters are exogenous events, so we use the exogenous variation from natural disasters as a natural experiment design to estimate the effect of disasters on child test scores and child health. When a certain group is exposed to the causal variable of interest, such as a disaster, and other groups

are not, Difference in Difference model (DID) can be used in estimation. For child health, we use two types of data: child height under 5 and self-reported general health condition, while test scores are obtained from the national child test scores at age 11. In conjunction with the DID model, for analysis of the impact of disasters on child health, we also used zero inflated negative binomial and an ordered logit model for analysing self-reported data on child health. The results confirm that child test scores are significantly affected by disasters, but there are no serious impacts of disasters on child health, conditioned on survived.

The third contribution is a study on the impact of disasters on household expenditures and food demand. We employ a DID model to estimate the total impact of disasters on various types of household expenditures. For comparison, we use a Linear Approximate Almost Ideal Demand System (LA-AIDS) model to estimate the net impact of disasters on expenditures. In the LA-AIDS model we control for the price of foods, while in the DID model we do not. Furthermore, the LA-AIDS model also estimates the price elasticities of demand and the expenditure elasticity of demand. The findings show that there is a negative impact of disasters on educational expenditures, and no impact of disasters on total household expenditures. Yet, we found a net negative impact of disasters on expenditures when controlling for prices.

Dedication

To my father Herry Subagyo, my mother Rahayu Widati, and my little family Mohammad Masykuri and Kammiel Imanana.

Declaration

This thesis, *Human Capital Outcomes for Children: The Impact of School Subsidies and Natural Disasters*, has been written by myself. It has not been submitted in any form for the award of higher degree elsewhere.

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Chapter 1

Introduction

According to Sweetland (1996), the development of human capital theory can be classified into two stages: early economic viewpoints and economic foundation studies. The first stage was dominated by the thoughts of prominent economists such as Adam Smith, John Stuart Mill, Alfred Marshall and Irving Fisher. The discussion of human capital theory in this first stage began in 1776 when Adam Smith, in his book *"An Inquiry into the Nature and Causes of the Wealth of Nations"*, discussed the importance of human beings as labour, specifically with regard to national wealth. Smith mentioned two major components of human capital which created productive labour. The first component was the importance of the quality of labour inputs, and the second was about the development of human capital through education, or training. Almost a century after Adam Smith, in 1848, John Stuart Mill considered human abilities as economic values by recognizing all activities that could improve their productivity. He also stated that it was impossible to measure wealth per person. In 1890, Alfred Marshall argued that we could measure wealth per person by examining all the things which contribute to making people more efficient, technologically. He defined human abilities as an agent of producing wealth. In 1906, Fisher posed an empirical problem in valuing human abilities. His argument encouraged other economists to design empirical methods for human capital analysis.

After no significant development in human capital theory for more than five decades, in the 1960s there was a beginning of an economic foundation for human capital theory. At least three economists contributed significantly to human capital theory. In

1958, Jacob Mincer, a father of modern labour economics, developed, with Gary Becker, an empirical foundation of human capital theory. Mincer also developed the so called Mincerian equation, which models personal income as a function of human capital. The model pioneered the use of years of schooling and years of work experience as measures of human capital. His work confirmed that more years used for schooling was compensated by higher earnings in the future.

In 1960, Gary Becker examined the determinants of the rate of return to human capital. He compared the income of college graduates and the income of high school graduates to measure the impact of education. The difference in income reflected the cost of pursuing study in college. He designed an important methodology in measuring human capital investment, or rate of return on human capital investment. He used the costs of education and the economic returns on education investment as inputs into the internal rate of return on the investment. Becker concluded that education is an investment that adds to human capital, just like investments add to physical capital. Becker was awarded the Nobel Prize for his contributions to the development of human capital theory.

A year after Becker, in 1961, Theodore Schultz introduced human capital theory, particularly human capital investment in education, training and health. He argued that investment in human capital could increase worker earnings and the national output. He argued that knowledge and skill from education can raise productivity, so that workers can compete with others, and increase their earnings. Furthermore, Schultz also discussed how differences in earnings cause differences in access to education and health. For instance, in poor countries basic needs still take first priority rather than education, but in order to raise the standard of living and increase economic growth, those countries should be concerned about long-term investment in education. He believed that investment in education can lead to an increase in productivity.

1.1.Human Capital Situation in Indonesia

The United Nations Development Programme (UNDP) measures national development with the Human Development Index (HDI). If human capital theory categorises human beings as inputs in the production process for raising income and wealth, HDI focuses on the results of the development process for human beings. This index tells us about the situation of a country in term of the level of income per person and other indicators related to human development, such as health and education. As HDI is a result of the development process of human beings, it is therefore very important to pay attention to several indicators of human development in order to know the level of human development in a country.

Human development indicators are classified into three dimensions: health, education and living standards. The health indicator uses a life expectancy at birth indicator. For education, there are two main indicators: mean years of schooling for adults and expected years of schooling for children. The UNDP defined mean years of schooling as the average number of years of education received in a life-time by people aged 25 years and older, while expected years of schooling is the total number of years of schooling that a child of school entrance age can expect to receive if prevailing patterns of age-specific enrolment rates stay the same throughout the child's life. For living standard, UNDP uses gross national income per capita as a measure.

There are two steps to calculating the HDI. The first step is creating the dimension index for life expectancy index, education index and GNI index. Dimension index is calculated by using the following formula:

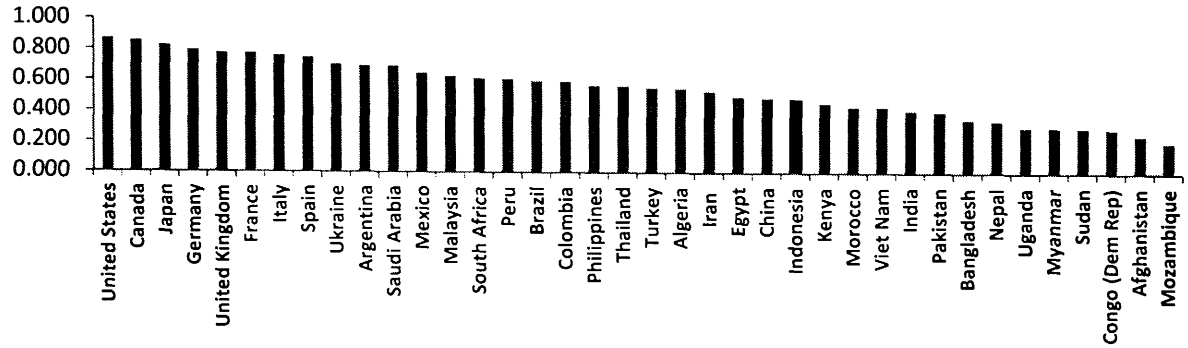
$$Dimension\ index = \frac{actual\ value - minimum\ value}{maximum\ value - minimum\ value} \tag{1.1}$$

The maximum values are the highest values for each indicator in the time series (1980-2011), and the minimum values are set at 20 years for life expectancy, 0 years for both type of education indicators, and $100 for GNI per capita. The education index is calculated from the geometric mean of the mean years of schooling index and the expected years of schooling index. The second step is calculating the HDI by using the geometric mean of the three dimension indices. The HDI formula can be written as:

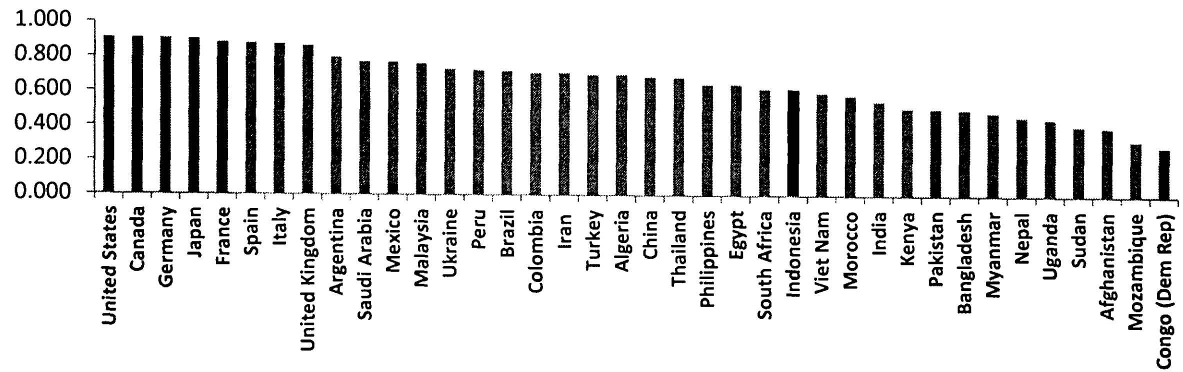
$$HDI = \sqrt[3]{I_{life} * I_{education} * I_{income}} \tag{1.2}$$

Figure 1.1 presents the situation of HDI in Indonesia in 1990 and 2011 in comparison with other countries. From Figure 1.1, we can see that there is a relative position of the country to other countries and how the position can be changed over time. We picked the top 40 populous countries whose HDI data was measured in 1990 and 2011. The United States had the highest HDI among the most populous countries in the world, and was followed by Canada and Japan in second and third place in 1990. Indonesia was positioned after China and categorised in the medium human development level. In comparison with other countries in Southeast Asia, Indonesia was still behind Malaysia, Thailand and the Philippines, but in front of Vietnam and Myanmar.

Figure 1.1: Human Development Index 1990 and 2011



HDI 1990



HDI 2011

Source: UNDP 2013 in http://hdrstats.undp.org/en/countries/profiles/idn.html

In 2011, the position of some countries was changed, but some still retained the same position. The United States was still the highest, and was followed by Canada and Germany in second and third place. Japan moved to fourth place. Indonesia seemed to have a similar position to 1990, in medium human development, and was still behind Malaysia, Thailand and the Philippines in the Southeast Asia region. By looking at the HDI, we can see in comparison with other countries that Indonesia is relatively low in terms of human development.

Based on the value of HDI, countries are classified into four levels of human development (HD): (1) very high HD, (2) high HD, (3) medium HD, and (4) low HD. According to the most recent Human Development Report, in 2011, Indonesia was classified at a medium human development level with HDI equal to 0.617, and was ranked in 124th place in 187 countries. For comparison, in the same year, the highest HDI is Norway with an index of 0.943, and the lowest HDI is Congo with an HDI of 0.286. Indonesia is below the average of the world which is 0.682 or the regional average of 0.671. In addition, the latest human development indicators show that as regards the health situation in Indonesia, life expectancy at birth is 69.4 years. For education, expected years of schooling for children are 13.2 years, and mean years of schooling for adults are 5.8 years. For income, UNDP uses Gross National Income per capita converted to international dollars using purchasing power parity (PPP) rates. Indonesia is $3716 in 2011.

Table 1.1 presents Indonesia's progress in each indicator every five years from 1990 to 2011, based on the Human Development Report of UNDP. Between 1990 and 2011, Indonesia's life expectancy at birth increased by 7.3 years, expected years of schooling increased by 2.8 years, mean years of schooling increased by 2.5 years, and Indonesia's GNI per capita increased by approximately 85%. Although all HDI indicators and the HDI value itself seem to be increasing over time, the HDI value is always under the HDI's world average and the rank of Indonesia's HDI did not improve over time. However, the total number of countries included is also bigger. These phenomena may be because other countries also improve all HDI indicators over time, so the rank tends to be steady.

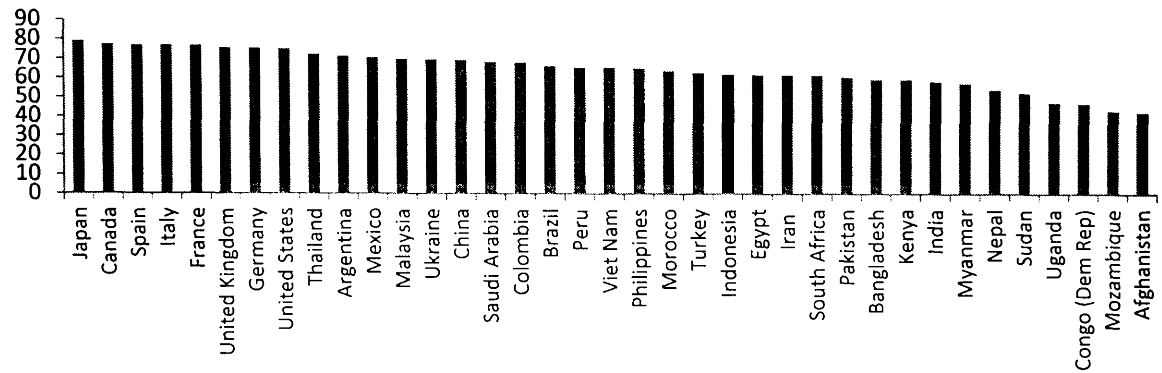
Table 1.1: Indonesia's HDI Trends

HDI value and Indicators	1990	1995	2000	2005	2010	2011
World HDI average	0.594	0.613	0.634	0.660	0.679	0.682
HDI value	0.481	0.527	0.543	0.572	0.613	0.617
Life expectancy at birth	62.1	64	65.7	67.1	68.9	69.4
Expected years of schooling	10.4	10.5	11.1	11.8	13.2	13.2
Mean years of schooling	3.3	4.2	4.8	5.3	5.8	5.8
GNI per capita (2006 PPP$)	2007	2751	2478	2840	3544	3716
Rank of HDI	76	104	109	110	125	124
Total number of countries	130	174	174	177	187	187

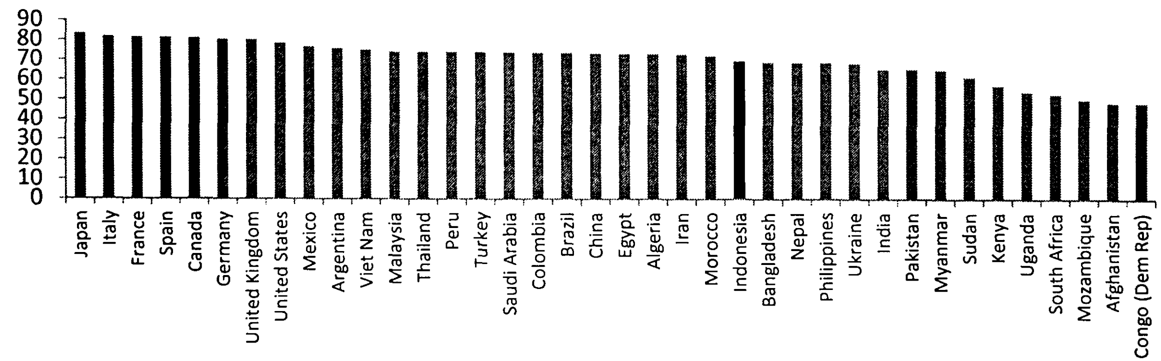
Source: UNDP 2013 in http://hdrstats.undp.org/en/countries/profiles/idn.html

Figure 1.2 to Figure 1.5 shows the indicators of the human development index across countries in 1990 and 2011. All the Indonesia figures are in black. Figure 1.2 presents the life expectancy at birth. Japan has the highest life expectancy at birth in both 1990 and 2011. In comparison with other countries, Indonesia's life expectancy at birth in both 1990 and 2011 seems to have the same position, which is in the middle group. Among the top four populous countries in the world, with the United States, China, and India, Indonesia still has a better value of life expectancy than India, but it is inferior compared to the USA and China.

Figure 1.2: Life expectancy at birth in 1990 and 2011



Life expectancy at birth (years) in 1990

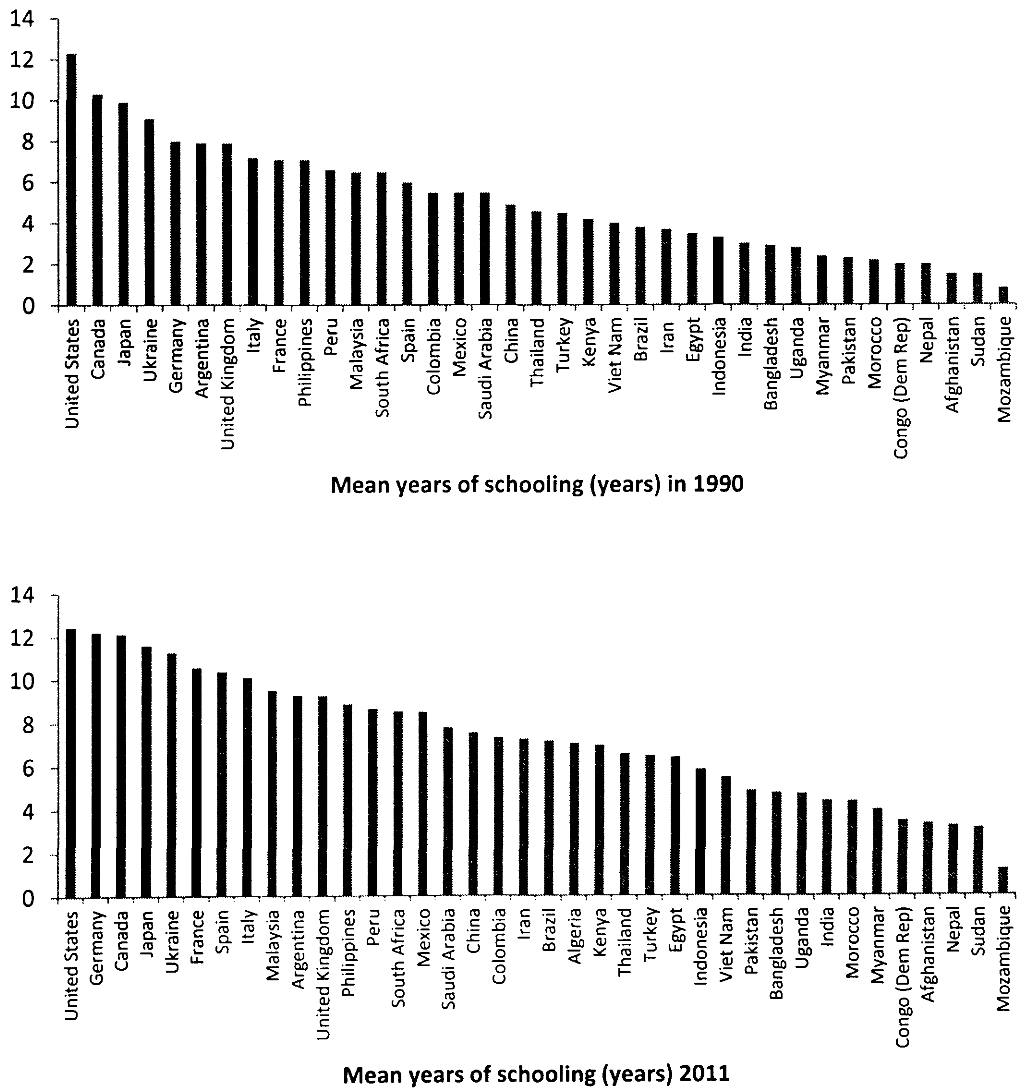


Life expectancy at birth (years) 2011

Source: UNDP 2013 in http://hdrstats.undp.org/en/countries/profiles/idn.html

Figure 1.3 illustrates the mean years of schooling in 1990 and 2011 across the chosen countries. The United States has the highest mean years of schooling in 1990 and 2011. In comparison with the USA, Indonesia's mean years of schooling is almost half of the USA in both years.

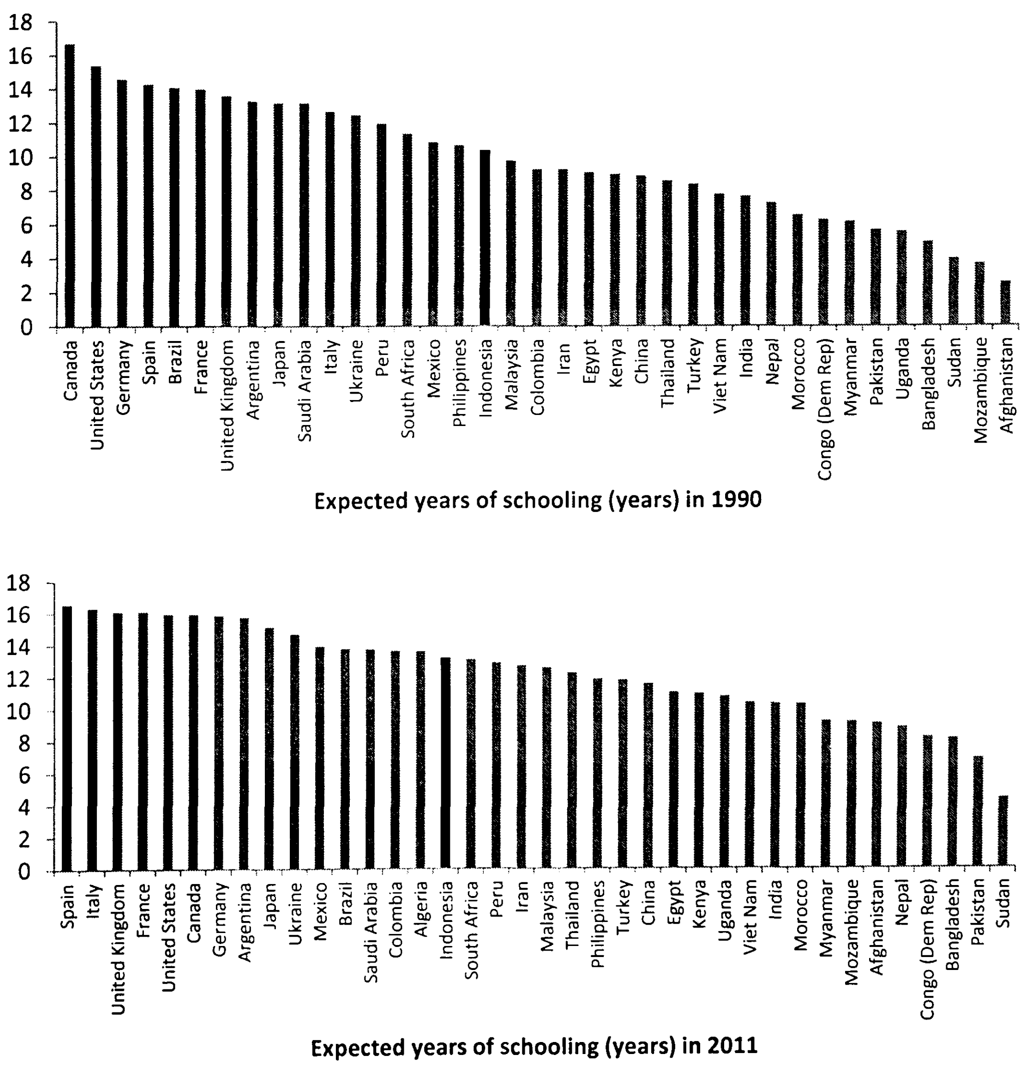
Table 1.3: Mean years of schooling in 1990 and 2011



Source: UNDP 2013 in http://hdrstats.undp.org/en/countries/profiles/idn.html

In comparison with Southeast Asian countries, Indonesia is also far behind Malaysia, the Philippines and Thailand in 1990 and 2011, although in 2011, Thailand is close to Indonesia and seemed to have a lower relative position. In 2011, Indonesia succeeded in increasing the mean years of schooling, but it is still in the middle group and seems to be in a similar position to 1990.

Figure 1.4: Expected years of schooling in 1990 and 2011

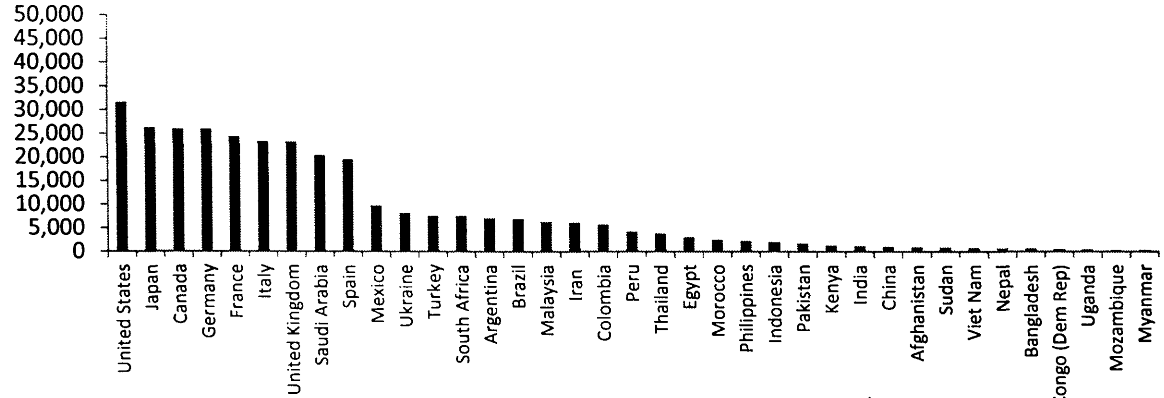


Source: UNDP 2013 in http://hdrstats.undp.org/en/countries/profiles/idn.html

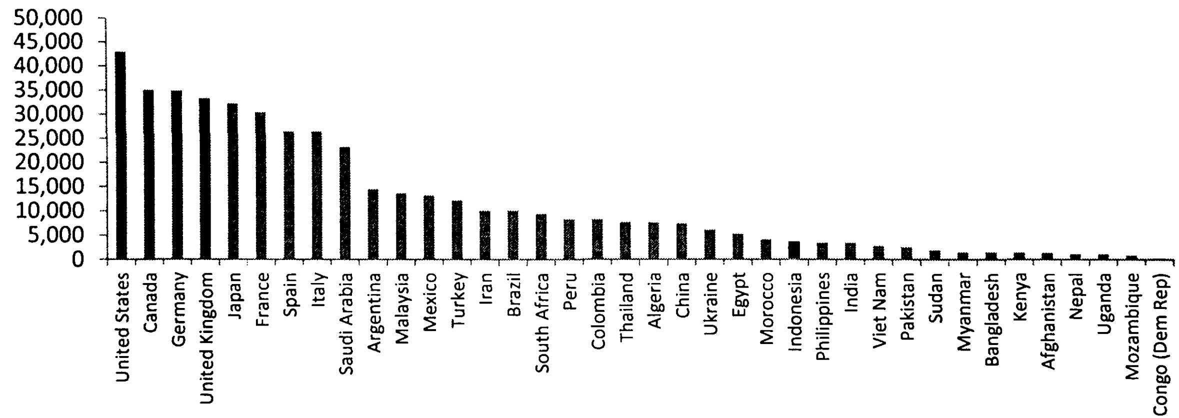
Figure 1.4 shows the expected years of schooling in 1990 and 2011. This education indicator is regarded more highly than the mean years of schooling. In comparison with other countries, especially Southeast Asian countries, Indonesia has the highest values in 2011, but just behind the Philippines in 1990. It indicates that in Indonesia children receive more education than adult had received, on average. Figure 1.5 presents the income indicator of HDI, Gross National Income per capita. In 1990 and 2011, the highest GNI per capita is the United States. The position of Indonesia's GNI per capita in 1990 and 2011 seems similar in both years and is still very low in comparison with other countries, especially developed countries.

Moreover, according to the Ministry of Manpower and Transmigration, in 2012 the unemployment rate was about 6%. Of the people who were unemployed, 28% graduated only from primary school, 23% from junior high school, 26% from senior high school, 13% from vocational senior high school, and about 10% from university. These statistics show that unskilled and less educated workers have a greater chance of becoming unemployed. In addition, the labour force of Indonesia in 2012 was 119.39 million people, of which the number of people in employment was about 112.9 million people. In general, the labour force is still dominated by primary school graduates, who comprise 55.7 million people (46.66%). The educated labour force that has graduated from University and Diploma courses is about 11.17 million people (9.36%). If we look at the proportion of working people, based on their main job, it is around 40% of Indonesian people work in the agricultural sector, 15% in trade, 10% in manufacturing, 15% in services, and the rest are distributed across construction, hotels and restaurants, communication, finance and insurance, mining, electricity and gas.

Figure 1.5: GNI per capita in PPP terms in 1990 and 2011



Gross National Income per capita (Constant 2005 PPP $) in 1990



Gross National Income per capita (Constant 2005 PPP$) in 2011

Source: UNDP 2013 in http://hdrstats.undp.org/en/countries/profiles/idn.html

With regard to education, the net enrolment rate[1] in Indonesia in primary schools was around 95%, followed by junior high school, which was approximately 70% in 2010. The net enrolment rate of senior high school was around 50% and the lowest one is university enrolment rate, which is around 12%. There has been a moderate increase in the percentage of net enrolment rate at junior high school, senior high school level and higher education in Indonesia from 2000 to 2010.

1.2.Overview of Natural Disasters in Indonesia

Indonesia is an archipelagic island country in Southeast Asia with approximately 17,500 islands, but only around 6,000 of these are inhabited. There are five big islands: Sumatra, Java, Kalimantan, Sulawesi and Papua. Java is the most populous island; Jakarta the capital city of Indonesia is located here. Indonesia's total land area is 1,919,317 square kilometres and the population is 242.3 million people. Geographically, Indonesia is situated on the world's 'Ring of Fire', where a large number of earthquakes and volcanic eruptions occur in the basin of the Pacific Ocean, and also lies at the meeting point of Pacific, Australian, Eurasian and Philippines Plates. All these conditions make Indonesia vulnerable to many kinds of natural disasters. Almost every year Indonesia experiences natural disasters such as floods, landslides, earthquakes, tsunamis and droughts.

[1] Net enrolment rate is calculated from the total number of students in a certain age of schooling at primary school, divided by the total number of the population in that age of schooling and then multiplied by 100%. The same method is used to calculate for junior, senior high school and university level net enrolment rates.

In addition, around 6,200 people were killed and 700 thousand people were affected by disasters on average per year between 1980 and 2010[2]. Around 90% of the regions of Indonesia are vulnerable to disasters. For instance, the west coast of Sumatra and the southern coast of Java, are vulnerable to earthquakes and tsunamis. In addition, Jakarta, West Java, Central Java, East Java, North Sumatra and Riau are vulnerable to floods and landslides. Drought usually occurs in Riau, South Sumatra, North Sumatra, East Kalimantan, Central Kalimantan, South Kalimantan, West Kalimantan and East Nusa Tenggara. Neumayer and Plumper (2007) measure the strength of disasters in each region using the number of people killed during the disasters divided by the total population. In the last decade, Aceh has the highest percentage of fatalities with 3.71%, and is followed by Yogyakarta with 0.15%. Other regions such as West Sumatra, West Papua, and North Sumatra are around 0.01%.

According to the National Disaster Management Agency (BNPB) in Indonesia, more than 4000 disasters occurred in the last decade, 2000-2011 and some of them were very destructive, killing many people in several Indonesian regions. The most destructive one was the earthquake and tsunami in Aceh on 26th December 2004 with a 9.1 - 9.3 moment magnitude scale and the longest duration in the world of around 10 minutes. This disaster killed approximately 230,000 people in fourteen countries, more than half of whom, 126,915, were from Indonesia. In addition, according to BNBP, 37,063 people were missing and 655,000 people were made homeless across Aceh Province. The second destructive disaster was an earthquake on 26th May 2006 in Yogyakarta Province. Estimates claimed that more than 6,000 people were killed in a 6.3 magnitude earthquake and about 130,000 were left homeless. Another serious

[2] Prevention web, serving the information needs of the disaster reduction community, January 2013. http://www.preventionweb.net/english/countries/statistics/?cid=80 [accessed 3 January 2013].

disaster was the floods in Jakarta in February 2007. Around 30 people died and approximately 340,000 were left homeless. Another earthquake in West Sumatra, 5.8-6.4 on the Richter scale, killed approximately 50 people on 6 March 2007.

1.3.Contribution of the Thesis

As already discussed above, Becker (1964) argued that human capital is an important characteristic of each individual which may affect their output of economic value. It has an extraordinary characteristic of being accumulated over a long period of time, since the growth of human capital can be affected by its inputs. For instance, human capital outcomes for children are influenced by several inputs, such as nutrition, education and their health condition when they were young. Considering that children are the future generations who will take over all roles in future development, it is very important to seriously examine any factors which may affect human capital outcomes for children.

The concept of human capital is very important in a country with a large population, like Indonesia. As the fourth most populous country in the world after China, India, and the United States, Indonesia has abundant human resources, especially since the population is relatively young. Because of this, turning human resources into human capital is urgently needed, otherwise unemployment will be a serious problem for this country. In the process of transforming human resources into human capital, investment in the education and health sectors of the national economy must become the first priority, since only with education and health will it be possible to produce highly productive human capital with knowledge and skills.

The total population of Indonesia was about 242.3 million people in 2011, and approximately 20% of the population were children under 10 years old. It is suggested that the Government of Indonesia must pay serious attention to providing both good education and good health services for children, as education and health are the most important factors that may affect human capital outcomes for children. In addition, the government should also consider other factors that may affect the outcome that cannot be controlled by human beings, such as natural disasters, as Indonesia is located on the Pacific Ring of Fire, which makes it very vulnerable to disasters. By learning from the previous experience of disasters, it is hoped that Indonesia can have a better response in coping with disasters, especially for young children, who are believed to be the most vulnerable to the disasters.

To the best of my knowledge, there is still limited research on human capital outcomes for children in Indonesia, especially as regards the effects of disasters. One study conducted by Cameron and Worswick (2001) focused only on the impact of crop failure on educational expenditures. This research is interesting, since they analyse whether households could cope with their normal consumption during hard times, by defining permanent income and transitory income. Educational expenditure was chosen instead of other expenditures because of the social benefits. Using Indonesian Family Life Survey data from 1993, Cameron and Worswick (2001) found that households were not able to smooth out consumption fluctuations during the time of crop loss so they were most likely to reduce educational expenditure, especially for girls.

On the other hand, there are several papers on school subsidies in Indonesia, such as Sparrow (2007), Duflo (2001), and other research institutions such as SMERU (2006). Sparrow (2007) evaluated the impact of the social safety net in education (Jaring Pengaman Sosial, JPS) on school enrolment after Indonesia was hit by a financial crisis in 1997/1998. Using instrumental variable regression, he confirmed that the JPS program was an effective instrument for protecting the education of the poor, especially for those who are most vulnerable to the effects of the crisis. This program could increase the school attendance by 1.2% for children aged 10-12 and 1.8% for children aged 13-15.

Another famous study was conducted by Duflo (2001), which examined a school subsidy by Indonesia's government for a school construction programme (The INPRES program). Between 1973/1974 and 1978/1979, 61,807 new schools were constructed and it spent over 500 million USD, calculated using the exchange rate in 1990. The World Bank (1990) observed that it was the fastest primary school construction program ever undertaken in the world. The research suggested that the INPRES program increased the years of education by 0.25 to 0.40 years, and increased the probability of a child completing primary school by 12%. The results also suggest that the program led to an increase of 3 to 5.4% in earnings. The program successfully increased not only education levels but also wages. All the previous papers discussed the impact of school subsidies on educational attainment. In comparison with previous studies, the school subsidy studied in this thesis is different in terms of the type of school subsidy, the measure of educational attainment, and also different in its methods of evaluation.

The main focus of this thesis is to examine the factors that may affect human capital outcomes for children, specifically the effects of a school subsidy and natural disasters. In addition, we also look at the effect of disasters on household expenditures, including educational expenditures, which may affect investment in human capital for children. We analyse the latest school subsidy program which was designed by the government of Indonesia in 2005, the School Operational Assistance Program (the so-called BOS). This study is important since BOS, nationally, is the biggest school subsidy program, as BOS is distributed to all primary schools in Indonesia and receives a bigger allocation from national budgets compared to previous school subsidies in Indonesia. Therefore, this study evaluates an early phase of the implementation of the BOS program and considers whether there is a significant impact of the BOS program on children's outcomes, as measured by test scores. This evaluation could be used in advising the government in making decisions relating to school subsidy policies in Indonesia in the future. More detail about the effect of the BOS program on child test scores in Indonesia is presented in Chapter 3. Furthermore, as Indonesia experiences natural disasters almost every year, by studying this impact on human capital outcome for children from previous experiences, we can have a better respond to future potential disasters, especially in relation to children.

This thesis contributes to the international literature in this area in several aspects. First, compared to other literature generally, this study uses survey data with self-reported information. In Chapter 3, this study uses self-reported information on whether children get school subsidies from the government. This allows us to estimate the impact of the treatment rather than the intention to treat. Chapters 4 and 5 use self-reported data on whether they are affected by disasters or not. In the main data set that is used in this thesis, the IFLS survey, individuals are categorized as affected by the disasters if they reported that their households experienced death or major injuries to a household member, direct financial loss to the household, or relocation of a household member. To the best of my knowledge, almost all earlier studies defined an affected individual only by measuring the policies or shock before and after, and there is no definition that describes an individual as affected or unaffected.

Second, this study used a measure of school quality, test scores, as a measure of educational outcomes, while most of the earlier studies used a quantity measure of schooling, such as school enrolment, school attendance, number of years completed or drop-out rate. Chapter 3 examines the impact of school subsidies on test scores, and Chapter 4 investigates the impact of disasters on child test scores.

Thirdly, the BOS program is an example of a specific school subsidy program aiming to support basic education in Indonesia. The subsidy for each student who is eligible is distributed to the school directly and will be managed by the school for operational expenses so that the students will be free from all kinds of fees during their schooling. The students themselves only receive a small amount of money for their transportation allowance. An evaluation of this school subsidy policy may also have relevance for other countries considering adopting similar ideas.

Fourthly, in Chapter 4, we examine the impact of disasters across the distribution of test scores using Quantile Regression, so we can see in detail the effects of disasters by groups of outcomes. Fifth, this study presents the impact of disasters on child health using two different measures of child health: height of child as an objective measure and self-reported health condition as a subjective measure. The purpose of using these two measures that height is a permanent effect whereas self-reported health is likely to be a short effect.

Sixth, in Chapter 5, compared to other literature that discusses the impact of disasters on expenditure or budget, this study uses a variety of data of household expenditures and also of income (wages). In addition, regarding food expenditures, we allow for those who get food from market purchases and those who get food from their own production from their farm. Seventh, we also investigate the net effect of disasters on expenditures of main foods, such as rice, vegetable, fish and meat. Another important contribution is about the consequences of natural disasters on food demand. Here, the impact of disasters can be manifested in two ways: through increases in the price of goods and through an affect independent of food prices. Lastly, we also provided the impact of disasters on living standards regarding different levels of household expenditure.

1.4.Organization of the Thesis

The remainder of this thesis is organized as follows. Chapter 2 presents the main data that is used in this thesis. This thesis primarily uses micro-survey data at individual and household level from the Indonesia Family Life Survey (IFLS) data for the years 2000 (IFLS3) and 2007 (IFLS4). In this chapter, we discuss sample design, response rate and data collection for both individual and household level data, and also for community and facility data. In addition, all variables that we use in the thesis are also presented in this chapter with brief descriptive statistics. Furthermore, this chapter provides a brief discussion about selected papers which have used IFLS data that are relevant to our study.

Chapter 3 discusses the impact of the school operational assistance program (BOS) on child test scores. This study provides an early observation of the impact of BOS on child test scores, since BOS was launched in 2005 and the survey was conducted in 2007 and 2008. BOS was designed for all students at primary schools and junior high schools. The original idea of BOS was to provide the operational costs of schooling per student, so that each student could go to school without paying any fees. The funding goes to the school directly as school operational costs and is managed by the teachers and also controlled by the school committee (school principal and student's parent representative). The school operational costs that can be financed from BOS are: procurement of consumables, student activities (enrichment programs and other extracurricular programs), textbooks, admission fees for new students, school maintenance, examination fees, transportation cost for poor students and other operational expenses - as long as they are not for staff salaries.

By transferring money directly to the schools, students do not receive any money except for poor students, who are eligible to get the assistance for transportation cost. In the beginning of the BOS program, the funding could not cover all students at schools so only selected students who were categorized as poor students were eligible to get the BOS and the remaining students, who were categorized as rich students, had to pay school fees. This study uses three different methods: Ordinary Least Square (OLS), Instrumental Variable (IV) and Propensity Score Matching (PSM) estimation. OLS is used as conventional method and estimates the effect of school subsidy on average by assuming that BOS is exogenous, while IV estimation is used to deal with endogeneity of BOS and also correct for selection bias based on unobservable characteristics. PSM is used to estimate the average treatment effect in the absence of selection on unobserved characteristics. The results confirm that the BOS can increase student performance. Paradoxically it does not help very poor students, yet it helps less poor students.

Chapter 4 examines the impact of natural disasters on child test scores and child health. As there have been an increasing number of intensely destructive disasters in the last decade in Indonesia, and also considering that children are believed to be the most vulnerable to natural disasters, studying the impact of disasters on human capital outcomes for children is very important in Indonesia. This chapter examines the impact of disasters, especially big earthquakes, small earthquakes and floods, on child test scores and child health. These three disasters were picked up because they have a higher percentage of the ratio between fatalities to the population and evacuated people to the population. The detailed explanation is contained in Chapter 4.

As natural disasters might be considered an exogenous condition that may affect the economy, so we use the exogenous variation from natural disasters as a natural experiment design to estimate the effect of disasters on child test score and child health. According to Wooldridge (2010) for example when a specific group is exposed to the causal variable of interest, such as a disaster and others are not, a difference in differences method (DID) can be used in estimation. The DID method can be used to predict the missing counterfactual or the potential outcome of treatment group in the absence of natural disasters. This chapter discussed child test scores and child health.

For child health, we use two types of data: child height under 5, and self-reported general health condition. In addition to DID method, for the impact of disasters on child health analysis, we also used zero inflated negative binomial, and also ordered logit model for analysing self-reported data on child health. The results confirm that child test scores are significantly affected by disasters, but that there are no serious impacts of disasters on child health.

Chapter 5 extends the analysis by estimating the effects of disasters on household expenditures and food demand. Disasters not only kill and injure local people but it also disrupt local economies, so in addition to observing the impact of disasters on human capital outcomes for children, it is also important to examine the response of households in coping with disasters, especially in trying to maintain the same standard of living after disasters. There may be destruction of infrastructure, property, assets and production processes that may affect the local economy as well as household welfare. We used several types of household expenditure as household welfare indicators, such as total expenditures, food expenditures, and educational expenditures. For food expenditures, we looked separately at market-purchased and own-produced expenditures. In addition to household expenditures, we also looked at the impact of disasters on income using the wages of heads of households.

For estimation, we employed a difference in differences (DID) method in this chapter to estimate the total impact of disasters on various types of household expenditure. In the DID model we did not control the price of goods. For comparison, we used Linear Approximate Almost Ideal Demand System (LA-AIDS) model. The purpose of estimating using this model is to isolate the effect of disaster induced prices changes from other effects. In contrast DID regression is reduced form and captures the total effect but does not isolate the price effect from other effects. Furthermore, the LA-AIDS model also estimates the price elasticity of demand and the expenditure elasticity of demand. Overall, this chapter provides estimates of the effect of disasters on the living standards of households. The analysis shows that there is no impact of disasters on total household expenditures, but we found a net negative impact on expenditures when we control for prices. These finding suggests either that households are possibly able to anticipate disasters and smooth their consumption, or that the government and aid agencies are good at distributing disaster relief to offset the entire effect of the disasters.

Finally, Chapter 6 summarizes the findings and provides conclusion and policy recommendations. This chapter also suggests some policy implications related to improving the human capital outcomes for children in Indonesia.

Chapter 2

Data Sources

2.1. Introduction

The main data source for all chapters in our research is the Indonesia Family Life Survey (IFLS). It is a longitudinal survey that was started in 1993. There are 4 waves: IFLS1 (first wave) in 1993, IFLS2 (second wave) in 1997, IFLS2+ in 1998 with a sub sample of 25% of IFLS households, IFLS3 (third wave) in 2000, and the latest wave IFLS4 in 2007. IFLS2+ was conducted to look at the impact of the Asian financial crisis in 1997-1998. The first and the second waves of IFLS were conducted by RAND in collaboration with Lembaga Demografi, University of Indonesia. The third and the fourth waves were conducted by RAND in collaboration with the Population Research Center, University of Gadjah Mada. IFLS is a survey that has been conducted to provide economic, social and demographic information of the household and community facilities in Indonesia. The survey data was collected at individual and household levels and there is also information from the communities where households and individuals were located. Since IFLS is a longitudinal survey, data are available for the same individuals from multiple points in time, so it is possible to observe information of the dynamics of behaviour at the individual, household, family and community levels, for instance, changes in education, labour income, or health condition.

At individual and household levels, the IFLS survey is about behaviours and outcomes related to wealth (consumption, income and assets); human capital (education, health, migration and labour market outcomes); marriage, fertility and contraceptive use;

processes underlying household decision-making, such as the choice of food eaten at home, child education and other decisions on how they spend money; transfers among family members and inter-generational mobility; and participation in community activities. Moreover, the survey is also accompanied by information from the communities, such as physical and social environment, infrastructure, employment opportunities, food prices, access to health and educational facilities, and the quality and prices of services available at those facilities.

2.2. Sample Design and Response Rate of IFLS Household Survey

This section discusses the sampling and how the sample changed from IFLS1 as the basis for the next waves. Moreover, response rates from each wave are also explained, Considering the complexity of the IFLS data, RAND and its partner decided to separate the individual or household survey from the community and facility survey. For the IFLS individual or household survey, the first sample design for IFLS1 is the most important design since it would be the basis for the next IFLS sample (IFLS2, IFLS3 and IFLS4). IFLS2 drew its sample from IFLS1, IFLS3 drew its sample from IFLS2 and IFLS1, and IFLS4 drew its sample from IFLS3, IFLS2, and IFLS1.

2.2.1. IFLS1 Household Survey

The IFLS1 sampling scheme was stratified on provinces and urban/rural location, then randomly sampled within the provinces (Strauss et.al, 2009). The provinces were selected according to the populous regions in order to capture the number and diversity of the population, culture and socio-economic trends of Indonesia. The sample is representative of about 83% of the Indonesian population and contains over 30,000 individuals living in 13 of the 27 provinces in 1993 (today Indonesia has 33 provinces). The 13 provinces are four provinces on Sumatra (North Sumatra, West Sumatra, South Sumatra and Lampung), all five of the Javanese provinces (DKI Jakarta, West Java, Central Java, DI Yogyakarta and East Java), and four provinces covering Bali, West Nusa Tenggara, South Kalimantan and South Sulawesi. Figure 2.1 shows the IFLS provinces.

Figure 2.1: IFLS Provinces Map

Source: RAND 2010, family life survey http://www.rand.org/labor/FLS/IFLS/

In each province, enumeration areas (EA) were randomly chosen from the Indonesian National Socio-economic Survey (SUSENAS = Survei Sosial Ekonomi Nasional) data, a national socio-economic survey that was designed by Central Bureau Statistics (BPS), based on the 1990 census, with approximately 60,000 households. In SUSENAS, each EA contains around 200 to 300 households. Within selected EAs in IFLS surveys, households were randomly selected by adopting the same sample frame that was used from SUSENAS. According to BPS, a household is defined as a group of people whose members reside in the same dwelling and share food from the same cooking pot.

Table 2.1: IFLS 1 Household Enumeration Areas

Province	1990 Population (000)	IFLS Sample EAs Urban	Rural	Total
North Sumatra	10391	16	10	26
West Sumatra	4041	6	8	14
South Sumatra	6403	8	7	15
Lampung	6108	3	8	11
DKI Jakarta	8352	40	0	40
West Java	35973	31	21	52
Central Java	28733	19	18	37
DI Yogyakarta	2923	16	6	22
East Java	32713	23	22	45
Bali	2798	7	7	14
West Nusa Tenggara	3416	6	10	16
South Kalimantan	2636	6	7	13
South Sulawesi	7045	8	8	16
Total	151532	189	132	321

Source: Frankenberg et al. (1995)

Table 2.1 presents household Enumeration Areas (EAs); this table provides information about the size of the population from the 1990 population survey across provinces and the distribution of EAs across provinces in total and separately by urban and rural areas. There are 321 enumeration areas in the 13 provinces, of which 189 EAs are urban and 132 EAs are rural. IFLS randomly selected 20 households in urban EAs and 30 households in rural EAs, with an over-sampling of urban EAs and EAs in smaller provinces to facilitate urban-rural and Javanese–non-Javanese comparisons. The different number of households between urban and rural is to minimize the transportation costs in rural EA.

Table 2.2 provides information of the household response rate in IFLS1 by province. This table is based on an overview and field report of the 1993 Indonesian Family Life Survey by Frankenberg et Al. (1995). A total of 7,730 households were sampled and complete interviews were conducted with 7,039 households in late 1993 and early 1994. The response rate of complete interviews is about 91%, while the complete interviewed rate across provinces is ranged from 87% to 97%.

Table 2.2: IFLS 1 Household Response Rate Across Provinces

	Number of Households Survey						
	Complete		Partial		None		Total
Province	(1) number HH	% (1)/(4)	(2) number HH	% (2)/(4)	(3) number HH	% (3)/(4)	(4)
North Sumatra	543	87.6	20	3.2	57	9.2	620
West Sumatra	335	93.1	15	4.2	10	2.8	360
South Sumatra	340	91.9	8	2.2	22	5.9	370
Lampung	269	89.7	5	1.7	26	8.7	300
DKI Jakarta	724	90.5	7	0.9	69	8.6	800
West Java	1084	86.7	27	2.2	139	11.1	1250
Central Java	858	93.3	21	2.3	41	4.5	920
DI Yogyakarta	438	87.6	40	8	22	4.4	500
East Java	1032	92.1	13	1.2	75	6.7	1120
Bali	340	97.1	0	0	10	2.9	350
West Nusa Tenggara	402	95.7	5	1.2	13	3.1	420
South Kalimantan	312	94.5	11	3.3	7	2.1	330
South Sulawesi	362	92.8	13	3.3	15	3.8	390
Total	7039	91.1	185	2.4	506	6.5	7730

Source: Frankenberg et al. (1995)

In addition, a partial interview[3] was obtained from 185 households (2.4%), so in total IFLS1 successfully interviewed 93.5% from the total households sampled or 7,224 households (7,039 HHs with complete interviews, and 185 HHs with partial interviews). The remaining 6.5% of households was not interviewed. There were several reasons, such as the building was vacated, the household refused, no-one was at home, or illness.

[3] Roster level information was already obtained, but only a subset of selected household members was interviewed.

To reduce the cost of survey, not all household members were interviewed, so a sampling scheme was used to select several members within a household to provide detailed individual information. IFLS1 conducted detailed interviews with the following household members: the household head and his/her spouse; two randomly selected children of the head and spouse, aged 0 to 14; an individual aged 50 or older and his/her spouse, randomly selected from remaining members; a randomly selected 25% of the households for an individual aged 15 to 49 and his/her spouse, randomly selected from the remaining members. The last rule was especially for a household with a large family; for instance, a family with 10 household members including 8 adults, in addition to a head of a household and his/her spouse, and also any other individual aged 50 or older and his or her spouse as the main respondents; if there were still any adults left, the surveyor would select about 25% of the adults aged 15 to 49 who had not been interviewed by then.

2.2.2. IFLS2 Household Survey

IFLS2 re-interviewed the 7,224 households that were interviewed in 1993. Table 2.3 shows the number of households that were interviewed in IFLS1 and IFLS2 by provinces. This table also provides the household response rate for IFLS2. The total number of households interviewed in IFLS2 was 7,698, of which 6,820 were original IFLS1 households and 878 were *split-off households*. Split-off households were from IFLS1 household members who had left their IFLS1 household and IFLS had tracked and interviewed them in their new locations. The response rate of the IFLS1 households was 94.4%. One reason for this high rate of retention was the effort to follow households that moved from their original housing structure. If an entire household or respondent moved then they were tracked, as long as they still resided in any one of the 13 IFLS provinces, regardless of whether they moved across those provinces. The complete interviewed rate of the IFLS1 households across the provinces ranged from 87% to 97%.

In the case of household members, IFLS also tried to keep a high response rate for individual members of IFLS1 households. All individual household members who provided detailed individual level data in 1993 (panel respondents) were to be tracked and interviewed in IFLS2. IFLS2 had priority and targeted two groups of IFLS1 household members for tracking and interview in 1997 if they moved out from IFLS1 households. First came all individuals with completed and detailed individual level information in IFLS1, and second were all IFLS1 household members who were 26 years old or older in 1993.

IFLS2+ was conducted in mid-1998 in order to examine the immediate impact of the Asian economic crisis that had hit Indonesia from January 1998. A 25% sub-sample of the IFLS households was taken from 7 of the 13 provinces (West Nusa Tenggara, Central Java, Jakarta, West Java, South Kalimantan, South Sumatra and North Sumatra) that IFLS covers. Within those, 80 EAs were purposively selected in order to match the full IFLS sample. As in IFLS2, all households that had moved since the previous interview to any IFLS province were tracked. In addition, new households (split-offs) were added to the sample, using the same criteria as in IFLS2 for tracking individuals who had moved out of the IFLS household. For interviewing individuals within households, the same rules used in IFLS2 were mostly used.

Table 2.3: IFLS 2 Household Response Rate Across Provinces

Province	IFLS1 (1) Total HH sampled	IFLS1 (2) Total HH interviewed	% (2)/(1)	IFLS2 (3) Total IFLS1 HH interviewed	% (3)/(2)	(4) Split-off HH	(3)+(4) Total HH interviewed
North Sumatra	620	563	90.8	504	89.5	44	548
West Sumatra	360	350	97.2	329	94.0	50	379
South Sumatra	370	348	94.1	318	91.4	55	373
Lampung	300	274	91.3	259	94.5	38	297
DKI Jakarta	800	731	91.4	642	87.8	65	707
West Java	1250	1111	88.9	1066	95.9	141	1207
Central Java	920	879	95.5	868	98.7	135	1003
DI Yogyakarta	500	478	95.6	451	94.4	49	500
East Java	1120	1045	93.3	1004	96.1	117	1121
Bali	350	340	97.1	322	94.7	43	365
West Nusa Tenggara	420	407	96.9	402	98.8	54	456
South Kalimantan	330	323	97.9	296	91.6	51	347
South Sulawesi	390	375	96.2	359	95.7	36	395
Total	7730	7224	93.5	6820	94.4	878	7698

Note: Source of data from Frankenberg and Thomas (2000); column (2) = table 2.2 (1)+(2)

2.2.3. IFLS3 Household Survey

The sampling approach in IFLS3 was to re-interview all original IFLS1 interviewees, plus split-off households from both IFLS2 and IFLS2+. Table 2.4 presents the IFLS3 household response rate. A total of 8,347 households were targeted to be interviewed in IFLS3, which consisted of 7,138 IFLS1 HH, 865 IFLS2 split-off HH, and 344 IFLS2+ split-off HH. From 7,138 IFLS1 households, 6,800 IFLS1 households could be contacted. It was about a 95% response rate of IFLS1 households. For IFLS3 target households, in total there were 8,347 IFLS3 target households; 7,928 households could be contacted, or around a 95% response rate. In addition to the IFLS3 target HH, IFLS3 also interviewed 2,646 new split-off households in IFLS3. Hence, in total, 10,574 households were contacted in IFLS3; 3,774 were split-off households since IFLS1 and 6,800 were IFLS1 households.

Table 2.4: IFLS 3 Household Response Rate

	(1) Target HH	(2) All members died	(3) HH Contacted	(4) Response rate %=(3)/(1)
IFLS1 HH	7,138	32	6,800	95.3
IFLS2 split-off HH	865	2	819	94.7
IFLS2+ split-off HH	344		309	89.8
IFLS3 split-off HH			2,646	
IFLS3 target HH	8,347		7,928	95.0
Total HH			10,574	

Source: Strauss et al. (2004)

Table 2.5 shows the provincial distribution of interviewed households. There were a number of IFLS1 HH interviewed in 1993 and 2000 across various provinces. In total, 6,800 IFLS1 households were re-contacted in 2000, or about a 94.1% response rate. In addition, 10,574 households were contacted, and 10,435 households were interviewed. This was because there were households whose members had died since the last survey, or who had joined other IFLS households. In general, the complete interviewed rate of the IFLS1 households across provinces in 2000 ranged from 83% to 98%.

Table 2.5: IFLS 3 Household Response Rate Across Provinces

Province	(1) IFLS1 HH interviewed in 1993	(2) IFLS1 HH interviewed in 2000[a] Number HH	%=(2)/(1)	(3) Split-off	(4) Total HH contacted (3)+(2)	(5) Total IFLS3 HH interviewed
North Sumatra	563	507	90.1	241	748	738
West Sumatra	351	325	92.6	192	517	507
South Sumatra	349	331	94.8	228	559	550
Lampung	274	257	93.8	164	421	414
DKI Jakarta	731	610	83.4	355	965	958
West Java	1111	1065	95.9	603	1668	1658
Central Java	878	859	97.8	523	1382	1362
DI Yogyakarta	478	438	91.6	203	641	636
East Java	1044	1025	98.2	462	1487	1465
Bali	340	325	95.6	160	485	482
West Nusa Tenggara	407	399	98.0	278	677	668
South Kalimantan	323	307	95.0	202	509	488
South Sulawesi	375	352	93.9	163	515	509
Total	7224	6800	94.1	3774	10574	10435

Note: a= Includes IFLS1 households whose members died, or joined other IFLS households:
Source: Strauss et al. (2004)

As in IFLS2, households that moved were followed as long as they still resided in IFLS provinces. In IFLS3, the rule was expanded; in the case of households moving to a location that was assessed to be near the border of IFLS provinces, and thus within cost-effective reach of the enumerator, these households were to be followed, since there were also a small number of households who moved to non-IFLS provinces, such as Southeast Sulawesi, Central Kalimantan, and East Kalimantan.

2.2.4. IFLS4 Household Survey

The target households for IFLS4 were the original IFLS1 households, minus those of whom all their members had died by 2000, plus all of the split-off households from

1997, 1998 and 2000. Table 2.6 presents the IFLS 4 household response rate. In total, IFLS contacted 13,995 households, including those that died between waves, those that relocated into other IFLS households and new split-off households. A total of 10,994 households were targeted in 2007; IFLS re-contacted 9,962 households, or 90.6%. From the 10,994 households, 7,135 were original IFLS1 households, 3,859 were old split-off households. From the 13,995 contacted households, 13,535 households were actually interviewed. The difference between the 13,535 households interviewed and the 13,995 households contacted was those whose members had died since the last survey was completed, or other joint IFLS households. In addition, 4,033 new split-off households IFLS4 were added as contacted households in 2007.

Table 2.6: IFLS 4 Household Response Rate

	(1) Target HH	(2) All members died	(3) HH Contacted	(4) Response rate %=(3)/(1)
IFLS1 households	7,135	144	6,596	92.4
IFLS2 split-off households	876	7	769	87.8
IFLS2+ split-off households	335	2	295	88.1
IFLS3 split-off households	2,648	15	2,302	86.9
IFLS4 main household/target	10,994		9,962	90.6
IFLS4 split-off households			4,033	
Total			13,995	

Source: Strauss et al. (2009)

Table 2.7 shows the household response rate across the target provinces. In general, the complete interviewed rate of the IFLS1 households across the target provinces in 2007 was ranged from 75% to 98%, with DKI Jakarta with the lowest percentage and West Nusa Tenggara with the highest percentage. In total, 6,596 IFLS1 households were re-contacted in 2007, or about 91.3% of the response rate.

Table 2.7: IFLS 4 Household Response Rate Across the Provinces

Province	(1) IFLS1 HH interviewed in 1993	(2) IFLS1 HH interviewed in 2007[a] number HH	% =(2)/(1)	(3) Split-off	(4) Total HH contacted	(5) Total IFLS4 HH interviewed
North Sumatra	563	493	87.6	532	1025	998
West Sumatra	351	314	89.5	421	735	714
South Sumatra	349	301	86.2	435	736	712
Lampung	274	256	93.4	329	585	569
DKI Jakarta	731	551	75.4	637	1188	1147
West Java	1111	1038	93.4	1227	2265	2207
Central Java	878	840	95.7	973	1813	1733
DI Yogyakarta	478	435	91.0	382	817	786
East Java	1044	1009	96.6	932	1941	1869
Bali	340	316	92.9	330	646	625
West Nusa Tenggara	407	399	98.0	484	883	858
South Kalimantan	323	303	93.8	376	679	653
South Sulawesi	375	341	90.9	341	682	664
Total	7224	6596	91.3	7399	13995	13535

Note: a= Includes IFLS1 households whose members had died, or who had joined other IFLS households; Source: Strauss et al. (2009)

Table 2.8 summarizes re-contact rates for each survey wave. For IFLS1, 33,081 individuals were eligible and alive at the time of the survey. For cost reasons IFLS1 implemented a within-household sampling scheme, which involved individual interviews with the household head and his/her spouse, up to two of their children aged 0-14 who were randomly selected, and a randomly selected member aged 50 or older and his/her spouse. For a randomly selected 25% of the households, an individual aged 15 to 49 and his/her spouse were also randomly selected from the remaining members on the household roster. With this scheme, from 33,081 individuals, 22,588 individuals were tracked and contacted for individual interviews, and 22,019 household members could be interviewed, or around 97% of the 22,588 who were eligible to be interviewed.

Table 2.8: IFLS Completion Rate of Individual Respondents

Row		IFLS1		IFLS2		IFLS3		IFLS4	
number	Status HH	number	%	number	%	number	%	number	%
1	Eligible for survey			33081		39601[a]		44915	
2	Died between the waves			854		790		2610	
3	Eligible for survey and alive (row1-row2)	33081		32227		38811		42305	
4	Assessed/contacted (%=row4/row3)			26948	83.6	32586	84	32636	77.1
5	Eligible to be tracked and interviewed	22588		23049		32189		32757	
6	Interview conducted (%=row6/row5)	22091	97.5	21073	91.4	29440	91.5	28351	86.5
7	Refused (%=row7/row5)	569	2.5	244	1.1	261	0.8	367	1.1
8	No interview conducted (%=row8/row5)			1732	7.5	2488	7.7	4039	12.3
9	New entrants in this wave			5404		6104		12096	
10	Total sample interviewed this wave (row4+row9)	22019		32352		38690		44732	
11	Total potential sample for next wave (row3+row9)	33081		37631		44915		54401	

Note: a = There were 1970 new entrants in 2000 from IFLS2+; Source: Thomas et al., 2010

In IFLS2, of the 33,081 household members in IFLS1 that were eligible for the survey, 854 died between the waves or before IFLS2 was done. 32,227 were eligible for survey and alive, and 26,948 of these were interviewed in IFLS2. Over 91% of the "target respondents" were interviewed (row 06), about 1% refused and the rest were lost to follow-up. In IFLS3, 790 respondents died between the waves, 38,811 respondents were eligible for interview, of which 32,189 were eligible to be tracked and interviewed. 91.5% were interviewed and just below 1% refused. The rest were lost to follow-up. In IFLS3 there were slightly over 6,000 new entrants, and over 38,000 people were individually assessed in the survey. Almost 45,000 people were eligible for the next wave (Strauss et al., 2004). In IFLS4, 2,610 died between the waves, and there were 42,305 potential respondents, of whom 32,757 were target respondents. Of these people, 86.5% were tracked and interviewed with 1% refusing and the remaining 12% lost to follow-up (Thomas et al., 2010).

In short, Thomas et al. (2010) concluded that fourteen years after the baseline, attrition in IFLS remains low. In IFLS surveys, there are relatively few respondents who refuse to participate, and so the attrition is mainly because respondents who move are lost to follow-up. Predicting movers correctly is very important. Yet, there are so many factors that cannot be observed, such as ambition, willingness to take risks and patience that may affect migration decisions. Strauss et al. said that the first follow-up of IFLS in 1997 and an interview outcome ten years later, in 2007, depended not only on observed characteristics of the respondents but also the interview in 1997 and the characteristics of the interviewers, including unobserved characteristics. Here, IFLS was successfully interviewing the same respondents in subsequent survey waves because of at least two reasons. The first was having good enumerator skills, such as carrying a sense of empathy towards the respondents and building trust with respondents. The second is about the quality of information that enumerators collect.

In order to ensure the low attrition of IFLS, Table 2.9 presents information about household movement since IFLS1. According to this table, the number of households who moved to non-IFLS provinces is tiny, at approximately 1%. It means that almost 99% of households are still reachable to be interviewed, as the rule of tracking is that as long as households move to an IFLS province, then IFLS is able to track and interview them.

Table 2.9: Households' Movement

	IFLS2		IFLS3		IFLS4	
Relocation	HH	%	HH	%	HH	%
Did not move	6125	89.8	6098	58.4	5771	42.6
Moved within village	212	3.1	1278	12.2	964	7.1
Moved within district	99	1.5	601	5.8	1120	8.3
Moved within municipality	120	1.8	693	6.6	1138	8.4
Moved within province	122	1.8	1001	9.6	2828	20.9
Moved to another IFLS province	73	1.1	690	6.6	1540	11.4
Moved to non-IFLS province	69	1	74	0.7	175	1.3
Total	6820		10435		13536	

Source: Strauss et al. (2009)

2.3. Characteristics of Respondents on 2000 Data (IFLS3)

This section explores the characteristics of respondents in 2000 for those who were interviewed in 2007 and those who were not, as we used two of the latest waves on IFLS data, IFLS3(2000) and IFLS4(2007). Table 2.10 reports the comparison between respondents who were interviewed in 2007 and those who were not. Column 1 is respondents who were interviewed in 2007 and 2000, and Column 2 is for respondents who were interviewed in 2000 but not interviewed in 2007. The difference between Columns 2 and 1 is presented in Column 3.

For individual characteristics, the average number of years schooling for those who were interviewed in 2007 was 7.3 years on average, and 8.1 years for those who were not interviewed in 2007. The difference between those groups was 0.8 years. Here, respondents who were not interviewed had a slightly better education than those who were interviewed. In addition, those who were not interviewed in 2007 had less educated fathers and mothers. In terms of height, they were approximately 2 cm shorter than those who were interviewed. Moreover, relative to those who were interviewed in 2007, respondents who were not interviewed were 11% less likely to be married and earn 2.6 times less.

For household characteristics, Table 2.10 reports that 28% of those who were interviewed owned a farm business in 2000, and only 15% of those who were not interviewed lived in a household that owned a farm business. The level of household expenditure per capita was higher for those who were interviewed by around 49%. In sum, Table 2.10 shows that there are large and significant differences in the respondent characteristics between those who were interviewed in 2007 and those who were not re-interviewed. Of the characteristics of respondents as they were measured in 2000, the target respondents who were most likely to suffer from attrition from the 2007 survey were those who were better educated, had a less educated father and mother, were shorter, single, were less likely to have their own farm business and were from a household with lower per capita expenditure.

Table 2.10: Characteristics of Respondents in 2000 by Interview Outcome in 2007

Characteristics of respondents	Interview Outcome in 2007					
	Respondent interviewed		Respondent not interviewed		Difference (2)-(1)	
	1		2		3	
	Value	SD	value	SD	value	SE
Individual characteristics						
Education (years):						
Respondent	7.32	4.72	8.11	4.43	0.79	0.045
Father	8.97	4.02	8.04	4.12	-0.93	0.058
Mother	7.97	4.03	6.84	4.01	-1.13	0.053
Height (cm)	150.83	15.21	148.78	19.93	-2.05	0.428
Ratio of moved by age 12	0.85	0.36	0.82	0.38	-0.02	0.005
Ratio of married	0.66	0.47	0.54	0.50	-0.12	0.006
Log(monthly earning)	15.45	1.24	14.49	1.30	-0.95	0.021
Observation (individuals)		31,834		13,229		
Household characteristics						
Ratio of HHs who own a farm business	0.28	0.45	0.15	0.36	-0.12	0.014
Ratio of HHs who own a non-farm business	0.38	0.49	0.28	0.45	-0.09	0.015
Log(per capita exp)	13.05	0.73	12.65	0.85	-0.40	0.023
Household size	4.35	2.02	4.77	2.00	0.41	0.065
Observation (households)		13,538		1,068		

Note: SD is Standard Deviation; SE is Standard Error of Means

Thus the IFLS suffers from considerable attrition. Although there is considerable attrition, estimates may still be robust to this problem. To explore the potential for attrition inducing biased estimates, we estimated an uncomplicated earnings-equation model using the individual data in 2000 (IFLS3) only who do not attrit in 2007 (IFLS4) compared to a sample that excludes those that eventually attrit. We estimated earnings-equation using data from 2000 (IFLS3), and we re-estimated the same model using 2000 data after dropping data for those who attrit by 2007. As we can see in Table 2.11, Column 1 is the estimation result by using all observation in the 2000 data, and Column 2 is the estimation results by using the 2000 data after dropping data for those who attrit by 2007.

Table 2.11: The earnings-equation estimates

Dependent variables: log earning	All observations (1)	Without attrition (2)
Age	0.104***	0.102***
	(0.00327)	(0.00402)
Age2	-0.00111***	-0.00109***
	(3.72e-05)	(4.43e-05)
Male	0.425***	0.460***
	(0.0261)	(0.0294)
Secondary education	0.516***	0.539***
	(0.0223)	(0.0256)
Higher education	1.271***	1.335***
	(0.0365)	(0.0423)
Height	0.0162***	0.0164***
	(0.00157)	(0.00177)
Urban	0.374***	0.376***
	(0.0210)	(0.0236)
Constant	9.467***	9.386***
	(0.384)	(0.449)
Observations	13,424	10,393
R2	0.291	0.293

Note: Standard errors in parentheses and asterisk denote statistical significance: *10%, ** 5%, *** 1%.

Table 2.11 shows the estimation results of earning-equation for testing the attrition. The results suggest that although those who drop out of the sample are different from those who remain in the sample, there is no significant effect on the regression results. As we can see, the coefficient of each variable has a similar value both with attrition and without attrition. For instance, the age coefficient with attrition is 0.104, and without attrition is 0.102. The male coefficient is 0.425 for estimation with attrition and 0.460 is for estimation without attrition. Hence, we should not worry about attrition bias in the estimation results by using IFLS data 2000 and 2007.

We also conducted a F-test to examine whether parameters of equation 1 of the data are equal to those of equation 2 on table 2.11. The null hypothesis is parameters in equation 1 are equal to parameters in equation 2. If the null hypothesis is rejected, two equations have different slopes and intercepts. With a F-statistic is equal to 0.92 and P-value equal to 0.56, we fail to reject the null hypothesis at 0.05 significance level. This means that there are no difference estimators between those two equations.

2.4. Sample Design and Response Rate of the IFLS Community and Facility Survey

For the community and facility survey, all information is about the characteristics of communities, including the facilities that are around the household. In past waves, these data had been collected only in the original 312 IFLS1 EAs or communities (9 of them are the same as other EAs that had already been interviewed and resided in the same larger community, thus making up 321 communities in total). Data was collected from the official village/township leader and a group of his/her staff were interviewed about aspects of community life; in visits to local health facilities and schools, staff representatives were interviewed about the staffing, operation and usage of their facilities, prices and the availability of appropriate equipment and supplies.

For health facilities, measures of process quality were taken; data on prices of goods were collected from three complementary sources: from a large local market, two stores or street stalls and an interview with a group of up to three knowledgeable local informants.

IFLS sampled schools and health care providers from information provided by household respondents. There were several strata of public facilities including health care and school types with the quota for each enumeration area: government health centres (3 units); private clinics and practitioners, including doctors, midwives, nurses and paramedics (5 units); community health posts (2 units), community health post for the elderly (1 unit), traditional health practitioners (2 units), community informants (2 units), primary schools (3 units), junior high schools (3 units) and senior high schools (2 units). Most of the information was gathered from the official village or township leaders and their staff and also staff representatives for health centres or health facilities and schools. Information about prices was collected from around 4 persons per village and the market was also visited to get market price information directly.

For each enumeration area lists of facilities in each strata of public facilities were constructed by gathering information provided by the household regarding the names and locations of facilities that they used or knew. For the health facility in each EA, IFLS compiled a list of facilities from household responses about the names and locations of facilities that the respondent knew about. The names and locations provided were added to the sampling frame. Household respondents did not need to have actually used a health facility for it to be relevant to the facility sample. Though someone in the household may well have used a facility that was mentioned, any facility known to the respondent was relevant. On the other hand, for the lists of schools, the sample was based on the names of candidate schools that were obtained from household responses, in which (typically) the household head verified the name and location of all schools currently attended by household members under the age of 25. Each school in the candidate list had at least one member of an IFLS household attending. Not all identified health facilities and schools were eligible for interview. A facility was excluded if it had already been interviewed in another EA, and if it was more than 45 minutes away by motorcycle. The facilities that were located in another area were eligible for interview so long it was in a reachable area (about 45 minutes away by motorcycle).

The facilities on each list were ranked by frequency of mention. These ranked lists provided frames for each stratum from which a sample of two to four facilities was drawn. In all strata, the most frequently mentioned facility was always visited. Additional facilities were randomly selected to fill the quota for that stratum. Because IFLS sampled randomly from sample frames constructed by householder knowledge of facilities in 2007, IFLS may not necessarily have re-sampled facilities that were sampled in IFLS1, 2 or 3; however, many facilities would have been the same.

Table 2.12: The Number of Community Facilities in IFLS1

Facility type	Total number of facilities	Average number of facility per EA	
		Urban	Rural
Government health centres	993	3.1	3.1
Private clinics and practitioners	1439	2.25	2.25
Elementary schools	944	1.9	1.7
Junior high schools	900	2.8	2.8
Senior high schools	584	2.9	3

Source: Frankenberg et al. (1995)

Table 2.12 presents the distribution of community facilities by facility type and the average number of facilities per enumeration area in IFLS1. For health facilities, in addition to 993 government health centres, there were also 1,439 private clinics and practitioners provided. For school facilities, IFLS1 compiled information about 944 elementary schools, 900 junior high schools and 584 senior high schools. For IFLS2, the number of community facilities is presented in Table 2.13. In total, there were an increasing number of community facilities, except government health centres. In addition, there were also new community facilities in IFLS2 and the IFLS1 community facilities that were re-interviewed in IFLS2.

Table 2.13: The Number of Community Facilities in IFLS2

Facility Type	IFLS1 CF	Re-interviewed CF IFLS1		New CF IFLS2	Total Facilities
		%	Number		
Government health centres	993	66.5	662	259	921
Private clinics and practitioners	1439	40.4	582	1249	1831
Elementary schools	944	64.9	612	351	963
Junior high schools	900	55.3	498	447	945
Senior high schools	584	44.2	258	360	618

Source: Frankenberg and Thomas (2000)

For the IFLS1 CF re-interviewed rate, government health centres have the highest percentage with 66.5%, and private clinics and practitioners have the lowest, with around 40%. This is not surprising since there are numerous private facilities, so the sampling rates are smaller, plus the yearly turnover is larger. Hence, we can also see that for new CF IFLS2, private clinics and practitioners have a larger number.

Table 2.14: The Number of Community Facilities in IFLS3

Facility Type	IFLS1 CF	IFLS1 re-interviewed		IFLS1 or IFLS2 re-inter viewed	New CF IFLS3	Total Facilities	Facilities interviewed in IFLS1, IFLS2, IFLS3 (Panel facilities)	
		%	Number				%	number
Government health centres	993	63.1	627	732	211	943	53.3	529
Private clinics and practitioners	1439	32.8	472	859	1045	1904	22.6	325
Elementary schools	944	53.4	504	641	319	960	44.3	418
Junior high schools	900	50.3	453	647	304	951	38.1	343
Senior high schools	584	33	193	284	334	618	21.6	126

Source: Strauss et al. (2004)

The number of community facilities in IFLS3 is presented in Table 2.14. There is a similar pattern for the IFLS1 re-interviewed rate, with the highest rate around 63% for government health centres, and the lowest rate at 32% for private clinics and practitioners. In addition, there is also a percentage rate for CFs that could be interviewed in IFLS1, IFLS2, and IFLS3. In comparison with the re-interviewed rate for IFLS1 CFs, the re-interviewed rates are smaller but still have a similar pattern. In total, the numbers of community facilities that were interviewed are not that different from IFLS2.

Table 2.15: The Number of Community Facilities in IFLS4

Facility Type	IFLS1 CF	IFLS1 re-interviewed		IFLS1 or IFLS2 or IFLS3 re-interviewed	new CF IFLS4	Total IFLS4	Facilities interviewed in IFLS1, IFLS2, IFLS3, IFLS4 (Panel facilities)	
		%	Number				%	Number
Government health centres	993	52.4	520	662	290	952	40.0	397
Private clinics and practitioners	1439	16.1	232	582	1013	1595	8.5	123
Elementary schools	944	40	378	518	448	966	28.4	268
Junior high schools	900	40.8	367	602	357	959	26.1	235
Senior high schools	584	27.4	160	274	359	633	12.8	75

Source: Strauss et al. (2009)

From the latest survey, Table 2.15 presents the number of facilities interviewed in IFLS4. There are community facilities from IFLS1 only that could be re-interviewed in IFLS4, community facilities from IFLS1, 2 or 3 that were re-interviewed individually in IFLS4, and panel community facilities that were interviewed in IFLS4, 3, 2 and 1. In addition, there are also new facilities that were interviewed only in IFLS4. In total, the interviewed facilities in IFLS4 number around 950 public health clinics, approximately 1,600 private health clinics and over 2,500 schools. It was the same case with the previous wave: the highest re-interviewed rate for IFLS1 CF was around 50% for government health centres, and the lowest re-interview rate was in private health facilities, at 16%.

2.5. Questionnaires

Data was collected by using questionnaires. There were separate questionnaires for individual or household questionnaires and community facility questionnaires. Individual and household questions were classified into four books, based upon the category of respondent (head of HH, spouse, child, adult). For instance, the head of HH was interviewed about the general information of the household, such as health, education, income and basic information about household members. The adult respondent questions included enquiries about marriage and fertility. Children were asked about general childhood conditions, such as health and education. In general, all instruments were to cover all information on the household level, such as consumption, income, welfare, education, migration, employment, marital status, fertility, contraception, health status, elderly health condition, utilizing health services, health insurance, transfer from and to HH, HH decision making and community participation.

In addition, community and facility questionnaires were separated in to several books, according to the type of facilities. For example, school questionnaires for school facilities, health centre questionnaires for health centres, and market price questionnaires. Overall, information on community level was about the physical condition of the area, the social condition, infrastructure, job opportunities, prices of needs, access to health facilities, access to education facilities, quality and health facility services, quality and education facility services, social activities, social security programs (2000), poverty alleviation programs (2007), decentralization and good governance (2007).

RAND collected all IFLS questionnaires together from each wave and they can be downloaded all the questionnaires from the IFLS RAND official website in the data and documentation section[4]. In addition, there is also an overview and field report of each wave, which explains all of the questions asked[5].

2.6. IFLS Data for Chapters

Based on the sample of datasets above, this study used two waves of micro data for IFLS3(2000) and IFLS4(2007), and will examine the education, health, expenditure and disasters sections. The main reason why we only use the last two waves is because those two waves provide complete information on data that are needed, especially data about disasters. Using the two latest waves of IFLS data, we constructed three different datasets in this study. The first data set is a cross-section data at the individual level, from IFLS4 only. We used IFLS4 since all data about the school operational assistance program (BOS) as a new scheme of school subsidy and its information is only provided in IFLS4. Using this data set we examined the impact of BOS on child test scores. In addition, we also used this data for analysing the impact of disasters on child test scores. The main variable used in this data set is the child test score at primary school, information about the year of test, and school subsidy. Furthermore, for disasters, we used information about people who were being affected by disasters, including the type of disasters. Table 2.16 presents descriptive statistics of all variables that are used in those studies. From table 2.16, the main variables for chapter 3 are BOS, test score and poverty index. BOS as the school subsidy program is represented by the BOS dummy variable, equal to 1 if individuals received BOS and 0 otherwise. From IFLS survey data, we determined BOS students based on self-

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[4] http://www.rand.org/labor/FLS/IFLS/download.html

[5] Frankenberg et Al. (1995); Frankenberg and Thomas (2000); Strauss et al. (2004); Strauss et al. (2009).

reported information from the survey. They reported whether they received BOS. For test score, it was obtained from the national test score that was conducted at Grade 6 (last grade at primary school). The IFLS surveyor asked whether they could show the certificate of national test score, and recorded. If they could not show the certificate, the surveyor asked and recorded the test scores if they remembered. The scale of test scores is 0 to 10.

For the poverty index, it was constructed by adding 8 poor criteria. There are 8 dummies for poor criteria, which are equal to 1 for each criterion, and 0 otherwise. The 8 criteria are: no electricity at home, less water source, no toilet, inappropriate stove, health cards, low income, landless and no house. The poverty index, therefore, ranges from 0 to 8. The 0 value means not poor, and the 8 is the poorest. In addition to poverty index, we also observed information of households who receive poor letter, since we used this information for Instrumental Variable regression as instrument for BOS. Children from poor family are eligible to get BOS by showing poor letter as evidence. Poor letter was given to the family who meet at least 1 criteria. The family is identified by using poverty indexes. Using those poverty indexes, head of village or staffs of village issued the letter, and when head of village or staffs of village are absent, the community figures usually can issue the poor letter. Head of village and staffs of village are more accountable in issuing poor letter because they should use 14 criterions from Central Bureau Statistics (BPS).

Table 2.16: Descriptive Statistics for Cross-Section Data from IFLS4

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
BOS	A dummy variable equal to 1 if individual received BOS	35944	0.030	0.17	0	1
Test score	Child test scores	7544	6.530	1.22	2.12	9.67
Poverty index	A poverty index, household with 8 value is the poorest	35944	2.420	1.27	0	8
No electricity	A dummy variable equal to 1 if household has no electricity	35944	0.330	0.47	0	1
Less water source	A dummy variable equal to 1 if household has less water	35944	0.180	0.38	0	1
No toilet	A dummy variable equal to 1 if household has no toilet	35052	0.060	0.24	0	1
Inappropriate stove	A dummy variable equal to 1 if household has inappropriate stove	35944	0.070	0.25	0	1
Healthcard	A dummy variable equal to 1 if household has a health card	34993	0.290	0.45	0	1
Low income	A dummy variable equal to 1 if household has low income	35046	0.820	0.38	0	1
Landless	A dummy variable equal to 1 if household has landless	35053	0.190	0.39	0	1
No house	A dummy variable equal to 1 if household has no house	35053	0.090	0.29	0	1
Head of village	A dummy variable equal to 1 if a head of village determined which households are categorised as poor households	35053	0.035	0.18	0	1
Staff of village	A dummy variable equal to 1 if staff of village determined which households are categorised as poor households	22274	0.029	0.16	0	1
Other of village	A dummy variable equal to 1 if other of head or staff of village determined which households are categorised as poor households	22274	0.018	0.13	0	1
Rank of HCI prov	Rank of Head Count Index at provincial level, the lowest rank is for the poorest province	35944	10.89	6.38	1	23
Java	A dummy variable equal to 1 if individual in java region	32510	0.190	0.39	0	1
D (Disaster Region)	A dummy variable equal to 1 if individual is in disaster region	42571	0.139	0.35	0	1
A (Affected by disaster)	A dummy variable equal to 1 if individual is in disaster region and affected directly by disasters	42571	0.037	0.19	0	1
Big_earthquake_region	A dummy variable equal to 1 if individual is in big earth quake region	42571	0.043	0.20	0	1

Affected_big earthquake	A dummy variable equal to 1 if individual is in big earth quake region and affected by big earth quake	42571	0.024	0.15	0	1
Small_earthquake_region	A dummy variable equal to 1 if individual is in small earth quake region	42571	0.040	0.20	0	1
Affected_small earthquake	A dummy variable equal to 1 if individual is in small earth quake region and affected by small earth quake	42571	0.006	0.08	0	1
Floods_region	A dummy variable equal to 1 if individual is in floods region	42571	0.056	0.23	0	1
Affected_floods	A dummy variable equal to 1 if individual is in floods region and affected by floods	42571	0.008	0.09	0	1
D2006	A dummy variable equal to 1 if individual in disaster region taking the test in 2006	42571	0.001	0.03	0	1
D2007	A dummy variable equal to 1 if individual in disaster region taking the test in 2007	42571	0.002	0.04	0	1
A2006	A dummy variable equal to 1 if individual in disaster region and affected by disaster taking the test in 2006	42571	0.0004	0.02	0	1
A2007	A dummy variable equal to 1 if individual in disaster region and affected by disaster taking the test in 2007	42571	0.001	0.03	0	1
Male	A dummy variable equal to 1 if male	42544	0.488	0.50	0	1
Age	Age in years	42544	27.251	19.29	0	100
Urban	A dummy variable equal to 1 if lives in urban area	42571	0.527	0.50	0	1
Household size	The size of household	42571	4.551	1.95	1	22
Primary school	A dummy variable equal to 1 if the highest education background is primary school	42571	0.370	0.48	0	1
Secondary school	A dummy variable equal to 1 if the highest education background is secondary school	42571	0.358	0.48	0	1
Higher education	A dummy variable equal to 1 if the highest education background is higher education or university	42571	0.072	0.26	0	1
Father primary	A dummy variable equal to 1 if father's highest education background is primary school	42571	0.144	0.35	0	1
Father secondary	A dummy variable equal to 1 if father's highest education background is secondary school	42571	0.151	0.36	0	1

Father higher education	A dummy variable equal to 1 if father's highest education background is higher education or university	42571	0.037	0.19	0	1
Mother primary	A dummy variable equal to 1 if mother's highest education background is primary school	42571	0.187	0.39	0	1
Mother secondary	A dummy variable equal to 1 if mother's highest education background is secondary school	42571	0.170	0.38	0	1
Mother higher education	A dummy variable equal to 1 if mother's highest education background is higher education or university	42571	0.032	0.18	0	1
Public school	A dummy variable equal to 1 if public school	10707	0.870	0.33	0	1
Wage per year (1000 Rp)	Wages or salaries per year in thousand rupiahs	23510	10,600	28,100	105	1,000
Income of father per year (1000 Rp)	Income of father per year in thousand rupiahs	30202	9,565	21,300	3	950,000
Income of mother per year (1000 Rp)	Income of mother per year in thousand rupiahs	12683	5,954	11,900	3	360,000
Household_ food exp per month (1000 Rp)	Household food expenditure per month in thousand rupiahs	33052	1,237	952	71	14,600
Household_exp per month (1000 Rp)	Household expenditure per month in thousand rupiahs	34483	1,791	1,808	46	51,900

In addition to the main variables, we also used other explanatory variables, such as a dummy head of village equal to 1 if a head of village determined which households are categorised as poor households and 0 otherwise. On the other hand, the dummy staff of a village is equal to 1 if the poor category for households was determined by the staff of a village. As the excluded category for village officer dummy, we defined other of village as the value equal to 1 if the poor category for households was not determined by the head of village or the staff of village, such as community figures, head of RT (Rukun Tetangga=a group of several households in a small neighbourhood), village midwife, NGO and other. There is also a rank of Head Count Index (HCI) for the provincial level. It measures the percentage of the population that is considered as poor or living below the poverty line. The rank is ordered from the highest percentages to the lowest one. The smaller the rank of HCI, the poorer the province is. Java dummy variable is equal to 1 if individuals reside in java and 0 otherwise.

In Chapter 4, for analysis of the impact of disasters on child test scores, there are several important variables that are presented in Table 2.16. One key variable is the disaster variable. A disaster region is defined as a region which has a bigger disaster than other regions. Neumayer and Plumper (2007) measure the strength of a disaster using the number of people killed during the disaster divided by the total population as a proxy of the strength of the disaster, but this study uses two proxies as a measure of the strength of a disaster. Besides using the percentage of number of people killed to the total population, this study also uses the percentage of the number of people evacuated from the population instead. The region which experiences disasters almost every year that affect the economy can be captured using this proxy.

For our empirical analysis, we have determined disaster regions as DI Yogyakarta, DKI Jakarta and West Sumatra. We picked those three provinces since only those three provinces are completely covered by IFLS survey data. Yogyakarta, with a big earthquake, had the highest percentage of both dead and evacuated people. In terms of the percentage of evacuated people, West Sumatra, with a small earthquake, had an above average percentage, and in terms of the percentage of dead people, although West Sumatra had a below average percentage, the value was just below DI Yogyakarta, which was quite high compared to other provinces. DKI Jakarta experienced several floods, and although the percentage of dead people was quite low, the percentage of evacuated people was above average; another strong argument was that DKI Jakarta experienced floods almost every year and always presented severe problems.

Based on disaster data information above, we define a dummy D (Disaster region) and a dummy A (being affected by disaster). D is a dummy variable equal to 1 if an individual is from a disaster region and 0 otherwise. A is a dummy variable equal to 1 if an individual is in a disaster region and is affected directly by the disaster and 0 otherwise. We created the same dummy variables for D and A for each type of disasters (big earthquake, small earthquake and floods). In addition, we also have D2006, D2007, A2006 and A2007. These are also related, with dummy variables of D and A. D2006 is equal to 1 if children in a disaster region took the test in 2006 and 0 otherwise. D2007 is for children taking the test in 2007. Furthermore, A2006 is equal to 1 if children in disaster regions and affected by a disaster took the test in 2006, and there is a similar meaning for A2007.

The second data set is panel data, which consists of IFLS3 and IFLS4 at the individual level. We used this dataset to examine the impact of disasters on child health. The main reason why we used panel data for this study is because we need data on child health before and after disasters to observe whether there is any impact from disasters. IFLS3 provides information before disaster, and IFLS4 provides information after disaster. The main variables that we use in this research are the height of a child aged 2 to 5 years old in cm, and self-reported-data on health, which reported general health condition, the previous year's health condition, the number of days in bed, and the number of days absent because of poor health. Table 2.16 shows the descriptive statistics from panel data provided by IFLS3 and IFLS4 at the individual level

Some of the important variables in Chapter 4, for the analysis of the impact of disasters on child health that are presented in Table 2.17, have been explained in the previous table. Those variables, such as A, D, and also A and D for each type of disaster have the same meaning as the previous variables in Table 2.16. Moreover, there are several important health variables which are not presented in Table 2.16, like general health, days missed, days in bed, last year's health, the water system, the garbage system, and the wet season.

Table 2.17: Descriptive Statistics for Panel Data IFLS4 and IFLS3 at Individual level

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
D (Disaster region)	A dummy variable equal to 1 if individual is in disaster region	73056	0.098	0.297	0	1
A (Affected by disaster)	A dummy variable equal to 1 if individual is in disaster region and affected directly by disasters	73056	0.025	0.156	0	1
Big_earthquake_region	A dummy variable equal to 1 if individual is in big earth quake region	73056	0.029	0.169	0	1
Affected_big earthquake	A dummy variable equal to 1 if individual is in big earth quake region and affected by big earth quake	73056	0.016	0.125	0	1
Small_earthquake_region	A dummy variable equal to 1 if individual is in small earth quake region	73056	0.022	0.148	0	1
Affected_small earthquake	A dummy variable equal to 1 if individual is in small earth quake region and affected by small earth quake	73056	0.004	0.060	0	1
Floods_region	A dummy variable equal to 1 if individual is in floods region	73056	0.040	0.196	0	1
Affected_floods	A dummy variable equal to 1 if individual is in floods region and affected by floods	73056	0.004	0.061	0	1
Height	Height of individual in cm	69790	140.922	27.157	40.00	196.50
Height of father	Height of father in cm	22549	161.316	6.460	102.80	192.60
Height of mother	Height of mother in cm	28046	150.482	5.580	102.60	193.20
General health	Rank value for the degree of general health condition, 1 is for very healthy and 4 if for unhealthy	23342	1.974	0.474	1	4
Days missed	Number of days missing regular activities because of poor health condition	23328	1.372	2.813	0	71
Days in bed	Number of days lying in bed because of poor health condition	23326	0.337	1.383	0	41
Previous year's health	Rank value for the degree of previous year's health condition, 1 is for much better now and 5 is for much worse	21993	2.541	0.762	1	5
Wet_season	A dummy variable equal to 1 if the individual was born in the wet season	73056	0.512	0.500	0	1

Male	A dummy variable equal to 1 if male	73056	0.485	0.500	0	1
Age	Age in years	73056	26.569	18.789	0	101
Urban	A dummy variable equal to 1 if lives in urban area	73056	0.525	0.499	0	1
Household_size	The size of household	73056	4.523	1.956	1	22
Household_exp per month (1000 Rp)	Household expenditure per month in thousand rupiahs	66988	1,719.155	1,752.429	25.42	51,900.00
Father primary	A dummy variable equal to 1 if father's highest education background is primary school	73056	0.139	0.346	0	1
Father secondary	A dummy variable equal to 1 if father's highest education background is secondary school	73056	0.130	0.336	0	1
Father higher education	A dummy variable equal to 1 if father's highest education background is higher education or university	73056	0.032	0.177	0	1
Mother primary	A dummy variable equal to 1 if mother's highest education background is primary school	73056	0.182	0.386	0	1
Mother secondary	A dummy variable equal to 1 if mother's highest education background is secondary school	73056	0.144	0.351	0	1
Mother higher education	A dummy variable equal to 1 if mother's highest education background is higher education or university	73056	0.026	0.159	0	1
Age in month	Age in months	46639	341.161	223.727	0	1201
Year	Year of IFLS wave	73056	2,004.076	3.452	2000	2007

For general health condition, the respondents were asked about their general health condition at the time of the survey, and the answer was designed in closed questions, which consisted of rank data: (1) very healthy, (2) somewhat healthy, (3) somewhat unhealthy and (4) unhealthy. For last's year health condition, respondents were asked about the health condition 12 months ago in comparison with the condition at the time of the survey, and the data consisted of: (1)much better now, (2) somewhat better now, (3) about the same, (4) somewhat worse, and (5) much worse. In comparison with general health condition, last's year health condition represented the child health condition that was closer to the time of disasters. As the big earthquake was occurred in May 2006, floods in January 2007, and small earthquake in March 2007, while IFLS4 survey was conducted in November 2007 to May 2008. For count values, days missed and days in bed are the total number of days missing from regular activities and lying in bed for each child due to a poor health condition in the previous 4 weeks from the time of the survey.

Moreover, at the community level, we provide information about the water supply and the garbage system in the community. Dummy water system is equal to 1 if there is a good system or supply for drinking water and dummy garbage system is equal to 1 if there is a good system for garbage disposal in the community. There is also information about the wet season. Dummy wet season is equal to 1 if the child was born in the wet season and 0 otherwise.

The third data set is the IFLS panel data formed from IFLS3 and IFLS4 at the household level. Here we obtain all variables at the household level only. We use this data set to study the impact of disasters on household expenditure and food demand.

The main data that we use are information on various household expenditure, shares of expenditure, several prices of foods for food demand estimation and also information about disasters. Table 2.18 presents the descriptive statistics of all variables.

As presented in Table 2.18, there are some important variables that are not seen in previous tables. Those variables are the main variables used in Chapter 5 for analysis of the impact of disasters on household expenditure and food demand. All price variables are both at market level and household level, and some relate to expenditure on foods. For price, there are two different types of prices according to the source of information: price at market level and price at household level. Prices at market level are obtained from community level, which is from market informants, while prices at household level are obtained from households. For food expenditures, there are three different types of food expenditure: market purchased expenditures, own produced expenditures, and total food expenditures. Market purchased expenditure is the expenditure of food from market purchases and own produced expenditure is food expenditure that is estimated from a household's own production from their farm. The sum of those two expenditures is the total food expenditure.

For all prices and expenditures, we only observed 5 types of important foods: rice, vegetable, meat, fish and oil. Furthermore, we also considered the number of household members across age categories. We classified age into 6 groups: under 6 years, 6 to 12 years old, 13 to 18 years old, 19 to 23 years old, 24 to 60 years old and over 60.

Table 2.18: Descriptive Statistics for Panel Data IFLS3 and IFLS4 at Household Level

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
Market price of:	Price of good at market level					
Rice (per kg)		20094	3,919.83	1,557.26	1,550	15,000
Vegetables (per bunch)		20094	690.19	624.61	150	8,000
Meat (per kg)		20094	40,851.04	12,989.99	13,000	70,000
Fish (per kg)		20094	11,867.62	4,452.61	900	45,000
Cooking oil (per kg)		20094	7,602.77	4,312.22	1,000	28,000
Household price of:	Price of good at household level					
Rice (per kg)		20079	3,624.43	1,678.34	715	20,000
Vegetables (per bunch)		20085	917.86	655.74	100	6,660
Meat (per kg)		20015	36,819.20	22,800.53	200	100000
Fish (per kg)		20089	12,791.89	5,906.82	1,200	92,850
Cooking oil (per kg)		20086	7,873.33	4,451.19	320	49,000
Market purchased exp per month (1000 Rp):	The expenditure of food from market purchases					
Rice		21218	89.89	149.31	0	3,900.00
Vegetables		21218	57.89	82.41	0	1,824.33
Meat		21218	63.73	128.93	0	4,255.33
Fish		21218	42.84	73.02	0	1,820.00
Cooking oil		21218	27.79	52.77	0	2,972.67
Total exp market purchases		21218	636.18	628.87	0	13,500.00
Own produced exp per month (1000 Rp):	The expenditure of food that is estimated from a household's own production from their farm					
Rice		21218	28.02	72.09	0	2,166.67
Vegetables		21218	13.98	30.12	0	654.33
Meat		21218	10.55	49.54	0	1,408.33

Fish		21218	5.64	33.66	0	2,166.67
Cooking oil		21218	1.70	10.72	0	485.33
Total exp on own prod		21218	100.33	169.71	0	2,903.33
Total food exp per month (1000 Rp):	The sum of market purchased expenditure and own produced expenditure					
Rice		21218	117.45	153.09	0	3,939.00
Vegetables		21218	71.67	88.43	0	1,945.67
Meat		21218	74.10	140.69	0	4,580.33
Fish		21218	48.32	79.25	0	2,383.33
Cooking oil		21218	29.41	54.74	0	3,189.33
Household_food		21218	758.27	707.80	0	14,600.00
Number of household members	Number of household members across age categories					
Num_under6	Under 6 years old	21218	0.50	0.68	0	5
Num_6to12	6 years old to 12 years old	21218	0.55	0.78	0	6
Num_13to18	13 years old to 18 years old	21218	0.50	0.78	0	10
Num_19to23	19 years old to 23 years old	21218	0.46	0.77	0	15
Num_24to60	24 years old to 60 years old	21218	2.55	1.57	0	13
Num_over60	Over 60 years old	21218	0.36	0.73	0	5
Year	Year of IFLS wave	21218	2,003.58	3.50	2000	2007
Urban	A dummy variable equal to 1 if lives in urban area	21218	0.51	0.50	0	1
D	A dummy variable equal to 1 if household is in disaster region	21218	0.09	0.29	0	1
A	A dummy variable equal to 1 if household is in disaster region and affected directly by disasters	21218	0.02	0.15	0	1
Big_earthquake_region	A dummy variable equal to 1 if household is in big earth quake region	21218	0.03	0.17	0	1
Affected_big earthquake	A dummy variable equal to 1 if household is in big earth quake region and affected by big earth quake	21218	0.02	0.12	0	1

Small_earthquake_region	A dummy variable equal to 1 if household is in small earth quake region	21218	0.03	0.16	0	1
Affected_small earthquake	A dummy variable equal to 1 if household is in small earth quake region and affected by small earth quake	21218	0.00	0.06	0	1
Floods_region	A dummy variable equal to 1 if household is in floods region	21218	0.04	0.19	0	1
Affected_floods	A dummy variable equal to 1 if household is in floods region and affected by floods	21218	0.00	0.07	0	1
Educational exp (1000 Rp)	Educational expenditure per month in thousand rupiahs	12383	177.47	310.76	0.01	4,241.67
Hhexp per month (1000 Rp)	Household expenditure per month in thousand rupiahs	20791	1,451.96	1,574.08	15,833.33	51,900.00
Wage per year (1000 Rp)	Wages or salaries per year in thousand rupiahs	17380	8,270.51	17,749.72	102.00	1,000,000.00
Cpi	Consumer Price Index	21058	1.16	0.36	0.748	1.62
Father primary	A dummy variable equal to 1 if father's highest education background is primary school	21218	0.01	0.07	0	1
Father secondary	A dummy variable equal to 1 if father's highest education background is secondary school	21218	0.01	0.11	0	1
Father higher education	A dummy variable equal to 1 if father's highest education background is higher education or university	21218	0.00	0.03	0	1
Mother primary	A dummy variable equal to 1 if mother's highest education background is primary school	21218	0.00	0.05	0	1
Mother secondary	A dummy variable equal to 1 if mother's highest education background is secondary school	21218	0.00	0.01	0	1
Mother higher education	A dummy variable equal to 1 if mother's highest education background is higher education or university	21218	0.00	0.01	0	1
Household_size	Household size	21058	4.91	1.96	1	22

2.7. Relevant IFLS Papers

This section briefly discusses selected literatures which use IFLS data that are relevant to this study but all these studies are different in methodology and focus. A considerable amount of literature that has used IFLS data in their work has been published in recent years. With regard to the disasters study, Brown and Wong (2011) investigated the link between poverty and vulnerability with respect to disasters from forest fires. Using panel data of IFLS, they used a utility model to estimate both the households' vulnerability in total and their food consumption. In addition, they used OLS to estimate the effect of forest fires on vulnerability. The results confirmed that households with a high degree of exposure to smoke from the fires were more vulnerable in total consumption than households with lower exposure, but they were no more vulnerable in food consumption. In comparison with our study, this study only considered forest fires, while our study used several types of disasters.

Pangaribowo and Tsegal (2011) is similar to our study on food demand. They studied demand for food in Indonesian households by using 3 waves of IFLS data (IFLS2, IFLS3 and IFLS4). Using Quadratic Almost Ideal Demand System, they observed the food expenditure patterns across income groups and regional differences. The results showed that the poorest households' expenditure was dominated by staple food expenditure, while the richest households' expenditure was on vegetables, fish and meat. Most of the food price elasticities were found to be elastic, except staple food and oil. In comparison with our study, the methodology that we employed was different. We used Linear Approximate Almost Ideal Demand System (LA-AIDS), but the results are similar with the results in our study.

Gill and Satriawan (2010) examined the impact of a supplemental feeding program (*Program Makanan Tambahan-PMT)* on child nutritional status in the aftermath of the financial crisis from 1998 to 2000. Using two round panel data of Indonesia Family Life Surveys (IFLS2 and IFLS3) which covered the condition pre- and post-crisis, they observed the nutritional status of young children at age 12 to 24 months at the time of the survey in 2000. By employing difference in differences methods, they measured the impact of the program on the treatment group (children with the PMT program). The results confirmed that the program had a significant impact on children in a group aged 12 to 24 months at the time of the survey but no effect on children younger or older than this group.

Another interesting study on the impact of disasters on consumption and expenditure was conducted by Cameron and Worswick (2001). They studied the impact of crop loss due to weather shocks and drought on household education expenditure in Indonesia. This research is interesting since they analyse whether households could cope with their consumption during hard times by defining permanent income and transitory income. They only focus on educational expenditure to avoid the measurement error of total expenditure because the non-food expenditure is not well recorded. Cameron and Worswick (2001) designed a model of educational expenditure in response to crop loss to investigate whether households are able to smooth consumption or not in the time of crop loss. The finding from this study shows that households were not able to smooth consumption during the time of crop loss so they were most likely to reduce educational expenditure, especially for girls.

Newhouse and Beegle (2005) studied the effect of school type on the academic achievement of junior high school students in Indonesia. Using 3 waves of IFLS data (IFLS1, IFLS2 and IFLS3), they estimated using OLS, fixed-effects and instrumental variable estimation and found that students who graduate from public junior secondary schools, controlling for a variety of other characteristics, score 0.15 to 0.3 standard deviations higher on the national exit exam than comparable privately-schooled peers. In addition, the results also provide indirect evidence that higher quality inputs at public junior secondary schools promote higher test scores.

Borghans, Dupuy, and Wu (2008 examine the educational expenditure in response to an aggregate shock (Asian financial crisis) to human capital investment behaviour. They defined human capital investment as parents' decisions over the financing of their children's education and the types of school that the children attend, such as formal or informal, religious or non-religious school. The results show that when the cost of education rose disproportionately, then consumption levels changed and caused education expenditure to fall. In such circumstance, some children were still able to receive some education, which could be formal or informal, but there are still questions about whether parents from different income levels were still able to maintain the educational quality attained by their children. Using a national evaluation test score - EBTANAS (Evaluasi Belajar Tahap Akhir Nasional) - national achievement test scores for a measure for educational outcome, they found that the Asian financial crisis caused some children to self-select themselves out of transition to drop out of education, despite passing their tests.

Another interesting study on education was conducted by Thomas et al. (2004), which discussed the effect of the financial crisis in 1998 on education and also looked at the relation between education and household expenditure at the time after the crisis. Using two waves of IFLS data (IFLS1, IFLS2 and IFLS2+), they assessed the impact of the crisis by estimating Engle curve for educational expenditure in measuring the change in real education expenditure and linear regression. The results showed that on average household spending on education declined, most dramatically among the poorest households. Spending reductions were particularly marked in poor households with more young children, while there was a tendency to protect education spending in poor households with older children. In addition, they found that the school enrolments decreased most for young children and those from the poorest households. In urban areas, young children from low-resource households in 1997 were less likely to be enrolled in school in 1998 if they had older siblings living in the household, and on the other hand, older children in these households were more likely to be in school if they had younger siblings.

Chapter 3

The Impact of the School Operational Assistance Program (BOS) on Child Test Scores in Indonesia: An Evaluation Using Matching Method

3.1. Introduction

Investment in human capital, especially in child education, is considered to be among the most effective ways for countries to improve their national welfare and reduce poverty in the long term. Becker (1964) pointed out that investment in human capital raises earnings in later life. Undoubtedly, promoting educational attainment can raise living standards on average and contribute to the reduction in absolute poverty by enabling individuals to generate income and access better-paid jobs. Many governments in developing countries have made this issue one of this top national priority by ensuring that the national budget allocation to education is increased. Many governments have promoted human capital investment, especially on children, by designing subsidy programs such as PROGRESA (Programa de Educación, Salud y Alimentación) in Mexico, PRAF (Programa de Asignación Familiar) in Honduras, PETI (Programa de Erradicaçao do Trabalho Infantil) in Brazil, FA (Familias en Acción) in Colombia, and BOS (Bantuan Operasional Sekolah) in Indonesia. School Operational Assistance, or BOS in Indonesia, started in 2005 and has been the biggest school subsidy program in Indonesia during the last two decades. An important issue addressed in this chapter is to evaluate the impact of BOS on student performance at primary school, especially in improving the quality of education as measured the child test scores.

This chapter contributes to the international literature in several aspects. First, compared to other literature, this study uses survey data with self-reported information on whether children get a school subsidy from the government. This allows us to estimate the impact of the treatment rather than the intention to treat (people eligibility). Second, this study examines the impact of school subsidies on a measure of school quality, test scores, while most of the earlier studies looked at the impact of school subsidies on a quantity measure of schooling, such as school enrolment or dropping out. Third, the BOS program is an example of a specific school subsidy program to support basic education in Indonesia. The subsidy for each student who is eligible is distributed to the school directly and is managed by the school for operational expenses so that the students will be free from all kinds of fees during their schooling. The students only receive a small amount of money for their transportation allowance. An evaluation of this school subsidy policy is important to inform whether this kind of policy is appropriate to adopt in other countries.

According to the World Bank, Indonesia has a relatively low percentage, at 3%, of GDP allocated to education, or about 13% of public expenditure[6]. It is relatively low if we compare it with developed countries such as Denmark, which has the highest percentage of public spending on education at 8% of GDP, or around 30% of public expenditure. Moreover, based on the poverty line definition of the Central Bureau of Statistics of RP 182,636.00, or US$20 per person per month, Indonesia - with a population of 235 million - still had approximately 30 million people, or around 13 per cent , living in poverty in 2010. However, according to the World Bank poverty definition of US$2 per person per day, Indonesia has 116 million people (49%) who

[6] Source of data: The World Bank (2010), http://data.worldbank.org

live in poverty. The Government of Indonesia realizes that such extreme poverty implies that income is usually only just sufficient for subsistence and not sufficient to finance schooling; therefore the government has to consider its policies regarding financing education.

As a part of financing education, the Government of Indonesia has designed several school subsidy programs especially to support basic education in the last two decades, such as the JPS (Jaring Pengaman Sosial) scholarship program, the BKM (Bantuan Khusus Murid) program, and the BOS (Bantuan Operasional Sekolah) program[7]. The BOS program is the most recent school subsidy program with the biggest allocation of national budget. The main purpose of the BOS program is to support 9 years of basic education in Indonesia so that all poor children can get access to basic education free of charge. In 2005, when BOS was launched, it was only allocated to poor students who met certain criteria, so those children were entitled to get free education. In 2009, BOS was allocated to each school based on the total number of students, so all students at primary and junior high school were free from school fees, although well-off students still paid some school operational costs, such as extracurricular, enrichment or other student activities.

This study uses three different methods: Ordinary Least Square (OLS), Instrumental Variable (IV) and Propensity Score Matching (PSM) estimation. OLS is used as a conventional method and estimates the effect of school subsidy on average by assuming that BOS is exogenous, while IV estimation is used to deal with endogeneity of BOS and also correct for selection bias based on unobservable characteristics. In

[7] Further discussion about school subsidy policies reform in Indonesia is in Section 3 of this chapter.

addition, IV estimates the effect of the treatment on those individuals whose behaviour is affected by treatment. That is, IV estimation provides an estimate of the causal effect for those individuals who change the treatment status because of the instrument. Moreover, PSM is used to estimate the average treatment effect in the absence of selection on unobserved characteristics.

Our main finding is that the BOS program has a positive and significant effect on child test scores. Students who receive subsidies on average raise their test score. OLS estimation suggested that test scores can be raised by 0.358 points, and IV estimation resulted in a bigger value by 3.3 points. Furthermore, PSM also suggested that the BOS program in Indonesia increased test scores by 0.26 points. In comparison with other estimation, IV estimation resulted in a bigger value. It is because of the local average treatment effect when the instruments generated the treatment effects exceeded those generated from OLS and PSM estimations. Overall, in the early program, BOS successfully improved average student performance. Yet, when the analysis was broken down by student type we found evidence that, BOS does not help very poor students, but does help less poor students. All of our work is conditional on being at school to take the test. We envisage that the mechanism by which BOS affect test scores is through encouraging attendance up to age 11 at least.

This chapter is organized as follows. The next section discusses a review of the literature on the effects of school subsidies on schooling. The third section outlines the school subsidy reforms in Indonesia and is followed by students' and BOS description. The fifth section presents data sources and is followed by methodology. The seventh section discusses the finding on child test scores and evaluates the estimation results. The last section concludes with policy recommendations.

3.2. Literature Review

This section reviews the previous school subsidy studies using micro data. Many countries use conditional cash transfers (CCT) as the type of subsidy. CCT is a type of subsidy by giving money to the poor in return for fulfilling specific behavioural conditions. The conditions are made to minimize the failures from the aim of subsidy while transferring money to the poor. Janvry and Sadaulet (2006) underlined that CCT can assist the use of subsidy more efficient if we implement three rules. The first is a rule to select the poor. The second is eligibility among the poor and the last one is calibration of transfers, particularly if budgets are insufficient to offer large universal transfers to all the poor. Conditionality is used to try to ensure that the subsidy has the desired effect such as in increasing school enrolment, decreasing school dropout rate, or increasing student performance. In addition to the type of subsidy, the methods that the previous studies used are also varies. Some studies use randomized experiments, and other studies implement different methods, such as instrumental variable regression, propensity score matching, or linear parametric regression. The literatures are reviewed separately for developed and developing countries.

3.2.1. Developed Country Studies

A considerable number of studies have focused their attention on school subsidies in developed countries. The US study for New York City (NYC), was conducted by Riccio et al. (2010). The program, known as Opportunity NYC, is a conditional cash transfer program for poor families. The recipients should use the subsidy for developing children's education or other activities related with developing human capital. The finding showed that there was no effect on some educational outcomes, such as educational achievement, for primary and secondary school students.

In the United Kingdom, Dearden et al. (2005) examined the effect of conditional cash transfer paid to children aged 16-18 in full-time education on school dropouts in the UK in 1999. The Education Maintenance Allowance (EMA) program was targeted at students who completed the last year of compulsory education in Year 11 in summer 1999. This program was introduced to subsidize children to remain in school for up to two years beyond the statutory age in the UK (Dearden et al., 2005). By using Kernel-based propensity score matching, a multinomial probit and a linear regression model, they estimated the impact of the program on school dropouts. Dearden et al. (2005) confirmed that EMA had a positive and significant impact on school participation.

In 1986, the government of Australia introduced the school subsidy program, AUSTUDY, to increase school participation in higher education and reduce youth unemployment. Dearden and Heath (1999) estimated the impact of AUSTUDY on the probability of completing the final two years of secondary school. They used instrumental variables, where the eligibility for AUSTUDY was used as an instrument for AUSTUDY receipt. They found that the AUSTUDY program had been successful in increasing school participation by approximately 3%, especially for those who were from poor family backgrounds.

3.2.2. Developing Country Studies

The most influential study of school subsidy program in developing countries was the study on the Mexican PROGRESA poverty program by Behrman and Todd (1999). PROGRESA was created in 1997 to provide a conditional cash grant and to support education, health and nutrition for rural poor families in Mexico, especially for children and their mothers. In the case of educational grants, the recipients had to meet some requirements that were designed by the Federal government, such as maintaining school attendance for children at 85% and above. Behrman and Todd (1999) tried to evaluate the impact of PROGRESA on education for poor families in the initial stages by using a randomized social experiment. This approach was used to ensure the similarity of characteristics in both observables and unobservables between the treatment and control areas. Treatment was randomly assigned at the local level, not at the household level to ensure that the control was not contaminated. In general they found that there was no difference between treatment and control area means.

Using the same data that was used by Behrman and Todd (1999), Schultz (2004) re-examined the effect of the PROGRESA school subsidy on school enrolment in Mexico. He also used a randomized design to analyse the data and this was followed by two steps analysis. Firstly, he used difference in differences between the treatment and control groups to see the impact of subsidy on school enrolment. Secondly, probit model was adopted to estimate the effect on the probability of being enrolled in school. The determinants of school enrolment include the household characteristics, such as the years of schooling completed by father and mother, the eligibility of children (from the poor family), the area of living where the PROGRESA was implemented, the distance to the nearest school and the school and community characteristics. Schultz found that there was a significant difference in school enrolment between the areas where PROGRESA was implemented and where it was not.

Nicaragua created a similar conditional cash transfer program in 2000, Red de Proteccion Social (RPS), modelled on the PROGRESA conditional cash transfer program. This program was targeted at poor households and conditioned the cash transfer on school attendance and health service. Maluccio and Flores (2005) conducted an evaluation of that area level using the evaluation design based on a randomized, community-based intervention with measurements before and after the intervention in both treatment and control communities. They selected 42 randomly administrative areas into the program. Each administrative area had around 100 households. 21 areas were for treatment areas and 21 areas were for control areas. They found that RPS successfully increased the net school enrolment by 12.8% on average and decreased the number of working children by 5.6%.

Honduras is another country with a similar cash transfer program, along with Mexico, Ecuador and Nicaragua. Glewwe and Olinto (2004) evaluated the impact of the conditional cash transfer program (Program de Asignacion Familiar, PRAF) on schooling. They used demand and supply side methods to examine the program. The demand side was the approach when the household received the cash transfer conditional on school attendance of the children while the supply side was the approach when the assistance goes to the school directly. Glewwe and Olinto (2004) confirmed that the demand side approach is more effective than the supply side, increasing the school enrolment by 1-2% and reducing the drop-out rate by 2-3%.

In a more recent study in Ecuador, another developing country in Latin America, Schady and Araujo (2008) examined the impact of conditional cash transfers on school enrolment. The cash transfer program, the Bono de Desarrollo Humano (BDH), was a huge program from 2004 with a total budget of approximately 0.7 percent of the Gross Domestic Product of Ecuador and was targeted at poor families with children aged 6-17. It was evaluated using a reduced form regression, where the dependent variable was a dummy variable of school enrolment as a function of child and household characteristics and dummy variable of BDH that takes value 1 if the household received the cash transfer. They found that the probability that the child was enrolled in school increased by 3.2% to 4% when the household received the cash transfer.

Attanasio, Fitzsimons and Gomez (2005), in a study of the impact of the conditional cash programme in Colombia, Familias en Action (FA), on school enrolment, found that a monthly subsidy for education paid to eligible mothers whose children attended school was an effective programme to increase school enrolment, both in urban and rural areas. They used average information of the school enrolment in the treatment group either with or without program and the control group then estimated the counterfactual for the treatment group without the programme. Estimation was by linear regression because of its greater efficiency. They confirmed that the program increased school enrolment both in urban and rural areas.

Pakistan has a further example of a school subsidy programme in developing countries. In this case, the transfer is made to the school. Kim, Alderman and Orazem (1999) studied the impact of this school subsidy, the Urban Fellowship Program, on school enrolment, particularly for poor girls. This study observed that in Pakistan there is a culture which prevents girls from going to school. To overcome this problem, the government of Pakistan introduced private schools for girls to increase girls' enrolment, especially in poor regions. These private schools are supported by the government and receive school subsidies which are allocated to the poor girls' tuition fees. They define the treatment group as the households which reside in the region where a girls' private school is created, while the control group is the households which reside outside the program's region. They found that the girls' school subsidy can increase the enrolment rate, not only for girls but also for boys. This result suggests that girls' education is complementary with boys' education.

India provides subsidies for school meals. Afridi (2010) evaluated the impact of school meals on school participation in rural India. This study used school panel data and household data which was estimated by difference-in-differences. Afridi (2010) estimated two different models. The first model was for both public and private schools while the second was only for public schools. All models confirmed that there was a negative and insignificant effect of school meals subsidy on school enrolment. Furthermore, the school meals subsidy program had a significant impact on the daily attendance decision. There was a larger and significant increase in girls' attendance in the lower grades, but an insignificant effect for boys of lower grades. This was because the cash value of the school meals subsidy was relatively larger for lower grade students, and encouraged the parents to send their children to school more regularly, especially girls in lower grades. As a result, this program was found to reduce gender disparity in education.

There have been some empirical studies on Indonesian earlier school subsidies. The most famous study was conducted by Duflo (2001), which examined a school subsidy by Indonesia's government for the school construction programme. Between 1973/1974 and 1978/1979, 61,807 new schools were constructed and it spent over 500 million USD, calculated using the 1990 exchange rate. The World Bank (1990) observed that it was the fastest primary school construction program ever undertaken in the world. The research suggested that an investment in infrastructure causes a rise in school enrolment and educational attainment. An increase in educational attainment caused an increase in earnings. Another school subsidy study was conducted by Sparrow (2007). He evaluated the impact of the social safety net in education (Jaring Pengaman Sosial, JPS) on school enrolment after Indonesia was hit by the financial crisis in 1997/1998. Using instrumental variable regression, he confirmed that the JPS program was an effective policy for protecting the education of the poor, especially for those who were most vulnerable to the effects of the crisis. This program was found to increase school attendance by 1.2% for children aged 10-12 and 1.8% for children aged 13-15.

Table 3.1 shows the impact of school subsidy in various countries as a percentage of a standard deviation in the dependent variable. It shows the estimated effect of school subsidies on enrolment rate, dropout rate or test score in various selected countries. The highest impact of the program was found in Pakistan, where the school subsidy program was estimated increase the outcome by 68 % of SD while the US gave the lowest impact of only 1.87% of SD. Compared to other studies, the effect of school subsidy on student performance in this chapter is quite large at 21.3%.

Table 3.1: The effect of school subsidies in various countries

Study	Country	Marginal effect	Prop of SD	Dependent variable
Dearden and Heath (1999)	Australia	0.038	7.70%	enrolment rate
Dearden et al. (2005)	UK	0.045	7.20%	dropout rate
McPherson and Schapiro (1991)	US	0.0086	1.87%	enrolment rate
Schultz (2004)	Mexico			
	Female	0.0092	4%	enrolment rate
	Male	0.008	3%	enrolment rate
Schady and Araujo (2004)	Ecuador	0.032	7.60%	enrolment rate
Afridi (2010)	India			
	Girls 1st grade	1.768	5.50%	enrolment rate
Kim, Alderman and Orazem (1999)	Pakistan	0.33	68%	enrolment rate
Glewwe and Olinto (2004)	Honduras	0.02	2.20%	enrolment rate
Maluccio and Flores (2005)	Nicaragua	0.128	19.39%	enrolment rate
Sparrow (2007)	Indonesia	0.008	2.60%	enrolment rate
Duflo (2001)	Indonesia	0.03	17.60%	dropout rate
This study (2012)	Indonesia	0.26	21.3%	test score

Note: SD=Standard Deviation

3.3. School Subsidy Policies Reform in Indonesia

This section outlines the school subsidy programs in Indonesia since 1970. The Government of Indonesia has paid more attention to education since Independence Day in 1945 by making education one of the national constitution objectives. For a country whose population structure has a huge proportion of young people, the most important national concern in education is how to provide basic education. In 1994, the basic education policy changed from a focus on children aged 6-12 in the old policy to a new focus on children aged 6-15, especially from poor families. Based on the population survey in 2005, the number of children of school age is approximately 20%, out of 235 million people.

In the President Soeharto era, a huge amount of money was allocated to the primary school construction project, the program that was named the SD Inpres Project. More than 61,000 primary schools were constructed between 1973/1974 and 1978/1979 throughout the country and according to Duflo (2001), the budget was over 500 million USD at 1990 exchange rates. The whole budget was funded by the oil boom revenue from 1973 to 1980. Based on the Presidential instruction, each school was given a target to enrol approximately 120 students with 3 teachers, and the local governments and society had a responsibility to provide additional school subsidies if there was insufficient funding for implementation.

In 1998, after Indonesia was hit by the Asian economic crisis, the school subsidy began to be used as an important policy. At this time, the school subsidy was a part of the social safety net program, which was known as the JPS (Jaring Pengaman Sosial) program. JPS was very useful in assisting the families who suffered from the crisis, especially in supporting education expenditure. JPS in education was allocated to two types of school subsidies: scholarships for students and block grants for schools. Scholarships were distributed to the students directly while block grant was distributed to the school. Sparrow (2006) pointed out that the JPS program appeared to fully support poor families in supporting household expenditure while the block grant, Dana Bantuan Operasional (DBO), was intended to keep the school operating during the crisis. Both subsidies were distributed as cash transfers to the students and schools.

The JPS subsidy covered 6% of students in primary school, 17% of students in junior high school and 10% in senior high school, and the amount of money per student per annum was RP 120,000 or equivalent to $12 for primary school, RP 240,000 ($24) for junior high school and RP 300,000 ($30) for senior high school. The students who were eligible to get the scholarships were: (1) students from poor families; (2) students at grades 4, 5 and 6 for primary school and all levels for junior and senior high schools; (3) dropped-out students or students vulnerable to dropping out for economic reasons. The government used data from the National Family Planning Coordinating Agency (Badan Koordinasi Keluarga Berencana Nasional, BKKBN) for selecting the students who were eligible to get subsidies. According to BKKBN standards, there are five categories of family prosperity level: Pre-prosperous Families, Prosperous I, Prosperous II, Prosperous III and Prosperous III Plus. The school subsidies were distributed to the two lowest BKKBN household levels (Pre-Prosperous and Prosperous I). All the funds for the 5-year program (1998-2003) were from the Government of Indonesia, the World Bank and the Asian Development Bank.

In 2001, the Government of Indonesia decided to reduce the fuel subsidy and allocated the funds to education, health and infrastructure instead. The purpose of distributing the funds to these three sectors was: to accelerate the 9-year compulsory basic education program; to secure health services for the poor; and to develop village infrastructures, particularly for remote and poor villages. With respect to the education goal, the Government of Indonesia used the funds to add more scholarships for poor students and block grants for the schools. This school subsidy, which was known as Special Assistance for Students (Bantuan Khusus Murid, BKM), was distributed to the students as a cash transfer and covered 20% of all students in primary school, junior high school and senior high school. Expenditure was the same as the JPS scholarship program while the block grants for the school, which were known as Special Assistance to

School (Bantuan Khusus Sekolah, BKS), were bigger than DBO in the JPS program. The BKM and BKS programs lasted 4 years, from 2001 to 2004.

In July 2005, The BKM and BKS were superceded by the School Operational Assistance Program (Bantuan Operasional Sekolah, BOS). This program was still part of the Fuel Subsidy Compensation Program but the concept of BOS was slightly different from the previous subsidy programs. BOS was designed to support poor students with free access to basic education and to reduce the financial burdens on the rest of the students. In 2005, all poor students had priority to receive BOS so that they could go to school without paying any fees, while wealthier students still had to pay some fees but not as much as if there were no BOS program. The idea of the BOS program was, as its acronym School Operational Assistance, suggest to support each school in financing their operational costs, such as textbook procurement, school exams, general and daily tests, consumables procurement (notebooks, chalks, pencils, lab materials, etc.), stationery, maintenance costs, electricity and telephone costs, student activities costs (remedial, extracurricular). Thus, for financing the operational costs, each school received funds from the government and same wealthier students, who still had to pay some fees. The amounts of the subsidies were RP 235,000 per student per annum for primary school and RP 325,000 for junior high school. The subsidies were distributed every 3 months (January-March, April-June, July-September and October-December).

In 2009, the BOS policy was changed. BOS was now allocated for all students (poor and rich students) who were registered at primary and secondary schools. To simplify the distribution, BOS was sent to schools directly and distributed to each school based on the total number of students. Thus, the main purpose of the BOS program 2009 was to ensure that all school-age children could go to school without paying any school operational costs and this was the difference between the BOS program 2009 and the BOS program 2005. In addition, for the BOS program 2009, poor students got an additional assistance for transportation and a uniform allowance. Moreover, in 2009, the government changed the objective of the BOS program. The previous goal was only to accelerate the 9-year basic education programme and a new goal was added - to increase the quality of basic education. The amount of money was also increased to RP 400,000 per student per annum for primary schools and RP 575,000 for junior high schools per annum.

The poor students got free access to basic education and were also eligible to receive the transport and uniform allowances. This was determined by the school committee and their poor status had to be proved by a letter from the village head. The school committee consisted of the teachers, school principal and same parents or guardians of the students. To guarantee that the poor students could go to school without paying any cost, both in public and private schools, the central government set up monitoring teams which consisted of representatives of central, provincial and local government to control the implementation of the BOS program.

Table 3.2 shows a summary of the amount of assistance for each school subsidy program in Indonesia for basic education after the primary school construction project in the 1970s (SD Inpres program), from 1998 until now. There are three big programs which support basic education system in Indonesia. All of them have the goal of increasing net enrolment in primary and junior high school.

Table 3.2: The Amount of School Subsidies

No	Program	Year	Unit	Nominal value (Rupiah)		Real value (Rupiah) (2007=100)	
				Primary School	Junior High School	Primary School	Junior High School
1	JPS Scholarship*	1998-2003	per poor student per annum	120,000	240,000	240,712.07	481,424.15
	JPS Block grant	1998-2003	per school per month	2,000,000	4,000,000	4,011,867.90	8,023,735.81
2	BKM Scholarship*	2001-2004	per poor student per annum	120,000	240,000	191,748.45	383,496.89
	BKM Block Grant	2001-2004	per school per semester	40,000,000	50,000,000	63,916,148.72	79,895,185.90
3	BOS**	2005-2009	per poor student per annum	235,000	325,000	260,443.26	360,187.49
		2009-now	per student for all students per annum	400,000	575,000	341,792.70	490,472.53

Note:*Given directly to the student, **given to schools on the basis of the number of students
1 USD=RP 10,000; Source: SMERU (2006)

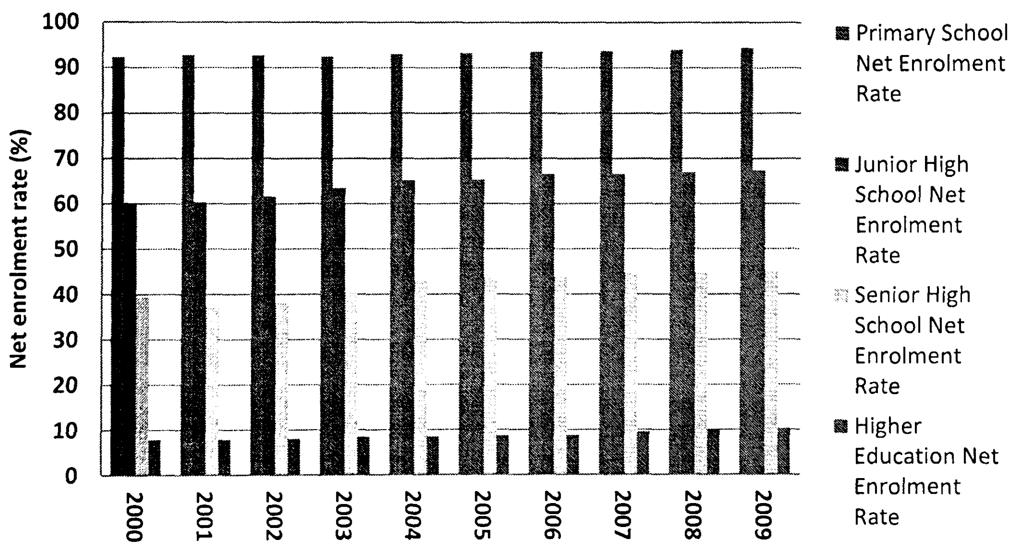
Even though the nominal value of BKM scholarship per student per annum is the same as the JPS scholarship, the real value is lower than the previous program. For instance, the real value of the JPS scholarship program for primary school students per student per annum in 2007 rupiah was RP 240,712 while the BKM scholarship program per student per annum was RP 191,748. On the other hand, for the first BOS program in 2005-2009 the real value of the scholarship is a little higher than the previous ones, but it increased significantly after 2009. Besides all the assistance for the students, there are block grants for schools in the JPS and BKM programs, but not for the BOS program, since the BOS funds were given to the schools based on the number of students in each school for all operational expenses.

3.4. Profile of Students and BOS at Basic Education in Indonesia

The 9 year basic education goes from primary school to junior high school and these levels of schooling are a compulsory part of the structure of education in Indonesia. There are 6 main levels of schooling in Indonesia, from play group to university. First, play group, is normally for children aged between 3-4 years. Second, kindergarten, is usually for children aged between 5-6 years. Neither of these first two levels of schooling is compulsory. Third, primary school, is a 6-year basic education. Fourth, junior high school, is a 3-year basic education. Both primary school and junior high school are compulsory and are known as 9-year basic education for children aged 7 to 15 years. Fifth, senior high school, is three years of schooling after 9-year basic education and is not compulsory. Lastly, higher education is from undergraduate to post graduate programs.

The main goal of the 9-year basic education program and the BOS program is, therefore, to ensure that all Indonesian citizens attain the junior high school level free of charge. Currently, the net enrolment rate of junior high school in Indonesia is approximately 70%. By implementing the BOS program, the Goverment of Indonesia has set a target to achieve approximately 100% of junior high school gross enrolment rate or approximately 80% for the net enrolment rate[8]. Figure 3.1 represents the net enrolment rate in each level of education from 2000 to 2009.

Figure 3.1: Net Enrolment Rate on Each Level of Schooling from 2000 to 2009



Source of data: Central Bureau of Statistics Indonesia (Badan Pusat Statistics, BPS)

[8] Gross enrolment rate is calculated from the total number of students at primary school and also students at non-formal education equal to primary school level (could be elderly who enrol in non-formal education equal to primary school level) divided by the total number of people in that age of schooling and multiplied by 100%.

Net enrolment rate is calculated from the total number of students at primary school age (only those who enrol in formal education at primary school) divided by the total number of people in that age of schooling and multiplied by 100%.

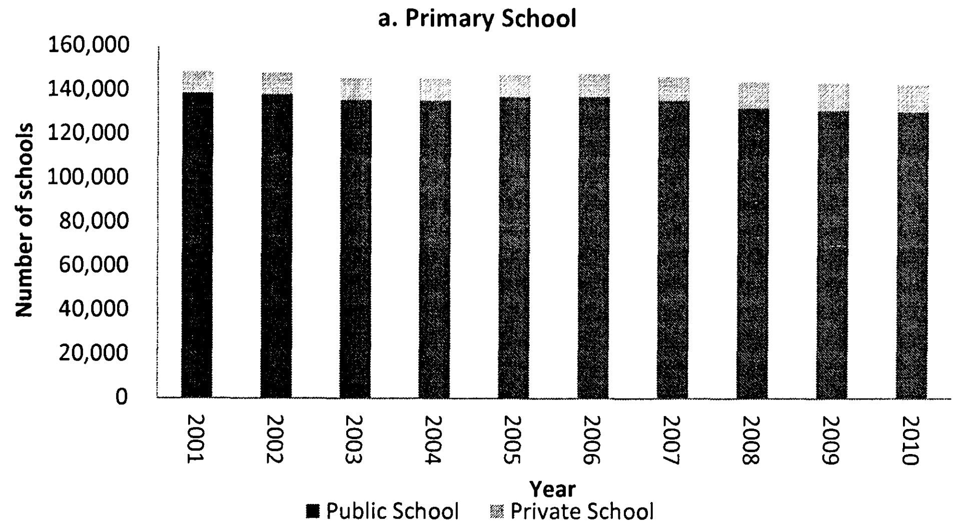
Gross enrolment rate could be more than 100% because there are students who are outside the official school age, for instance 25-year-olds who went to primary school. The same way is used to calculate the junior high school gross and net enrolment rates.

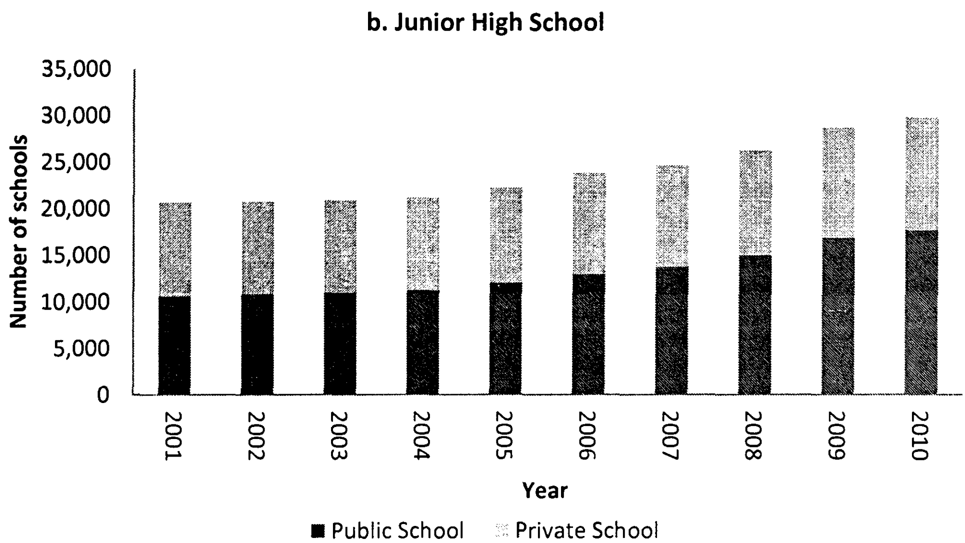
The figure shows that the highest net enrolment rate in Indonesia in 2009 is primary school at around 95%, followed by junior high school at approximately 70%. The net enrolment rate of senior high school is around 45% and the lowest one is university enrolment rate, which is approximately 10%. The figure shows a significant increase in the net enrolment rate at junior high school and senior high school level in Indonesia from 2000 to 2009 but only a slight increase for primary school and higher education net enrolment rate.

To achieve the net enrolment target, the Government of Indonesia has increased the number of junior high schools significantly. Figure 3.2 demonstrates the number of schools at primary school and junior high school levels from 2001 to 2010. There has been a significant rise in the number of junior high schools, both public and private, and a slight decrease in the number of primary schools in Indonesia from 2000 to 2010.

The number of primary public schools is approximately 140,000 schools, which is large compared to private schools, which number only around 10,000 schools. The number of schools decreased slightly for both public and private during this period. On the other hand, the number of junior high schools increased gradually, especially the public schools. In 2001 the number of public and private schools were similar with around 10,000 schools, but by the end of 2010 the numbers of public schools had risen significantly to approximately 18.000 schools, while the numbers of private schools increased slowly to 12,000 schools (see figure 3.2).

Figure 3.2: The Number of Schools for Primary and Junior High School Levels

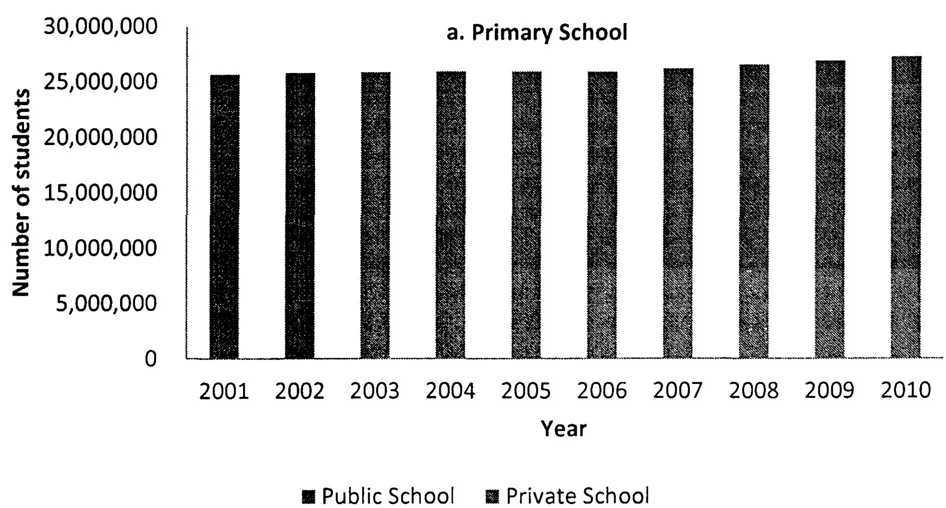


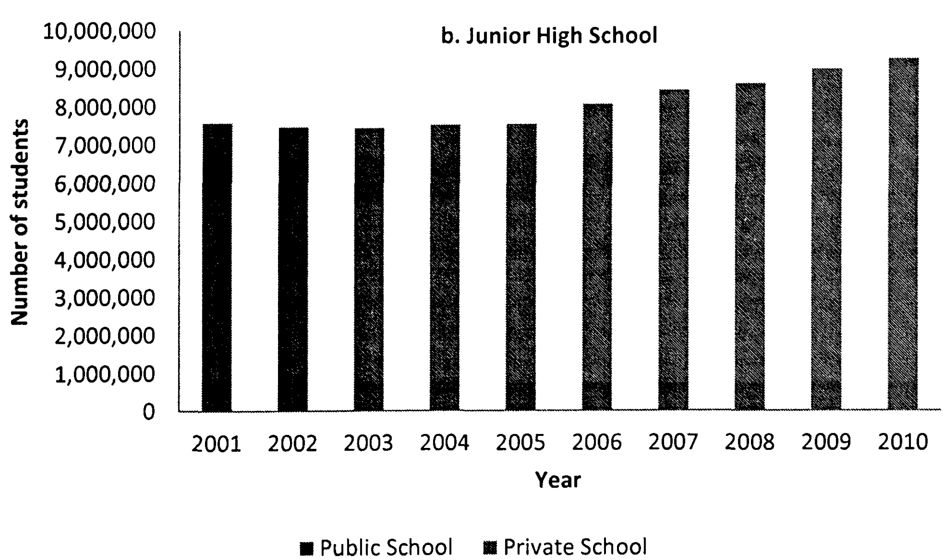


Source of data: Central Bureau Statistics of Indonesia (Badan Pusat Statistics, BPS)

In addition, the trend in the number of students at primary schools shows a slight increase while the trend in the number at primary schools shows a small decrease during the last 10 years, both in public and private schools. According to the education data base from the directorate general for basic education in Indonesia, all students could be enrolled in primary schools by increasing the number of classrooms and classes in existing primary schools. For example, nationally in 2007 the number of classes was 974,412 and the number of classrooms was 891,594, then in 2009 the number of classes was increased to 1,009,232 and the number of classrooms was 899,016. However, the trend in the number of junior high school students has shown a significant increase since 2005, especially for public schools (figure 3.3). This reflects the government's commitment to provide a 9-year basic education.

Figure 3.3: The Number of Primary and Junior High School Students

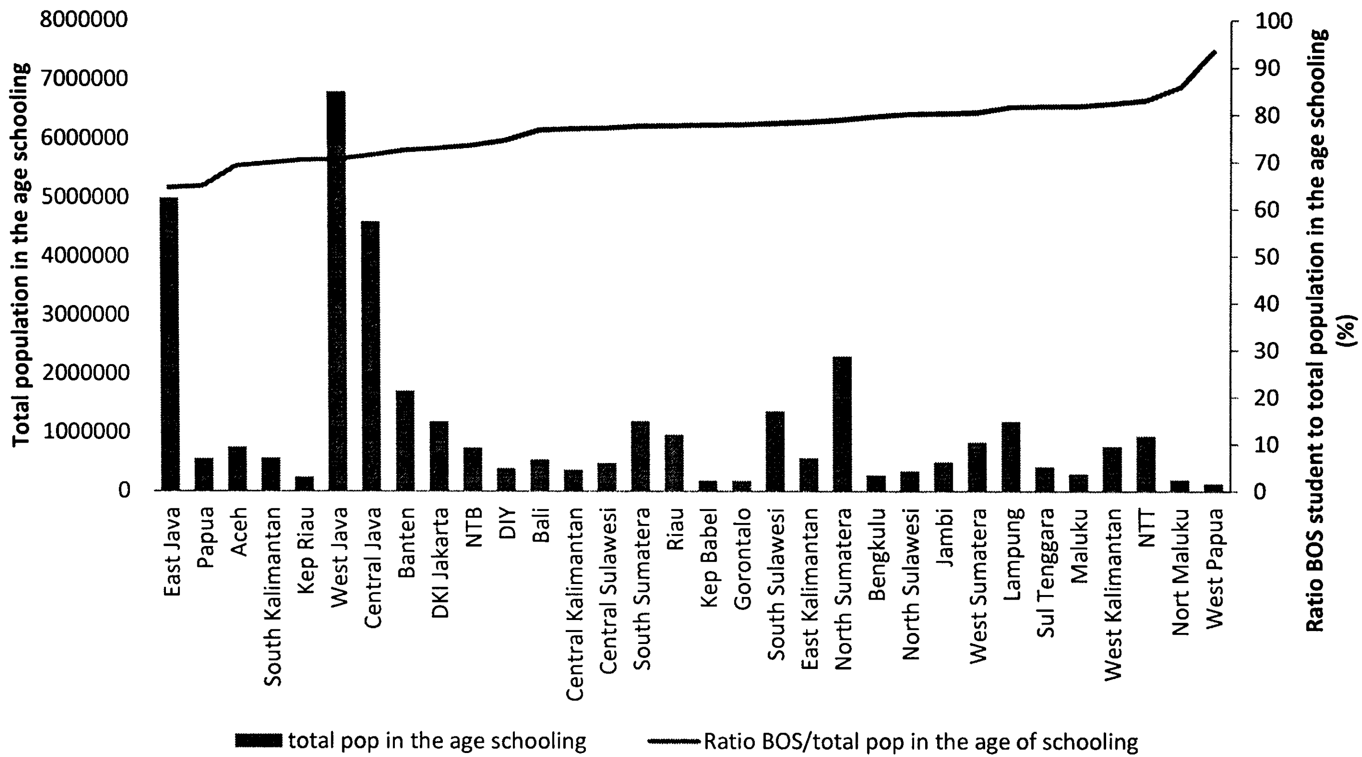




Source of data: Central Bureau Statistics of Indonesia (Badan Pusat Statistics, BPS)

Based on the previous evidence, the government of Indonesia has made a significant effort to improve resources and to increase the net enrolment rate at every level of education. By implementing the BOS program, the government signalled its intention to increase the net enrolment rate, particularly for basic education. As we can see in Figure 3.4, according to the latest population census in 2010, the BOS program still does not cover all children at the primary school level. We can see that the ratio of the total number of BOS students to the total number of children at the primary school level for all regions in Indonesia is below 90%, except in West Papua. It is because West Papua has children of school age less than other provinces. In addition, as regions with higher numbers of children of school age seem to have a lower enrolment, such as East Java, West Java and Central Java. In fact, there are still many children at the primary school level who do not receive BOS as their financial support to provide free access to basic education. These children are not registered at primary school level. It could be because they are categorised as street children, helping their parents to earn money, or their parents are not keen to encourage their children to go to school because they live in remote areas.

Figure 3.4: Ratio of BOS students to total number of children at primary school age in 2010 by region



Source: Ministry of Education and Culture of the Republic of Indonesia

3.5. Data Sources

The main source of the micro data used in this research is the Indonesia Family Life Survey (IFLS) data which has been discussed in Chapter 2. In particular, this chapter uses data from IFLS4 (2007). We cannot use panel data (IFLS3 and IFLS4), since the old BOS was started in 2005 and IFLS3 was in 2000. Moreover, we also use school subsidies data from the Ministry of Education and Culture of the Republic of Indonesia (MEC) and other data from the Central Bureau of Statistics of Indonesia (BPS). IFLS provides educational information at individual, household and community levels. MEC provides information about school subsidies at the aggregate level, and some demographic information comes from BPS.

3.5.1. BOS Data

We only estimate the early version of BOS since we only have data 2007 (IFLS4). As explained in section 3, BOS was launched in 2005 to enable poor students to have free access to basic education. Using the IFLS survey data, we determined BOS students based on self-reported information. We generated BOS as a dummy variable equal to 1 if students reported that they received BOS and 0 otherwise. Table 3 shows BOS participation rate at primary school and junior high school based on IFLS survey data 2007. The percentage of students who receive BOS in each grade is below 20% at primary school and below 15% at junior high school.

Table 3.3: BOS Participation Rate

Primary School Grade	Percentage of student Non BOS	BOS	Number of students
1	85.51	14.49	856
2	81.89	18.11	795
3	84.07	15.93	703
4	83.46	16.54	665
5	85.03	14.97	715
6	87.02	12.98	131
Junior High School Grade			
1	87.35	12.65	490
2	85.25	14.75	400
3	85.02	14.98	227

Source: calculated from IFLS 4

The number of students who receive BOS is lower than the government's expectation and the data suggest that BOS is failing to support all students for all nine years of basic education. In comparison, a study by SMERU in selected regions in 2006 found that there were only a few poor students who received BOS from the total number of poor students in the study regions. Table 3.4 shows the number of poor students who received BOS from the school samples.

Table 3.4: The percentage of poor BOS students in selected samples

		Poor students		Poor students with BOS		
Province	Total number of Students	Number	% of total students	Number	% of total students	% of total poor students
East Java	2957	1002	33.9	242	8.2	24.2
North Sulawesi	3173	-	-	296	9.3	-
North Sumatra	2841	940	33.1	256	9	33.1
West Nusa Tenggara	1740	568	32.6	111	6.4	32.6

Source: SMERU 2006

The proportion of BOS students in IFLS survey data is larger than in the SMERU study. That has occurred because IFLS data was collected in 2007 while SMERU was base in 2005 when BOS was new. In more recent years, the allocation of the national budget for BOS has been larger, so BOS is expected to cover more children or even all children of school age.

3.5.2. Poor Criteria

Even though the purpose of BOS is to provide nine years of basic education free of charge for all children, in the first phase of implementation of BOS in 2005, there were not enough funds to cover all children at that level of education, so the government decided to prioritize the allocation of funding for children from poor families using 'poor criteria' prepared by the Central Bureau of Statistics (Badan Pusat Statistik, BPS). The government then developed school committees to implement and monitor BOS funding allocation across the regions in Indonesia. School committees consist of students' parents, teachers and the head of the school. Poor students do not pay any cost for their school fees and they receive money for transportation cost and uniform allowance. From 2009, the BOS program covered all students, including pocket money for the poor. Based on the Central Bureau of Statistics Indonesia, there are 14 criteria to define a poor family (see Table 3.5).

This research uses only eight criteria, because of the lack of information in the data set. The variable poverty index is calculated from the household poor criteria information by adding up all dummy variable criteria that we are generated from household level. Households having values of 0 means that no poor criteria are met; in other words, the family is not poor. Households having values of 8 mean that 8 criteria have been met, which means that the family is very poor. The eight criteria used are: (1) A family with no electricity at home; (2) a bad quality of water resource; (3) no toilet at home; (4) not a standard stove; (5) having a health allowance card; (6) low income level; (7) no house or an improper house; (8) landless.

Table 3.5: Poor Criteria

No.	14 Criteria
1	**No house or improper house with size less than 8m2 per person**
2	The floor is made from land or bamboo
3	The wall is not permanent, such as bamboo or wood with low quality
4	**A family with no electricity at home**
5	**The quality of water resource**
6	**No toilet at home**
7	**Low quality of stove availability**
8	**Having a health allowance card**
9	**Low income level –under RP 600,000 or approximately US$60 per month**
10	No education for head of household or with the maximum level at primary school
11	**Landless**
12	Milk, meat, chicken consumption is only once in a week
13	Only buy one set of clothes in a year
14	No assets or savings

Note: All bold sentences are 8 'poor criteria' that are used in this research

In addition to these poor criteria, we also use information about the decision maker at the village level who determines whether households are a poor family as an exclusion criterion in our Instrumental Variable regressions. We created two dummy variables: a dummy for whether the head of the village determines whether the family is poor or not, and a dummy variable for whether the staff of the village make this decision. The excluded category captures everyone except the head of the village and the staff of the village who make decisions whether the family is poor, such as community figures, head of RT (Rukun Tetangga=a group of several households in a small neighbourhood), village midwife, NGO and other. Village officers (head and staff of village) have an obligation to determine whether the families are poor or not based on the poor criteria from village data. Formally, poor students should present a poor letter, which is issued by the village officers to prove that they are poor and eligible to receive BOS. Hence, we identify assumption that local administrative mechanism affects who receive the BOS, but we assume that local administrative does not affect the test scores.

Table 3.6 shows the proportion of BOS and non-BOS students by poor criteria. In total, the numbers of BOS students are around 10% from the total number of children of school age (6 to 15 years old). Furthermore, Table 3.6 also presents the number of BOS students for each poor criterion by the person who determines households to be in the poor family category. From 1,013 BOS students, around 40% of students have 0 criteria, or are not poor students. It is very significant numbers BOS which was allocated to non-deserving students, or it could be that students who meet certain poor criteria but the criteria were not included in the 8 criteria which is used in this research. In fact, if we see the number of children without BOS, there are still a lot of poor students who did not receive BOS in 2007. It could be true since 2007 was the early stage of the implementation of the BOS program, so BOS was not distributed equally among poor students.

Table 3.6: The number of BOS and non-BOS students by poor criteria

		BOS Students					Non-BOS Students	
		Village decision maker						
Poor Criteria	Number of children (1)	Head of village (2)	Staff of village (3)	other (4)	Total (5)=(2)+(3)+(4)	% (6)=(5)/(1)	Number (7)	% (8)=(7)/(1)
0	4,374	220	150	50	420	9.60	3,954	90.40
1	1,591	81	64	13	158	9.93	1,433	90.07
2	984	45	30	16	91	9.25	893	90.75
3	879	41	39	21	101	11.49	778	88.51
4	899	62	43	27	132	14.68	767	85.32
5	580	44	26	8	78	13.45	502	86.55
6	167	12	10	7	29	17.37	138	82.63
7	11	1	0	0	1	9.09	10	90.91
8	5	0	3	0	3	60.00	2	40.00
total	9,490	506	365	142	1013	10.67	8,477	89.33

Source: calculated from IFLS data

Furthermore, from 5,116 children of school age who meet various poor criteria, only 38% of those children, or about 1,950 children, receive poor letters; 51% are administered by heads of the villages, 31% by staff of the village, and 18% by other village officers. Table 3.7 presents the proportion of students with poor letters that were distinguished between BOS and non-BOS by village decision maker. From 1000 poor students who got poor letters from heads of the villages, 51% of students are with BOS and 49% are not. From 596 poor students with poor letters from staff of the villages, 61% students are with BOS, and 39 students are not. For 348 students with poor letters from other village officers, 41% students received BOS, and 59% students did not receive BOS. Hence, the probability of getting BOS is higher for those who are administered by village officers.

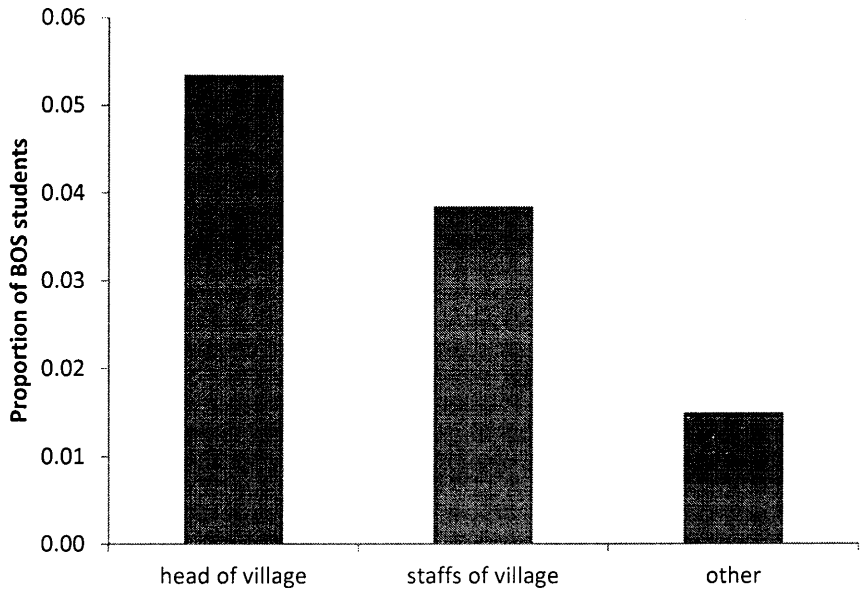
Table 3.7: Proportion of students by village decision maker

	Proportion of students with:				
	poor letter	BOS		no BOS	
		#	%	#	%
head of village	1,000	506	51	494	49
staff of village	596	365	61	231	39
other	348	142	41	206	59
Total	1,944	1,013	52	931	48

Source: calculated from IFLS data

Figure 3.5 presents the proportion of students granted BOS by the village decision maker. Among those children of school age within the village, only 5.5% of students with BOS received a poor letter from the head of the village, around 4% of students received a poor letter from staff of the village, and 1.5% students received a poor letter from other village officers.

Figure 3.5: Proportion of students with BOS by village decision maker



The differences are because there is a possibility of different decision maker in issuing poor letter in a village. For instance, when the head of village is absent, so staff of village will be responsible in issuing the poor letter, and if head of village and staffs of village are absent, there will be another person such as midwife, or other community figures in issuing the letter. There is clearly variation of differences in judgements by different types of decision makers. It can be explained by using individual characteristics such as the proportion of father's education background from BOS student, the proportion of gender from BOS student, and the proportion of urban/rural areas from BOS student that are shown from figure 3.6 to 3.8.

Figure 3.6: Proportion of father's education background from BOS students by village decision maker

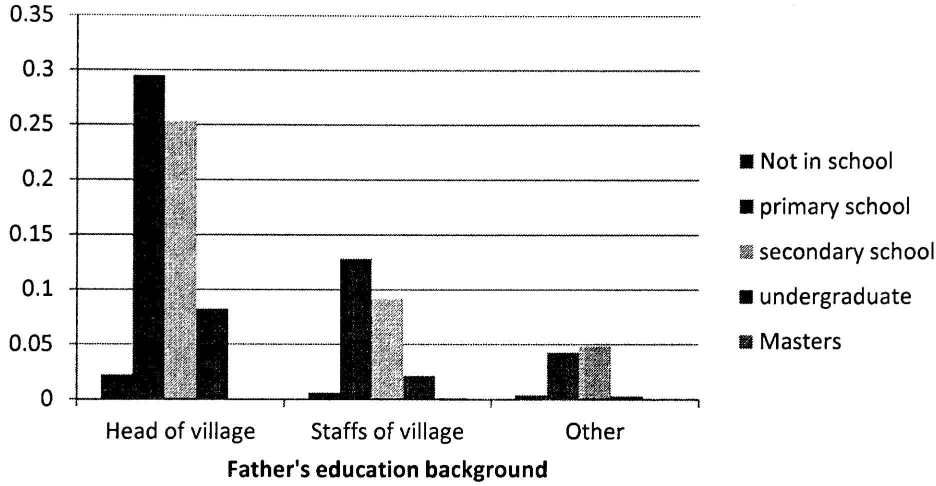


Figure 3.7: Proportion of gender from BOS students by village decision maker

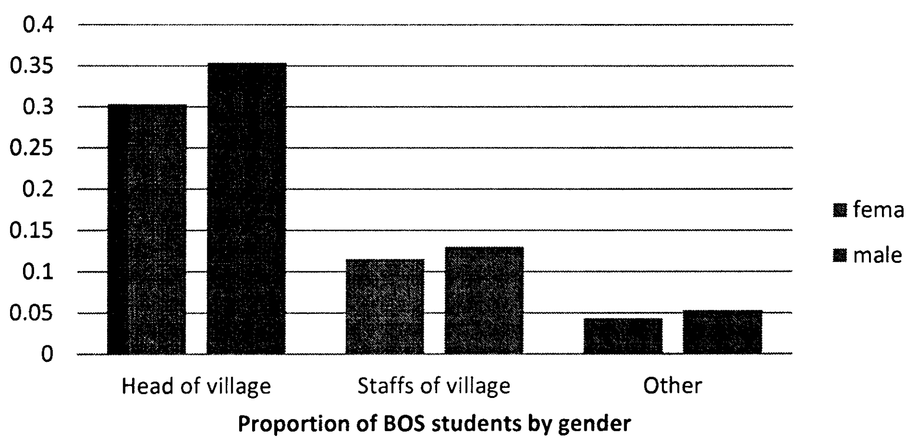
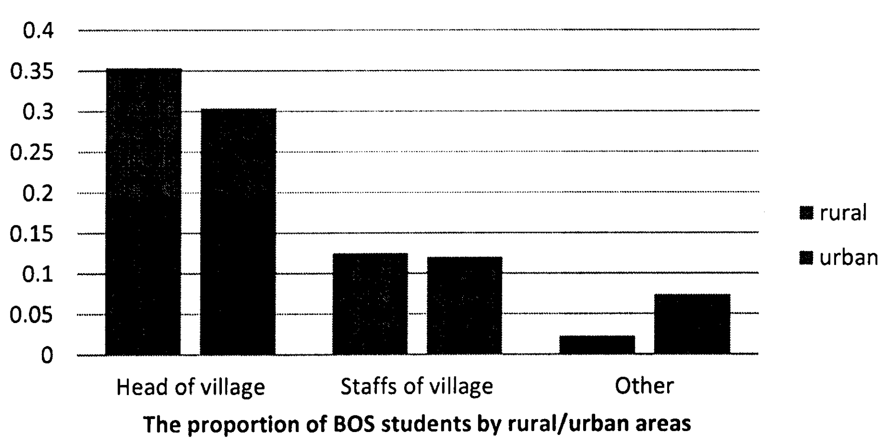


Figure 3.8: Proportion of urban/rural from BOS students by village decision maker



3.5.3. Student test score

Test scores are obtained from the test score in primary school at age 11 or in children's final year of primary school. All questions in the test are multiple choices and are marked using computer. The test is conducted nationally by Ministry of Education and Culture of The Republic of Indonesia at the same time and standard for all regions in Indonesia. The test is conducted in each primary school and monitored by other teachers from different school, and the results of the test are announced in a month later.

The test score is continuous variable and ranges from 0 to 10. It is calculated from the average scores of 3 subjects (Maths, Science and Indonesian Language). Test score data from the IFLS surveys are taken only from the respondents who could show test certificates and excludes the respondents who could not show certificates, since sometimes the information is not complete. For instance, they only mentioned 2 subjects out of 3 or they only mentioned the total score without mentioning each of the subjects individually, because they did not remember their scores in detail. Figure 3.9 presents the child test score distributions for BOS and non-BOS students.

Figure 3.9: Test Scores Distribution

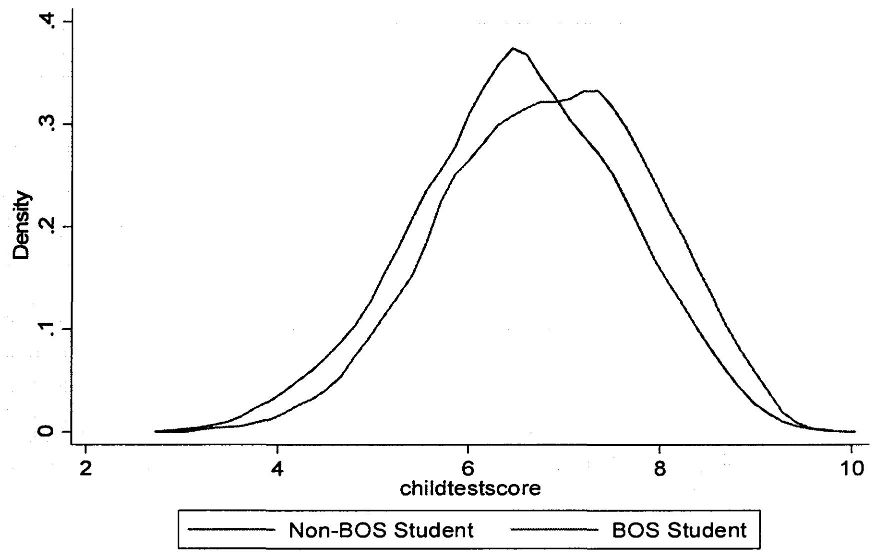


Table 3.8 shows the descriptive statistics of test scores from BOS students and non-BOS students. BOS students have higher average test scores than non BOS students.

Table 3.8: Students' test score in 2007

	BOS	Non-BOS
Mean	6.56	6.50
SD	1.36	1.25
Observation	276	6320

Source: calculated from IFLS data

In addition, we also performed t-test to test whether there were significantly different test scores between BOS and Non-BOS students. A t-statistic of -3.76 and a p-value 0.0002, implies that the mean scores are statistically different from each other at the 1% significant level.

Table 3.9 describes the distribution of students' test score by level of education of the father and mother. In general, the higher the level of education of the father and mother the higher the test scores of the student. More than half of students' test scores below 6.5 out of 10 are from students whose parental backgrounds are not higher than junior high school. The highest test scores are found for students whose father's education is at doctoral level.

Table 3.9: Distribution of students' test score by parental education background (%)

The highest level of parental education	Father education Average test score	%	Mother education Average test score	%
No schooling	6.26	4.76	6.24	7.97
Primary school	6.40	48.93	6.40	54.78
Junior high school	6.46	15.47	6.53	16.24
Senior high school	6.66	22.12	6.85	16.05
College D1, D2, D3	6.96	2.90	7.02	2.63
Bachelor's	7.03	5.45	7.06	2.22
Master's	7.26	0.33	7.70	0.11
Doctorate	8.35	0.03		
Observation		6405		6528

Source: calculated from IFLS data

3.5.4. Education Expenditure

Apart from school fees (such as registration fees, tuition fees and exam fees), there are also other education costs incurred during schooling, for instance: textbooks cost, uniform cost, transportation cost, housing and food cost, and any additional courses which students take outside school. Table 3.10 describes the various costs of students in primary school and junior high school per year.

Table 3.10: The average costs to individuals of school spending (rupiah) per annum in 2007

Variable	Rural	Urban
Registration fees	58,250	234,369
Tuition fees	83,800	317,748
Exam fees	16,833	40,262
Book costs	66,687	134,050
Uniform costs	62,942	112,433
Transportation costs (A)	134,215	282,019
Housing costs and food (B)	299,338	560,758
Additional course costs (C)	20,803	96,588
Total	742,868	1,778,227
Total – (A+B+C)	288,512	838,862

Source: calculated from IFLS4; Note: 1 USD= 10,000 RP

The data is taken from IFLS survey data 2007. The average of registration fees in rural area is RP 58,250 per year while in urban areas it is RP 234,369, which is almost four times the registration fees from rural areas. These registration fees are only paid once during their schooling in primary school and are set by the school committee (school teachers, school principal and student's parent representative), and under control from local government. The average of the tuition fees in rural areas is RP 83,800 per year and for exam fees it is RP 16,833, while in urban areas the tuition fees are over three times the tuition fees in rural areas and for exam fees it is RP 40,262. Other costs which are excluded from the school fees and are very significant expenses for each student are transportation costs, housing costs and food for students who live far away from their schools. These students need to rent a boarding house and spend some money for their own food. The housing costs and food costs are usually incurred for students at junior high school. If we compare the total school expenses to the amount of school subsidy which was shown in Table 3.2, the school subsidy is only sufficient for school fees or even only enough for tuition fees if the students live in urban areas. The remainder of the education expenditures must be covered by the household. That is why there are still some children of school age who cannot afford even basic schooling.

3.5.5. Parental Education Background

Table 3.11 presents parental education background of both fathers and mothers of BOS students and non-BOS students in 2007. Most parents only have a primary school education. However, the proportion of parents with only primary education is higher for BOS students than non-BOS students. The higher the education level, the smaller the proportion of fathers and mothers. In general, however, the parents of non-BOS students are slightly more educated than BOS students.

Table 3.11: Parental Education

The highest level of parental education	Father		Mother	
	BOS (%)	Non-BOS (%)	BOS (%)	Non-BOS (%)
No schooling	3.26	4.15	5.28	6.98
Primary school	46.59	40.12	51.10	43.54
Junior high school	15.77	17.14	19.42	19.11
Senior high school	23.60	26.90	18.13	22.12
College D1, D2, D3	2.75	3.46	2.19	3.31
Bachelor's	7.93	7.44	3.88	4.65
Master's	0.10	0.72	0.00	0.28
Doctorate	0.00	0.07	0.00	0.00

Source: calculated from IFLS data

3.5.6. Financial Background

Table 3.12 depicts parental income and household expenditure. Students who receive BOS in urban areas have less parental income and household expenditure than non-BOS students. On the other hand, in rural areas, students receiving BOS have slightly higher parents' income than non-BOS students but lower household expenditure. It seems that BOS is well targeted in the urban areas in terms of parental income, but not in the rural areas. This may be because in rural areas, the income from their own production is not calculated as parental income. Besides that, the definition of poor criteria is not only based on income but also on other criterion.

Table 3.12: Parental Income and Expenditure

	Monthly father's income (Rupiah)		Monthly mother's income (Rupiah)		Monthly household expenditure (Rupiah)	
Area	BOS	Non-BOS	BOS	Non-BOS	BOS	Non-BOS
Urban	1,018,030	1,396,295	564,096	891,020	2,430,776	2,876,353
Rural	851,462	781,559	524,495	462,151	1,744,994	1,894,586

Source: calculated from IFLS data

In addition, the monthly household expenditure is a little higher than the aggregate of both father's income and mother's income but the families could afford all the monthly household expenditure. This is likely to be because there is income from other household members that is not calculated.

3.6. Research Methodology

This section outlines the research methodology used in this chapter to evaluate the effects of BOS program on child test score. We used three different methodologies to address the relevant issues: Ordinary Least Squares (OLS) estimation, Instrumental Variable (IV) regression, and Propensity Score Matching (PSM) estimation. OLS is used as the conventional method and estimates the effect of school subsidy on average and assuming BOS is exogenous, while IV estimation is used to deal with endogeneity of BOS and also correct for selection bias based on unobservable characteristics. In addition, IV estimates the effect of the treatment on those individuals whose behaviour is affected by treatment. That is, IV estimation provides an estimate of the causal effect for those individuals who change the treatment status because of the instrument. Moreover, PSM is used to estimate the average treatment effect in the absence of selection on unobserved characteristics.

3.6.1. Ordinary Least Squares Estimation

Ordinary Least Squares estimation is used to estimate the basic econometrics model of the impact of the BOS program on child test scores. The econometric models used in this chapter can be written as:

$$Test\ Score_i = \alpha_0 + \alpha_1 BOS_i + \alpha_2 X_i + \varepsilon_i \tag{3.1}$$

The dependent variable in this equation (Test $score_i$) is child test score at age 11 for individual i. The average child test scores across subjects are used rather than total child test scores in order to make them comparable across different age groups of children, since there was a change in the total number of subjects tested from 2002. Before 2002, the number of subjects tested was 5 subjects: (1) Moral and civil education, (2) Bahasa Indonesia, (3) Maths, (4) Science and (5) Social studies. Starting in 2002, the number of subjects tested was only 3 subjects: (1) Bahasa Indonesia, (2) Maths, and (3) Science. For test scores before 2002, we used test scores from the same subjects with the subjects that were tested after 2002. The main explanatory variable is BOS, a dummy variable for the school subsidy, with a value equal to 1 if the children receive BOS and 0 otherwise. In addition, the vector X_i contains the other explanatory variables to capture individual and household characteristics, such as the poverty index, gender, area where they live, rank of provincial HCI, household size, household expenditure, type of schooling (public or private), parental education background and whether they reside in Java or outside Java. The use of ordinary least squares estimation is problematic since BOS may be endogenous, and OLS fails to address some very important potential sources of endogeneity, so we also provide estimation by using instrumental variable regression in section 3.6.2.

3.6.2. Instrumental Variables Estimation

BOS may be an endogenous variable – an observable explanatory variable that is correlated with the unobservable error term. The endogeneity of BOS could arise at least from three sources: reverse causality or simultaneity, spurious correlation, or self-selection. The simultaneity problem is one source that we should worry about the endogeneity problem of BOS since students may increase their test scores because they received BOS, or they received BOS because their test scores were high. In the case of a spurious correlation problem, BOS and test scores may both be correlated with an omitted variable but not directly with each other. Self-selection is another cause of endogeneity of BOS. It may be that students who perform better at school become more interested in doing well and choose to receive BOS, whereas students who perform less well at school choose not to receive BOS.

Blundell, Dearden and Sianesi (2005) said that IV can overcome the OLS bias that results from endogeneity of the explanatory variables. IV corrects for the endogeneity problem by using good instruments. This instrument is correlated with the causal variable of interest, BOS, but uncorrelated with any other determinants of the dependent variable. This variable has a clear effect on BOS in the first stage regression, and the only reason of relationship between test scores and BOS is from the first stage. According to Angrist and Pischke (2009), good instruments come from a combination of institutional knowledge and ideas about processes determining the variable of interest.

Hence, IV estimates the average treatment effect of BOS among those individuals whose treatment status is influenced by changing an exogenous regressor that satisfies the exclusion restriction. The treatment effect that we estimate is the average treatment effect for those who adjust their treatment status because theay react to the instrument. That is, IV estimates the Local Average Treatment Effect (LATE) of the impact of BOS=1 on subset of individuals. Card (2001) and Lang (1993) suggest that LATE estimates from IV could exceed OLS estimates, because they estimate average effects for a specific group, whereas OLS estimates, in the absence of omitted variables and measurement error biases, estimate the average effect across everyone. Imbens and Angrist (1994) said that instrumental variables estimated a LATE under very weak conditions. There are two potential weaknesses: IV estimates the effect of a treatment on a generally unidentifiable sub-population; and the LATE estimate will vary depending on the particular instrumental variables that are used. In the case of our study, the IV estimate is a LATE for those whose BOS status affected by the identity of the decision maker in the village.

We used two dummy variables as instrument for BOS: a dummy for whether the head of the village determines whether the family is poor or not, and a dummy variable for whether the staff of the village make this decision. The excluded category captures everyone except the head of the village and the staff of the village who make decisions of whether the family is poor, such as community figures, head of RT

(Rukun Tetangga=a group of several households in small neighbourhood), village midwife, NGO and other. Village officers have an obligation to determine whether the families are poor or not, based on village data. Formally, poor students should present a poor letter which is issued by village officers to prove that they are poor and eligible to receive BOS. Thus, these two variables are good exclusion restrictions, since these variables are highly correlated with a probability of receiving BOS, but there is no reason to believe these would be a correlation with test scores. As the head of the village is the person who is elected from local elections in the village level by all people who meet the criteria to be electors, and staff of the village are the people who are appointed by the head of the village. The head of the village and the staff of the village are also accountable and more objective in issuing poor letters. The outcome should be based on whether the family is poor or not, instead of the student's ability. Hence, the instruments should be uncorrelated with test scores beyond their impact on the likelihood of getting BOS.

Thus, the model that is used for instrumental variable regression can be written as:

First stage equation:

$$BOS_i = \beta_0 + \beta_1 Head\_village_i + \beta_2 Staff\_village_i + \beta_3 X_i + \mu_i \tag{3.2}$$

Second stage equation:

$$Test\ Score_i = \alpha_0 + \alpha_1 \widehat{BOS_i} + \alpha_2 X_i + \varepsilon_i \tag{3.3}$$

In the first stage equation, the BOS dummy is the dependent variable. We used a dummy of head of village and staff of village as the instrument variable for BOS with other of village officers as the excluded category. Moreover, the vector X_i contains the other explanatory variables to capture individual and household characteristics, such as poverty index, gender, area where they live, rank of provincial HCI, household size, household expenditure, type of schooling (public or private), parental education background and whether they reside in Java or outside Java. For the second stage equation, we have the same variables as in the OLS estimation.

3.6.3. Propensity Score Matching Estimation

We used matching method to get the estimation result from the average treatment effect in the absence of selection based on unobserved characteristics. Here, we can compare the matching estimation to the IV estimation that IV can avoid the bias because of the correlation of observable and unobservable characteristics in the equation. According to Blundell, Dearden and Sianesi (2005), matching method is defined as a non-parametric approach that attempts to find a comparison group from all the non-treated so that the selected group is similar to the treatment group in term of their observable characteristics. The only remaining difference between two groups is participation in BOS program, therefore, the outcomes from the comparison group is the right sample for the missing information on the outcomes of the treatment group. In addition, as IV estimation has important issue in choosing instrumental variable, matching method also has important issue in choosing matching variable. The only different is IV variables should satisfy exclusion restriction in outcome equation conditional on the treatment, while matching variables should satisfy the impact on outcome and treatment equations (Blundell, Dearden and Sianesi, 2005).

Propensity Score Matching (PSM) estimation method is adopted when there is a wide range of matching variables. According to Rosenbaum and Rubin (1983), propensity score is a feasible method to match the variables by using balancing score. Blundell, Dearden and Sianesi (2005) said that by definition propensity score matching is when treatment and non-treatment observations with the same value of propensity score have the same distribution of density scores. Hence, PSM match treated and untreated observations on the estimated probability of being treated (propensity score).

This chapter uses PSM to estimate the average treatment effect in the absence of selection on unobserved characteristics. PSM requires selection on observables assumption when conditioned on an appropriate set of observable attributes. Obviously, there is variability in selections that influences the selection process for the treatment group and the control group. The treatment group is recipients of school subsidies who meet poor criteria. Only poor students and those who meet poor criteria that are prepared by the Central Bureau of Statistics will be categorized into the treatment group as recipients of BOS (BOS-students). To prove whether the students are poor enough, students should show a letter from the village head to the school committee. For those who can prove themselves as poor, they will receive a treatment.

In non-experimental studies, the essential problem is the missing counterfactual. It is impossible to have outcomes of the same unit in both treatment conditions at the same time (Holand, 1986). PSM uses information from other students that do not get BOS (Non-BOS students) as a control group to identify what would have happened to students in the absence of the intervention (BOS). By comparing the outcomes from BOS students relative to observationally similar groups (non-BOS students), it is possible to estimate the effects of the intervention.

3.6.3.1. The PSM Model

Following Caliendo and Kopeining (2005) and Sianesi (2006), the core model will consist of treatment outcome and control outcome of individuals. An observed outcome of individual i can be expressed as:

$$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i} \tag{3.4}$$

In the above equation, $D_i \in \{0,1\}$ is treatment indicator. D_i is equal to one if the individual i receives BOS as a treatment and zero otherwise. Y_i is the potential outcome of individual i, Y_{1i} is the potential outcome of individual i when the individual receives BOS as the treatment outcome or when D_i is equal to one. Y_{0i} is the potential outcome of individual i when the individual does not receive BOS as control outcome, or when D_i is equal to zero. Thus, the treatment effect for an individual can be written as the following equation:

$$\tau_i = Y_{1i} - Y_{0i} \tag{3.5}$$

The fundamental problem of causal inference/counterfactual problem makes it impossible to observe the potential outcome of individuals for both treatment (Y_{1i}) and control (Y_{0i}) conditions at the same time, so only one potential outcome for each individual can be observed, thus estimating the treatment effect of an individual is impossible.

In this chapter we estimate the average treatment effect on the treated (ATET). ATET estimates the average among those who got the treatment or received BOS. ATET can be formulated as:

$$\tau ATET = E[Y_{1i} - Y_{0i} | D_i = 1] \tag{3.6}$$

$$\tau ATET = E(\tau | D_i = 1) = E[Y_{1i} | D_i = 1] - E[Y_{0i} | D_i = 1] \tag{3.7}$$

$E[Y_{1i}|D_i = 1]$ is the potential outcome of students who receive BOS (BOS students) and is potentially observable. $E[Y_{0i}|D_i = 1]$ is the potential outcome of BOS students when they did not receive BOS and cannot be observed because it is the missing counterfactual.

To calculate ATET, it is essential to find a substitute for $E(Y_{0i}|D_i = 1)$. One possible way is by using the potential outcome of non-BOS students who do not receive treatment or BOS $E(Y_{0i}|D_i = 0)$ because the potential outcome from BOS students who did not receive treatment $E(Y_{0i}|D_i = 1)$ is not observed at the same time when those individuals received treatment. So, we can estimate ATET by using:

$$E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0] = \tau ATET \tag{3.8}$$

Hence, ATET is estimated from the potential outcome of BOS students who receive treatment, $E[Y_{1i}|D_i = 1]$, minus the potential outcome of non-BOS students who did not receive treatment, $E[Y_{0i}|D_i = 0]$.

3.6.3.2. Assumptions and Five Steps of PSM

In matching methods, there are assumptions to be applied in order to get a comparison group similar to the treatment group in observable characteristics (Sianesi, 2006):

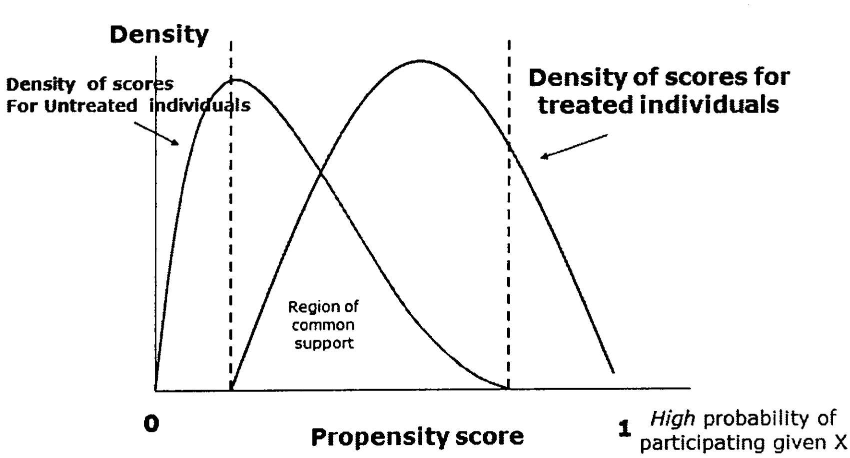
1. Conditional Independence Assumption (CIA)

The potential outcomes are independent of the treatment assignment based on the observable attributes of covariates X which are not influenced by treatment (Caliendo and Kopeinig, 2005). Here, we should control for observable differences in characteristics between the treated group or BOS students and non-treated group or non-BOS students; the outcome that would result in the absence of treatment is the same in both cases. This identifying assumption for matching, which is also the identifying assumption for the simple regression estimator, is known as the Conditional Independence Assumption (CIA).

2. Common Support

Common support is the condition when there is a region of the support of matching variable that is overlap in the distribution of density scores from treated and untreated groups. The treated and untreated individual must have similar probabilities or treatment. As illustrated on figure 3.10, the region of common support is the range of the score which overlaps between density of scores for untreated individuals and density of scores for treated individuals.

Figure 3.10: Common Support Region



The data can be estimated by using the five steps of Propensity Score Matching (PSM) Estimation. The five steps are as follows:

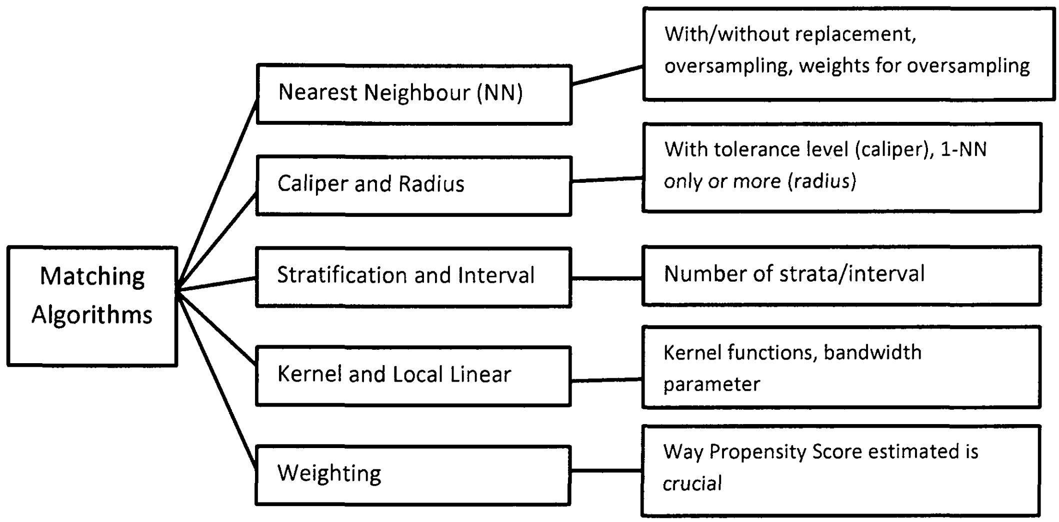
1. Estimate the Propensity Score

According to Caliendo and Kopeinig(2005), there are two steps to be conducted when estimating the propensity score: choice of model and choice of variables that should be included in the model. For the model choice, any discrete choice model can be used, such as Binary Logit, Binary Probit, Multinomial Logit, Conditional Logit and Multinomial Probit. The choice of model is not critical when the treatment is only binary, but when the model uses multiple treatment, some assumptions must be satisfied. Moreover, for the choice of variables, the choice must be based principally on economic theory and previous empirical research findings.

2. Choosing a Matching Algorithm

There are a few different matching algorithms. According to Caliendo and Kopeining (2006), the matching algorithms are divided into five different groups: Nearest Neighbour(NN), Caliper and Radius, Stratification and Interval, Kernel and Local Linear and Weighting (see figure 3.11).

Figure 3.11: Different Matching Methods



Source: Caliendo and Kopeining (2006)

This chapter used Near Neighbour matching (NN). We estimate the average treatment effect on the treated using NN matching with replacement and without replacement. NN with replacement is a matching method where one treated unit is matched to more than one non-treated unit. It brings a trade-off between bias and variance. NN with replacement can yield better matches because controls that look similar to many treated units can be used multiple times, and the order in which the treated units are matched does not matter. In the case of NN without replacement, the ordering has to be done before estimating.

3. Having Common Support

Common support is a critical step in matching estimation. This depends on whether or not overlap occurs between treated and non-treated groups. The common support condition ensures that matches for treated and untreated groups can be found.

4. Assessing the Match Quality

Tests must be conducted to assess the matching quality, such as test for standardised bias, test for equality of means before and after matching (t-test) and test of joint equality of means in the matched sample (F-test). If there is bad matching quality or there are still any differences, it is better to take a step back and redo the same steps until the matching quality is satisfactory. If after re-specification and re-assessment the matching quality and the results are not satisfactory, it indicates that the Conditional Independence Assumption fails to be met and alternative evaluation approaches should be used.

5. Estimating the Standard Errors and Sensitivity Analysis.

To deal with the problem of understated standard errors because of variation beyond the normal sampling variation when estimating, Lechner (2002) suggests using bootstrapped standard errors. Bootstrapped standard errors are used when the sampling distribution of parameter may not be of any standard distribution. Bootstrapped standard errors rely upon the assumption that the current sample is representative of the population. Besides that, sensitivity analysis should be applied to estimate the level of bias in observational studies (Guo and Fraser, 2010). Based on Rosenbaum and Rubin (1983) and Rosenbaum (2005), sensitivity analysis should be conducted routinely to see sensitivity of findings to hidden bias when the treated and untreated groups may differ in ways that have not been measured. Wilcoxon's signed-rank test is one method of sensitivity analysis that was developed by Rosenbaum (2002).

3.7. Empirical Results

3.7.1. Ordinary Least Squares Estimation

Table 3.12 shows estimation results of Ordinary Least Squares. All variables are statistically significant. The BOS dummy as the variable of interest has a positive effect on child test score. BOS students have a higher test score by 0.358 points on average compared to non-BOS students or 29.3% of standard deviation. This is a small effect of BOS on test scores, as the mean of test scores is 6.53. The poor variables have a negative effect on child test score. It indicates that the poorer the students, the lower the test score will be. Females have a higher test score compared to males, by 0.076 points on average or 6.2% of standard deviation. Children from a large household size are also negatively correlated with child test scores. Looking at Column 2 in Table 3.13, column 2 allows for literation effects between BOS and its poor criteria. We can spot the response of each type of child on the test score, based on their poor criteria for both with and without BOS. There is information about the magnitude of child test scores for each type of child in each poor criterion for both children with and without BOS. The interaction between BOS variable and poverty index represents children with BOS in each poor criteria, while poverty index only captures information of children in each poor criterion without receiving BOS.

Table 3.13: The impact of BOS on child test score

Dependent variable: child test score	(1) Coefficient	SE	(2) Coefficient	SE
BOS	0.358***	0.076	1.913***	0.129
Poor				
Poor (satisfied 1 criteria)	-0.248**	0.117	-0.231**	0.118
Poor (satisfied 2criteria)	-0.284**	0.116	-0.271**	0.116
Poor (satisfied 3 criteria)	-0.319***	0.119	-0.304**	0.120
Poor (satisfied 4 criteria)	-0.313**	0.124	-0.299**	0.125
Poor (satisfied 5 criteria)	-0.349**	0.139	-0.292**	0.138
Poor (satisfied 6+ criteria)	-0.869***	0.190	-0.825***	0.194
BOS*Poor				
BOS*Poor (satisfied 1 criteria)			-1.593***	0.256
BOS*Poor (satisfied 2criteria)			-1.512***	0.168
BOS*Poor (satisfied 3 criteria)			-1.531***	0.183
BOS*Poor (satisfied 4 criteria)			-1.511***	0.253
BOS*Poor (satisfied 5 criteria)			-2.400***	0.605
BOS*Poor (satisfied 6+ criteria)			-2.218***	0.220
Male	-0.076**	0.036	-0.077**	0.036
Urban	0.322***	0.038	0.325***	0.038
Rank of provincial HCI	-0.012***	0.003	-0.012***	0.003
HH size	-0.027***	0.010	-0.028***	0.010
Log of HH expend on food	0.117***	0.034	0.117***	0.034
Father secondary	0.266***	0.054	0.271***	0.054
Father higher education	0.444***	0.099	0.455***	0.099
Mother secondary	0.284***	0.065	0.276***	0.065
Mother higher education	0.514***	0.145	0.508***	0.145
Public school	-0.120***	0.036	-0.122***	0.036
Java	0.193***	0.037	0.193***	0.037
R^2		0.13		
Observation		3284		

Note: dependent variable is child test score with scale 0-10, SE is robust standard error; *Significant at 10%, **significant at 5%, ***significant at 1%

OLS estimation suggests that poor students are basically insignificantly different from non-poor student. For instance, looking at Column 2 in Table 3.13 with interactions between BOS and poor criteria, we see that the average impact of BOS on child test score is 1.9. Table 3.14 presents the impact of BOS for each BOS student in each poor criterion from column 2, the impact of BOS on test score for poorer students with BOS is none or even worse. For instance, students with 5 poor criteria are worse by

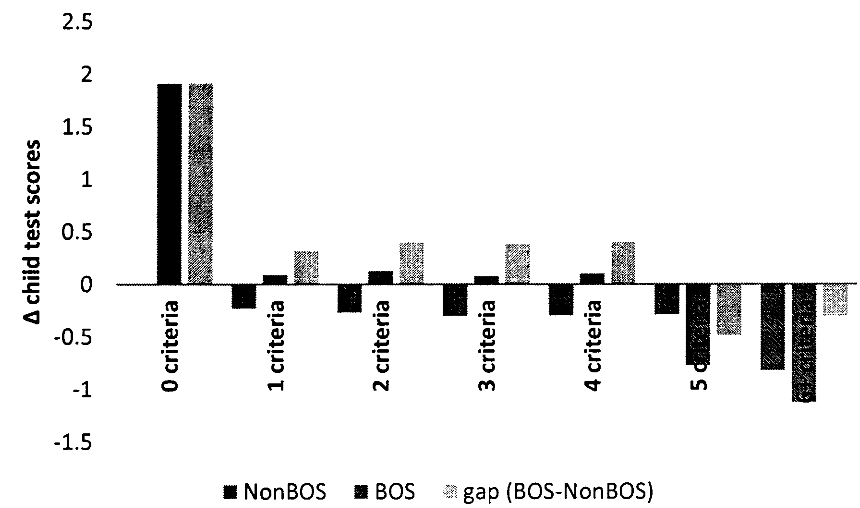
0.779 (1.913-0.292-2.4), and students with 6 poor criteria are worse by 1.13 (1.913-0.825-2.218), which is calculated from the difference between the coefficients of BOS without interaction 1.913 plus the coefficient of poverty index, plus coefficient of BOS interaction with poverty index.

Table 3.14: The impact of BOS on child test scores by poor criteria from OLS regression

Poor criteria	Non-BOS	BOS	gap (BOS - Non-BOS)
0 criteria	0	1.913	1.913
1 criteria	-0.231	0.089	0.32
2 criteria	-0.271	0.13	0.401
3 criteria	-0.304	0.078	0.382
4 criteria	-0.299	0.103	0.402
5 criteria	-0.292	-0.779	-0.487
6+ criteria	-0.825	-1.13	-0.305

Furthermore, Figure 3.12 also presents the different results of child test scores between BOS students and non-BOS students by poor criteria from OLS estimation. For non-BOS students, the higher number the poor criteria satisfied, the lower the test scores will be. For BOS students, students who meet 1 to 4 criteria seem to have a better effect with higher test score, but students with 5 or 6 poor criteria tend to have lower test scores. According to Table 3.14 and Figure 3.12, it seems that BOS did not help very poor students; even their test scores were worse. Yet, for less poor students, BOS seems to work well; this shows from the positive values of gap between BOS students and non-BOS students with 1 to 4 criteria. In short, BOS does not help the very poor students but it helps the less-poor students more. For the very poor student, the impact of BOS on test score is very low. This could be true because BOS only covers school fees, while other educational costs such as textbooks, uniforms, transportation, food, housing/boarding house costs are not covered by BOS. For very poor students, the cost of going to school is very expensive. So, although the poor get the BOS, their test scores are still lower. Due to a potential endogeneity problem of BOS, hence, this chapter applies instrumental variable regression to estimate the impact of BOS on child test score.

Figure 3.12: The impact of BOS on child test scores by poor criteria from OLS regression



As note, estimation in table 3.13 is obtained from individuals who could prove their test scores using certificate issued by government in the time of IFLS survey. For those who cannot show certificate are dropped from this estimation, since the test scores data are not complete. This selection issue may cause bias. Yet, we also provide estimation by using imputation missing value for those who have incomplete test score. As there are three subjects that were tested (bahasa Indonesia, math, and science), so if there is a missing value in one subject for test scores, then this missing value will be substituted by the average score from the scores that are not missing. For instance, if math score is missing, we imputed the score of math from the average score of bahasa Indonesia and science of the child score. In the case, there are 2 scores missing (math and bahasa Indonesia), we imputed the missing values using score from science, so all three scores will be the same. Although there may be an issue of a measurement error, imputation for missing values is appropriate since the measurement error is on dependent variable, and test score is variable on the left hand side, so it will not cause a bias but will increase imposition, as missing values are random. The results is similar to table 3.13 especially on the coefficient of variable interest, BOS (see Appendix table A3.1).

3.7.2. Instrumental Variable Estimation

To correct for the endogeneity, we conducted IV regression for analysing the impact of school subsidy on child test scores and the results are reported in Table 3.16. Moreover, the first stage regression of IV regression is presented in Table 3.15. Both of the excluded instruments (village officer variables) are significant. Only a few of the included instruments are statistically significant which is what we would expect because these variables are not part of the BOS criteria. In order to ensure that we used the right instruments for BOS, we conducted a test for the instrumental variables. The first test is an F test of the excluded instrument. With F statistics value equal to 10.53 and P value of F test equal to 0.0000 which is smaller than the significant level at 0.05, the results show that all excluded instruments (dummy of head of village and staff of village) highly correlated with BOS. In addition, we also conducted a Sargan test, a test conditional on at least one being valid. It is a test for over-identifying restrictions. The hypothesis being tested with the Sargan test is that the instrumental variables are uncorrelated with the residuals, and therefore they are acceptable instruments. If the null hypothesis is not rejected, it means that the instruments are valid. The results confirmed that the null hypothesis is not rejected at Sargan statistics equal to 0.022 and P value equal to 0.8818.

Table 3.15: First Stage Least Square Estimation

Dependent variable: BOS	Coefficient	SE
Male	-0.007	0.010
Urban	-0.006	0.010
Rank of provincial HCI	0.000	0.001
HH size	0.002	0.003
LHH food expenditure	-0.005	0.009
Father secondary	-0.015	0.014
Father higher education	0.049	0.035
Mother secondary	0.018	0.019
Mother higher education	-0.018	0.040
Public school	-0.010	0.010
Java	-0.014	0.010
Poverty Index:		
Poor (satisfied 1 criteria)	0.036***	0.012
Poor (satisfied 2criteria)	0.058***	0.011
Poor (satisfied 3 criteria)	0.044***	0.013
Poor (satisfied 4 criteria)	0.050***	0.018
Poor (satisfied 5 criteria)	0.008	0.029
Poor (satisfied 6+ criteria)	0.003	0.074
Head_of village	0.076***	0.027
Staff_of village	0.081**	0.038
Observation		3284

Note: SE is Standard Error; *Significant at 10%, **significant at 5%, ***significant at 1%

Table 3.16 column 1 reports the IV regression without interacting the BOS variable with the poverty index. Column 2 reports the results with BOS and poverty index interaction. Looking at Column 1, the 2SLS estimates suggest that the BOS program seems to be relevant and has a significant positive effect on child test scores. The direction of the results is consistent with the findings from the OLS analysis but the size of the BOS program effect on child test scores from IV estimates is bigger than OLS and looks over value. It indicates that students with BOS who are influenced by the head of the village and also the staff of the village will have a bigger effect on test scores than those who are influenced by other village officers, as head of village and staff of village are the instrument variables for BOS. In addition, we predict that village staffs are more accountable and objective in categorizing people as poor than other village officers who are more likely to have a personal relationship.

In addition, the higher effect of BOS on child test scores in IV regression than in OLS regression may be because it is a local average treatment effect (LATE). According to the previous studies that measure LATE (Angrist and Kruger, 1991; Acemonglu and Angrist, 2001), the instruments often generate treatment effects that exceed those generated from OLS. In addition, Card (2001) suggests that the higher IV results could occur because they approximate average effects among compliers, whereas the OLS estimates approximate average effects among everyone. In this study, the IV estimates correspond to students who receive BOS because of the way it is administrated by village officers. Furthermore, students who are at the margin of qualifying for BOS, would experience a large increase in test score if they did receive BOS. Hence, the BOS effect is quite large. On the other hand, as regards students with very poor criteria, the effect of BOS is very small. Thus, giving BOS to somebody who is not very poor according to poor criteria can result in a very large effect.

Table 3.16: Instrumental Variable Regression

Dependent variable: child test score	1		2	
	Coefficient	SE	Coefficient	SE
BOS	3.304***	1.261	0.284***	0.092
Poor				
Poor (satisfied 1 criteria)	-0.532***	0.147	-0.431***	0.137
Poor (satisfied 2criteria)	-0.619***	0.156	-0.433***	0.133
Poor (satisfied 3 criteria)	-0.626***	0.157	-0.499***	0.137
Poor (satisfied 4 criteria)	-0.655***	0.174	-0.506***	0.147
Poor (satisfied 5 criteria)	-0.550***	0.192	-0.514**	0.204
Poor (satisfied 6+ criteria)	-1.329***	0.356	-1.190**	0.520
BOS*Poor				
BOS*Poor (satisfied 1 criteria)			0.140	0.251
BOS*Poor (satisfied 2criteria)			-0.098	0.165
BOS*Poor (satisfied 3 criteria)			0.273**	0.110
BOS*Poor (satisfied 4 criteria)			0.248**	0.127
BOS*Poor (satisfied 5 criteria)			0.211	0.224
BOS*Poor (satisfied 6+ criteria)			0.101	0.596
Male	-0.099*	0.052	-0.121**	0.042
Urban	0.347***	0.053	0.329***	0.044
Rank of provincial HCI	-0.012***	0.004	-0.013***	0.004
HH size	-0.043***	0.014	-0.036***	0.012
Log of HH expend on food	0.177***	0.049	0.165***	0.040
Father secondary	0.309***	0.078	0.274***	0.064
Father higher education	0.218	0.187	0.353**	0.139
Mother secondary	0.197**	0.097	0.245***	0.078
Mother higher education	0.574**	0.245	0.517***	0.183
Public school	-0.098*	0.055	-0.129***	0.043
Java	0.147***	0.056	0.103**	0.044
Test of excluded instrument				
F statistics		10.53		
P value		0.000		
Sargan test				
Sargan statistics		0.022		
P value		0.881		
Observation		3284		

Note: dependent variable is child test score with scale 0-10; *Significant at 10%, **significant at 5%, ***significant at 1%; SE is standard error[9].

[9] There is another sensible estimation to do by generating dummy variables as instrument for BOS*Poor using head of village and staff of village which are interacted with Poverty index.

Furthermore, looking at Column 2, there is an interaction between BOS and the poverty index. Detailed calculation about the effect of BOS on child test scores by poor criteria is presented in Table 3.17 and Figure 3.13.

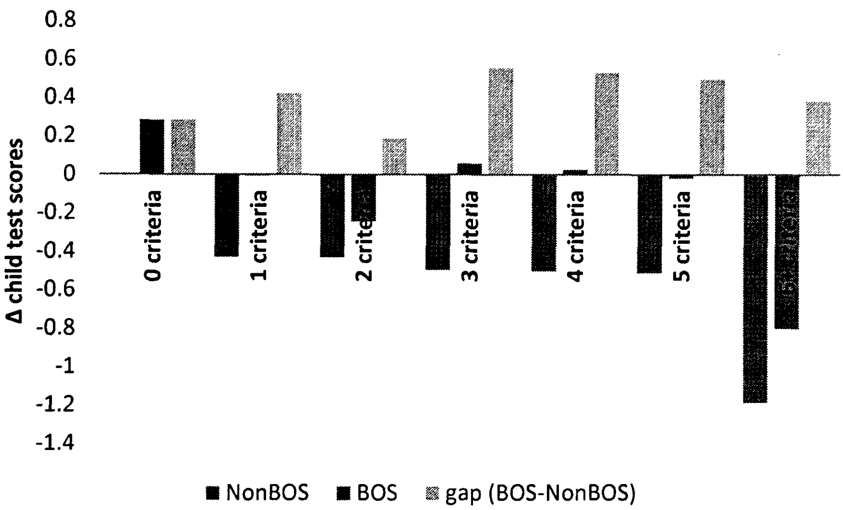
Table 3.17: The impact of BOS on child test scores by poverty criteria from IV regression

Poor criteria	Non-BOS	BOS	gap (BOS - Non-BOS)
0 criteria	0	0.284	0.284
1 criteria	-0.431	-0.007	0.424
2 criteria	-0.433	-0.247	0.186
3 criteria	-0.499	0.058	0.557
4 criteria	-0.506	0.026	0.532
5 criteria	-0.514	-0.019	0.495
6+ criteria	-1.19	-0.805	0.385

Note: Only using 2 instruments with multiple endogenous regressors.

The results suggest that BOS students who satisfied each poor criterion have higher test scores than those who are without BOS (non-BOS). For instance, BOS students who satisfied 3 criteria increase their test score by 0.058 (0.284-0.499+0.273), and 0.026 (0.284-0.506+0.248) for students with 4 criteria. The difference between BOS students and non-BOS students is presented in Table 3.17 and Figure 3.13. It show that the gap is positive and significantly higher for BOS students, and it seems that BOS has a larger effect on poor students than non-poor students. Poor students who satisfied 3 criteria with BOS have a test score 0.557 point higher than those without BOS, and also have higher test scores than those who are not poor students (0.284). This suggests that OLS results may be biased because those who get BOS may be better students and not poorer students.

Figure 3.13: The impact of BOS on child test scores by poverty criteria from IV regression



3.7.3. Propensity Score Maching Estimation

Following the Caliendo and Kopeninig study (2005), the variables used in PSM should satisfy the Conditional Independence Assumption (CIA) where the outcome variables must be independent of the treatment conditional on the propensity score. Heckman, Ichimura and Todd (1997) suggest only including the variables which simultaneously influence the decision for receiving the school subsidy and the test score outcome. Matching on a large number of variables or on criterion variables gives to a dimensionality problem. Propensity score matching is a solution to the dimensionality problem and can be estimated using any probability model, such as probit or logit model. Since most of the statistics literature prefer using the logit, this study also uses the logit model to get the prediction of propensity score, although any probability model can be applied (Dehejia and Wahba, 1998), and the results in the literature are typically robust to the method used. The probability of getting a school subsidy is determined by various individual characteristics, e.g., gender, poor dummies, rank of province based on head count index, household expenditure on food, area, school administration and parental education background. Table 3.18 shows the results of the logit model.

Table 3.18: BOS Logit Model

Dependent Variable: BOS	Parameter estimates		Average Marginal Effect	
	Coefficient	SE	Marginal effect	SE
	(1)	(2)	(3)	(4)
Poor				
Poor (satisfied 1 criteria)	0.730**	0.288	0.013***	0.004
Poor (satisfied 2criteria)	0.917***	0.283	0.018***	0.004
Poor (satisfied 3 criteria)	0.926**	0.287	0.018***	0.004
Poor (satisfied 4 criteria)	1.026***	0.294	0.021***	0.005
Poor (satisfied 5 criteria)	1.039***	0.314	0.022***	0.006
Poor (satisfied 6+ criteria)	1.172***	0.414	0.026**	0.011
Male	0.098	0.066	0.003	0.002
Urban	0.119*	0.070	0.003*	0.002
Rank of provincial HCI	-0.046***	0.006	-0.001***	0.000
HH size	0.049***	0.018	0.001***	0.001
Log of HH expend on food	-0.162**	0.062	-0.005**	0.002
Father secondary	0.262***	0.090	0.007***	0.003
Father higher education	0.582***	0.158	0.016***	0.004
Mother secondary	0.120	0.101	0.003	0.003
Mother higher education	0.321	0.206	0.009	0.006
Public school	2.300***	0.077	0.065***	0.003
Head of Village	0.301***	0.071	0.009***	0.002
Staff of Village	0.293***	0.077	0.008***	0.002
Java	-0.191***	0.068	-0.005***	0.002
Constant	-3.333***	0.895		
Observation				33014

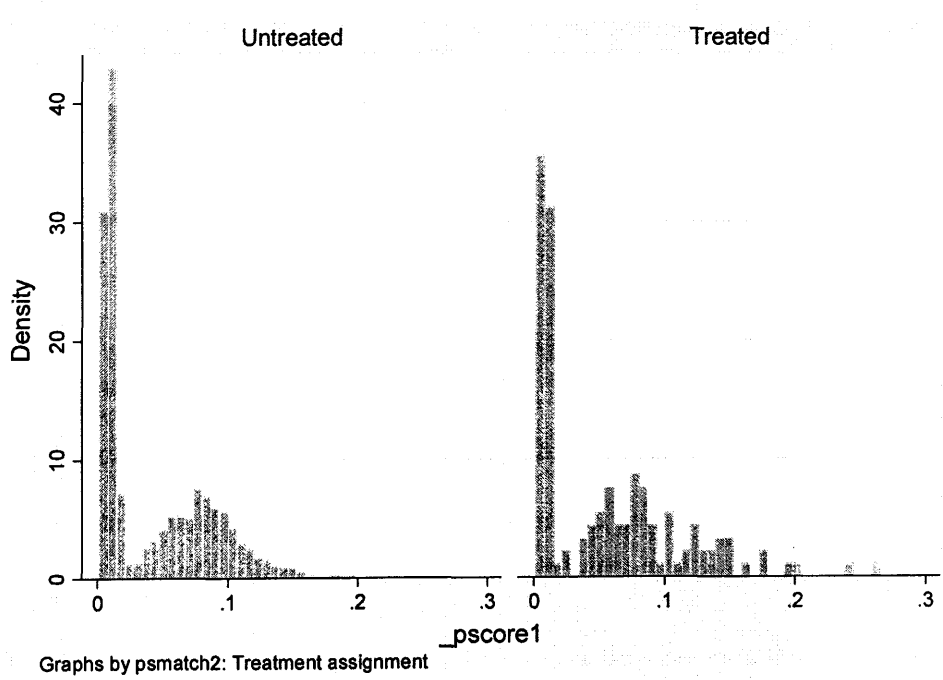
Note: dependent variable is BOS where 1 is for recipient and 0 otherwise
*Significant at 10%, **significant at 5%, ***significant at 1%

Looking at Column 1 of Table 3.18, most variables are significant at typical significance levels and only a few variables are not. The variables poor, urban, public school, rank of provincial HCI, the number of household members (hhsize) and household expenditures on food are significant. Those variables have the most influence on the probability of getting a school subsidy. Column 3 shows the marginal effect of the variables. For instance, students who satisfy 5 poor criteria have a higher probability of getting a school subsidy by 2.2 per cent than those who do not satisfy any criteria.

3.7.3.1. Choosing Matching Algorithms

This study uses Near Neighbour Matching, since the distribution of data is a little different in treated and untreated groups. As shown in Figure 3.14, the distribution of the treated group seems to have a higher propensity score than the untreated group which is what is supposed to happen.

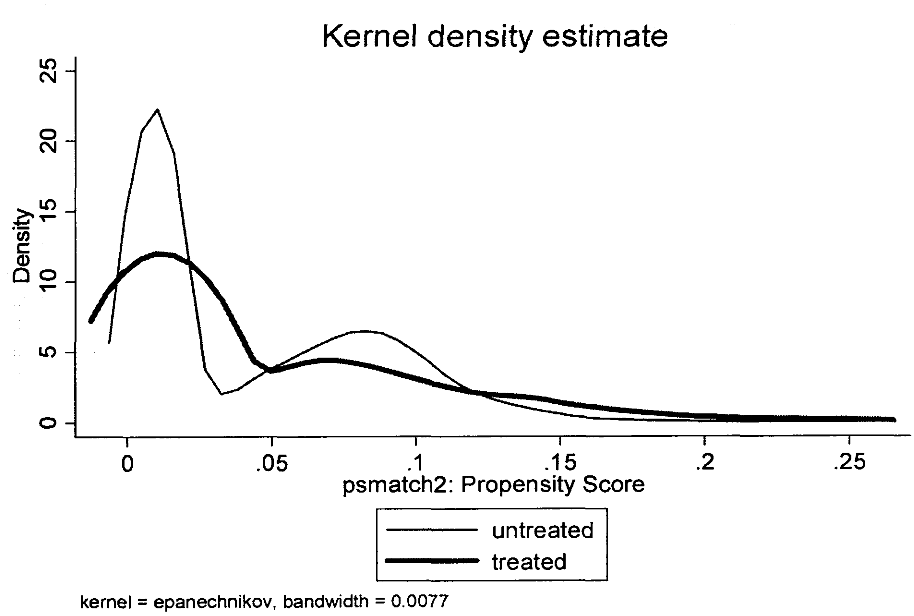
Figure 3.14: The comparison of propensity score distribution before matching



3.7.3.2. Checking the common support

Following Sianesi (2006), we check for common support. The common support condition requires that there exists treated and non-treated units with similar values of the propensity score after matching. Figure 3.15 confirms that the common support holds. There is an overlap propensity score between treated and control groups.

Figure 3.15: Propensity score distribution and common support for propensity score estimation



3.7.3.3. Assessing the match quality

In order to check the success of the matching for all independent variables, there are some tests to be done after matching. Caliendo and Copeinig (2005) suggest assessing the quality of matching by using a standardised bias test, t-test for testing the equality of means before and after matching and an F-test for the joint equality of means in the matched sample.

3.7.3.3.1. Test of standardised bias

The standardised bias test is used to check the reduction of bias after matching. According to Rosenbaum and Rubin (1985), the standardised bias approach is calculated from the difference in means of the treated and untreated variables as a percentage of the square root of the average variance in both groups. Table 3.19 shows the standardised bias of variables before and after NN matching.

Table 3.19: Standardised bias from NN matching

	Before Matching	After Matching
Child test score	30.1	24.7
Poor	4.6	-6.5
Male	-9.3	-7.9
Urban	-12.2	-9.0
Rank of provincial HCI	-4.5	5.6
HH size	8.3	5.1
Log of HH expend on food	-5.0	0.7
Father secondary	-14.3	2.9
Father higher education	16.7	4.5
Mother secondary	-0.2	-1.6
Mother higher education	0.5	-7.7
Public school	-7.8	-1.1
Staff of Village	1.2	-8.5
Java	-18.1	-20.3

8 out of 14 of the variables have less bias after matching than before matching, although 6 variables have a higher bias after matching. Caliendo and Copeinig (2005) stated that there is no clear standard of success for bias reduction in matching methods.

3.7.3.3.2. Test for equality of the mean before and after matching (t-test)

Rosenbaum and Rubin (1985) also suggested a t-test of the difference of covariate means for treated and control groups. Table 3.20 displays the p-value of the t-test for equality of the means before and after matching. Before matching, some of the covariate means are different between treated and control groups, but after matching only one (child test score) is significantly different between groups.

Table 3.20: Test for equality of the mean before and after matching (t test)

	P value of t test	
	Before matching	NN with replacement
Child test score	0.000	0.024
Poor	0.566	0.548
Male	0.228	0.459
Urban	0.112	0.397
Rank of provincial HCI	0.540	0.598
HH size	0.320	0.615
Log of HH expend on food	0.522	0.947
Father secondary	0.076	0.772
Father higher education	0.012	0.695
Mother secondary	0.978	0.884
Mother higher education	0.948	0.476
Public school	0.309	0.915
Staff of Village	0.880	0.439
Java	0.019	0.056

3.7.3.3.3. Test of Joint Equality of Means in the Matched Sample (Hotelling Test)

After testing the difference of covariate means individually, a joint test for equality of means in all covariates can be conducted. Using the Hotelling test in Stata, the result shows that the P value of the F test is greater than 5%, which is 0.36. It indicates that the null of joint equality of means is not rejected, so the conditioning variables are well balanced jointly.

Table 3.21: Hotelling Test After Matching

	Mean for BOS=1	Mean for BOS=0
Child test score	6.84	6.56
Poor	2.46	2.55
Male	0.47	0.50
Urban	0.46	0.51
Rank of provincial HCI	10.22	9.89
HH size	5.30	5.25
Log of HH expend on food	13.84	13.82
Father secondary	0.16	0.15
Father higher education	0.08	0.07
Mother secondary	0.15	0.15
Mother higher education	0.02	0.02
Public school	0.42	0.43
Staff of Village	0.20	0.24
Java	0.43	0.53
Hotelling p-value, that means are different for two groups	-	0.36
Observation	178	3105

3.7.3.4. Results

Having checked the quality of matching is satisfactory, it is then possible to estimate the Average Treatment Effect on the Treated (ATET) because the control group now has similar characteristics to the treated group. Table 3.22 shows the effect of school subsidy on student performance. The results indicate that there is a statistically significant impact of school subsidy on test score at 5% significant level for NN matching with replacement and without replacement. For individuals in the treatment group, the treatment has raised the test score by 0.26 points on average for NN matching with replacement, and by 0.28 points on average for NN without replacement. To check that our results are robust, we carried out a number of additional estimation experiments with different matching estimators. Especially, we have tested calliper matching and also kernel matching. Table 3.22 shows the various results from several types of matching methods and the estimated treatment effects are very similar to those obtained from NN with replacement and without replacement.

Table 3.22: The Effect of School Subsidy on Student Performance

Matching method	Effect	SE	BS SE	P-value
NN with replacement	0.265	0.118	0.129	0.040
NN without replacement	0.281	0.116	0.126	0.036
Kernel	0.313	0.081	0.084	0.000
Radius Caliper	0.312	0.082	0.076	0.000

Note: SE(Standard Error of estimator); BS SE(Bootstraped clustered standard error)

Recall that the OLS coefficient estimate was 0.358 bigger than the matching estimate 0.265. On the other hand, using IV estimation it was found to be bigger than PSM at about 3.20 points. Hence, there is a higher estimated effect of BOS on child test scores using IV regression than using OLS or PSM estimations. This may consistent with a local average treatment effect (LATE) interpretation. This suggest that higher IV results could occur because they estimate the average effects for the group whose BOS status is affected by the instruments, whereas the OLS estimates approximate average effects among everyone, and PSM estimates the average effects of treatment on the treated, which affects people generally.

Furthermore, IV does not tell us whose behaviour is affected by its instruments. These 'compliers' receive BOS because of the identity of the local administrator, rather than because of the official criteria. For example, BOS may be received because of family connections. The estimates imply that the effect of BOS from the students whose test score in the margin is quite large.

3.7.3.5. Evaluation: Sensitivity Analysis

According to Rosenbaum (2002), selection bias occurs when two individuals with the same observed covariates have a different probability of receiving treatment. To deal with selection or hidden bias, Rosenbaum suggested that sensitivity analysis be conducted using Wilcoxon's signed rank test to get Rosenbaum bounds. Table 3.23 shows the results of this sensitivity analysis for the study of the effect of the school subsidy on students' tests scores using Wilcoxon's signed rank test. The point estimation of Rosenbaum's bounds of this study for the p-values with $\Gamma=1$ is very close to the estimation in the propensity score matching analysis. The estimation effect of NN matching is 0.26 and the Hodges-Lehman point estimate is 0.269 and both results are significant at 5%.

Table 3.23: The Rosenbaum sensitivity analysis

Γ	p-value of Wilcoxon's signed-rank test		Hodges-Lehman point estimate	
	Upper bound	Lower bound	Upper bound	Lower bound
1	0.010	0.010	0.269	0.269
1.1	0.037	0.002	0.206	0.332
1.2	0.099	0.000	0.153	0.391
1.3	0.203	0.000	0.102	0.439
1.4	0.341	0.000	0.050	0.492
1.5	0.493	0.000	0.002	0.540

Table 3.23 also shows that for a small increase of $\Gamma=0.2$, p value increases to 0.099 in the upper bound, which is above the threshold of p value 0.05. In this case, a hidden bias or selection bias of size $\Gamma=1.2$ is sufficient to explain the observed difference in test scores between the treatment group and the control group. Hence two units that appear similar and have the same covariates could differ in their odds of receiving the

treatment by as much as a factor of 1.2. Because 1.2 is a small value, it shows that this study is sensitive to hidden bias. For Hodges-Lehman point estimate interpretation, for example when Γ=1.1, matched students might differ in their test scores by a factor of 1.1 due to hidden bias. The range is between 0.206 and 0.332.

3.8. Conclusions

Our research indicated that poorer students had lower average test scores. This finding suggests that the Government of Indonesia needed to develop a subsidy program to provide a basic level of education for all students. Another important finding is that parental education background is positively related to test scores. Moreover, Estimation using OLS, IV and PSM all suggested that the BOS program has a positive and significant effect on child test scores. Students who receive subsidies attain higher test scores. OLS estimation suggested that test scores can be raised by 0.358 points or 29.3% of standard deviation, and IV estimation resulted in a much larger value of 3.3 points or about 270% of standard deviation. Furthermore, PSM also suggested that the BOS program in Indonesia increased test scores by 0.26 points or 21.3% of standard deviation. We interpret our IV estimates as a local average treatment effect Overall, the early version of the program, BOS successfully improved student test scores performance.

We further attempt to estimate the impact of BOS by the depth of poverty that the child experienced. OLS estimation concludes that BOS does not help very poor students, and helps less poor students more. On the other hand, IV estimation concludes that for those students who got BOS, but they are in the margin for being entitled or not quite poor, they do well with BOS. Hence, the BOS effect is quite large. In addition, for those students with very poor criteria, the effect of BOS is very small. Thus, giving BOS to somebody not very poor according to poor criteria results in a very big effect. In conclusion, the BOS program is successful at raising child test scores. As a school subsidy policy, BOS is a good at helping poor students to get an access to education, especially basic education, since the government can ensure the use of subsidy for schooling, as the funding goes to the school directly and is managed by the teachers and monitored by the school committee.

Chapter 4

The Impact of Natural Disasters on Human Capital Outcomes for Children

4.1. Introduction

Natural disaster always affects different aspects of individual life. It affects in almost every part of our life such as emotional, economic, physical, social, and environmental. Children are believed to be very vulnerable to disasters. The increasing frequency of disasters and the intensity of their destruction motivate an analysis of the impacts of disasters, especially in terms of human capital outcomes for children. This chapter uses a micro level survey data set from IFLS which covers approximately 83% of the Indonesian population within the survey area. There are two main objectives. The first objective is to examine the effects of natural disasters on child test scores and examine whether different types of disasters have different impacts. Moreover, we also investigate the children who took the test immediately after a disaster compared to those whose tests a year after a disaster. The second objective is to investigate the effects of natural disasters on child health. Similar to the impact on child test scores, we also examine whether different types of disasters have different impacts on child health. Three types of disasters are defined in this chapter: big earthquakes, small earthquakes and floods. These types of disasters were chosen because of their intensity, as measured by the percentage of people killed, and the percentage of people evacuated.

This chapter contributes to the international literature in several respects. First, compared to other literature, this study uses self-reported data, on whether households are affected by disasters or not. In our data, individuals are categorized as affected by the disasters if they reported that their households experienced death or major injuries to household members, direct financial loss to the household, or relocation of household members. That definition seems more accurate rather than only using general information before and after the shock, and there has been no sense of which individual is affected or unaffected. Second, this study investigates the impact of disasters on child test scores. Previous studies investigate the impact of disasters on a quantity measure of educational outcome - such as school enrolment or attendance - rather than the quality of outcome. Third, this study examines the impact of disasters across the distribution of test scores using Quantile Regression, so we can see in detail the effects of disasters by groups of outcomes. Fourth, this study presents the impact of disasters on child health using two different measures of child health: height of child as an objective measure and self-reported health condition as a subjective measure. The purpose of using these two measures that height is a permanent effect whereas self-reported health is likely to be a short effect.

A considerable amount of literature has been published, especially those which have focused on the effect of disasters on child human capital outcomes. In child education, some researchers found that there is a negative impact of disasters on children's schooling. This impact becomes our concern because there is a wide literature that indicates that schooling has important effects in lifecycle earnings. Harmon and Walker (1995); Ashenfelter and Krueger (1994); Ashenfelter and Zimmerman (1993) point out that there are positive and significant effects of schooling on wages. Other studies (Currie and Thomas, 1999; Neale and Johnson, 1996; Murnane, Willett and Levy, 1995; Zax and Rees, 1998) confirm that test scores taken during schooling have a significant impact on the future labour market or outcomes.

In addition, almost all studies on the impact of natural disasters on child education use school enrolment or school participation as a measure of schooling such as Ureta (2005), Jacoby and Skoufias (1997), Baez and Santos (2007), Guarcello, Kovrava and Rosati,(2008). Only limited studies use other measures such as number of year grades completed such as Maccini and Yang (2008). In child health, earlier studies generally found that there is a negative impact of disasters on children with only a few studies finding no impact. The most famous studies were conducted by Hoddinott and Kinsey (2000 and 2001), which pointed out that the impact of disaster differs by gender. In brief, most studies on educational outcomes emphasise a quantity measure by using school enrolment or participation rate and very few use quality a measure such as test scores. Studies of the impact of disasters on child health have covered various aspects but there are no studies that discuss the impact on different age categories.

A major innovation of this research, that differs from the previous literature is to separate the effects of disasters into two parts. The first effect is calculated for individuals in disaster regions, both those who report that they are affected and those who are unaffected but lived in a disaster area, while the second effect is an additional effect for those who report that they have been directly affected by disaster. In addition, we calculated these effects for the impact of specific natural disasters (big earthquakes, small earthquakes and floods). We also estimate the impacts on children who took the test immediately after the disaster compared to those who took the tests a year after disaster.

Our first major finding is related to the effects of disasters on child test scores. Natural disasters affect all of the children in disaster regions, both those who declare they are affected and those who are unaffected by the disaster. Those who are affected by disasters had a lower test score than those who were unaffected but lived in disaster region. Moreover, children who took the test just after the disaster have lower test scores than children who took the test more than a year after the disaster. There are also different impacts from different types of natural disasters and we find that only large earthquakes are associated with lower test scores for all children in the disaster region. Being in a region that is hit by a natural disaster has the biggest impact on child test score in the lowest quantile of conditional test scores. The largest additional impact of natural disasters to those who have been affected by disasters is on children at the median of the test score distribution.

The second major finding is on the impact of disasters on child health. We found that, conditional on survival, disasters have no serious impact on child health. This finding is confirmed by all our estimation results using the height of the child or self-reported health measures. For the height of the child, none of the children who have been affected by disasters have a lower height compared to those who are unaffected by disasters. The same result is obtained for the impact of specific natural disasters on child health. The result from self-reported health data is similar to results from the height data. Only the dependent variable which uses last year's health condition has a significant impact from disasters. It indicates that children in disaster regions who have actually been affected by disasters have a bigger probability of being unhealthy.

In short, disasters result in serious impacts on child test scores but do not affect child health significantly. Since a disaster is a temporary event, our results are consistent with the government and state agencies compensating well for any impact. It seems natural that child health would be top priority, rather than child education, at a time of a disaster. This is not surprising, since all agencies deal with the immediate impact at the time of disasters, such as child health, rather than long-term impacts such as education. Our results suggest that the Government also needs to consider supporting the victims of disasters to compensate for any child education effects of disaster. This may require more resources devoted to longer term disaster relief.

This chapter is organized as follows. The next section presents a review of the literature on the effects of natural disasters on human capital outcomes for children. The third section profiles Indonesia's natural disasters and is followed by data sources. The fifth section discusses methodology used in the impact of disasters on child test scores, and is followed by discussion of its empirical findings. The seventh sections are the methodology used in the impact of disasters on child health and is followed by the discussion of its empirical findings. The ninth section is robustness checks, and the last section concludes with the policy recommendations.

4.2. Literature review

This section reviews the previous research on the impact of natural disasters on human capital outcomes for children. A growing body of literature has investigated the effects of disasters in developing rather than in developed countries. In this chapter, the discussion of literature can be classified into three strands. The first strand of the literature focuses on the impact of disasters on health. The second focuses on the impact of disasters on education and the last strand studies the impact of disasters on nutrition.

4.2.1. The Effects of Disasters on Health

A considerable number of studies have focused their attention on the impact of natural disasters on health, using various measures of a health. The most famous study was by Hoddinott and Kinsey in 2000 and 2001. In 2000, they examined the impact of drought on adult health in Zimbabwe, using body mass index as a measure. There were three reasons why body mass was used for adult health measurement (Hoddinott and Kinsey, 2000). First, body mass was one of the alternatives for adult health measurement. Second, previous studies indicated that there was a relationship between body mass index and agricultural productivity. Third, a huge number of health indicators were related to body mass index. Using individual-level fixed-effect estimation to deal with unobservable characteristics, they estimated health using the log of body mass index and controlled for individual, household and community covariates. There was a reduction in the body mass of women but not men. These important findings confirmed that only women in poor households were affected by the drought. Thus, this study pointed out that there were different impacts of disasters by gender.

Hoddinott and Kinsey (2001) estimated the effects of disaster on other health measures. They investigated the reactions of the height of young children to drought in rural Zimbabwe. They identified five reasons why they used the height of young children aged 12-24 months. First, the individuals who were more vulnerable to weather shocks were believed to be very young children. Second, the growth rate and height of young children was a good indicator for health status. Third, by using the measurement of height, the authors could examine the impact of natural disasters at the individual level. Fourth, according to previous studies, children with slow height growth would perform less well in school than children who had normal height growth. Fifth, height was possibly a useful indicator to examine whether the impact of natural disasters on children was permanent or transitory. Hoddinott and Kinsey (2001) measured child growth as the difference between child height in period t+1 and t. They estimated child growth as a function of child height in period t, child care, child characteristics, and health and sanitation environment. The findings confirmed that children aged 12-24 months have lower than normal growth, in terms of height, of approximately 1.5 to 2cm after the shock.

A further prominent study on the effects of disasters on health was by Baez and Santos (2007). Using panel data from the Living Standards Measurement Study (LSMS) in 1998, 1999 and 2001 in Nicaragua, they examined the impact of Hurricane Mitch on children's education, health and labour force participation. They observed two health measurements: the prevalence of illness and conditioning on sickness. The research design to calculate the effects of the shock was a difference in difference analysis (DID). The effects of the shock were obtained from the difference of child outcomes after shock (2001) and pre-shock (1998) in disaster areas minus the difference of child outcomes after shock (2001) and pre-shock (1998) in non- disaster areas. Baez and Santos (2007) found that the hurricane had a negative impact on health for children in rural area. However, in general, they found no statistically significant difference between the proportion of children who were sick before and after the hurricane.

Ninno and Lundberg (2004) examined the impact of floods on child health and nutrition in Bangladesh. Using a three-round household survey in seven flood-affected areas collected between November 1998 and November 1999. Child height at 60 months old was adopted as a measure of children's health. For measurement of child growth, they used the change in height-for-age. In the empirical model, they used health inputs, the child's, household's and community's characteristics, and lagged health as independent variables. This findings suggested that children who experienced by the flood were badly affected. There was also evidence that the prevention program from the government was more effective than the post-disaster program in protecting child health.

Akresh et al. (2007) studied the impact of economic shock (civil war and crop failure) in Rwanda in the 1980s, on children's health at birth for several years after the shock. The height for age of children was used as a proxy for health. They found that boys and girls born after civil war were both negatively impacted, with height for age 0.30 and 0.72 standard deviations lower respectively. In the case of crop failure, only girls were affected, by 0.41 standard deviation lower height for age, and the impact was bigger for girls from poor families.

In a recent study, Rhodes et al. (2010) examined the impact of Hurricane Katrina, which hit the USA on 29 August 2005, on the mental health of low-income parents in New Orleans. Using psychological distress and perceived distress as measures of mental health outcome from approximately 1,000 participants, they found that higher levels of hurricane- related loss and stressors were associated with worse health conditions. Higher baseline resources predicted fewer hurricane-associated stressors, but the consequences of Hurricane Katrina persisted for a year or more and were most severe for those experiencing the most stressors and loss.

Study by Aguero and Deolalikar (2011) on the effect of civil conflict between April and June 1994 on health in Rwanda found that the negative effect of crises on health goes well beyond early childhood. They used height of adult women in Rwanda, and the result confirmed that the adult height of children was lower than older children and those who were from neighbouring countries. They used large household survey data, focusing on female respondents aged 15-49 years old, and difference in differences method to estimate the effect of the shock.

4.2.2. The Effects of Disasters on Education

According to previous studies on natural disasters, there were heterogeneous effects of natural disasters on education. Some studies found that disasters caused negative effects on schooling, while others found no effects. This was because the degree of disaster effects varies among individuals, households and regions. In the case of schooling, some school buildings may have suffered heavy damages that caused important effects on the schooling process, while some others were unaffected. Moreover, the effects on teachers might also disrupt the schooling process.

Ureta (2005) investigated the impact of natural disasters on school enrolment in Nicaragua using a test of mean difference and duration of schooling function. He analysed urban and rural areas separately. To compare: in 1998, prior to the hurricane, overall school enrolment rate for a treatment group was slightly higher than a control group by 4% from 77 percentage bases for urban area and 6% from the base percentage of 52 for rural area. In 1999, soon after the hurricane hit Nicaragua, school enrolment rates of individuals in hurricane areas were affected but not by much. In urban areas, enrolment rates decreased from 86.6% to 84.4%. Similarly in rural areas, it decreased from 63.9% to 63.4%. This worse condition in urban areas might be because of migration from rural to urban areas.

Still in the case of Nicaragua, Baez and Santos (2007) examined the effect of hurricane on school enrolment. Using the same data set as Ureta (2005) but different methodology (difference in difference analysis), they found that there was no significant effect on school enrolment. They looked at the difference of school enrolment rate between 1998 and 2001. The school enrolment rate increased significantly, by 5.9% for the treatment group and 8.5% for the control group in rural areas. This was because there was an important development of the education sector in Nicaragua at that time. Because of this reason, Baez and Santos (2007) tried to control for the characteristics of individual and household, and also for fixed regional effects and local public programs. After controlling for these characteristics, the model could reduce unexplained variance from the characteristics of individual and households when they are nor controlled, and confirmed that there was no significant effect of the hurricane on school enrolment.

Guarcello, Kovrava and Rosati (2008) pointed out that different natural disasters have varied impacts on schooling. They studied the impact of floods and droughts on schooling in rural Cambodia. Using data from the Cambodia Socio-Economic Survey 1999 and 2003-2004, and applying propensity score matching and difference in difference estimates, they found that children who experience both floods and droughts experienced negative and significant effects on schooling. Schooling was also reduced if a child experienced only a drought, but not so badly as if they had experienced both disasters, while floods seemed to have no effect on schooling in rural Cambodia.

The pioneering work of research in Indonesia on the effect of natural disasters on education outcomes was Maccini and Yang (2008), using the third wave (the 2000 wave) of the Indonesia Family Life Survey. They focused especially on the weather shocks in early-life on future education outcomes and completed grades of schooling as education outcome measures. In addition, Maccini and Yang (2008) used rainfall measurement from the closest rainfall station to the child's birth place as a measure of weather shocks. Using a reduced-form linear regression, the result suggested an interesting and different result between females and males. For females, the result confirmed that the relationship between education outcome and rainfall was positive and significant. It indicated that the higher the rainfall at the time of birth, the higher the year grade completed would be. Lower rainfall by 20% leads to 0.22 fewer years of schooling for females. On the other hand, the result was not statistically significant for males.

In a similar study of weather shocks in agriculture in Côte d'Ivoire, Jensen (2000) pointed out that the weather shock in agriculture reduced the school enrolment rate by one-third to one-half and the impact on males and females was almost the same. This study applied OLS and fixed-effects regression. Equally important, in India, Jacoby and Skoufias (1997) reported the effects to school attendance in rural India in times of drought. By using a model of human capital investment under uncertainty and Village Level Studies Survey data set from the International Crops Research Institute for the Semi-Arid Tropics (CRISAT), they confirmed that the weather shocks in rural India reduced school enrolment.

Another study in rural Honduras, by Gitter and Barham (2006), examined the effects of a hurricane which occurred in October 1998 on school attainment. In comparison to other studies which used school enrolment or the number of years completed as measures of educational outcome, they used a different measure, the so-called SAGE (the School for AGE) measurement, that has been developed by Patrinos and Psacharopoulos (1997). This measurement considers two important elements: the current status of school-age children and the number of years of schooling. SAGE score was obtained from the percentage of the total number of years of school completed (S) divided by the difference between the age of children (A) and their age when they started their schooling (E). A 100 score implies that children kept up with their schooling at their age and a score of less than 100 implies that children who missed some schooling or did not participate at school. Using a two stage least square model, they found that children who were affected by the hurricane had a lower SAGE score.

A recent study conducted by Bustelo, Arends-Kuenning and Lucchetti (2012) investigated the impact of earthquakes on schooling in Colombia. They identified the short and medium term impact of earthquakes on schooling by combining two cross-sectional household surveys before an earthquake and one six years after an earthquake. Using school enrolment as a measure of schooling for two different groups of children at primary school and secondary school, they confirmed that both short and medium term effects of disasters were negative on school enrolment. Short-term effects were stronger than the medium effects. This was not surprising, since a year after an earthquake all the infrastructures of schooling were still being refurbished, so this affected the process of schooling.

4.2.3. The Effects of Disasters on Nutrition

The most influential study on the effect of natural disasters on nutrition was the study conducted by Baez and Santos (2007). Their study of natural disasters, especially the effect of natural disasters on health, nutrition, child labour and school enrolment, has inspired other researchers to study other natural disasters particularly in relation to children's well-being. Baez and Santos (2007) estimated the effects of a hurricane on nutrition in Nicaragua in 1998. Considering the hurricane as a natural experiment, they exploited the medium- term effect of disasters on children's well-being by using difference in difference analysis and a panel data household-level survey from Living Standards Measurement Study (LSMS) 1998, 1999 and 2001 respectively. The results indicated that the hurricane badly affected the nutrition of children in the medium term.

There are some studies that discussed the influence of weather on investments in children, especially on nutrition. As pointed out by Jensen (2000), in Côte d'Ivoire, the weather shock had affected households in reducing their investment in children. Using child weight for height (WFH) in the age range 0-10 as a measure of nutritional status, the results confirmed that there was a negative effect of weather shocks on child nutrition. Malnutrition was suffered by both boys and girls and was nearly double compared with the condition before the weather shocks.

In Ethiopia, Woldehanna (2009) examined the effect of economic shocks on nutritional achievement on children aged 5. The economic shocks were recorded before and after child birth, such as crops failure, death of livestock, severe illness or injury, job loss/source of income, natural disaster and others. Using longitudinal data of children in 2002 and 2006 and household's utility maximisation function subject to income and health constraint, Woldehanna (2009) estimated the impact of shocks on children's height. The model had child height for age as the dependent variable and economic shocks before and after child birth, and household characteristics as control variables. To reduce the endogeneity problem, lagged values of explanatory variables are used. The finding confirms that there is a significant effect of economic shocks both after birth and before birth on the nutrition and height of children. Children in rural areas were more at risk than in urban areas.

The most recent study conducted by Bustelo, Arends-Kuenning and Lucchetti (2012) examined the impact of the 1999 Colombian Earthquake on child nutrition in the short and medium term. They confirmed that the earthquake influenced all households by reducing their investment in child nutrition. The short-term effect was stronger than the medium-term effect.

Table 4.1: Summarises the literature on the impact of natural disasters on human capital outcomes for children

Type of Disaster	Country/Authors	The effects of natural disasters on human capital outcome for children		
		Health	Nutrition	Education
Earthquakes	Colombia: Bustelo, Arends-Kuenning and Lucchetti (2012)		Negative	Negative: school enrolment
Floods	Bangladesh: Ninno and Lundberg (2004)	Negative: child height at a maximum of 60 months old		
	Cambodia: Guarcello, Kovrava and Rosati (2008)			No effects
Winds/ storms/hurricanes	Nicaragua: Ureta (2005)			-(DiD)Negative: school enrolment in rural and urban area -(survival function)Positive: school enrolment in rural area Negative: urban area
	Nicaragua: Baez and Santos(2007)	Negative: children in rural areas (the prevalence of illness and the utilization of medical service)	Negative	No impact: school enrolment
	Honduras: Gitter and Barham (2006)			Negative: SAGE score
	New Orleans: Rhodes et Al. (2010)	Negative: mental health (psychological distress)		

Droughts/ Weather shocks	Zimbabwe: Hoddinott and Kinsey (2000)	Negative: weight of women in poor households		
	Zimbabwe: Hoddinott and Kinsey (2001)	Negative: the height of growth children aged 12-24		
	Cambodia: Guarcello, Kovrava and Rosati (2008)			Negative
	Indonesia: Maccini and Yang (2008)			Negative: female year grade completed but not male
	Côte d'Ivoire: Jensen (2000)		Negative: child weight for height	Negative: child school enrolment
	India: Jacoby and Skoufias (1997)			Negative: child school enrolment
	Ethiopia: Woldehanna(2009)		Negative: child height	
	Rwanda: Akresh et.al (2007)	Civil war: Boys and girls were negatively affected. Crop failure: only girls were negatively affected		
	Rwanda: Aguero and Deolalikar (2011)	Negative: height of children was lower than control groups		

4.3. Indonesia Natural Disaster Profile

This section outlines the occurrences of natural disasters used in our empirical analysis and provides a description of the disaster data used.

4.3.1. Indonesia Natural Disaster by Region

The data which we use for our empirical study are from the last decade of disasters, 2000-2011. More than 4000 disasters occurred and were recorded by the National Disaster Management Agency (BNPB) across various regions and some of them were very destructive and killed many people in some regions in Indonesia. The most destructive one was the earthquake and tsunami in Aceh on 26th December 2004 with a 9.1 - 9.3 moment magnitude scale, and the longest duration in history, of around 10 minutes. This disaster killed approximately 230,000 people in fourteen countries, and more than half of the people, 126,915, were from Indonesia. In addition, according to BNBP, 37,063 people were missing and 655,000 people were made homeless across Aceh province. The second destructive disaster was an earthquake on 26th May 2006 in Yogyakarta Province. More than 6,000 people were killed in a 6.3 magnitude earthquake and about 130,000 were left homeless. Another serious disaster was the floods in Jakarta in February 2007. Around 30 people were killed and approximately 340,000 left homeless. Another earthquake in West Sumatra that measured 5.8-6.4 on the Richter scale killed approximately 50 people on 6 March 2007.

Table 4.2: Total number of disasters, deaths and evacuations from 2000 to 2011

No	Province	Total number of disasters	Population	% death/pop	% evacuations /pop
1	Aceh	204	4,494,410	3.713	23.539
2	Bali	58	3,890,757	0.001	0.039
3	Bangka-Belitung	73	1,223,296	0.004	0.036
4	Banten	63	10,632,166	0.001	0.523
5	Bengkulu	22	1,715,518	0.007	0.038
6	DI Yogyakarta	44	3,457,491	0.146	40.973
7	DKI Jakarta	59	9,607,787	0.001	6.908
8	Gorontalo	43	1,040,164	0.002	5.731
9	Jambi	43	3,092,265	0.001	2.539
10	West Java	691	43,053,732	0.003	1.822
11	Central Java	863	32,382,657	0.006	2.965
12	East Java	388	37,476,757	0.001	0.480
13	West Kalimantan	53	4,395,983	0.001	3.601
14	South Kalimantan	108	3,626,616	0.002	6.042
15	Central Kalimantan	16	2,212,089	0.000	0.278
16	East Kalimantan	60	3,553,143	0.002	2.983
17	Riau Kepulauan	6	1,679,163	0.000	0.000
18	Lampung	87	7,608,405	0.001	0.066
19	Maluku	29	1,533,506	0.005	0.591
20	North Maluku	30	1,038,087	0.001	1.526
21	West Nusa Tenggara	83	4,500,212	0.001	2.104
22	East Nusa Tenggara	253	4,683,827	0.008	1.144
23	Papua	35	2,833,381	0.007	1.241
24	West Papua	8	760,422	0.023	4.548
25	Riau	67	5,538,367	0.001	2.156
26	West Sulawesi	24	1,158,651	0.003	0.548
27	South Sulawesi	176	8,034,776	0.005	0.529
28	Central Sulawesi	77	2,635,009	0.005	2.904
29	South East Sulawesi	205	2,232,586	0.004	0.685
30	North Sulawesi	72	2,270,596	0.006	5.187
31	West Sumatra	183	4,846,909	0.042	4.429
32	South Sumatra	58	7,450,394	0.001	0.094
33	North Sumatra	146	12,982,204	0.010	1.101
	Total	4,327	237,641,326	-	-
	Average			0.076	2.835

Source: BNPB. Note: rows in grey are for IFLS provinces.

Table 4.2 shows the total number of disasters during the last decade across various provinces. Rows in grey are IFLS regions where all IFLS data samples were taken from. We provide the percentage of population killed and the percentage of population evacuated in order to see the region which suffered the most from disasters. Aceh province has the highest percentage of deaths to population and also the total number of evacuated people to population. It is not surprising since the most destructive disaster during the last decade was in Aceh. As Aceh is an outlier due to the huge number of victims from the impact of the earthquake and tsunami in 2004 and is not in the IFLS sample, we excluded Aceh from the following discussion.

Neumayer and Plumper (2007) suggest that it is better to use the ratio of dead people to the population rather than the total number of deaths to categorize disaster regions. Because of the extensive impact of disasters, we also consider the effect of disasters by seeing the total number of evacuated people for determining disaster regions. The reason is to capture the effect of disasters like floods: although they result in only a few deaths, almost every year, some regions regularly experience floods and they always present a problem in terms of big numbers of evacuated people.

Figure 4.1 shows the distribution of the percentage of the number of dead and evacuated people to the population across the regions. The dark colour is for the percentage of evacuated people to the population, while the light colour is for the percentage of dead people to the population. After excluding Aceh region, Yogyakarta had the highest percentage of both ratios. West Sumatra and West Papua were in second and third places in terms of the percentage of deaths and evacuated people. In terms of the percentage of evacuated people, some regions with high percentages were

DKI Jakarta, South Kalimantan, Gorontalo and North Sumatra. This information is used in the empirical analysis to define disaster regions for further analysis,

Figure 4.2 shows the distribution of disasters across regions in Indonesia weighted by mortality, while Figure 4.3 is a simple count of the number of disasters. The gradation of colour from white to dark red means the greater the number of disasters in the region. The figures confirm that Java and Sumatra islands are dominated by regions that have more disasters than other regions. In addition, Aceh and Southern Java have the biggest disasters by having a greater number of dead people from disasters.

Figure 4.1: Percentage of total number of dead and evacuated people to the population

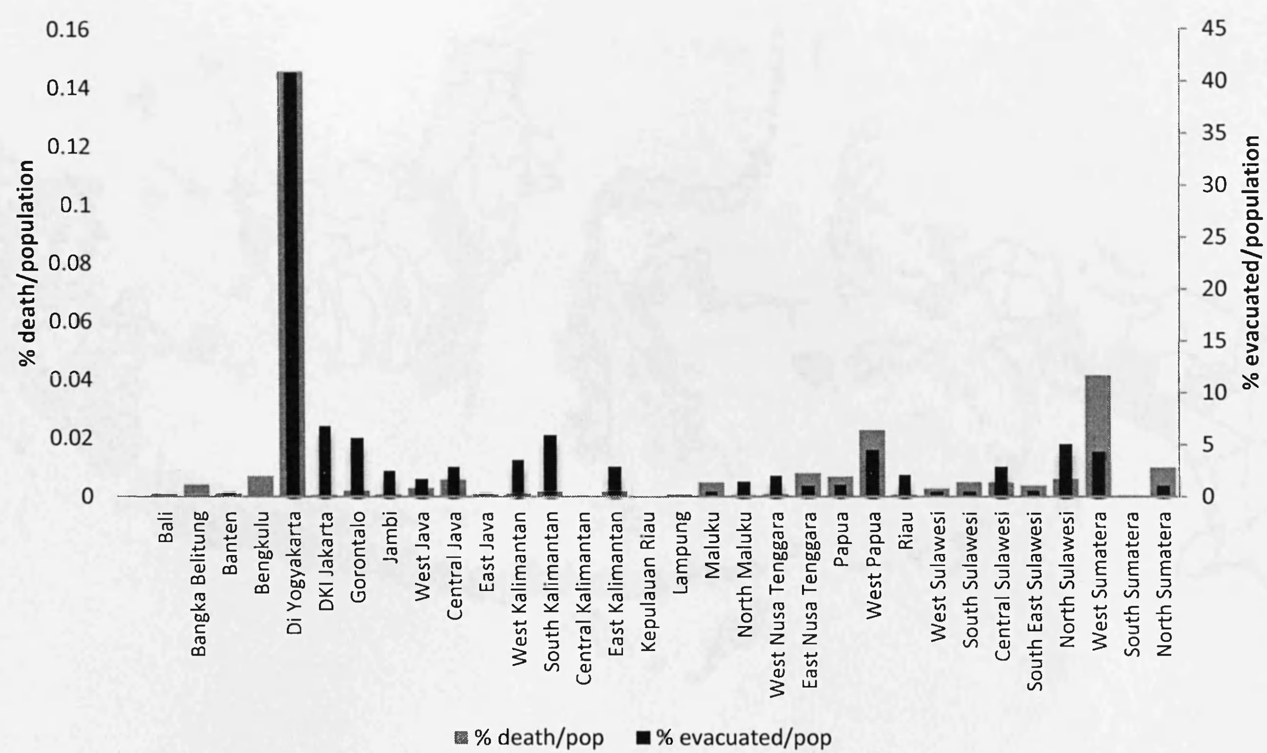


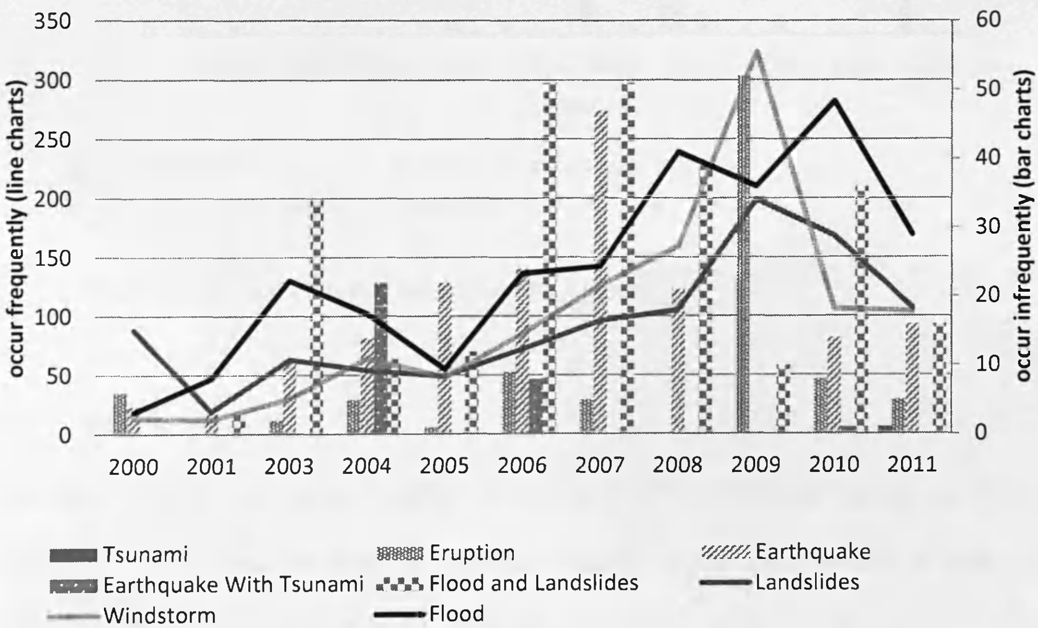
Figure 4.2: The distribution of disasters (weighted by mortality)

Figure 4.3: The distribution of disasters (unweighted)

4.3.2. Indonesia's Natural Disasters by Year

Compared with the distribution of disasters by region, Figure 4.4 shows the total number of occurrences from various types of disasters by year in Indonesia. From 2000 to 2011, Indonesian natural disasters were dominated by windstorms, floods and landslides. There were also an increasing number of occurrences of those three disasters than others on average, but there is no information on the intensity of these disasters. In comparison with landslides, windstorms and floods, earthquakes with tsunamis or earthquakes are only of low occurrence but the effects of these disasters result in a huge human and financial loss.

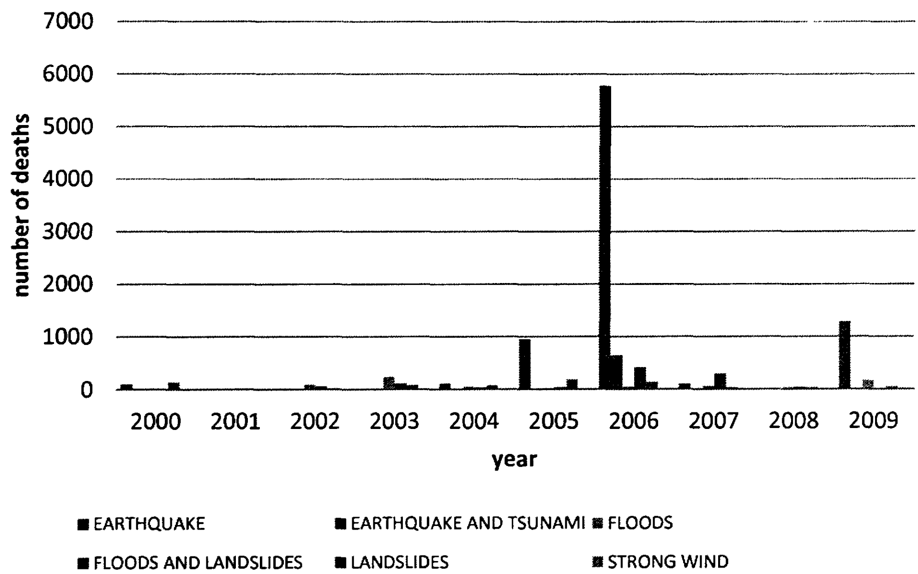
Figure 4.4: The number of occurrences for each type of disaster by year



Source: National Disaster Management Agency

In order to capture the intensity of disasters, Figure 4.5 demonstrates the number of deaths for each disaster by year. After excluding the tsunami with earthquake in Aceh in 2004, due to a huge number of victims, the earthquake in Yogyakarta in 2006 resulted in the highest number of deaths. Compared with the number of occurrences from Figure 4.4 above, although the frequency of the occurrence is quite high, floods, windstorms and landslides inflict a lower number of deaths.

Figure 4.5: The number of deaths in each type of disaster by year



Source: National Disaster Management Agency

4.4. Data Sources

This study uses the Indonesian Family Life Survey IFLS4 (2007) and some from IFLS3 (2000), the same data set from the previous chapter as the main source of data for estimating the impact of disasters on child test score and child health. In addition, there are two other data sets used: an official disaster data base from the National Disaster Management Agency (BNPB=Badan Nasional Penanggulangan Bencana) of Indonesia and statistics of Indonesian data from the Central Bureau of Statistics of Indonesia (BPS=Badan Pusat Statistik). IFLS provides all educational, health and disaster information at individual, household and community level. We also use additional information from BNPB to define disaster regions and the degree of disasters, and some demographic information from BPS.

4.4.1. Disaster Data

The main data in this chapter is related to disasters. IFLS defines households as being affected by a disaster if the disaster was severe enough to cause death or major injuries to a household member, cause direct financial loss to the household, or cause household members to relocate. IFLS reports several types of natural disasters, such as earthquakes, tsunamis, landslides, floods, volcanic eruptions and windstorms. Another important definition is disaster region. Since most of the regions in Indonesia experienced disasters, it is important to determine which disaster region is a treatment group. Disaster region is defined as a region with heavily damaged by disasters and a lot of people are affected by disaster (dead and evacuated) than other regions. According to Neumayer and Plumper (2007), in order to measure the strength of a disaster, they use the number of people killed during the disasters divided by the total population as a proxy of the strength of the disaster, but this study uses two proxies as a measurement of the strength of a disaster. Besides using the percentage of the number of people killed to the total population, this study also uses the percentage of the number of people evacuated to the population. For this reason, the region which experiences disasters almost every year which affect the economy can be captured by using this proxy.

As already discussed in Section 3 of this chapter, this study excludes Aceh from the list of disaster regions, since Aceh is an outlier and also is not covered in IFLS surveys.

Referring to the percentage of the total number of dead and evacuated people to the total population in each region, a disaster region can be defined as a region above the average of both percentages which consist of Aceh and DI Yogyakarta (see Table 4.3). Table 4.3 shows all the regions above the average of the percentage which are already ranked from the highest percentages and highlights provinces with IFLS data.

Table 4.3: Disaster Region Definition

No	Province	% death/pop		Province	% evacuated/pop
1	Aceh	3.71	1	Aceh	23.54
2	DI Yogyakarta	0.15	2	DI Yogyakarta	40.97
3	West Sumatra	0.04	3	DKI Jakarta	6.91
4	West Papua	0.02	4	South Kalimantan	6.04
5	North Sumatra	0.01	5	Gorontalo	5.73
6	East Nusa Tenggara	0.01	6	North Sulawesi	5.19
7	Bengkulu	0.01	7	West Papua	4.55
8	Papua	0.01	8	West Sumatra	4.43
9	North Sulawesi	0.01	9	West Kalimantan	3.60
.					
.					
33	Kepulauan Riau	0.00	33	Kepulauan Riau	0.00
	Average of Percentage	0.076			2.835

For our empirical analysis, we have determined the disaster regions as DI Yogyakarta, DKI Jakarta and West Sumatra. We picked those three provinces since only those three provinces are completely covered by IFLS survey data. South Kalimantan is covered in IFLS survey data but the total number of respondents who experienced disasters is not adequate, while West Kalimantan, Gorontalo, North Sulawesi and West Papua are not covered in IFLS surveys. Furthermore, natural disasters can be determined based on the occurrences of disasters in each disaster region. Yogyakarta, with a big earthquake, has the highest percentage for both dead and evacuated people. In terms of the percentage of evacuated people, West Sumatra, with a small earthquake, is above average, and in terms of the percentage of dead people, although West Sumatra is below average the value is just below DI Yogyakarta, which is quite high compared to other provinces. DKI Jakarta has floods, and although the percentage of dead people is quite low the percentage of evacuated people is above average. Another big factor is that DKI Jakarta experienced floods almost every year and always presents severe problems.

Based on the disaster data information above, we define dummies D (Disaster region) and dummies A (being affected by disaster). D is equal to 1 if individuals are in a disaster region at the time of the disaster and A is equal to 1 if individuals are in a disaster region and were affected by disaster. As explained above, in instances where the individuals suffered financial loss or where one or more household member died or suffered major injuries, this is defined as affected by disaster.

4.4.2. Educational data

The important data on education is child test score. Child test score is obtained from a test score in primary school at age 11 or in their final year of primary school. All questions in the test are standard for all regions in Indonesia and the test is conducted nationally at the same time. The test score is continuous value and ranged from 0 to 10. It is calculated from the average scores, which consist of 3 subjects (Maths, Science and Indonesian Language). Test score data from IFLS survey is only taken from the respondents who could show certificates of test and excludes the respondents who could not show certificates, since sometimes the information is not complete. For instance, they only mentioned 2 subjects out of 3, or they only mentioned the total score without mentioning each of the subjects because they did not remember their scores in detail.

Figure 4.6: Child test score distribution in a disaster region and a non-disaster region

a. Big earthquake region (Yogyakarta)

b. Small earthquake region (West Sumatra)

c. Flood region (Jakarta)

d. Non-disaster region

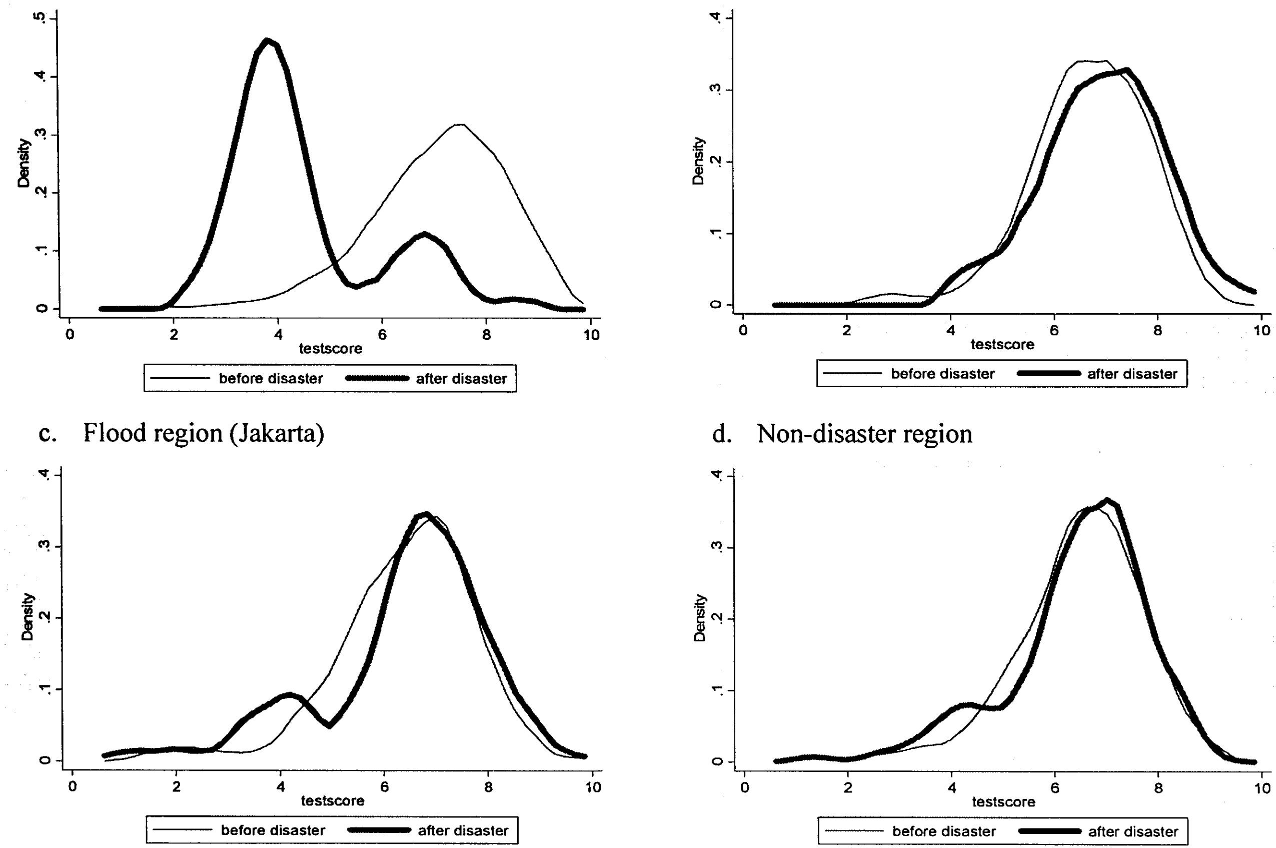


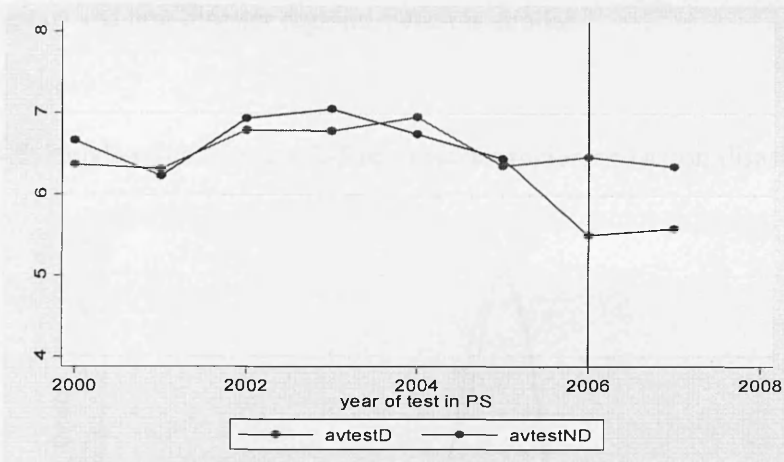
Figure 4.6 presents the comparison distribution between child test score in a disaster region (big earthquake, small earthquake and flood) and a non-disaster region in the time before and after a disaster. It seems that child test scores in big earthquake regions were badly affected by disaster, while child test scores in small earthquake and flood regions are not badly affected if we compare them before and after a disaster.

Figure 4.7 shows the common trend of child test scores for children in a disaster region and a non-disaster region, and also for those who are affected or unaffected by disasters. Before three types of disasters (big earthquake, small earthquake and flood) occurred in 2006, the average child test score on both a disaster region and a non-disaster region were similar, but after disasters there was a big gap between child test score in a disaster region and a non-disaster region. The same results are obtained for affected and non-affected child test score. The difference of child test score before a disaster between those two groups was not that large, but after disasters a huge gap could be seen. It seemed that child test scores in a disaster region were badly affected by the disasters, especially for those who were affected by disasters.

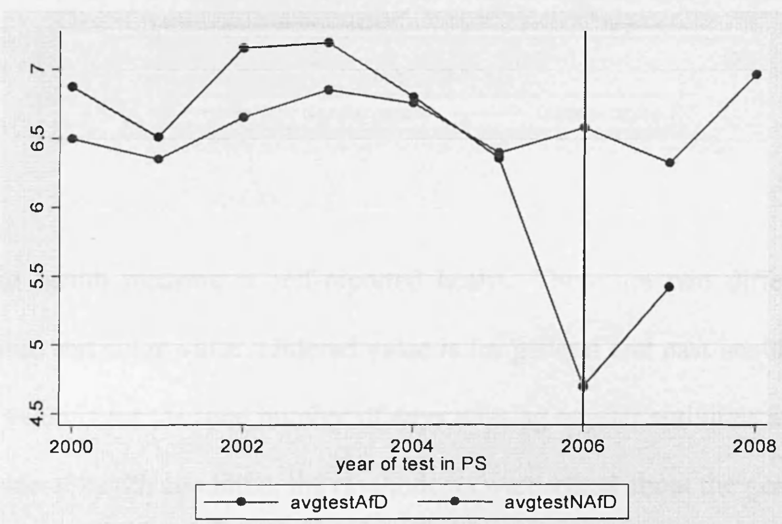
Dummies for parental educational background were also included. Dummy primary school is equal to 1 if the parent went to primary school, dummy secondary school is equal to 1 if the parent went to secondary school and dummy higher education is equal to 1 if the parent went to university.

Figure 4.7: Common Trend of Child Test Scores

a. Child test scores in disaster and non-disaster regions



b. Child test scores of affected and non-affected children

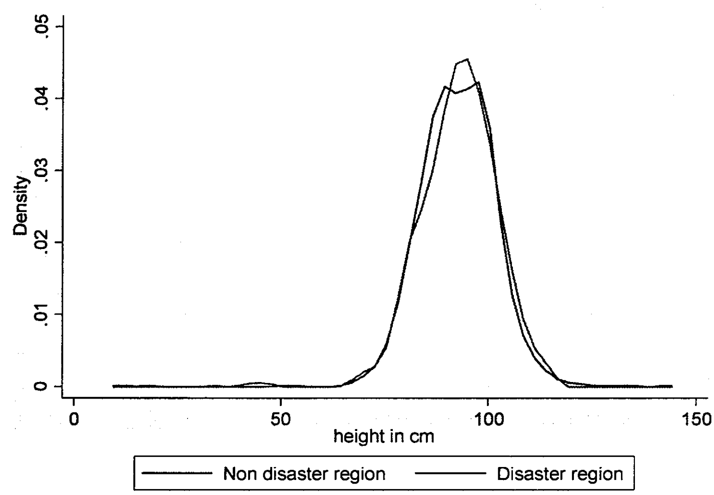


Source: Calculated from IFLS data wave 4 2007

4.4.3. Health Data

Two important types of health data are used in this chapter. The first is height of child measured in cm. We used height of child at ages 2-5 years old, since we believe that in this age group children are in the stage of important growth, known as the golden age. Furthermore, children at an early age are believed to be more vulnerable to the effect of disasters. Figure 4.8 describes the distribution of child height at age 2-5 in disaster regions and non-disaster regions, which is similar.

Figure 4.8: Height of child at age 2-5 in a disaster region and a non-disaster region



The second health measure is self-reported health. There are two different types: ordered value and count value. Ordered value is for general and past health condition and count value is for the total number of days missing regular activities and lying in bed. For general health condition, the respondents were asked about the general health condition at the time of survey, and the answer was designed in closed questions, which consisted of ranked data: (1) very healthy, (2) somewhat healthy, (3) somewhat unhealthy and (4) unhealthy. For the previous year's health condition, respondents were asked about the health condition 12 months ago in comparison with the condition at the time of the survey and the data consisted of: (1)much better now, (2) somewhat better now, (3) about the same, (4) somewhat worse, and (5) much worse. In comparison with general health condition, last's year health condition represented the child health condition that was closer to the time of disasters. As the big earthquake was occurred in May 2006, floods in January 2007, and small earthquake in March 2007, while IFLS4 survey was conducted in November 2007 to May 2008. Count values were defined as the total number of days missing regular activities and lying in bed for each child due to a poor health condition in the last 4 weeks from the time of survey. Moreover, at the community level, we provide information about the water supply and garbage system in the community. Dummy water system is equal to 1 if there is a good system or supply for drinking water and dummy garbage system is equal to 1 if there is a good system for garbage disposal in the community.

In summary, the means of key variables of this chapter can be seen in Table 4.4. There is separate data information for disaster region and non-disaster region data. In general, child test score in disaster regions are significantly different before and after disasters, but child test scores before and after disasters were similar in non-disaster regions. To calculate whether there is any difference between before and after disasters, we conducted t tests of difference in means. The results show that for disaster regions, where t statistics are equal to 8.24 and p value is equal to 0.000, we reject the null hypothesis. There is, therefore, a different test score of children who took the test before disasters or after disasters in disaster regions. On the other hand, for non-disaster regions, where t statistics are equal to 0.523 and p value is equal to 0.601, here we fail to reject the null hypothesis. This result confirms that there is no difference of test score from children who took the test before disasters or after disasters in non-disaster regions. For child height, t tests of difference in means shows that t statistics are equal to -1.77 and p value is equal to 0.07, we fail reject the null hypothesis. The results confirm that child height data is similar in disaster and non-disaster regions. In addition for self-reported data, the mean of each level for general and last year health condition, and also mean of days missing and lying in bed in disaster region and non-disaster region are not very different.

Table 4.4 Means of key variables

	Disaster Region		Non-Disaster Region	
Variable	Mean	SD	Mean	SD
1. Child test scores				
Before	6.51	1.28	6.49	1.25
After	5.37	1.72	6.46	1.33
2. Child health				
height age 2-5 (cm)	92.87	9.00	92.58	9.11
general health				
very healthy	0.107	0.309	0.127	0.333
somewhat healthy	0.763	0.425	0.782	0.413
somewhat unhealthy	0.128	0.334	0.090	0.286
Unhealthy	0.001	0.037	0.001	0.036
previous year's health				
much better now	0.127	0.333	0.097	0.296
somewhat better now	0.293	0.455	0.301	0.459
about the same	0.471	0.499	0.523	0.499
somewhat worse	0.076	0.266	0.049	0.217
much worse	0.003	0.059	0.002	0.043
days missing	0.43	1.94	0.33	1.34
days in bed	2.52	0.73	2.42	0.74
3. Disaster dummy				
A	0.34	0.48	0.00	0.00

Source: calculated from IFLS4

4.5. Methodology: The Impact of Disasters on Child Test Scores

This section outlines the research methodology used in this chapter to examine the effects of natural disasters on child test score and child health. For child test scores, we used Difference in Differences (DiD) method and Quantile Regression. Difference in differences (DiD) estimation is used when a certain group is exposed to the causal variable of interest, such as a change in government policy or a change in environment due to a big shock including disasters, and others are not. As natural disasters are exogenous conditions that affect the economic environment, we use this exogenous variation from natural disasters as a natural experiment to estimate the effects of disasters on child test score and child health in the affected area. The key assumption is on the potential outcome of the treatment group in the absence of natural disasters, and how to get this group when there is no data on what would have happened to individuals affected by natural disasters if the disasters had not occurred. Therefore, DiD tries to find the solution to estimate this group by using other individuals that we cannot observe at the same time. Moreover, Quantile Regression is used to examine the impact of disasters across the distribution of test scores, so we can see in detail the effects of disasters by groups of outcomes.

On the other hand, Bertrand, Duflo and Mullainathan (2004) demonstrated that DiD estimates have a potential problem of serial correlation. They said that DiD has at least three factors that potentially cause serial correlation problems. First, DiD usually uses a time series data set. Second, dependent variables in DiD usually have a positive serial correlation. Third, an intrinsic factor of DiD model, the treatment variable can change very little. Those three issues can support each other so true standard error of parameter of treatment variable can understate the standard deviation. To deal with a serious overestimation of t values and significance levels in DiD estimation, we should pay attention to the length of the time series data, the serial correlation of the dependent variables and we should also correct the estimation. Bertrand, Duflo and Mullainathan (2004) offered 5 possible solutions to correct the serial correlation problem: parametric method, block bootstrap, ignoring time series information, empirical variance-covariance matrix, and arbitrary variance-covariance matrix. Here, we collapse the data into pre and post period so we only have one period before and one period after the treatment (disaster) to lead to spurious inference in DiD model. Thus, OLS estimation provides a consistent standard error.

4.5.1. Difference in Differences Method

To illustrate the research design of DiD method, this study defines Y_{0i} as a particular outcome of individual i in the absence of natural disasters and Y_{1i} as a particular outcome of individual i who experienced disasters in the region affected by disasters. Furthermore, a_{it} is equal to 1 if the individuals reported that they were affected directly by the disasters and a_{it} is equal to 0 if the individuals were not affected directly by disasters. The definition of affected directly by disasters is if the disaster was severe enough to cause death or major injuries to a household member, cause direct financial loss to the household, or cause household members to relocate. Hence, DiD model can be written as:

$$Y_{it} = \alpha_1 D_{it} + \alpha_2 (D_{it}\, x\, a_{it}) + u_{it}$$

$$Y_{it} = \alpha_1 D_{it} + \alpha_2 A_{it} + u_{it} \qquad (4.1)$$

Note: $A_{it} = D_{it}\, x\, a_{it}$ and $u_{it} = \gamma_r + v_t + \varepsilon_{it}$

Where α_1 is the effects of disasters to all of the individuals who live in a disaster region at the time of a disaster. α_2 is the effects of disasters for individuals who have been affected directly by disaster. γ_r is region effect, v_t is time effect, ε_{it} is random error, $D_{it}=1$ is only for people in the disaster region in the time after disaster, $A_{it}=1$ is only for people in the disaster region in the time after disaster who have been affected by disaster directly. Furthermore, α_1 and α_2 are parameters of interest. Overall, $\alpha_1 + \alpha_2$

are the effect of disasters. When $D_{it}=0$ and $A_{it}=0$ then $Y_{it}=0$, and when $D_{it}=1$ and $A_{it}=1$ then $Y_{it}=\alpha_1+\alpha_2$.

Note that D_{it} and A_{it} in equation (4.1) above are interaction terms. D_{it} indicates a dummy observation in a disaster region after disasters and A_{it} as interaction effect represents a dummy indicating individuals in a disaster region who have been affected by disaster. A_{irt} is an intensity effect of disasters, which is a subset of D_{it}, so A_{it} would be a marginal effect of being affected by disasters. This model can be expanded by including individual covariates X_{it} and can be written as:

$$Y_{it} = \alpha_1 D_{it} + \alpha_2 A_{it} + \psi X_{it} + u_{it} \tag{4.2}$$

Thus, there are two treatment groups: the first group is individuals in a disaster region at the time of the disaster and after disaster, and the second group is individuals in a disaster region who report that they have been affected by the disaster. Furthermore, the control group is comprised of individuals who are in a non-disaster region and are those in a disaster region but not affected the disaster. The equation of child test score can be written as:

$$Test\ score_i = \alpha_0 + \alpha_1 D_i + \alpha_2 A_i + \psi X_i + \gamma_r + v_t + \varepsilon_i \tag{4.3}$$

The dependent variable in this equation (Test $score_i$) is child test score at age 11 for individual i. The average child test scores are used rather than total child test scores in order to make it comparable with different age groups of children, since there was a change in policy on the total number of subjects tested in 2002. Before 2002, the number of subjects tested was 5 subjects: (1) Moral and civil education, (2) Bahasa Indonesia, (3) Maths, (4) Science and (5) Social studies. Starting in 2002, the number of subjects tested was only 3 subjects: (1) Bahasa Indonesia, (2) Maths, and (3) Science. For test scores before 2002, we used test scores from the same subjects with the subjects that were tested after 2002. In addition, IFLS also reported the condition of whether the child could show the test score certificate or not. To avoid measurement error on child test score, this study only uses data from children who can prove their test score using test score certificates[10].

The main explanatory variables are D_i and A_i, which capture the natural disaster variables. In addition, vector X_i contains the other explanatory variables to capture individual and household characteristics, such as age, gender, area where they live, and parental education background. The variables γ_r and v_t are used to control for regions and year fixed effects respectively. The inclusion of the regional dummy variables reduces the potential bias from unmeasured regional shocks. Year dummy variables are useful to control for year specific characteristics and control for potential changes in the yearly test score.

Moreover, in order to see whether different types of disasters have different impacts on child test score and child health, this chapter replaces the main explanatory variables, which are dummies D_i and A_i using specific dummy variables of D_i and A_i, which belong to specific types of disasters. There are 3 dummies for D_i (big earthquake, small earthquake and flood), and the same 3 dummies for A_i.

4.5.2. Quantile Regression

Least squares regression can capture the change in the mean of the dependent variable if there is a change in independent variables. Yet sometimes, a single mean curve is not informative enough, conditional quantile functions provide a more complete view.

[10] We also estimated the impact of disasters on child test scores using test scores data with imputation for missing value, but there is an issue of measurement error (see Appendix table A4.1).

Koenker and Bassett (1978) introduced quantile regression as a simple minimization problem yielding the ordinary sample quantiles in the location model[11]. This method generalizes naturally from the linear model a new class of statistics. Quantile regression is very useful for looking at the complete picture information about the relationship between the outcome Y_i child test scores and the covariates X_i, including the variables of interest (D_i and A_i) at any different points in the conditional distribution of Y_i. Quantile regression is more robust for data with outliers. For instance, by looking at the median regression rather than mean regression, the mean regression minimizes expected squared error while median regression minimizes the expected absolute error. Quantile regression can be written as:

$$\hat{Q}_\tau (Y|X) = X^T \hat{\beta}_\tau \quad (4.4)$$

Where τ is choice of quantile level (0.05, 0.1, 0.15, 0.2, ..., 0.9, 0.95), X^T is covariates, and $\hat{\beta}_\tau$ is parameter of interest. For this study, we can express the quantile regression model as:

$$Q_\tau (Test\ score_i) = \alpha_0 + \alpha_1 D_i + \alpha_2 A_i + \psi X_i + \gamma_r + \nu_t + \varepsilon_i \quad (4.5)$$

4.6. Empirical Results: The Impact of Disasters on Child Test Scores

This section discusses the results of the impact of natural disasters on child test scores. There are several main estimation results: (1) the average impact of natural disasters, (2) the impact of natural disasters in the first and second year aftermath and (3) the impact of specific natural disasters. DiD model is applied to estimate the outcome of interest. In addition, we applied Quantile Regression to find out the impact of disasters on a different group of children's test scores. By using QR, we can see the

[11] The detail explanation about regression quantile is discussed by Koenker and Bassett (1978).

extent to which the effect of a disaster differs across the distribution of conditional test scores.

Moreover, the estimation results of this study are only the lower bound estimates of the impact of natural disasters on child test score and child health. As Baez and Santos (2007) note, the reasons why the results are only a lower bound are that the natural disasters are an aggregate shock, so it is possible that households who live in a non-disaster region are indirectly affected by the disasters. Furthermore, households who live in disaster regions will normally receive financial assistance after disasters and those in a non-disaster region will not. Although physically they were not hit by disasters, they probably needed more financial aid due to the macro effects of disasters.

4.6.1. Difference in Differences Method

Table 4.5 illustrates the difference in difference (DiD) estimation of the effect of natural disasters on child test scores. The first column reports the average test scores before disasters, the second column reports the average test scores after disasters, and the third column is the difference between the after-disaster child test scores and the before-disaster child test scores. The rows present the average of child test scores in disaster regions, non-disaster regions and the difference of those two regions. The after-disaster child test scores in disaster regions decreased by 1.14 points compared to before-disaster scores. Child test scores in non-disaster regions decreased by only 0.03 points, and the difference between those two regions is -1.11 points as a DiD estimate of the impact of natural disasters on child test scores.

Table 4.5: Difference in difference estimates of the effect of disasters on child test scores

	Before disasters (1)	After disasters (2)	After-Before (3)
Disaster region	6.51	5.37	-1.14
	(0.02)	(0.18)	(0.14)
Non-disaster region	6.49	6.46	-0.03
	(0.02)	(0.05)	(0.05)
DR-NDR difference	0.02	-1.09	-1.11
	(0.03)	(0.19)	(0.15)

Note: Standard errors in parentheses

For regression version of DiD estimators, there are six specifications based on different sets of control variables, which consist of sets of individual characteristics, interaction variables with the dummy variables of interest (D and A) and also year dummies and regional dummies. The coefficient on D represents the average impact of natural disasters on child test scores for children who took tests after a disaster in a disaster region, while the coefficient on A represents the additional impact of natural disasters on child test scores for those being affected by disasters in disaster regions. Table 4.6 shows the average impact of natural disasters on child test scores. Both specifications confirm that natural disasters reduce child test scores. Lower test scores are not only suffered by children who are affected by disasters but also children who are not affected by disasters in a disaster region. This is not surprising since most of the school buildings, transportation, telecommunication and infrastructure are destroyed and teachers are also affected by disasters, so it is likely that all the schools are closed down at the time of disasters. However, those who are affected by disasters have an even lower test score than those who are not affected.

Table 4.6: Results of the Impact of Natural Disasters on Child Test Scores

Dependent variable: test score	1	2
D	-0.894***	-0.900***
	(0.280)	(0.276)
A	-0.994***	-1.054***
	(0.270)	(0.276)
Age		0.000598
		(0.0159)
Urban		0.264***
		(0.0278)
Male		-0.0692*
		(0.0376)
Father_secondary school		0.00673
		(0.0477)
Father_higher education		0.327***
		(0.0676)
Mother_secondary school		0.190***
		(0.0586)
Mother_higher education		0.464***
		(0.137)
Year dummies	yes	Yes
Region dummies	yes	Yes
Observation	5073	5067

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

In Model 2, by controlling individual characteristics, year dummies and regional dummies, the occurrence of natural disasters decreases child test score by 0.900 for children in a disaster region who took the test after a disaster. For those who are affected by natural disasters there is a further reduction, by 1.054, so being affected by disaster caused an even lower test score. In addition, children in urban areas have a better test score by 0.26 on average than children in rural areas. Moreover, boys seem to also suffer a lower test score than girls - at 10% significance levels, by approximately 0.07 on average. Similarly we find that higher parental education background is associated with higher the child test scores, especially for maternal education background.

As already note in chapter 3 about test score data, the results in table 4.6 are also only used test score data from children who can show test score certificate in the time of IFLS survey. For those who cannot show certificate are dropped from this estimation, since the test scores data are not complete. This selection issue may cause bias. Yet, we also provide estimation by using imputation missing value for those who have incomplete test score. The results is not quite different to table 4.6 especially on the coefficient of variable interest, D and A (see Appendix table A4.1).

Table 4.7 shows the model with interaction of explanatory variables with D and A. Column 2 and Column 3 are the continuation of Column 1. Column 1 shows all the magnitude of coefficient variables when A=0 and D=0. Column 2 shows the magnitude of coefficient from the interaction of all explanatory variables with A or with condition A=1 and D=1, while Column 3 is the magnitude coefficient of all explanatory variables from the interaction with D when A=0 and D=1. The idea of running this model specification is to investigate whether some people are more badly affected by disasters than others.

Table 4.7: Results of the Impact of Natural Disasters on Child Test Score by including covariates' interaction with A and D dummies' variables

	Dependent variable: test score (1)	(continuous) Interaction with A (2)	(continuous) Interaction with D (3)
D	-1.424***		
	(0.306)		
A	-0.712***		
	(0.221)		
	A=0;D=0	A=1;D=1	A=0;D=1
Age	0.000715	-0.0935	-0.599**
	(0.0159)	(0.119)	(0.217)
Urban	0.263***	0.896**	-0.650**
	(0.0264)	(0.405)	(0.282)
Male	-0.0783**	0.691**	0.183
	(0.0355)	(0.265)	(0.234)
Father_secondary school	0.00613	0.621	-0.725**
	(0.0521)	(1.233)	(0.322)
Father_higher education	0.337***	-0.742**	-0.245
	(0.0702)	(0.322)	(0.364)
Mother_secondary school	0.196***	-1.632***	1.302***
	(0.0547)	(0.568)	(0.283)
Mother_higher education	0.450***	-1.262*	1.308***
	(0.143)	(0.635)	(0.270)
Year dummies		Yes	
Region dummies		Yes	
Observation		5056	

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

The results show that the interactions with A in column 2 are positive and significant effect for urban and male, but negative and significant for father and mother education background. That means that being affected by the disaster students in rural areas and females have lower test score than in urban areas or male students relative to not being affected directly by the disaster. Furthermore, students who are affected directly by the disaster with higher parental education backgrounds also have lower test scores relative to not being affected directly by the disaster. Column 3 shows that the interaction of D with age, urban and father's education background has a negative coefficient, a positive coefficient for the interaction with maternal education background. This means that being in a disaster region (but not being affected by a disaster) has a more negative effect of being in an urban area relative to not being in a disaster region.

Table 4.8 Results of the Impact of Natural Disasters on Child Test Score in the First and Second Year Aftermath

Dependent variable: test score	1	2
D2006	-1.662*** (0.223)	-1.646*** (0.226)
D2007	-0.645*** (0.0988)	-0.658*** (0.102)
A2006	-1.248*** (0)	-1.318*** (0.0132)
A2007	-0.820*** (0.155)	-0.875*** (0.164)
Age		0.000359 (0.0159)
Urban		0.262*** (0.0276)
Male		-0.0725* (0.0373)
Father_secondary school		0.0149 (0.0505)
Father_higher education		0.346*** (0.0722)
Mother_secondary school		0.184*** (0.0604)
Mother_higher education		0.442*** (0.142)
Year dummies	yes	yes
Region dummies	yes	yes
Observation	5062	5056

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Table 4.8 compares the results of the impact of natural disasters on child test scores for children who took the test just after the disasters in 2006 and one year after the disasters in 2007. The results confirm that children from the year test of 2006 in a disaster region suffered a lower test score than those who took a test one year after the disasters, in 2007. Most possibly, that is because the test in 2006 was taken approximately only a month after disaster occurred and the children may have had less concentration in taking the test at that time, due to the disaster's influence.

Children's test scores in 2006 in disaster regions decreased by 1.6 on average and decreased by an additional 1.2 for those who were affected by a disaster. In 2007, children's test scores in disaster regions decreased by 0.6 on average, and for those who were affected by disasters suffered a negative marginal effect of approximately 0.7. In addition, other significant explanatory variables seem to have the same impact and similar coefficients with the model in Table 4.6.

Table 4.9 provides the results of the impact on child test scores from three specific natural disasters. The results are from a big earthquake in Yogyakarta, a small earthquake in Sumatra Barat and a flood in Jakarta. The results indicate that only a big earthquake had a negative impact on child test score. The result also confirms that children in a big earthquake region suffer a significantly lower test score by approximately 2.5, while other disasters, for small earthquakes region is positive and significant, and for floods region and affected floods dummy are not significant. Furthermore, other significant control variables: urban, male and parental education background in Model 2 has a similar impact to Table 4.6.

Table 4.9: Results of the Impact of Specific Natural Disasters on Child Test Scores

Dependent variable: test score	1	2
Big_earthquake_region	-2.524***	-2.555***
	(0.131)	(0.140)
Small_earthquake_region	0.417**	0.378**
	(0.151)	(0.167)
Floods_region	-0.0231	-0.0467
	(0.118)	(0.115)
Affected_big earthquake	-0.279	-0.231
	(0.211)	(0.205)
Affected_small earthquake	0.0920	0.0110
	(0.228)	(0.250)
Affected_floods	-0.213	-0.213
	(0.320)	(0.324)
Age		0.00139
		(0.0156)
Urban		0.263***
		(0.0279)
Male		-0.0784**
		(0.0365)
Father_secondary school		0.00285
		(0.0534)
Father_higher education		0.319***
		(0.0642)
Mother_secondary school		0.184***
		(0.0615)
Mother_higher education		0.444***
		(0.135)
Year dummies	yes	yes
Region dummies	yes	yes
Observation	5062	5056

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

4.6.2. Quantile Regression

Table 4.10 compares the estimation results across quantiles and OLS. There are two different specifications: (1) estimation without control variables and (2) estimation with control variables. The coefficients on D and A vary across quantiles. In Specification 1, most noticeably, the highly statistically significant coefficient of D has a much greater impact at the low quartile (q=0.25) of child test scores, reducing it by approximately 1.75. For the coefficient on A, the biggest impact on child test score occurs at the median regression (q=0.50), decreasing it by approximately 2.39.

Table 4.10: Results of Impact of Natural Disaster on Child Test Score Across Quantiles

(1) Estimation without control variables	OLS	QR_25	QR_50	QR_75
D	-0.439**	-1.750***	-0.547**	-0.439**
	(0.213)	(0.280)	(0.224)	(0.213)
A	-0.954***	-0.646*	-2.397***	-0.954***
	(0.283)	(0.372)	(0.298)	(0.283)
(2) Estimation with control variables				
D	-0.893***	-1.977***	-0.580***	-0.581***
	(0.199)	(0.296)	(0.221)	(0.203)
A	-1.060***	-0.672*	-2.511***	-1.046***
	(0.265)	(0.394)	(0.294)	(0.270)
Age	0.00241	0.0174	-0.00416	0.00405
	(0.00962)	(0.0143)	(0.0106)	(0.00981)
Urban	0.273***	0.218***	0.225***	0.290***
	(0.0386)	(0.0573)	(0.0428)	(0.0394)
Male	-0.0753**	-0.0228	-0.121***	-0.178***
	(0.0353)	(0.0523)	(0.0390)	(0.0360)
Father_secondary school	-0.0340	-0.0553	0.00306	0.0236
	(0.0505)	(0.0750)	(0.0559)	(0.0515)
Father_higher education	0.291***	0.219	0.378***	0.357***
	(0.0920)	(0.136)	(0.102)	(0.0937)
Mother_secondary school	0.165***	0.222***	0.122**	0.193***
	(0.0512)	(0.0759)	(0.0566)	(0.0521)
Mother_higher education	0.444***	0.402**	0.545***	0.495***
	(0.109)	(0.162)	(0.121)	(0.111)

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

In Specification 2, the quantile regression results are not very different from Specification 1. The lower group of children's test score is badly affected by natural disaster while the middle and upper group have similar impact and are less affected than the lower group. In addition, for those who are affected by disaster, the middle group of children's test score are worst affected by disaster but the lower group is not significantly affected. The upper group is also affected but not as badly as the middle group. It might be that the academic ability of the middle group is only moderate while the upper group is dominated by more able children, so the affected children in the middle group of test score were badly influenced by this condition, more so than the upper group of test score, while the lower group of test score were also affected but not as much as the middle group or upper group. The quantile regression results differ considerably from the OLS coefficients.

4.7. Methodology: The Impact of Disasters on Child Health

This section discusses the methodology that is used to estimate the impact of disasters on child health. We used DiD method to estimate the impact of disasters on height of child. In addition to DiD method, Ordered logit is used to estimate the impact of disasters on general and last year's health condition. As general and last year's health condition are categorical data that are naturally ordered, so ordered logit is an appropriate method. Furthermore, Zero Inflated Negative Binomial (ZINB) which estimate model for dependent variables with count data is used to estimate the impact of disasters on days lying in bed and days missing from main activities of each child due to a poor health condition. Days missing and days lying in bed are count data that contain very large proportion of zero values, therefore ZINB is the right method for these data. All data that is used for ordered logit and ZINB methods is from self-reported health condition.

Data set that is used in this section is repeated cross-section data, since the child height data that are used in the sample are for different children in the two periods. We use IFLS4 from 2007 and IFLS3 from 2000 as the main data. Data in 2000 and 2007 are different children at age 2-5 years old. Here we compare the condition before the disasters in 2000 and after the disasters in 2007, by using children age 2-5 in each year, so the data set is not panel data but repeated cross-section.

4.7.1. Difference in Difference Method

For the impact of disasters on child health, we use DiD model for the equation, with child height as the dependent variable. The equation for child height can be written as:

$$height_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 A_{it} + \psi X_{it} + \gamma_r + v_t + \varepsilon_{it} \qquad (4.6)$$

Height of child is measured in cm for individual i in year t. Height of child is only measured from children aged 2-5 years old. The main explanatory variables are D_{irt} and A_{irt}, which capture the natural disaster variables. In addition, vector X_{it} contains the other explanatory variables to capture individual, household and community characteristics, such as age, gender, household expenditure, household size, area where they live, parental height, maternal education background and community facilities, such as garbage system and water supply. We also add a wet season dummy as an explanatory variable to capture the influence of the weather at the time of birth to child health. The variables γ_r are used to control for regions. The inclusion of the regional dummy variables reduces the potential bias from unmeasured regional shocks.

4.7.2. Ordered Logit

Data in this section is panel data, since we used data IFLS3 and IFLS4) from the same individuals in two different periods, 2000 and 2007. Using dependent variables from categorical data that are naturally ordered and take a value from 1 to 4 in estimation, ordered choice model is the best model to apply. The use of OLS in this case could lead to predicted values lying outside the range of possible values of the dependent variable. We choose ordered logit model since we can interpret the coefficient directly as ordered log-odds coefficients or we can transform it into odds, while in the ordered probit model coefficients are z-scores, and we could only transform them into predicted probabilities using the standard normal distribution.

According to Greene (2010), the ordered logit model specification that we use can be written as:

$$Y_{it}^{*} = vt + \gamma r + \alpha_1 D_{it} + \alpha_2 A_{it} + \psi X_{it} + \varepsilon_i \tag{4.7}$$

and the observed dependent variable equation as:

$$
\begin{aligned}
Y_i &= 0 \; if \; Y_i^{*} \leq \mu_0, \\
&= 1 \; if \; \mu_0 < Y_i^{*} \leq \mu_1, \\
&= 2 \; if \; \mu_1 < Y_i^{*} \leq \mu_2, \\
&= 3 \; if \; \mu_2 < Y_i^{*} \leq \mu_3, \\
&\quad \cdot \\
&\quad \cdot \\
&= J \; if \; \mu_{j-1} \leq Y_i^{*}
\end{aligned}
$$

Where Y_{it}^{*} is a dependent variable with an ordered value, X_{it} is explanatory variables, D_{it} is a dummy in a disaster region and in the time after disasters, A_{it} is a dummy in a disaster region and being affected by disasters, and ε_i is the error term, which has a standard logistic distribution. Y_{it}^{*} is an unobserved variable. The μ's are unknown parameters related to various threshold points. In this study, there are two ordered logit estimations. In the first model, y is the level of general health conditions with the order: (1) very healthy, (2) somewhat healthy, (3) somewhat unhealthy and (4) unhealthy. For the second model, y is last year's health condition with the order: (1)

much better now, (2) somewhat better now, (3) about the same, (3) somewhat worse, and (5) much worse. The explanatory variables are the same as the DiD model for child height estimation.

Athey and Imbens (2006) show difference in differences models can be extended to discrete outcomes which allow the researcher to non-linear estimations. Puhani (2008) shows that "the sign of the treatment effect in a non-linear DiD model with a strictly monotonic transformation function of a linear index (like probit, logit, or tobit) is equal to the sign of the coefficient of the interaction term" (Puhani, 2008,p.7). Since an ordered logit can be interpreted as a combination of binary logits, Puhani's (2008) result should also be applicable to ordered logit models like the one we use here.

4.7.3. Zero Inflated Negative Binomial (ZINB)

A zero inflated negative binomial regression is applied for this study since the dependent variable, days missing regular activities and days lying in bed are count variables. These variables contain very large proportion of zero values. It happened since most of children are healthy or never get sick and a few children may experience with poor health condition so they missed regular activities in few days. Therefore, we used ZINB that allow for estimates using data with an excess zero outcome. ZINB allows combining a binary model for children who never get sick and a count model for children who experienced poor health condition. Following Hall (2000) The ZINB model can be written as:

$$Y_i \sim \begin{cases} 0, with\ probability\ p_i \\ binomial\ (n_i, \pi_i), with\ probability\ 1 - p_i \end{cases} \tag{4.8}$$

$$Y_i = \begin{cases} 0, with\ probability\ p_i + (1 - p_i)(1 - \pi_i)^{n_i} \\ k, with\ probability\ (1 - p_i)\binom{n_i}{k}\pi_i^{n_i}(1 - \pi_i)^{n_i - k}, k = 1, \dots, n_i \end{cases} \tag{4.9}$$

Where Y_i is the count for the i^{th} subject, p_i is probability whether a child will always healthy, and $(1 - p_i)$ is probability whether a child will miss regular activities because of unhealthy. n_i is the total number of days from children at risk of being sick, k is equal to 1, ..., n_i . π_i is the success probability for each day. We do not use Zero Inflated Poisson (ZIP), since ZIP must meet the assumption that the variance must be equal to the sample's mean, and in our case, the variance exceeds the mean (overdispersed), so the ZIP is inefficient. Therefore, we used ZINB.

4.8. Empirical Results: The Impact of Disasters on Child Health

4.8.1. Results

This section presents the estimation results from the impact of disasters on child health. There are separate model specifications between objective measurements and self-reported data. Different methods were also applied. DiD model is for height measurement. Ordered logit is for self-reported general health measurement with ordinal data for dependent variables, and Zero Inflated Negative Binomial is for dependent variables with count data. We present the results in two different estimations: the impact of natural disasters on child health, and the impact of specific natural disasters on child health.

For the first two results, each of the estimate has 5 different models and all of them are estimated using difference in difference (DiD) method. The first model that uses the objective measure height of child aged 2-5 years old adopts Ordinary Least Square DiD estimation. The second to the fifth models use subjective measure, which is self-reported data about health conditions from children below 15 years old. This second model, with general health condition as a ranked dependent variable (very healthy, somewhat healthy, somewhat unhealthy and unhealthy) uses ordered logit in DiD. The same method is applied for the third model, which has last year's health condition as the dependent variable (much better now, somewhat better now, about the same, somewhat worse, and much worse). In addition, for the fourth and fifth models, ZINB are applied. This is because the dependent variables are count data with many zero values (days missing regular activities and days in bed).

As a comparison, Table 4.11 provides the simple DiD estimation results of the effect of disasters on child height. The first column reports the average child height before disasters, the second column reports the average child height after disasters, and the third column is the difference between after-disaster child height and before-disaster child height. The rows present the average of child height in disaster regions, non-disaster regions and the difference of those two regions. The difference of child height between after- and before- disaster in disaster regions is increased by 1.19 points. Child height in non-disaster regions increased by 1.05 points, and the difference in those two regions is 0.14 points, as a DiD estimation of the impact of natural disasters on child height was not significant statistically.

Table 4.11: DiD estimates of the effect of disasters on child height, ages 2-5 years old

	Before (1)	After (2)	After-Before (3)
Disaster region	95.65	96.84	1.19
	(0.48)	(0.45)	(0.68)
Non-disaster region	94.28	95.33	1.05
	(0.22)	(0.18)	(0.28)
DR-NDR difference	1.37	1.51	0.14
	(0.55)	(0.48)	(0.59)

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Table 4.12 shows the impact of natural disasters on child health. There are 5 different specification models according to the type of dependent variables. All those models show that disaster region dummies (D) are not significant. It indicates that disasters have no serious impact on child health in disaster regions. This may indicate that state agencies have provided sufficient compensation for victims, especially children. In addition, the dummy for being affected by disasters (A) is only significant for general health condition and last year's health condition variables. However, both of these models have different effects.

There is a negative and significant sign on A for general health condition and positive and significant sign for last year's health condition. Negative sign for A means that general health condition of children in the time of survey is healthier for children who were affected by disasters, but a positive sign for A indicated that children who were affected by disasters are unhealthier for last year's general health condition than those who were not affected. This is not surprising, since last year's health condition is closer to the time when the disaster occurred. For Model Specifications 4 and 5 with count variables, days missing regular activities and days in bed as dependent variables, none of the variables of interest are significant. The same condition is for Model Specification 1, with height of child as the dependent variable.

Table 4.12: the Impact of Natural Disasters on Child Health

Dependent variable	Difference in Difference				
	OLS	Ordered Logit	Ordered Logit	ZINB	ZINB
	1	2	3	4	5
	Height (2-5 year)	General health	Last year's health	Days missing	Days In bed
D	3.128	-0.182	0.967	-0.006	0.122
	(3.803)	(0.742)	(0.751)	(0.046)	(0.098)
A	-0.465	-0.556***	0.334***	-0.004	-0.051
	(0.765)	(0.130)	(0.108)	(0.079)	(0.157)
Age	0.842***	-0.005***	-0.002	-0.005***	-0.001
	(0.071)	(0.002)	(0.001)	(0.001)	(0.002)
Age2	-0.003***	0.000	0.000**	0.000***	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Urban	0.851***	0.140***	0.025	0.047	-0.024
	(0.286)	(0.050)	(0.042)	(0.031)	(0.068)
Male	0.914***	-0.054	-0.013	0.002	0.039
	(0.257)	(0.044)	(0.037)	(0.029)	(0.062)
Hhsize	-0.159*	0.005	0.035***	0.005	0.016
	(0.083)	(0.013)	(0.011)	(0.008)	(0.017)
Lhh_expenditure	0.888***	-0.225***	-0.109***	0.031	0.007
	(0.244)	(0.041)	(0.035)	(0.026)	(0.055)
Mother_secondary	0.137	-0.021	-0.112***	-0.044	-0.107
	(0.297)	(0.051)	(0.043)	(0.032)	(0.068)
Mother_high school	0.909*	-0.119	0.008	-0.082	-0.237*
	(0.497)	(0.091)	(0.078)	(0.060)	(0.138)
Water_system	0.110	0.230***	0.017	0.064	-0.062
	(0.432)	(0.074)	(0.062)	(0.044)	(0.095)
Garbage_system	1.136**	-0.238***	0.009	-0.017	-0.053
	(0.467)	(0.083)	(0.070)	(0.050)	(0.111)
Wet_season	0.001	-0.059	-0.018	0.000	0.058
	(0.261)	(0.045)	(0.038)	(0.029)	(0.062)
Mother_height	0.211***				
	(0.024)				
Father_height	0.163***				
	(0.022)				
Time dummies	yes	Yes	yes	yes	Yes
Regional dummies	yes	Yes	yes	yes	Yes
Observation	2624	10962	10375	10960	10959

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; For models 2,3,4 and 5: the negative sign for the coefficient indicates that the individual is healthier.

Table 4.13 shows the impact of specific natural disasters such as big earthquakes, small earthquakes and floods on child health. There are no significant impacts of all disaster variables (Affected_big earthquake, Big_earthquake_region, Affected_small earthquake, Small_earthquake_region, Affected_floods, and Floods_region) on height of child at 2-5 years, number of days missing and number of days in bed in Models 1, 4 and 5. On the other hand, general health condition has a positive correlation with big earthquake region dummy.

The results indicate that children in a big earthquake region were healthier at the time of survey than children in a non-big earthquake region. In addition, Affected_big earthquake and Floods_region are also significant at 1 % with last year's health condition. Affected_big earthquake dummy has a positive sign and Floods_region dummy has a negative sign. It shows that children who were affected by a big earthquake were less healthy last year than those who were not affected by a big earthquake, while children in a flood region were healthier last year than those children in a non-flood region.

Table 4.13: the Impact of Specific Natural Disasters on Child Health

	Difference in Difference				
	OLS	Ordered Logit	Ordered Logit	ZINB	ZINB
	1	2	3	4	5
	height (2-5 years)	General health	Last year's health	Days missing	Days in bed
Big_earthquake_region	2.035	-0.847***	-0.555*	-0.021	-0.120
	(1.464)	(0.265)	(0.226)	(0.114)	(0.208)
Affected_big earthquake	-1.458	-0.210	0.556***	0.051	0.225
	(1.244)	(0.213)	(0.184)	(0.144)	(0.247)
Small_earthquake_region	0.607	-0.178	0.179	-0.009	-0.211
	(1.289)	(0.241)	(0.200)	(0.082)	(0.252)
Affected_small earthquake	1.623	-0.531*	0.105	-0.154	-0.053
	(1.938)	(0.305)	(0.243)	(0.199)	(0.488)
Floods_region	0.823	-0.150	-0.609***	-0.002	0.114
	(1.267)	(0.233)	(0.197)	(0.063)	(0.138)
Affected_floods	-1.328	0.120	0.430*	-0.159	-0.176
	(1.738)	(0.298)	(0.260)	(0.157)	(0.407)
Additional control	yes	Yes	yes	yes	Yes
Time dummies	yes	Yes	yes	yes	Yes
Regional dummies	yes	Yes	yes	yes	Yes
Observation	2624	10962	10375	10960	10959

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; For Models 2,3,4 and 5: the negative sign for the coefficient indicates that the individual is healthier; Additional controls: age, age2, urban, male, hhsize, lhh_expenditure, mother secondary school, mother high school, water system, wet season, and for OLS estimates plus mother height, father height.

4.9. Further Robustness Checks

We conduct several robustness checks to ensure that our results are robust. First, we re-estimated our models excluding the rural child test scores. This was done since most of the income of parents in rural areas come from the agricultural sectors. So crop failure is associated with decreasing test scores. The results are presented in Table 4.14. All results confirm that the coefficient of variables of interest is close to the OLS results obtained without excluding the rural area data. As we can see from

Column 1, using OLS estimation, all variables of interests (A and D) are highly significant at 1%. Secondly, according to Bertrand, Duflo and Mullainathan (2004) there is a potential serial correlation problem in the DiD model. We examine this by collapsing the time into two periods - before and after disasters - then re-estimating.

Table 4.14: Results of the Impact of Natural Disasters on Child Test Score, Excluding Rural Area

Dependent variable: test score	1 OLS
D	-1.031***
	(0.287)
A	-0.829**
	(0.352)
Age	0.007
	(0.014)
Male	-0.080
	(0.050)
Father_secondary school	-0.003
	(0.082)
Father_higher education	0.306**
	(0.126)
Mother_secondary school	0.128***
	(0.074)
Mother_higher education	0.371***
	(0.135)
Year dummies	yes
Region dummies	yes
Observation	2669

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%;

Another check for serial correlation is by aggregating the time dimension of child test scores. We aggregated year test when the children were tested into two periods: before disasters and after disasters. We re-estimated across these two periods and these are reported in Table 4.15. Our result shows that the effect of disasters for both variables of interest is statistically significant at the 1% level, and the coefficient of those variables is similar. This suggests that our estimates are not a result of serial correlation.

Table 4.15: The Impact of Natural Disasters on Child Test Scores by Aggregating Data

Dependent variable: test score	1	2
D	-0.901***	-0.967***
	(0.199)	(0.199)
A	-0.959***	-0.943***
	(0.276)	(0.278)
Age	-0.001	-0.023***
	(0.010)	(0.006)
Urban	0.265***	0.257***
	(0.039)	(0.039)
Male	-0.069*	-0.061*
	(0.035)	(0.035)
Father_secondary school	0.002	0.004
	(0.057)	(0.057)
Father_higher education	0.324***	0.327***
	(0.096)	(0.097)
Mother_secondary school	0.191***	0.185***
	(0.054)	(0.054)
Mother_higher education	0.460***	0.468***
	(0.111)	(0.111)
Year dummies	yes	yes
Region dummies	yes	yes
Observation	5067	5067

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; Column 1 is the original OLS regression; column 2 is for aggregating data.

4.10. Conclusion

One major finding of this research that differs from the previous literature is that the effects of disasters can be divided into two parts. The first effect is calculated for individuals in disaster regions, both those who are affected and those who are unaffected by disasters, while the second effect is an additional effect for those who have been directly affected by disaster. In addition, we also calculated these effects for the impact of specific natural disasters (big earthquakes, small earthquakes and floods). For the impact on child test scores, we also estimate the impacts on children who took the test just after the disasters and also when they took the test a year after the disasters.

Our main findings are as follows. The first major finding is related to the effects of disasters on child test score. Natural disasters affect all of the children in disaster regions, both those who are affected and unaffected by disasters, by reducing their test score. Those who are affected by disasters had an additional lower test score than those who were not affected. Moreover, children who took the test just after the disaster have a lower test score than children who took the test more than a year after the disaster. There are also different impacts of different types of natural disasters and only terrifying and destructive natural disasters are associated with lower test score for all children in the disaster region. Being in a region that is hit by natural disasters has the biggest impact on child test score in the lowest quantile of test scores. Moreover, the largest additional impact of natural disasters to those who have been affected by disasters is on children at the median of the test score distribution.

The second major finding is on the impact of disasters on child health. We found that disasters have no serious impacts on child health. This finding is confirmed by all the estimation results, using height of child or self-reported health measures. For height of child, none of the children who have been affected by disasters have a lower height compared to those who are not affected by disasters. The same result is obtained on the impact of specific natural disasters on child health. The result from self-reported health data is also similar to results from the height data. Only the dependent variable which uses last year's health condition has a significant disasters impact. It indicates that children in a disaster region and those who are affected by a disaster have a bigger probability of being unhealthy. In conclusion, child test scores are significantly affected by disasters, but there are no serious impacts of disasters on child health. It implies that since disaster is a temporary event, so all the government and state agencies provide good compensation for the short term impacts such as child health, but less attention for the long-term impacts such as child education.

In terms of gender, there is no different impact of disasters on girls' child test score and boys' for those who lived in a disaster region and were directly affected by disasters. In terms of area, the impacts of disasters on child test scores show that children in rural areas suffered more than children in urban areas. In the long term, related with child education, we recommended that the government should give more consideration and priority to rural than urban areas, and quickly rebuild school buildings and facilities for children. By providing enough assistance for the victims, especially children, we hope that human capital outcomes of children are not badly affected by the shock that was caused by disasters, as future lives of children are definitely influenced by the outcomes from when they were young.

Chapter 5

Natural Disasters, Family Expenditures and Food Demand

5.1. Introduction

Natural disasters are always associated with the disruption of local economies and injuring local people. Disasters are likely to be negatively correlated with human capital outcomes and also to have a negative effect on the local economy. The destruction of property, assets, infrastructure and crop loss will affect the local economy and the well-being of households who are directly affected. All these direct impacts of disasters disturb the flow of goods and services and also the production process as a result of scarce resources. Consequently, these conditions cause the price of goods and services to increase. Households usually respond to those difficulties by cutting their consumption, especially for non-essential goods. For low income elasticity essential goods such as food, households will try to smooth their consumption, although the price of food may also increase due to the reduction in food supply, arising from crop loss, and disruption to distribution channels.

We have several objectives in this chapter. First, we look at the way households respond to natural disasters by adjusting household expenditure. Since the demand and/or supply may be shifted because of a disaster and its aftermath. In addition to household expenditures, we also estimated the impact of disasters on wage. The second main objective is to examine whether there are different impacts from different types of disasters. We observe three types of disasters: big earthquakes, small earthquakes and floods. The third objective is to observe the price and expenditure elasticities of food demand by estimating a Linear Approximate Almost Ideal Demand

System (LA-AIDS) as a structural model of expenditure. Related to the change in food prices, we also use our structural model to examine the effect of disasters on living standards of households, and whether there is any different impact for the poor and the rich. Lastly, we attempt to find out whether there is any different effect of disasters on household expenditures, with and without controlling for market prices.

This chapter contributes to the international literature in several respects. First, compared to other literature that discusses the impact of disasters on expenditures, this study uses a variety household expenditure and considers to impact on income (wages). In addition, for food expenditures we provide separate estimates for those who get food from market purchases and those who get food from their own production. Second, we also investigated the net effect of disasters on expenditure shares of main food items such as rice, vegetables, fish and meat. Here, the impact of disasters can be observed in two ways: disasters increase the price of these items and disasters affect household spending independently of their effect on food prices. Finally, we also estimate the impact of disasters on living standards at different levels of household total expenditure.

As natural disasters have increased in number and in their intensity of destruction in the last few years in Indonesia, it becomes very important to examine the impacts of disasters on human beings and the local economy in disaster regions. There are several types of disasters that have often occurred in Indonesia, from the less harsh to the very destructive ones, such as floods, earthquakes, tsunamis, landslides, wind storms, droughts and volcanic eruptions. Natural disasters always leave serious problems for the people in disaster regions, especially for a country like Indonesia which is highly populated. A lot of literature has confirmed that disasters are negatively associated with many aspects of people's lives, such as human capital outcomes, consumptions, the local economy and others. Considering all these factors, studies of the impact of disasters - especially for Indonesia - are needed and become very important in order to have a better response when disasters occur in the future.

For our empirical analysis, we have determined the disaster regions as DI Yogyakarta, DKI Jakarta and West Sumatra. We picked these three provinces based on the highest percentage for both dead and evacuated people in the region. Furthermore, natural disasters can be determined more specifically based on the occurrences of disasters in each disaster region. Yogyakarta, with big earthquakes, has the highest percentage for numbers of both dead and evacuated people. In terms of the percentage of evacuated people, West Sumatra, with small earthquakes, is above average, and in terms of the percentage of dead people, although West Sumatra is below average with a value just below DI Yogyakarta, which is quite high compared to other provinces. DKI Jakarta has problems with floods, and although the percentage of deaths is quite low the percentage of evacuated people is above average, and another big factor is that DKI Jakarta experiences floods almost every year and always presents severe problems.

This study uses panel data from Indonesian Family Life Survey IFLS4 (2007) and IFLS3 (2000), the same data set from the previous chapter, which is the main source of data for estimating the impact of disasters on family expenditures and food demand. In addition, there are two other data sets used: an official disaster data base from the National Disaster Management Agency (BNPB=Badan Nasional Penanggulangan Bencana) of Indonesia and statistics of Indonesia data from the Central Bureau of

Statistics of Indonesia (BPS=Badan Pusat Statistik). In comparison with Chapter 4, in this chapter we employ IFLS data at household level but not at individual level.

Moreover, we used two different methods for estimation. The first method is difference in differences (DID) analysis. We used DiD method for estimating the impact of disasters on household expenditures. DID is used to estimate the potential outcome of the treatment group when there is no data on what would have happened to individuals affected by natural disasters if the disasters had not occurred. Besides DID, we employ the Linear Approximate Almost Ideal Demand System (LA-AIDS) model. In LA-AIDS model we look at the impact of disasters on food share expenditures, controlling for prices. We use the parameter estimates from the LA-AIDS model to calculate the price and expenditure elasticities. LA-AIDS corresponds to a well-defined preference structure, since it is derived from a consumer expenditure function, which allows us to conduct welfare analysis. Many studies (see, for example Blundell et.al (1993)) demonstrated the usefulness of AIDS for such work.

Our main findings are as follows. The first finding is related to the effect of disasters on total household expenditures. We find that being in a disaster region, whether a household is affected by the disaster or not, has no impact on total household expenditure. For the impact of disasters on food expenditures, there are differences between market-purchased and own-produced expenditures for households who are affected directly by disasters. Disasters are positively associated with market-purchased expenditures, but negatively associated with own-produced expenditures. Crop loss results in higher market prices and higher market demand. For educational expenditure, only households who are directly affected by disasters have lower educational expenditure. In addition, there appear to be no significant impacts of disasters on wages. Moreover, looking separately at different disasters, only households who are affected directly by big earthquakes and floods reduced household expenditure and educational expenditure, and there is no significant impact for those who are directly affected by small earthquakes.

Furthermore, we found that in general, all proportions of total share expenditures on food in disaster regions (expenditure share on rice, vegetables, fish and oil) are negatively affected by disasters. In addition, for market-purchased food, expenditure share on rice, fish and oil are negatively affected by disasters, while for own-produced food, only the expenditure share of rice is negatively affected and significant. Overall, there are no additional impacts for households in disasters regions that are directly affected by disasters in all expenditure types. With regards to the elasticities, all own-prices elasticities are negative, as we expected. Moreover, all income elasticities are positive and less than 1.

This chapter is organized as follows. The next section presents a review of the literature on the effects of natural disasters on income or expenditure and food demand. The third section is about data sources and is followed by the methodology with discussion on difference in differences (DiD) model. The fifth section discusses the research finding using the DiD model. The sixth section uses the Linear Approximate Almost Ideal Demand System (LA-AIDS) model, and is followed by the discussion of the empirical findings from the LA-AIDS model. The last section concludes with some policy recommendations.

5.2. Literature Review

A considerable amount of literature has been published on the effects of disasters on welfare, especially on income or expenditure. Some studies use income as the outcome variable, other studies use household expenditure. The most influential study on the effects of disasters on family income is Ureta (2005) which examined the impact of Hurricane Mitch in Nicaragua in November 1998 on family budgets and child schooling. Using the Living Standards Measurement Survey Data 1998 and 2001 for Nicaragua, where the 1998 survey provided the pre-treatment data and the 2001 survey provided the post-treatment data, Ureta defined a control group as the area that was hit by Mitch but in which households were not affected, particularly in rural areas, and the treatment group as the area affected by Mitch.

Ureta estimated the impact of disasters on family income using the difference in differences approach. The estimation was run separately between rural and urban areas and the findings reported that the impact on family income was different between rural and urban areas. In rural areas, family income of households affected by hurricanes decreased from C$ 19,316 to C$ 18,705 in a year after a disaster, or approximately 3%, but in 2001 family income increased significantly in real terms, by almost 16%. Moreover, for urban areas, households affected by hurricanes suffered a greater loss in income than rural areas, from C$ 36,563 to C$ 23,720. This was about 35% lower than before the disaster occurred. Two years after the disaster, household income was back to the pre-disaster condition at 1998 income levels. The most interesting feature of Ureta's study was that households in urban areas were more badly affected by disasters than households in rural areas.

A recent study by Jacobsen (2012) examined the impact of Hurricane Mitch 1998 on households' income in Nicaragua, especially on rural income generation or agricultural productive assets. Using the same data set as Ureta (2005) - Nicaraguan Living Standards Measurement Studies (LSMSs) - Jacobsen estimated the impact of disasters by using a difference in differences model. Although Jacobsen used the same data as Ureta, Jacobsen developed some important analysis that was not used by Ureta. He measured the relative impact of the hurricane among affected households. In addition, he also verified whether a geographical poverty trap existed in the disasters area. Jacobsen found that households were not affected seriously by disasters in their ability to generate income based on their productive asset, therefore they could maintain their consumption levels after the disasters occurred. Furthermore, he also confirmed that households at the lower end of the wealth distribution were more sensitive and vulnerable to the shocks. The poorest households were badly affected.

Another study on the effect of disasters on expenditure was conducted by Kochar (1999). He explored the impact of crop shock on consumption in rural India. Using a panel data set from Indian Farm Households from 1979 to 1984, Kochar (1999) applied a dynamic model by considering the agricultural season in two stages: the planting stage and the output stage. Each stage was influenced by the price of output, female and male family labour hours, and the time of crop shock. This study used information on aggregate household consumption, labour hours of family members, gender, place of work of family members (whether they worked only for the farm or somewhere other than the farm), and other observed covariates. The important finding from this study was that households could smooth their consumption during the time of crop shock by increasing their hours of work and shifting from own-farm production to the labour market.

An interesting study on the impact of disasters on consumption and expenditure was conducted by Cameron and Worswick (2001). This research is interesting since they analyse whether households could adjust their consumption during hard times in respond to permanent income and transitory income. For expenditures, they only focused on educational expenditure, to avoid measurement error in total expenditure because of the poor reported of non-food expenditures. Cameron and Worswick studied the impact of crop loss due to weather shocks and drought on household education expenditure in Indonesia.

Cameron and Worswick (2001) estimated a model of educational expenditure in response to crop loss. First, they estimated permanent and transitory income separately. Then, they estimated the total expenditure equation as a function of permanent income, transitory income and household characteristics. Households who could smooth their consumption during the time of crop loss have a marginal propensity to consume out of permanent income near one while that for transitory income was zero. Therefore, a zero coefficient on transitory income was evidence that households could smooth their consumption. Using Indonesian Family Life Survey data from 1993, Cameron and Worswick (2001) examined educational expenditure. In contrast to Kochar (1999), they found that households were not able to smooth consumption during the time of crop loss so they were most likely to reduce educational expenditure, especially for girls.

A study by Baade, Baumann and Matheson (2007) focused on estimating the economic impact of Hurricane Katrina in New Orleans and the Gulf Coast of the USA on 29 August 2005 by using the experiences of two other disasters in 1992: Hurricane Andrew in Miami and the Rodney King riots in Los Angeles. They used taxable sales data in order to get a good indicator of economic wellbeing. Taxable sales data is highly correlated with economic activity, such as personal income and with gross domestic regional product at the city level. They found that social disasters (riots) had a long-term negative effect on the Los Angeles economy, while natural disasters (Hurricane Andrew) had a short-term positive effect on the Miami economy. Using the results of the two previous disasters, they applied their experiences to New Orleans following Hurricane Katrina.

Baez and Santos (2008) examined the effects of two strong earthquakes in 2001 on household income and poverty in El Salvador. They explored the long-term consequences of disasters on human and economic welfare. Using 700 households from a longitudinal survey of rural households and linear probability difference in difference models, they found that earthquakes caused households' income to fall by one third. Furthermore, in the long term, the earthquakes had negative effects on potential earnings through reduction in physical and human capital accumulation. Poor households were more likely to take their children out of school in the face of disasters. This conclusion is similar to Cameron and Worswick's (2001) study in Indonesia, where households were more likely to cut educational spending on education, especially for girls' education, during hard times. Overall, disasters are negatively associated with economic development.

Dorosh and Smith (2003) examined the impact of floods in 1998 in Bangladesh on household income, consumption and nutritional outcomes. They also observed the impact of price changes due to disasters on household food security. Using a panel data set covering 757 rural households, they observed how households in Bangladesh cope with disasters in several ways: reducing expenditure, selling assets and borrowing. More than 60% of poor people borrowed money immediately following the flood. They used the money borrowed to purchase food and to finance other expenses, such as health, education and production. In addition, using an econometric analysis of household calorie consumption with household fixed effect, they examined the impact of price changes on household food security. They estimated that expenditure elasticity of demand for calories (rice) is 0.363 and the rice price elasticity is -0.142. Further interesting finding is that Bangladesh imported rice from India in order to stabilize the price of rice. Without this import, they predicted that the price of rice would have increased by around 19%.

Study by Zhang and Law (2010) also confirmed that disasters caused food price inflation in China. They found that various food expenditure elasticities were positive, especially the expenditure elasticities for meat and poultry; were over one. They indicated that pressure on food price inflation is likely to be more intense in developing economies when demand rises, since expenditure elasticities on luxury food items like meat are larger than in advanced economies. They also observed that in addition to food yields, food production costs and global commodity prices in supply side factors, natural disasters also affected food price inflation, but not as a major driver.

5.3. Data Sources

This study uses panel data of Indonesian Family Life Survey IFLS4 (2007) and IFLS3 (2000), the same data set from the previous chapter as the main source of data for estimating the impact of disasters on family expenditures and food demand. In addition, there are two other data sets used: an official disaster data base from the National Disaster Management Agency (BNPB=Badan Nasional Penanggulangan Bencana) of Indonesia and statistics of Indonesian data from the Central Bureau of Statistics of Indonesia (BPS=Badan Pusat Statistik). In contrast to Chapter 4, in this chapter we employ IFLS data at household level, not at individual level.

The data used in this chapter are household expenditures data, prices data and other household characteristics data. As we study the impact of disasters on household expenditures and food demand, disasters data are also used in this chapter, but we do not discuss it again in this chapter since this has already been explained in Chapter 4 in Sections 3 and 4.

5.3.1. Disasters

As we already discussed in Chapter 4, IFLS defines households as being affected by a disaster if the disaster was severe enough to cause death or major injuries to household members, cause direct financial loss to the household, or cause household members to relocate. IFLS reports several types of natural disasters, such as earthquakes, tsunamis, landslides, floods, volcanic eruptions and windstorms. Another important definition is 'disaster region'. Since most of the regions in Indonesia experienced disasters, it is important to determine which disaster region is a treatment. A disaster region is defined as a region which has bigger disasters than other regions. Neumayer and Plumper

(2007) suggest that it is better to use the ratio of dead people to the population rather than the total number of deaths to categorize disaster regions. Yet this study uses two measures the percentage of the number of people killed to the total population, and the percentage of the number of people evacuated to the population. The reason is to capture the effect of disasters like floods: although they result in only a few deaths, almost every year, some regions regularly experience floods and they always present a problem in terms of big numbers of evacuated people.

We have determined disaster regions as Yogyakarta, Jakarta and West Sumatra. We picked those three provinces since only those three provinces are completely covered in the IFLS survey data[12]. Furthermore, a specific natural disaster can be identified in each disaster region. Yogyakarta, with a big earthquake in May 2006, has the highest percentage for both percentages of dead and evacuated people. In terms of the percentage of evacuated people, West Sumatra with a small earthquake in early 2007 is above average, and in terms of the percentage of dead people, although West Sumatra is below average, the value is just below Yogyakarta, which is quite high compared to other provinces. Jakarta, with floods in January 2007, has a percentage of death people which is quite low but the percentage of evacuated people is above average, and another big factor is that Jakarta experiences floods almost every year and always presents severe problems.

Based on the disaster information above, we define dummies D (disaster regions) and dummies A (being affected by disaster). D is equal to 1 if individuals are in a disaster region after the time of the disaster and A is equal to 1 if individuals are in a disaster

[12] Detailed explanation about how to determine disaster regions is already explained in Chapter 4

region and were affected by the disaster. As explained above, if there were individuals who suffered financial loss or had one or more household member who died or suffered major injuries, this is defined as being affected by disaster. Table 5.1 presents the number of households affected and not affected by disasters in each of the three disaster regions. Yogyakarta, with a big earthquake, has a bigger number of affected households, with almost 50% of households affected by disasters, while the percentages of households affected by disasters for Jakarta and West Sumatra are not bigger than 15%.

Table 5.1: The number of households in disaster regions reported in IFLS survey

	Not affected		Affected		Total number of HH
	number	%	number	%	
West Sumatra	875	86.5	136	13.5	1,011
Jakarta	1,450	89.2	176	10.8	1,626
Yogyakarta	628	50.6	612	49.4	1,240

5.3.2. Household Expenditures

This study uses three main types of household expenditures: total household expenditure, educational expenditure and food expenditures. All values of household expenditures are calculated monthly. Total expenditure is defined as all expenditures, including food expenditures and non-food expenditures. Food expenditure is constructed from two main components: market-purchased and own-produced food expenditures. Market-purchased expenditure is calculated from household food consumption which is purchased, while own-produced expenditure is calculated from the total values of food obtained from own-production or gift or other assistance.

Table 5.2 presents the comparison of average expenditures in 2000 and 2007. All values are in real terms with 2002 as the base year. The average total household expenditures in the year 2000 was about 1,200,000 rupiahs per month, and increased by approximately 2% in 2007. For educational expenditures, in 2000 the average educational expenditure was 134 thousand rupiahs, and increased by around 23% in 2007. Furthermore, for food expenditures, market-purchased expenditure was about 5 times the own-produced expenditure. In 2000, consumption of food from market purchases was about 550,000 rupiahs and from own-produced food was around 110,000 rupiahs. In 2007, consumption of food from market purchases increased by approximately 2%, while for own-produced food, consumption decreased by less than 1%. In comparison with other expenditures, educational expenditure has the highest growth rate.

Table 5.2: Household expenditures per month (thousand rupiah)

Type of expenditures	Average HH expenditures		Expenditures per person	
	2000	2007	2000	2007
Total expenditures	1,243	1,267	341	410
Educational expenditures	134	165	36	54
Food expenditures (market-purchased only)	559	566	149	178
Food expenditures (own-produced only)	118	117	36	41

Note: mean of household size in 2000=5.1, mean of household size in 2007=4.7

Furthermore, in order to get the real figure of the growth in household expenditure, household expenditure per person is provided. In Table 5.2, since the mean household size decreased between 2000 and 2007, the average of total household expenditure per person increased by approximately 20%, and by the same percentage for market-purchased food expenditures. The growth of educational expenditure per person seems quite high at about 50%. These phenomena indicate that in general, all types of household expenditures are higher in 2007 than in 2000.

Figure 5.1: The average of total expenditures in 2000 and 2007 by provinces

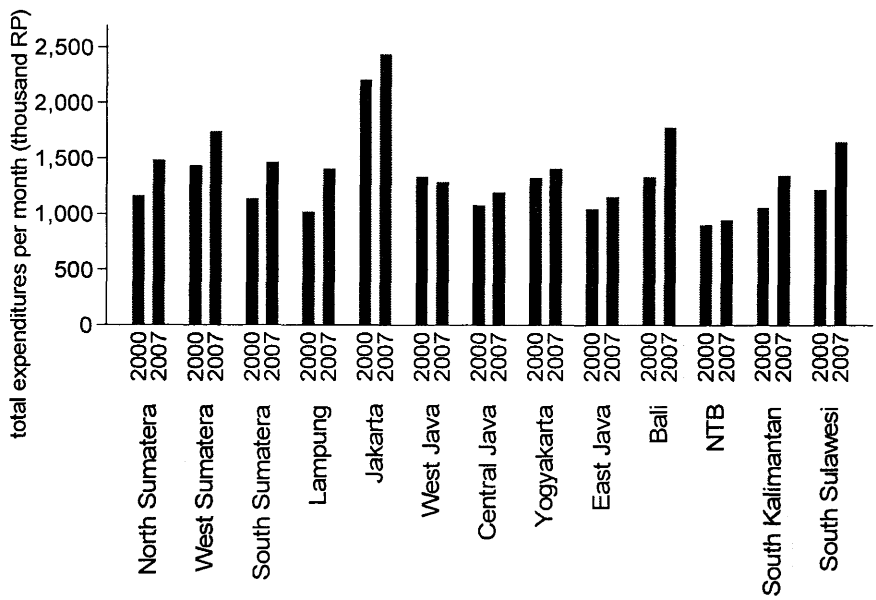


Figure 5.1 presents the average of total expenditures in real values in 2000 and 2007 across the provinces. As we expected, Jakarta has the highest values of total expenditures in both years at approximately 2.5 million rupiahs per month in 2007 and around 2.2 million rupiahs per month in 2000. Bali and South Sulawesi have a higher growth in total expenditures from 2000 to 2007 than other regions. In addition to Jakarta, Yogyakarta and West Sumatra as disaster regions have average levels of expenditures. It seems in general that the averages of total expenditures are not seriously affected by disasters, especially in Jakarta and West Sumatra. Meanwhile, Yogyakarta, with a big earthquake, had a low growth of total expenditures.

Table 5.3: Share of household expenditures on food in 2000 and 2007

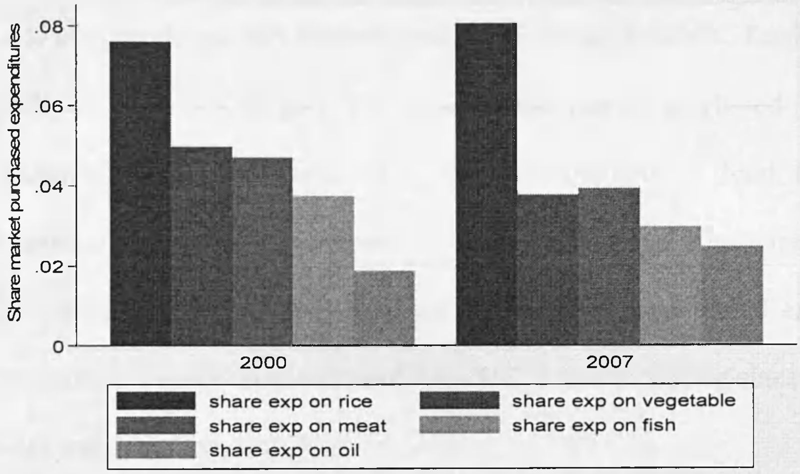
Types of share expenditures	2000	2007
Market-purchased consumption		
Share expenditure of rice	0.077	0.081
Share expenditure of vegetables	0.050	0.038
Share expenditure of meat	0.047	0.039
Share expenditure of fish	0.038	0.030
Share expenditure of oil	0.019	0.025
Own-production consumption		
Share expenditure of rice	0.032	0.028
Share expenditure of vegetables	0.016	0.013
Share expenditure of meat	0.008	0.008
Share expenditure of fish	0.006	0.005
Share expenditure of oil	0.002	0.001
Total food consumption		
Share expenditure of rice	0.109	0.109
Share expenditure of vegetables	0.066	0.051
Share expenditure of meat	0.055	0.048
Share expenditure of fish	0.044	0.035
Share expenditure of oil	0.021	0.026

Note: categories of share expenditures are only for 5 foods.

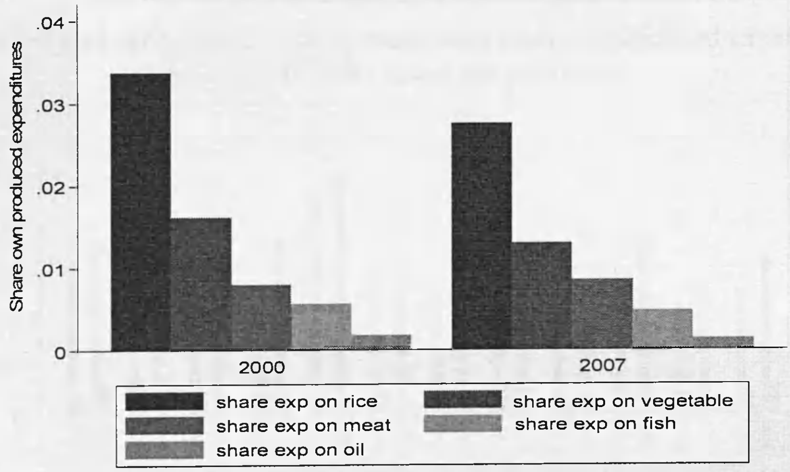
On the other hand, for share of food expenditures, we can see from Table 5.3 that the largest share is rice, comprising around 11% of total household expenditures and is followed by the share on vegetables and meat, comprising around 6% and 5%. The share of market-purchased rice is approximately 8%, while own-produced is only 3%. The shares are similar for vegetables and meat. For instance, the share of market-purchased vegetables is 5%, while for own-produced vegetables it is only 1%. This indicates that the contribution of foods from own production is very small.

Figure 5.2: Share of household expenditures in 2000 and 2007

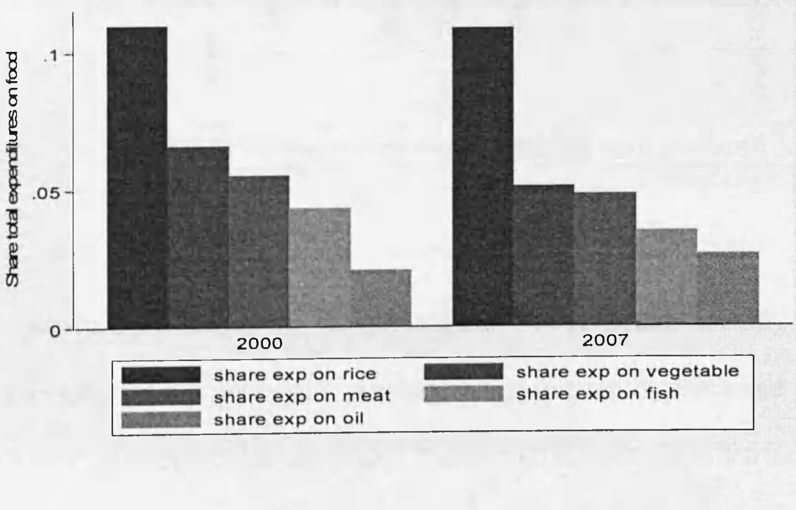
a. Share of market-purchased expenditures



b. Share of own-produced expenditures

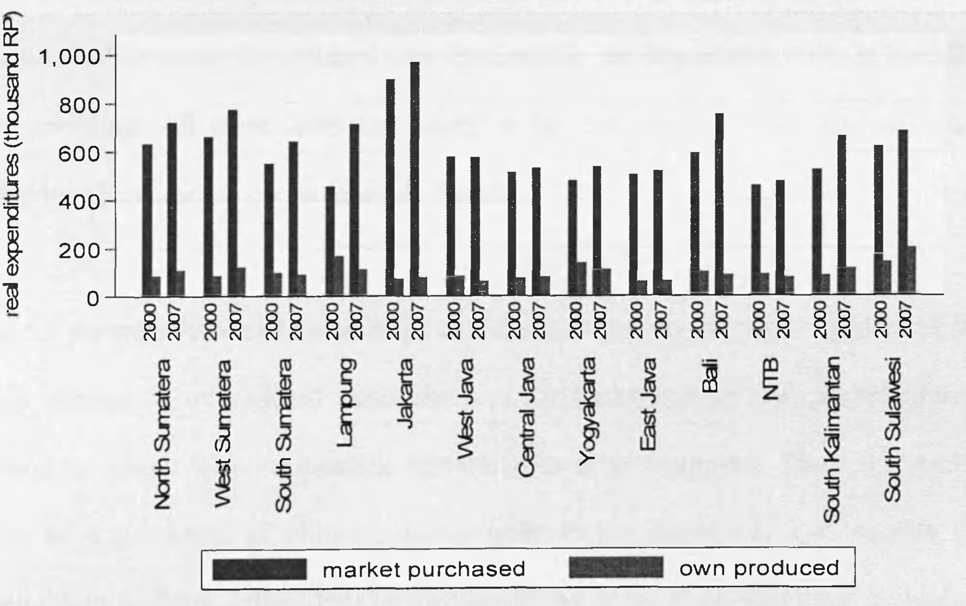


c. Share of total food expenditures



For illustration, Figure 5.2 presents the share of expenditures on five foods. In general, expenditures on rice are the biggest proportion of food expenditure for both market-purchased and own-produced, and expenditures on oil are the smallest. Looking at the share expenditure on foods, Figure 5.3 presents the market-purchased and own-produced expenditures in 2000 and 2007. The contributions of food from own production seems very small if we compare it to market-purchased consumption across the provinces. Jakarta is the province with the highest market-purchased expenditure and smallest share of own-produced expenditure. This is not surprising since Jakarta is the capital city and is highly urbanised.

Figure 5.3: Food expenditures: market-purchased and own-produced expenditures in 2000 and 2007 across the provinces



In addition, non-food expenditure is categorized into two groups: frequently purchased goods and services and less frequently purchased. For frequently purchased goods and services, the expenditures include electricity, water, phone, personal toiletries and other household items that are always consumed on a regular basis. For less frequently purchased goods and services, expenditures are calculated from goods and services that are relatively infrequently consumed, such as clothing, medicine and furniture.

5.3.3. Educational Expenditures

Educational expenditure was calculated from all formal educational costs for children living in the household and outside the household, and covers educational costs for children at any level of education, from primary school to higher education. Moreover, this expenditure is calculated from all spending on school fees, school supplies and transportation. School fees are a sum of tuition fees, registration fees, exam fees, school contributions and laboratories' fees. School supplies are calculated from uniforms, books and other schooling needs. For transportation costs, pocket money is included in this cost. Furthermore, for children who live outside the household, there is boarding house spending. All these costs are based on the previous year and the values are divided by 12 in order to create monthly figures.

Table 5.4 presents the variety of average real expenditures on education. In general, the biggest portion of educational expenditure is for transportation and pocket money, followed by school fees; the smallest portion is for school supplies. There is a similar pattern of expenditure of children living both in the household and outside the household. In addition, school fees for children living in the household have the highest growth, with an increase of almost 60% from 2000 to 2007.

Table 5.4: Real educational expenditures using 2002 as the base year (rupiahs)

	2000		2007		% growth
	Number HH	costs	Number HH	costs	
Expenditures for children in HH:					
School fees	5587	41,785.63	3866	66,223.14	58.48
School supplies	5547	18,709.34	5565	20,495.55	9.55
Transportation & pocket money	5392	55,705.22	5556	77,934.67	39.91
Total (a)	5869	108,638.50	5841	137,490.40	26.56
Expenditures for children outside HH:					
School fees	626	120,600.00	511	145,939.30	21.01
School supplies	477	37,620.63	501	47,456.55	26.15
Transportation & pocket money	493	119,547.50	563	135,854.10	13.64
Boarding house	343	116,816.10	330	134,297.40	14.96
Total (b)	793	242,680.40	802	273,260.20	12.60
Total average (a)+(b)	6183	134,246.30	6200	164,876.80	22.82

Note: HH=household

For those households with children living outside the household, which is less than 15% of the total number of households, allocation for educational expenditure is much bigger than households with children living only in the household. This may be true because these households usually pay school fees for higher education, which is more expensive than primary and secondary education. In addition, for those who live far away from the school, they also have to pay housing rent, since higher education institutions are mostly located in the big cities.

Figure 5.4: The average of real educational expenditures in 2000 and 2007 by provinces

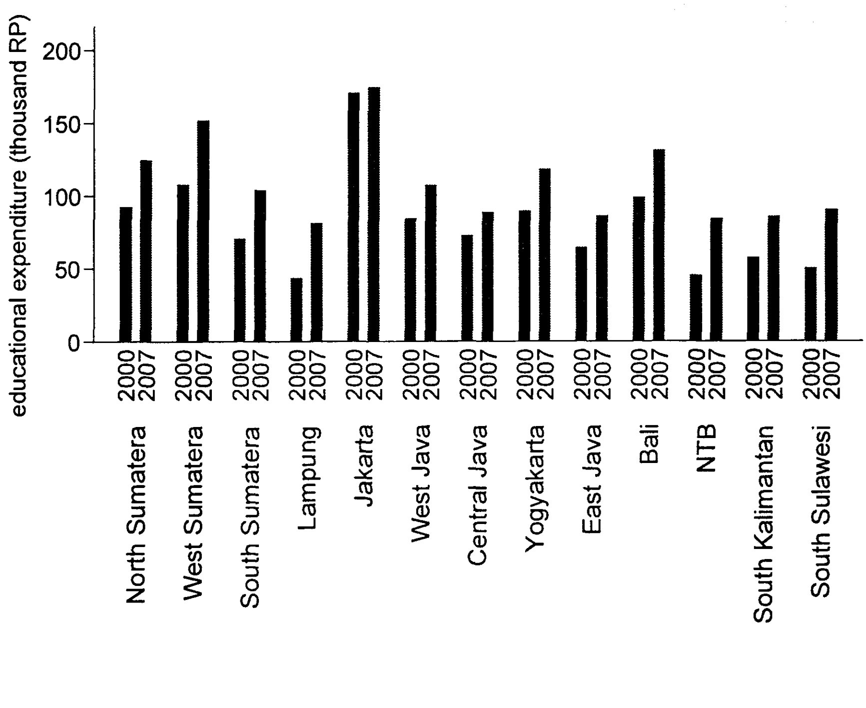


Figure 5.4 presents the average of real educational expenditures in 2000 and 2007 across the provinces. Almost all provinces show that the average educational expenditures in 2007 are greater than 2000; only Jakarta has a similar average of educational expenditures. In addition, Jakarta also has higher educational expenditures than other provinces in both years. This indicates that as the biggest city in Indonesia, all costs in Jakarta are higher than other regions, including education costs.

5.3.4. Price of Goods

This study used two different sources for prices of goods: prices of goods from households (household price) and prices of goods from the market (market price). Since there is no direct information about prices of goods at household level in IFLS data, prices of goods from households are calculated from total expenditures on good x divided by total quantity purchased of good x. On the other hand, price of goods from the market level can be obtained directly from IFLS data. Thus, household prices are instrumented by using market prices for minimize the measurement errors.

Table 5.5: The average of household and market prices in 2000 and 2007 (Rupiah)

	2000		2007	
	Household	Market	Household	Market
Price of rice (per kg)	2,153.56	2,697.73	4,876.31	4,958.76
Price of meat (per kg)	22,744.57	27,741.94	48,859.69	51,995.15
Price of fish (per kg)	11,657.19	10,431.11	13,756.76	13,088.82
Price of oil (per kg)	3,935.46	3,235.83	11,220.06	11,315.14
Price of vegetable (per bunch)	594.81	354.91	1192.66	975.22

Note: market price is retail price, household price is price that HH actually pay

Table 5.5 illustrates the different values of prices, between the household price which was collected from the household level and the market prices which were obtained from the market level in each community. There are variations of price information between these two types of prices in both years. Some are higher in household levels, and others are higher in market levels. Table 5.5 has strongly encouraged us to use prices at the market level as instruments for prices at the household level.

Table 5.6: Correlation coefficient

Price of foods	R
Price of rice	0.6594
Price of vegetables	0.2737
Price of meat	0.5356
Price of fish	0.0705
Price of oil	0.7617

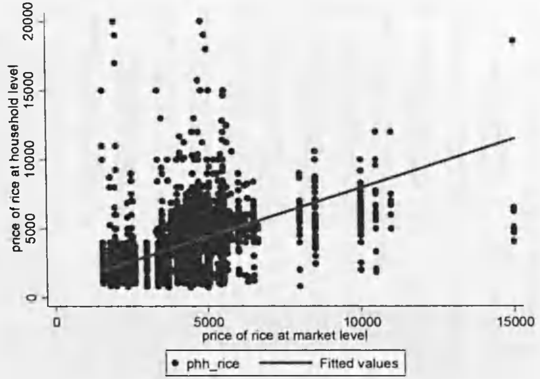
Note: r is coefficient correlation

To examine whether the prices of foods at the market level are good instruments, we present the correlation coefficient and scatter diagram between the prices at market level and household level. Table 5.6 presents the correlation coefficient of food prices at market level and household level. It seems that the correlation of both prices for vegetables and fish are quite low, but if we look at the scatter diagrams in Figure 5.5., there is positive correlation between the price of goods at market level and household level for each good. Furthermore, we also conducted a test for the instrumental variable of price of goods at market levels for ensuring that we used valid instruments for price of goods at household levels. The detailed information of the tests is presented in Table 5.14.

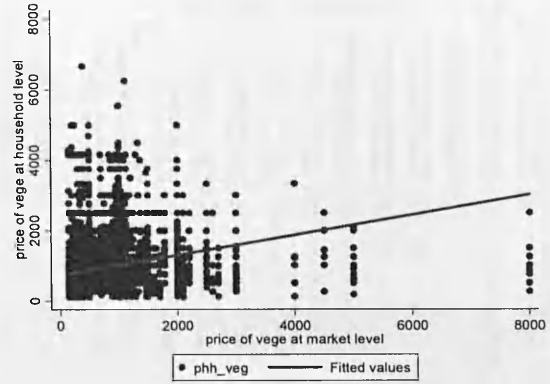
Figure 5.6 demonstrates the variation of prices before and after disasters across the provinces. All price values have already been deflated by using the consumer price index. Looking at the disaster regions (West Sumatra, Jakarta and Yogyakarta), the gap between prices in 2000 and 2007 for all the prices of goods are similar to the average gap in other regions. It suggests that the changes in prices are not driven by disasters.

Figure 5.5: Scatter diagrams of food prices at market level and household level

a. Price of Rice

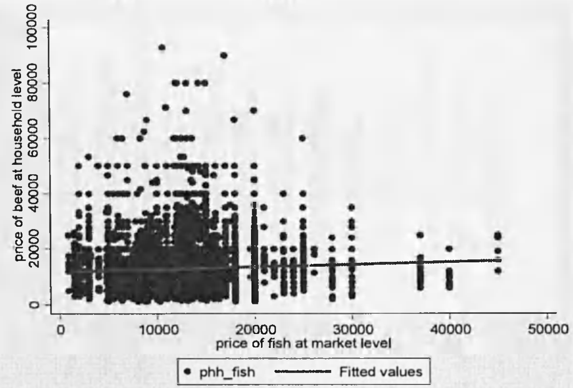


b. Price of Vegetables



c. Price of Meat

d. Price of Fish



e. Price of Oil

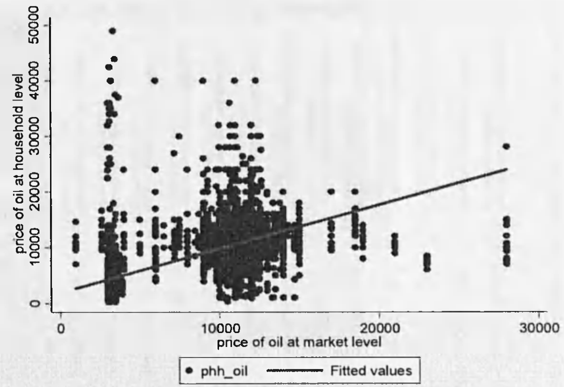
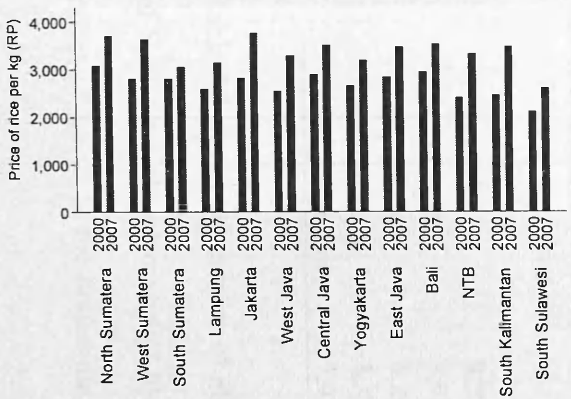
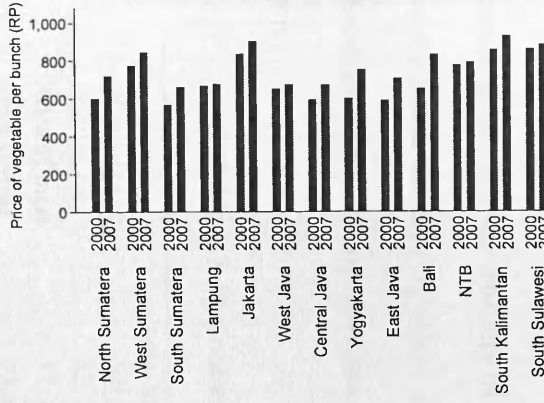


Figure 5.6: Real prices of goods in 2000 and 2007 across the provinces

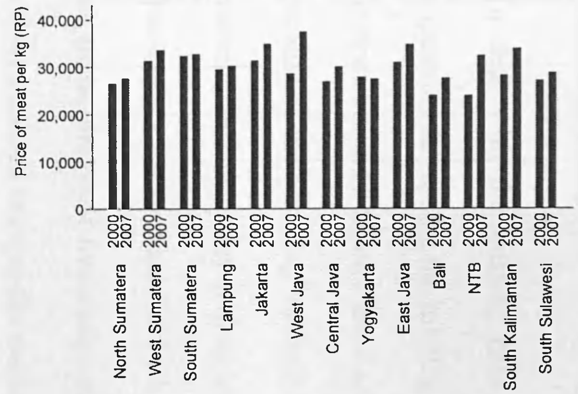
a. Price of rice



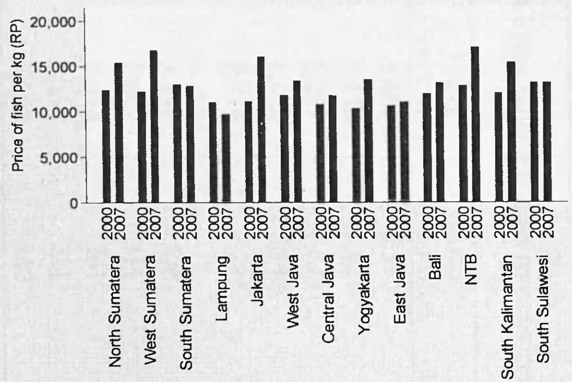
b. Price of vegetables



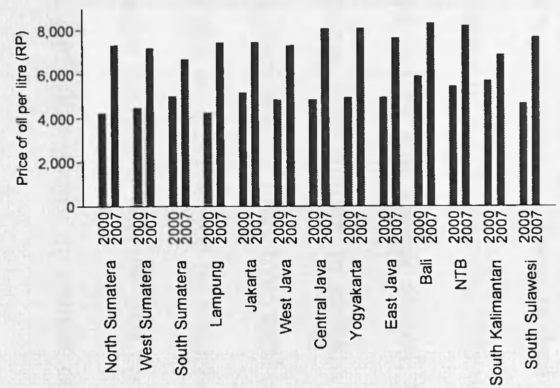
c. Price of meat



d. Price of fish



e. Price of oil



To deal with the missing data problem on the price of goods, we used mean imputation to replace the missing values. As we already explained in Chapter 2, data from community facility level and the price of goods at market level were missing because of the sampling methods in the community facility survey. IFLS listed all the markets, and they were ranked by frequency of mention. These ranked lists provided frames for each stratum, from which a sample of two to four facilities were drawn. In all strata, the most frequently mentioned facility was always visited. Here, missing values occurred because the markets were not in the sample. In addition, in the case of the price of goods at household level, we generated the price from total expenditure on certain goods over the quantity of goods that were consumed by households. It is also possible that the missing values could arise because it may be that there were some households that did not consume those particular goods, so cannot compute a unit price.

Table 5.7: The number of missing values and its imputation

Market price	Total missing values	Village imputation	District imputation	Total observation
Price of rice	12,751	6,401	6,350	20,094
Price of meat	12,359	6,438	5,921	20,094
Price of fish	13,584	5,249	8,335	20,094
Price of oil	12,310	4,868	7,442	20,094
Price of vegetables	12,151	6,612	5,539	20,094
Household Price				
Price of rice	8,296	7,758	538	20,079
Price of meat	9,913	9,602	311	20,085
Price of fish	6,294	6,033	261	20,015
Price of oil	8,338	8,117	221	20,089
Price of vegetables	7,029	6,289	740	20,086

Table 5.7 shows the number of missing values for each price of good and the number of values which were solved by using village and district imputation. In general, prices of goods at the household levels have less missing values than the prices of

goods at the market levels. Here, if the price of goods is missing, then each missing value will be substitued by the average price of goods from the smallest and closest community level to the households, which is village level. If there is still any missing value, the imputed price value is based on the average at district level, a higher community level than the village level. For instance, if the price of rice is missing, we imputed the price of rice from the average price of rice in the village level at the same time that the survey was conducted. If there was still any missing values, we used the average price of rice at the district level to impute the missing values of the price of rice. We did the same for both prices of goods, at household level and market level.

5.4. Methodology: DID Model

This section outlines the research methodology used in this chapter to examine the effects of natural disasters on family expenditures and food demand. We used two different methods for estimating. The first method is difference in differences (DID) analysis. We used this analysis for estimating the reduced form impact of disasters on household expenditures.

Besides DID, we employed the Linear Approximate Almost Ideal Demand System (LA-AIDS) model that is discussed in Section 5.6. In the LA-AIDS model we impose a structure that allows us to isolate the impact of disasters on food share expenditures, controlling for prices. We use the parameter estimation from the LA-AIDS model to calculate the price and expenditure elasticities.

5.4.1. The Concept of DID Model

The detailed explanation of DID model has already been explained in Chapter 4. Conceptually, the DID model can be expanded by including household covariates X_{ht} and can be written as:

$$Y_{ht} = \alpha_1 D_{ht} + \alpha_2 A_{ht} + \psi X_{ht} + u_{ht} \tag{5.1}$$

Thus, the equation (5.1) estimates the effect of disasters ($\alpha_1 + \alpha_2$) on the potential outcome of household h in time t (Y_{ht}) as measures by using household expenditures by controlling household covariates X_{ht} such as area, household size, parental education background, number of household member per age categorized, and also region and year fixed effects respectively.

5.4.2. Household Expenditure Equation

All the equations of DID models that are used in this chapter have the same variables on the right hand side, and we separately estimated all equations by using OLS. The complete DID model in this study can be written as:

$$Lhhexp_{ht} = \alpha_{01} + \alpha_{11} D_{ht} + \alpha_{21} A_{ht} + \psi_1 X_{ht} + \gamma_{1r} + \nu_{1t} + \varepsilon_{1ht} \tag{5.4}$$

$$Lbuyexp_{ht} = \alpha_{02} + \alpha_{12} D_{ht} + \alpha_{22} A_{ht} + \psi_2 X_{ht} + \gamma_{2r} + \nu_{2t} + \varepsilon_{2ht} \tag{5.5}$$

$$Lownexp_{ht} = \alpha_{03} + \alpha_{13} D_{ht} + \alpha_{23} A_{ht} + \psi_3 X_{ht} + \gamma_{3r} + \nu_{3t} + \varepsilon_{3ht} \tag{5.6}$$

$$Leducexp_{ht} = \alpha_{04} + \alpha_{14} D_{ht} + \alpha_{24} A_{ht} + \psi_4 X_{ht} + \gamma_{4r} + \nu_{4t} + \varepsilon_{4ht} \tag{5.7}$$

$$Lwages_{ht} = \alpha_{05} + \alpha_{15} D_{ht} + \alpha_{25} A_{ht} + \psi_5 X_{ht} + \gamma_{5r} + \nu_{5t} + \varepsilon_{5ht} \tag{5.8}$$

The dependent variables in the equations above are $Lhhexp_{ht}$, $Leducexp_{ht}$, $Lbuyexp_{ht}$, $Lownexp_{ht}$, and $Lwages_{ht}$. $Lhhexp_{ht}$ is log of total household expenditure. $Leducexp_{ht}$ is log of educational expenditure. $Lbuyexp_{ht}$ is log of food expenditure from market purchases. $Lownexp_{hr}$ is log of food expenditure from estimating values of own production. $Lwages_{ht}$ is log of head of household wages. All household expenditures and wages are measured using monthly household expenditures. The main explanatory variables are D_{ht} and $A_{ht,}$ which capture the natural disaster variables. D_{hrt} is a dummy variable, equal to 1 if household h was in the disaster region with expenditure after disaster. A_{ht} is a dummy variable, equal to 1 if household h was in the disaster region and was affected by a disaster. In addition, vector X_{ht} contains the other explanatory variables to capture household characteristics such as area where they live, household size and number of children or adults in certain age groups. The variables γ_r and v_t are region and year fixed effects respectively. The inclusion of the regional dummy variables reduces the potential bias from unmeasured regional effects. Year dummy variables are useful to control for year specific characteristics and control for other changes in the year before and after disasters. Moreover, in order to see whether different types of disasters have a different impact on household expenditure, this chapter replaces the main explanatory variables, which are dummies D_{ht} and $A_{ht,}$ by using dummy variables of D_{ht} and $A_{ht,}$ which belong to specific types of disasters. There are 3 dummies for D_{ht} (for big earthquake, small earthquake and flood), and the same for 3 dummies for A_{ht}. In order to check the sensitivity of dummy variables of interest (D_{ht} and A_{ht}), we also estimated the DID model equation by dropping all the control variables except D_{ht} and A_{ht}.

5.5. Empirical Results: DID Model

This section discusses the results of the impact of natural disasters on household expenditures. There are two main estimation results: (1) the average impact of natural disasters on household expenditures and food expenditures, and (2) the impact of natural disasters on educational expenditure and wages. We present the results of the impact of disasters on share expenditures and food demand using the LA-AIDS demand system model in Section 5.7.

5.5.1. The Impact of Disasters on Total and Food Expenditures

In the DID model, we estimated separately the impact of disasters on the types of expenditures using OLS. Total household expenditures and food expenditures (market- purchased and own-produced expenditures) are presented together, since food expenditures have a bigger share of total expenditures. Educational expenditure and wages are presented separately. Table 5.8 presents the estimation results for total and food expenditures. There is no negative effect of being in a disaster region after a disaster. This is indicated from all of the coefficients on D. Households increased their expenditures of own-produced food by approximately 20% on average, significance at the 10% level. This could arise because these households were not directly affected but preferred to consume more from their own production, since the price of foods in the market probably increased, due to the disaster. On the other hand, for households who were affected directly by the disaster, their own production expenditures were lower following, perhaps because of the destruction of their farm. Therefore, these households purchase more food from market, although the values were not significant.

Moreover, looking at other explanatory variables, total household expenditures and market- purchased expenditures in urban are higher than in rural, but own-produced expenditure in urban is lower than in rural. This is true because all farms are located in rural areas. For household size, all values are positively correlated with expenditures and are highly significant. It shows that the bigger the number of total household members, the greater the household expenditures will be. In general, the father's education background has no effect on expenditures, but maternal education background seems to have a positive and significant effect on total and market-purchased expenditures, but is negatively correlated with own-produced expenditures. This may arise, because household expenditures are usually managed by the mother, and the higher is maternal education the greater these expenditures will be, as the higher the maternal education, the wealthier they are, and thegreater variety of goods may be demanded, especially luxury goods. In addition, more highly-educated mothers are less likely to be farm workers so they may have lower own produced food.

Table 5.8: Results of the Impact of Natural Disasters on Total Household Expenditures and Food expenditures

	Total HH exp		Food exp: buy only		Food exp: own prod	
	1	2	3	4	5	6
D	-0.000792	0.0283	-0.00799	0.0236	0.172*	0.182*
	(0.0663)	(0.0532)	(0.0663)	(0.0488)	(0.0817)	(0.0851)
A	-0.00743	-0.101	0.0951	-0.00134	-0.192***	-0.197***
	(0.0507)	(0.0592)	(0.0615)	(0.0731)	(0.0597)	(0.0628)
Urban		0.324***		0.282***		-0.203***
		(0.0229)		(0.0270)		(0.0424)
Household size		0.136***		0.156***		0.0456***
		(0.00745)		(0.00848)		(0.0135)
Father secondary school		-0.0742		-0.128		-0.194
		(0.140)		(0.103)		(0.285)
Father higher education		0.399		-0.0231		0.289
		(0.340)		(0.0798)		(1.128)
Mother secondary school		0.235***		0.178		-0.168
		(0.0766)		(0.109)		(0.255)
Mother higher education		0.521		0.675**		-0.252***
		(0.336)		(0.291)		(0.0285)
Number of HH member age:		-0.0993***		-0.0583***		-0.0692***
Under 6		(0.0109)		(0.0124)		(0.0165)
6 to 12		-0.0578***		-0.0558***		-0.0522**
		(0.00716)		(0.00777)		(0.0222)
13 to 18		-0.00621		-0.0493***		0.0192
		(0.00761)		(0.0111)		(0.0121)
19 to 23		0.0246**		0.00565		0.0252
		(0.00870)		(0.00788)		(0.0158)
24 to 60		0.0591***		0.0683***		0.0206*
		(0.00565)		(0.00643)		(0.00980)
Over 60		-0.101***		-0.123***		0.0200
		(0.0105)		(0.00635)		(0.0192)
Region dummies	yes	yes	Yes	yes	yes	yes
Time dummies	yes	yes	Yes	yes	yes	yes
Observation	20,791	20,791	20,682	20,682	15,797	15,797

Note: Robust standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Total households members in each household up to 18 years old and over 60 years old are negatively correlated with all expenditures, especially total and market-purchased expenditures, while the total numbers of adults in households between 19 to 60 years old are positively correlated with expenditures. This indicates that the age group of household members under 18 and over 60 do not require a lot of expenditures, especially for those aged under 18 - they are still of school age and do not account for a lot of expenditure, while household members aged between 19 to 60 need more expenditure, since those household members typically to have jobs and usually their needs are more varied.

Table 5.9: Results of the impact of specific disasters on household expenditures

	Total HH exp		Buy only		Own produced	
	1	2	3	4	5	6
Big_earthquake_region	0.0903**	0.0587*	0.134***	0.114***	0.0353	0.0326
	(0.0332)	(0.0326)	(0.0375)	(0.0329)	(0.0577)	(0.0547)
Affected_big earthquake	-0.111***	-0.190***	-0.0422***	-0.133***	-0.206***	-0.205***
	(0.000)	(0.00235)	(0.000)	(0.00234)	(0.000)	(0.00650)
Small_earthquake_region	0.0844**	0.123***	0.0138	0.0508	0.281***	0.325***
	(0.0332)	(0.0313)	(0.0375)	(0.0320)	(0.0577)	(0.0531)
Affected_small earthquake	0.145***	0.0412***	0.282***	0.196***	-0.0470***	-0.0360***
	(0.000)	(0.00560)	(0.000)	(0.00675)	(0.000)	(0.00973)
Floods_region	-0.0996**	-0.0419	-0.0939**	-0.0357	0.206***	0.197***
	(0.0332)	(0.0328)	(0.0375)	(0.0327)	(0.0577)	(0.0558)
Affected_floods	0.0121***	-0.0187***	0.105***	0.0658***	0.0314***	0.0154*
	(0.000)	(0.00257)	(0.000)	(0.00296)	(0.000)	(0.00740)
Additional controls	no	yes	No	yes	no	yes
Region dummies	yes	yes	Yes	yes	yes	yes
Time dummies	yes	yes	Yes	yes	yes	yes
Observation	20,791	20,791	20,791	20,791	15,797	15,797

Note: Robust standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; Additional controls: urban, household size, parental educations, number of household members.

Table 5.9 presents the impact of specific natural disasters on household expenditures. The results show that households in a big earthquake region who were affected directly by a big earthquake were badly affected. This is shown from the coefficient of all expenditure categories which are negatively correlated with A in 'Big earthquake'. There was no significant effect from small earthquake disasters; in fact, those households who were not affected directly by a small earthquake in a small earthquake region have positive and significant impacts of disasters on total household expenditures, and those households who are affected directly by disasters also have positive impacts of disasters on total expenditures and market-purchased expenditures. Disasters are only negatively correlated with own-produced expenditure for those households who are affected directly by a small earthquake. This is very true since the farms of households who are affected directly were often destroyed during small earthquakes. Moreover, for households in a floods region, there was positive and significant impact of floods on own-produced expenditures for those households who live in a flood region but were not directly affected. This could arise because those who were directly affected by floods suffered destruction of their farms, which led to a reduction in production and caused an increase in the price of foods. For those who are not directly affected by floods, then, they could provide for their food needs from their own production instead of buying from the market. In addition to own-produced expenditure, for households in flood regions, floods will have caused lower total and market-purchased expenditures.

5.5.2. The Impact of Disasters on Educational Expenditure and Wages

The results of the impact of disasters on educational expenditure and wages are quite different from food and total expenditures. Especially for educational expenditure, disasters have reduced educational expenditure for those who are affected directly by disasters. As presented in Table 5.10, the impact of disasters on educational expenditures shows that the results in Columns 1 and 2 for D and A variables were negatively associated with educational expenditures, but only the A variables are significant. It indicates that all households that live in disaster regions and are not affected directly by disasters have no serious impacts on educational expenditures. On the other hand, for households who are directly affected, they are more likely to reduce educational expenditures in smoothing their consumption on food, since Table 5.8 shows that food expenditures, especially for market- purchased expenditures, are not affected by disasters.

Table 5.10: Results of the Impact of Natural Disasters on Educational Expenditure

	log educational expenditure			
	1	2	3	4
D	-0.0782	-0.0407		
	(0.0598)	(0.0547)		
A	-0.162*	-0.281***		
	(0.0872)	(0.0797)		
Big_earthquake_region			0.0441	-0.0853
			(0.119)	(0.108)
Affected_big earthquake			-0.251*	-0.279**
			(0.133)	(0.121)
Small_earthquake_region			0.0366	0.138
			(0.0996)	(0.0910)
Affected_small earthquake			0.236	0.0204
			(0.189)	(0.173)
Floods_region			-0.213**	-0.138*
			(0.0850)	(0.0777)
Affected_floods			-0.464***	-0.481***
			(0.175)	(0.160)
Additional controls	no	yes	no	yes
Region dummies	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
Observation	12,383	12,383	12,383	12,383

Note: Robust standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; Additional controls: urban, household size, parental educations, number of household members.

Furthermore, Columns 3 and 4 show the impact of specific disasters on educational expenditures. The results show that only households in big earthquake and flood regions and those that were affected directly by big earthquakes and floods have lower educational expenditures. These phenomena could be true because only large disasters are negatively associated with educational expenditures. In fact, for households who live in flood regions, their educational expenditures are also affected by floods. This might arise because some goods were destroyed by the floods, so in order to smooth food consumption, they cut educational expenditures.

Table 5.11: The impact of disasters on wages

	log wages			
	1	2	3	4
D	0.103**	0.105**		
	(0.0489)	(0.0461)		
A	0.0546	-0.0290		
	(0.0694)	(0.0654)		
Big_earthquake_region			0.155*	0.139
			(0.0917)	(0.0864)
Affected_big earthquake			0.0185	-0.0790
			(0.102)	(0.0959)
Small_earthquake_region			0.130	0.0827
			(0.0884)	(0.0832)
Affected_small earthquake			-0.0190	-0.0947
			(0.162)	(0.153)
Floods_region			0.0598	0.102
			(0.0682)	(0.0644)
Affected_floods			0.125	0.0990
			(0.137)	(0.129)
Additional controls	no	yes	No	yes
Region dummies	yes	yes	Yes	yes
Time dummies	yes	yes	Yes	yes
Observation	17,481	17,371	17,481	17,371

Note: Robust standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; Additional controls: urban, household size, parental educations, number of household members. Wages is measured from monthly income basis.

Table 5.11 shows the impact of disasters on wages. Columns 1 and 2 are the results of the impact of disasters on wages in general. It seems that disasters are negatively associated with wage only for households who are affected directly by disasters. The possible explanation for this is that households who were affected directly by disasters lost their property or the head of households lost their jobs, causing a decrease in wages. On the other hand, there is positive and significant impact of disasters on wages for those households in disaster regions who were not directly affected by disasters. This indicates that for survivors, there was a shock positive to labour demand because there was a clean-up and reconstruction work to be done after a disaster. In the case of specific natural disasters, all variables are not significant. Only D in big earthquake without controlling for other variables is positively associated with wages, although it is only significant at 10%.

In addition, it is important to report about the disaster relief or aid after disasters, since it could affect the income of the victims. Soon after disaster occurred, in the first week, an immediate aid was distributed to the disaster region such as foods, tents, and cloths by the government and other agencies. It was followed by an intermediate aid that was distributed in cash to the victims whose houses were destroyed by disasters to reconstruction and rebuild it. It took at least 6 months until these aids were distributed. For instance, in the case of big earthquake in Yogyakarta, each household whose house was destroyed received money approximately 15 million rupiahs. Thus, considering the results from table 5.11 that shows individuals in disaster region especially in big earthquake region have a higher wages, it seems that aids do not affect the wages since, the survey was conducted from November 2007 to April 2008 and it was around 18 months after the disaster. The wages itself was measured from the last month income from the time survey.

5.6. Methodology: LA-AIDS Model

There are four important aspects that are explained in this section: the concept of the LA-AIDS model, elasticities, the estimation procedure, and welfare effects.

5.6.1. The Concept of the LA-AIDS model

This study employs the demand specification which was proposed by Deaton and Muellbauer (1980) and referred to as the Almost Ideal Demand System model. Deaton and Muellbauer defined preferences by a representation of the cost or expenditure function. The AIDS specification yields household expenditure share for good i defined as:

$$w_i = \frac{p_i q_i}{X} \tag{5.9}$$

where p_i is price for good i, q_i is quantity for good i , and X is the total expenditure on all goods in the demand system, can be written as:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \, lnP_j + \beta_i \ln\left(\frac{X}{P}\right) \tag{5.10}$$

where w_i is the share of total expenditure allocated to the i^{th} good, P_j is the price of the j^{th} good within the group, X is total expenditure on the group of goods being analysed, P is the price index, α, β, γ are parameters, and the subscripts i and j denote goods (i, j=1,..., n).

The price index (P) is defined as:

$$lnP = \alpha_0 + \sum_k \alpha_k \, lnP_k + \frac{1}{2} \sum_j \sum_k \gamma_{kj} \, lnP_k lnP_j \tag{5.11}$$

Substituting 5.11 into 5.10 results in a highly nonlinear model, and Deaton and Muellbauer (1980) suggest known as a linear approximation to the price index using Stone's price index. Stone's price index (P*), which is used as a linear approximation to 5.11, can be written as:

$$lnP^* = \sum w_k lnP_k \qquad (5.12)$$

Where w_k is the share to good k in total expenditure. However, this price index may cause a simultaneity problem because the w_k is item on both sides of the share equation. we use share expenditure as a measurement of w_k. To avoid this problem, following Haden(1990), we use the mean of shares across all households instead of household shares for w_k.

$$lnP^* = \sum \overline{w}_k lnP_k \qquad (5.13)$$

where P* is Stone's price index, $\overline{w}_k$ is the mean of share expenditure, P_k is the price of good. Therefore, the approximation of the AIDS demand function in budget share is:

$$w_i = \alpha_i^* + \sum_j \gamma_{ij}\, lnP_j + \beta_i \ln\left(\frac{X}{P^*}\right) \qquad (5.14)$$

Blanciforti, Green and King (1986) named this model as the "Linear Approximation of the Almost Ideal Demand System" (LA-AIDS).

Economic theory imposes three sets of restrictions on the parameters of the AIDS model.

1. Adding up:

$$\sum_{i=1}^{n} \alpha_i = 1 \quad \sum_{i=1}^{n} \gamma_{ij} = 0 \quad \sum_{i=1}^{n} \beta_i = 0 \qquad (5.15)$$

2. Homogeneity:

$$\sum_{j=1}^{n} \gamma_{ij} = 0 \qquad (5.16)$$

3. Symmetry:

$$\gamma_{ij} = \gamma_{ji} \qquad (5.17)$$

where the coefficient of γ_{ij}represents the changes in relative prices, while β_i coefficient represents the changes in real expenditure. The β_i coefficient sums to zero and β_i are positive and less than 1 for necessities, more than 1 for luxury goods and negative for inferior goods. If restrictions 1,2 and 3 hold, then the LA-AIDS share expenditure equation above represents a system of demand functions, with the adding-up condition that the total share expenditure is equal to one ($\sum w_i = 1$). Moreover, homogeneity and symmetry imply that the demand functions are homogeneous of the degree zero in prices and total expenditure, and must satisfy Slutsky symmetry[13]. The adding-up condition implies that one of the demand equations can be dropped from the system, so the estimation is performed on the remaining demand (n-1) equations.

5.6.2. Elasticities

Income (expenditure) elasticities of the LA-AIDS model can be written as:

$$\eta_{i,x} = \frac{dlnq_i}{dlnX} = 1 + (\frac{dw_i}{dlnX})/w_i \tag{5.18}$$

Using Stone's price index (P*), and $\frac{dw_i}{dlnX} = \beta_i$, the expenditure elasticities can be expressed as:

$$\eta_{i,x} = 1 + \beta_i/w_i \tag{5.19}$$

Uncompensated demand elasticity of AIDS and LA-AIDS (η_{ij}) can be written as:

$$\epsilon_{ij} = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} - \frac{w_j}{w_i}\beta_i \tag{5.20}$$

With δ_{ij} is the Kronecker delta where $\delta_{ij} = 1$ for $i = j$ and $\delta_{ij} = 0$ for $i \neq j$.

[13] The Slutsky symmetry restriction comes from the fact that the Hicksian (compensated) demand of the cost function is a symmetric matrix. Hicksian is from the change of Marshallian (uncompensated) demand in the Slutsky equation, which compensates to maintain a fixed level of utility. According to Haag et al. (2009), maximization of utility implies that consumer demand systems have a Slutsky matrix, which is symmetric everywhere. Demand systems with non-linear Engel curves and Slutsky symmetry could be imposed with linear or non-linear cross-equation restrictions.

5.6.3. LA-AIDS estimation procedures

In estimating the LA-AIDS model, there are 6 equations of budget share expenditures on rice, vegetables, meat, fish, oil and all other goods (everything else) with their respective prices and real expenditures. The LA-AIDS demand system can be written as:

$$w_{rice} = \alpha_1 + \gamma_{11} ln\widehat{P_{rice}} + \gamma_{12} ln\widehat{P_{veg}} + \gamma_{13} ln\widehat{P_{meat}} + \gamma_{14} ln\widehat{P_{fish}} + \gamma_{15} ln\widehat{P_{oil}} + \gamma_{16} ln\widehat{P_{others}} + \beta_1 ln\left(\frac{X}{P^*}\right) + \theta_1 D_{hrt} + \rho_1 A_{hrt} + \sigma_1 Urban_{hrt} + \mu_1 \tag{5.21}$$

$$w_{veg} = \alpha_2 + \gamma_{21} ln\widehat{P_{rice}} + \gamma_{22} ln\widehat{P_{veg}} + \gamma_{23} ln\widehat{P_{meat}} + \gamma_{24} ln\widehat{P_{fish}} + \gamma_{25} ln\widehat{P_{oil}} + \gamma_{26} ln\widehat{P_{others}} + \beta_2 ln\left(\frac{X}{P^*}\right) + \theta_2 D_{hrt} + \rho_2 A_{hrt} + \sigma_2 Urban_{hrt} + \mu_2 \tag{5.22}$$

$$w_{meat} = \alpha_3 + \gamma_{31} ln\widehat{P_{rice}} + \gamma_{32} ln\widehat{P_{veg}} + \gamma_{33} ln\widehat{P_{meat}} + \gamma_{34} ln\widehat{P_{fish}} + \gamma_{35} ln\widehat{P_{oil}} + \gamma_{36} ln\widehat{P_{others}} + \beta_3 ln\left(\frac{X}{P^*}\right) + \theta_3 D_{hrt} + \rho_3 A_{hrt} + \sigma_3 Urban_{hrt} + \mu_3 \tag{5.23}$$

$$w_{fish} = \alpha_4 + \gamma_{41} ln\widehat{P_{rice}} + \gamma_{42} ln\widehat{P_{veg}} + \gamma_{43} ln\widehat{P_{meat}} + \gamma_{44} ln\widehat{P_{fish}} + \gamma_{45} ln\widehat{P_{oil}} + \gamma_{46} ln\widehat{P_{others}} + \beta_4 ln\left(\frac{X}{P^*}\right) + \theta_4 D_{hrt} + \rho_4 A_{hrt} + \sigma_4 Urban_{hrt} + \mu_4 \tag{5.24}$$

$$w_{oil} = \alpha_5 + \gamma_{51} ln\widehat{P_{rice}} + \gamma_{52} ln\widehat{P_{veg}} + \gamma_{53} ln\widehat{P_{meat}} + \gamma_{54} ln\widehat{P_{fish}} + \gamma_{55} ln\widehat{P_{oil}} + \gamma_{56} ln\widehat{P_{others}} + \beta_5 ln\left(\frac{X}{P^*}\right) + \theta_5 D_{hrt} + \rho_5 A_{hrt} + \sigma_5 Urban_{hrt} + \mu_5 \tag{5.25}$$

$$w_{others} = \alpha_6 + \gamma_{61} ln\widehat{P_{rice}} + \gamma_{62} ln\widehat{P_{veg}} + \gamma_{63} ln\widehat{P_{meat}} + \gamma_{64} ln\widehat{P_{fish}} + \gamma_{65} ln\widehat{P_{oil}} + \gamma_{66} ln\widehat{P_{others}} + \beta_6 ln\left(\frac{X}{P^*}\right) + \theta_6 D_{hrt} + \rho_6 A_{hrt} + \sigma_6 Urban_{hrt} + \mu_6 \tag{5.26}$$

Where $\alpha_i, \beta_i, \gamma_{ij}, \theta_i, \rho_i, \sigma_i$ are parameters to be estimated, μ_i are error terms. For share expenditures, we have: w_{rice} is share expenditure on rice, w_{veg} is share expenditure on vegetables, w_{meat} is share expenditure on meat, w_{fish} is share expenditure on fish, w_{oil} is share expenditure on cooking oil, and w_{others} is share expenditure for everything else (all other goods). For the price of goods, we used log of price from a linear prediction (log price hat). In tha IFLS data, we generated the price of goods at the household level by dividing expenditures of certain goods with the quantity purchased. Since we used this price of goods from household levels, we are concerned about measurement error in the prices, so we instrumented the price of goods at the HH level using the price of goods at the market level. Here, we estimated the price for LA-AIDS model by using the following equation:

$$lnHHP_i = \delta_0 + \delta_1 lnMP_i + \theta_i D_{ht} + \rho_i A_{ht} + \sigma_i Urban_{ht} + \gamma_r + v_t + \mu_i \quad (5.27)$$

Where $lnHHP_i$ is log price of good i at HH level, $lnMP_i$ is log price of good i at market level. In addition, we add other explanatory variables in the model, including dummy disaster regions (D_{ht}), and dummy affected by disasters (A_{ht}). An urban dummy is also included on the model, and variables γ_r and v_t are used to control for regions and year-fixed effects respectively. Once we obtain the estimates from is regression, then we can obtain the linear prediction of the log price of goods to use in the LA-AIDS model. Therefore, we have $ln\widehat{P_{rice}}$ for price of rice, $ln\widehat{P_{veg}}$ for price of vegetables, $ln\widehat{P_{meat}}$ for price of meat, $ln\widehat{P_{fish}}$ for price of fish, $ln\widehat{P_{oil}}$ for price of oil, and $ln\widehat{P_{others}}$ for price for other goods. We assumed that other goods are the numeraire good, so $\widehat{P_{others}}$=1 and the prices of other goods are defined relative to $\widehat{P_{others}}$. When we estimated the LA-AIDS model, $\widehat{P_{others}}$ will be omitted since the log of 1 is zero.

By imposing homogeneity, adding-up and symmetry, the equation for w_{others} is dropped to avoid singularity due to the adding-up condition. All equations above are estimated jointly using Zellner's Semingly Unrelated Regressions (SUR) in Stata 12.

5.6.4. Measuring Living Standard

According to Deaton and Muellbaur (1980), the demand system can be derived from the expenditure function.

$$\log E(p, U) = A(p) + B(p)U \tag{5.28}$$

Where:

$$A(p) = \sum_i \sum_j \gamma_{ij} logP_i \, logP_j + \sum_i \alpha_i logP_j \tag{5.29}$$

$$B(p) = \prod_{i=1}^{n} P_i^{\beta_i} \tag{5.30}$$

The corresponding indirect utility function:

$$U = \frac{logE - A(p)}{B(p)} \tag{5.31}$$

U is an indirect utility of LA-AIDS model or living standard, it can be poor or rich and can be measured by using money metric of utility; p is the price of foods, E is the total expenditure. We have two conditions (before disasters and after disasters) which influence the value of price, and we assume that before disasters the price is equal to 1, and after disasters the price is equal to 1 plus the change of price that we can measure from price estimation without controlling for price at market level. According to the above condition, we can write before disasters as: $A(P_0)$ = 0, $B(P_0)$ =1, then $U = logE$, and after disasters as: $A(P_1)$ = certain values, $B(P_1)$=certain values, then the value of U depends on the category of U as poor or rich. For poor, we used the income definition from the Central Bureau Statistics of Indonesia of 250,000 rupiahs per month and we also calculated for the poorest, which is obtained from the lowest income of income distribution at 15,000 rupiahs per month. For the rich, we used an income of 5 million rupiahs. Then we calculated for the welfare effect of disasters as: $Disaster\ effect = E(P_1, U) - E(P_0, U) = A(P_1)\ - A(P_0) + \ [B(P_1) - B(P_0)]U.$

5.7. Empirical Results: LA-AIDS Model

The LA-AIDS model was estimated using Seemingly Unrelated Regression (SUR) in STATA 12. The purpose of estimating using this model is to isolate the effect of disaster induced prices changes from other effects. In contrast DID regression is reduced form and captures the total effect but does not isolate the price effect from other effects.

5.7.1. First Stage Regressions: Predicting Household Prices

Table 5.12 presents the first stage least square regression for the prices of goods. The table shows the regression of price of goods at market level, and D and A variables on price of goods at household level. The predicted values of household prices from this regression are used in the second stage regression of the LA-AIDS model. Almost all prices of goods at market level are significant and positively correlated with the price of goods at household level, only fish has no significant value but is still positively associated with the price at household level. D is positively correlated with the price of goods at household level for rice, vegetables, fish and oil. It indicates that the price of goods tends to increase when disasters occur. On the other hand, there are negative correlations of A on the price of rice and fish, and positive correlations of A on the price of vegetables, meat, and oil. The results especially for rice would be consistent with aid agencies bringing enough staple foods to disaster regions to stabilize prices.

Table 5.12: First stage least square regression for price of goods

Dept var: Log of household price	Rice	Vegetables	Meat	Fish	Oil
log market price	0.0332***	0.0736***	0.0425*	0.00680	0.0348***
	(0.00696)	(0.00812)	(0.0250)	(0.00714)	(0.0124)
D	0.00308	0.221***	-0.126***	0.204***	0.00667
	(0.00994)	(0.0212)	(0.0136)	(0.0150)	(0.0108)
A	-0.0382***	0.0673**	0.0324*	-0.0391*	0.0570***
	(0.0141)	(0.0302)	(0.0193)	(0.0212)	(0.0153)
Urban	0.0872***	0.0171**	0.0686***	0.0386***	0.0153***
	(0.00393)	(0.00836)	(0.00534)	(0.00587)	(0.00423)
Time dummies	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes
Observation	19,574	19,574	19,574	19,574	19,574

Note: Robust standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Table 5.13 shows the results of price regressions without controlling for the price at the market level. This is to investigate the transmission mechanism of the disaster effect on the price of goods. By controlling for market prices, as in Table 5.12, we are able to identify the additional effect of disasters on household prices beyond their impact on market prices.

Table 5.13: The effect of disasters on price without controlling market price

Dept var: Log of household price	Rice	Vegetables	Meat	Fish	Oil
D	0.00614	0.227***	-0.124***	0.203***	0.00899
	(0.00975)	(0.0209)	(0.0134)	(0.0147)	(0.0106)
A	-0.0395***	0.0626**	0.0354*	-0.0386*	0.0410***
	(0.0138)	(0.0296)	(0.0189)	(0.0209)	(0.0151)
Urban	0.0889***	0.0249***	0.0695***	0.0400***	0.0152***
	(0.00384)	(0.00823)	(0.00527)	(0.00579)	(0.00418)
Time dummies	yes	Yes	yes	yes	yes
Regional dummies	yes	Yes	yes	yes	yes
Observation	20,079	20,085	20,015	20,089	20,086

Note: Robust standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Here, we want to observe the total effect of disasters on the prices which households pay. This will be used later in evaluating the welfare impact of disasters. The results show that prices of rice, vegetables, fish, and oil are positively associated with disasters.

5.7.2. Parameters of the LA-AIDS model

Table 5.14 shows the parameters of the LA-AIDS model with homogeneity and symmetry restrictions imposed. It can be seen from the level of significance of each parameter that almost all parameters are significant at 1% and a few are at 5%. Almost all shares expenditures are negatively correlated with D and are highly significant. Only share expenditure on meat is positively correlated with D but it is only significant at 10%. Only the meat and fish shares are negatively associated with A. It seems that households reduce their expenditures on meat and fish when the disasters occured, as those two goods are not staple foods. Almost all estimates show that urban has negative effect on the shares of all food expenditures. It means that all household food expenditures in urban areas are lower than in rural areas.

We also estimated the LA-AIDS model using the original prices of goods at the household level. This estimation does not instrument the prices of goods at the household level. In general, the results are not very different, especially for the price and expenditure elasticities, and the effect of disasters on living standards is only slightly different. The detailed results are presented in the Appendix. The complete tables of those LA-AIDS models are in Tables A5.1 to A5.4.

Table 5.14: Parameters of LA-AIDS Demand System with Homogeneity and Symmetry Restriction

	Share equations of total expenditures				
	1	2	3	4	5
Parameters	Rice	veg	meat	Fish	Oil
γ_{i1}	0.0340***	-0.00990***	-0.00378***	-0.0244***	0.00403***
	(0.00256)	(0.00143)	(0.000661)	(0.00109)	(0.00149)
γ_{i2}	-0.00990***	-0.0179***	-0.00173***	0.0278***	0.00179**
	(0.00143)	(0.00131)	(0.000322)	(0.000742)	(0.000741)
γ_{i3}	-0.00378***	-0.00173***	-0.000520	0.00285***	0.00319***
	(0.000661)	(0.000322)	(0.000634)	(0.000271)	(0.000556)
γ_{i4}	-0.0244***	0.0278***	0.00285***	0.00484***	-0.0111***
	(0.00109)	(0.000742)	(0.000271)	(0.000807)	(0.000607)
γ_{i5}	0.00403***	0.00179**	0.00319***	-0.0111***	0.00208
	(0.00149)	(0.000741)	(0.000556)	(0.000607)	(0.00131)
β_i	-0.0373***	-0.00376***	0.00131***	-0.00231***	-0.00516***
	(0.000906)	(0.000440)	(8.96e-05)	(0.000441)	(0.000225)
θ_i	-0.0124***	-0.00502***	0.000505*	-0.0108***	-0.00175***
(D)	(0.00265)	(0.00127)	(0.000259)	(0.00126)	(0.000649)
ρ_i	0.00839*	0.00985***	-0.00153***	-0.00599***	0.00431***
(A)	(0.00488)	(0.00233)	(0.000471)	(0.00231)	(0.00119)
σ_i	-0.0426***	-0.00948***	2.06e-05	-0.0108***	-0.00708***
(Urban)	(0.00139)	(0.000662)	(0.000139)	(0.000655)	(0.000349)
F statistics of excluded instruments:					
Price of rice			6558.29		
Price of vegetables			1291.69		
Price of meat			3282.58		
Price of fish			32.67		
Price of oil			10364.23		
Observation			19,574		

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; F statistics of excluded instruments is a test of the joint significance of the excluded instruments in the first stage regression.

Moreover, Table 5.14 also presents the F-statistics to test the excluded instruments from the first stage regression. The value of F statistics are the same for all share equations, since we used exactly the same endogenous variables instruments and other covariates on the right hand side of the share equation. For comparison, we also estimated the LA-AIDS model using data with missing values. In fact, with the number of only 5,849 observations, which is less than the estimation with imputation of the missing values of 19,574 observations, the results are similar, especially for the elasticities, and for the effect of disasters on living standards there is only slightly different value. This suggests that the missing values do not bias the results. The complete results are presented in Appendix tables A5.5 to A5.8.

Table 5.15: Parameters of LA-AIDS Demand System with Homogeneity and Symmetry Restriction on the Impact of Specific Natural Disasters

	Share equations of total expenditures				
	1	2	3	4	5
Parameters	rice	Veg	meat	fish	Oil
γ_{i1}	0.0343***	-0.0100***	-0.00379***	-0.0245***	0.00404***
	(0.00259)	(0.00146)	(0.000674)	(0.00110)	(0.00153)
γ_{i2}	-0.0100***	-0.0187***	-0.00179***	0.0283***	0.00224***
	(0.00146)	(0.00134)	(0.000335)	(0.000751)	(0.000776)
γ_{i3}	-0.00379***	-0.00179***	-0.000467	0.00287***	0.00319***
	(0.000674)	(0.000335)	(0.000632)	(0.000276)	(0.000573)
γ_{i4}	-0.0245***	0.0283***	0.00287***	0.00455***	-0.0112***
	(0.00110)	(0.000751)	(0.000276)	(0.000809)	(0.000625)
γ_{i5}	0.00404***	0.00224***	0.00319***	-0.0112***	0.00174
	(0.00153)	(0.000776)	(0.000573)	(0.000625)	(0.00137)
β_i	-0.0373***	-0.00362***	0.00131***	-0.00243***	-0.00513***
	(0.000908)	(0.000441)	(8.95e-05)	(0.000440)	(0.000225)
θ_i (D)	-0.0186***	-0.000732	0.00113**	-0.0190***	-0.000492
Big earthquake	(0.00544)	(0.00260)	(0.000522)	(0.00257)	(0.00132)
ρ_i (A)	0.0121	0.00924***	-0.00283***	-0.00157	0.00402**
Big earthquake	(0.00742)	(0.00354)	(0.000704)	(0.00350)	(0.00178)
θ_i (D)	0.00429	-0.0102***	0.000676	0.00533**	0.00230**
Small earthquake	(0.00442)	(0.00211)	(0.000427)	(0.00209)	(0.00108)
ρ_i (A)	0.0161	0.00788	0.000466	-0.000149	0.00120
Small earthquake	(0.0117)	(0.00558)	(0.00111)	(0.00552)	(0.00281)
θ_i (D)	-0.0218***	-0.00296	0.000116	-0.0191***	-0.00549***
Floods	(0.00383)	(0.00186)	(0.000378)	(0.00182)	(0.000950)
ρ_i(A)	0.00529	0.000650	-0.000395	-0.00378	0.00315
Floods	(0.0106)	(0.00505)	(0.00100)	(0.00500)	(0.00254)
σ_i	-0.0416***	-0.00972***	3.96e-05	-0.00996***	-0.00684***
(Urban)	(0.00140)	(0.000669)	(0.000141)	(0.000659)	(0.000354)
Observation	19,574	19,574	19,574	19,574	19,574

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Table 5.15 presents the result of the LA-AIDS model from the impact of specific natural disasters on food shares. Similar to Table 5.13 above, almost all parameters are significant at 1%. Almost all A variables from each type of disasters are not significantly correlated with the food shares. Only A for big earthquakes in vegetables, meat and oil shares are significant. Vegetables and oil shares are positively correlated with A but meat share is negatively correlated with A. In addition, for D variables from each type of disasters, there are several values with negative and significant correlation to household food shares, and few are positive. For big earthquake, only D in rice and fish shares has negative sign and is significant. For small earthquake, vegetables share has negative sign and is significant, while fish and oil shares has positive sign. For floods, D in rice, fish and oil shares are negative. Those phenomena could be true because different type of disasters have different impacts on different foods.

5.7.3. Price and Expenditure Elasticities

Table 5.16 shows the price and total expenditure elasticities obtained from the LA-AIDS estimates in Table 5.14. For price elasticities, all values in bold are own-price elasticities and other coefficients in the matrix of commodities are cross-price elasticities. All own-price elasticities are negative, as we expected from the theory of demand.

Rice is price inelastic as expected because it is a staple good. Fish is also price inelastic. Vegetables and meat are price elastic. Oil is price inelastic reflecting its status as a necessity. For cross-price elasticities, negative values show that both commodities are complements, while positive values indicate that both commodities are substitutes. For instance, rice has a complementary relationship with fish (-0.620), and meat has a substitution relationship with fish (0.073). In expenditure elasticities for rice, when incomes increase by 10%, households would like to increase expenditure on rice by approximately 8%. In addition to rice, when incomes increase by 10%, households would like to spend more on vegetables, meat and oil, by around 9%. Fish has a unit total expenditure elasticies.

Table 5.16: Price and expenditure demand elasticities

Price elasticities	Rice	Vegetables	Meat	Fish	Oil	Other
Rice	**-0.650*****	-0.071***	-0.034***	-0.211***	0.045***	-0.079**
	(0.024)	(0.013)	(0.006)	(0.010)	(0.014)	(0.033)
Vegetables	-0.164***	**-1.306*****	-0.030***	0.483***	0.032**	-0.015
	(0.025)	**(0.023)**	(0.006)	(0.013)	(0.013)	(0.039)
Meat	-1.733***	-0.799***	**-1.231*****	1.234***	1.394***	0.134
	(0.292)	(0.142)	**(0.280)**	(0.119)	(0.245)	(0.508)
Fish	-0.620***	0.717***	0.073***	**-0.873*****	-0.283***	-0.014
	(0.028)	(0.019)	(0.007)	**(0.021)**	(0.016)	(0.043)
Oil	0.194***	0.088***	0.135***	-0.460***	**-0.907*****	-0.051
	(0.063)	(0.031)	(0.024)	(0.026)	**(0.056)**	(0.096)
Other	1.972***	0.371**	0.086	-1.173***	-1.281***	**-0.975***
	(0.302)	(0.149)	(0.281)	(0.125)	(0.253)	**(0.522)**
Expenditure	0.818***	0.897***	0.938***	1.036***	0.916***	1.041***
Elasticities	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)	(0.018)
Budget shares	0.109	0.058	0.051	0.039	0.024	0.720

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; All values on bold are own price elasticities; $\sum_{i=1}^{n} w_i = 1; \sum_{i=1}^{n} w_i \eta_i = 1; -w_j = \sum_{i=1}^{n} w_i \in_{ij}$

For the effect of disasters on households' standard of living, we used the information from our price estimation in Table 5.13 without controlling for market price to get the total effect of a disaster on the price that households pay for their foods. As we have discussed in Section 5.6.4 of this chapter, we used equation 5.28 to estimate the impact of disasters on the standard of living. By assuming that prices before disasters are 1, and prices after disasters are 1 plus the change in price that we obtained from our price estimation, we can calculate the effect of disasters on the standard of living using indirect utility function. We classified the standard of living into three levels: poorest, poor and rich. For the poor standard of living, as an extreme expenditure value of the poorest, we pick the minimum value of household expenditure at approximately RP 15,000 per month. Another expenditure value for comparison is the poverty line from the Central Bureau of Statistics with RP 250,000 per month. For the rich standard of living, we used the expenditure measure of RP 5 million per month. The effect of disasters of each level of households' standard of living is in Table 5.17. For the poorest households, their living standard is lower by 2.42% and for the poor households it is lower by 2.22% than their living standard before the disasters. On the other hand, for the rich households, their standard living is lower by 2% than before the disasters. As we expected, poor households suffered more than rich households, although the differences are small. The overall effects of disasters are small compared to average annual changes in the incomes on average. Thus we can conclude that there is no different effect of disasters in term percentage terms between the poor and the rich on income. This effect was measured as medium term effect that may be smaller than immediate effects.

Table 5.17: The effect of disasters on living standard

	Monthly expenditure (RP)	Effect of Disasters
Poorest	15,000	-2.42%
Poor	250,000*	-2.22%
Rich	5,000,000	-2.00%

Note: Note: 1 US$ = RP 10,000; * Indonesian poverty line on July 2012

5.8. Conclusion

This paper finds that there are no significant effects of disasters on total household expenditures for households living in disasters regions, whether they are affected directly by disasters or not. In the case of food expenditures, for households who are affected directly by disasters, there are negative and significant impacts of disasters on own-produced expenditures, but a positive impact on market-purchased expenditures. For educational expenditures, only households who are affected directly by disasters have lower educational expenditures. Furthermore, there is no significant impact of disasters on wages. In addition, the results show that only large natural disasters are associated with lower household expenditures, so the different types of disasters have different effects on household expenditures. In comparison with the results that control for prices, we obtained the net effects of disasters on household expenditures in addition to their impact on prices. In general there is negative and significant impact of disasters on expenditures after controlling for prices.

In the case of food demand estimates, the results show that rice and oil have price inelastic demand, while vegetables, meat and fish are price elastic. In addition, the total expenditure elasticity of demand for rice is less elastic than other foods at approximately 0.8. Expenditure elasticity of demand for vegetables, meat and oil are about 0.9, while expenditure elasticity for fish is unity. Using the prices, our estimates suggests that the impact of disasters on living standards are more negative for poor households than for rich households, although the difference is quite small. The small estimated price impact in associated with disasters suggests that disaster relief is relatively effective. However we are not able to estimate what the effect would have been in the absence of disasters relief.

Chapter 6

Conclusion and Policy Implications

This thesis contains a series of related studies about the human capital outcomes for children arising from school subsidy reform and natural disasters. The first study is about an evaluation of the impact of the school operational assistance program on child test scores. The second is an examination of the impact of natural disasters on child test scores and child health. The third is a study on the impact of disasters on household expenditures and food demand. The last study is indirectly related to human capital outcomes for children through educational expenditures, as well as on food demand. All studies in this thesis rely on the Indonesia Family Life Survey data 2000 and 2007.

In Chapter 3, an attempt was made to look at the impact of government policy on school subsidy, the school operational assistance program (BOS), on children's outcomes. All the estimation using OLS, IV and PSM methods suggest that the BOS program has a positive and significant effect on child test scores. Students who receive subsidies have higher test score. OLS estimation suggested that test scores can increase by 0.358 points, and IV estimation resulted in a much larger value of 3.3 points. PSM also suggested that the BOS program in Indonesia raises test scores by 0.26 points. We interpret the IV results as a local average treatment effect. Overall, in the early program, BOS successfully improved student performance. We also produced some suggestive estimates of a long-term effect, because child test scores are associated with higher future earnings.

Chapter 4 examined the impact of disasters on child test scores and child health, and Chapter 5 inspected the impact of disasters on household expenditure and food demand. In chapter 4, we used a DID model to predict the missing counterfactual. For child health, we used two types of data: child height under 5, and self-reported general health condition. In addition to the DID estimates of the impact of disasters on child health analysis we also used zero inflated negative binomial, and also ordered logit model for analysing the self-reported information on child health. The results confirm that child test scores are significantly affected by disasters, but there are no significant impacts of disasters on child health.

This study finds that child test scores are significantly affected by disasters, but there are no serious impacts from disasters on child health. For child test scores outcomes, natural disasters affect all child test scores of the children in disaster regions, both those who are affected and those who are not affected directly by disasters, by reducing their test score. Those who are affected by disasters had an additional lower test score than those who were not affected. Moreover, children who took the test just after the disaster have a lower test score than children who took the test more than a year after the disaster. There are also different impacts of different types of natural disasters and only terrifying and destructive natural disasters are associated with lower test scores for all children in the disaster region.

For child health outcome, we found that disasters have no serious impacts on child health. This finding is confirmed by all the estimation results using height of child or self-reported health measures. For height of child, none of the children who have been affected by disasters have a lower height or growth compared to those who are not affected by disasters. The same result is obtained on the impact of specific natural disasters on child health. The result from self-reported health data is also similar to results from the height data. Only the dependent variable which uses last year's health condition has a significant impact from disasters. It indicates that children in a disaster region and who are affected by disaster have a bigger probability of being unhealthy.

Finally in Chapter 5, for estimation, we employed a difference in differences (DID) model in this chapter to estimate the total impact of disasters on various types of household expenditures. In the DID model we did not control the price of goods. For comparison, we used a Linear Approximate Almost Ideal Demand System (LA-AIDS) model to estimate the net impact of disasters on expenditures, as in LA-AIDS model we controlled for the price of foods. Furthermore, LA-AIDS model also estimated price elasticity of demand and expenditure elasticity of demand. Those two elasticities explained the pattern of food consumption, which is very important for economic analysis.

This chapter finds that there are no significant total effects of disasters on total household expenditures for households living in disaster regions, whether they are affected directly by the disasters or not. In the case of food expenditures, for households who are affected directly by disasters there are negative and significant impacts of disasters on own- produced expenditures, but a positive impact on market-purchased expenditures. For educational expenditures, only households who are affected directly by disasters have lower educational expenditures. Furthermore, there is positive and significant impact of disasters on wages for those households in disaster regions who were not directly affected by disasters. This indicates that for survivors, there was a shock positive to labour demand. Furthermore, looking at the impact of disasters on living standards, poor households are more likely to have a greater negative impact than rich households, although the effect is quite small. Overall, there is no impact of disasters on total household expenditures, but we found net negative impact of expenditures by controlling for prices.

Overall, there is negative impact of disasters on educational expenditures, and no impact of disasters on total household expenditures. Yet, we found a net negative impact of disasters on expenditures by controlling for prices. Hence, in order to maintain children's education, especially for those who went to primary school and secondary schools, the Government should pay attention to the schooling process soon after a disaster, when conditions return to normal, since it is possible for some households to decide not to send their children to school, as they do not have funding for educational costs such as transportation costs and pocket money. Moreover, for household consumption, especially food consumption, in the time of disasters, controlling the price of goods to be stable is very important to help support households to maintain consumption at the time of disasters, as disasters cause the prices of goods to increase.

This thesis contributes to the international literature in this area in several aspects. First, compared to other literature generally, this study uses survey data with self-reported information. In Chapter 3, this study uses self-reported information on whether children get school subsidies from the government. This allows us to estimate the impact of the treatment rather than the intention to treat. Chapters 4 and 5 use self-reported data on whether they are affected by disasters or not. In the main data set that is used in this thesis, the IFLS survey, individuals are categorized as affected by the disasters if they reported that their households experienced death or major injuries to a household member, direct financial loss to the household, or relocation of a household member. To the best of my knowledge, almost all earlier studies defined an affected individual only by measuring the policies or shock before and after, and there is no definition that describes an individual as affected or unaffected.

Second, this study used a measure of school quality, test scores, as a measure of educational outcomes, while most of the earlier studies used a quantity measure of schooling, such as school enrolment, school attendance, number of years completed or drop-out rate. Chapter 3 examines the impact of school subsidies on test scores, and Chapter 4 investigates the impact of disasters on child test scores.

Thirdly, the BOS program is an example of a specific school subsidy program aiming to support basic education in Indonesia. The subsidy for each student who is eligible is distributed to the school directly and will be managed by the school for operational expenses so that the students will be free from all kinds of fees during their schooling. The students themselves only receive a small amount of money for their transportation allowance. An evaluation of this school subsidy policy may also have relevance for other countries considering adopting similar ideas.

Fourthly, in Chapter 4, we examine the impact of disasters across the distribution of test scores using Quantile Regression, so we can see in detail the effects of disasters by groups of outcomes. Fifth, this study presents the impact of disasters on child health using two different measures of child health: height of child as an objective measure and self-reported health condition as a subjective measure. The purpose of using these two measures that height is a permanent effect whereas self-reported health is likely to be a short effect.

Sixth, in Chapter 5, compared to other literature that discusses the impact of disasters on expenditure or budget, this study uses a variety of data of household expenditures and also of income (wages). In addition, regarding food expenditures, we allow for those who get food from market purchases and those who get food from their own production from their farm. Seventh, we also investigate the net effect of disasters on expenditures of main foods, such as rice, vegetable, fish and meat. Another important contribution is about the consequences of natural disasters on food demand. Here, the impact of disasters can be manifested in two ways: through increases in the price of goods and through an affect independent of food prices. Lastly, we also provided the impact of disasters on living standards regarding different levels of household expenditure.

Furthermore, we realize that there is also a limitation of our study. The availability of IFLS data is the first thing that we should consider about. For analysis the impact of BOS on child test score, we only have short period observation since BOS was implemented in 2005. In addition, for the impact of natural disasters on child test scores and child health are also used short period of time. Although we can see the change of environment that surrounds children, such as policies or shocks, can affect their outcome in the short term. The results of these, imply crucial inputs in terms of the impacts of government policy (BOS) and natural shocks (disasters) that children experienced. Moreover, an important area for further research regarding human capital outcomes for children, especially on child education and health that it could be worth measuring the impact of disasters on children's outcome in the long term, if there is enough historical data of disasters, and also children's earnings in adulthood. Regarding child health, we can also measure the impact of disasters on health in the long term when the child becomes an adult. Moreover, if we have panel data with more time series, it would be nice to measure the impact of disasters on permanent and transitory income.

Moreover, for analysis the impact of BOS on child test scores, it is also possible to re-estimate and focus using Instrumental Variable regression with comprehensive analysis. For example, we can try to use any possible instrument for BOS that we can generate such as an interaction between village decision maker and the original poverty index, or we can try to estimate poverty index using ordered logit/probit first, and then use the result from ordered logit/probit as poverty index. Furthermore, for analysis the impact of disasters on children outcomes and household expenditure, we can only focus on the biggest disasters (big earthquake), since this disaster resulted the most significant impact than other type of disasters.

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Appendix

Table A3.1 is OLS estimation using child test score with imputation for missing values.

Table A3.1: The impact of BOS on child test score

Dependent variable: child test score	(1)	(2)
BOS	0.356***	1.818**
	(0.0838)	(0.863)
Poor		
Poor (satisfied 1 criteria)	-0.106	-0.109
	(0.0901)	(0.0902)
Poor (satisfied 2criteria)	-0.198**	-0.199**
	(0.0883)	(0.0883)
Poor (satisfied 3 criteria)	-0.192**	-0.187**
	(0.0907)	(0.0908)
Poor (satisfied 4 criteria)	-0.130	-0.130
	(0.0964)	(0.0967)
Poor (satisfied 5 criteria)	-0.229**	-0.242**
	(0.111)	(0.112)
Poor (satisfied 6+ criteria)	-0.0573	-0.102
	(0.171)	(0.173)
BOS*Poor		
BOS*Poor (satisfied 1 criteria)		-1.346
		(0.890)
BOS*Poor (satisfied 2criteria)		-1.453*
		(0.874)
BOS*Poor (satisfied 3 criteria)		-1.665*
		(0.879)
BOS*Poor (satisfied 4 criteria)		-1.473*
		(0.888)
BOS*Poor (satisfied 5 criteria)		-1.155
		(0.933)
BOS*Poor (satisfied 6+ criteria)		-1.763*
		(0.899)
male	-0.160***	-0.160***
	(0.0284)	(0.0284)
urban	0.153***	0.153***
	(0.0304)	(0.0305)
rank_HCIprov	-0.0109***	-0.0109***
	(0.00229)	(0.00229)
hhsize	-0.0551***	-0.0551***

	(0.00820)	(0.00820)
lhhfood	0.0476*	0.0480*
	(0.0270)	(0.0270)
Father secondary	0.153***	0.151***
	(0.0393)	(0.0394)
Father higher education	0.285***	0.284***
	(0.0768)	(0.0768)
Mother secondary	0.393***	0.394***
	(0.0459)	(0.0459)
Mother higher education	0.489***	0.488***
	(0.117)	(0.117)
Public school	-0.251***	-0.251***
	(0.0360)	(0.0360)
Java	0.158***	0.158***
	(0.0292)	(0.0292)
Constant	6.276***	6.273***
	(0.380)	(0.380)
Observations	7,215	7,215
R-squared	0.072	0.073

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.1 is DID estimation for the impact of disasters on child test scores using child test score with imputation for missing values.

Table A4.1 Results on the Impact of Disasters on child test scores

VARIABLES	(1) Test score	(2) Test score
D	-1.061***	-1.079***
	(0.335)	(0.329)
A	-0.923***	-0.986***
	(0.197)	(0.201)
age		0.000819
		(0.0155)
urban		0.306***
		(0.0241)
male		-0.0701*
		(0.0375)
Father secondary		-0.00268
		(0.0489)
Father higher education		0.314***
		(0.0601)
Mother secondary		0.170***
		(0.0489)
Mother higher education		0.447***
		(0.123)
Constant	5.883***	5.395***
	(0.150)	(0.421)
Year dummies	yes	yes
Region dummies	yes	yes
Observations	9,867	9,858
R-squared	0.072	0.103

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5.1 to A5.4 are LA-AIDS Estimation using original price of goods at household level (without instrumented price of goods at household level).

Table A5.1: Parameters of LA-AIDS Demand System with Homogeneity and Symmetry Restriction

	share equations of total expenditures				
	1	2	3	4	5
Parameters	rice	veg	meat	fish	oil
γ_{i1}	0.0147***	-0.00356***	0.000166	-0.0100***	-0.00132***
	(0.000961)	(0.000535)	(0.000151)	(0.000560)	(0.000420)
γ_{i2}	-0.00356***	-0.00265***	-0.000166**	0.00722***	-0.000848***
	(0.000535)	(0.000467)	(8.47e-05)	(0.000349)	(0.000236)
γ_{i3}	0.000166	-0.000166**	7.82e-05	0.000630***	-0.000708***
	(0.000151)	(8.47e-05)	(0.000127)	(9.24e-05)	(0.000129)
γ_{i4}	-0.0100***	0.00722***	0.000630***	0.00649***	-0.00432***
	(0.000560)	(0.000349)	(9.24e-05)	(0.000503)	(0.000248)
γ_{i5}	-0.00132***	-0.000848***	-0.000708***	-0.00432***	0.00719***
	(0.000420)	(0.000236)	(0.000129)	(0.000248)	(0.000381)
β_i	-0.0350***	-0.00697***	0.00111***	-0.00202***	-0.00434***
	(0.000901)	(0.000428)	(7.02e-05)	(0.000443)	(0.000217)
θ_i	-0.00920***	-0.0102***	8.32e-05	-0.00955***	-0.000562
(D)	(0.00265)	(0.00126)	(0.000204)	(0.00129)	(0.000631)
ρ_i	0.00925*	0.00977***	-0.000930**	-0.00696***	0.00391***
(A)	(0.00490)	(0.00232)	(0.000375)	(0.00238)	(0.00116)
σ_i	-0.0428***	-0.00890***	-0.000269**	-0.0112***	-0.00675***
(urban)	(0.00138)	(0.000656)	(0.000107)	(0.000673)	(0.000330)
Observation	19,574	19,574	19,574	19,574	19,574

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Table A5.2: Parameters of LA-AIDS Demand System with Homogeneity and Symmetry Restriction on The Impact of Specific Natural Disasters

	share equations of total expenditures				
	1	2	3	4	5
Parameters	rice	veg	meat	fish	oil
γ_{i1}	0.0148***	-0.00365***	0.000160	-0.00996***	-0.00133***
	(0.000962)	(0.000535)	(0.000151)	(0.000560)	(0.000420)
γ_{i2}	-0.00365***	-0.00264***	-0.000145*	0.00727***	-0.000833***
	(0.000535)	(0.000467)	(8.49e-05)	(0.000349)	(0.000236)
γ_{i3}	0.000160	-0.000145*	7.92e-05	0.000632***	-0.000726***
	(0.000151)	(8.49e-05)	(0.000127)	(9.24e-05)	(0.000129)
γ_{i4}	-0.00996***	0.00727***	0.000632***	0.00634***	-0.00429***
	(0.000560)	(0.000349)	(9.24e-05)	(0.000502)	(0.000248)
γ_{i5}	-0.00133***	-0.000833***	-0.000726***	-0.00429***	0.00717***
	(0.000420)	(0.000236)	(0.000129)	(0.000248)	(0.000382)
β_i	-0.0350***	-0.00683***	0.00112***	-0.00221***	-0.00432***
	(0.000903)	(0.000429)	(7.04e-05)	(0.000443)	(0.000218)
θ_i (D)	-0.0145***	-0.00242	0.00155***	-0.0218***	-0.000531
Big earthquake	(0.00546)	(0.00259)	(0.000419)	(0.00265)	(0.00130)
ρ_i (A)	0.0129*	0.00672*	-0.00275***	-0.000397	0.00449**
Big earthquake	(0.00745)	(0.00353)	(0.000570)	(0.00361)	(0.00177)
θ_i (D)	0.00768*	-0.0137***	0.000121	0.00518**	0.00311***
Small earthquake	(0.00443)	(0.00210)	(0.000339)	(0.00215)	(0.00105)
ρ_i (A)	0.0152	0.00621	0.000646	0.00243	0.000996
Small earthquake	(0.0117)	(0.00556)	(0.000899)	(0.00570)	(0.00279)
θ_i (D)	-0.0192***	-0.0114***	-0.000644**	-0.0147***	-0.00331***
Floods	(0.00382)	(0.00182)	(0.000294)	(0.00186)	(0.000910)
ρ_i(A)	0.00490	-0.00113	-0.000254	-0.00191	0.00331
Floods	(0.0106)	(0.00503)	(0.000813)	(0.00515)	(0.00252)
σ_i	-0.0419***	-0.00899***	-0.000245**	-0.0105***	-0.00654***
(urban)	(0.00140)	(0.000661)	(0.000107)	(0.000677)	(0.000333)
observation	19,574	19,574	19,574	19,574	19,574

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Table A5.3: Price and expenditure demand elasticities

Price elasticities	rice	vege	meat	fish	oil	other
rice	**-0.829**	-0.014	0.002	-0.080	-0.005	-0.074
	(0.009)	(0.005)	(0.001)	(0.005)	(0.004)	(0.012)
vege	-0.049	**-1.039**	-0.003	0.130	-0.012	-0.028
	(0.009)	**(0.008)**	(0.001)	(0.006)	(0.004)	(0.014)
meat	0.020	-0.102	**-0.967**	0.259	-0.324	0.113
	(0.067)	(0.037)	**(0.056)**	(0.041)	(0.057)	(0.118)
fish	-0.252	0.189	0.016	**-0.831**	-0.110	-0.012
	(0.015)	(0.009)	(0.002)	**(0.013)**	(0.006)	(0.022)
oil	-0.036	-0.025	-0.030	-0.176	**-0.691**	-0.043
	(0.018)	(0.010)	(0.005)	(0.010)	**(0.016)**	(0.029)
other	0.146	-0.009	-0.020	-0.302	0.141	**-0.956**
	(0.072)	(0.041)	(0.056)	(0.045)	(0.060)	**(0.125)**
Exp elasticities	0.818	0.897	0.938	1.036	0.916	1.041
	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)	(0.018)
Budget shares	0.109	0.058	0.051	0.039	0.024	0.720

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; All values on bold are own price elasticities; $\sum_{i=1}^{n} w_i = 1; \sum_{i=1}^{n} w_i \eta_i = 1;\ -w_j = \sum_{i=1}^{n} w_i \in_{ij}$

Table A5.4: The effect of disasters on living standard

	Monthly expenditure (RP)	Effect of Disasters
Poorest	15,000	-2.87%
Poor	250,000*	-2.64%
Rich	5,000,000	-2.38%

Note: Note: 1 US$ = RP 10,000; * Indonesian poverty line on July 2012

Table A5.5 to A5.8 are LA-AIDS Estimation using price of goods at household level by instrumented using price of goods at market level without imputation for missing values.

Table A5.5: Parameters of LA-AIDS Demand System with Homogeneity and Symmetry Restriction

	share equations of total expenditures				
	1	2	3	4	5
Parameters	rice	veg	meat	fish	oil
γ_{i1}	0.0107*	-0.000788	0.000134	-0.00864***	-0.00139
	(0.00642)	(0.00395)	(0.00251)	(0.00322)	(0.00345)
γ_{i2}	-0.000788	-0.0353***	-0.0105***	0.0382***	0.00850***
	(0.00395)	(0.00381)	(0.00177)	(0.00270)	(0.00211)
γ_{i3}	0.000134	-0.0105***	-0.00888***	0.00605***	0.0132***
	(0.00251)	(0.00177)	(0.00201)	(0.00199)	(0.00127)
γ_{i4}	-0.00864***	0.0382***	0.00605***	-0.00394	-0.0316***
	(0.00322)	(0.00270)	(0.00199)	(0.00318)	(0.00189)
γ_{i5}	-0.00139	0.00850***	0.0132***	-0.0316***	0.0113***
	(0.00345)	(0.00211)	(0.00127)	(0.00189)	(0.00249)
β_i	-0.0301***	-0.00694***	-0.00360***	-0.00597***	-0.00461***
	(0.00130)	(0.000543)	(0.000710)	(0.000545)	(0.000352)
θ_i	-0.0111***	0.00101	0.00002	-0.00827***	0.00157
(D)	(0.00397)	(0.00186)	(0.00218)	(0.00174)	(0.00116)
ρ_i	-0.00005	0.00152	-0.00647	-0.00274	0.000621
(A)	(0.00779)	(0.00322)	(0.00425)	(0.00322)	(0.00208)
σ_i	-0.0483***	-0.0105***	-0.00203	-0.0132***	-0.00370***
(urban)	(0.00265)	(0.00122)	(0.00149)	(0.00123)	(0.000843)
Observation	5,849	5,849	5,849	5,849	5,849

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Table A5.6 : Parameters of LA-AIDS Demand System with Homogeneity and Symmetry Restriction on The Impact of Specific Natural Disasters

	share equations of total expenditures				
	1	2	3	4	5
Parameters	rice	veg	meat	fish	oil
γ_{i1}	0.0144**	-0.00373	-0.000731	-0.00656**	-0.00335
	(0.00686)	(0.00432)	(0.00258)	(0.00334)	(0.00365)
γ_{i2}	-0.00373	-0.0406***	-0.00993***	0.0414***	0.0129***
	(0.00432)	(0.00420)	(0.00184)	(0.00286)	(0.00228)
γ_{i3}	-0.000731	-0.00993***	-0.00768***	0.00435**	0.0140***
	(0.00258)	(0.00184)	(0.00204)	(0.00199)	(0.00131)
γ_{i4}	-0.00656**	0.0414***	0.00435**	-0.00475	-0.0344***
	(0.00334)	(0.00286)	(0.00199)	(0.00318)	(0.00193)
γ_{i5}	-0.00335	0.0129***	0.0140***	-0.0344***	0.0109***
	(0.00365)	(0.00228)	(0.00131)	(0.00193)	(0.00258)
β_i	-0.0302***	-0.00715***	-0.00382***	-0.00557***	-0.00455***
	(0.00132)	(0.000548)	(0.000719)	(0.000547)	(0.000356)
θ_i Big earthquake	-0.0345***	-0.000632	-0.0103*	-0.0190***	0.000265
	(0.0101)	(0.00419)	(0.00552)	(0.00416)	(0.00273)
ρ_i Big earthquake	0.00408	0.00352	-0.00141	0.000698	0.00223
	(0.0155)	(0.00641)	(0.00847)	(0.00635)	(0.00414)
θ_i Small earthquake	-0.00400	-0.00522**	0.000875	0.00395	0.00406**
	(0.00596)	(0.00256)	(0.00324)	(0.00248)	(0.00163)
ρ_i Small earthquake	0.0164	0.00602	-0.00669	0.000424	-0.00103
	(0.0141)	(0.00584)	(0.00770)	(0.00578)	(0.00378)
θ_i	-0.0100*	0.00908***	0.00231	-0.0175***	-0.00180
Floods	(0.00537)	(0.00261)	(0.00295)	(0.00235)	(0.00161)
ρ_i	-0.000552	-0.000421	-0.00362	-0.00460	-0.000460
Floods	(0.0126)	(0.00521)	(0.00688)	(0.00516)	(0.00337)
σ_i	-0.0484***	-0.0112***	-0.00167	-0.0123***	-0.00281***
	(0.00270)	(0.00126)	(0.00150)	(0.00124)	(0.000861)
Observation	5,849	5,849	5,849	5,849	5,849

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%

Table A5.7 : Price and expenditure demand elasticities

Price elasticities	rice	vegetable	meat	fish	oil	other
Rice	**-0.872*****	0.009	0.015	-0.068***	-0.006	-0.078
	(0.059)	(0.036)	(0.023)	(0.029)	(0.032)	(0.085)
Vegetable	-0.001	**-1.599*****	-0.175***	0.660***	0.149***	-0.033
	(0.068)	**(0.066)**	(0.031)	(0.046)	(0.036)	(0.115)
Meat	0.010	-0.201***	**-1.169*****	0.120***	0.259***	-0.020
	(0.049)	(0.034)	**(0.039)**	(0.039)	(0.025)	(0.085)
Fish	-0.206**	0.991***	0.164***	**-1.096*****	-0.811***	-0.043
	(0.083)	(0.070)	(0.051)	**(0.082)**	(0.049)	(0.153)
Oil	-0.038	0.373***	0.574***	-1.340***	**-0.515*****	-0.055
	(0.147)	(0.090)	(0.054)	(0.080)	**(0.106)**	(0.225)
Other	0.106	-0.574***	-0.410***	0.724***	-0.076	**-0.771****
	(0.198)	(0.141)	(0.093)	(0.133)	(0.129)	**(0.319)**
Expenditure	0.724***	0.881***	0.930***	0.846***	0.804***	1.071***
elasticities	(0.012)	(0.009)	(0.014)	(0.014)	(0.015)	(0.029)
Budget shares	0.109	0.058	0.051	0.039	0.023	0.719

Note: Standard errors in parentheses and asterisk denote statistical significance: *** 1%, ** 5%, * 10%; All values on bold are own price elasticities; $\sum_{i=1}^{n} w_i = 1; \sum_{i=1}^{n} w_i \eta_i = 1; -w_j = \sum_{i=1}^{n} w_i \in_{ij}$

Table A5.8: The effect of disasters on living standard

	Monthly expenditure (RP)	Effect of Disasters
Poorest	15,000	-2.53%
Poor	250,000*	-2.33%
Rich	5,000,000	-2.11%

Note: Note: 1 US$ = RP 10,000; * Indonesian poverty line on July 2012